THE PRIVATE AND EXTERNAL COSTS OF GERMANY'S NUCLEAR PHASE-OUT

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Abstract
Many countries have phased out nuclear power in response to concerns about nuclear waste and the risk of nuclear accidents. This paper examines the shutdown of more than half of the nuclear production capacity in Germany after the Fukushima accident in 2011. We use hourly data on power plant operations and a machine learning approach to estimate the impacts of the phase-out policy. We find that reductions in nuclear electricity production were offset primarily by increases in coal-fired production and net electricity imports. Our estimates of the social cost of the phase-out range from €3 to €8 billion per year. The majority of this cost comes from the increased mortality risk associated with exposure to the local air pollution emitted when burning fossil fuels. Policymakers would have to significantly overestimate the risk or cost of a nuclear accident to conclude that the benefits of the phase-out exceed its social costs. We discuss the likely role of behavioral biases in this setting, and highlight the importance of ensuring that policymakers and the public are informed about the health effects of local air pollution. (JEL: Q41, Q53, C53)

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC 2018) and the International Energy Agency (IEA 2019) both envisage nuclear power continuing to play an

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important role in mitigating climate change over the coming decades. This is because nuclear electricity generation produces minimal carbon emissions under normal operating conditions (Markandya and Wilkinson 2007). In contrast, burning fossil fuels to produce electricity is known to emit both global pollutants that contribute to climate change and local air pollutants that have negative consequences on human health (NRC and NAS 2010; Jaramillo and Muller 2016; Deschenes, Greenstone, and Shapiro 2017; Holland et al. 2018).

Despite this, many countries have explicit policies in place to phase-out nuclear power entirely, including Germany, Belgium, Spain, Switzerland, and South Korea. These phase-out policies were implemented primarily in response to concerns about long-term solutions for storing nuclear waste and public fears of catastrophic nuclear accidents. These fears intensified considerably following the incidents at Three Mile Island in 1979, Chernobyl in 1986, and Fukushima in 2011.

The decision to phase-out nuclear production in many countries seems to suggest that the expected costs of nuclear power exceed its benefits. Yet, it has proven difficult to empirically quantify the full range of economic and environmental impacts from large-scale shifts away from nuclear power. This paper aims to fill this important gap by documenting how the phase-out of nuclear power in Germany affected market and environmental outcomes.

The context of Germany's nuclear phase-out affords us several advantages over previous research studying closures of nuclear power plants. First, and most importantly, Germany shut down over 12 GW of nuclear production capacity during this period, with two thirds of this occurring over a few months in 2011. This is far larger than the reductions in capacity studied by previous research that focused on the shutdown of a small number of nuclear plants in the United States (Davis and Hausman 2016; Severnini 2017; Adler, Jha, and Severnini 2020). Second, Germany plans to shut down all of its remaining nuclear reactors by 2022. Our study thus provides timely and policy-relevant information on the consequences of Germany's nuclear phase-out moving forward. Third, studying electricity markets in the European context gives us the opportunity to examine how cross-border trade was impacted by a large shock to production in one country. Finally, Germany's nuclear phase-out was the direct result of political actions taken following extensive anti-nuclear campaigning in Germany as well as a sudden increase in the perceived risk of nuclear power following the Fukushima accident in Japan (Goebel et al. 2015). Importantly, the phase-out was not caused by changes in the economic or environmental conditions pertaining to nuclear production in Germany.

This paper adds to the relatively small literature that explores the effects of the nuclear phase-out on the German electricity sector. For instance, both Traber and Kemfert (2012) and Knopf et al. (2014) used mixed economic–engineering models of the power sector to forecast changes to capacity investments, electricity prices, and carbon emissions. More recently, Grossi, Heim, and Waterson (2017) use an event study framework to econometrically estimate the impact of the initial nuclear plant closures in 2011 on electricity prices over a 3 year window between 2009 and 2012. Another paper by Grossi et al. (2018), focuses on the impacts of the phase-out on electricity prices in neighboring countries. The broad consensus across this small existing literature is that nuclear power was replaced primarily by fossil-fuel-fired production, resulting in higher electricity prices and more carbon emissions.

We expand on this existing literature by estimating the spatially disaggregated impacts of the phase-out on production costs, net electricity imports, and local air pollution. Estimating plant-level changes in output due to the phase-out is especially important because the majority of the social cost of this policy stems from the increases in local air pollution caused by replacing some of the lost output from nuclear sources with coal-fired electricity production. We also do not consider just the initial nuclear reactor closures in 2011. Since our analysis runs to the end of 2019, we incorporate the subsequent incremental shutdowns of nuclear power plants over this period.

To proceed, we use a machine learning framework to estimate each plant's counterfactual output over time under a "no phase-out" scenario. This counterfactual allows us to identify which power plants increased their output in response to the nuclear plant closures. Our approach draws upon a growing literature exploring ways to use machine learning methods to construct counterfactuals (Varian 2014, 2016; Athey et al. 2021; Carvalho, Masini, and Medeiros 2018). A smaller number of papers have applied these techniques to evaluate policies in the energy sector. For instance, Burlig et al. (2020) study an energy efficiency program for schools in California using regularized regression methods to estimate counterfactual electricity consumption patterns. Both Souza (2020) and O'Neill and Weeks (2018) also examine programs aimed at encouraging energy savings, leveraging machine learning methods to construct counterfactuals that can identify important heterogeneity in treatment effects. We focus on a policy that affects electricity producers by altering the dispatch of power plants. Similar in spirit, Abrell, Kosch, and Rausch (2019) use a machine learning framework to predict the counterfactual dispatch of power plants as part of their analysis of the UK's carbon tax.

To conduct our analysis, we combine hourly data on observed power plant operations between 2010 and 2019 with a wide range of related information, including electricity demand, local weather conditions, wholesale electricity prices, fuel prices, and various plant characteristics. We use these data to train a machine learning algorithm that can predict plant operations based on market conditions. This allows us to predict the quantity of electricity produced by each power plant in Germany in each hour-of-sample under two scenarios: one with the nuclear phase-out and one without it. We interpret the difference in market and environmental outcomes between these two scenarios as the impact of the phase-out policy. The results of this estimation procedure indicate that the lost nuclear electricity production due to the phase-out was replaced primarily by coal-fired production and net electricity imports. This phase-out-induced increase in coal-fired production remains sizable and persists through 2019 across a variety of specifications, including a wide range of assumptions regarding the level of investment in renewables caused by the phase-out.

We use the predicted changes in plant-level electricity production due to the nuclear shutdowns to calculate the private and external costs of the phase-out. Our estimates of the social cost of the phase-out to German firms and residents range from €3 to €8 billion per year. The majority of this cost is due to the increased mortality risk from local air pollution exposure as a consequence of the increased use of fossil fuels for electricity production. We also find that the private costs of electricity production and wholesale electricity prices in Germany increased as a consequence of the phase-out, confirming and extending the results from the previous literature over a longer post phase-out period.[1]

Taken together, our analysis suggests that German citizens faced increased electricity prices and greater exposure to local air pollution as a result of the phase-out of nuclear power. The phase-out also made meeting national targets to reduce carbon emissions more challenging. Despite this, the phase-out continues to receive broad support, with more than 81% of German residents in favor of the policy in a 2015 survey (Goebel et al. 2015). Concerns about the risks of nuclear accidents and storing nuclear waste are central to anti-nuclear sentiment, and motivated the decision to phase-out nuclear power (Ethics Commission 2011).

The risks of nuclear power are difficult to quantify. Nevertheless, even the largest estimates of the expected benefits from reducing nuclear risks are much smaller than our estimates of the social costs of the phase-out (D'haeseleer 2013). For the expected benefits of the phase-out to be equal to the lower bound of our estimated social costs, policymakers would have to either exhibit a very high level of risk aversion or view nuclear accidents as being much more likely than the available evidence suggests (Wheatley, Sovacool, and Sornette 2017). Consistent with this, previous research has shown that people tend to greatly overestimate both the probability of a nuclear accident and the expected damages from such an event (Slovic, Fischhoff, and Lichtenstein 1979; Slovic 2010; Slovic and Weber 2010). The decision to phase-out nuclear power therefore suggests a preference for reducing exposure to low probability, highly uncertain, and potentially catastrophic nuclear accidents, even if this leads to relatively moderate damages from exposure to pollution emitted due to the prolonged reliance on fossil-fuel-fired electricity production. Such behavior is consistent with many components of prospect theory, in particular loss aversion and relying on "probability weighting" rather than objective probabilities (Kahneman and Tversky 1979; Barberis 2013).

Nuclear accidents were particularly salient in the immediate aftermath of the Fukushima crisis (Ethics Commission 2011; Goebel et al. 2015; Tanaka and Zabel 2018). By comparison, an incremental increase in mortality risk due to local air pollution exposure is far less salient. Research on the role of framing effects has documented a behavioral bias toward placing increased weight on the more salient aspects of a decision (Kahneman 2003). Consistent with this, policymakers appear to have made no mention of the impact of the phase-out on local air pollution when making their decision (BMWI 2010; Ethics Commission 2011). Further, subsequent studies of the impact of the phase-out have also focused exclusively on electricity

1. Neidell, Uchida, and Veronesi (2019) and He and Tanaka (2019) document increases in mortality stemming from policy-induced increases in retail prices and reductions in electricity consumption following the phase-out of nuclear power in Japan.

prices and carbon emissions (Knopf et al. 2011; Traber and Kemfert 2012; Knopf et al. 2014; Grossi, Heim, and Waterson 2017; Grossi et al. 2018).[2] The omission of local air pollution is especially troubling because the vast majority of the social costs of the phase-out originate from increases in air pollution due to increased output from fossil-fuel plants. This highlights the importance of ensuring that the public are informed about the health costs of local air pollution, and that policymakers incorporate these health costs into their decisions.

2. Background on Nuclear Power in Germany

The first nuclear power stations were built in Germany in the 1960s. Germany's nuclear production capacity expanded rapidly over the next three decades; the last nuclear reactor was commissioned in 1989. Despite no new reactors coming online in the 1990s and 2000s, roughly 25% of Germany's electricity production came from nuclear plants prior to 2011.

Nuclear power has long been controversial in Germany. There were protests as far back as the 1970s at a number of sites where nuclear facilities were either proposed or under construction. However, the Chernobyl disaster in Ukraine in 1986 created a focal point in the politics of nuclear power in Germany. Specifically, radioactive fallout affected much of the country and led to growing public concern. In 1998, the Schröder government took power through a coalition between the Social Democratic Party and the Green Party. Over the next 2 years, the Schröder government banned the construction of new reactors and negotiated a policy of phasing out nuclear power completely. This plan called for all nuclear reactors to be shut down by 2022.

The center-right Merkel government came to power in 2009. This government renegotiated the original phase-out policy by committing to extend the lifetimes of the existing reactors. This revised policy pushed back the shutdown of the last nuclear reactor into the 2030s. The extensions would be 8 years for the eight older reactors built up to and including 1980, and 14 years for the nine newer reactors built after 1980. However, the specter of nuclear disaster rose again due to the Fukushima incident on 11 March 2011. In response, public opposition to nuclear power intensified again, with an estimated 250,000 people taking to the streets nationwide to protest in the days and weeks following 11 March 2011. The resulting political pressure forced the Merkel government to declare a moratorium on planned extensions at existing nuclear power plants almost immediately after the Fukushima incident. In addition, eight older reactors were taken offline for testing.

By May of 2011, German policymakers decided to return to a version of the original plan: phase out all nuclear power by 2022. Specifically, of the seventeen reactors operating in 2011, the eight reactors already temporarily offline were closed

2. We note that the absence of academic studies and discussions by policymakers of the potential impact of the phase-out on local air pollution does not by itself imply that the general public is unaware of this issue.

immediately (8.4 GW of capacity), a ninth reactor was closed in 2015 (1.3 GW), a tenth in 2017 (1.3 GW), an eleventh in 2019 (1.4 GW), and the final six reactors (8.1 GW) will close in 2022. Our sample period ends in 2019. Consequently, our empirical analysis focuses on the closure of the nuclear reactors in 2011, 2015, 2017, and 2019, but does not forecast the impact of the planned closures in 2022.

The phase-out of nuclear power is part of a wide-ranging transformation of Germany's energy sector known as the *Energiewende*. The primary goal of this policy is to reduce Germany's carbon emissions by at least 80% by 2050 relative to 1990 levels (BMWi 2018). To achieve this, Germany has undertaken major investments in renewable electricity production, transmission grid infrastructure, and energy efficiency measures. The sweeping scope of the *Energiewende* policy highlights the importance of accounting for a host of potential time-varying confounders when assessing the impact of the nuclear phase-out. This motivates the development of our machine learning approach.

3. Data Description and Summary Statistics

This paper brings together a wide range of publicly available data on the German power sector. First, we obtain data on the hourly operation of the electricity grid in Germany from the European Network of Transmission System Operators for Electricity (ENTSOE). This includes hourly data on total electricity demand, aggregate electricity production by source type, and imports and exports in and out of Germany at border points. ENTSOE also provide data on unit-level electricity production for all power plants with production capacity greater than 100 MW.

However, the ENTSOE data are only available from 2015 to 2019. In order to study the nuclear phase-out beginning in March 2011, we supplement the ENTSOE data with data on hourly total production by source (e.g., nuclear, coal, natural gas, oil, etc.) from the European Energy Exchange for 2010–2019. A key advantage of our machine learning approach is that it allows us to combine hourly source-level data on electricity production from 2010 to 2019 with data on hourly plant-level output from 2015 to 2019 in order to construct a prediction of each plant's output in each hour-of-sample for the entire 2010–2019 sample period.

We also integrate data from Germany's four different transmission system operators (TSOs) that are each responsible for a different geographical area on the German grid: Amprion, TenneT, TransnetBW, and 50 Hertz. Each TSO reports hourly production from wind and solar sources for the period 2010–2019. The TSOs also provide data at the hourly level on electricity imports and exports in and out of Germany at border points, as well as the hourly total quantity of electricity demanded for their portion of the grid.

We utilize data on hourly wholesale electricity prices for both Germany and neighboring countries. These data are collected by ENTSOE and are accessible through Thomson Datastream.

We construct each fossil-fuel-fired plant's marginal cost in each day using data on input fuel prices and carbon emission prices gathered from the following two sources.

First, Thomson Datastream provides data on daily natural gas prices in Germany. The Intercontinental Exchange lists monthly coal and oil prices as well as the monthly permit prices for carbon dioxide emissions set by the European Union Emissions Trading System (EU ETS).[3] Assumptions on other components of variable costs and fixed costs for all sources (including nuclear, wind, and solar) are taken from a range of industry reports and are discussed in Section 6.2.

Our analysis of the environmental impacts of the nuclear phase-out also combines data from multiple sources. The European Environment Agency (EEA) reports annual carbon dioxide emissions for each power plant that participates in the EU ETS. The EEA also reports annual plant-level data on fuel inputs and local air pollution emissions.[4] Daily station-level weather data comes from Germany's national meteorological service (DWD), and daily ambient air pollution monitor data are from the German Environment Agency (UBA). Finally, we compile other electricity sector data and power plant level characteristics from a variety of different sources (Egerer 2016; Open Power System Data 2018; BNetzA 2020).

Table 1 provides summary statistics for the aggregate electricity sector and by type of plant in 2010 (the first year in our sample) and 2019 (the last year in our sample). The top panel documents the drastic shifts in the electricity production mix over this time period. Nuclear production almost halved while production from renewable resources more than doubled. Production from coal plants declined while production from natural gas plants grew, due primarily to relative changes in coal prices versus natural gas prices as well as increases in carbon permit prices. Since total electricity demand has remained largely flat over the 2010s, the additional production from renewables has also served to expand Germany's position as a net exporter of power to neighboring countries. Online Appendix Figure A.1 presents a more detailed breakdown of the quantity of electricity produced by different types of sources in Germany over 2010–2019.

Table 1 also documents that wholesale electricity prices fell by 30% from 2010 to 2019. The main driver of this decline in wholesale prices was the large increase in zero marginal cost production from wind and solar resources. A secondary driver was the fall in the price of natural gas. Natural gas plants are often the marginal source of generation in Germany, and the average marginal cost of gas-fired production fell by 17% between 2010 and 2019.

While wholesale prices decreased from 2010 to 2019, the revenues earned by plants outside of the wholesale market have increased significantly. Renewables in particular receive guaranteed payments well in excess of the wholesale price. For example, wholesale prices were roughly €37 per MWh in 2019 yet, renewable resources received additional subsidy payments averaging €130 per MWh in this year.[5] Fossil plants also earn sizeable non-market revenues, in large part due to the subsidies paid to combined

3. Specifically, we use the futures price corresponding to the nearest term monthly contract (i.e., the front month futures contract).

4. These data are collected as part of monitoring for the EU Large Combustion Plant Directive (LCPD).

5. These subsidies range from €60 per MWh for onshore wind to as much as €270 per MWh for solar panels (BNetzA 2020).

TABLE 1. Summary statistics.

Production and net imports annual totals (TWh)	2010	2019
Nuclear	134.7	69.5
Hard coal	93.9	53.4
Lignite	130.9	104.2
Gas	53.6	75.5
Oil	1.9	3.1
Hydro, solar, and wind	76.4	193.5
Net electricity imports	–2.4	–33.8
Total number of plants		
Nuclear	15	7
Hard coal	67	56
Lignite	31	34
Gas	176	209
Oil	33	30
Total capacity (GW)		
Nuclear	19.2	9.5
Hard coal	25.8	23.7
Lignite	20.2	21.0
Gas	22.8	26.2
Oil	3.8	3.7
Marginal cost (2019 € per MWh)		
Nuclear	11.2	10.0
Hard coal	46.2	43.6
Lignite	38.8	44.2
Gas	57.2	46.9
Oil	145.8	141.5
Wholesale electricity price (2019 € per MWh)	53.21	37.21

Notes. This table reports summary statistics for Germany's electricity generation sector in 2010 and 2019. Annual electricity production data is taken from BNetzA (2020). If data for 2019 are not yet available, we extrapolate values based on more up-to-date data from Fraunhofer ISE. The power plants in our sample are those listed in BNetzA's Power Plant List, compiled by Open Power System Data (2018). Electricity prices are from ENTSOE and Thomson Reuters. Marginal costs are calculated by the authors based on various sources, full details of which can be found in Section 6.2. All monetary values are in constant 2019 € .

heat and power plants that produce both electricity and useful heat. Due to this dramatic increase in payments made outside of the wholesale market, the prices faced by end-use consumers of electricity in Germany have actually risen from 2010 to 2019 despite the reduction in wholesale electricity prices (BNetzA 2020).

The second and third panels of Table 1 report the total number of plants and the total amount of production capacity at the beginning of 2010 versus the beginning of 2019 for each of the major conventional sources of power in Germany: nuclear, hard coal, lignite, natural gas, and oil. The shutdown of nuclear plants is evident from the decline in both the number of plants and the amount of nuclear capacity.[6] The capacity of fossil-fuel plants has remained largely flat. As documented in the fourth panel of Table 1, outside of renewables, nuclear plants have the lowest marginal costs, followed by lignite, hard coal, natural gas, and lastly the small number of peaking oil plants.

4. Event Study Framework and Results

In response to the Fukishima nuclear accident in Japan, the German government suddenly and unexpectedly shut down eight nuclear reactors on 15 March 2011. We can thus analyze the impact of these closures on market outcomes using the event study framework formulated in Davis and Hausman (2016) and more recently implemented by Grossi, Heim, and Waterson (2017). Specifically, we apply this event study framework to estimate how total electricity production from each fuel type i in each hour-of-sample t responds to changes in electricity demand before versus after 15 March 2011.

The independent variables of interest are equally spaced bins of net electricity demand interacted with an indicator for observations after 15 March 2011. For the purpose of this event study, "net electricity demand" is defined as electricity demand net of production from renewable sources. We consider net demand because production from renewable sources has near-zero marginal costs and is "non-dispatchable": Wind and solar resources are only able to produce when the wind is blowing or the sun is shining.[7] In order to implement the event study approach, we restrict the sample to observations less than 12 months before or after 15 March 2011 and estimate the following regression:

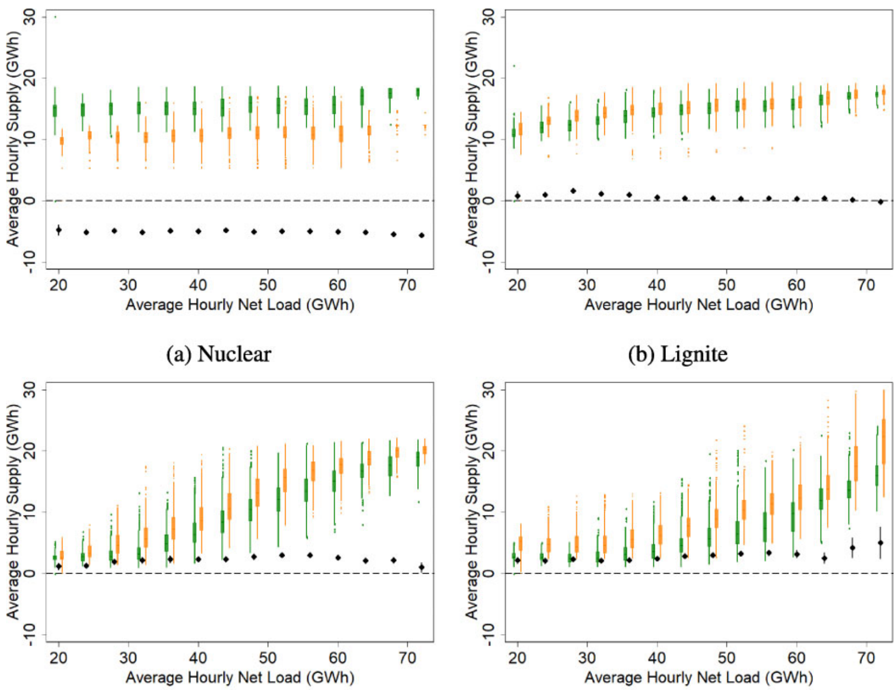
$$G_{i,t} = \sum_b [\mathbf{1}\{L_t \in B_b\}(\alpha_{i,b} + \beta_{i,b} \cdot \mathbf{1}\{t \geq 3/15/2011\})] + \gamma_m + \varepsilon_{i,t}, \quad (1)$$

where $G_{i,t}$ is the total quantity of electricity produced by fuel type i in hour-of-sample t. L_t is net demand in hour t, and $\mathbf{1}\{L_t \in B_b\}$ is an indicator that takes on the value one if L_t is in bin B_b and is zero otherwise. Next, the indicator $\mathbf{1}\{t \geq 3/15/2011\}$ takes on the value one if the observation corresponds to an hour-of-sample on or after 15 March 2011 and is zero otherwise. Finally, we include month-of-year fixed effects (i.e., γ_m) and cluster standard errors by week-of-sample.

Figure 1 plots the coefficient estimates of interest (i.e., $\hat{\beta}_{i,b}$) along with their 95% confidence intervals. Panel (a) of this figure shows that hourly electricity production from nuclear sources dropped by roughly 5 GWh on average across all levels of net demand. Panels (b)–(d) demonstrate that this lost nuclear production was offset in large part by increases in electricity production from fossil-fuel sources. Specifically,

6. One nuclear reactor closed at the end of 2019. We also exclude the two reactors at the Kruemmel power plant from our analysis because this plant was already in long-term shutdown since 2009.

7. In making this assumption, we follow Davis and Hausman (2016).



(a) Nuclear

(b) Lignite

(c) Hard Coal

(d) Natural Gas

FIGURE 1. Event study estimates of the effect of the 2011 nuclear plant closures on nuclear and fossil-fuel electricity production. This figure plots the results from an event study analysis of the effects of the nuclear phase-out in Germany in 2011. Values are plotted to show how the impact varies between source types and across each bin of net demand (i.e., electricity demand minus production from renewables). The pre-period spans the year prior to 15 March 2011, and the post-period spans the year after. The left-shifted box plots correspond to the pre-period electricity production, while the right-shifted box plots correspond to the post period electricity production. The points in black correspond to the estimated coefficients of the difference, with 95% confidence intervals constructed based on standard errors that were clustered by week-of-sample. Panel (a) presents the estimates for nuclear production, while panels (b)–(d) present the corresponding estimates for production from lignite, hard coal, and natural gas, respectively.

production from lignite increased by roughly 1 GWh on average at low levels of net demand. Production from hard coal increased by 2–3 GWh on average across all levels of net demand. Finally, gas-fired electricity generation also increased by roughly 2 GWh on average, and by as much as 6 GWh for hours-of-sample with very high net demand.

There are several limitations to this event study approach. First, hourly plant-level data on electricity production are not available prior to 2015. Consequently, the event study framework cannot be used to explore heterogeneity in how different plants respond to the nuclear phase-out beginning in 2011. This heterogeneity is especially important because the amount of local air pollution emitted per MWh of production can vary significantly across plants burning the same type of fuel. In addition, the monetary damage from local air pollution emissions is also tied directly to the number of people exposed to this pollution; the same level of pollution emissions from two different plants can have very different damages based on the number of people living near each of these plants.

Second, the event study framework relies on the assumption that changes in power plant operations around 15 March 2011 are caused by the nuclear reactor closures rather than changes in other factors that determine production behavior. To ensure that this assumption holds, we examine the impact of the phase-out in a fairly narrow window around the initial 2011 shutdowns. Focusing on this narrow window allows us to argue that electricity suppliers could only respond to the nuclear shutdowns in the very short-run by adjusting output. However, subsequent nuclear plant shutdowns occurred incrementally and were pre-announced. As such, firms may have been able to take actions in anticipation of these later closures.

Finally, other important economic factors changed over our 2010–2019 sample period. For example, coal and natural gas plants had similar marginal costs in 2011. However, coal prices decreased precipitously from 2011 to 2015, while natural gas prices increased over this period. Coal plants were thus increasingly more likely to produce in place of natural gas plants from 2011 to 2015 even absent any changes in nuclear power production. In addition, many older coal and gas plants were retired between 2010 and 2019, and a number of new fossil-fuel-fired plants came online during this period as well. Summarizing, it is unlikely that market outcomes before versus after March 2011 were driven solely by the phase-out, especially as we look further in time after the 2011 shutdown decision.

Combined, these concerns motivate the development of a machine learning approach that can estimate the spatially disaggregated impacts of the nuclear phase-out over a longer time horizon controlling flexibly for changes over time in other important economic factors.

5. Machine Learning Methodology and Validation

We develop a machine learning approach to more credibly estimate the economic and environmental impacts of the series of nuclear plant closures that occurred between 2011 and 2019. The first subsection discusses the construction of the dependent and independent variables, while the second subsection provides details on the random forest algorithm used to estimate the relationship between these variables. We next describe how we use our estimates to calculate hourly output for each plant in each of two scenarios: with the nuclear phase-out versus without the nuclear phase-out. The final two subsections discuss robustness to changes in other economic factors due to the phase-out and performance of the model, respectively.

5.1. Constructing the Training Dataset

We train our machine learning algorithm to predict power plant operations using a data set of roughly 6.5 million observations. The goal is obtain estimates of the hourly quantity of electricity produced by each “dispatchable” plant in the sample in scenarios with versus without the nuclear phase-out. “Dispatchable” plants include all fossil-fuel power plants (i.e., lignite, hard coal, natural gas, oil) and each border point.

All other sources of power production (i.e., nuclear, wind, solar, hydro, biomass, waste, and pumped storage) are treated as “non-dispatchable”. Other than any ex-ante adjustments made to explicitly account for the impact of the phase-out on total production from nuclear and renewables sources, we assume that the levels of output from non-dispatchable sources are determined exogenously and are thus equal to observed output levels for both the phase-out and no-phase-out scenarios. The net electricity demand that must be met by “dispatchable” sources is equal to total electricity demand minus the output from non-dispatchable sources.

Strictly speaking, many “non-dispatchable” plants can actually vary their output in response to market conditions. However, this tends to be the exception rather than the rule. The bulk of non-dispatchable output comes from wind and solar resources. These resources have near-zero marginal costs and so will generally produce as much as possible based on how much the wind is blowing or the sun is shining. Renewable sources are also generally remunerated through fixed price feed-in-tariffs, reducing their incentive to respond flexibly to market conditions. The operations of many other types of non-dispatchable sources are driven by important factors outside of the electricity market, such as seasonal rainfall for hydro and the supply characteristics of input fuels for waste. As such, it seems reasonable to take the operations of these plants as largely invariant to the changes in market conditions in our model. Further details on how we model output from non-dispatchable sources in the phase-out and no-phase-out scenarios are provided later in this section and in Online Appendix B.

Hourly data on plant-level electricity production are available for all EU member states since 2015 from ENTSOE.[8] We also model electricity imports and exports at each border interconnection between Germany and its neighboring countries. For example, consider the hourly net electricity imports from France to Germany. If France exports 50 MWh of electricity to Germany, this border point would be modeled as “producing” 50 MWh. Conversely, if France imports 50 MWh of electricity from Germany, this border point would be modeled as “producing” −50 MWh.

Our analysis is primarily based on changes occurring within Germany’s national borders. This is due both to data availability and our aim of evaluating whether a national policy decision, the nuclear phase-out, ultimately benefited stakeholders in Germany. In reality though, the German electricity grid operates in a manner that is fully integrated with neighboring Luxembourg and Austria. Rather than extending our analysis to directly model the behavior of plants located outside of Germany, we capture these interconnections through our modeling of cross-border flows at border

8. The data include only plants with capacity greater than 100 MW. This covers 100% of production from nuclear plants, 95% from lignite plants, 85% from hard coal plants, 50% from gas plants, and 45% from oil plants. We treat the operating behavior of these plants as being representative of the remaining plants with capacity less than 100 MW, conditional on a range of other plant characteristics including technology type, combined heat and power functionality, and location.

points. For instance, our model is able to capture that net imports from Austria to Germany are sizable in the winter due to output from seasonal hydro plants across the border in the Alps. We believe our approach is sufficient to capture the core dynamics of interest. Moreover, moving to explicitly modeling plants in Luxembourg and Austria would be unlikely to significantly alter our findings in large part because border flows with these two countries are small relative to the role of in-country production in Germany.

The dependent variables considered in the machine learning approach are the production levels from each of the power plants and border points in the sample. In all cases, we normalize the relevant dependent variable by dividing output by the maximum production capacity of each power plant or the maximum transfer capacity of the border point. Our algorithm focuses on dependent variables that are bounded between 0 and 1; we rescale the flows from border points from their original scale of −1/1 to 0/1 when applying the algorithm. We refer to this rescaled output as the *operating rate*.

The independent variables include net electricity demand, local weather, each plant's marginal cost, the availability of other power plants, an indicator for whether the plant operates as a combined heat and power plant, and a wide range of power plant characteristics such as fuel type, efficiency, technology, and location. We estimate a model that predicts the operating rate for each power plant and border point in each hour using these independent variables. Importantly, we have data on all of the independent variables from 2010 to 2019. This allows us to predict hourly electricity production for all plants over the 2010–2019 period, despite only observing hourly plant-level production from 2015 onward.

We also build a predictive model for wholesale electricity prices. However, there is no cross-sectional variation in these prices; the hourly wholesale electricity price is the same throughout Germany. In this case, the independent variables for the time-series model of electricity prices include electricity demand, national average weather, and the marginal cost of the plant with the largest marginal cost among plants operating in the hour-of-sample.[9]

5.2. *Random Forest Algorithm*

We predict outcomes using a random forest regression algorithm (Breiman 2001). In particular, we use the quantile regression forest algorithm (Meinshausen 2006). random forests are especially well-suited for our empirical context for several reasons.

First, each plant's production is based on a potentially complex combination of factors such as the marginal costs and availability of other plants, electricity demand at different locations, and transmission constraints. Consequently, the relationship

9. In order to assuage concerns that the marginal cost of the marginal unit is a function of the phase-out policy, we calculate this magnitude separately for the phase-out and no-phase-out scenarios based on the intersection between the supply curve and the net demand implied by the scenario considered. See Online Appendix B.2.2 for further discussion.

between plant-level production and the independent variables listed above is likely to be highly non-linear and include multiple interactions. Random forest methods are well-suited to use variation in the data in order to find these interactions rather than pre-specifying how independent and dependent variables relate using polynomials or splines as in a more standard regression framework.[10]

Second, the random forest algorithm ensures that the support of possible predictions of an outcome is bounded by the support of the observed values of this outcome variable in the training data set. This prevents nonsensical predictions such as plants producing negative amounts of electricity or producing greater than their capacity (e.g., operating rates above 100% or below 0%).[11]

Third, the quantile regression forests algorithm produces predictions for the full conditional distribution of the outcomes rather than just their expected value. This property allows us to make corrections to ensure that the total electricity supply implied by our predictions equals electricity demand. It is typically impossible to impose the constraint in this kind of empirical approach that electricity supply matches demand. However, the quantile random forest algorithm allows us to find, for each month-of-sample and each scenario considered, the percentile of the distribution of predicted plant-level output that ensures that total electricity supply equals demand.

Online Appendix B.4 provides more details on the determinants of the percentile chosen (e.g., net demand) as well as sensitivity analyses that show our main results are not driven by differences in the percentiles chosen across the factual phase-out versus counterfactual no-phase-out scenarios.

5.3. Implementation for our Application

We use the trained machine learning model to construct two data series. First, we predict hourly plant-level electricity production at each fossil-fuel plant and border point using the observed values of the independent variables over 2010–2019. This provides us with electricity production levels at each plant and border point in the "factual" scenario with the nuclear phase-out. The machine learning model is necessary for estimating plant-level production even in the factual scenario because there is no hourly plant-level production data prior to 2015.

Second, we use the model to estimate hourly production for the same set of plants and border points in the counterfactual scenario where there was no nuclear phase-out. Put another way, we predict plant-level production and point-level flows assuming that the nuclear reactors that were shut down in 2011, 2015, 2017, and 2019 would have remained operational until the end of 2019. To do this, we first calculate the amount of electricity these nuclear plants would have produced in each hour-of-sample if they had remained online. We assume that the nuclear plants that were shut down

10. Capturing these kinds of non-linear effects is not a capability unique to random forests. Other machine learning algorithms (e.g., kernel-based methods) can also capture non-linearities.

11. Random forests are not alone in being able to bound variables in this way. Logistic regression methods, for example, also have this desirable property through their use of a sigmoid function.

would have operated at 80% of their capacity on average over the period to the end of 2019.[12] We also assume that all of the reactors that were shut down between 2011 and 2019 would have continued to operate until at least the end of 2019 in the absence of the phase-out.[13,14] The resulting estimate of counterfactual nuclear output in the absence of the phase-out is also adjusted to account for seasonal fluctuations in output that primarily reflect the timing of annual maintenance in the summer months.[15] We subtract our estimated counterfactual nuclear output from net electricity demand, thus reducing the production needed from the remaining plants and border points.

Our exposition has thus far focused on hourly plant-level production and point-level net flows. However, we utilize a similar approach to assess the impact of the phase-out on wholesale electricity prices. Further details on this, and the implementation of our machine learning algorithm in general, can be found in Online Appendix B.

5.4. Accounting for Other Impacts of the Phase-Out

Our approach adjusts the level of net demand faced by fossil-fuel plants and border points to reflect the nuclear production lost due to the phase-out. In doing so, we hold independent variables other than net demand fixed at their historically observed values for both the phase-out and no-phase-out scenarios. This assumption seems reasonable for independent variables such as those based on plant characteristics, temperature, and the seasonality of demand. Our approach also follows previous literature in assuming that fuel prices are unaffected by the phase-out (e.g., Grossi, Heim, and Waterson 2017).

However, the phase-out potentially impacted the level of investment in wind and solar resources. Namely, the incentives to invest in renewables might not have been as strong in the absence of the phase-out. To account for this, we assume that annual renewable production in the no-phase-out scenario would have been 30 TWh lower by 2020. We chose 30 TWh based on changes made to Germany's renewable energy

12. Many nuclear plants in Germany consistently achieve operating rates of around 90%. However, we opt for a lower value to capture the fact that the plants that were first to shut down tended to be older. In addition, even absent the phase-out, these plants would have needed to be taken offline for a period of time for reactor extension upgrades.

13. The original reactor extension policy envisaged increasing the operating lifetimes of Germany's nuclear reactors by between 8 and 14 years. In addition, the market conditions for nuclear plants have not been as challenging in Europe as in the United States, largely because natural gas prices in Europe have been systematically higher than those in the United States until recently. Consequently, even the oldest plants that were shut down in 2011 would have been likely to remain in operation until the end of 2019 absent the phase-out.

14. The Kruemmel nuclear power plant was placed in long-term shutdown in 2009; this plant is not assumed to be turned back on in the "no-phase-out" scenario.

15. We make this adjustment based on observed fluctuations in monthly total nuclear production from 2012 to 2014 because there were no nuclear shutdowns during this period.

targets in response to the phase-out decision.[16] A 30 TWh per year reduction amounts to a 15% decrease in renewable production by the end of our study period.

We decrease the aggregate level of renewable production in the counterfactual no-phase-out scenario by proportionally adjusting observed total hourly output from wind and solar resources.[17] To demonstrate the sensitivity of our findings to different assumptions on how much of the investment in renewables is due to the phase-out, we also explore a low-case scenario where there is no response from renewable investment, and a high-case scenario where the response from renewables is twice as large.[18]

It is also plausible that the phase-out altered the incentives to invest in fossil-fuel power plants. Prior studies have demonstrated that, if the phase-out had not occurred, the amount of fossil-fuel generating capacity necessary to ensure that demand is met during peak hours in Germany would have been 4 GW lower by 2020 (Traber and Kemfert 2012) and 8 GW lower by 2030 (Knopf et al. 2014). We account for this phase-out-induced increase in investment in fossil generating capacity.[19] However, the resulting increases in fossil investment costs are quite small, and do not affect the conclusions drawn from the analysis.

Finally, phase-out-induced increases in wholesale electricity prices may have decreased total consumer demand for electricity. However, changes in wholesale prices are likely to have only a muted impact on customer demand because the commercial and residential customers that make up around half of Germany's total demand are highly price-inelastic.[20] Phase-out-induced increases in electricity prices would lead to decreases in net electricity demand, and thus would have the same directional

16. Specifically, in 2010, Germany planned on producing at least 30% of its electricity from renewables by 2020. However, this target was increased to 35% following the 2011 phase-out decision (Jacobs 2012). The difference between these two targets requires a change in annual renewable production of roughly 30 TWh per year by 2020.

17. We assume that the decrease in renewable production in the absence of the phase-out grows linearly from 0 TWh per year in 2010 to the assumed amount of 30 TWh per year in 2020. To take 2015 as an example, in our baseline scenario, we assume that 15 TWh of the renewable power produced in that year was due to the nuclear phase-out. Total wind and solar production in that year was 114 TWh; therefore, in the counterfactual without the nuclear phase-out, the new total renewable production would be $114-15 = 99$ TWh. This new total is 84% of the original; we multiply the observed values for renewable production in each hour in 2015 by 0.84 to calculate the counterfactual no-phase-out hourly levels of renewable production.

18. Previous research on the phase-out typically assumes that investment in renewables did not accelerate due to the nuclear plant closures (Traber and Kemfert 2012; Knopf et al. 2014).

19. We assume that 4 GW less fossil generating capacity would be needed in the no phase-out scenario by the end of 2019. The scale of the proportional adjustment in observed fossil capacity in each year is based on assuming the decrease in fossil capacity grows linearly from 0 GW in 2010 to the assumed amount of 4 GW in 2020. For example, we assume that 2 GW of the fossil capacity online in 2015 was due to the nuclear phase-out. Total fossil capacity in 2015 was 80 GW; in the counterfactual without the phase-out, the new fossil capacity is $80-2 = 78$ GW. This new total is 97% of the original, and we multiply the observed fossil capacity in 2015 by 0.97.

20. Larger industrial customers are more price-elastic, and the rates they pay for electricity are also more responsive to changes in wholesale electricity prices. This is in part because the prices paid by larger industrial customers do not incorporate any portion of the renewable subsidies that smaller customers fund through their bills (BNetzA 2020). Still, even a conservative assumption regarding the price-elasticity of

impact as the various renewable investment scenarios we explore. Consequently, the renewables sensitivity analyses should help capture the range of possible phase-out-induced changes in consumer electricity demand.

5.5. Model Performance

Figure 2(a) compares observed hourly plant-level operating rates (i.e., percentage of capacity utilized) with the predictions from the machine learning model. Specifically the predicted electricity production (scaled on the *y*-axis) is plotted against the observed production (*x*-axis) so that observations on the 45-degree line indicate perfect prediction accuracy. Each pixel in the figure represents the predicted versus observed operating rate in increments of 2% and darker areas correspond to a higher number of plant-hour (or plant-year) observations.

We check the out-of-sample cross-validated performance to avoid overfitting and to give a fair assessment of how the model may perform when used to make predictions for the counterfactual no-phase-out scenario. For the hourly data in panel (a), the cross-validated out-of-sample R^2 is 0.41.

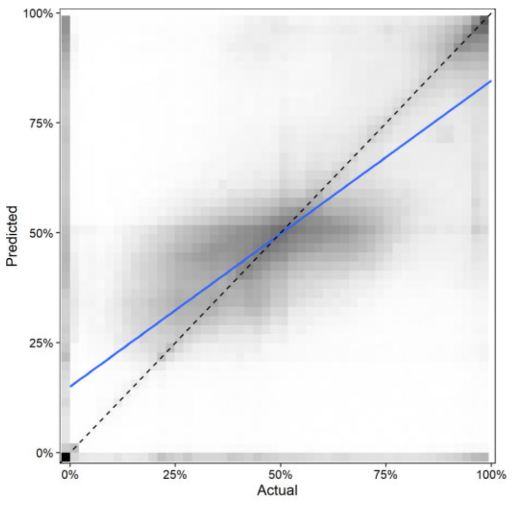
However, even this small level of prediction error understates the relevant prediction accuracy of the machine learning model. Specifically, we will primarily use the predictions from our model to compare outcomes under the phase-out and no-phase-out scenarios at the plant-year level. We therefore also evaluate the predictive performance of the model at this level of aggregation. Specifically, Figure 2(b) plots predicted versus observed annual average operating rates. As the figure shows, the performance is substantially improved, with most of the observations clustered close to the 45-degree line, and the areas of systematic error largely disappear. The cross-validated out-of-sample R^2 rises to 0.84.

Lastly, we also use the machine learning model to predict counterfactual hourly wholesale prices. This model performs well, with a cross-validated out-of-sample R^2 of 0.88. By far the most important predictor in this model is the marginal cost of the marginal plant. This is consistent with how prices are determined in the wholesale market.

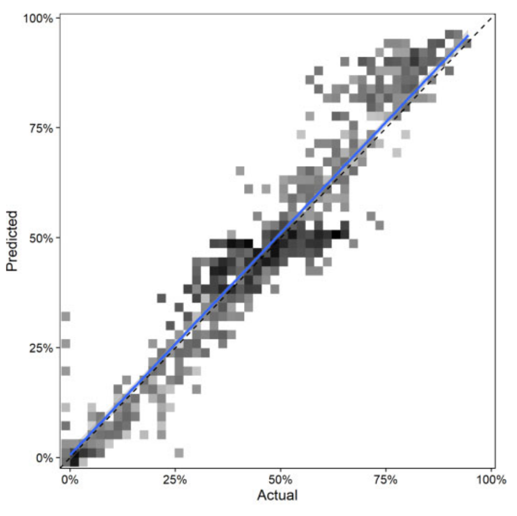
6. Results on the Impact of the Phase-Out

This section presents the main results on the full range of impacts of the nuclear phase-out over the 2010–2019 analysis period. Specifically, we compare the market and environmental outcomes with versus without the nuclear phase-out using the predictions from our machine learning model.

these consumers is unlikely to result in a large change in demand given that we estimate a relatively small increase in wholesale prices due to the phase-out.

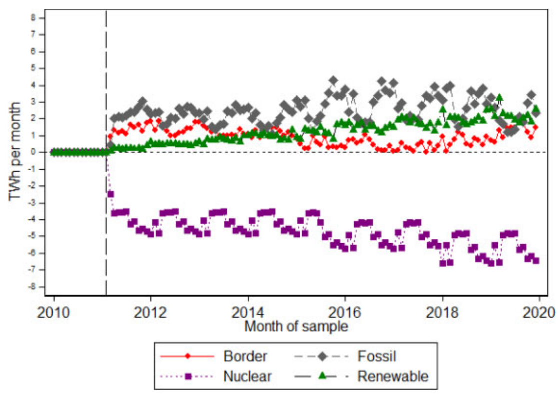


(a) Hourly Data

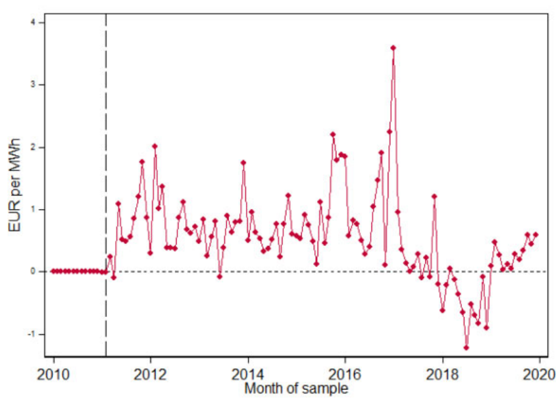


(b) Annual Data

FIGURE 2. Machine learning model performance: plant-level electricity production. This figure illustrates the accuracy of the plant-level predictions from the machine learning model presented in Section 5. The model predicts the operating rate of each power plant in each hour, where a value of 0% means that a plant is offline, and a value of 100% means that the plant is running at maximum capacity. Values on the 45-degree line indicate perfect accuracy, and we summarize this both visually with the blue linear fitted line and by computing measures of R^2. We compute these metrics using out-of-sample five-fold cross-validation. Darker areas indicate higher numbers of plant-hour (or plant-year) observations. Each pixel represents the predicted versus actual operating rate in increments of 2%. Panel (a) shows prediction accuracy at an hourly timescale; the R^2 is 0.41. Panel (b) shows prediction accuracy after taking annual averages of our hourly predictions; the R^2 is 0.84.



(a) Electricity Production



(b) Wholesale Electricity Prices

FIGURE 3. Estimated impact of the nuclear phase-out on electricity production and prices. This figure plots the monthly difference between the predictions from our machine learning model with the phase-out minus without the phase-out. The start of the phase-out in March 2011 is marked by the vertical black dashed line. Panel (a) reports the estimates for all fossil-fuel-fired electricity production (diamonds), net imports (circles), renewable electricity production (triangles), and nuclear production (squares). Panel (b) presents the change in wholesale electricity prices.

6.1. Generation, Net Imports, and Prices

Figure 3(a) reports the monthly average difference in predicted production and net imports (in TWh) with the phase-out minus without the phase-out policy. We report monthly average differences in fossil-fuel-fired electricity production (gray diamonds), net imports (red circles), renewable electricity production (green triangles), and nuclear electricity production (purple squares). The start of the nuclear phase-out in March 2011 is marked by the vertical black dashed line.

Total nuclear production decreases by roughly 4 TWh per month immediately after the announcement of the policy, with an additional reduction of 2 TWh per month later

TABLE 2. Estimated impact of the nuclear phase-out on wholesale electricity prices, electricity production by source, and net imports.

	Average with phase-out (1)	Average without phase-out (2)	Change (3)	Change (%) (4)
Production (TWh per year)	433.1	433.4	−0.3	−0.1
Nuclear	81.5	139.1	−57.6	−41.4
Lignite	147.2	139.6	7.6	5.4
Hard coal	86.1	69.4	16.7	24.1
Gas	31.6	26.7	4.9	18.4
Oil	7.7	6.5	1.2	18.5
Net electricity imports	−36.8	−47.4	10.6	22.4
Wind + solar	116.0	99.5	16.5	16.6
Wholesale prices (Euros per MWh)	37.9	37.3	0.6	1.6

Notes. This table reports annual average electricity production by source and wholesale electricity prices with versus without the nuclear phase-out, as estimated using our machine learning approach. These annual averages are calculated using data spanning from 2012 to 2019.

in the sample period as more nuclear plants are taken offline. The observed seasonal fluctuations of this impact are due to the fact that nuclear reactors typically schedule their maintenance and refuelling outages in the summer months.

In our baseline scenario, we assume that some of this lost nuclear production was replaced by accelerated investment in renewable sources due to the phase-out policy. Consistent with this assumption, Figure 3 documents a steady rise in phase-out-induced increases in renewable electricity production, with an additional 2.5 TWh per month by 2020.

We use our machine learning model to estimate the remaining contribution of various dispatchable sources in replacing the lost nuclear production. We find that the phase-out caused a large increase in fossil-fuel-fired electricity production of 2–3 TWh per month, which persists over our entire sample period. The phase-out also caused a smaller increase in net imports of electricity of around 1 TWh per month. The largest contributors to net imports were the Czech Republic and France, which is consistent with the higher levels of market integration for these countries highlighted by Grossi et al. (2018).

Figure 3(b) reports the estimated impact of the nuclear phase-out on wholesale electricity prices in euros per MWh. The estimates show that the phase-out resulted in an increase in wholesale prices of around 1 euro per MWh, although this difference diminished in recent years, and was in fact negative for part of 2018. The estimates also suggest that the phase-out may have exacerbated episodic increases in prices.

Table 2 presents the annual averages of electricity production and prices over the 2012–2019 sample period with versus without the phase-out. The estimates reveal that the phase-out caused wholesale electricity prices to increase by €0.6 per MWh on average, a 1.6% increase relative to the prices that would have prevailed on average if the phase-out had not occurred. Nuclear production fell by an average of 57.6 TWh per year during the phase-out period, corresponding to a 41.4% decline. Average annual generation from fossil-fuel plants increased by 16.7 TWh for hard coal, 7.6 TWh for lignite, and 4.9 TWh for gas. The phase-out also caused net imports to increase by 10.6 TWh per year on average. Under our base-case assumption for renewables investments, we see an increase in average annual renewable production of 16.5 TWh due to the phase-out.

A caveat with our approach is that, following prior research that has modeled the German electricity sector (Egerer 2016), we do not adjust wholesale prices when calculating the predictions of net imports with versus without the nuclear phase-out. However, Grossi et al. (2018) demonstrate that prices in neighboring countries rose due to the phase-out in the short-run. Consequently, since we do not adjust wholesale prices in neighboring countries when calculating predictions, the phase-out-induced increase in the quantity of net imports reported in Table 2 is likely an upper bound. Our estimate of the overall social cost of the phase-out to *German producers and residents* is thus likely to be conservative because the bulk of our estimated cost comes from increases in local air pollution due to increases in coal-fired production in Germany rather than increases in net imports.

6.2. Private Costs and Benefits

Table 2 showed that the phase-out caused fossil-fuel and renewable generation to increase, and nuclear production to decrease. Table 3 reports the changes in average annual total variable costs, fixed costs, and revenues implied by this change in generation mix. The central component of variable costs is calculated by multiplying each plant's hourly production with our estimate of its marginal cost in the hour. For fossil-fuel plants, marginal costs are calculated as the sum of the plant's fuel cost per MWh and an assumed amount of variable operating and maintenance costs that differs by fuel type. Fuel costs are calculated by converting the price of the relevant input fuel to euros per MWh based on the calorific content of the fuel and the plant's thermal efficiency (i.e., how well the plant converts units of input heat to units of electricity output).

Other variable operating and maintenance costs, as well as any fixed investment and maintenance costs, vary by source type. These magnitudes are taken from a recent study on generation costs (EIA 2019). The key benefit of this study is that it draws on a wide range of reported cost data from actual plants. It is thus better suited for our retrospective analysis of the phase-out policy.[21]

We assume that nuclear plants have a marginal cost of approximately €10 per MWh based on prior research on Germany's power sector (Egerer 2016). This is confirmed by company reports from two European nuclear plant operators, EON and EDF, which

21. The EIA values are similar to corresponding estimates from other studies, which are commonly used in the literature (e.g., Lazard 2019).

TABLE 3. Estimated impact of the nuclear phase-out on wholesale revenues and private costs.

	Average with phase-out (1)	Average without phase-out (2)	Change (3)	Change (%) (4)
Wholesale Revenues ($\frac{\textbf{Bn. euros}}{\textbf{year}}$)	17.30	17.43	−0.13	−0.7
Nuclear	2.99	5.04	−2.05	−40.6
Lignite	5.43	5.06	0.37	7.3
Hard coal	3.19	2.54	0.65	25.6
Gas	1.18	0.98	0.20	20.4
Oil	0.28	0.23	0.05	21.5
Wind + solar	4.22	3.57	0.65	18.2
Variable costs ($\frac{\textbf{Bn. euros}}{\textbf{year}}$)	7.82	6.92	0.90	13.0
Nuclear	0.78	1.34	−0.56	−41.8
Lignite	3.70	3.50	0.20	5.7
Hard coal	2.63	2.12	0.51	24.1
Gas	1.38	1.18	0.20	17.0
Oil	0.94	0.77	0.16	20.6
Net electricity imports	−1.61	−2.00	0.39	19.5
Wind + solar	0.00	0.00	0.00	.
Fixed costs ($\frac{\textbf{Bn. euros}}{\textbf{year}}$)	21.98	21.71	0.28	1.3
Nuclear	1.57	2.73	−1.16	−42.5
Lignite	1.03	1.00	0.03	3.0
Hard coal	1.29	1.26	0.04	3.2
Gas	0.63	0.62	0.02	3.2
Oil	0.10	0.10	0.00	0.0
Net electricity imports	0.00	0.00	0.00	.
Wind + solar	17.35	16.00	1.35	8.4

Notes. This table reports average annual total wholesale revenues and private costs under the phase-out and no phase-out scenarios. All entries are annual averages over 2012–2019 based on predictions from our machine learning model. Wholesale revenues are defined as the product of each plant's hourly production with the hourly wholesale electricity price. Variable costs are the product of each plant's hourly production with its marginal cost in the hour. Marginal costs include fuel costs per MWh as well as variable operating and maintenance costs (in € per MWh). Fixed costs are the product of each plant's capacity with its annual fixed capital expenditure as well as fixed operating and maintenance costs (in € per MW per yr).

also have marginal fuel costs of approximately €10 per MWh over our analysis period. The same industry reports indicate that the other fixed operating, maintenance and investment costs at these plants likely amount to a further €20 per MWh, resulting in overall costs for the continued operation of existing nuclear plants of roughly €30 per MWh. Beyond this, we also account for the costs of the nuclear power plant lifetime extensions that were explicitly affected by the phase-out policy. Keppler (2012) argues that extending the lifetime of the nuclear reactors in Germany would have required investments of roughly €500 million per reactor, or €8.5 billion in total. These investment costs were avoided due to the nuclear phase-out.

Wind and solar power are assumed to have zero marginal operating costs. To account for the fixed operating and capital costs of renewables, we rely on levelized cost values for wind and solar plants from the International Renewable Energy Agency (IRENA 2020). These values are specific to Germany and capture annual average costs for plants built in each year. Lastly, for net imports, we quantify the costs as being the net quantity of imported electricity multiplied by the wholesale price in the relevant neighboring country.

Revenues are calculated as the product of plant-level production and wholesale electricity prices. Due to a lack of data, we do not include any additional revenues plants may receive outside of the wholesale market, such as capacity payments, ancillary services payments, and subsidies. As such, our measure of revenues understates the actual revenues accrued by power producers. This is particularly relevant for renewable sources which derive a large portion of their revenues from subsidies.

Table 3 reports estimates of the impact of the nuclear phase-out on revenues and private costs for power plants. The table is structured like Table 2. The first result, not surprisingly, is that the nuclear phase-out had a large effect on the revenues of the nuclear plants that were shut down. Specifically, total wholesale revenues across all nuclear plants declined by €2.05 billion per year on average as a result of the phase-out. Despite this, wholesale revenues are still larger than nuclear plants' variable and annualized fixed costs in both scenarios, indicating the continued profitability of nuclear power over our analysis period.

The revenues previously earned by the shutdown nuclear plants were primarily redistributed to both fossil plants (hard coal, lignite, and natural gas plants) and to renewables. The increased use of these other sources led to a net increase in variable costs. This was largely driven by fossil-fuel plants, with €0.20, €0.51, and €0.20 billion per year in additional variable costs for lignite, hard coal, and natural gas power plants. There was also an increase in fixed costs. This was largely driven by new renewable plants, with €1.35 billion per year in additional fixed costs outweighing the savings from cancelling the nuclear reactor lifetime extensions.

The redistribution of profits among electricity producers has interesting implications for the political economy surrounding the nuclear phase-out. In particular, the four large firms that owned nuclear plants in Germany—E.ON, RWE, EnBW, and Vattenfall—all publicly opposed the policy. These firms have since been awarded €2.4 billion in compensation from the German government to cover losses they incurred as a result of the phase-out. However, it is possible that their opposition was tempered somewhat by the fact that, in addition to their nuclear plants, all four companies had large fossil plant portfolios both in Germany and across Europe. Our finding that fossil plants played a large role in replacing the lost nuclear production indicates that any reduction in their profits due to the nuclear closures may have been cushioned by the increased profitability of their fossil plants. Moreover, if these firms' nuclear plants had remained open, they would have been subject to a new nuclear fuel tax. This tax would have greatly reduced the inframarginal rents earned by nuclear plants. So, while public concern about nuclear risks was likely the key determinant of the phase-out decision in 2011, the policy might also have been more aligned with the interests of firms than it first seemed.

Lastly, Germany remains a net exporter throughout our sample period, both with and without the phase-out. The phase-out did reduce net exports, and valuing the change at the electricity prices of the relevant neighboring countries resulted in a net increase in variable costs (i.e., lost export revenues) of €0.39 billion per year. This calculation holds fixed the prices of neighboring countries at observed levels across the phase-out and no-phase-out scenarios. However, even if we assume that the increases in prices in neighboring countries due to the phase-out estimated in Grossi et al. (2018) persisted to the end of 2019, this would only increase the total private costs to Germany by about 3.3%.[22] Even this 3.3% increase in private costs is likely to be an upper bound because: (1) as mentioned above, the phase-out-induced increase in the quantity of net imports we estimate is likely to be an upper bound and (2) the increases in prices found by Grossi et al. (2018) for 2011 and 2012 may have dissipated from 2013 to 2019.

6.3. External Costs

This subsection presents an analysis of the environmental costs associated with the increase in fossil-fuel-fired production caused by the nuclear phase-out. Specifically, burning fossil fuels emits both global pollutants such as carbon dioxide that contribute to climate change and local air pollutants that adversely impact the health of exposed populations.

We begin by describing how we estimate the change in carbon emissions due to the phase-out. We first calculate the change in the amount of fuel burned by each fossil-fuel plant due to the phase-out using our predictions of each plant's hourly production and thermal efficiency. We then use the carbon intensity of different fuels documented in industry reports to convert changes in fuel burned to changes in plant-level CO_2 emissions.[23]

We also estimate the change in emissions of air pollutants due to changes in each plant's production levels caused by the phase-out. Similar to the approach for CO_2 emissions, we translate changes in fuel use into changes in emissions using plant-level emissions rates for each local air pollutant from the EU LCPD. The LCPD database provides annual plant-level data on fuel inputs and emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter (PM). The LCPD data covers the vast majority of large fossil plants in Germany.[24] We assign the small number of plants not

22. Grossi et al. (2018) use an approach similar to the event study analysis in Section 4, finding that the phase-out led to increases in wholesale prices in neighboring countries in 2011 and 2012. This would increase the price of additional imports to Germany by just under 10%. If we assume those price increases persist to the end of 2019, and apply them to the 10.6 TWh per year of additional net imports in Table 2, then this would still only increase total private costs by 3.3%.

23. The carbon intensities we use are 93.6 tCO2/TJ for hard coal, 55.9 tCO2/TJ for gas, and 74.0 tCO2/TJ for oil. We consider three different intensities for lignite depending on the mining region that the plant sources its coal from. These are 113.3 tCO2/TJ (Rhineland), 111.2 tCO2/TJ (Lusatian), and 102.8 tCO2/TJ (Central).

24. The data covers 99% of lignite capacity, 98% of hard coal capacity, 90% of gas capacity, and 91% of oil capacity.

in the LCPD database an emissions factor based on the average emissions factor of plants with the same fuel type.

We next monetize the damages caused by local air pollution emissions. For this, we rely on two studies that estimate the health impacts of ambient air pollution in Europe (EEA 2014; Jones et al. 2018). In particular, Jones et al. (2018) provide estimates of the annual health damages from the ambient air pollution emitted by roughly 400 of the largest coal-fired power plants in Europe. We use these data to convert our predicted increases in plant-level kilotons of SO_2, NO_x, and PM emissions into monetized health damages.[25]

Table 4 presents the results of this analysis. Specifically, this table reports the fuel-specific average annual total emissions of CO_2 (in megatonnes, Mt) and three local air pollutants: SO_2, NO_x, and PM (in kilotonnes, Kt). Lignite and hard coal plants are by far the two largest polluters, contributing more than 90% of the emissions of each of the pollutants listed. Emissions from lignite and hard coal plants also contribute the most in terms of mortality and monetized pollution damages.

In aggregate, the phase-out led to an increase in CO_2 emissions of 26.2 Mt per year among lignite, hard coal, gas, and oil plants. This corresponds to a 11% increase relative to the scenario without the nuclear phase-out. This increase in CO_2 emissions was primarily attributable to an increase in emissions from hard coal plants, with lignite, gas, and oil making up the remainder. Valuing these carbon emissions at a social cost of carbon of $125/tCO2 would imply that the phase-out resulted in climate damages of €3.0 billion per year (Carleton and Greenstone 2021). However, increases in carbon emissions in Germany might be offset by decreases in carbon emissions elsewhere since German power plants are covered by the EU ETS (a carbon cap-and-trade market spanning the EU). For this reason, we exclude climate damages from our preferred estimates of the social cost of the phase-out.

However, previous work suggests that political considerations play a role in the total number of credits allocated as part of the EU ETS (Koch et al. 2016). The phase-out may have led to more credits being put into circulation through this political channel. Consequently, our core estimate of the social cost of the phase-out, which does not include climate damages, represents a lower bound; the social cost may be larger than our estimate if regulators increased the EU ETS cap due to political pressure from German policymakers following the phase-out.

The phase-out also led to a roughly 10%–11% increase in the emissions of each of the three ambient air pollutants considered. Again, this increase is due primarily to increased emissions from hard coal plants. However, the phase-out also led to

25. We assume that increased emissions at a given fossil-fuel plant in Germany would have the same health damages per unit of emissions as if they were emitted at the nearest location for which we have health damages estimates. The capacity weighted average distance between each of the power plants in our data set and the closest of the 400 locations with damage estimates from Jones et al. (2018) is 0.9 km for lignite plants, 0.2 km for hard coal plants, 12 km for gas plants, and 20 km for oil plants. Consistent with Jones et al. (2018) and many other studies, our approach assumes that the marginal damage per unit of pollutant emissions is linear and additive.

TABLE 4. Estimated impact of the nuclear phase-out on annual CO_2 emissions and local air pollution mortality damages.

	Average with phase-out (1)	Average without phase-out (2)	Change (3)	Change (%) (4)
CO_2 emissions ($\frac{\text{Mt}}{\text{year}}$)	264.5	238.3	26.2	10.99
Lignite	167.5	159.1	8.5	5.34
Hard coal	77.6	62.8	14.8	23.56
Gas	13.2	11.2	2.0	17.79
Oil	6.1	5.2	1.0	19.40
SO_2 emissions ($\frac{\text{Kt}}{\text{year}}$)	127.2	115.7	11.4	9.85
Lignite	86.2	82.3	3.9	4.74
Hard coal	35.0	28.2	6.8	24.15
Gas	0.9	0.8	0.1	12.35
Oil	5.0	4.4	0.6	13.51
NO_x emissions ($\frac{\text{Kt}}{\text{year}}$)	175.8	158.8	17.1	10.77
Lignite	111.5	105.8	5.6	5.29
Hard coal	48.7	39.5	9.2	23.30
Gas	9.0	7.8	1.3	16.71
Oil	6.7	5.6	1.0	17.73
PM emissions ($\frac{\text{Kt}}{\text{year}}$)	4.61	4.18	0.42	10.04
Lignite	3.02	2.88	0.14	4.86
Hard coal	1.41	1.15	0.26	22.60
Gas	0.06	0.05	0.01	21.37
Oil	0.12	0.11	0.02	18.70
Mortality ($\frac{\text{Excess deaths}}{\text{year}}$)	6,852.8	6,053.0	799.8	13.21
Lignite	3,779.1	3,590.6	188.5	5.25
Hard coal	2,616.7	2,074.0	542.7	26.17
Gas	267.2	228.6	38.6	16.88
Oil	189.8	159.7	30.1	18.85
Monetized excess mortality ($\frac{\text{Bn. euros}}{\text{year}}$)	17.24	15.22	2.01	13.20
Lignite	9.51	9.03	0.47	5.20
Hard coal	6.58	5.22	1.36	26.07
Gas	0.67	0.58	0.10	17.39
Oil	0.48	0.40	0.08	19.91

Notes. This table reports estimates for emissions of CO_2 as well as three local air pollutants: SO_2, NO_x, and PM, and estimates of the mortality damages from all three of these local air pollutants. All values are average annual totals based on predicted plant-level generation from 2012 to 2019 for fossil-fuel-fired plants in Germany. Emissions are the product of each plant's hourly generation with our estimate of their emissions rate. We ignore other small sources of emissions from biomass, landfill gas, or waste plants. The estimates in the table are emissions and damages in Germany and do not consider changes in emissions in neighboring countries due to changes in net imports. The air pollution damages reported in the last row of the table only include the monetized costs associated with premature mortality due to air pollution exposure.

large proportional increases in emissions from gas and oil plants, as shown in column (4).

The bottom two rows of Table 4 report the estimated impacts of the phase-out on annual mortality and on annual monetized mortality damages associated with excess emissions of SO_2, NO_x, and PM. From 2012 to 2019, emissions from fossil plants in the phase-out scenario account for almost 6,900 excess deaths per year, corresponding to a monetized damage of €17.2 billion in mortality costs each year. By comparing these estimates to the estimates from the no-phase-out scenario, we can attribute 800 excess deaths per year on average to the phase-out. This corresponds to €2.0 billion per year in monetized damages, and represents a 13% increase in damages relative to the scenario without the nuclear phase-out.[26] 91% of the monetized mortality damages from the phase-out are driven by emissions from lignite (23% of damages) and hard coal plants (68% of damages).

Our focus thus far has been on external costs incurred as a consequence of phase-out-induced changes in output from plants in Germany.[27] However, the phase-out also resulted in an increase in net imports. This will have changed external costs in neighboring countries. To get a sense of the potential external costs associated with the increase in net imports, we calculate the emissions intensity of imports for each neighboring country and then follow the same valuation approach set out above. We find that increased net imports resulted in additional monetized damages of €0.25 billion per year. The vast majority of this is due to increased emissions in the Czech Republic, and to a lesser extent Denmark and the Netherlands. Despite being the largest source of additional imports, France has a relatively clean electricity supply mix and so does not see a significant increase in external costs. Overall, the external costs of imports are small relative to the impacts from changes in production in Germany.

6.4. *Alternative Estimates of Local Air Pollution Costs*

The health damages in Table 4 are calculated by linking data on plant-level emissions rates to pollution exposure using atmospheric chemistry modeling. As a complement to these estimates, Online Appendix C presents a secondary approach to estimate the external costs imposed by increased ambient air pollution caused by the phase-out. In this approach, we use granular air pollution monitor data to examine how changes in output from hard coal and lignite plants affect ambient $PM_{2.5}$ concentration levels.

26. We use an estimate of the value of statistical life (VSL) of €2.56 million for Germany, which follows from Jones et al. (2018) and convert to 2019 values by adjusting for inflation. In the robustness analysis below, we also consider a larger VSL of €6.7 million taken from Viscusi and Masterman (2017), which is more in line with valuations undertaken by the US EPA.

27. The pollution transport model used by Jones et al. (2018) captures the fact that emissions at power plants in Germany can cause health impacts in neighboring countries. We are unable to fully disentangle these cross-border dependencies with the available information, so a small portion of damages from emissions from German plants is incurred by people in neighboring countries.

The estimates from this approach indicate that the phase-out resulted in 334 additional excess deaths per year.

Taken together, the results in Table 4 and Online Appendix Table C.2 paint a consistent picture of the impact of the nuclear phase-out on pollution-caused excess death. Our estimates attribute 330–800 excess deaths per year to the increase in air pollution caused by the nuclear phase-out. This amounts to monetized health damages of €0.9–€2.0 billion per year during the 2012–2019 period. Our preferred estimate is the €2.0 billion per year in damages calculated based on reported emissions (Table 4). This is because the analysis using reported emissions considers a more complete set of pollutants and draws on a more sophisticated analysis of pollution transport and exposure. The results presented in Online Appendix Table C.2 based on our estimated relationship between $PM_{2.5}$ levels and electricity production serve as a valuable complementary validation exercise based on an entirely distinct approach.

6.5. Social Costs

This subsection brings the analysis together by summarizing the benefits and the full range of private and external costs of the nuclear phase-out. The private costs of the phase-out consist of the aggregate changes in the variable and fixed costs incurred by power plants in Germany as well as any costs from changes to net imports. The external costs of the phase-out are measured by the damages from mortality and morbidity caused by the additional air pollution attributable to phase-out-induced changes in the electricity production mix.[28] The sum of measured private and external costs is our estimate of the social cost of the nuclear phase-out.

Table 5 reports the estimates of the aggregate annual private and external costs of the phase-out. The top panel reports social costs as well as each private and external cost component for the base-case assumptions on the growth of renewables driven by the phase-out and the VSL used to monetize pollution-caused premature mortality. The phase-out led to a replacement of low cost nuclear production with higher cost sources such as fossil fuels and net imports. This resulted in private costs increasing by €1.2 billion (or 4.1%) on average per year in Germany, mostly due to an increase in variable costs. This increase in private costs, however, is smaller than the €2.1 billion annual increase in external costs associated with the phase-out. Specifically, burning fossil fuels to produce electricity rather than using nuclear plants led to an increase in local air pollution emissions, which in turn led to increases in premature mortality and adverse morbidity events. Overall, we estimate that the annual social cost of the nuclear phase-out is €3.3 billion per year.

The bottom panel reports the estimates of annual social costs with and without the phase-out for six scenarios based on assumptions on the growth of renewables induced by the phase-out (the low-case, base-case, and high-case scenarios described

28. Morbidity costs per MWh of output are reported in Jones et al. (2018); we apply the same methodology as for mortality in Table 4 to calculate aggregate morbidity costs.

TABLE 5. Impact of the phase-out on annual average private and external costs.

	Average with phase-out (1)	Average without phase-out (2)	Change (3)	Change (%) (4)
Social costs ($\frac{\text{Bn. euros}}{\text{year}}$)	48.27	44.95	3.32	7.4
	Private			
Variable	7.82	6.92	0.90	13.01
Fixed	21.98	21.71	0.28	1.29
	External			
Mortality	17.24	15.22	2.01	13.20
Morbidity	1.23	1.10	0.13	11.82

	Average with Phase-out (1)	Average without Phase-out (2)	Change (3)	Change (%) (4)
Base VSL, low renewables	48.27	44.82	3.45	7.7
Base VSL, base renewables	48.27	44.95	3.32	7.4
Base VSL, high renewables	48.27	45.05	3.21	7.1
High VSL, low renewables	76.14	68.04	8.10	11.9
High VSL, base renewables	76.14	69.57	6.57	9.4
High VSL, high renewables	76.14	71.01	5.13	7.2

Notes. This table reports annual averages over 2012–2019 of the private and external costs incurred with versus without the phase-out. Private costs are the variable and fixed costs associated with power plants in Germany plus any changes in net imports (valued at the wholesale electricity price). External costs consist of excess mortality and morbidity costs from air pollution emissions. The "Social Costs" row reports the sum of private and external costs.

in Section 5.4) and the VSL used to monetize the excess deaths (base and high). Following Jones et al. (2018), the base-case VSL we use is €2.56 million. We also consider an alternative VSL of €6.7 million, taken from Viscusi and Masterman (2017), which is in line with the approach taken by the US Environmental Protection Agency.[29]

We also examine the implications of three scenarios for renewables investment in response to the phase-out. Our base-case scenario assumes that the phase-out induced investments in renewables to produce an additional 30 TWh per year by 2020. In the low-case renewables scenario, we assume no additional renewables investment due to the phase-out, and in the high-case scenario, we assume that the phase-out caused investments in renewables sufficient to increase production by an additional 60 TWh per year by 2020.[30]

29. The lower VSL we consider is derived from studies based on stated preference methods and may thus suffer from hypothetical bias. In contrast, the high-case estimate of the VSL is derived from studies using revealed preference methods (Viscusi and Masterman 2017).

30. It is possible that changing the pace and scale of investment in renewable sources could have additional dynamic impacts on costs, such as promoting learning-by-doing or spurring new grid infrastructure

Column (3) of the bottom panel of Table 5 reports the estimated change in annualized social costs (sum of private and external costs) attributable to phase-out. Across the six scenarios, the social costs range from €3.21 to €8.10 billion per year. The €3.32 billion estimate reported in the top panel of the table can be seen under the “Base VSL, Base Renewables” row. A higher assumed VSL necessarily leads to higher external costs and hence total costs. This is evident by comparing the rows with “base VSL” versus “high VSL” in the bottom panel.

Looking across the “base VSL” rows, we observe that social costs fall as the assumed growth of renewables attributable to the phase-out increases. Higher renewable growth leads to increased private costs. This is because investment in renewables is expensive relative to increased production from fossil-fuel plants. However, higher renewable growth also decreases external costs. This is because the additional renewables displace fossil-fuel production, decreasing the monetized health impacts from local air pollution. We find that the increase in private costs across the “low”, “base”, and “high” renewables scenarios is smaller than the reduction in monetized health impacts as renewables grow from the low-case to the high-case. This effect is even more pronounced in the “high VSL” rows where we assume that the premature mortality due to air pollution exposure is more costly.

There are some noteworthy limitations to the analysis in Table 5. While nuclear power plants emit virtually no global or local air pollution, nuclear energy does come with catastrophic accident risk and requires storing the waste that results from nuclear production. Estimates from the literature suggest that the external costs of nuclear power due to waste storage and accident risk fall between €1 and €4 per MWh (D’haeseleer 2013). This wide range is due to differing estimates of accident probabilities and severity, as well as varying assumptions on discount rates. If we value the external costs of nuclear power at €4 per MWh, then the expected benefits from the nuclear phase-out are very small at just €0.2 billion per year. This is clearly far smaller than the €3–€8 billion per year in annual social costs estimated above. Even if we assume that the external costs of nuclear power are an order of magnitude larger than those from existing literature, then the expected benefits of the nuclear phase-out are still smaller than our central estimate of the social cost of the phase-out policy.

7. Conclusions and Policy Discussion

Following the Fukushima disaster in 2011, German authorities made the unprecedented decision to immediately shut down almost half of the country’s nuclear power plants, and to shut down all of the remaining nuclear power plants by 2022. We quantify the economic and environmental costs of this decision. Our analysis indicates that

investments. These dynamic impacts are not incorporated into our analysis, and are likely second order relative to the capital and operating costs associated with renewable investments.

the phase-out of nuclear power has come with an annual social cost to Germany of roughly €3–€8 billion per year. The majority of this cost is due to the 800 excess deaths per year resulting from the local air pollution emitted by coal-fired power plants operating in place of the shutdown nuclear plants. The scale of the social costs from the nuclear phase-out exceeds even the largest estimates of the expected benefits from the phase-out.

In light of the scale of the costs we identify, it is striking that the nuclear phase-out continues to receive widespread support, with more than 81% in favor in a 2015 survey (Goebel et al. 2015). Concerns about the risks of nuclear accidents and storing nuclear waste are at the core of the anti-nuclear sentiment, and motivated the decision to phase-out nuclear power (Ethics Commission 2011). Thus far, we have compared the social costs of the phase-out against its *expected* benefits. However, nuclear accident risks are highly uncertain, and the costs associated with nuclear waste disposal are also arguably uncertain. It is therefore possible that a sufficiently risk-averse policymaker could phase-out nuclear to avoid the tail risks associated with nuclear accidents and waste disposal, even though the costs of the phase-out are higher than its benefits in expectation.

To get a sense of the level of risk aversion implied by the decision to proceed with the nuclear phase-out, we calculate the probability of a major nuclear accident that would result in the expected benefits from the phase-out being equal to its costs. For this back-of-the-envelope calculation, assume that, absent the phase-out, nuclear plants would have been shut down in the same order but approximately 10 years later, with the last plants closing in 2032 instead of 2022. With the phase-out starting part way through 2011, this gives roughly two decades over which the policy would reduce nuclear production. Our estimate for the cost of the phase-out is €3–€8 billion per year; this implies a cumulative cost of the phase-out of around €60–€160 billion over this 20 year period. The estimated cost of the Fukushima accident is 35–80 trillion yen, or €280–€640 billion (JECR 2019). Assume for simplicity that there can either be no accidents or there can be one Fukushima magnitude accident during this 20 year period. The probability of this Fukushima-scale accident occurring would have to be anywhere from around 1 in 10 to as high as 1 in 2 for the expected benefits of the phase-out to be equal to the expected costs.[31] A 1 in 10 chance, let alone a 1 in 2 chance, is far greater than even the most conservative estimates of the probability of an accident of this magnitude occurring in Germany. For instance, Wheatley, Sovacool, and Sornette (2017) estimates that there is a 50% chance that a Fukushima event (or larger) occurs every 60–150 years across the entire *global* fleet of nuclear reactors. Germany had less than 4% of the world's nuclear reactors in 2011.

We can also examine how costly a single nuclear accident would have to be in order to rationalize the phase-out decision based on expected costs and benefits. Using the estimates from Wheatley, Sovacool, and Sornette (2017), a Fukushima

31. €160 billion/€280 billion = 0.57, which we approximate as 1 in 2, and €60 billion/€640 billion = 0.094, which we approximate as 1 in 10.

event (or larger) might plausibly occur in Germany over a 20 year period with a probability between 1 in 150 and 1 in 375.[32] This nuclear accident would have impose social costs between €9 trillion and €60 trillion for the expected benefits of the phase-out to be equal to its costs.[33] This is orders of magnitude greater than current estimates of the cost of the Fukushima accident. Both of these calculations, while simple in their approach, indicate that policymakers would have to exhibit an extremely high level of risk aversion in order the rationalize the phase-out decision.

However, key behavioral factors may affect decision-making in this setting. Prospect theory predicts that people will over-weight the risk associated with low-probability events, and tend to be risk averse when they face even a small chance of incurring a large loss (Kahneman and Tversky 1979; Barberis 2013). In our case, the choice is between a high probability of incurring a moderate loss due to increased electricity prices and worse air pollution versus a low probability of incurring a very large loss due to a nuclear accident. Here, loss aversion rationalizes a preference for avoiding the "low probability, high damage" option. Indeed, existing evidence suggests that people tend to greatly overestimate both the probability of a nuclear accident and the expected damages from such an event, including a number of studies focused on Germany (Slovic, Fischhoff, and Lichtenstein 1979; Slovic 2010; Slovic and Weber 2010).

The extreme level of risk aversion required to justify the phase-out decision also points to another behavioral explanation: salience. While the scientific literature on the harmful effects of air pollution is now definitive, there is still relatively limited public understanding of the scale of the adverse health consequences of local air pollution exposure. This might be due to the difficulty in attributing any single death entirely to air pollution exposure from a given power plant. Instead, air pollution concentration levels are the result of a wide range of different emitters, and air pollution has a small but persistent effect on mortality risk. Similarly, the costs of climate change will primarily be borne by future generations, and linking a future climate event to the carbon emissions from a power plant smokestack today is even less straightforward. In contrast, a nuclear accident is a highly visible event that can be clearly linked back to a nuclear reactor.

Local air pollution emissions are almost certainly less salient than carbon emissions, particularly at the time when the phase-out decision was made. Germany has long had an ambitious set of policies to reduce carbon emissions as part of its *Energiewende* program. There is widespread support for these policies to tackle climate change, even when the upfront costs have been substantial. For example, renewable subsidies in Germany exceeded €25 billion per year in 2017, and the charges to fund these payments now make up about a quarter of the electricity price paid by

32. $(50\% \times 4\% \times (20\,\text{years}/60\,\text{years})) = 0.0067 =$ 1 in 150, and $(50\% \times 4\% \times (20\ \text{years}/150\ \text{years})) = 0.0027 =$ 1 in 375. This assumes reactors in Germany are just as prone to accidents as the average reactor in the world.

33. €60 billion/0.0067 = €9 trillion and €160 billion/0.0027 = €60 trillion.

residential households (BNetzA 2020). The issue of local air pollution, on the other hand, has not received the same level of national attention. In fact, policymakers appear to have made no mention of air pollution at the time of the decision (BMWI 2010; Ethics Commission 2011). Subsequent studies of the impact of the phase-out have also focused exclusively on electricity prices and carbon emissions (Knopf et al. 2011; Traber and Kemfert 2012; Knopf et al. 2014; Grossi, Heim, and Waterson 2017; Grossi et al. 2018).

The relative salience of the different impacts of the nuclear phase-out was further exacerbated in our setting by the Fukushima crisis in 2011. The German government clearly acknowledged this when making their decision, stating that "the risks of nuclear energy have not changed since Fukushima, but the perception of the risks has" (Ethics Commission 2011). For example, Tanaka and Zabel (2018) demonstrated how the increased salience of nuclear accident risks due to the Fukushima incident affected house prices in the U.S. Interestingly, the study finds that the effects largely dissipated by 2 years after the Fukushima accident. This highlights an important challenge for policymakers—highly salient events can galvanize the public into supporting large-scale policy changes, but they can also make it harder to weigh the merits of those policy changes in the moment.

Regardless of the underlying causes, it is clear that Germans care deeply about climate change, yet they are distinctly anti-nuclear. Policymakers in Germany and around the world thus face a difficult tradeoff. On the one hand, there is a strong case to be made that nuclear power still has an important role to play in the shift away from carbon-intensive fossil fuels (IPCC 2018; IEA 2019). Many citizens are also willing to incur substantial costs upfront to reduce the risk of climate change. However, many of those same citizens have historically been more concerned about the risks of nuclear energy than about the health impacts of local air pollution from using fossil fuels. Clearly, it is vital that economists are able to credibly estimate and convey the costs and benefits of large policy changes. Beyond that, our findings underscore the importance of understanding the behavioral factors that can influence the way those costs and benefits are evaluated by policymakers and the public.

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Supplementary data

Supplementary data are available at *JEEA* online.