Choosing Between Environmental Ills: A Study of the Phase-Out of Nuclear Power in Germany

Stephen Jarvis, Olivier Deschenes, and Akshaya Jha*

Abstract

Many countries have phased out nuclear electricity production in response to concerns about nuclear waste and the risk of nuclear accidents. This paper examines the impact of the shutdown of roughly half of the nuclear production capacity in Germany after the Fukushima accident in 2011. We use hourly data on power plant operations and a novel machine learning framework to estimate how plants would have operated differently if the phase-out had not happened. We find that the lost nuclear electricity production due to the phase-out was replaced primarily by coal-fired production and net electricity imports. This shift away from nuclear also increased both electricity prices and the average operating cost of German electricity production. Combined, we estimate that the cost of the nuclear phase-out has been approximately 9-11 billion dollars per year, with the majority of these costs due to increased levels of local pollution which impose significant health burdens. In light of these costs we discuss the role of both salience and attitudes to risk when societies must trade off a range of large and uncertain environmental harms.

JEL Codes: Q4, Q5, C4

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*Jarvis: Energy and Resources Group, University of California at Berkeley. Berkeley, CA 94720. Email: jarviss@berkeley.edu. Deschenes: Department of Economics, 2127 North Hall, University of California at Santa Barbara. Santa Barbara, CA 93106. Email: olivier@econ.ucsb.edu. Jha: H. John Heinz III College, Carnegie Mellon University. 4800 Forbes Ave, Pittsburgh, PA 15213. Email: akshayaj@andrew.cmu.edu. The authors wish to acknowledge the Library at the University of California, Berkeley, which provided support for the completion of this research.

1 Introduction

The Fifth Intergovernmental Panel on Climate Change Assessment Report (IPCC 2013) and the 21st United Nations Climate Change Conference ("COP21") have both recommended that nuclear power should be a part of the global solution to climate change. 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 pollutants that have negative consequences on human health (NRC and NAS (2010); Jaramillo and Muller (2016); Holland et al. (2018)). Despite this, many countries have substantially decreased the share of their electricity production from nuclear sources. This has been driven by a number of factors, including high costs for new nuclear projects, concerns about long-term solutions for storing nuclear waste, and public fears of catastrophic nuclear accidents, particularly following the incidents at Three Mile Island in 1979, Chernobyl in 1986, and Fukushima in 2011.

This paper examines the economic and environmental costs of the shut down of half of the seventeen nuclear reactors in Germany following the Fukushima accident in 2011. This empirical context affords us several advantages over previous studies on the market and environmental implications of nuclear power. First, Germany shut down over 8 GW of nuclear production capacity over a few months in 2011, far larger than the reductions in capacity studied by previous research that focused on the United States (Davis and Hausman (2016); Severnini (2017)). Second, the remaining nuclear reactors in Germany are already scheduled to shut down by 2022 and so our study is particularly timely in helping understand the likely impacts of the conclusion of this phase-out policy. Third, studying electricity in the European context also provides us the opportunity to examine how cross-border trade was impacted by a large shock to production in one country. Lastly, and importantly, Germany's nuclear phase-out was not caused by changes in economic or environmental conditions pertaining to nuclear production in Germany. Instead, it was the direct result of political actions taken following extensive anti-nuclear campaigning in Germany and a sudden increase in the perceived risk of nuclear power following the accident in Japan in 2011 (Goebel et al., 2015). As such this policy offers an ideal context to study how salience and societal attitudes towards risk can affect policy decisions that must trade off multiple uncertain environmental risks.

There have been a handful of studies that have examined the impacts of the phase-out of nuclear power in Germany. In the years immediately following the phase-out decision in 2011 several studies sought to explore the likely long-term impacts of the policy on the electricity sector. For instance, both Traber and Kemfert (2012) and Knopf et al. (2014) used mixed economic-engineering models of the power sector to simulate future changes to capacity investments, electricity prices and carbon emissions out into the 2020s and 2030s. In general they found the phase-out would increase electricity prices and carbon emissions, primarily because fossil generation tended to play a significant role in replacing the output from the closed nuclear plants. More recently, empirical studies have sought to examine the impacts of the initial nuclear plant closures in 2011. The closest of these to our paper is Grossi, Heim and Waterson (2017) which uses an event study framework to econometrically estimate the impact of the phase-out on electricity prices over a three year window between 2009 and 2012. They find a substantial 8.7% increase in electricity prices resulting in costs to German consumers of roughly €1.75 billion in 2012.

In this paper we take a broader stroke at this question estimate both the economic and environmental costs of the nuclear phase-out in Germany, that includes both the initial reactor closures in 2011 and the subsequent incremental shutdowns up until the end of 2017. To this end, we develop a new machine learning framework to empirically simulate hourly power plant dispatch and predict which power plants stepped in and increased their output in response to the nuclear plant closures. In doing so, this paper contributes a new method that builds on Davis and Hausman (2016) in order to empirically assess how a change in electricity production or consumption at one location propagates throughout the electricity transmission network. For example, recent studies have explored which power plants adjust production in response to changes in electricity consumption at a given location, whether it be plugging in an electric vehicle Holland et al. (2018), installing a more energy efficient appliance, or siting new wind and solar resources (Callaway, Fowlie and McCormick (2018)). Our paper also contributes to the small but growing literature in energy and environmental economics that combines machine learning with causal inference techniques (Cicala (2017); Burlig et al. (2017)).

This paper combines hourly data on observed power plant operations between 2010-2017 with a wide range of related information, including power plant characteristics, estimates of plant-level marginal costs, electricity demand and local weather conditions.

Using these data, we first simply document that production from nuclear sources declined precipitously after March of 2011. This lost nuclear production was replaced by production from coal- and gas-fired sources in Germany as well as imports from surrounding countries. We then more formally examine this result using our machine learning algorithm, which predicts 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. Consistent with the aforementioned descriptive trends, 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.

We then use these estimates of the changes in plant-level generation to calculate some key elements of the costs and benefits of the phase-out. Consistent with the prior literature we examine the impact of the phase-out on electricity prices. However, we also extend the analysis further this by estimating how the phase-out affected both private power plant operating costs and external environmental costs. In particular, no prior studies has quantified the potential health impacts of the phase-out due to increases in local pollutant emissions. Nuclear plants have substantially lower marginal costs and lower direct pollutant emissions than fossil fired units, and so we find that the nuclear phase-out resulted in both an increase in production costs, a large redistribution of operating profits from the nuclear sector to the fosissl sector, as well as an important increase in pollution emissions. We value the external damages created by these pollution emissions and find that the health impacts of increased local pollution concentrations constitute by far the largest component of the overall net costs of the phase-out policy. Overall we estimate the expected costs of the phase-out as being approximately $9-11 billion per year. However, the various costs and benefits that make up this figure vary in their certainty, salience and risk profile. As such we conclude with a discussion of the challenges of policymaking in this setting.

This paper proceeds as follows. The next section provides background on the the German electricity sector during our sample period. Section 3 lists the data sources used for this analysis and shows descriptively how electricity prices, production by fuel type, costs, air pollution and other outcomes changed over time. In Section 4, we discuss results from a simple event study approach. We describe the machine learning approach to estimating the impacts of the nuclear phase-out on plant-level and market-level outcomes in Section 5. Section 6 presents our estimates of the economic and environmental impacts of the nuclear phase-out in Germany. Finally, we discuss the policy implications of our findings in Section 7.

2 Background on Nuclear Power in Germany

The first nuclear power stations were constructed in Germany in the 1960s. Over the next three decades nuclear capacity expanded rapidly with the last reactor commissioned in 1989. Despite no new reactors coming online in the 1990s and 2000s, Germany consistently generated around a quarter of its electricity from nuclear power over this period.

Despite having a sizable fleet of reactors, nuclear power has long been controversial in Germany. In the 1970s there were protests at a number of sites where nuclear facilities were either proposed or under construction. A major moment in the politics of nuclear power in Germany was the Chernobyl disaster in Ukraine in 1986. 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 (SPD) and the Green Party. Over the next two years the Schröder government banned the construction of new reactors and negotiated a policy of phasing-out nuclear power completely, with the last reactors scheduled to close by 2022.

In 2009, the center-right Merkel government came to power and renegotiated the original phase-out policy by committing to extending the lifetimes of the newest reactors, pushing back the final shutdown timeline into the 2030s. Despite public demonstrations against these changes the new phase-out timeline was agreed in 2010. Then in March 2011 the Fukushima nuclear accident occurred, once again raising the specter of nuclear disasters.[1] Within a matter of days the Merkel government declared a moratorium on planned extensions at existing nuclear power plants and immediately took eight older reactors offline for testing. Just over a week later the largest anti-nuclear demonstration in the country's history took place, with an estimated 250,000 people taking to the streets nationwide. The decision was made in May that year to return to the original final phase-

[1] A 2013 report by the United Nations Scientific Committee on the Effects of Atomic Radiation concluded that "in general, [radiation] doses were low and that therefore associated risks were also expected to be low. A discernible increase in cancer incidence in the adult population of Fukushima Prefecture that could be attributed to radiation exposure from the accident was not expected."

out date of 2022. Of the seventeen reactors operating in 2011, the eight reactors already temporarily offline were closed immediately (8.4 GW of capacity), a ninth reactor 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. For the rest of this paper we examine the impacts of the nuclear phase-out up until the end of 2017. Henceforth we refer to this as "the nuclear phase-out" but to be clear this means we look at the closure of the nuclear reactors in 2011, 2015 and 2017, but not the subsequent closures in 2019 and 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 CO_2 emissions by 80-95% by 2050 relative to 1990 levels (BMWi, 2018). To achieve this Germany has undertaken major investments in renewable energy generation, power grid infrastructure, and energy efficiency measures. Whilst the legislative underpinnings of the *Energiewende* were enacted in late 2010, government support for renewable energy began much earlier with the Electricity Feed-in Act in 1991 and the Renewable Energy Sources Act in 2000. These policies provided guaranteed feed-in-tariffs for renewable generators and gave them first priority for inputting power to the grid. Lastly, in 2019, the German government committed to phasing out coal power by 2038.

3 Data and Summary Statistics

This paper uses data from many different sources in order to assess the market and environmental implications of the first seven years of the nuclear phase-out in Germany. First, we obtain plant-level hourly electricity production of all power plants with production capacity greater than 100MW from 2015-2017 from the European Network of Transmission System Operators for Electricity (ENTSOE). We supplement these data with hourly total production by source (e.g. nuclear, coal, natural gas, oil, etc.) from the European Energy Exchange (EEX) from 2010-2017. Hourly production from wind and solar sources for the sample period 2010-2017 is also reported by each of Germany's four transmission system operators (TSOs): Amprion, TenneT, TransnetBW and 50Hertz. The data provided by the TSOs also include the hourly level of electricity imports and exports in and out of Germany at border points, as well as the hourly total quantity of electricity demanded in Germany.

For electricity and natural gas prices in Germany and neighboring countries we use data accessed through Thomson Datastream. Monthly data on coal and oil prices as traded on the Intercontinental Exchange Inc (ICE) were accessed through Quandl. ICE also provides data on monthly permit prices for carbon dioxide emissions set by the European Union Emissions Trading System (EU ETS). We use these price data to construct plant-specific marginal cost estimates. Annual carbon dioxide emissions for each plant that participates in the EU ETS is provided by the European Environment Agency. We also collect annual plant-level data on fuel inputs and local pollution emissions from the European Environment Agency. This data is collected as part of monitoring for the EU Large Combustion Plant Directive. Station-level weather data comes from Germany's national meteorological service (DWD) and local pollution monitor data is from the German Environment Agency (UBA). Finally, we compile other electricity sector data and power plant level characteristics from a variety of different sources (Open Power System Data, 2018; BNetzA, 2018; Egerer, 2016).

[Table 1 about here.]

Table 1 provides summary statistics for the electricity sector in 2010 (the first year in our sample) and 2017 (the last year in our sample). The top panel shows that, despite the closure of more than 10 GW of nuclear capacity over this period, total installed electricity generating capacity grew from 172.2 to 217.6 GW over this period. This is due primarily to the rapid growth in renewable generating capacity, from 52.1 to 112.5 GW (bottom panel). Net generation increased by roughly 40 TWh between 2010 and 2017. Average wholesale electricity prices also declined precipitously from \$70.7 in 2010 to \$41.8 in 2017 (2017 constant USD). Finally, Germany is a net exporter of electricity over our entire sample period; annual net electricity exports increased from 3.5 TWh in 2010 to 33.5 TWh in 2017.

The middle panel of Table 1 reports summary statistics for the major types of power plants in Germany (nuclear, hard coal, lignite, natural gas, and oil). The extent and implication of the 2011 Nuclear Phase-Out is evident as nuclear generation roughly halved after 2011. At the same time, the number of coal power plants (hard coal and lignite) also dropped due to the closure of older and smaller plants. The scale of the coal generation sector remained constant during this period as average capacity by plant increased, and the small decline in hard coal generation was essentially offset by an increase in lignite generation. The marginal cost of generation for both type of coal plants fell significantly in real terms during the 2010-2017 period, driven by a reduction in the price of coal. The 2010s were also a period of growth for the gas sector: 26 plants were added and annual generation increased from 53.6 TWh to 72.3 TWh. Appendix Figure B.1 presents a more detailed breakdown of the generating sources of electricity in Germany over the period 2010-2017.

[Figure 1 about here.]

Figure 1 shows the estimated marginal cost of each power plant in our sample operating in 2011. We assume that biomass, waste, hydroelectric, wind and solar resources have zero marginal operating cost. Next are the nuclear units for which we assume a marginal operating cost of approximately $10/MWh based on prior research on Germany's power sector (Egerer, 2016). The next segment of the curve contains all fossil units, which display a wide range of marginal costs (derived from our data), typically ordered from lignite, hard coal, gas, and then oil.

Figure 1 highlights that nuclear units uniformly had lower marginal costs than fossil fuel fired units over our analysis period. At the same time, nuclear generation also produces virtually no emissions of carbon dioxide or local pollutants, unlike fossil generation. We would thus expect that the shutdown of nuclear reactors will lead to an increase in both the costs of production and pollution emissions. However, we cannot simply compare market and environmental outcomes before versus after the shutdown of nuclear plants to infer the impact of the 2011 Nuclear Phase-Out. This is because, as mentioned above, economic conditions in Germany's wholesale electricity market changed drastically over time. For example, coal prices decreased precipitously and substantial renewable generating capacity was installed from 2010-2017. The next sections discuss two distinct approaches to identify the impact of the nuclear phase-out on the relevant market and environmental outcomes separately from secular time trends in economic factors.

4 Impact of the Nuclear Phase-Out: Event Study Regressions

The sudden and unexpected nature of the phase-out decision in response to the Fukishima crisis in Japan allows us to analyze the impact of the initial round of nuclear reactor closures in 2011 using the event study framework formulated in Davis and Hausman (2016) and more recently implemented by Grossi, Heim and Waterson (2017). To do this, we use hourly data on aggregate generation by source and total electricity demand. Specifically, our event study framework estimates how total electricity production by each fuel type i in each hour t changes at different levels of electricity demand either side of a "window" around the 2011 closure event.

The independent variables of interest are equally-spaced bins of net electricity demand interacted with an indicator for observations after March 15^{th} 2011. We consider "net electricity demand", electricity demand net of production from renewable sources, because output from renewables is dependent on the weather and because of their near zero marginal cost these sources will almost always produce as much as possible. In our primary specifications, we restrict the sample to observations less than 12 months before or after March 15^{th} 2011.

We estimate the following event study specification:

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

where $G_{i,t}$ is the total quantity of electricity produced by source 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, $\mathbf{1}\{t \geq 3/15/2011\}$ is an indicator that takes on the value one if the observation corresponds to an hour-of-sample on or after March 15^{th} 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 2 plots the estimates of the β coefficients along with the corresponding 95% confidence intervals. Panel (a) shows that average hourly electricity production from nuclear sources dropped by roughly 5 GWh across all levels of net demand. Panels (b)-(d) of Figure 2 then show that this lost nuclear production was offset in large part by increases in electricity production from all fossil-fuel fired sources. Specifically, 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 during very high net demand periods.

[Figure 2 about here.]

While the event study results provide a simple examination of the data, there are several limitations to this approach. First, hourly plant-level data on electricity production are not available prior to 2015. Thus the event study framework around the 2011 closures cannot be used to explore heterogeneity in how different plants respond to the nuclear phase-out. This heterogeneity is especially important because the amount of local air pollution emitted per MWh of production can vary significantly across plants of a given source type, and the health damages this causes are also highly location dependent.

Second, the event study framework relies on the interpretation that changes in power plant operations around this 2011 period are caused by the closures rather than by changes in other determinants of aggregate generation decisions. This forces us to examine the impact of the phase-out in a fairly narrow window around the initial 2011 shutdowns, noting that firms had limited alternate ways to immediately respond to the sudden closure of eight nuclear reactors in March 2011. 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 were already changing over this period independently of the nuclear phase-out in 2011. For example, coal and natural gas plants had similar marginal costs in 2011. However, coal prices decreased precipitously from 2011-2015 while natural gas prices increased over this period, potentially resulting in changes to the dispatch order of coal versus natural gas plants independently from the nuclear phase-out. In addition, many older coal and gas plants were retired between 2010 and 2017, and a number of new fossil plants came online during this period as well. Many of these changes over our analysis period are evident in Table 1. In summary, it is unlikely that market outcomes before versus after March 2011 were driven solely by the reduction in nuclear capacity, especially as one looks further in time after the 2011 shutdown decision.

5 Impact of the Nuclear Phase-Out: A Machine Learning Approach

5.1 Methodology

We use a machine learning approach in order to derive a more credible estimate of the market and environmental impacts of the series of nuclear closures that occurred between 2011 and 2017. This machine learning approach has two advantages over the event study framework discussed in the previous section. First, hourly plant-level data on electricity production are not available prior to 2015 and so the event-study results are based on hourly aggregate electricity production data by source for these years. As we noted earlier, plant-level heterogeneity is potentially very important, particularly for estimating local pollution impacts where changes to pollution concentrations and the resulting health effects can be highly localized. The machine learning algorithm allows us to use the more recent plant-level data to estimate plant-level heterogeneity in response to the nuclear phase-out over our entire analysis period.

Second, as discussed earlier, a variety of economic factors relevant for electricity production decisions changed over time independently from the nuclear phase-out. The event study framework affords us only limited ability to control for these factors. In contrast, using the machine learning approach, we can estimate the impact of the nuclear phase-out on plant-level economic and environmental outcomes while controlling for a wide range of observed market factors that change over time independent from the nuclear phase-out. Importantly, the goal of the machine learning applications in this paper is to best predict market outcomes for different values of the input variables. We do not seek to identify causal parameters in this component of the analysis.[2]

[2] To be clear, the Random Forest algorithm we use only reports outcome predictions, so there are no estimated coefficients.

5.2 Data

We train our machine learning algorithm to predict power plant operations using a data set of roughly 4.5 million observations. The outcome of interest is the hourly quantity of electricity produced by each "dispatchable" plant in our sample. This excludes production sources such as renewables that have near-zero marginal cost and thus operate whenever possible (recall that we incorporate renewables by netting their production from total electricity demand). Hourly data on power-plant level electricity generation is available for all EU member states since 2015 from ENTSOE.[3] We incorporate imports and exports for each border interconnection between Germany and its neighboring countries by effectively treating each border interconnection point as a power plant. For example, the hourly net electricity imports from France to Germany is one such border point and we estimate the amount of electricity transferred across this border in much the same way as for a power plant located in Germany. In all cases we normalize our dependent variable by dividing through using the maximum production capacity of each power plant or border point. This means that our dependent variable is bounded 0/1 and our model is designed to predict the operating rate of each plant, such that a value of zero means the plant is offline and a value of one means it is generating at its maximum output.

The independent variables include electricity demand, local weather, each plant's marginal cost, the availability of other power plants, and a wide range of power plant characteristics such as fuel type, efficiency, technology, and location. We estimate a predictive model that takes these independent variables as inputs and generates a predicted operating rate for each power plant in each hour. Importantly, we have data on these independent variables from 2010-2017. This allows us to predict hourly, plant-level electricity production from 2010-2017 using our model despite only having actual observations of 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. Consequently, our independent variables for the time-series model

[3] More specifically, the data are available for plants with capacity greater than 100 MW. This covers 100% of generation from nuclear plants, 95% from lignite plants, 85% from hard coal plants, 50% from gas plants and 45% from oil plants. We effectively treat the operating behavior of these plants as being representative of the remaining plants with capacity less than 100MW.

of electricity prices include electricity demand, national average weather, and overall plant marginal costs.

5.3 Empirical Methods

To predict the outcomes of interest, we use the Random Forest regression algorithm (Breiman, 2001). In particular we use the Quantile Regression Forest algorithm as in Meinshausen (2006). Random Forests have a number of very useful properties for constructing a predictive model of plant-level electricity production. 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 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.[4]

In addition, the structure of the Random Forest algorithm means that the support of possible outcome predictions is bounded by the support of the outcome values in the training data-set. This prevents non-sensible predictions such as plant operating rates of less than 0% or greater than 100%. Finally, using the Quantile Regression Forests algorithm allows us to produce predictions for the full conditional distribution of the outcomes, rather than just their expected value. We use this to better understand the uncertainty in our analysis, and also to make corrections that ensure our final results produce outcomes that meet certain physical constraints (e.g. that electricity supply equals electricity demand). More details on this can be found in the appendix.

We use the machine learning predictive model to construct two data series in order to implement the empirical analysis. First, we predict hourly plant-level electricity production at each dispatchable plant (i.e. each fossil plant or border point) using the actual, observed values of the independent variables over 2010-2017. This yields electricity pro-

[4]In their application for predicting housing values, Mullainathan and Spiess (2017) report that the Random Forest method results in the most accurate predictions, as measured by out-of-sample R^2, among the various methods evaluated (e.g., OLS, Regression Tree, LASSO, and Ensemble).

duction levels in the "factual" scenario with the nuclear phase-out. The machine learning model is essential in part because we do not have hourly plant-level production data prior to 2015.

Second, we use the model to calculate production for the same set of dispatchable plants in each hour-of-sample in the counterfactual scenario where there was no nuclear phase-out. This amounts to using the model to predict plant-level generation assuming that the nuclear reactors that were shutdown in 2011, 2015, and 2017 would have stayed operational throughout 2010-2017. To do this we estimate the amount of electricity these nuclear plants would have produced in each hour-of-sample if they had remained online.[5] We then use this amount to adjust the total net electricity demand downward, thus reducing the amount of generation needed from the remaining dispatchable sources. For our baseline analysis we keep all of the other independent variables unchanged at their actual values. A natural concern for evaluation is that the phase-out led to changes in some of the other independent variables. In Section 5.5 and Appendix Section B, we discuss the various sensitivity analyses we implemented that account for how the values of some of the other independent variables, such as the available production capacity from other plants, may have shifted in response to the phase-out.

Finally, we calculate different market and environmental outcomes using the predicted hourly electricity production from each plant with versus without the nuclear phase-out. Though the description above focused on hourly plant-level production, we utilize a similar approach for wholesale electricity prices, as we report below.

5.4 Model Validation

This subsection presents figures and tables comparing the observed outcomes with the predicted outcomes from our machine learning algorithm.

[Figure 3 about here.]

[5] To do this we assume a relatively conservative annual average operating rate for these plants of 80%. This seems reasonable given the plants that closed tended to be older. Newer nuclear plants often achieve operating rates of 90-95%. We then also account for the fact that nuclear plants tend to go on maintenance during the summer months when demand is lower, allowing them to achieve higher operating rates in winter months when demand is highest. Here we use the observed fluctuations in monthly nuclear generation from 2012 to 2014. We use this period as there were no shutdowns during these years and so they offer a consistent measure of the seasonal pattern of nuclear plant operations.

Figure 3 reports the actual and predicted wholesale price in 2017 USD per MWh, as well as the difference between the two (i.e., the prediction error). To improve visibility, we average these prices and differences from the hourly to the daily level. It is evident that the machine learning model delivers very accurate predictions; the difference between observed versus predicted prices is nearly zero throughout the entire period, although there are some idiosyncratic exceptions, like the large negative error on December 25th, 2012. Nevertheless, the adjusted R^2 from the regression of actual average daily price on the average daily predicted price is 0.98.

Figure 4a compares observed hourly plant-level operating rates (i.e., percentage of capacity utilized) with the predictions from the machine learning model. As part of the application, we check the out-of-sample cross-validated performance to avoid overfitting and give a fair assessment of how the model may perform when used to make predictions about our counterfactual scenario. The cross-validated out-of-sample R^2 is 0.61 and the mean squared error (MSE) is 0.061.[6] Since we will use the predictions from the machine learning model to evaluate the counterfactual scenario at the plant-month and plant-year levels, we also evaluate the predictive performance of the model at these levels of aggregation. Figure 4b shows how the model performs at predicting operating rate at the the same set of plants over the same time period but collapses all hourly values to plant-level annual averages. As the figure shows, the performance is substantially improved and the areas of systematic error largely disappear. The cross-validated out-of-sample R^2 rises to 0.93 and the Mean Squared Error falls to 0.006.[7]

[Figure 4 about here.]

Finally, we conduct alternative out-of-sample validation checks of the pre-2015 plant-level generation predictions. Since we do not observe hourly plant-level electricity production for this sample period, we instead use data from air pollution monitors in Germany spanning the entire 2010-2017 analysis period. Specifically, another test of the accuracy of the Random Forest predictions is to determine if variation in predicted generation is correlated with actual observed variation in ambient air pollution at nearby stations.

[6]By comparison, a simple OLS regression with linear effects with the same independent variables only achieves an out-of-sample R^2 of 0.37 and an MSE of 0.091.

[7]A simple OLS regression with linear covariates is still clearly inferior with an out-of-sample R^2 of 0.63 and an MSE of 0.025.

To this end, we match each power plant to its closest air pollution monitor.[8] We then estimate simple panel regressions of daily average ambient pollution concentrations (for 5 pollutants) on daily total generation at the plant level, conditional on plant fixed effects and year and month fixed effects. The plant fixed effects control for time-invariant plant characteristics such as age, source fuel, and capacity, while the year and month fixed effects control for trends and seasonality in air pollution and generation patterns.

[Table 2 about here.]

Table 2 reports the results of this analysis. Each row reports the coefficient estimate, along with standard errors clustered by plant, from separate regressions for 5 air pollutants: PM_{10}, $PM_{2.5}$, SO_2, CO, and NO_2. For ease of interpretation, both the dependent variables and the plant-level generation variables are standardized to have a mean of 0 and a standard deviation of 1. The columns correspond to different estimation samples. Column (1) is from models where the dependent variable is (standardized) actual plant-day generation. In column (2) the dependent variable is standardized predicted daily generation in the 2015-17 training data set, and in column (3), the dependent variable is standardized predicted generation in the 2011-17 sample. The key comparison to assess the validity of the Random Forest prediction algorithm is between columns (1) and (2). The estimates in column (1) confirm that air pollutant concentrations respond to variation in actual daily plant-level generation, except for SO_2. For example, a standard deviation increase in daily generation leads to a 0.157 standard deviation increase in average daily concentration of PM_{10} (with a clustered-robust t-ratio of 9.3), or roughly a 1% increase in daily concentrations . Similarly, a standard deviation increase in daily generation at a given plant leads to 0.15 to 0.20 standard deviations increases in $PM_{2.5}$, CO, and NO_2 concentrations. All these coefficient estimates are highly significant, with cluster-robust t-ratios in excess of 9 or 10. Column (2) replicates the analysis, but the daily plant-level generation predicted by the Random Forest model is used has the explanatory factor for ambient air pollution. The resulting coefficient estimates are slightly larger in magnitude (ranging from 0.20 to 0.27) but overall exhibit the same patterns and statistical significance has the models with the actual generation in column (1). Finally, column (3) reports estimates where the explanatory factor is also the predicted

[8] The average distance between power plants and air pollution monitors is 6.5 km, with a range of 0.25 to 31 km.

generation, but where the panel regressions are estimated over the entire 2010-17 sample period. In light of the standard errors, the estimates are similar to those reported in columns (1) and (2), ranging from 0.15 to 0.25, depending on the pollutant. Taken together, the analysis in Table 2 reveals that additional electricity generation leads to higher concentrations of ambient air pollutants, and importantly for our coming analysis, that the Random Forest predicted plant-level generation appear accurate and meaningful even outside the training data set where we do not have actual generation numbers to compare it with.

5.5 Sensitivity Analyses

This subsection discusses the robustness checks pertaining to our machine learning methodology, particularly with respect to the way we construct the counterfactual scenario where the 2011 phase-out had not happened. The base case analysis effectively assumes that the primary impact of the phase-out decision was the reduction in electricity generation from the nuclear plants that closed relative to the counterfactual scenario where those plants remained open. We are assuming that all other predictors would not have changed as a result of the phase-out policy relative to what actually happened during our analysis period.[9] For many of the predictors this seems entirely justified (e.g., plant characteristics, temperature, and seasonality of demand were not changed by the 2011 phase-out). However, for other predictors, this assumption is not as straightforward to defend. For example, the phase-out may have led to an increase in retail electricity prices, which may have reduced electricity demand. Second, over longer timescales the phase-out likely impacted decisions on the extensive margin (e.g., by accelerating investment in new replacement capacity). We deal with both of these issues by conducting sensitivity analyses.

The first sensitivity we conduct focuses on accounting for how the phase-out affected the fossil plants that were available to fill in for the closed nuclear plants. Prior studies of the nuclear phase-out have shown that if the phase-out had not gone ahead the amount of fossil capacity necessary to maintain supply security would have been 4 GW lower by 2020 (Traber and Kemfert, 2012) and 8 GW lower by 2030 (Knopf et al., 2014). This

[9] Note that this is still a much less restrictive assumption than the one required for the event study approach.

could be due to fewer new fossil plants being built or to older existing plants closing early. To capture this we re-run the analysis for the counterfactual scenario but this time we remove 2.8 GW of fossil capacity by 2017 that we determine was a direct response to the need to maintain supply security following the nuclear phase-out.[10] In general this sensitivity should alter the composition of the fossil plants available to meet net electricity demand.

The second sensitivity we conduct accounts for the fact that in the absence of the nuclear phase-out the incentives to invest in renewable generation may not have been as strong. To do this we re-run our prediction analysis for the counterfactual scenario but this time we assume that renewable generation would have been 30 TWh lower by 2017. We arrive at this amount based on changes made to Germany's renewable energy targets in response to the phase-out decision. In 2010 a target of generating 30% of the country's electricity from renewables by 2020 was planned, but following the 2011 phase-out decision this was increased to 35% (Jacobs, 2012). We approximate the difference between these two targets as requiring a change in renewable generation of roughly 30 TWh. This amounts to an 8% increase in net electricity demand by 2017 for the counterfactual case where the phase-out had not gone ahead. Based on the prior literature we interpret this 8% increase in net electricity demand as a relatively large response. For example, other studies that have modeled the phase-out effectively assumed that investments in renewables had virtually no scope to accelerate in response to the nuclear closures (see Traber and Kemfert (2012) and Knopf et al. (2014)). Furthermore, any changes to wholesale power prices created by the phase-out were unlikely to be passed on to investors in renewable capacity because all renewable capacity in Germany is remunerated through feed-in-tariffs that provide a guaranteed above-market price for the electricity produced. As such any relative change to wholesale electricity prices created by the phase-out would not have affected the revenue streams received by renewable generation. All of this seems consistent with the lack of any sudden, sharp change in renewables investment in the years following the 2011 decision. With these arguments

[10] Getting to 4 GW less by 2020 and 8 GW less by 2030 can be achieved by assuming a steady linear trend of fossil capacity falling by 0.4 GW per year from 2011 to 2030. For our 2010-2017 analysis period we achieve this with the following modifications: Irsching opens in 2012 instead of 2011, Weisweiler (Blocks C & D) closes in 2011 instead of 2012, Boxberg opens in 2013 instead of 2012, KW Walsum opens in 2014 instead of 2013, GKM Mannheim (Blocks 3 & 4) closes in 2012 instead of 2015, Westfalen (Block E) opens in 2015 instead of 2014, Westfalen (Block C) closes in 2015 instead of 2016, Moorburg (Blocks A & B) opens in 2018 instead of 2015 and KW Voerde (Blocks A & B) closes in 2016 instead of 2017.

in mind we take this sensitivity as capturing a very bullish outlook on the potential of renewables to respond, and so these results should be viewed as a conservative estimate of the impacts of the phase-out.

A third sensitivity we considered exploring was the scope for the phase-out to affect customer demand. In the absence of the phase-out wholesale electricity prices would have been lower. As such customer demand would likely have been higher, either due to direct adjustments by any price-elastic consumers or through reduced incentives to invest in energy efficiency improvements. However, there are good reasons to think that any changes to wholesale power prices created by the phase-out were unlikely to result in significant changes to customer demand. This is because the commercial and residential customers that make up around half of Germany's total demand are highly price-inelastic and wholesale electricity prices only contribute to around a quarter of their final retail price, with the remainder being network charges, renewable subsidy fees and taxes (BNetzA, 2018). Larger industrial customers are likely more price-elastic and their final retail prices are more heavily driven by wholesale electricity price fluctuations. In general though the impact of any demand effects would be in the same direction as the renewable investment case discussed above, and so we view our second sensitivity as being sufficiently conservative to account for this kind of response as well.

6 Economic and Environmental Impacts of the Nuclear Phase-Out

This section presents the results from the machine learning algorithm described in the previous section. Specifically, we compare model-predicted market and environmental outcomes with versus without the nuclear phase-out.

6.1 Private Costs and Benefits of the Phase-Out

This subsection examines how the nuclear phase-out affected wholesale electricity prices, electricity production, revenues and operating costs. All currency units are converted from nominal Euros to constant 2017 USD.

[Figure 5 about here.]

Figure 5 presents our estimates of the key impacts from the nuclear phase-out. First among these is Figure 5a which reports the monthly average difference in generation and net imports (in TWh) due to the nuclear phase-out policy. We report the estimates for all fossil-fired electricity production (grey diamonds), net imports (red circles), and nuclear production (purple squares). The start of the nuclear phase-out in March 2011 is marked by the vertical black dashed line. Note that the "with" minus "without" phase-out differences are null before this point. Necessarily, the first result that emerges is the stark reduction in nuclear generation of 3-5 TWh per month. The apparent cyclicality of the impact is driven by the observed historical seasonality of nuclear generation, where nuclear reactors typically schedule their maintenance and refuelling outages in the summer months.

The phase-out also caused a large increase in fossil generation of 2-3 TWh per month and a smaller increase in net imports of electricity. Importantly, these increases are calculated taking into account the rise in renewable generation which is netted out from the net load variable used in the Random Forest application. Another notable result in Figure 5a is that the stark increase in fossil-fuel fired electricity production starting in March 2011 does not seem to be temporary.

Figure 5b is constructed similarly and reports the impact of the nuclear phase-out on real wholesale prices (in 2017 USD per MWh). The estimates clearly show that the phase-out caused an increase in wholesale prices, ranging from roughly 0.5 to 6 dollars per MWh.[11] Another key result in Figure 5b is that the increase in wholesale prices persists through the end of 2017. This mirrors the persistence of the change in fossil fuel generation. Finally, the figure also shows that the phase-out may have exacerbated episodic increases in prices, such as the large price spike in January 2017 which occurred during an unusual cold spell in Europe (European Commission, 2017).

[Table 3 about here.]

Column (1) in Table 3 reports annual average estimates for wholesale electricity price and electricity generation in the scenario without the phase-out. Column (2) reports

[11] Table 3 below reports the average difference by month.

these outcomes for the scenario with the phase-out. Column (3) reports the difference between the two to give the impact of the phase-out. Column (4) then provides this as a percentage by dividing column (3) by column (1). The estimates reveal that the phase-out caused real wholesale electricity price to increase by $1.8 per MWh, a 3.9% increase relative to the prices that would have prevailed if the phase-out had not gone ahead. Consistent with Figure5a, nuclear generation was reduced by an average of 53.2 TWh per year during the phase-out period (corresponding to a 38% decline). The next rows decompose the previously documented increase in fossil generation by source. The largest increases, both in absolute and in proportionate magnitudes are from hard coal and gas generation. Annual average Hard coal generation increased by 28.5 TWh (32%) while gas generation increased by 8.3 TWh (26%). Finally, the phase-out caused net imports to increase by 10.2 TWh per year on average, although this still meant Germany was a net exporter of electricity.

[Table 4 about here.]

Table 4 is constructed similarly to Table 3 but instead examines the impact of the nuclear phase-out on financial outcomes for power plants, once again organized by plant fuel type. We report estimates of average annual revenues (hourly plant generation multiplied by hourly wholesale price), operating costs (hourly plant marginal cost multiplied by hourly wholesale price), and operating profits (the difference between revenues and operation costs).[12] For net imports we quantify revenues and costs as the net import of electricity multiplied by the wholesale price in the relevant neighboring country.[13] All the entries in Table 4 are in billions of dollars (2017 USD) per year.

The nuclear shutdown had a large effect on the revenues and operating profits of firms that own the nuclear plants that shutdown. Average annual revenues across all nuclear plants declined by $2.2 billion per year. Given the low operating costs of nuclear plants the vast majority of this comprises lost inframarginal rents as reflected by operating

[12]Operating costs and profits are only based on variable inputs and do not account for capital investments or depreciation.

[13]It is important to keep in mind that our analysis likely overestimates the contribution of net imports and underestimates their cost. This is because we have assumed that the phase-out caused no change to the prices of neighboring countries. Fully modeling these interconnected countries in the same manner that we have here would entail a prohibitive amount of additional data collection and would be unlikely to dramatically alter the overall findings given the dominant role of domestic generation in meeting Germany's electricity demand. Most likely prices in interconnected electricity markets would have been increased by the phase-out. As such our net import cost estimates are likely to be a lower bound.

profits declining by $1.6 billion, a 35% reduction. This decline in profits is even after accounting for increased revenues at the nuclear plants that remained open and were able to benefit from the increase in wholesale electricity prices. These lost nuclear plant revenues were primarily redistributed to fossil plants, most notably hard coal and natural gas plants. Operating profits also shifted from the closed nuclear plants to fossil plants, although at less than one-for-one ratio since operating costs per MWh are higher at fossil plants. Even taking this into consideration, the phase-out caused average annual operating profits at fossil plants to increase by around $0.7 billion, primarily at lignite and coal plants.

6.2 External Costs and Benefits of the Nuclear Phase-Out

In this section we present two separate analyses of the impact of the nuclear phase-out on external damages caused by the increase in fossil-based generation documented in the previous section. These emissions contribute to both a global externality (due to carbon emissions) and to local externalities (due to the emission of air pollutants that create local impacts on human health).

6.2.1 Estimating External Damages Using Reported Emissions Rates

First we estimate the change in carbon emissions caused by the phase-out. To do this we combine the predicted changes in hourly plant-level generation with plant characteristics (fuel type and efficiencies) to calculate the change in fuel inputs associated with the predicted change in electricity outputs due to the phase-out. We then make assumptions regarding the carbon intensity of different fuels to convert these changes in fuel inputs into changes in plant-level CO_2 emissions.[14]

Second we estimate the change in local pollution emissions due to the change in plant-level generation caused by the phase-out. To do this, we use a similar approach to the one used to calculate CO_2 emissions, although instead of using a single emissions intensity for each fuel we calculate plant-level emissions rates for each local pollutant. For this

[14] 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 then use three different intensities for lignite depending on the mining region a plant sources its coal from. These are 113.3 tCO2/TJ (Rhineland), 111.2 tCO2/TJ (Lusatian) and 102.8 tCO2/TJ (Central).

we utilize data from the EU Large Combustion Plant Directive (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.[15] We use this dataset to estimate the emissions rates of each of these pollutants for a given amount of fuel energy inputs at each plant. When emissions data is not available for a given plant we assign an emissions rate that is the average for that plant's fuel type. This set of estimated plant-level emissions rates allows us to convert our predicted changes in plant-level electricity generation into an associated set of predicted changes in plant-level local pollution emissions.

We next monetize the damages caused by the CO_2 and local air pollutant emissions. For CO_2, we monetize damages assuming a social cost of carbon of \$50/tCO_2. To convert the changes in local air pollutant emissions into expected changes in health damages we rely on two studies that estimate the health impacts of local pollution in Europe (EEA, 2014; Jones et al., 2018). In particular, the Jones et al. (2018) study provide local estimates of the annual health damages due to the air pollutant emissions for roughly four hundred of the largest coal-fired power plants in Europe. We can use these data to convert kt of emissions for SO_2, NO_x and PM at certain locations throughout Europe into monetized health damages. We then take our predicted increases in plant-level emissions and calculate the associated health damages.[16]

[Table 5 about here.]

Table 5 presents the results of this analysis of emissions outcomes. The table reports the fuel-specific annual emissions for CO_2 emissions (in Megatonnes, Mt), and for local pollutant emissions of SO_2, NO_x, and PM (in kilotonnes, kt). Lignite and hard coal are by far the two largest sources, contributing to more than 90% of emissions. Finally the table also reports the estimates of annual average mortality damages from local pollutant emissions in billions of USD per year. The phase-out led to an increase in CO_2 of 36.3

[15]More specifically, the data are available for 99% of lignite capacity, 98% of hard coal capacity, 90% of gas capacity and 91% of oil capacity.

[16]For each of the fossil plants in Germany we assume that increased emissions at that plant have the same health damages as if they were emitted at the nearest location for which we have health damages estimates. The mean distance from each of the power plants in our data set to one of these 400 locations with damage estimates is 29km and the median is 14km. There are also around 10% of the plants in our data set where the distance is effectively zero. These are coal plants in Germany that are among the 400 largest coal plants in Europe, and so have exact estimates of their health damages.

Mt per year. This corresponds to a 13% increase relative to the scenario without the nuclear phase-out. The increase was primarily attributable to an increase in emissions from hard coal plants of 25.8 Mt, with lignite and gas making up the remainder. In total, the 36.3 Mt increase amounts to a 13% increase relative to scenario without the nuclear phase-out. Valuing these using a social cost of carbon of $50/tCO2 results in estimated climate change damages of $1.8 billion.

The phase-out also led to a roughly 12% increase in emissions of all three local air pollutants (SO_2, NO_x, and PM). Again, this primarily comes from added emissions at hard coal plants, and to a lesser extent to added emissions at lignite and gas plants. The results on monetized damages in Table 5 reflect the combined annual average mortality damages for all three pollutants. Over our analysis period the local pollutant emissions from fossil plants were responsible for around $65 billion in mortality costs each year. Of this $8.7 billion per year can be attributed to the nuclear phase-out, representing a 15% increase in damages relative to the scenario without the nuclear phase-out.[17] This is due to an additional 1,100 excess deaths per year from poorer local air quality. The added generation from hard coal plants is again the key driver here, making up about 80% of the increase in mortality impacts.

6.2.2 Estimating External Damages Using Ambient Air Pollution Monitors

As an alternative to measuring damages using fuel inputs and reported emissions, we also compute damages using the estimated relationship between plant-level generation and recorded air pollution at nearby monitoring stations. This relationship was first documented in Table 2 which reported a significant relationship where increased generation leads to higher concentrations of PM_{10}, $PM_{2.5}$, CO and NO_2 concentrations. Here we proceed by estimating a daily monitor-level regression of ambient air pollution on daily plant-level generation using the data for 2010-2017:

$$P^{PO}_{s,d,m,y} = \alpha + \gamma \times Y^{PO}_{p,d,m,y} + \mu_p + \delta_m + \delta_y + u_{s,d,m,y} \tag{2}$$

where $P^{PO}_{s,d,m,y}$ is recorded air pollution concentrations at monitor s, on day d, in month m, and year y. $Y^{PO}_{s,d,m,y}$ represents daily generation at plant p (and where monitor s is the

[17] We use a Value of Statistical Life of $7.9 million for Germany taken from Viscusi and Masterman (2017).

closest to plant p). The model above includes plant fixed effects (to control for plant-specific factors that are correlated with local air pollution conditional on generation (i.e., the presence of specific pollution control equipment), as well as month and year fixed effects to control for trends and seasonality in pollution outcomes.

Once we obtain an estimate of the effect of each plant's production on locally-monitored air pollution levels, it is straightforward to compute the change in air pollution concentrations at each monitor caused by the phase-out. We simply need to multiply each coefficient estimate $\hat{\gamma}$ by the phase-out driven change in generation at plant p on a given date, that is: $\Delta POLL = \hat{\gamma} \times Y^{PO}_{p,d,m,y} - Y^{NPO}_{p,d,m,y}$. This estimated change in air pollution can converted into the change in premature mortality using the dose-response estimates from the ESCAPE project (Lancet 2014).[18] Specifically, we use the ESCAPE project to derive dose-response estimates of the effect of $PM_{2.5}$ (converting PM_{10} in $PM_{2.5}$ assuming that $PM_{10} = 0.5PM_{2.5}$) and NO_2 on premature mortality. [19] The hazard ratio for $PM_{2.5}$ is 1.07 (for a 5 micrograms per cubic meter change) while the hazard ratio for NO_2 is 1.01 (for a 10 micrograms per cubic meter change). Based on these hazard ratios, we use the standard formula to calculate the increase in mortality caused by the additional air pollution due to the phase-out: Finally, we use the same VSL of \$7.9 million for Germany taken from Viscusi and Masterman (2017) as in Table 5 to monetize the premature mortality estimates caused by the phase-out. For air pollutant j=$PM_{2.5}$ or NO_2, the monetized mortality damage is given by:

$$VSL \times POP \times MR \times \left(1 - \frac{1}{\exp(\rho_j \Delta POLL_j)}\right) \tag{3}$$

Where POP and MR are the population and mortality rate in the exposure group. We consider two such groups in the analysis below. The parameter ρ_j corresponds to the hazard ratios described above and $\Delta POLL_j$ is the change in ambient air pollution caused by the phase-out for air pollutant j.

The estimates of monetized mortality damages are reported in Table 6.

[Table 6 about here.]

[18]The European Study of Cohorts for Air Pollution Effects (ESCAPE) is one of the few studies on the impact of exposure to air pollution from Europe. It is based on 22 European cohort studies with a total study population of more than 350,000 participants.

[19]There are no dose-response functions for CO, and SO_2 in the ESCAPE project.

The estimates reported in Table 6 correspond to the average monthly impact of the phase-out on premature mortality in the post March 2011 period. The last row of each panel displays the (average) annual mortality damage in millions of 2017 USD. Columns (1) and (4) pertain to damages caused by additional $PM_{2.5}$ and PM_{10} air pollution, columns (2) and (5) are for NO_2, and columns (3) and (6) are for the total estimated air pollution damages (the sum of $PM_{2.5}$, PM_{10}, and NO_2 impacts).

The first panel of estimates in columns (1) to (3) assume that the estimated changes in ambient air pollution apply to the entire population of Germany. That is, the phase-out caused the exposure to air pollution to rise for all of Germany. A few key results emerge: First, there is clear evidence that the phase-out caused large and costly increases in premature mortality as all point estimates are sizable and statistically significant. Second, the change in $PM_{2.5}$ and PM_{10} air pollution caused by the phase-out lead to larger changes in premature mortality than the change in NO_2 air pollution (about 10 times more). Finally, the primary drivers of excess mortality are the hard coal and lignite power plants. The estimates in column (3) suggest that the additional hard coal generation caused by the phase-out lead to 2.7 billion in monthly mortality damages, while lignite lead to 1.3 billion in monthly mortality damages. In all, these estimates that assume that all of Germany's population is exposed to the added air pollution indicate large damages of 56.4 billion per year in 2017 USD as a result of the phase-out.

The assumption of full population exposure to the change in air pollution is probably unrealistic as air pollutant are dispersed around their sources and eventually deposited and absorbed over land and water bodies. The estimates in columns (3) to (6) restrict the exposure to the population living within 20 km of the fossil plants in our sample, roughly 7.5% of Germany's population. The estimates in columns (3) to (6) are thus necessarily smaller than those in columns (1) to (3) and represent our preferred estimates due to a more appropriate definition of the exposure population. The patterns in the estimates for the smaller exposure population are very similar to those for all of Germany: the change in $PM_{2.5}$ and PM_{10} air pollution from hard coal and lignite added generation causes most of the damages. Overall, this points to the phase-out causing annual premature mortality damages of 4.3 billion USD per year.

Taken together, the results in Tables 5 and 6 paint a remarkably consistent picture of the monetized mortality damages attributable to the nuclear phase-out, which range from 4.3 billion USD per year (preferred estimates from Table 6) to 8.7 billion USD per year (Table 5). This small range of estimates is therefore reassuring, especially since these estimates are based on two different and separate approaches. We also want to emphasize that these are precisely estimated and economically large, amounting to a roughly 10-15% increase in damages from air pollution related mortality due to emissions from Germany's power sector.

6.2.3 Estimating Risks from Nuclear Accidents and Waste Storage

Finally we attempt to incorporate the external costs of nuclear generation. Unlike fossil generation nuclear power does not produce significant emissions of carbon dioxide or local pollutants. However, nuclear energy does create unique waste storage and catastrophic accident risks that can impose large potential external costs on society. For instance, one recent estimate put the potential cost of the Fukushima accident over the next forty years at 35-80 trillion yen ($330-750 billion) (JECR, 2019). Most of this will not be incurred by TEPCO, the company in charge of the plant, and so represents an external cost for Japanese society as a whole. A review of the literature by Dhaeseleer (2013) put the likely external costs of nuclear power in the range of €1-4 per MWh. However, studies can range from finding effectively negligible costs to much higher costs of around $30 per MWh. The wide range here is essentially due to differing estimates of accident probabilities and severity, as well as varying assumptions on discount rates. To account for this uncertainty we examine a central value of $3 per MWh, but we also consider the impact on our findings of a much higher conservative value of $30 per MWh. This yields a reduction in expected external costs from nuclear power due to the phase-out of $0.2 billion per year, or $2 billion per year in the conservative case.

6.3 Total Costs and Benefits of the Nuclear Phase-Out

To summarize the overall impacts of the nuclear phase-out we now bring together all of our estimates of the various private and external costs associated with this policy. Private costs are the operating costs of the power plants in our analysis as well as any net costs from changes to imports and exports. External costs are comprised of climate damages from carbon emissions, health-related damages from mortality and morbidity caused by air pollution emissions, and lastly any costs associated with nuclear waste and accident risks.

[Table 7 about here.]

Table 7 reports the aggregated cost estimates. As already noted the replacement of low marginal cost nuclear generation with higher marginal cost sources like fossil plants and net imports meant the nuclear phase-out increased average operating costs in Germany by $1.6 billion per year. Whilst not trivial, these private costs are small relative to the external costs associated with the phase-out. Climate damages from increased CO_2 emissions alone were already larger than this at $1.8 billion per year. By far the largest impact of the phase-out though has been the external costs from local pollution emissions. We estimate these to be in the range of around $4.5 to $8.9 billion per year. This is driven primarily by an additional 1,100 excess deaths from poorer air quality, with only around $0.2 billion per year being due to morbidity costs. The expected average reduction in the external costs from nuclear waste and accident risks appear small by comparison at $0.2 billion per year. Overall we estimate the annual ongoing costs of the nuclear phase-out as approximately $10 billion per year.

6.4 Robustness Checks

Finally, it is important to consider the uncertainty in our findings. To do this we ran two sensitivity analyses that we described in section 7.

The first of these entailed accounting for how the phase-out may have affected the fossil plants available to meet net electricity demand. This sensitivity had minimal effects on the overall findings in large part because it merely altered the composition of fossil plants rather than the aggregate amount of generation provided by fossil sources. The main effect of this sensitivity was to slightly attenuate the change in wholesale electricity prices to a difference of $1.6 instead of $1.8 per MWh. However, aggregate private and external costs were largely unchanged from the $10 billion per year described previously.

The second sensitivity entailed accounting for how the phase-out may have accelerated investment in renewable sources. We estimated a scenario where the phase-out incentivized a steady increase in renewables such that it hit a target of an additional 30

TWh per year of renewable generation by 2020. Over our 2010 to 2017 analysis period this resulted in a reduction of net electricity demand of about 5 TWh per year. The result was to once again attenuate the change in wholesale electricity prices, but this time to an even smaller difference of \$1.3 instead of \$1.8 per MWh. The additional renewable generation also essentially displaced fossil generation one-for-one. This resulted in annual average private operating costs due to the phase-out of \$1.4 billion (versus \$1.6 billion in the baseline analysis), external climate damages costs of \$1.3 billion (versus \$1.8 billion in the baseline analysis) and a external mortality and morbidity damage costs to \$5.8 billion (versus \$6.8 billion in the baseline analysis). This meant a lower total cost estimate of \$8.7 billion per year (versus \$10 billion in the baseline analysis).

Lastly, two other key areas of uncertainty that play a large role in the underlying results are a) the Value of Statistical Life used to monetize mortality impacts, and b) the assumed external costs of nuclear waste and accident risks. For the Value of Statistical Life we currently use a \$7.9 million figure from Viscusi and Masterman (2017). This is a Germany specific estimate that we consider represents the most up-to-date analysis in the literature. Nevertheless, the Organization for Economic Cooperation and Development (OECD) also provides country specific values, and for Germany this is approximately \$3 million. Whilst the Viscusi and Masterman (2017) study discusses some of the shortcomings of the OECD estimates, this lower value at least provides a useful robustness check. It is also the Value of Statistical Life originally used in the Jones et al. (2018) study that informs part of our analysis of mortality effects. With that in mind, adopting this lower figure reduces the external mortality and morbidity damage costs to \$2.7 billion (versus \$6.8 billion in the baseline analysis). With this significantly more conservative assumption the total cost of the phase-out is \$6.1 billion per year (versus \$10 billion in the baseline analysis). Similarly, adopting a much more conservative view on the external costs of nuclear waste and accident risks by valuing these at ten times the level in our baseline analysis increases these particular net benefits of the phase-out from \$0.2 billion per year to \$2 billion per year. However, this is still not sufficient to offset the negative impacts of replacing this lost nuclear production with additional generation from fossil plants, even in our most conservative scenario.

7 Conclusions and Policy Discussion

Following the Fukashima disaster in 2011, Germany authorities took the unprecedented decision to immediately close half of the country's nuclear power plants (amount to a loss of ZZ in total production capacity), with the other half scheduled to be shutdown permanently in 2022. This paper presents the extensive analysis of the impact of this decision on electricity market and environmental outcomes. Our analysis indicates that the 2011 phase-out of nuclear power has so far resulted in an annual ongoing net cost to Germany of roughly $9-11 billion per year. This is primarily driven by the costs of around 1,100 excess deaths per year, which result from the increased use of coal-fired electricity production leading to higher levels of ambient air pollution.

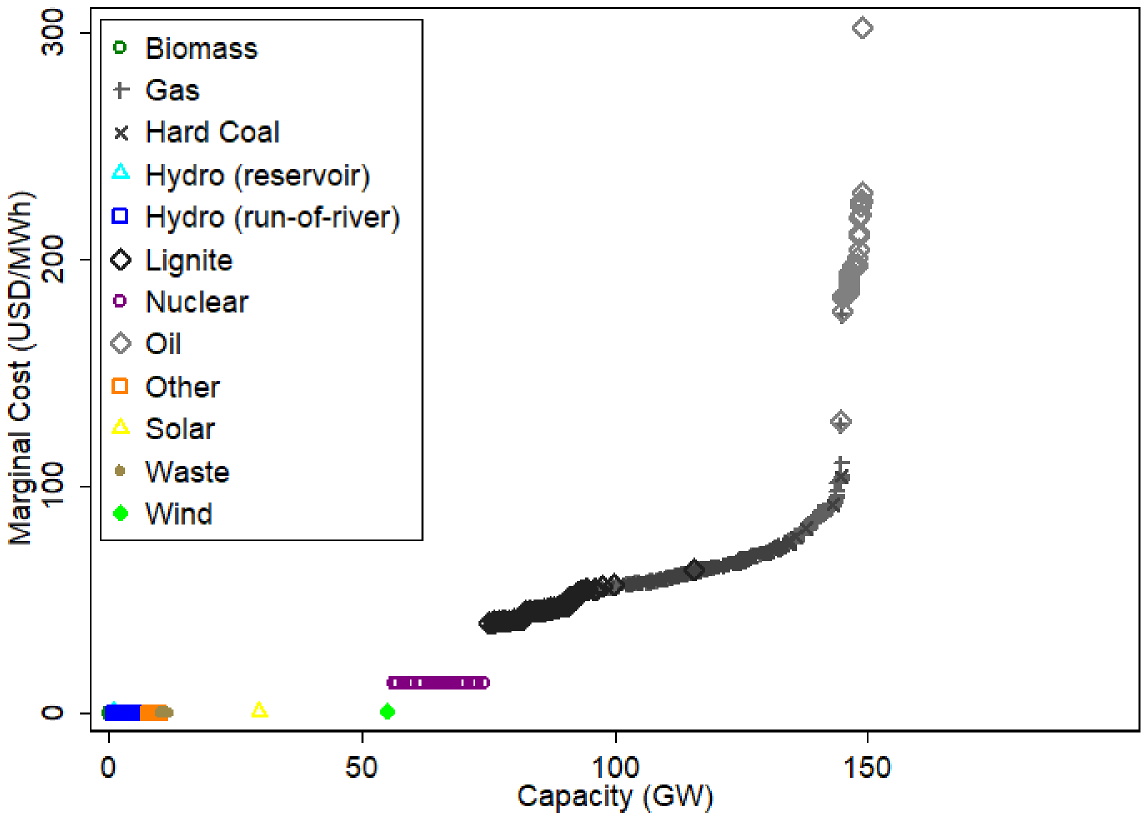
In addition to the ongoing, intensive margin market and environmental costs it is also important to account for changes to one-time investment costs prompted by the phase-out policy. To get a first-order estimate of these costs, we follow the existing literature and assume that the phase-out led to 8 GW of additional fossil capacity being required by 2030. Assuming half of this replacement capacity is coal (with capital costs of $3500/kW) and half is gas (with capital costs of $1000/kW) this amounts to a total cost of$9 in total. Keppler (2012) puts the cost of the nuclear lifetime extension policy at roughly €500 million per reactor, or €8.5 billion in total. The decommissioning and waste storage costs for the entire nuclear fleet have been estimated at around €50 billion, although these would have been incurred irrespective of the 2011 decision to accelerate the phase-out. Consequently, we assume that decommissioning and waste storage costs are unaffected by the policy. The cost of new fossil capacity is therefore fully offset by the avoided $10 billion cost of the nuclear reactor extensions, resulting in a decrease in net investment costs of $1 billion due to the phase-out. Therefore the nuclear phase-out did lead to a net reduction in one-time investment costs of roughly $1 billion as the investments to extend the lifetimes of the nuclear reactors were cancelled. However, these savings on the extensive margin are small relative to changes to annual ongoing costs on the intensive margin.

Given the apparently high cost of this policy one might think that it would be vastly unpopular. On the contrary, the nuclear phase-out retains widespread support, with more than 81% in favor of it in a 2015 survey (Goebel et al., 2015). When considered alongside the comparable levels of support for Germany's wider Energiewende program this is perhaps unsurprising. The costs of the transition to renewables alone are much larger than those we find for the nuclear phase-out, reaching €26 billion per year in 2017. These costs are also far more direct and visible to everyday citizens, with charges for renewable subsidies now making up about a quarter of the electricity price paid by residential households.

One important factor here may be the salience of the external costs of different sources of electricity. The harmful impacts of local pollution emissions from the power sector are increasingly well understood, but public understanding of the scale of these health impacts remains limited and has only began to appreciably increase in the last few years. Furthermore, the health impacts of fossil power are far less obvious than the potential risks of nuclear power, even if the relative probability of being affected is far higher. This is because attributing specific instances of mortality, morbidity or loss of property to emissions from a specific fossil power plant is difficult, and any effects are likely to be relatively incremental. Making the same kind of connection in the case of a catastrophic nuclear accident is far more straightforward.

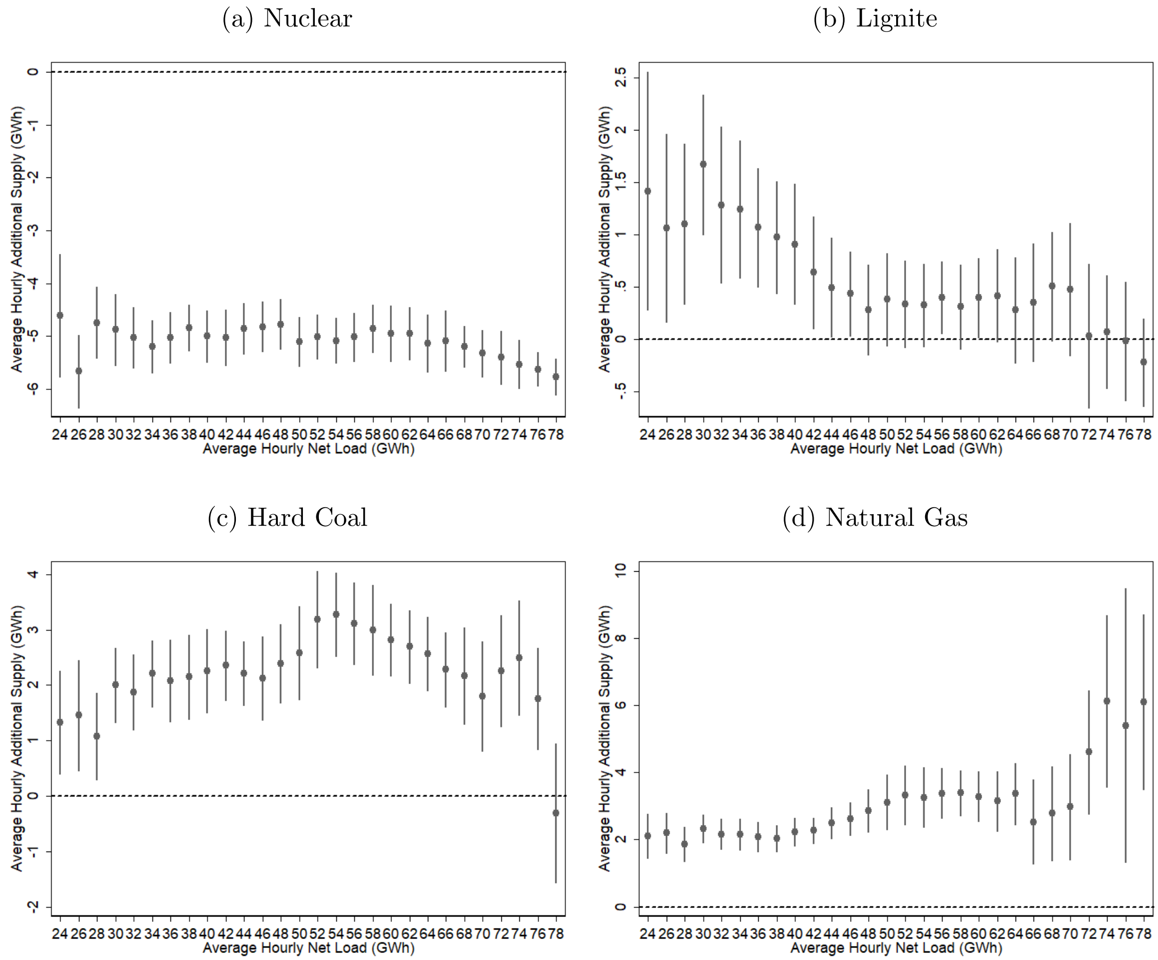
Deciding which energy sources to harness to meet the electricity needs of a modern economy necessarily involves difficult trade-offs. These trade-offs are particularly challenging when different energy sources create large external costs that are difficult to quantify and highly uncertain. In these settings it is not as straightforward to make a dispassionate assessment of relative expected costs. Instead choices increasingly hinge on societal attitudes towards uncertainty and the visibility of the risks in question. The strength of the anti-nuclear movement in Germany, and the continued popularity of the phase-out, point to a strong set of societal preferences for intergenerational equity and avoiding severe tail risks. At the same time though, the continued support for the Energiewende and the new commitment to phase-out coal indicate these attitudes apply just as much to climate change as they do nuclear accidents. In light of our findings regarding the immediate health impacts the nuclear phase-out policy has already incurred it will be interesting to see if those societal preferences continue to remain as strong as the last remaining nuclear plants approach their planned closures in 2022.

Figure 1: Marginal Cost Curve in 2011



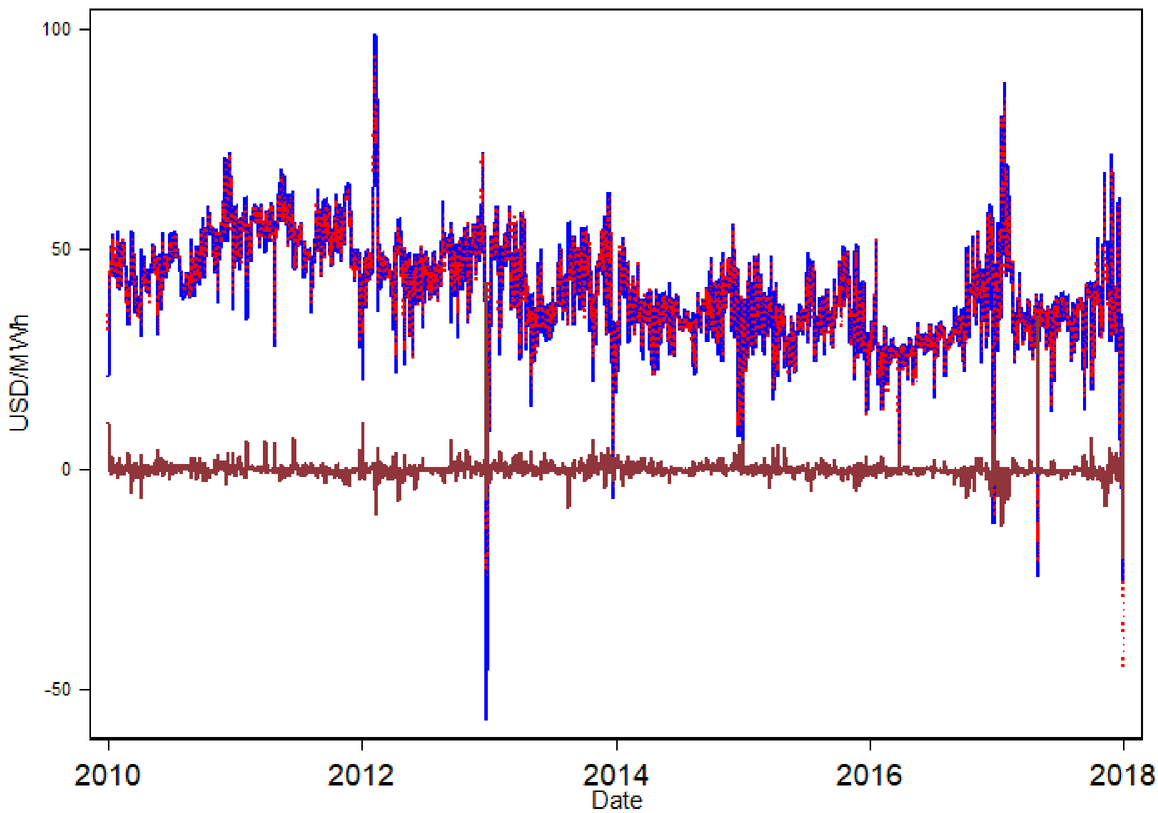
Notes: This figure plots our estimated marginal costs for electricity plants in Germany in 2011. All Euro values have been converted to 2017 US dollars. For coal, gas and oil plants marginal costs are calculated as fuel costs (accounting for plant-level efficiencies) plus an assumed amount of variable operating and maintenance costs that differs by fuel type. Nuclear plants are assigned a marginal cost of €10 per MWh based on the literature. Hydro, wind and solar have zero marginal costs. For simplicity the small amount of remaining sources are also assigned a marginal cost of zero here (i.e. biomass, waste and other). Marginal costs are for February 1st 2011 and so reflect coal, gas and oil prices at the time. Plants are ordered in terms of marginal cost to create an aggregate supply curve. For ease of presentation we do not show how imports and exports also factor into this supply curve here, although this is accounted for in our analysis.

Figure 2: Event-Study Estimates of the Impact of the 2011 Nuclear Closures on Hourly Generation



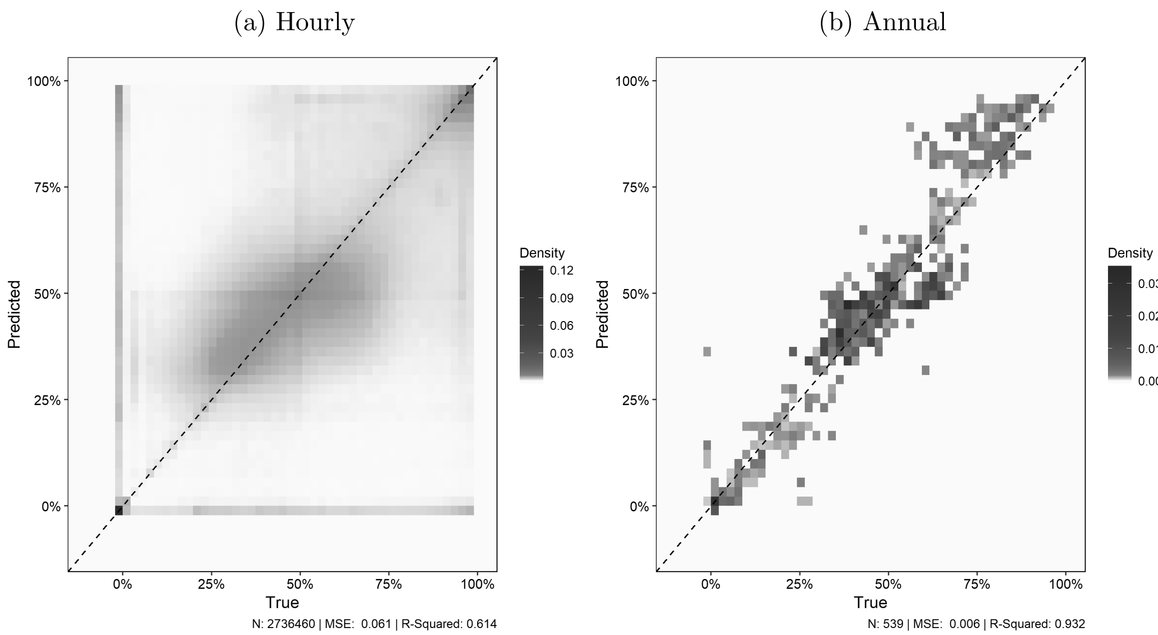
Notes: This figure plots the results from an event study analysis of the effects of the nuclear phase-out in Germany in 2011. The estimates correspond to post minus pre March 2011 changes in electricity generation by source. Panel (a) presents the estimates for nuclear production, separately for each of 10 equally sized bins of net demand (i.e.: electricity demand minus production from renewables). Panels (b)-(d) present the corresponding estimates for production from lignite, hard coal, and natural gas respectively. The panels also include the 95% confidence interval around each of the estimated effects; the standard errors used to construct these confidence intervals are clustered by week-of-sample.

Figure 3: Estimated Machine Learning Model Performance for Predicting Wholesale Electricity Prices



Notes: This figure illustrates the machine learning model prediction accuracy. The model predicts the wholesale electricity price in each hour over our full analysis period from 2010 to 2017. The figure depicts the observed wholesale electricity price (solid blue line), our model prediction (dotted red line) and the difference between these two (solid maroon line along the x-axis). Whilst the model predicts at the hourly level, the data in this figure have been averaged to a daily resolution for ease of presentation.

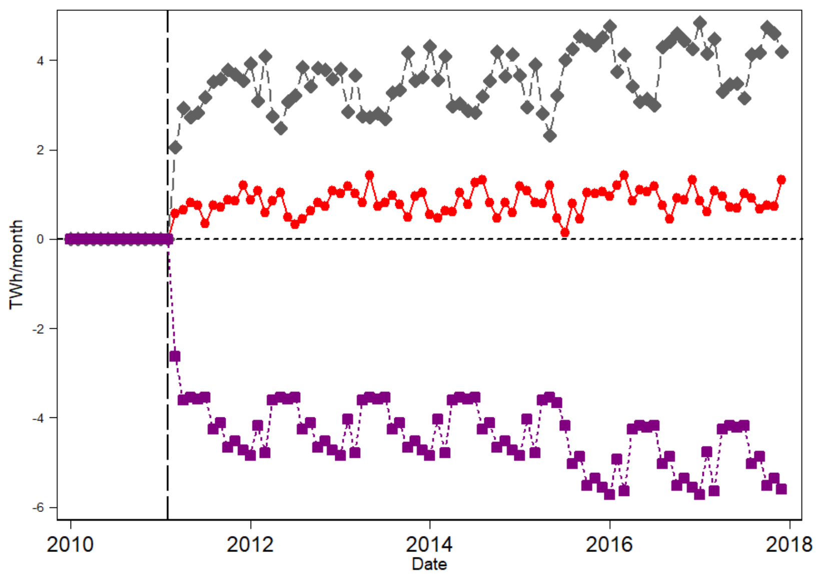
Figure 4: Estimated Machine Learning Model Performance for Predicting Plant-Level Electricity Generation



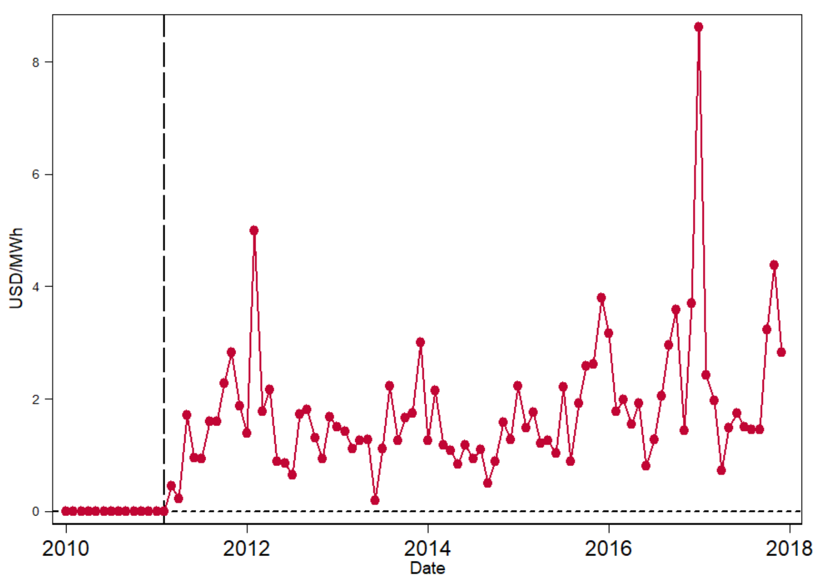
Notes: This figure illustrates the machine learning model prediction accuracy. The model predicts the operating rate of each power plant in each hour, where a value of 0% means a plant is offline and a value of 100% means it is running at maximum capacity. Values on the 45 degree line indicate perfect accuracy, and we summarize this both visually and by computing measures of Mean Squared Error and R-Squared. We compute these metrics using out-of-sample cross-validation to avoid overfitting and give a fair assessment of how the model may perform when used to make predictions about our counterfactual scenario. We use five-fold cross-validation. This effectively means dividing the the 2015-2017 training dataset into five randomly generated subsets, or "folds". We then estimate our predictive model using four fifths of the data and check its performance at predicting the remaining one fifth. We repeat this for each of the five folds and then average the resulting measures of performance. Panel (a) shows the performance at predicting at an hourly timescale. Panel (b) shows the improved performance at predicting at an annual timescale after averaging the hourly predictions. Darker areas indicate higher numbers of plant-hour (or plant-year) observations.

Figure 5: Impact of the Nuclear Phase-Out on Electricity Generation and Wholesale Electricity Prices

(a) Electricity Generation



(b) Wholesale Electricity Prices



Notes: This figure plots the primary monthly impacts from our machine learning analysis of the effects of the nuclear phase-out in Germany from 2010 to 2017. The start of the phase-out in March 2011 is marked by the vertical black dashed line. The plotted values correspond to the monthly difference between the predictions for the scenario with the phase-out and the predictions for the scenario without the phase-out. Panel (a) reports the estimates for all fossil-fired electricity production (grey diamonds), net imports (red circles), and nuclear production (purple squares). Panel (b) presents the change in wholesale electricity prices.

Table 1: Summary Statistics

	2010	2017
All Electricity Sector		
Total Capacity (GW)	172.4	217.6
Net Generation (TWh)	551.4	591.2
Wholesale Price (USD/MWh)	70.68	41.81
Net Imports (TWh / year)	-3.5	-33.5
By Source		
Nuclear Plants		
N	16	7
Average Capacity (MW / plant)	1,196.9	1,359.4
Annual Generation (TWh)	134.7	70.5
Hardcoal Plants		
N	109	87
Average Capacity (MW / plant)	236.5	288.0
Annual Generation (TWh)	93.9	83.5
Marginal costs (USD / MWh)	64.9	41.8
Lignite Plants		
N	74	61
Average Capacity (MW / plant)	274.0	344.1
Annual Generation (TWh)	130.9	137.9
Marginal costs (USD / MWh)	54.2	28.9
Gas Plants		
N	242	268
Average Capacity (MW / plant)	96.9	98.6
Annual Generation (TWh)	53.6	72.3
Marginal costs (USD / MWh)	77.6	41.8
Oil Plants		
N	53	50
Average Capacity (MW / plant)	79.0	80.6
Annual Generation (TWh)	1.9	3.8
Marginal costs (USD / MWh)	197.5	125.8
Renewables (Hydro, Solar, Wind)		
Total Capacity (GW)	52.1	112.5
Annual Generation (TWh)	60.6	157.1

Notes: This table reports various summary statistics for Germany's electricity generation sector in 2010 and 2017. All prices are in constant 2017 USD.

Table 2: Estimated Relationship Between Ambient Air Pollution and Electricity Generation

	Actual Daily Generation (GWh) 2015-17 (1)	Predicted Daily Generation (GWh) 2015-17 (2)	Predicted Daily Generation (GWh) 2010-17 (3)
PM10	0.157***	0.234***	0.168***
	(0.017)	(0.018)	(0.016)
PM2.5	0.154***	0.200***	0.150***
	(0.015)	(0.022)	(0.024)
SO2	-0.005	-0.007	0.028
	(0.033)	(0.041)	(0.023)
CO	0.189***	0.256***	0.250***
	(0.017)	(0.023)	(0.034)
NO2	0.202***	0.272***	0.205***
	(0.015)	(0.022)	(0.022)
Plant FE	Y	Y	Y
Year & Month FE	Y	Y	Y

Notes: Table 2 reports coefficient estimates from a panel regression of daily air pollution concentrations on daily plant-level generation. Both the dependent variable and the independent variable are standardized to have a mean of 0 and a standard deviation of 1. The regressions also include plant, month, and year fixed effects and the standard errors are clustered at the plant level. Asterisks denote p-value <0.05 (*), <0.01 (**), <0.001 (***).

Table 3: Estimated Impact of the Nuclear Phase-Out on Wholesale Price, Generation by Source, and Net Imports

	Average Outcomes (without phase-out)	Average Outcomes (with phase-out)	Change in Outcomes (due to phase-out)	Change in Outcomes (%) (due to phase-out)
	(1)	(2)	(3)	(4)
Generation (TWh/year)	574.2	574.4	0.2	0.0%
Nuclear	139.4	86.2	-53.2	-38.2%
Lignite	154.3	160.4	6.1	3.9%
Hard Coal	89.8	118.3	28.5	31.7%
Gas	31.6	39.8	8.3	26.2%
Oil	10.7	11.1	0.4	3.7%
Net imports	-27.4	-17.2	10.2	-37.1%
Renewables & Other	175.8	175.8	0.0	0.0%
Wholesale Prices ($/MWh)	45.5	47.3	1.8	3.9%

Notes: Table 3 reports the outcomes from our machine learning analysis for electricity generation and wholesale electricity prices. All values are annual averages and cover the period after March 2011 when the phase-out began. Note that renewable and other generation sources experience no change by construction. This is relaxed in one of our sensitivity analyses.

Table 4: Estimated Impact of the Nuclear Phase-Out on Revenues, Operating Costs, and Operating Profits

	Average Outcomes (without phase-out)	Average Outcomes (with phase-out)	Change in Outcomes (due to phase-out)	Change in Outcomes (%) (due to phase-out)
	(1)	(2)	(3)	(4)
Operating Revenues ($bn/year)	18.6	19.3	0.7	3.9%
Nuclear	6.4	4.1	-2.2	-35.0%
Lignite	7.1	7.6	0.6	8.0%
Hard Coal	4.3	5.8	1.5	34.4%
Gas	1.5	2.0	0.5	30.9%
Oil	0.5	0.5	0.0	7.0%
Net imports	-1.1	-0.7	0.4	-36.6%
Renewables & Other	-	-	0.0	0.0%
Operating Costs ($bn/year)	12.6	14.2	1.6	12.7%
Nuclear	1.7	1.0	-0.6	-37.9%
Lignite	4.9	5.1	0.2	4.0%
Hard Coal	3.7	4.9	1.1	30.1%
Gas	1.9	2.3	0.4	23.2%
Oil	1.8	1.9	0.0	2.5%
Net imports	-1.4	-0.9	0.4	-31.4%
Renewables & Other	-	-	0.0	0.0%
Operating Profits ($bn/year)	6.0	5.2	-0.9	-14.4%
Nuclear	4.7	3.1	-1.6	-33.9%
Lignite	2.2	2.6	0.4	17.0%
Hard Coal	0.5	0.9	0.3	63.6%
Gas	-0.4	-0.3	0.0	-8.1%
Oil	-1.3	-1.3	0.0	0.8%
Net imports	0.2	0.2	0.0	-5.9%
Renewables & Other	-	-	0.0	0.0%

Notes: Table 4 reports estimates operating revenues, costs and profits. All values are annual averages and cover the period after March 2011 when the phase-out began. Operating revenues are the product of each plants' hourly generation with the hourly wholesale electricity price. We ignore any additional revenues plants may receive, such as capacity payments, ancillary services payments, subsidies etc. Operating costs are the product of each plants' hourly generation with its hourly marginal cost. We ignore any additional costs plants may incur, such as start-up or shut-down costs, trading transaction costs etc. We also focus here on ongoing operating costs and so do not consider investment costs. Operating profits are operating revenues minus operating costs. Note also that renewable and other generation sources are excluded here as we avoid making explicit assumptions about their marginal costs or their revenues (e.g. additional non-market subsidies). We would expect them to experience no *change* in costs or revenues though given their overall generation is unchanged and almost all renewable sources receive a fixed above-market price for their electricity.

Table 5: Estimated Impact of the Nuclear Phase-Out on CO2 Emissions and Local Air Pollution Mortality Damages

	Average Outcomes (without phase-out)	Average Outcomes (with phase-out)	Change in Outcomes (due to phase-out)	Change in Outcomes (%) (due to phase-out)
	(1)	(2)	(3)	(4)
CO2 Emissions (Mt/year)	280.3	316.6	36.3	13.0%
Lignite	175.9	182.8	6.9	3.9%
Hard Coal	82.2	108.0	25.8	31.4%
Gas	13.6	17.0	3.3	24.5%
Oil	8.6	8.9	0.3	3.6%
SO2 Emissions (kt/year)	135.8	151.7	15.9	11.7%
Lignite	91.4	94.7	3.2	3.5%
Hard Coal	37.2	49.5	12.3	33.0%
Gas	1.0	1.2	0.2	18.4%
Oil	6.2	6.3	0.2	2.5%
NOx Emissions (kt/year)	189.7	213.4	23.7	12.5%
Lignite	116.8	121.5	4.7	4.0%
Hard Coal	52.5	69.0	16.5	31.5%
Gas	10.0	12.1	2.2	21.8%
Oil	10.4	10.7	0.3	2.9%
PM Emissions (kt/year)	4.9	5.5	0.6	12.2%
Lignite	3.2	3.3	0.1	3.9%
Hard Coal	1.5	2.0	0.5	30.3%
Gas	0.1	0.1	0.0	24.6%
Oil	0.1	0.2	0.0	3.3%
Pollution Damages ($bn/year)	56.6	65.3	8.7	15.4%
Lignite	30.5	31.6	1.2	3.9%
Hard Coal	21.9	28.8	6.9	31.5%
Gas	2.2	2.8	0.6	25.0%
Oil	1.9	2.0	0.1	3.6%

Notes: Table 5 reports estimates for emissions of CO_2 as well as three local pollutants: SO_2, NO_x), and PM. Finally estimates of the mortality damages from local air pollutant emissions are included. All values are annual averages and cover the period after March 2011 when the phase-out began. Emissions are the product of each plants' hourly generation with our estimate of the emissions rate. Emissions rates are in turn the product of a) the amount of fuel required to produce one unit of electricity, and b) the emissions intensity of the fuel. Emissions estimates are limited to fossil plants in Germany. We ignore other potential sources of emissions in the electricity sector, such as emissions from smaller biomass, landfill gas or waste plants that are grouped with other zero-emissions renewables like solar, wind and hydro. We also do not estimate emissions due to changes in net imports. In reality we would expect any increase in net imports to Germany should entail some increase in emissions in neighboring countries where these imports are provided by fossil plants. Given the relatively small role played by net imports though this omission likely does not significantly affect our findings. For damages the table only presents estimates of mortality impacts to ensure consistency with the complementary analysis using pollution monitor data. Elsewhere we do calculate climate change damages. Furthermore, the Jones et al. (2018) study also measures some non-mortality impacts on morbidity (e.g. asthma attacks, lost work days etc) and these are included in the overall summary of total costs at the end of this section.

Table 6: Estimated Impact of the Nuclear Phase-Out on Ambient Air Pollution Mortality Damages

	Post March 2011 Change in Outcomes Population: All Germany			Post March 2011 Change in Outcomes Population: Living Within 20 km of fossil plants		
	(1) PM2.5 & PM10 Pollution Damage	(2) NO2 Pollution Damages	(3) Total Pollution Damages	(4) PM2.5 & PM10 Pollution Damage	(5) NO2 Pollution Damages	(6) Total Pollution Damages
Hard coal	2,448.7*** (357.2)	240.3*** (35.0)	2,689.0*** 392.3	180.1*** (26.3)	17.7*** (2.6)	197.8*** (28.9)
Lignite	1,194.1*** (288.8)	117.0*** (28.3)	1,311.2*** (317.2)	87.8*** (21.2)	8.6*** (2.1)	96.4*** (23.3)
Gas	653.9*** (108.0)	64.0*** (10.6)	718.0*** (118.6)	48.1*** (7.9)	4.7*** (0.8)	52.8*** (8.7)
Oil	148.4*** (34.2)	14.5*** (3.3)	163.0*** (37.8)	10.9*** (2.5)	1.1*** (0.2)	12.0*** (2.8)
Aggregate Annual Damages (Mil. USD / year)	**53,341.2**	**3,079.1**	**56,420.3**	**3,922.8**	**385.2**	**4,308.0**

Table 7: Overall Estimated Impact of the Nuclear Phase-Out on Total Costs

	Average Outcomes (without phase-out)	Average Outcomes (with phase-out)	Change in Outcomes (due to phase-out)	Change in Outcomes (%) (due to phase-out)
	(1)	(2)	(3)	(4)
Total Costs ($bn/year)	85.2	97.4	10.0	11.7%
Private Costs				
Operating Costs	12.6	14.2	1.6	12.7%
External Costs				
Carbon Emissions Climate Damages	14.0	15.8	1.8	13.0%
Local Pollution Mortality				
Method 1 - reported emissions	56.6	65.3	8.7	15.4%
Method 2 - pollution monitors	-	-	4.3	-
Local Pollution Morbidity	1.6	1.9	0.2	14.1%
Nuclear Waste and Accidents	0.4	0.3	-0.2	-38.2%

Notes: This Table reports the overall estimates of net ongoing costs. Private costs are the operating costs of the power plants in our analysis any net costs from imports and exports. External costs are comprised of climate damages from carbon emissions, mortality and morbidity costs from air pollution emissions, and nuclear waste and accident risk costs. For the total costs we average our two methods for estimating the external costs of local pollution on mortality. It should also be noted that the measure of operating costs in columns (1) and (2) is incomplete in that it does not include the costs of renewable and other sources. As discussed previously these are assumed to be invariant to the phase-out and so this does not affect the change in costs reported in column (3).

List of Tables

List of Figures

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Appendices

A Descriptive Trends: Additional Tables and Figures

[Figure 6 about here.]

Appendix Figure B.1 presents a more detailed account of annual electricity generation by source as well as total imports and exports. The precipitous drop in nuclear generation following the 2011 closure of nine reactors as well as the rapid growth in wind and solar renewables are evident in the figure.

B Further Detail on the Predictive Dispatch Model

Studies of the electricity sector traditionally utilize some form of electricity dispatch model that combines engineering and economic modeling tools to simulate the operation of the power grid. Instead here we opt to employ a more empirical approach. As such our approach can be thought of as a kind of empirically derived dispatch algorithm based on the observed operational decisions that power plants have taken. The primary benefit of this kind of approach is that it requires fewer explicit assumptions about the impact of complex issues like market structure, idosyncratic policy subsidies or the nuances of plant-specific factors like combined-heat and power capability. Where a more traditional simulation modeling framework has to take a stance on these subjects by either ignoring them or adding additional model architecture to simulate them explicitly, an empirical approach such as this determines the impact of these factors on plant dispatch based on actual observed plant operations. Nevertheless, it is important to be aware of the limitations of this more empirical approach, not least the fact that it is constrained to examining scenarios that are sufficiently similar to observed outcomes. This is why other studies in this area tend to focus on ex post policy assessments, or identifying marginal impacts. Moreover, this kind of approach does not appear to offer particularly robust insights for a given plant in a given hour and so should not be seen as a substitute for more explicit modeling of the grid where short-term physical constraints are of interest.

Ultimately we envision this kind of approach as a useful complement to more traditional modeling tools, particularly in an ex post policy assessment setting.

For this analysis we utilize a Random Forest algorithm. We think this has a number of useful properties for the application at hand. First, we do think that the relationship between our predictors and outcome is highly non-linear, including many complex interactions. Random Forests are well-suited to finding these interactions without us having to make many strong assumptions at the outset (e.g. no need to pre-specify polynomials, splines and interactions as in a more standard least squares regression framework). Second, the structure of the Random Forest regression algorithm means that the support of possible outcome predictions is bounded by the support of the outcome values in the training dataset. This means the predictions from our model will be effectively continuous but will also have a natural bounding of 0-1, thus avoiding the risk of making erroneous predictions (e.g. >100% or <0%). Third, using Quantile Regression Forests allows us to make predictions of the full conditional distribution of our outcome, rather than just its expected value. Clearly there is uncertainty about whether a given plant will operate in a given hour conditional on the covariates for that plant-hour. Usually a central estimate is what we are interested in, and we do in fact find that both the mean and median of the potential predictions produced by our model perform reasonably well (see Figure 4). However, being able to characterize the distribution of potential outcomes means we can a) examine the uncertainty in our results, and b) reframe our final estimation to calculate the most likely changes to generation outcomes that still meet physical requirements (i.e. that demand equals supply).

Our Random Forest model is estimated using a training dataset of roughly 4.5 million observations that have information on both our dependent variable and a set of independent variables. The most important covariates are the three variables we use to capture the core interactions between supply and demand in each hour. These are as follows:

- Net Load. Net load is defined here as total electricity demand minus all low marginal cost or inflexible generation. Here this is taken to be electricity demand minus generation from renewables (wind, solar, hydro, biomass, waste) and nuclear. Another way of thinking about this net load variable is as a measure of "required flexible generation".[20]

[20]We also include lags and leads of net load to capture the fact that many power plants have dynamic

- Marginal Cost. When a plant is deciding whether to produce its primary decision mechanism will be to consider whether its marginal cost is less than the electricity price it will be paid for its output. In electricity markets such as Germany's the electricity price is effectively set by the marginal cost of the most expensive plant necessary to meet demand (i.e. the clearing plant that is on the margin). To best represent this we first construct estimates of each plant's marginal cost. We then estimate the marginal cost of the clearing plant, where this is the last fossil plant (or border point) necessary to meet net load in a given hour. Our "marginal cost" variable is then calculated for a given plant as its own marginal cost minus the marginal cost of the clearing plant for that hour. In general negative values should correspond to plants producing and positive values should correspond to plants not producing.

- Available Capacity. Where the "marginal cost" variable captures the position of a plant in the supply curve in terms of price, the "available capacity" variable captures the position of a plant in the supply curve in terms of quantity. For each plant we calculate the total amount of capacity from other fossil plants (or border points) with a lower marginal cost. Our "available capacity" variable is then calculated as the total amount of capacity with a lower marginal cost than a given plants minus net load for that hour. Once again negative values should correspond to plants producing and positive values should correspond to plants not producing.

The relative importance of each of our covariates is illustrated in Figure B.2a. As expected the net demand, relative marginal cost and available capacity are all particularly important covariates. However, it is noteworthy that the two most important covariates are the source type (i.e. lignite, hard coal, gas, oil or border point) and whether a fossil plant is combined-heat and power. This reflects the fact that different types of electricity generators face different operational constraints. For example, many natural gas plants in Germany are combined-heat and power. As such, whilst they may have higher marginal costs of generating electricity than coal plants, the additional revenues they get outside the electricity market for providing heating services means they often

constraints affecting their operations from hour to hour (e.g. the speed at which they can "ramp up" their output, or the minimum amount of time they have to be offline before they can restart). This means our model can capture the fact that a plant's decision to operate at any given moment depends on past and future conditions, as well as current net load.

operate more frequently than their pure electricity marginal cost would suggest.

[Figure 7 about here.]

An important consideration when making out-of-sample predictions using a predictive model such as this is ensuring that the training dataset provides sufficient support across the predictor variables. To the extent that this is the case the algorithm is largely performing the kind of interpolation exercise it is optimized for. In general we can be fairly confident this is the case for the vast majority of predictors, not least because the portfolio of fossil power plants and the underlying power grid does not change very much over the entire 2010-2017 period. Rescaling certain variables can also help in this regard.[21] The main variables of interest here are the three we use to approximate the interaction between supply and demand; namely net load, plant marginal costs, and the amount of available capacity. Almost by definition the counterfactual scenario will contain some periods where these variables fall outside the range in the training dataset. Even so, there is such wide variation in both electricity demand, renewable generation and plant marginal costs that for the vast majority of cases the overlap is very good, as can be seen in Figures B.2b, B.2c and B.2d.

The machine learning application we use is designed to predict (as accurately as possible) how dispatchable flexible sources like fossil plants and border flows make intensive margin decisions to increase or decrease their output in order to meet the residual demand left after accounting for renewable and nuclear output. Net load, the relative marginal cost of each plant, and the amount of alternative available capacity are key predictors in the analysis not only because they play a significant role in explaining plant operating decisions, but also because they are the variables we modify in order to construct the counterfactual scenario. For the scenario with the phase-out the net load variable is the observed net load given the phase-out decision as shown in Figure B.3a. For the counterfactual scenario without the phase-out nuclear generation would have been higher and so net load would have been lower, as shown in Figure B.3b.[22] The reduction in net

[21]For example, we rescale the marginal costs of each plant by the marginal cost of the last plant needed to clear the market. This means that even if fuel prices increased across the board causing marginal costs to double relative to the training dataset, the rescaling would ensure these still fell on a similar relative range.

[22]It is worth highlighting that from the perspective of these flexible sources we are treating an increase in generation from renewables or nuclear as functionally equivalent to a decrease in total electricity demand.

load also feeds through into the marginal cost and available capacity variables. If net load is lower, the marginal cost of the clearing plant would also be lower. This means that plants that were already "out-of-merit" are even less likely to operate, and plants that were "in-merit" have their inframarginal rents reduced, lowering the likelihood of operating for plants close to the margin. This is illustrated in the schematic in Figures B.3c and B.3d.

[Figure 8 about here.]

Figure B.4 shows the median model predictions for how the nuclear phase-out impacted aggregate electricity production in Germany at the plant-level. The prior expectation is that the nuclear phase-out reduced nuclear generation and so increased fossil generation to fill the gap, and so we would expect points to tend to lie above the horizontal zero line. This is in fact what we see, with the largest response coming from the hard coal plants.

[Figure 9 about here.]

Doing this using the median predictions displayed in Figure B.4 we find around 40 TWh per year of additional supply from higher fossil generation and net imports. However, it is important to note that there is no constraint in our estimation process that the total amount of estimated replacement generation should match the lost nuclear output. The amount of lost nuclear generation is around 50 TWh per year and so using the median predictions actually leads us to underestimate the level of replacement generation. To remedy this and calculate the most likely allocation of replacement generation we utilize the information our quantile regression model provides us on the full conditional distribution of potential changes to output. To do this we generate predictions for the 10th, 25th, 50th, 75th and 90th percentiles. We then find the combination of these percentiles that fully replaces the lost nuclear generation with the most likely set of plant-level changes (i.e. closest to the median). Essentially this can be thought of as finding the percentiles closest to the median that produce a change in annual total generation equal to the annual lost nuclear output. In our particular case this only requires moving a few percentiles from the median to get the desired outcome.

Finally, Figure B.5 also illustrates where the replacement generation was located. Most of the fossil generation was in the industrial regions in the west and south of the country. Changes to net imports were primarily at the borders with Denmark, France and the Czech Republic.

[Figure 10 about here.]

Figure B.1: Electricity Production by Source: 2010-2017

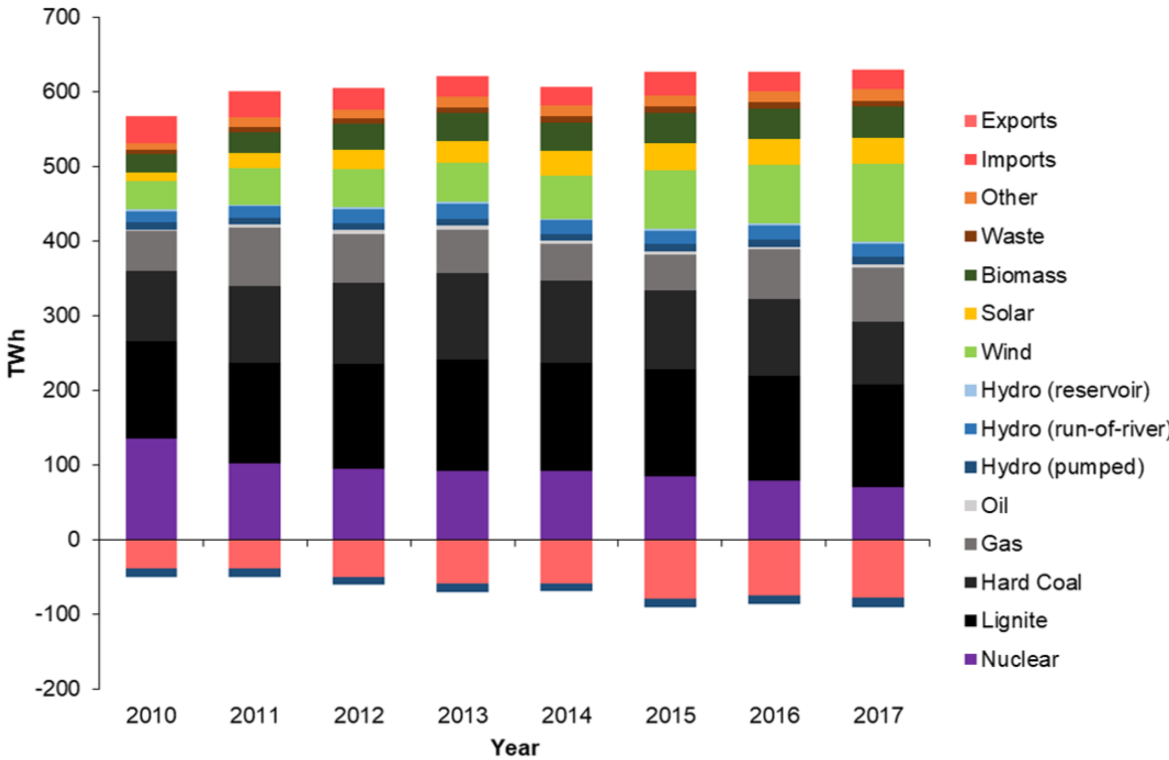
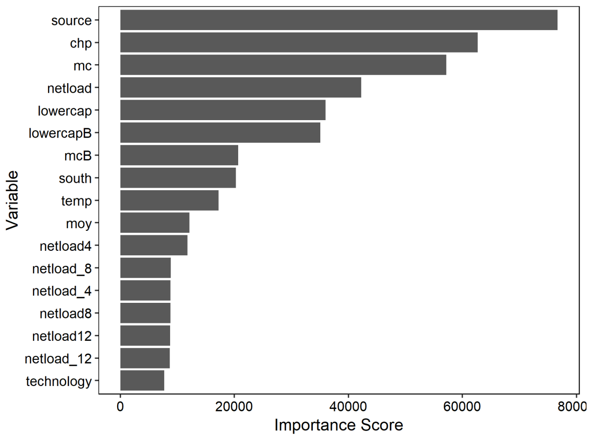
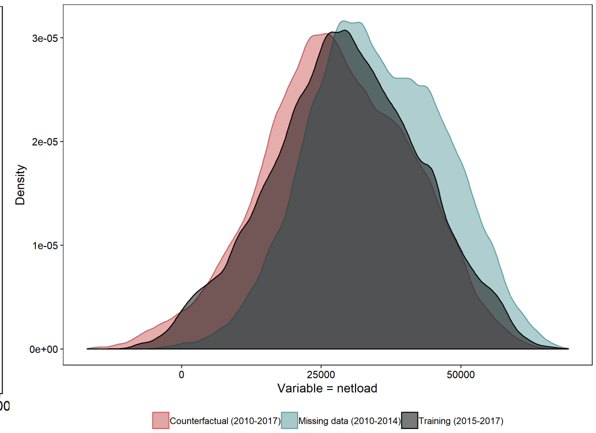


Figure B.2: Machine Learning Model Diagnostics

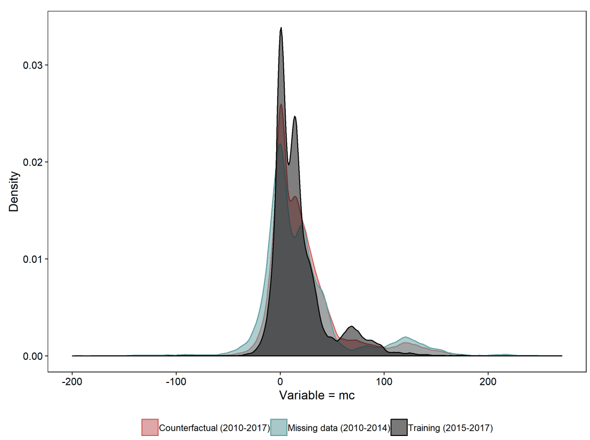
(a) Variable importance scores



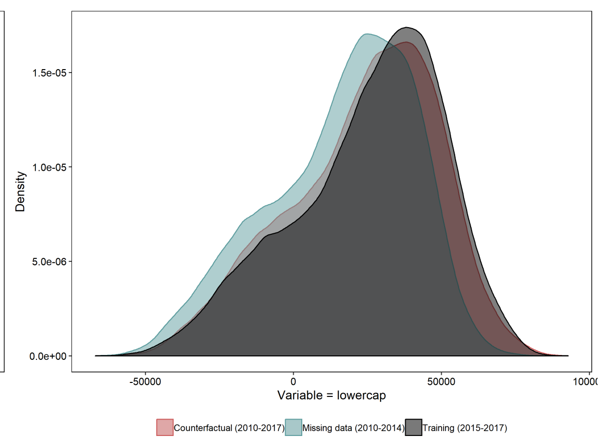
(b) Support of Net Demand



(c) Support of Marginal Cost



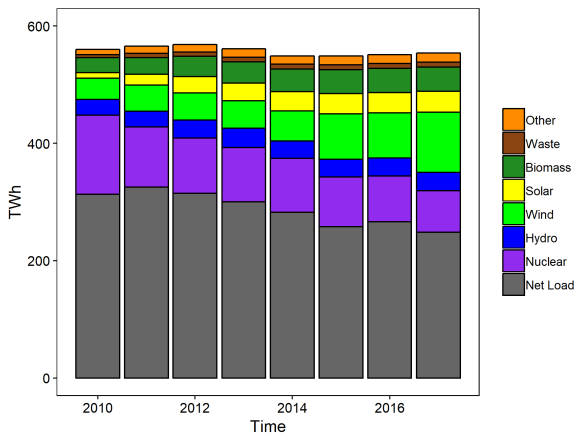
(d) Support of Available Capacity



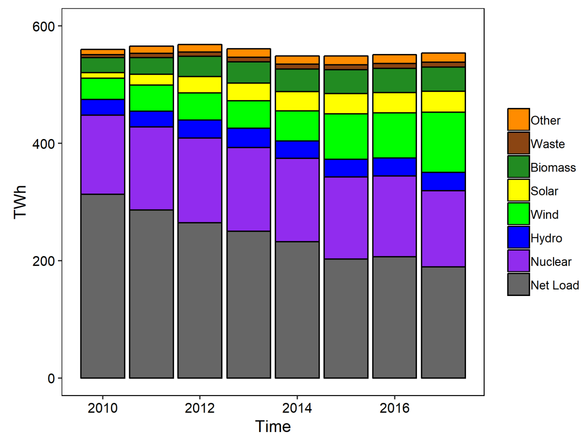
Notes: This figure illustrates a range of key model diagnostics related to the machine learning estimation. Panel (a) shows the importance scores for each of the variables included in the estimation. These are a standard measure for Random Forests and indicate the relative importance of each variable to predicting the outcome of interest. The abbreviated names in the figure are as follows: source = source type (e.g. lignite, hard coal, gas, oil or border); mc = marginal cost relative to clearing unit; mcB = marginal cost relative to clearing unit (including border capacity); lowercap = amount of capacity with a lower marginal cost; lowercapB = amount of capacity with a lower marginal cost (including border capacity); chp = presence and scale of combined-heat and power capability; technology = technology type (e.g. steam turbine, combined cycle turbine or transfer); temp = local temperature; south = indicator for whether located in the south of the country; moy = month-of-year; dow = day-of-week; hod = hour-of-day; netload = electricity load minus generation from wind, solar, hydro and nuclear; netloadX = difference between current net load and net load X hours ago; netload_X = difference between current net load and net load X hours ahead. Panels (b-d) show the support of three key variables: net demand, the relative marginal cost and the available capacity. The grey area shows the distribution of observations in the original 2015-2017 training set. The blue area shows the distribution of observations in the missing 2010-2015 data. The red area shows the distribution of observations in the counterfactual scenario across the full 2010-2017 analysis period.

Figure B.3: Net Demand and Scenario Implementation

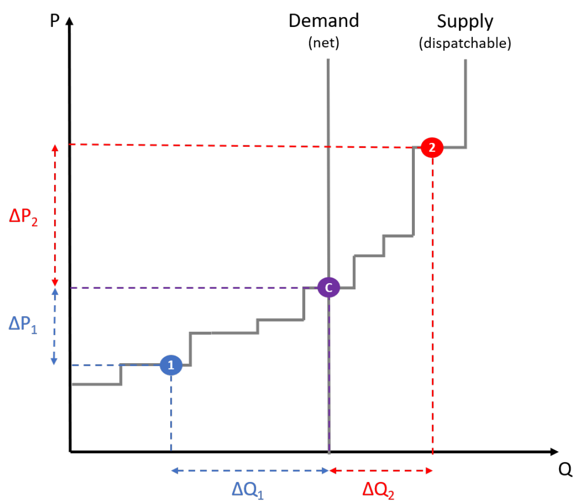
(a) Estimated Net Demand (With Phase-Out)



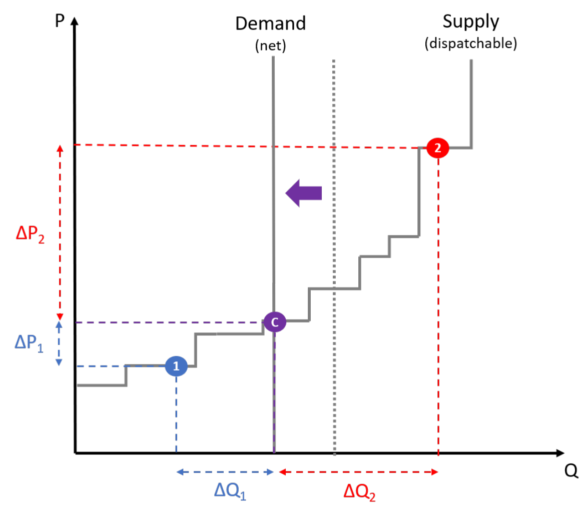
(b) Estimated Net Demand (Without Phase-Out)



(c) Net Demand Illustration (With Phase-Out)

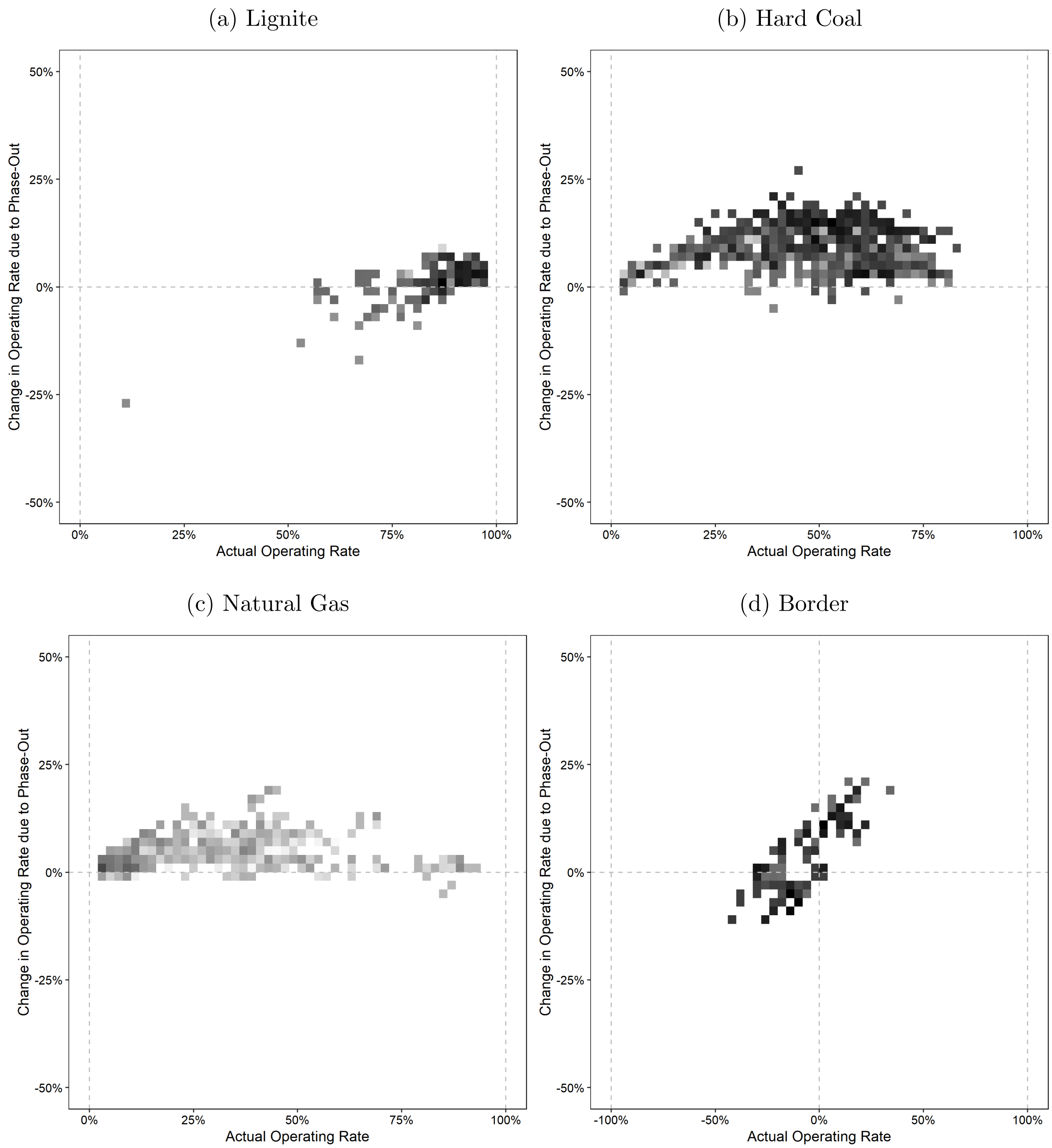


(d) Net Demand Illustration (Without Phase-Out)



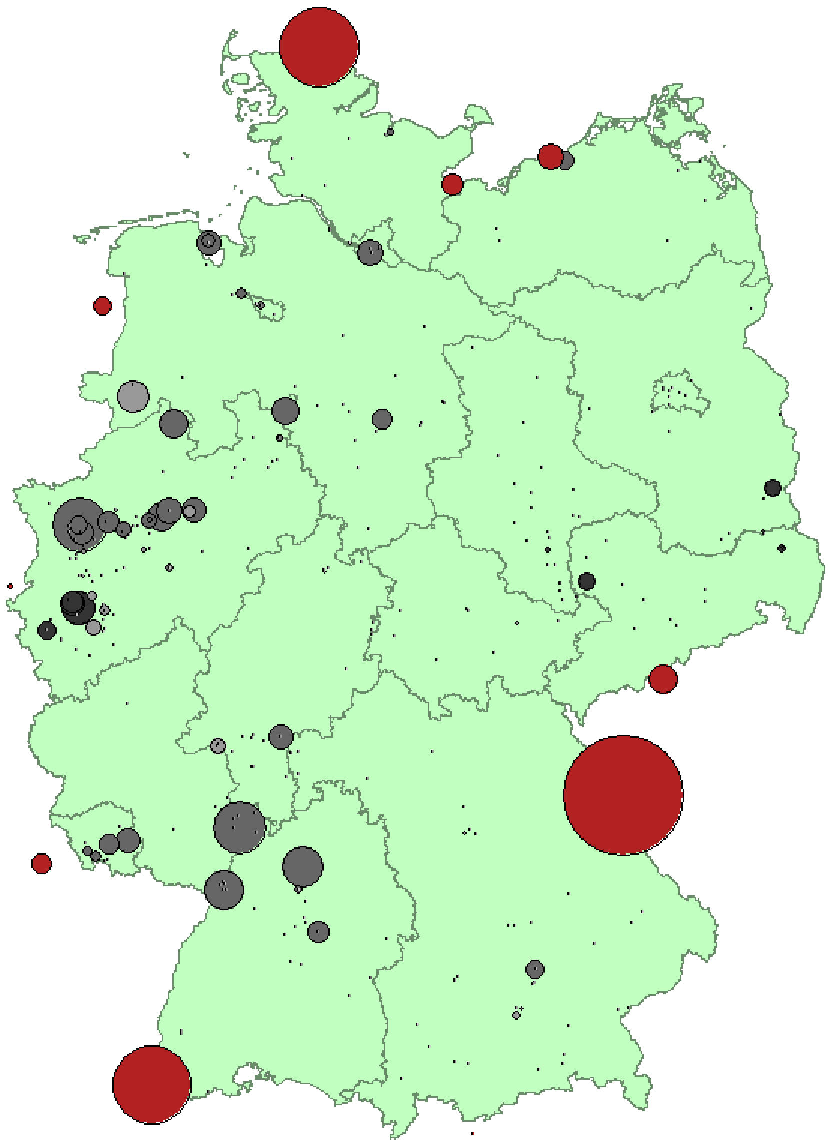
Notes: This figure illustrates the role of the net electricity demand variable in the analysis. Panels (a) and (b) show the level of net demand both with and without the phase-out respectively. Note the growing wedge of renewable generation displacing net demand in both scenarios. This displacement is further added to by the larger amount of nuclear generation in panel (b). This is the amount of nuclear generation we estimate would have been produced by the closed nuclear plants if the nuclear phase-out had not happened. Panels (c) and (d) then provide a diagram illustration of how changing the net demand feeds through into the estimation process. This happens because altering net demand alters the position where net demand intersects with the supply curve of dispatchable capacity. This intersection point is indicated by the clearing fossil plant (or border point) that is "on-the-margin" (purple). Altering the clearing fossil plant (or border point) affects the relative marginal cost (ΔP) and available capacity (ΔQ) values for all dispatchable supply. These two variables are illustrated for a high marginal cost plant (red) and a low marginal cost plant (blue).

Figure B.4: Plant-level changes to generation due to the phase-out



Notes: This figure illustrates the plant-level disaggregation of the machine learning prediction model results. The model predicts the operating rate of each power plant in each hour, where a value of 0% means a plant is offline and a value of 100% means it is running at maximum capacity. All results here are based on plant-level annual average operating rates. The x-axis plots each plant's operating rate in the baseline scenario with the phase-out. The y-axis then plots the impact of the phase-out on plant-level operations. This is determined by the difference between the predictions in the scenario with the phase-out versus the scenario without the phase-out. Darker areas indicate higher numbers of plant-year observations. Each panel refers to a different type of dispatchable electricity source. Panel (a) covers lignite plants, (b) covers hard coal plants, (c) covers gas plants and (d) covers border points. Oil plants are not shown here as they are a very small portion of total capacity and are largely invariant to the phase-out.

Figure B.5: Map of plant-level changes in generation due to the Phase-Out



Notes: This map illustrates the location of the fossil plants or border points that increased their electricity generation as a result of the nuclear phase-out policy. The size of the circle reflects the amount of additional generation provided by that fossil plant or border point. Points in red are border points and points in grey are fossil plants. The darkest grey are lignite plants, then hard coal, natural gas, and finally oil plants are the lightest grey.