Choosing between environmental ills

A study of the phase-out of nuclear power in Germany

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Abstract

Germany began phasing out nuclear power in 2011. This research examines the impacts of this decision. We use empirical data on power plant operations and a novel machine learning framework to estimate how power plants would have operated differently if the phase-out had not happened. Despite the substantial investments Germany has made in renewables, we find that much of the replacement generation to date came from fossil sources, particularly coal. We also find that the phase-out caused changes to flows between Germany and neighboring countries, primarily through reduced exports. Overall we find that the phase-out has raised costs in the electricity sector whilst also slowing Germany's attempts to reduce CO2 emissions. We estimate the total net ongoing costs of the phase-out at around $6-7 billion per year between 2011 and 2017. Roughly half of these costs are due to increased levels of local pollution which impose significant health burdens. Furthermore, over this period less than half of Germany's nuclear capacity has actually been taken offline. As such we expect the costs of the phase-out to rise substantially as the remaining plants are closed by 2022.

Introduction

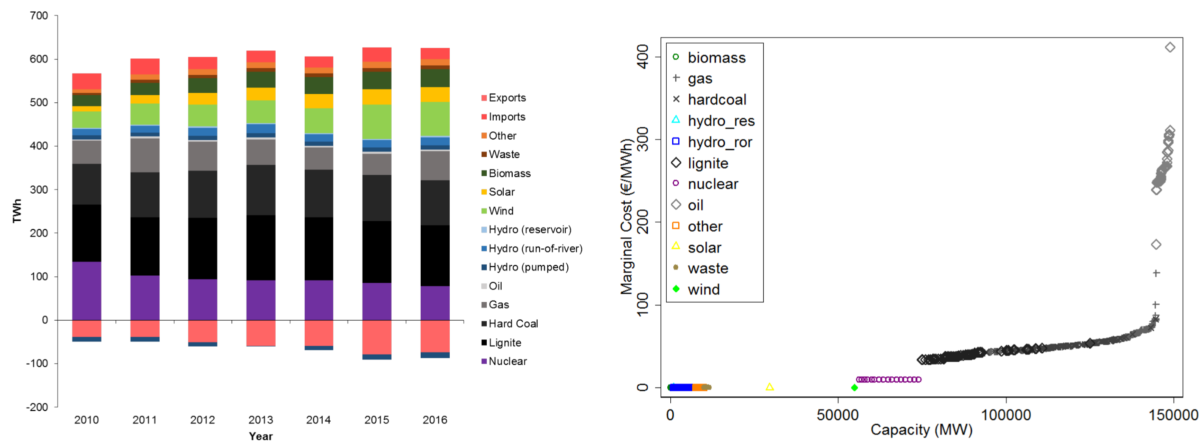
In 2011 the Fukishima nuclear meltdown led to Japan's fleet of nuclear power stations being taken offline. The crisis also precipitated major changes in Germany. Within a matter of days Germany declared a moratorium on planned extensions at existing nuclear power plants and immediately took 7 older reactors (amounting to 8GW of capacity) offline. The decision was made later that year to completely phase-out nuclear power, with the remaining 12 reactors (12GW of capacity) being shuttered by 2022.

The phase-out of nuclear power in Germany offers a fascinating case study of the challenges of balancing commitments to tackle climate change with long-standing political opposition to nuclear power. In the years preceding the decision as much as 25% of Germany's electricity generation came from nuclear sources, and so the impacts of this sudden change were substantial. A number of studies were conducted at the time of the decision, although these were based on power grid simulation models and primarily focused on the future impacts on investment, electricity prices and carbon emissions (Traber and Kemfert, 2012). However, now that the phase-out is approaching completion there is scope to conduct the first comprehensive empirical analysis of the actual economic costs and benefits of the phase-out decision.

Understanding the impacts of the phase-out process is of pressing importance because the role of nuclear power as a low-carbon source of energy remains controversial, with some regions investing in new capacity (e.g. the UK, China) whilst others are following Germany's lead and closing existing plants (e.g. Switzerland, California).

To date, much of the replacement generation in Germany likely came from fossil fuel sources. This research looks to quantify the extent to which this true, and what the costs might have been. There is a compelling case to be made that the phase-out has made it harder for Germany to meet its climate goals, whilst also raising costs in the electricity sector and imposing significant health burdens due to increased levels of local pollution.

Figure 1: Germany's Electricity Supply



(a) Electricity generation by source, 2010-2016[1]

(b) Electricity supply curve in 2011

Key Literature

There is a range of research looking at the role of nuclear power in the electricity sector. Davis and Wolfram (2012) studied the improvements in operating efficiency of nuclear plants following privatization. A recent paper by Davis and Hausman (2016) looked at the impacts of the closure of a nuclear power station in California. Tanaka and Zabel (2018) look at the impact of the Fukishima crisis on house prices near nuclear power plants. Specifically in the German context there were a number of studies at the time of the phase-out decision examining the potential impacts, notably Traber and Kemfert (2012).

Moreover, a key impact of the phase-out decision was almost certainly the increased use of fossil fuel generation, particularly coal. The external costs of fossil fuel electricity generation have been extensively studied. Jaramillo and Muller (2016) look at the damages from energy production in the US from 2002-2011. Deschênes, Greenstone and Shapiro (2017) examine the extent of defensive investments to mitigate the negative impacts of poor air quality. Furthermore, impacts are not just limited to the combustion of fossil fuels. Jha and Muller (2017) study the local environmental costs of fine particulates that are emitted during the handling and storage of coal near power plants.

Lastly, there is a growing literature exploring new empirical methods to study the power sector. A number of recent papers have sought to empirically estimate the marginal source of generation in power grids (Holland et al., 2016; Callaway, Fowlie and McCormick, 2018; Borenstein and Bushnell, 2018). There have also been a few attempts to go further and more fully simulate the operation and dispatch of power plants in the electricity grid using empirical methods (Davis and Hausman, 2016), including machine learning methods (Cicala, 2017). Another application of machine learning methods in a causal setting is Burlig et al. (2017).

[1]Source: BNetzA Monitoring Reports

Methods and Initial Findings

The analysis in this paper can be broken into two key steps. The first step involves estimating how power plants would have operated differently in the absence of the phase-out decision. The goal here is to identify which generation sources stepped in to replace the lost output from the shuttered nuclear power plants. The counterfactual is a situation where the prior lifetime extension policy had remained in place. The second step involves calculating the economic costs and benefits in light of the estimated changes in power plant operations. This includes changes to private costs (e.g. changes to total operating costs of power plants) and external costs (e.g. environmental externalities from changes to pollution emissions). The data for this research is collected from a diverse range of sources as shown in Table 1 below.[2]

Table 1: Key data sources on the German power sector

Name	Source	Period	Frequency	Notes
Power plant characteristics	OPSD	2010-2017	Annual	Open Power System Data with additional info BNetzA, ENTSOE and DIW
Generation by plant	ENTSOE	2015-2017	Hourly	Coverage based on plants >100MW
Electricity demand	TSOs	2010-2017	Hourly	
Cross-border imports/exports	TSOs	2010-2017	Hourly	Additional data from ENTSOE
Wind and solar generation	TSOs	2010-2017	Hourly	
Generation by source (nuclear, coal, gas, oil etc.)	EEX	2010-2017	Hourly	Coverage based on companies that report to EEX
Carbon emissions by plant	EEA	2010-2017	Annual	Coverage based on Emissions Trading System (ETS)
Fuel inputs and emissions of SO2, NOx and PM by plant	EEA	2010-2016	Annual	Coverage based on the Large Combustion Plant Directive (LCPD)
Coal, oil and carbon prices	ICE	2010-2017	Monthly	Accessed via Quandl
Natural gas prices	NetCon-nect	2010-2017	Hourly	Accessed via Thomson Datastream
Electricity prices	Various	2010-2017	Hourly	Accessed via Thomson Datastream

Estimating changes in power plant operations - event study regression

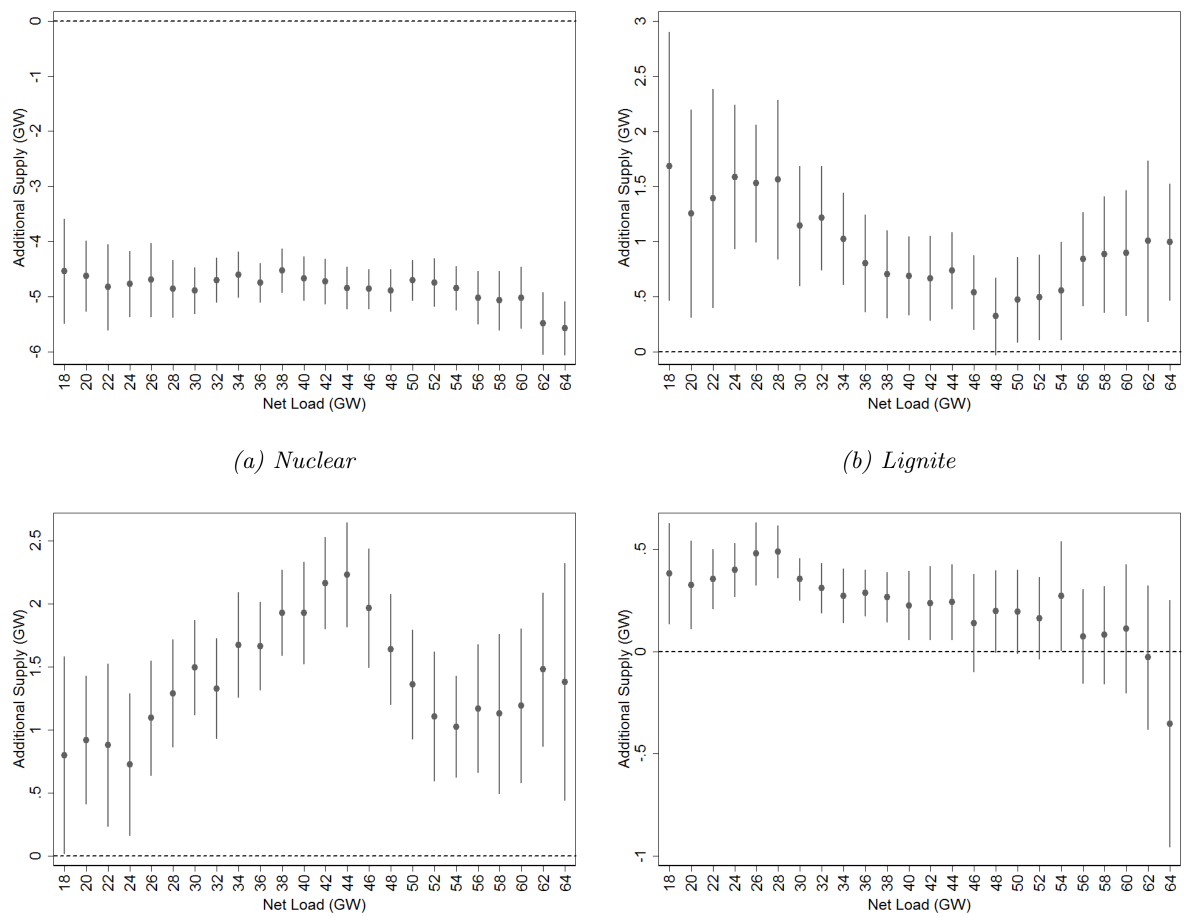
As a starting point we first implement an approach based on Davis and Hausman (2016) "generation regressions" framework. The sudden and unexpected nature of the phase-out decision in response to the Fukishima crisis means it is possible to look at the initial set of power plant closures using an event study framework. We are able to collect hourly data on aggregate generation by source-type for Germany going back to 2010. We also collect data on total electricity demand and generation from renewables. We then create a variable that is load minus renewables, L, and divide this into a set of equally sized bins, b. These are then interacted with an indicator for the shutdown date in March 2011, S. We then estimate the following specification, where the β coefficients estimate the change

[2] OPSD = Open Power System Data project. BNetzA = German Federal Network Agency, or Bundesnetzagentur. TSO = Transmission System Operator, of which the four in Germany are Amprion, TransnetBW, TennetDE and 50 Hertz. ENTSOE = European Network of Transmission System Operators for Electricity. DIW = German Institute for Economic Research. EEX = European Energy Exchange. EEA = European Environment Agency. ICE = Intercontinental Exchange.

in generation from a given source type, i, in each demand bin as we move from the pre- to the post-period.

$$G_{it} = \sum_{b} (\alpha_{ib} \cdot \mathbf{1}\{L_t \in b \cap S_{it} = 0\}) + \sum_{b} (\beta_{ib} \cdot \mathbf{1}\{L_t \in b \cap S_{it} = 1\}) + \gamma + \epsilon_{it} \tag{1}$$

Figure 2: Coefficient Plots from Event Study Analysis



(a) Nuclear

(b) Lignite

(c) Hard Coal

(d) Natural Gas

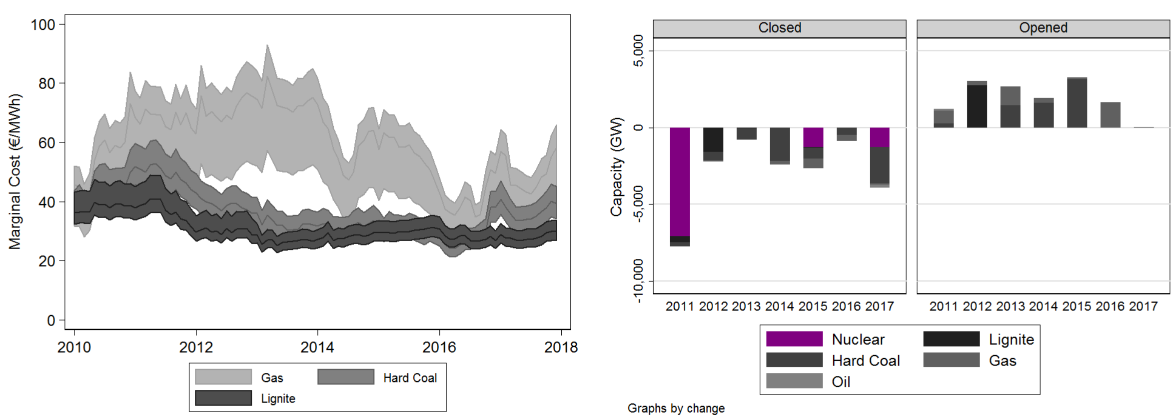
This analysis offers some useful insights. As expected there is a clear reduction in nuclear generation of around 4.5GW across all levels of demand. In response to this we see an increase in generation from all fossil sources, with lignite increasing by as much as 1.5GW at low levels of demand and hard coal increasing by almost 2GW at medium levels of demand.

However, there are clear limitations to this approach. Firstly, we can't say anything about plant-level changes. This is because we lack plant-level generation prior to 2015. This is important because we think that costs can vary significantly across plants of a given source-type, particuarly with respect to the external costs of local pollution emissions. Secondly the event study framework limits us to examining changes in a narrow window around the initial 2011 shutdowns.[3] This is because the nuclear plant closures at this point were unexpected and a large number occurred simultaneously, so it is easier to identify changes from the pre- to the post-period. Subsequent plant shutdowns occurred incrementally and were clearly timelined. As such the impacts will be harder to discern and the identification strategy is less credible. Thirdly, there are good reasons to be concerned about possible

[3]The current analysis uses a one year pre-period and a two year post-period.

confounders to this event study approach. Many factors relevant to power plant dispatch were changing over this period besides the nuclear shutdowns. For example, Figure 3a highlights how movements in the prices of gas and coal caused a large number of fossil plants to shift around in the merit order. At the start and end of the period natural gas and hard coal plants had similar marginal costs, but between 2011 and 2015 high gas prices and low coal prices caused a significant divergence to emerge. Figure 3b also shows how nuclear plants were not the only ones shutting down. Many older coal and gas plants were retired between 2010 and 2017, and a large number of new fossil plants came online during this period as well. Both of these factors mean it is difficult to defend the assumption that the only thing affecting outcomes in the power grid around the event study window was the reduction in nuclear capacity, and this is a greater issue the further out one looks after the initial 2011 decision.

Figure 3: Potential Confounders of Event Study



(a) Variation in Plant Marginal Costs

(b) Capacity Additions/Retirements

Estimating changes in power plant operations - machine learning

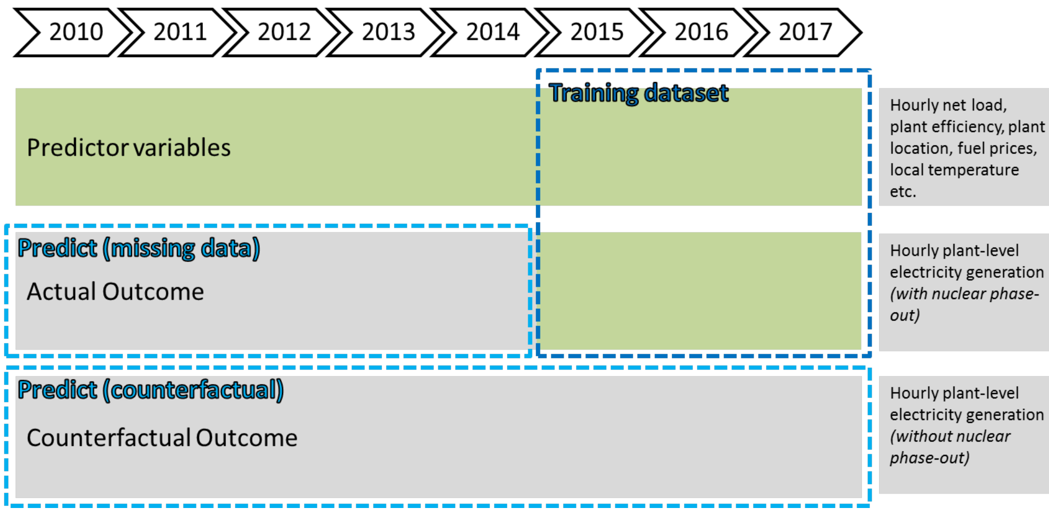
To better estimate how the phase-out decision affected outcomes for the electricity sector we therefore employ a novel machine learning approach. The general estimation strategy involves using a large dataset of observed power plant operations to train a machine learning algorithm. This dataset contains hourly observations of electricity generation for many hundreds of power plants spanning several years. To make these values comparable across plants of widely varying size these generation values are divided by each plants' capacity to get a consistent load factor variable bounded 0-1.[4] This is the dependent or outcome variable. For every observation a set of independent variables or predictors is assembled that are likely to be relevant to a given power plant's decision to operate in a given hour. This includes things like electricity demand, local temperature, prices for fuels like gas or coal, and a range of power plant characteristics like fuel type, efficiency, location, and so on.[5] A predictive model is then estimated that can take these independent variables as inputs and output a predicted load factor for a given power plant in a given hour. Once such a predictive model has been estimated, the independent variables are modified to approximate the conditions that would be expected to prevail in the counterfactual scenario and a new set of predictions are generated. These are then compared to the observed behavior to understand how the phase-out

[4]A value of zero means the plant is not operating and, a value of 0.5 means it is running at 50% and a value of 1 means it is running at its maximum. To incorporate border flows into the estimation a slightly different approach is necessary given that these sources can both import (generate) and export (demand).

[5]For some of these predictors (e.g. electricity demand) lags and leads are included to capture the fact that many power plants have dynamic 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 mean that a plant's decision to operate at any given moment also depends on past and future conditions.

decision changed power plant operations. Full details on the estimation approach can be found in the appendix.

Figure 4: Diagram of Estimation Strategy



With respect to the specifics of the German context explored here, hourly data on power-plant level generation is available for all EU member states since 2015.[6] Prior to this the only available data for Germany is aggregate hourly generation by source type (this was the data used in the earlier event study analysis). As a result the training dataset only spans the years 2015-2017.[7] However, the necessary data on the predictor variables is available back to 2010. As such the machine learning estimation approach employed here has the advantage of being able to solve two problems simultaneously. The first is the estimation of the counterfactual scenario. The second is the filling in of the missing data pre-2015. This is illustrated in Figure 4.

The precise mechanics of modifying the independent variables to predict outcomes in the counterfactual scenario centers around the "net load" variable. 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 and solar), hydro and nuclear. Because total generation must equal total demand for the grid to balance this effectively leaves fossil fuel generation and imports/exports as the remaining sources available to supply net load. As such this net load variable could also be interpreted as "required flexible generation". The basic intuition is that the grid is operated such that low marginal cost and inflexible sources such as renewables and nuclear are always dispatched first to meet demand. The residual demand remaining after this is then met by fossil plants and border flows increasing or decreasing their output. This ordering is reflected in the supply curve in Figure 1b. Observed net load given the phase-out did happen is shown in Figure 5a. If the nuclear phase-out had not happened nuclear generation would have been higher and so net load would have been lower, as shown in Figure 5b. It is worth highlighting here 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.

This approach rests on the assumption that the primary impact of the phase-out decision was the reduction in electricity generation from nuclear plants in Germany relative to the counterfactual scenario where the plants remained open. We are assuming these caused a one-for-one shift in net load, but that all other factors would not have changed relative to what actually happened.[8] For many of the predictors this seems entirely justified (e.g. plant characteristics, temperature, weather, electricity demand etc.). However, for other predictors this is not as straightforward to defend. For example, over longer timescales the phase-out likely impacted decisions on

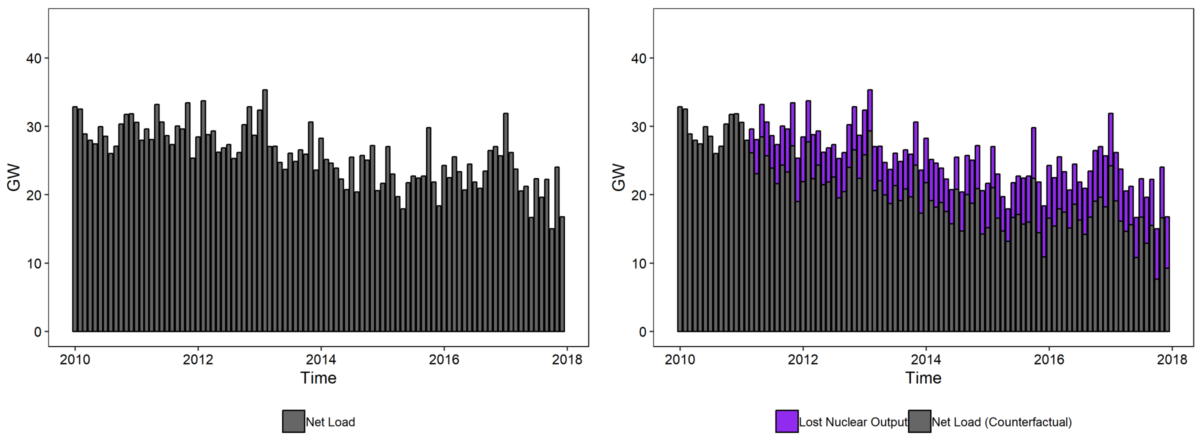
[6]More specifically this applies to plants with capacity >100MW.

[7]The training dataset also includes hourly data on imports/exports for each border interconnection between Germany and its neigboring countries. This data is available for our entire period back to 2010.

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

the extensive margin by accelerating investment in new replacement capacity and/or delaying retirements of old existing capacity. Given the location of Germany's nuclear power plants there is also evidence that the closures exacerbated existing north-south transmission constraints. It is also plausible that the amount of additional fossil generation that was required due to the phase-out could have altered prices in connected markets relative to the counterfactual (e.g. prices for coal, gas or carbon allowances) and that in turn this would have altered certain plants' marginal costs. There are range of ways we seek to mitigate these issues. For example, to try and account for transmission constraints we include a "north-south" location variable to allow plants located in the south to respond differently to those in the north. In the case of capacity investment we focus on conducting sensitivity analyses by identifying capacity investments that were likely additional and re-running the analysis assuming these plants were not built. This work is ongoing.

Figure 5: Average Monthly Net Load, 2010-2017



(a) Net Load (with phase-out)

(b) Net Load (without phase-out)

Another important consideration is that to make out-of-sample predictions using a predictive model it is important that the training dataset provides sufficient support across the predictor variables. In general we can be fairly confident 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.[9] The main point of concern here is the net load variable. Almost by definition the counterfactual scenario will contain some periods where net load falls below the smallest value in the training dataset.[10] Even so, there is such wide variation in both electricity demand and renewable generation that for the vast majority of cases the overlap is very good, as can be seen in Figure 6a. In the cases where this isn't true we will conduct additional work to consider how the predictive model behaves at these thresholds, including how sensitive our findings are to this. This can be found in the appendix.

With these assumptions in mind we can proceed to estimating our predictive model. There are many different ways this could be done. The simplest starting point would be to use a linear regression. This would be a logit model given our dependent variable is effectively bounded 0-1. However, the relationship between our outcome and our predictors is almost certainly not a simple linear one with each of the predictors being independent of one another. As such our predictions would be substantially improved by estimating a more flexible regression with higher order polynomials and interactions. At this point it would be sensible to leverage the benefits of

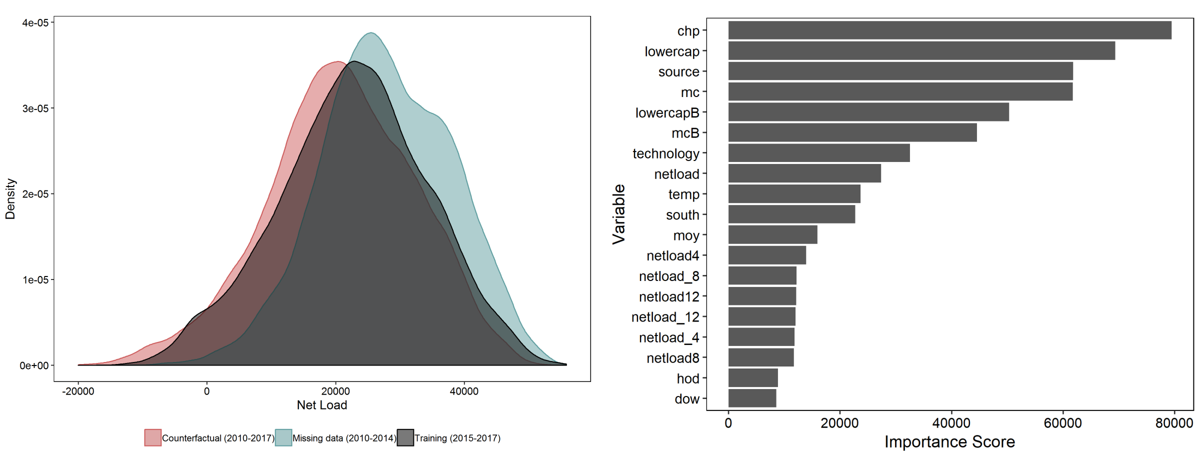
[9]For example, we rescale the marginal costs of each plant by the marginal cost of the last plant needed to clear the market. This means that even if fuel prices increased across the board causing marginal costs to double relative to the training dataset, the rescaling would ensure these still fell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

[10]This is because all periods are taken to have some lost nuclear output, and so the periods when net load was already at its lowest during the training period of 2015-2017 will be decreased further such that they fall outside the original support.

machine learning methods and implement some form of regularization to avoid overfitting. LASSO would be a natural candidate here. Importantly though there is no reason to limit ourselves to approaches based on the standard linear regression model. For the results shown here a Random Forest algorithm was used (Breiman, 2001), specifically Quantile Regression Forests as in Meinshausen (2006).

Random Forests have a number of very useful properties for the application envisaged here. First, we do in fact 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 LASSO). 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 7). 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).

Figure 6: Model Diagnostics



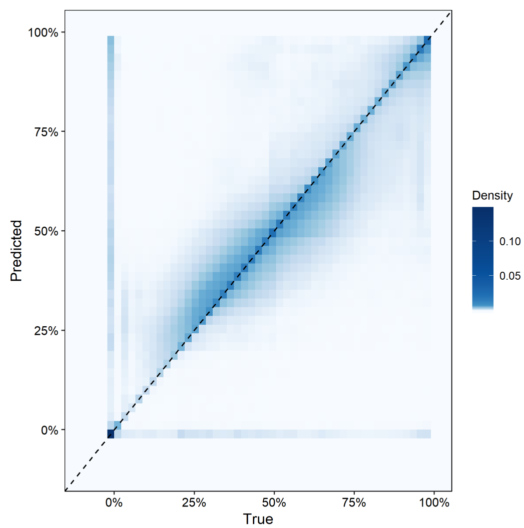
(a) Support of net load *(b) Variable importance scores*

Our Random Forest model is estimated using a training dataset of roughly 4.5 million observations and 20 covariates. The relative importance of each of these covariates is illustrated in Figure 6b.[11] Figure 7a shows how our the median predictions from our estimated model perform when compared against the original 2015-2017 plant-level hourly data that formed the training dataset. In general the performance is reasonably good with

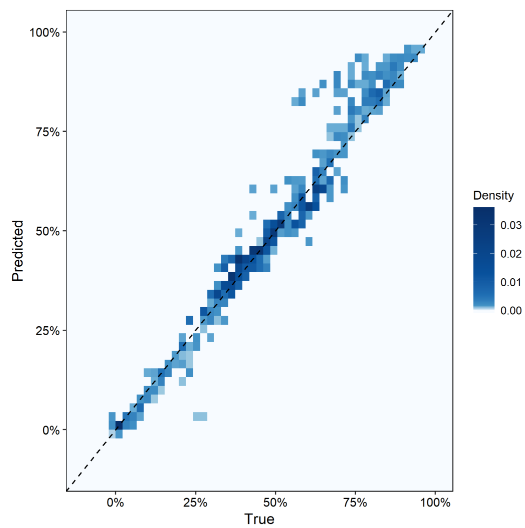
[11]Full details on the covariates used can be found in the appendix. The abbreviated names in the figure are as follows: source = source type (e.g. lignite, hard coal, gas, oil or border); mc = marginal cost relative to clearing unit; mcB = marginal cost relative to clearing unit (including border capacity); 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.

an out-of-bag R-squared of 0.7, although there are some notable areas where the predictions are systematically wrong.[12] Importantly though, for this particular application we are less interested in whether the model performs well for a given plant-hour - rather we are interested in whether the model accurately estimates plant operations over an extended period of time. Figure 7b shows how the model performs at predicting the same data but collapses all hourly values to plant-level annual averages. Here the performance is substantially improved. We also conduct additional validation checks of the out-of-sample pre-2015 predictions and find broadly encouraging results.[13] Further validation checks will be conducted against ambient pollution data from monitors located near individual power plants.

Figure 7: Model Performance



(a) Hourly



(b) Annual

Now that we have our desired predictive model we can conduct the intended analysis. First we generated predictions for every power plant or border point in every hour between 2010 and 2017. We then modified the “net load” predictor variable to reflect that this would be lower in the counterfactual scenario where the nuclear phase-out had not happened. We then generated a new set of predictions for every power plant or border point in every hour between 2010 and 2017. These were then compared to get an estimate of how each power plant’s operations were altered by the nuclear phase-out.

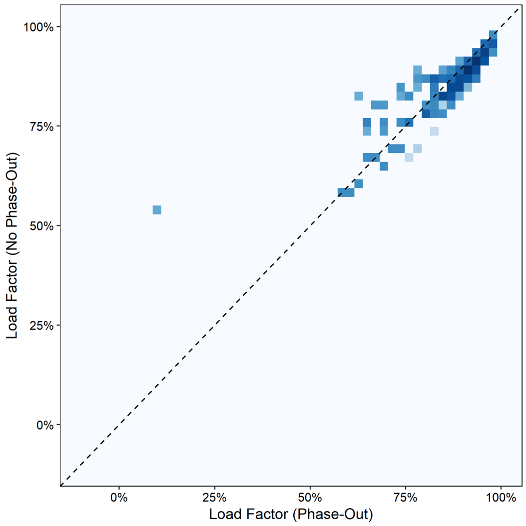
Figure 8 shows these impacts broken down by each of the main source-types. Oil plants are not shown here as they are a very small portion of total capacity and are largely invariant to the phase-out. Here we display results that use the median predictions. Where points lie on the 45 degree line they have the same load factor irrespective of whether the phase-out occurred. Points lying below the 45 degree line reflect an increase in fossil generation due to the nuclear phase-out and vice versa for points above the 45 degree line. 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 below the 45 degree line. This is in fact what we see.

- For the lignite plants shown in Figure 8a, these are very low marginal cost baseload plants and so run very

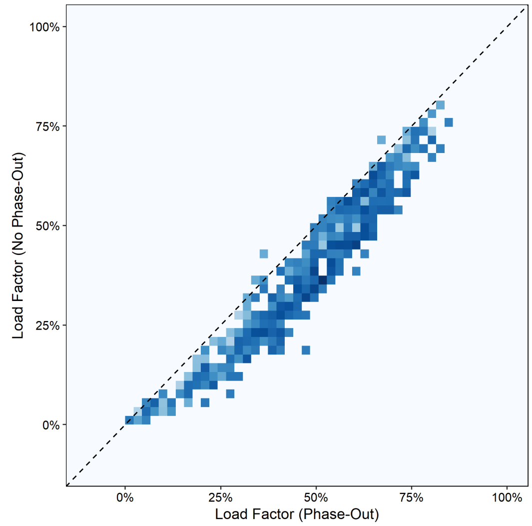
[12] A more detailed discussion of this can be found in the appendix.

[13] To do this we collected annual plant-level data on fuel inputs and local pollution emissions from the EU Large Combustion Plant Directive and the EU Emissions Trading System. This data is available back to 2010 and so can be used to check our efforts to fill in the missing pre-2015 data on plant-level electricity generation. Using information on plant characteristics (fuel type, capacity, efficiency) and assumptions about the emissions factors for different fuels we were able to estimate annual electricity generation by plant from the emissions and fuel input data. We then compared these to our predictions of power plant generation.

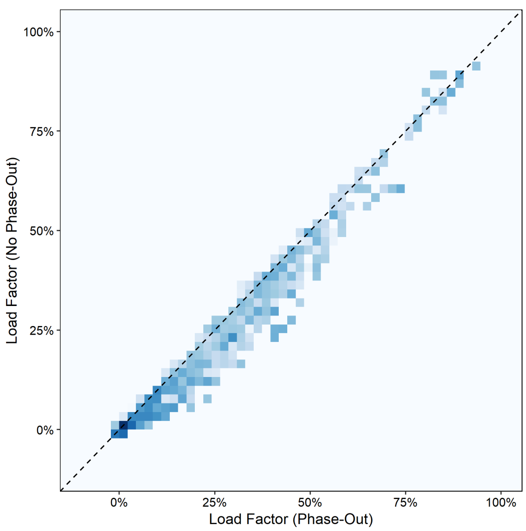
Figure 8: Predicted changes due to the phase-out



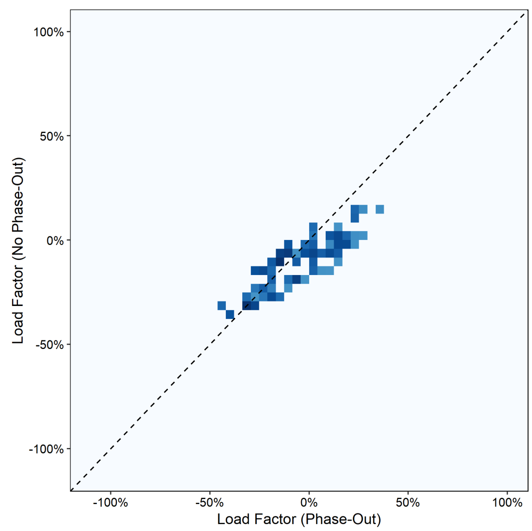
(a) Lignite



(b) Hard Coal



(c) Natural Gas



(d) Border

often, hence their high load factors (i.e. 70-90%). As such they have little scope to increase their generation further, hence there being no clear effect from the phase-out.

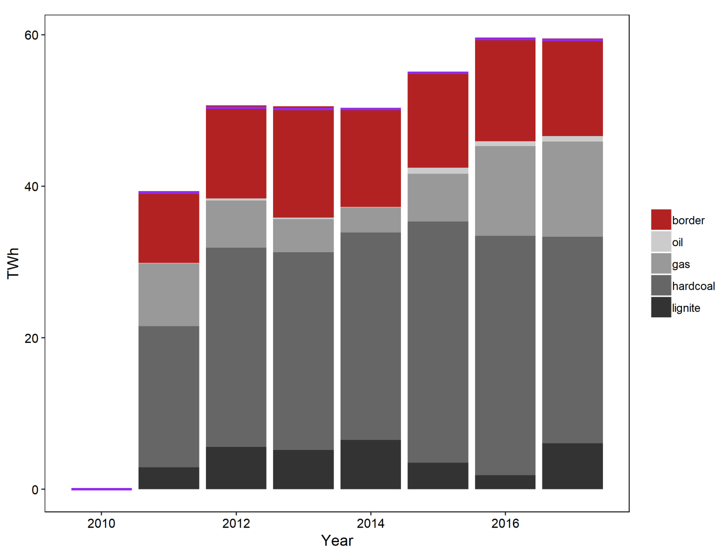
- The hard coal plants shown in Figure 8b have higher marginal costs than the lignite plants and so have lower load factors (i.e. 20-80%). This also means that these plants tend to be on the margin, making them more likely to be in a position to provide the additional generation necessary to replace the lost nuclear output. This is reflected in hard coal plants having load factors around 10-15% higher as a result of the phase-out.

- Figure 8c highlights the impacts for gas plants, which can be broken into three broad groups. The first portion are the more efficient conventional combined cycle gas plants. These plants occupy a similar place in the merit order to the hard coal plants. As such they have similar load factors (i.e. 0-70%) and experience similar increases of 10-15% due to the phase-out. The second portion are inefficient high cost "peaker" plants which operate very infrequently. As such they have very low load factors and so face minimal opportunities to change their operations. The third and final portion are combined heat and power plants. Their activities are heavily dictated by their incentives to provide heating and so have a wide range of load factors. Unsurprisingly they are also largely unresponsive to the nuclear phase-out.

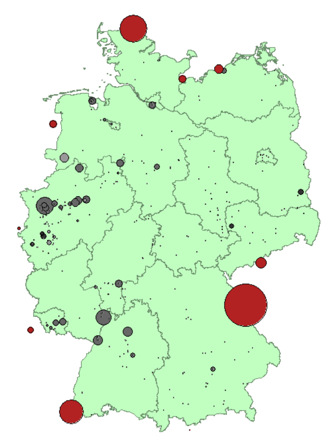
- Finally, Figure 8d shows the results for imports and exports at border points. Imports, like generation from domestic power plants, are classed as positive and exports are negative (note the change in axis scales). Border points rarely import or export at their maximum capacity in Germany, and over the course of a year positive exports often cancel out negative exports. As such most points have load factors clustered in the -50% to 50% range. Here again we find that most border points see a shift towards greater net imports due to the phase-out.

Combining these results together we can estimate the aggregate change in generation due to the phase-out. Doing this using the median predictions displayed in Figure 8 we find 200 TWh of additional fossil generation and 50 TWh of additional 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. As such using the median predictions in this case actually leads us to underestimate the level of replacement generation (250 TWh of predicted replacement generation vs 360 TWh of lost nuclear output). 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).[14] This can be seen in Figure 9a below. We find that more than three quarters of the 360 TWh of lost nuclear generation was replaced by fossil generation, primarily hard coal. The remainder came from changes to net imports. Figure 9b 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 9: Aggregate changes in generation due to the Phase-Out



(a) Source of Replacement Generation



(b) Location of Replacement Generation

[14]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 this particular case this only requires moving a few percentiles from the median. Full details can be found in the appendix.

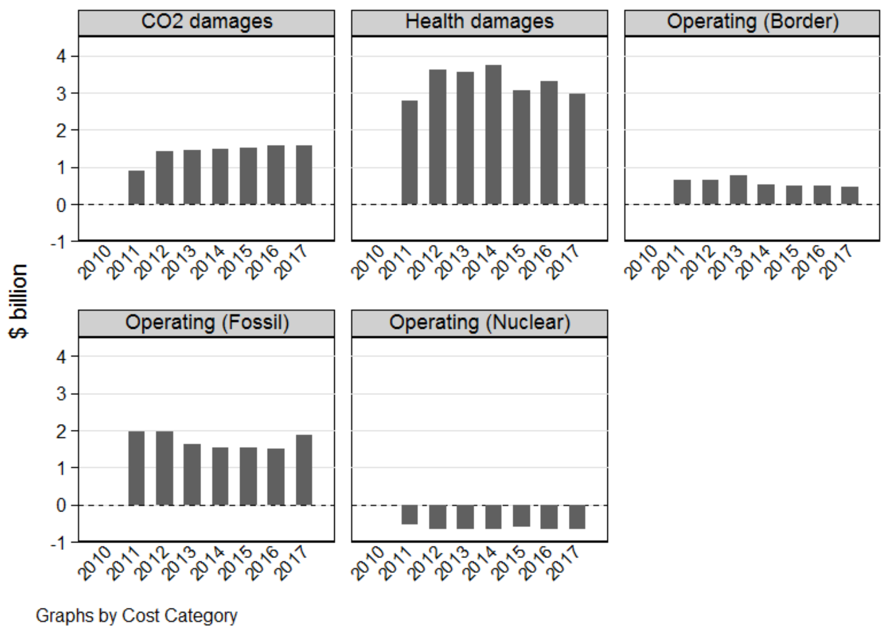
Linking generation changes to local pollution

[INSERT TEXT ON EMPIRICAL ANALYSIS OF LOCAL POLLUTION]

Calculating the economic costs and benefits

In assessing the costs and benefits of the phase-out we try to focus on the national costs and benefits to Germany. The main potential costs we examine are the higher electricity costs faced by end-consumers due to increased electricity prices, the increased operating costs incurred by producers at fossil plants, the increased climate change damages due to increased carbon emissions, and the health impacts of increased local pollution concentrations experienced by people living near fossil power plants. The main potential benefits we examine are the reduced operating costs incurred by nuclear plants, including the costs of nuclear waste storage. We also hope to find some existing literature that can help us value the reduced risk of nuclear accidents. Figure 10 shows our current estimated annual costs and benefits for a selection of these categories.

Figure 10: Phase-Out Costs



Our calculation of changes to power plant operating costs takes the predicted load factors in each scenario and multiplies them by each plants' capacity to get estimated generation for each plant in MWh. This is then multiplied by the estimated marginal cost of each plant in €/MWh to get total operating costs in Euros. The marginal costs of fossil plants tend to fall in the €30-60/MWh range, and can sometimes be in excess of €200/MWh. This is always well in excess of the marginal costs of nuclear plants, assumed here to be €10/MWh. The cost of changes to net imports is taken to be the spot wholesale price in the relevant neighboring country. After converting all the resulting values to US dollars we find a net increase in cumulative operating costs since the phase-out began in 2011 totaling $12 billion. This is comprised of an increase in fossil generation operating costs of $12 billion, an increase in net import costs of $4 billion and a reduction in nuclear generation operating costs of $4 billion.

[INSERT TEXT ON ELECTRICITY PRICE IMPACTS]

Next we estimate the resulting change in carbon emissions. To do this we combine our predicted changes in plant-level operations with plant characteristics (fuel type and efficiencies) to calculate the change in fuel inputs associated with the estimated change in electricity outputs. We then take assumptions regarding the carbon intensity of different fuels to convert these changes in fuel inputs to changes in plant-level CO2 emissions. Here we find a cumulative increase of 230 Mt of CO2 emissions. To put this in perspective total emissions from California's entire in-state power generation over the 2011-2017 period were 273MtCO2e. If we assume a social cost of carbon of $50/tCO2e that translates into $10 billion in additional climate damages due to the nuclear phase-out.[15]

Finally, we estimate the impact of local pollution. For this we start with local pollution emissions data collected as part of the EU Large Combustion Plant Directive (LCPD). This is annual plant-level data on fuel inputs and emissions of suplhur dioxide (SO2), nitrous oxides (NOx) and particulate matter (PM). The LCPD data covers the vast majority of large fossil plants in Germany. We use this dataset to estimate the emissions rates of each of these pollutants for a given TJ of fuel energy inputs at each plant. Where emissions data is not available for a given plant we assign an emissions rate that is the average for that plant's fuel type. As with the CO2 emissions analysis above we then combine our predicted changes in plant-level operations with plant characteristics (fuel type and efficiencies) and our estimates of the emissions rates of different fuels. These elements allow us to convert our predicted changes in plant-level electricity generation into an associated set of predicted changes in plant-level local pollution emissions. Because we are using observed plant-level data on emissions rates this should help account for pollution control technologies installed at each plant. This is much more important to do for local pollutant emissions than for CO2. Here we find a cumulative increase in local pollution emissions of 103kt of SO2, 150kt of NOx and 4kt of PM.

Next we convert these changes in local pollutant emissions into expected changes in health damages. To do this from the ground up would require a) using some form of pollution transport model that can allow us to convert changes in emissions at a given power plant into changes in pollution concentrations in the surrounding area, and then b) a set of dose-response functions and population exposure data that can allow us to convert changes in ambient pollution concentrations into the expected health damages. This is precisely the kind of integrated analysis that has been undertaken for the US using models like AP3 (see Holland et al. (2018)). Importantly for our purpose there have been some similar analyses conducted in Europe, most notably by the European Enviroment Agency and the Beyond Coal campaign (EEA, 2014; Jones et al., 2018). To get an initial estimate of the health impacts we therefore rely on a set of outputs from these studies that include estimated health impacts and valued damages due to local pollutant emissions for 400 of the largest coal plants in Europe.[16] We treat these data as essentially giving us a way to convert tonnes of emissions for SO2, NOx and PM at certain locations throughout Europe into euros of health damages. 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 dataset to one of these 400 locations with damage estimates is 29km and the median is 14km.[17] We then take the predicted increases in plant-level emissions we calculated above and calculate the associated health damages. We find that the additional local pollution emissions resulting from the nuclear phase-out led to a cumulative increase in health costs of $23 billion. If we value these health costs using the US EPA's assumption for the Value of a Statistical Life the costs of local pollution rises to as much as $66 billion.

Bringing all these factors together we get an annual ongoing net cost from the nuclear phase-out of roughly $6-7 billion per year. This amounts to a total cumlative cost of $45 billion up to the end of 2017. To give some sense of scale, a number of press articles discussing the costs of the nuclear phase-out highlight the vast sums needed to decomission the nuclear plants once they cease generating. To date the utilities in Germany have had

[15] Because a portion of these damages are internalized by the EU ETS carbon price, the damages from the additional CO2 emissions are valued based on the difference between the assumed true social cost of carbon and the EU ETS carbon price.

[16] Conveniently the pollution emissions data used for this is the same EU LCPD data mentioned above.

[17] There are also around 10% of the plants in our dataset where the distance is effectively zero. These are coal plants in Germany that make into the 400 largest coal plants in Europe, and so have exact estimates of their health damages.

to set aside $45 billion to cover the costs of decomissioning the entire fleet of nuclear power plants. Of course, these decomissioning costs would be incurred at some point regardless of the accelerated phase-out decision, but they at least give some sense of the scale of the costs that have been associated with the nuclear phase-out to date. It is notable then that our estimate of the ongoing costs of the phase-out decision is already equal in size to the decomissioning costs for the entire nuclear fleet. This is after just the first six and a half years since the shutdowns began in 2011, and during this initial period less than half of Germany's nuclear capacity was actually taken offline. As such the costs we have estimated to date are likely to increase substantially as the remaining nuclear plants are closed between now and 2022.

[INSERT TEXT ON NUCLEAR WASTE STORAGE AND REDUCED ACCIDENT RISKS]

[INSERT TEXT ON CAPACITY INVESTMENT SENSITIVITY ANALYSIS]

Discussion & Conclusions

[INSERT TEXT ON OVERALL FINDINGS AND POLICY IMPLICATIONS]

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