(Mis)allocation of Renewable Energy Sources*

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Abstract

Policies to incentivize the adoption of renewable energy sources (RES) usually offer little flexibility to adapt to the varying benefits of those sources at different locations within the same jurisdiction. In this paper, we propose a general framework to evaluate the geographical misallocation of RES that is potentially caused by the uniform nature of feed-in-tariffs (FiT). After estimating the dispersion of the marginal benefits from solar production in Germany, we compute the social and private costs from the current configuration of residential solar photovoltaic (PV) plants relative to a reallocation scenario in which regions with a higher PV average productivity are given higher amounts of solar capacity, while keeping the system's total capacity fixed. We find that a 20% solar installation rate and with a conservative value for the social cost of carbon, the total value of solar PV would increase by about 5% relative to the current allocation. In addition, we estimate the size of the transmission capacity between the North and the South of Germany implied by the differences in marginal costs across those regions. Reallocating solar capacity with the possibility of exporting surpluses from the South to the North would yield gains that range from 14 to 22% depending on the rate of solar penetration. A benefit-cost analysis shows that additional transmission can be beneficial if there is sufficient RES capacity reallocated across regions.

JEL codes: H23, Q42, Q48, Q51

Keywords: Renewable energy sources, electricity markets, feed-in-tariffs, ancillary services, misallocation.

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1 Introduction

To many policy-makers, the decision to introduce renewable energy sources (RES) in electricity markets hinges on the size of its economic impacts: RES are still more costly than conventional technologies in some regions, they are not perfectly correlated with demand, their intermittency is problematic (they have a non-negligible unforecastable component), the storage costs are prohibitively high, and they are non-dispatchable (Baker et al. [2013]).[1] Feed-in-Tariffs (FiTs), a widely used policy to incentivize the deployment of RES, does not necessarily account for the costs and benefits of those technologies. FiTs guarantee a preferential rate paid to RES producers of electricity, they are regulated by the government, and specify long-term contracts of about 15 to 20 years. FiTs have been implemented in a number of jurisdictions including Australia, California, Germany, Ontario, and Spain. Usually the incentives differ by RES technology, i.e. solar versus wind, but do not account for the relative productivity of the technology, which largely depends on the specific location of the plant.

This paper provides a framework to quantify empirically the effects of misallocation of RES, potentially driven by the lack of location-specifc incentives in uniform FiT-type policies. Our contributions consist of three sets of results. First, making use of an extensive and high-frequency dataset on electricity production and demand, we measure the benefits from an additional unit of electricity output from RES due to the displacement of production from conventional sources in order to satisfy demand. These benefits include the private costs of production and grid reliability as well as the social costs of the emissions displaced. These results quantify the heterogeneity in the effects from RES over different subregions from the same electricity market where a FiT policy has been implemented as a uniform incentive. Our findings underline the misalignment between the policy design and the heterogeneity of the RES productivity. Second, we construct a series of counterfactual scenarios in which RES capacity gets reallocated to maximize its benefits while keeping the total amount of RES capacity constant within the entire market. We do this by placing capacity from regions

[1] More specifically, the cost of a technology to produce electricity is measured by the annual equalized cash flow of costs such that in present value, the sum of those cash flows over the lifetime of a generating plant with that technology, equals its total costs of production and construction. This is known as the levelized cost of electricity.

with low electricity productivity from RES into regions with higher RES productivity. Using micro-data from photovoltaic installations, we can then simulate the output in each of those counterfactual scenarios and compare the total gains against those from the actual allocation. Albeit the gains being positive by construction, it is an empirical question what the magnitude of such gains is. Third, electricity trade is an important factor in the reallocation of output from RES and therefore, we calculate the gains from an increase in transmission capacity between subregions. We compute the shadow cost of transmission and use it to back out the implied size of the transmission capacity for each level of marginal cost gaps across two different subregions of the market. Then, we reallocate RES assuming that the transmission capacity is expanded within that estimated range of capacity and compute the gains from reallocation for different levels of capacity expansion.

Our work is related to the literature that quantifies the value of the marginal output from RES (Callaway et al. [2018]), the value of displaced emissions in electricity markets using the exogeneity of wind and solar output (Abrell et al. [2019a], Cullen [2013], Novan [2015]), and the costs from the fluctuations in ancillary services due to RES expansions (Tangeras and Wolak [2019]). Our reallocation counterfactuals have similarities to those in Asker et al. [2019] for oil extraction and in Sexton et al. [2018] for solar panels. However, our work differs from the latter in that we use actual solar output data instead of output from a simulation model, our definition of benefits includes health benefits through the social cost of carbon of emissions avoided, and the savings from production and ancillary services costs, which has received little to no attention in the literature.[2] In our analysis of misallocation and trade, we extend the applicability of the methods in Joskow and Tirole [2005] and LaRiviere and Lu [2017], which contrast with those using natural experiments as in Davis and Hausman [2016].[3]

[2]One exception is Tangeras and Wolak [2019].

[3]This paper is also related to the challenging task of evaluating different stringency levels of policies that incentivize the adoption of RES. Reguant [2019] compares Renewable Portfolio Standards (RPS) and FiTs focusing on the distributional implications of each policy. Fell and Linn [2013] compare RPS, production subsidies, and FiTs using a simulation model but without accounting for uncertainty. Gowrisankaran et al. [2016] estimate the welfare impacts of RPS for different levels of solar requirements but leaving aside FiTs. Other studies that focus on tax and subsidy policies in electricity markets include Bahn et al. [2020], Borenstein [2012], Fowlie et al. [2016], Knittel et al. [2015], and Leslie [2018].

The analysis in this paper does not attempt to design the optimal structure of a FiT, but rather to quantify the benefits left on the table given its current structure. Abrell et al. [2019b] showed that renewable energy support policies such as FiTs can be designed to be as cost efficient as a carbon price policy.[4] However, we show empirically that a quota mandate in the form of a fraction of the total capacity in the region that should be RES, can also induce gains in the cost efficiency of RES. More specifically, our paper shows that in the presence of a flat incentive for RES adoption, the addition of a quota-type policy could have increased the gains from the costs savings of displacing conventional sources of electricity and the value of the associated emissions avoided.[5]

Since most FiT programs have very small or no variation in the amount of the incentive on output by geographical location or by time of the day, it is an empirical question whether this corresponds to a lack of variation in the marginal benefits of RES.[6] We focus our analysis on solar power in Germany, which has been the first country to implement large-scale FiTs for RES. Fell and Linn [2013] call the German case the *most prominent* example of this policy.[7] By concentrating only on solar energy, we provide a conservative measure of the inefficiency of this policy. The addition of wind capacity to our analysis would at best leave our estimates unchanged, but otherwise the potential gains from reallocation would increase. While FiTs have been an effective tool in increasing the penetration of RES, they are also expensive. In 2015 alone the total subsidy accounted for roughly 22 billion euros and financing the subsidy

[4]See also Wibulpolprasert [2016]. Similarly, in a theoretical exercise, Ambec and Crampes [2019] show that FiTs can be complemented with a price cap and capacity payments to obtain equivalent outcomes to a carbon tax.

[5]The design of these policies can also be tied to a revenue-neutrality constraint in which the taxes levied on emissions are such that the tax revenue equals the total amount spent in subsidies. We abstract from this way to design the policy and focus on the costs/benefits from the geographical dispersion of the RES. For an example of a welfare analysis on a revenue-neutral policy on emissions see Durrmeyer and Samano [2018].

[6]Borenstein and Bushnell [2018] document how the social marginal costs of electricity in the U.S. are in some regions above and in others below the retail price of electricity, which shows that if those prices were to be used for indexing tariffs, they would not correctly account for the potential benefits. Fowlie and Muller [2019] show through a theory model that under perfect information and heterogeneous damages, a non-uniform tax policy over damages is welfare improving, but these results turn ambiguous when there is no perfect information.

[7]We abstract from other forms of incentives in Germany, particularly for wind production, known as "technology banding" where there is heterogeneity in the incentives by giving an advantage to producers in locations with lower output productivity (see Fabra and Montero [2020] for a theoretical analysis).

has led to an intense political debate about how to distribute the total cost between different consumer groups (see for instance Gerster and Lamp [2019]). Reducing the misallocation of RES can have important implications on the effectiveness of FiT policies and potentially decrease their cost.

We combine high frequency data from the German electricity market on load and supply from renewable and non-renewable plants for each of the four transmission system operators (TSOs) together with day-ahead prices, fuel input prices, input-output tables on primary energy inputs and electricity output, as well as data on ancillary services. All these data sources are publicly available, which makes our approach widely applicable to other jurisdictions.

The average marginal benefit in each region can be decomposed into three main elements: displaced emissions, avoided operating costs, and avoided ancillary services. We focus on solar as the main distributed RES with uniform FiT. Our results show that although the heterogeneity in average marginal overall benefits across regions ranges only from 41.8 to 44.6 €/MWh, their components contain a larger range of variation. The mean avoided production costs across TSOs ranges from 19.8 to 29.6 €/MWh. The largest amounts of avoided emissions do not coincide with the largest savings in operating costs due to the differences in the technology portfolio mix in each TSO. We use a conservative value for the social cost of carbon (SCC) of 31.71 €/tCO_2 as our main specification, thus our marginal benefits and the reallocation gains they generate are much larger when using higher values for the SCC as in Abrell et al. [2019b]. The avoided ancillary costs constitute up to 2% of the overall marginal benefits but with large standard deviations.

Then we calculate the social and private costs from the potential misallocation of solar PV plants. We focus on small-scale residential solar installations and perform a counterfactual allocation of solar PV plants starting in regions with the highest average productivity. We do this for different values of solar capacity penetration and keeping total solar capacity in the market constant so that our results reflect solely the effects of reallocation and not of additions to the system. As the solar penetration increases, more of the existing solar capacity gets allocated to the regions with the highest average productivity until all the available solar capacity is placed in one region. Our results show that relatively low penetration rates of

25% for reallocation represent approximately 6% of gains in value (ancillary services, avoided production costs, and avoided emissions combined) relative to the current allocation. Not surprisingly, these gains are mostly due to the displacement of production costs and avoided emissions. However, because of the portfolio mix in the TSOs in Germany, avoided production costs represent a larger fraction of the reallocation gains than the value of displaced emissions for low values of the penetration rate but this relationship reverses once the allowed amount of solar capacity within the TSO is increased.

Finally, we contribute on the policy debate concerning the importance of transmission in the expansion of RES capacity. For this purpose, we split the largest TSO stretching from North to South Germany into two parts, with different average solar productivity, making the South region a net exporter of solar to the North region. We estimate that the average transmission capacity consistent with the observed gap in marginal costs across the two subregions is 3 GW, which is in line with current projects under construction.[8] Then, in a second step, we perform a counterfactual allocation of total installed solar capacity in Germany, taking into account the transmission constraint that allows the South region to export solar electricity to the North. We show that the gains from reallocation range from 14% to 22% depending on the rate of solar penetration. Using projected costs figures, we conclude that the net benefits of the project can be positive, even without accounting for other forms of RES or other interconnections.[9]

The paper is structured as follows. In section 2 we provide details on the institutional background. In section 3 and section 4 we describe the data and the quantitative results in detail. In section 5 we present the main results on the misallocation of solar capacity and the value of expansions in transmission capacity. Finally, section 6 concludes.

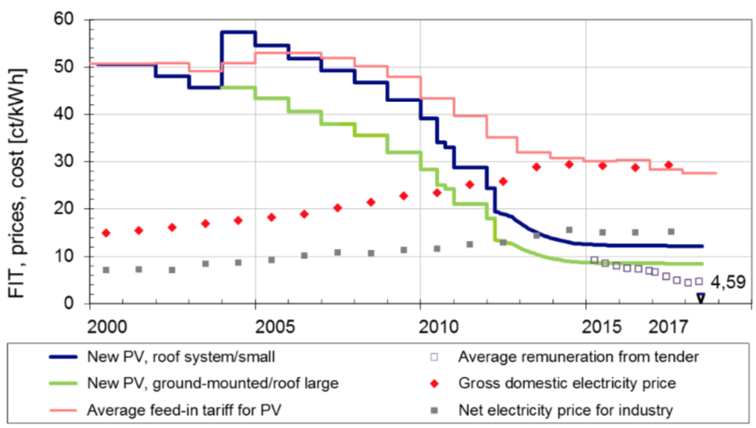
[8]See for instance the network development plan for Germany published in 2019, NEP 2030.

[9]The decrease in marginal costs across the two regions is a form of the effect of transmission expansions on competitiveness as in Wolak [2015].

2 Institutional Context

Germany was the first country to implement large-scale FiTs as part of the *Erneuerbare Energien Gesetz* (Renewable Energy Act) in 2000. FiTs can differ by installation size and type, but are otherwise uniform for each type of RES technology, not taking into account regional differences in sunshine radiation nor regional differences in electricity demand.

Figure 1: Evolution of FiTs for Solar (Germany)



Notes: Taken from Fraunhofer ISE (2018).

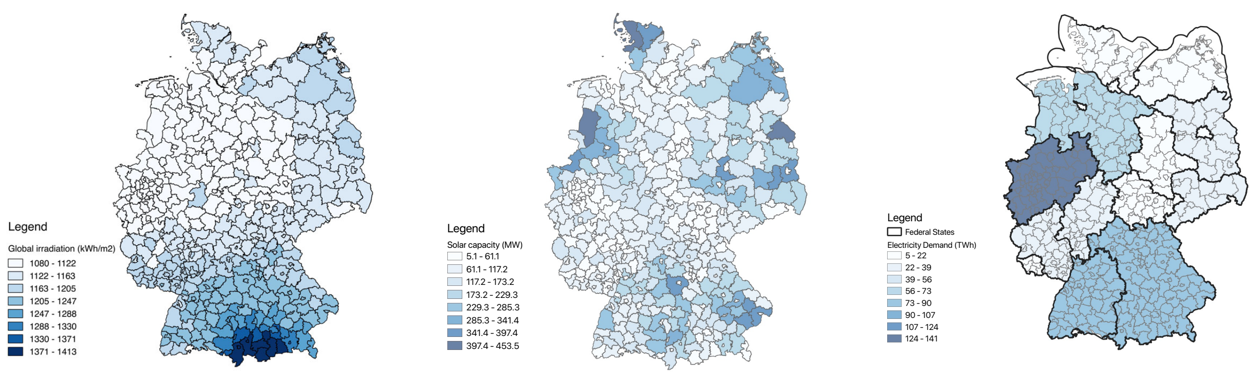
Figure 1 plots the evolution of FiTs for solar systems of different size together with the average electricity price paid by the residential and industry sectors for the years 2000 to 2017. While the overall FiTs have decreased significantly in this time period, mimicking the evolution of technology cost, the average FiT remains at about 30 euro-cents per kilowatt-hour (kWh). The large difference between costs for new installations and the average FiT stems from the fact that rates are set at the point in time when the installation is first time connected to the grid and guaranteed for 20 years. Rates for PV systems depend on system size and mounting. While recent reforms of the Renewable Energy Act have led to the introduction of renewable capacity auctions, smaller residential installations continue to receive FiT even after 2014.[10]

[10]The timing of 'entry' of new PV plants is mainly related to the national FiT policy rather than regional factors. We confirm this by plotting the share of new solar installations in each region relative to the total number of solar installations within the corresponding TSO over the period 2000-16 and we do not find any

Figure 2 displays the total variation in sunshine radiation, installed solar capacity, and electricity demand in Germany. While there is clearly more solar radiation in Southern Germany, we find most of the installed capacity in North-West and North-East Germany.[11] An ideal policy would have likely led to a larger amount of installed solar capacity in the South. Figure 2c shows that total electricity demand −residential, commercial, and industrial combined− also varies across regions, but it does so without a good overlapping with solar radiation nor with installed solar capacity. The question is thus whether the dispersion in potential productivity of installations aligns with the dispersion in marginal benefits. If this is not the case, it is of interest to quantify the value left on the table from installing panels in regions with low solar productivity instead of installing more solar capacity in regions where the panels would be more productive.

Figure 2: Regional Variation in Solar Radiation, Solar Installations and Electricity Demand

(a) Global solar radiation. (b) Installed solar capacity. (c) Electricity Demand.



Notes: Global solar radiation (long-term averages) measured in kWh / m^2 in Panel 2a, cumulative solar capacity (Dec 2016) in Panel 2b, and electricity demand (2015) at state level in Panel 2c. Darker areas represent higher solar radiation, more installed capacity, and higher electricity demand, respectively. Data sources: German Weather Service, Official RES registry, and Statistical Offices of the German States, respectively.

evidence of regional differences in installation timing. These series of plots are available upon request.

[11] We provide the total solar capacity for residential installations (< 10kW) in Appendix Figure A.2.

3 Data

Our primary data sources are publicly available data from the German electricity market. We obtain high-frequency data on load and supply from renewables and non-renewable plants for each of the four regulatory zones that are served by one of the Transmission System Operators (TSOs) in Germany for the years 2015 and 2016. The four TSOs are 50Hertz, Amprion, TenneT, and TransnetBW. These data were obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E) and are available at the 15-minute interval and for each type of production technology. Then, we combined these data with wholesale prices for Germany from the day-ahead market (EPEX) available at the hourly frequency.

To calculate the daily electricity production costs by technology (coal, natural gas, fuel oil), we enrich these data with detailed fuel prices for Germany obtained from Bloomberg and official input-output tables from the working group on energy balances (AG Energiebilanzen) to determine the conversion factors from primary energy to electricity. These data allow us to calculate electricity production costs as well as emission factors by technology. We do not employ wholesale electricity price data because it does not necessarily reflect the cost of production as market power may be an important component of the observed price levels.[12] Instead, we obtain the marginal cost for each time period as described in the next section. Therefore, our results do not reflect issues related to market power.

We also use data on the type, quantity, and cost of ancillary services at the TSO level. These data are available from the official tender platform at 15-minute intervals and describe the procurement of primary and secondary control reserves.[13] While system balancing takes place at the TSO level, there exists one common price for ancillary services in Germany.

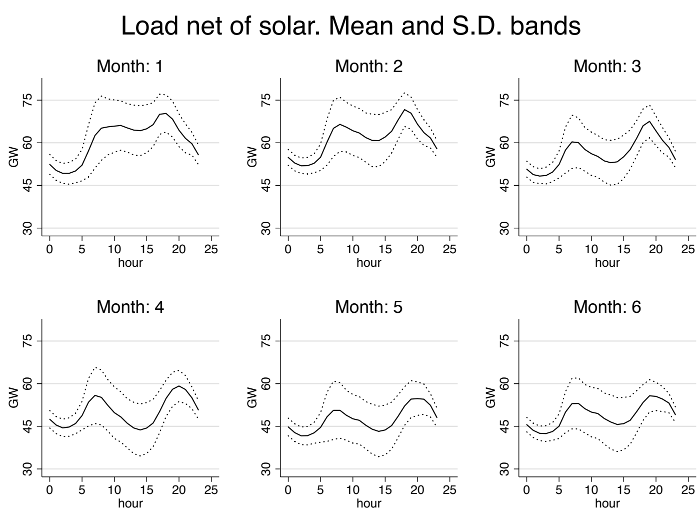
To gain some intuition on the effects of RES production on the rest of the system's production, Figure 3 plots the average residual system load (load net of solar) for the first six

[12] In addition, since there is a uniform wholesale electricity price for Germany, this price does not allow to disentangle regional differences in electricity supply and demand. TSOs are, for example, responsible for grid balancing in their area and congestion between the TSOs might lead to differences in marginal costs of production.

[13] http://regelleistung.net

months of 2015 together with one-standard deviation bands. There are several facts worth noting. First, electricity demand in Germany is higher in winter than in summer, which is mainly related to demand for electric heating. Second, the production profile of solar can lead to the well documented "energy duck curve". The double-hump shape is associated with the risk of RES over-generation during day-hours and the need for ramp-up at peak demand in the evening.[14] Finally, peak demand might shift to earlier hours in the summer. This exemplifies the variability in load caused by the introduction of renewables. Without them, the load profiles would be smoother and so would the ancillary services required. The repetition of the peak-cycle in one single day suggests a repetition of costs to maintain grid reliability. This will be quantified in the marginal ancillary costs at hourly level discussed in the next section.

Figure 3: Load Profiles Net of Solar



Notes: Each panel shows the hourly mean and standard deviation for load minus solar output in Germany. To facilitate the exposition we show only the first six months of 2015-16 combined. (January on the top left and April on the bottom left panel).

Figure A.3 in the Appendix, on the other hand, plots the average portfolio mix by TSO for the years 2015 and 2016. This graph documents clearly the heterogeneity in the production

[14]Similar patterns have been documented by Bushnell and Novan [2018] and Jha and Leslie [2019] in solar-rich jurisdictions.

mix. While 50 Hertz and Amprion have a large share of brown coal plants, TransnetBW shows the largest dependence on nuclear. Our analysis focuses on one well-defined market and abstracts from imports and exports to Germany. The variability of net load over time even when aggregated at the national level and the diversity in the portfolio mix across the different TSOs, suggest that not only the marginal benefits in each of those regions can be different but also over time.

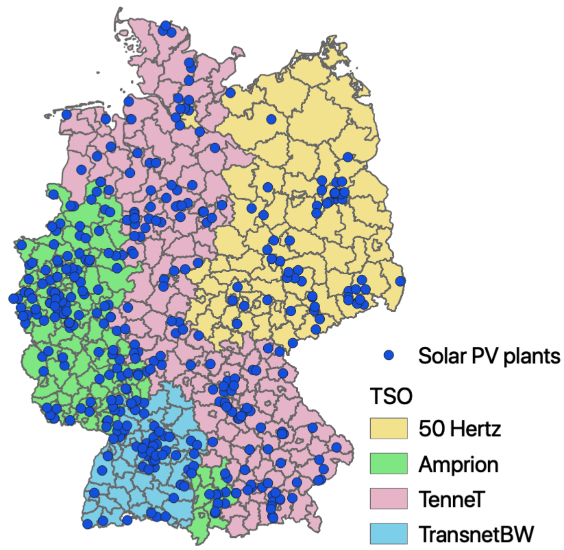
We complement the aggregated data at the TSO level with several disaggregated data sources. First, we obtain disaggregate data on all solar installations in Germany that are subject to FiTs.[15] We complement those data with solar PV production information from individual residential plants available from PV Output that provides us with the power produced at the PV station level at 15-minute intervals for a subset of all plants across Germany. More importantly, individual solar PV production data allow us to take into account plant heterogeneity in production (due to panel orientation, number and type of inverter, shading, etc.) and to have a distribution of solar PV output by TSO. Figure 4 shows the four TSOs and the location of the individual solar PV production plants in our dataset. Second, we obtain data on the location, technology, and installed capacity of conventional power plants in Germany from the Open Power System Data platform, which, in turn, are based on official statistics from the German Environmental Agency and the Federal Ministry for Economic Affairs and Energy. For all plants with an installed capacity of 100 MW or more, we furthermore obtain the history of plant unavailability and plant outages, which is available from the ENTSO-E at the 15-minute interval. Finally, we further complement our dataset with additional regional statistics on population, economic output, and energy demand from the Statistical Offices of the 16 states in Germany.

4 Quantifying the Marginal Benefits

We start our analysis by computing a measure of the value of an additional unit of electricity produced by RES. This is based on a combination of the short-term social and private costs

[15] These data are available from the network transmission operator Netztransparenz.de.

Figure 4: TSO Service Areas with Solar PV plants ($\leq$ 10 kW).



Notes: Each blue dot represents a residential solar PV installation (installed capacity $\leq$ 10 kW) for which we observe electricity generation data at high frequency. Data obtained from `PVoutput.org`.

associated with non-RES production. We separate the marginal benefits (MB) from one unit of production of electricity from renewables at region j and time t as:

$$\begin{aligned} MB_{jt} = & \quad \text{value of displaced emissions}_{jt} \\ & + \text{avoided operating costs}_{jt} \\ & \pm \text{avoided ancillary service costs}_{jt} \end{aligned}$$

in a similar manner as in Callaway et al. [2018]. The first component captures the social costs and the last two the private costs. Our final goal from this part of the analysis is to compare the distribution of MB_{jt} against the uniform nature of the FiT incentive. We abstract from capacity markets as Germany is an "energy-only market", in which only produced power is compensated.[16]

The avoided operating costs are the savings from the last MWh produced by the marginal plant that is no longer needed if RES output can replace it. Then, as pointed out in Callaway et al. [2018], the avoided operating costs can be expressed as a correlation of marginal costs

[16]See for instance a White Paper (2015) published by the Federal Ministry for Economic Affairs and Energy arguing against the introduction of capacity markets in a foreseeable future in Germany.

and RES output. Let λ_{jt} be the marginal cost in region j at time t and let ω_{jt} be the RES output at time t divided by the total RES production in a time interval $[0, T]$. Then, using the values of ω_{jt} as the realizations of the probability density of the RES output we obtain that the average avoided operating costs per time period are

$$E[\text{avoided operating costs}_j] \;=\; \sum_{t=1}^{T} \omega_{jt}\lambda_{jt} = \overline{\lambda_j} + T \times Cov(\omega_j, \lambda_j),$$

where $\bar{\lambda}_j$ is the expected value of λ_{jt} and we use the fact that $\sum_t \omega_{jt} = 1$. That expression makes clear that the weighted sum of marginal costs can be expressed as the average of marginal costs in region j and a term that depends on the correlation between marginal costs and solar output. The higher this correlation, the higher the value of avoided operating costs. Therefore, the geographical location of both the RES installation and the conventional sources is an important component of their value.

The same arithmetic applies to the case of emissions. Let e_{jt} be the emissions of the marginal plant at time t in region j. Then

$$E[\text{displaced emissions}_j] \;=\; \sum_{t=1}^{T} \omega_{jt} e_{jt} = \overline{e_j} + T \times Cov(\omega_j, e_j),$$

where $\bar{e}_j$ is the expected value of e_{jt}. This shows that a positive correlation of emissions and RES output increases the value of the displaced emissions. Therefore, the correlations in both cases can be increased by inducing higher installation rates in regions with higher solar productivity, higher emitting plants, and higher marginal costs.

The ancillary services costs would follow a similar valuation if the marginal cost of this production were known. However, the typical data for this component are of a different nature and we propose a new approach to account for these savings in subsection 4.2.

4.1 Avoided operating costs and emissions

For each 15-minute time interval t we sort the technologies by their marginal cost and form the perfectly competitive supply curve, i.e. the system's marginal cost. Then we intersect that curve with the demand at time t and store the value of the marginal cost associated to the technology at that intersection. We call that marginal cost λ_{jt}, where j identifies the

TSO. The underlying assumption is that load is dispatched by minimizing production costs.[17] Notice that this assumption on the ranking of the technologies to be dispatched (merit-order) makes sense even in the presence of market power as long as there is not strategic withholding, which would clearly change the order of the dispatched plants. We elaborate on the detailed procedure in Appendix section A.1. Table 1 shows the resulting simulated frequencies of the marginal technologies for the years 2015 and 2016 and Figure 5 the distribution of the marginal costs for each of the four TSOs. Consistent with other electricity markets, natural gas plants are the most frequent to be the marginal technology (62% of the time) followed by hard coal (36%) and then the rest of the technologies each with less than 2% of the time. The marginal costs distribution for TransnetBW is shifted to the left with respect to the other three TSOs in part because of its large share of nuclear capacity (the largest among the four TSOs).

In contrast to previous studies that focus on the German electricity market using an optimization problem [see for instance Abrell et al., 2019b], our fully data-driven approach allows us us to exploit several years of highly disaggregate data at the 15-minute level.

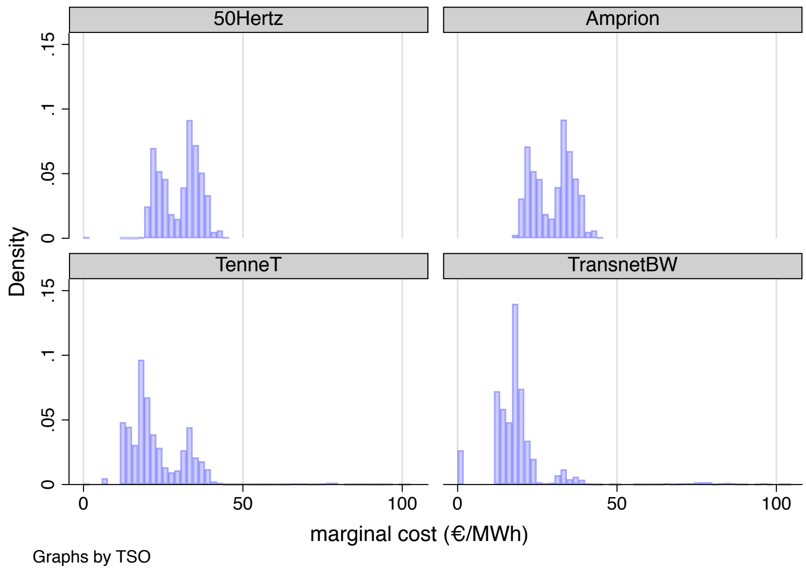
Table 1: Simulated Frequencies of Marginal Technologies

Source	Freq.	Percent
Natural Gas	172,501	61.45
Hard Coal	100,765	35.90
Nuclear	3,522	1.25
Oil	3,187	1.14
Brown Coal / Lignite	655	0.23
Hydro: River	46	0.02
Hydro: Pumped storage	24	0.01
Biomass	4	0.00

Notes: For each 15-minute interval of the day we compute the marginal cost of each of the technologies shown in the table, we sort them from lowest to highest marginal cost to obtain the system's marginal cost curve. Notice that the marginal cost for fossil fuels can change over time as we use fuel prices data to construct this curve. Finally, we select the technology that corresponds to the point in the marginal cost curve that intersects the net load in that time interval.

[17] We make the implicit assumption that each TSO balances demand and supply independently and that there is no interconnection between the entities. We relax this assumption in subsection 5.2, where we elaborate on transmission capacity between regions.

Figure 5: Distribution of Marginal Operating Costs by TSO



Notes: Each panel shows the histogram of λ_{jt} for a given TSO j.

Since we stored the identity of the marginal technology for each time interval, we can also compute the avoided emissions from those marginal plants. Then we use a social cost of carbon (SCC) of 31.71 €/tCO_2 as our baseline valuation to transform these emissions into euros per MWh.[18] We show the summary statistics of the avoided emissions multiplied by our baseline SCC value in the fourth column of Table 3. We also consider two higher values for the SCC, 50 and 100 €/tCO_2, which correspond to the two scenarios in Abrell et al. [2019b]. All our results are obtained using an SCC value of 31.71 €/tCO_2 unless otherwise specified. This places all of our results on the conservative side of RES valuations.

[18]The SCC is designed to measure climate change damages and includes effects on human health, agricultural output, property damages from flood risk, and changes in heating and air-conditioning costs. See EPA fact sheet. We chose the SCC in the US of 36 \$/tCO_2 at a discount rate of 3% annual for year 2015. This value is equivalent to 31.71 €/tCO_2 using an average of the exchange rate between the two currencies of 0.88 dollars per euro. The last two times this exchange rate applied were at the end of December 2019 and at the end of March 2020.

4.2 Ancillary services costs and renewables

The third component in our marginal benefits calculation has received little attention in the literature. One exception is Tangeras and Wolak [2019] who use a kernel regression to find the effect of renewables output on ancillary costs in California. Their results show that the effect can change signs depending on the amount of load and renewables. We opt for a new approach to estimate this effect that will allow us to reduce the computational burden of our reallocation simulations in the next section.

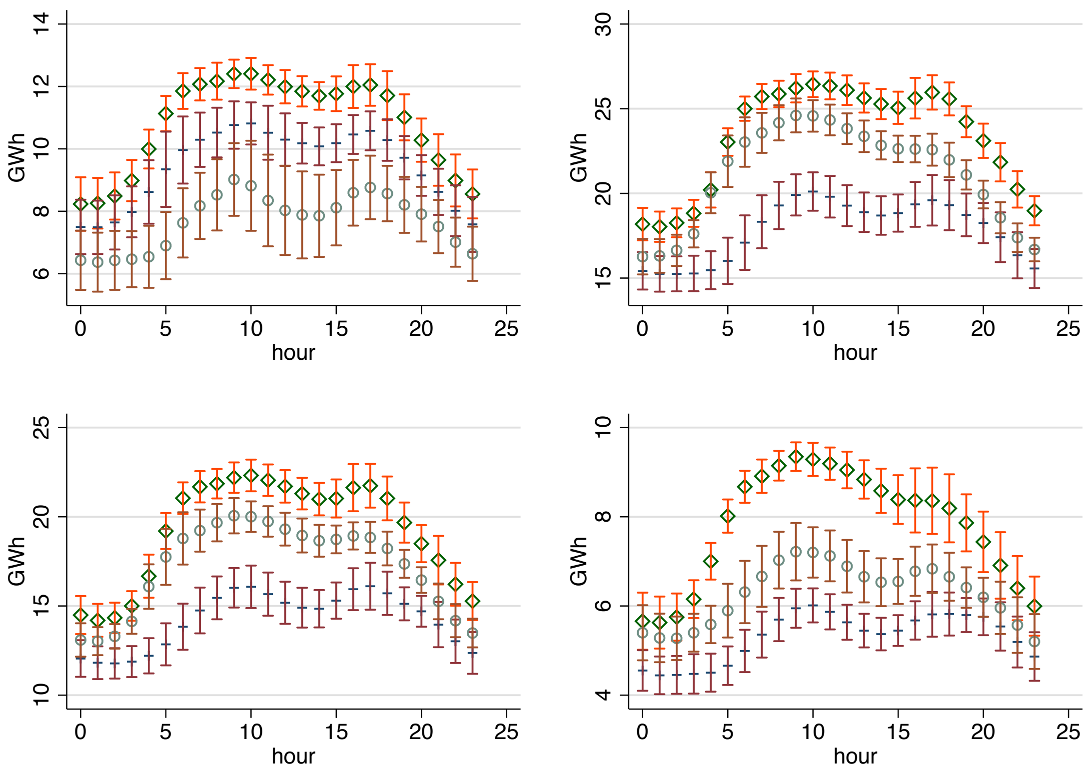
First, we cluster our data on categories of load profiles. To do so, we use the $k-$means clustering method, which is an unsupervised machine learning algorithm. Similarly approaches have been used by Reguant [2019], Bahn et al. [2020], and Green et al. [2011]. We define a data point as the vector of all the observed load amounts in one day aggregated at the hourly level and at the TSO level. To this vector we add an additional entry equal to the maximum of those 24 elements. The $k-$means clustering algorithm starts with k randomly chosen points and attempts to classify the remaining observations by the proximity to those initial points: each observation gets assigned to the closest of the k initial points. We use the Euclidian distance in our implementation and several different initial points to make sure our clusters are robust to that initial choice. Figure 6 shows the mean and standard deviation bands for each of the clusters in each TSO. We determine the number of clusters ($k = 3$) as the maximum value of k such that the standard deviation bands do not overlap for most of the hours in each TSO.

Then, for each of the clusters we estimate the relationship between the ancillary costs on solar output and load using a cubic polynomial that includes all the terms up to degree three including interactions. In addition, we include two-way fixed effects FEs of TSO, hour of the day, day of the week, month, and year as follows,

$$\begin{aligned} AS_t(R_t, Q_t) &= a_0 + a_1 R_t + a_2 R^2 + a_3 R^3 + a_4 Q_t + a_5 Q_t^2 + a_6 Q_t^3 + \\ &+ a_7 R_t Q_t + a_8 R_t Q_t^2 + a_9 R_t^2 Q_t + FE. \end{aligned}$$

where a_i are the parameters to estimate, R_t is the renewable output and Q_t the total load at time t. The marginal effect from an increase in renewable output on expected ancillary

Figure 6: Clusters of Load Profiles by TSO



Notes: The labelling of the clusters is consistent across the four panels: cluster 1 is identified by the filled circles markers, cluster 2 by the hollow triangles, and cluster 3 by the hollow circles. The range of vertical axes is different in each panel to ease readability. The number of clusters ($k = 3$) is the maximum value of k such that the standard deviation bands do not overlap for most of the hours in each TSO.

services is the derivative of the expression above with respect to R_t. We estimate this equation for each of the different clusters of load profiles.

We present the regression results in Appendix Table A.2. In these regressions we only include observations for which solar output is positive since otherwise the ancillary services are not related to solar production. Using these estimates we can compute the derivative of the ancillary services with respect to solar output and we evaluate it at each different time observation in our sample. This heterogeneity is used later in the paper when we calculate overall marginal benefits under different scenarios. Table 2 shows the mean of the values of such derivatives when evaluated at each of the time intervals in our sample. When these derivatives are evaluated at the mean values of load, we obtain quadratic functions that take on negative values for solar output of less than 1,800 MWh and positive values for larger output levels. Figure A.4 in the Appendix shows these relationships. While there are usually benefits related to some solar production in the electricity system, ancillary service costs increase as more solar needs to be connected to the grid; yet the exact response depends on an interplay of load and solar output. This finding is in line with Tangeras and Wolak [2019].

Table 2: Effect of Solar Output on Ancillary Services

	$\partial AS/\partial R$		
TSO	cluster 1	cluster 2	cluster 3
50Hertz	-1.21	-0.19	0.29
Amprion	0.91	0.56	-0.80
TenneT	-0.19	-0.11	-0.87
TransnetBW	-1.83	1.98	-0.20

Notes: Each number in the table, in €/ MWh, is the arithmetic mean of the values of $\partial AS/\partial R$ when this derivative is evaluated at each 15-minute observation using the coefficients in Table A.2.

We present in the Appendix Table A.3 the results from a quadratic and a cubic specifications for $AS_t(R_t, Q_t)$ when pooling all the observations instead of running different regressions by clusters. There, it is evident that by pooling all the observations, there is a loss of heterogeneity of the value of the derivative of interest and fewer coefficients are statistically significant. Therefore, we choose the specification that uses clusters as our main specification.

4.3 Total marginal benefits

The total expected value of the marginal benefits are shown in Table 3. As pointed out in the computation for each of the components of marginal benefits, there is a different value at each 15-minute interval and for each TSO. To simplify the exposition of these results we opt for showing the simple arithmetic means and the standard deviations only. There are several things worth noting. First, the avoided operating cost accounts, on average, for between 44% and 67% of the total marginal benefits. Second, the marginal effect of ancillary services with respect to renewables is small compared to the other two components. However, these are non-negligible amounts in the aggregate and they are all positive on average but with high volatility. This surprising result is supported by the broader trend in ancillary services and RES. While over the time period 2008 to 2015 wind and solar capacity have augmented roughly by 200% in Germany, the total amount of balancing reserves has decreased by 20%.[19] Finally, our results show heterogeneity for the four main regions as measured by the standard deviations of the marginal benefits.

Table 3: Expected Value and Standard Deviation of Marginal Benefits

TSO	avoided ancillary costs (€/MWh)	avoided operating costs (€/MWh)	avoided emissions (€/MWh)	total (€/MWh)
Amprion	0.01	29.43	12.39	41.83
	(1.53)	(6.3)	(2.04)	(6.18)
TenneT	0.46	22.53	21.59	44.58
	(1.08)	(9.94)	(7.28)	(7.93)
TransnetBW	0.80	19.76	23.37	43.93
	(1.64)	(13.23)	(7.68)	(16.48)
50Hertz	0.53	29.62	12.14	42.29
	(1.07)	(6.38)	(1.02)	(6.49)

Notes: The first three columns of results show each of the averages and standard deviations (in parentheses) of each of the components of marginal benefits. The last column contains the overall average and standard deviation (in parentheses) by TSO.

[19] Lion Hirth, 'Balancing power 2015', Neon Energie, last accessed online 12 June 2019.

5 Measuring Misallocation

In this section we measure the misallocation resulting from the current solar panel installations locations using our estimated measures for the marginal benefits and a ranking of TSOs with respect to their solar productivity −defined as solar output per unit of installed capacity−. A different approach is to allocate solar according to the ranking of the average expected marginal benefits from Table 3. Yet, this measure does not take into account the misallocation resulting from differences in solar radiation.[20] We exploit the heterogeneity in regional solar radiation to calculate a counterfactual allocation of solar installations in Germany such that regions with the highest productivity are assigned a larger amount of these installations. We focus on small scale residential solar installations in this setup. We compare this counterfactual allocation's output and total benefits to the output and benefits from the actual location of PV installations. Our measure of misallocation is the ratio of the two total benefit values from each scenario, where the value is based on the expected marginal benefits of solar in each region.

5.1 Reallocating RES

We start by computing the value of the actual solar allocation: each unit of observed solar output is valued at the MB_{jt} (different every 15-min in each TSO) and we take the sum over our sample period. This is the baseline value used below to compute the gains of each reallocation. Then we rank the TSOs by the productivity of their solar installations. Some regions with high solar radiation levels may have small levels of capacity installed and therefore, their output per unit of capacity is relatively high, which calls for an expansion of their installed capacity.

To determine the average solar productivity per TSO, we use individual solar plant-level production data aggregated at the annual level. We observe the production profile for approximately 240 stations in Germany during 2015 and 2016. Table 4 shows the results from

[20] Moreover, the ranking implied by the expected marginal benefits can change with the reallocation. Using an ex-ante fixed ranking, based on an exogenous characteristic, such as average solar radiation, overcomes this problem.

linear regressions without a constant of the annual output in kWh per kW of capacity installed on the set of TSO indicator variables and the characteristics of the solar installations.[21] We condition on year fixed-effects as well as on other PV panels characteristics with the goal to remove annual differences and the effects from particularities in the mounting of the solar panels. The coefficients on the TSO dummies measure the average productivity of the PV sites in each TSO. The table shows that the ranking, with respect to the size of the coefficients, is consistent across the specifications except for column (1), where we do not condition on any installation characteristics. Interestingly, the differences in average productivity across TSOs are not very large, especially when we control for system characteristics. We thus rely on columns (2) and (3) to define our ranking. In line with these estimates, residential solar plants are more productive in TransnetBW, followed by Amprion, 50 Hertz, and TenneT.

With this ranking at hand, we define γ as the maximum share of total capacity that is allowed to be covered with solar capacity in a given TSO. The interpretation of γ is therefore similar to that of a Renewable Portfolio Standards (RPS). However, instead of a mandate on the fraction of load to be covered by RES production, we define γ as a fraction of installed capacity and as a maximum share of total capacity, not a minimum.

Let $\mathcal{S}$ be the total amount of currently installed residential solar capacity in all the TSOs together. For a given value of γ we reallocate $\mathcal{S}$ as follows:

1. Add $\gamma\times$ (total capacity in the TSO with the *highest* average productivity) to the capacity of this TSO.

2. If $\mathcal{S}$ has not yet been depleted, add $\gamma\times$ (total capacity in the TSO with the *second* highest productivity) of capacity to this TSO.

3. If $\mathcal{S}$ has not yet been depleted, add $\gamma\times$ (total capacity in the TSO with the *third* highest productivity) of capacity to this TSO.

4. Continue until $\mathcal{S}$ has been completely reallocated.

[21]The estimated average productivity per TSO is in line with PV simulation models, e.g. as available online from the European Commission.

Table 4: Ranking of TSOs by Output per Unit of Capacity Installed

	(1)	(2)	(3)
TransnetBW	907.331***	988.127***	1037.727***
	(31.821)	(35.940)	(38.489)
Amprion	818.864***	927.586***	971.994***
	(22.174)	(30.437)	(32.935)
50 Hertz	820.226***	912.942***	966.330***
	(33.770)	(37.201)	(41.332)
TenneT	806.680***	894.915***	965.630***
	(22.579)	(28.738)	(33.769)
Controls:			
Year	✓	✓	✓
Panel orientation		✓	✓
Panel shading		✓	✓
Inverter size		✓	✓
Panel tilt			✓
N	485	485	464
R^2	0.920	0.928	0.930

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: output in kWh per kW of capacity installed. Control variables are included as categorial variables. The reference (omitted) category in column 2 are South facing solar plants with no shading and a large inverter size ($>$ 7000 Watts). Column 3 additionally conditions on tilt (15-40 degrees as omitted category). For each column, the magnitude of the coefficients define the ranking in solar productivity.

For the reallocation we rely on the observed output from the individual solar PV stations in each TSO and multiply it with a daily weight so that the sum of the output of all the stations in our sample is equivalent to the observed aggregated total TSO output. This allows us to obtain a distribution of gains in each TSO. We elaborate on the detailed algorithm in Appendix section A.1 where we also present a numerical example. We use the MB at the 15-min interval and TSO levels to multiply the newly allocated solar output in each TSO. When doing so, the effect on the ancillary services may change signs and large RES penetration rates could be associated with increases in the costs of these services. Although unlikely, if solar output from residential installations was enough to cover total load in the TSO, only the units needed to satisfy demand are valued at the MBs since the surplus does not displace any traditional technology. This occurs less than 0.01% of the times in our sample. When we introduce the possibility of transmission in subsection 5.2, the surplus will be valued at the MB of the importer of this excess.

Our results consist of reallocating only residential solar installation plants of no more than 10 kW of capacity. We set the minimum value for γ to be 0.0725 so that gains from reallocation are always positive in the benchmark case. A lower value of γ would imply that $\mathcal{S}$ is not fully reallocated among the four TSOs, leaving a fraction of $\mathcal{S}$ unused after allocating solar capacity in the least productive region. This would yield an inefficient allocation.

Our main outcome of interest is the ratio

$$\text{Reallocation value} \quad = \quad 100 \times \left(\frac{\text{value of reallocated solar capacity}}{\text{value of current allocation of solar capacity}} - 1 \right) \quad (1)$$

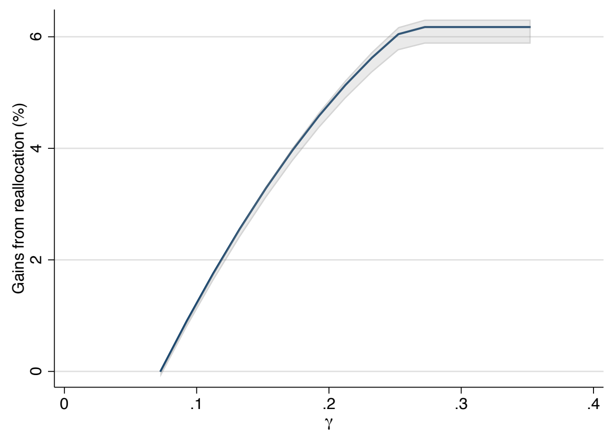
for a given value of γ. Therefore, when γ is small, we should have gains close to 0. Figure 7 shows the reallocation values expressed as percentages and for different values of γ and of the SCC. As the parameter γ increases, more of the existing solar capacity gets allocated to the most productive regions until all the existing capacity is placed in the region that is the most productive. At that point, increasing γ has no further effect since we are not adding extra solar capacity to the system, we are simply reallocating the existing capacity. We anchor the initial value of γ so that the gains are zero for our base value of the SCC. Interestingly, using larger values of the SCC increases the gains for medium to large values of γ but it results in negative gains for low values of γ, which are related to the portfolio mix of the TSOs that are assigned more solar capacity. Recall that the ranking for the reallocation is based on the average solar productivity, which might not coincide with the expected value of marginal benefits or levels of emissions at the margin (Table 3). Therefore, if we displace a large amount of conventional production in a low-emitting TSO, the overall gains are negative for low values of γ. On the other hand, as the rate of solar penetration increases, the gains are positive and larger in magnitude than in the baseline case with these higher values of the SCC.

To provide confidence intervals for our main estimates, for each value of γ we bootstrap 25 samples of the set of PV installations with replacement within each TSO and compute the gains from reallocation for each sample. In addition, to account for the uncertainty in demand, we regress load on its 1-hour lagged value and its 24-hours lagged value together with TSO, hour of the day, day of the week, month, and year dummy variables. We recover the residuals from this regression and calculate their standard deviations by TSO. At random, we add or subtract one standard deviation to the load before each one of the bootstrapped samples and compute the gains from reallocation. The bands around the main line in Figure 7 represent the 10th and the 90th percentiles of the bootstrapped samples. Consistent with the regressions above on average productivity, we see almost no uncertainty in the gains. This is mainly driven by the fact that most residential installations (in a given TSO) are rather homogeneous and produce similar output. For higher values of the SCC, the uncertainty bands are as narrow as in the baseline case because the variability in output and demand does not change.

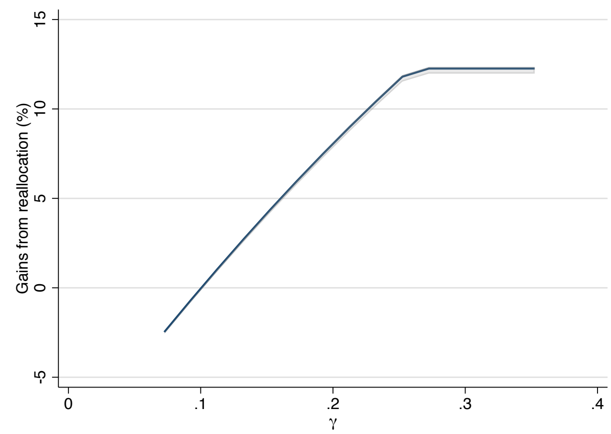
These results show that relatively low penetration rates of $\gamma = 20\%$ for reallocation represent between 4.5 and 5.2% of gains in value (avoided ancillary services + avoided production costs + avoided emissions) relative to the actual allocation using our baseline value of the SCC. These percentage changes may seem small. To put these changes in perspective, the increase in levels from the baseline to the reallocation configuration when $\gamma = 0.2$ is 79.7 million euros and 106.7 million euros when $\gamma = 0.3$. The first amount (79.7 million euros) is roughly equivalent to the production of 200,000 residential PV plants of average size valued

Figure 7: Value of Reallocation for Different Values of γ

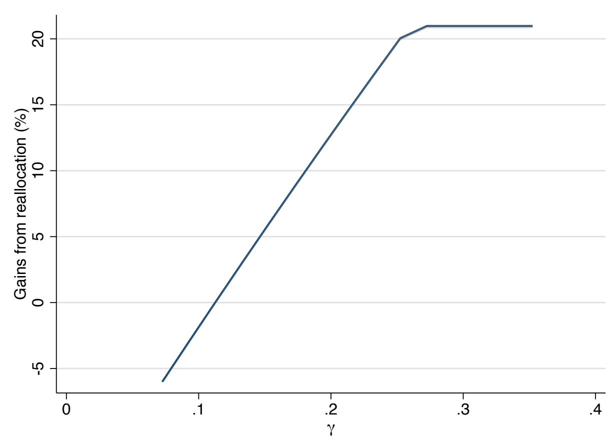
(a) SCC = 31.71 €/tCO_2



(b) SCC = 50 €/tCO_2



(c) SCC = 100 €/tCO_2



Notes: Each line represents the value of reallocated solar capacity as defined in Equation 1. For each value of γ we bootstrap 25 samples of the set of PV installations with replacement within each TSO and account for demand uncertainty (see main text for details) and then compute the gains from reallocation for each of the samples. The bands around the main line represent the 10th and 90th percentiles of gains from the bootstrapped samples.

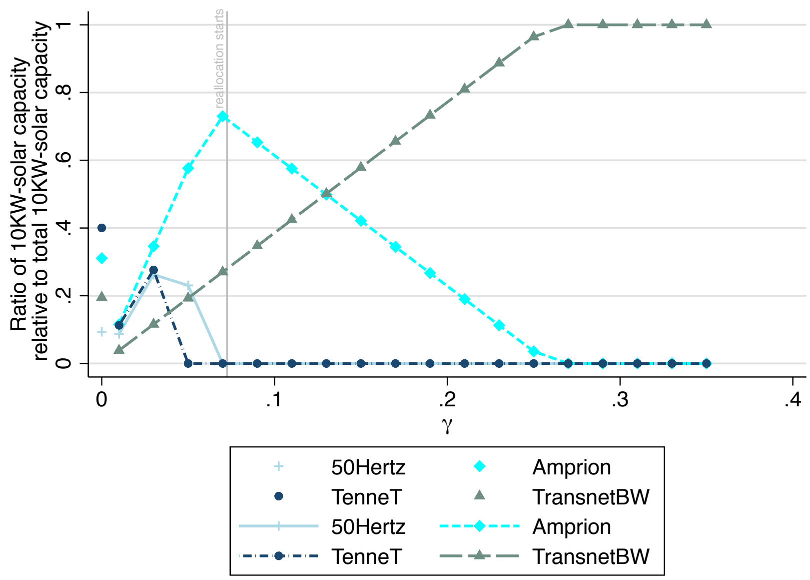
at an average wholesale electricity price of 30.30 €/MWh during our sample period, and to 267,000 PV plants of the same capacity when $\gamma = 0.3$.[22] In 2016, there were roughly 950,000 residential installations in Germany, therefore these values from misallocation represent approximately 21% and 28% of the market value of the production of all residential installations, respectively.

All these results use a relatively conservative measure of SCC. With a higher valuation of 50 €/tCO_2 as in the main specification in Abrell et al. [2019b], the gains from reallocation are about 7.5 and 12% when $\gamma = 0.2$ and 0.3, respectively. For a value of SCC of 100 €/tCO_2 as in the second specification in Abrell et al. [2019b], those gains are about 12 and 21% respectively and as shown in Figures 7b and 7c.

It is interesting also to see how the penetration rates change within each TSO as the reallocation parameter γ increases. As more capacity goes to TSOs with higher solar output productivity, some TSOs end up without any RES capacity at all. This is shown in Figure 8, which plots the ratio of the 10 kW-solar capacity with respect to total residential solar capacity in Germany for each TSO and at different values of γ. For sufficiently high values of the penetration rate γ, the TSO with the highest solar output productivity has a ratio of 1. The reason is that as the solar rate increases, more and more of the existing solar capacity gets reallocated to the most productive regions in detriment of the worst regions (total solar capacity is constant). When the rate γ is relatively high, it is possible to reallocate all the existing solar capacity into one single TSO, the one with the highest solar output productivity. The figure also depicts the actual allocation of solar at $\gamma = 0$. The vertical line indicates the minimum γ for which reallocation starts. If γ was below this threshold, only a small share of solar (smaller than the actual allocation) could be allocated to the TSO with the highest average productivity, TransnetBW, so more capacity would be installed in the second best TSO, Amprion and this would generate an inefficient allocation. Similarly, at very small values of γ there would be an unused amount of solar capacity even after reallocating capacity among the four TSOs, this would also generate an inefficient allocation.

[22]The average installation size for residential installation is 6.7 kW. Using the average annual production in Germany from Table 4 of 984 kWh / kW and the average wholesale electricity price, we find an annual production value of roughly 200 €per installation and year.

Figure 8: Ratio of Solar Capacity Relative to Total



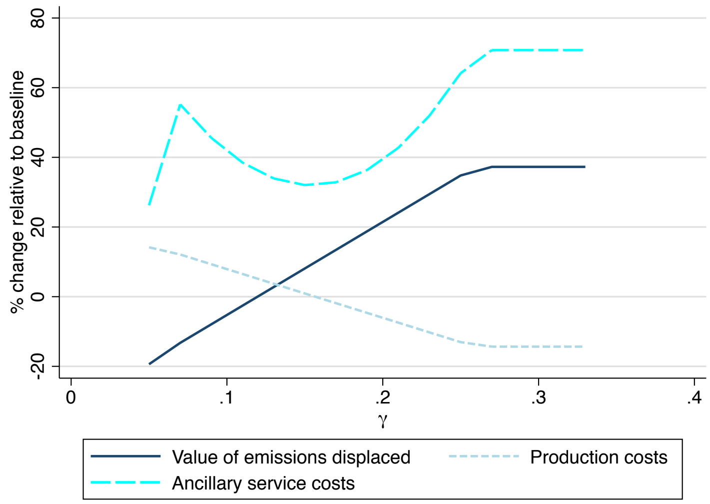
Notes: Increases in the solar rate γ allow for a higher reallocation of solar capacity in the best regions while lowering the reallocation amount to the worst regions. This occurs because total solar capacity remains constant. Markers at $\gamma = 0$ are the actual shares of 10kW-solar capacity before any reallocation.

While the total gains in Figure 7 are the net result of the combined changes in each of the three components of the marginal benefits, Figure 9 compares the percentage changes relative to their benchmark values of each of those components at each value of γ. Figure 10 shows the share of the contribution from each of the components (production costs, emissions, and ancillary services) to the total gains. For small values of solar penetration, the value of the emissions displaced shrinks relative to the baseline (negative sign) because some of the reallocated solar capacity no longer offsets high level emissions marginal plants in some TSOs. This is in line with the fact that larger values of the SCC lead to negative gains at low levels of γ in Figure 7. As the solar penetration increases, the size of this displacement is larger than the total value of offset emissions from the baseline even in low-emitting TSOs. This is consistent with the portfolio mix of technologies by TSO shown in Figure A.3 and with the frequencies of marginal technologies in Table A.5. The highest solar output productivity TSO, TransnetBW, is also the TSO with the largest share of nuclear power, which is a low-emitting source. At the same time, the other TSOs have large shares of high-emitting sources, therefore, a reallocation of solar capacity from those TSOs decreases the emissions until they are offset by the gains in the displacement in low-emitting TSOs, which depends as well on the relative frequencies of each technology being marginal.[23]

Production and ancillary services costs are higher than their baseline values when γ is low since the reallocation places more solar capacity in TSOs that do not necessarily have the highest marginal benefits. As γ increases we observe a diverging behavior. Production costs decrease because of the displacement of conventional production even beyond the level of production costs from the baseline. However, as γ increases, the ancillary services costs increase. This is because the ancillary costs as a function of solar output are increasing, therefore, as more capacity is installed in areas with higher solar output productivity, more solar output causes higher costs. This is a direct consequence of our estimates in subsection 4.2.

[23]The relatively high frequencies of hard coal being the marginal technology should not be confused with the fact that natural gas powered-plants have higher marginal costs. The frequencies shown in Table A.5 are obtained by solving for the perfectly competitive equilibrium in each time period and low levels of net load intersect some of the TSOs marginal cost curves at the hard coal production segments more often than at the natural gas plants. This has been documented by market analysts (see https://timera-energy.com/german-recession-power-prices-generation-margins/).

Figure 9: Changes in each Component Relative to Baseline

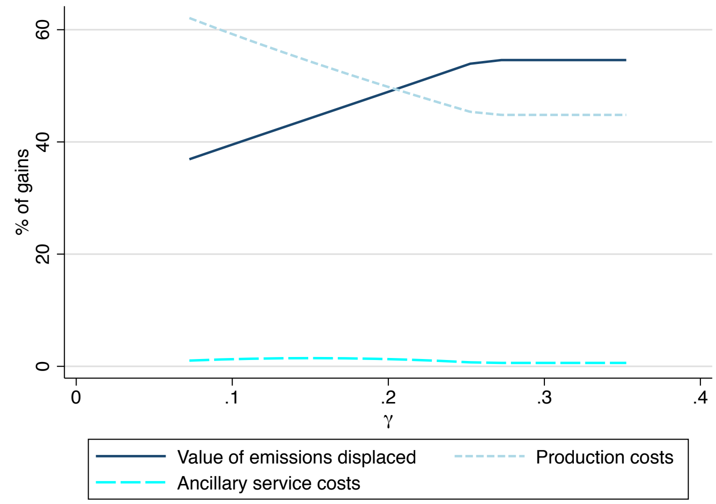


Notes: For each component we compute the difference of its value for a given value of γ and expressed as a percentage relative to the value of that component before any reallocation.

Figure 10 also highlights the trade-off a regulator (social planner) would face when reallocating solar capacity between evaluating the misallocation using a ranking of the TSOs by average solar productivity or a ranking based on expected marginal benefits. The former has for objective to limit production inefficiencies, while the latter is concerned with maximizing the expected marginal benefits (mainly social value in form of avoided emissions). If the regulator cares only about increasing the value of emissions displaced, the minimum value for γ should be approximately 0.13, with preferences for higher values of γ. On the other hand, at high values of γ the production costs are lower compared to the baseline. Note that our reallocation simulations allocate solar resources in line with average productivity (solar radiation), yet it calculates the gains in terms of expected marginal benefits in TSO j at time interval t. Hence, the reallocation gains take into account both of these elements.

Overall, consistent with Table 3, Figure 10 shows that the two main drivers of the benefits are the value of emissions displaced and the savings in production costs. Each of these components account for roughly 40 to 60% of total gains. The savings in ancillary services costs are much smaller.

Figure 10: Decomposition of Gains



Notes: At each value of γ, we compute the fraction of the value of each component relative to the total gains and express it as percentage.

5.2 The value of transmission

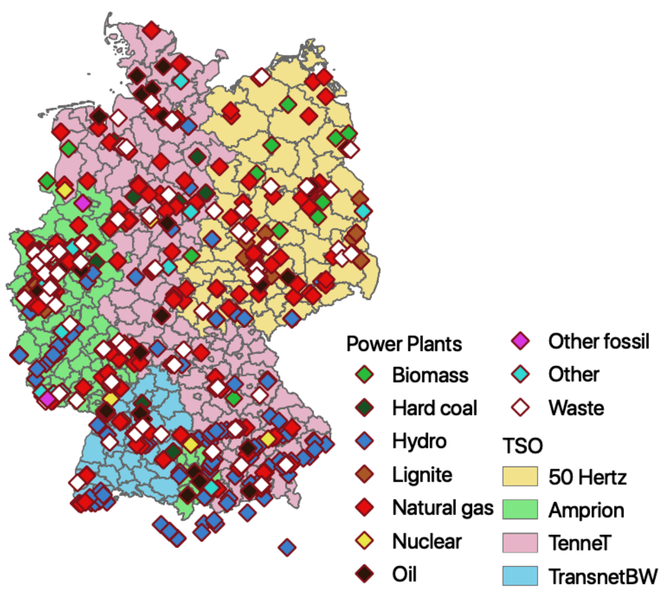
The increasing penetration of RES makes transmission lines more valuable and future investment in the transmission grid indispensable. This is especially true for large-scale wind and solar farms. Differences in the availability of RES energy paired with regional differences in expected energy demand growth led to the creation of the German Network Development Plan (*Netzentwicklungsplan, NEP*) in 2012.[24] Key projects discussed in the NEP are several high-voltage direct current lines between North and South Germany (see Appendix Figure A.5) with the objective to increase interchange capacity for electricity from RES production across regions. In particular, the NEP foresees different scenarios for increasing solar capacity investment in Southern Germany, as well as the development of wind farms in Northern Germany. While there are clear benefits from an increased interconnection of these regions, power line expansions have been largely criticized by the public based on their

[24]Several revisions to the original NEP have been made in recent years. We consider here the 2019 version, which focuses on the electricity market in 2030, NEP 2030.

cost and potential environmental and aesthetic impacts.[25] Total investment costs for these large-scale transmission lines are highly project-specific.

We contribute to this ongoing policy debate on the value of transmission, by focusing on a single TSO, TenneT, that stretches from North to South Germany. In a counterfactual analysis, we split TenneT into two independent entities, and repeat the calculation of the marginal benefits from solar in each of these areas. In a second step, we perform a reallocation focusing on all solar capacity in Germany and allowing for different degrees of transmission capacity between the two areas to determine the value of transmission.[26] In a final step, we compare the additional benefits from the interconnection to the total investment cost for different cost scenarios.

Figure 11: TSO Service Areas and Conventional Power Plants



Notes: Each symbol represents a conventional power plant. Markers outside the Germany boundaries correspond to hydro power plants under control of one of the TSOs. Data obtained from Open Power System Data.

[25]Two key projects are "Suedlink" and "SuedOstlink", both planned as direct current large-scale regional interconnections from North to South Germany with an approximate length of 700 km and 530 km, respectively. The projects encountered stark opposition by citizens' groups, which led to a re-evaluation of the power lines and the decision to implement them as underground cables. The total cost for these projects are estimated to be 10 billion euros (Suedlink) and approximately 5 billion euros for SuedOstlink.

[26]We focus on 'all' solar capacity rather than purely residential installations in this subsection to highlight the role of the transmission constraint.

We split TenneT based on administrative boundaries in a North and South region.[27] We start our analysis by constructing the expected marginal benefits for solar in the two regions. As load and electricity production data is only available at the TSO level, we construct demand and supply in the two subregions as follows.[28] Using the exact geo-location for each plant in TenneT we assign them to the North or South region and assume that their output is predominantly used in that region (see Figure 11 for conventional power plants).

To determine the average capacity utilization of conventional power plants, we use data from the US electricity market (Energy Information Agency) and assign these values to the installed capacity in North and South TenneT. Using data that are external to the German market, helps us to overcome potential endogeneity issues that would stem from using average observed technology shares for the German market. We combine these data with detailed information on plant unavailability for different generation units in TenneT. These data are available from ENTSO-E at high frequency for 'important' changes in capacity (changes of 100 MW or more in actual availability) for all technologies. We then can construct hourly supply curves for conventional power plants i using the following formula: avg. capacity factor$_a \times \sum_i$(capacity installed$_i$ $-$ capacity unavailable$_i$), by type of technology a. For solar production, which is always inframarginal, we observe the total solar output of all plants in Bavaria at high levels of disaggregation (15-minute) from TenneT. In the construction of the supply curves, we rely on the same marginal cost ordering that we used in section 4.

Regarding demand, we use data on the population shares to split total load in TenneT in the two regions. With the aggregate hourly supply and demand curves for each region, we can find their intersection to obtain the marginal technology similarly to our analysis in the previous section. We denote their marginal costs λ_N for the North and λ_S for the South regions, respectively. We provide additional statistics on the marginal cost estimates for the two regions in TenneT in section A.1 that show that the split leads to values that are

[27]To split the TSO, we ovelap the TSO area with state boundaries and use the state of Bavaria to define the South region within TenneT. Bavaria represents roughly half (46%) of the gross domestic product and about 41% of total population in TenneT.

[28]ENTSO-E provides high-frequency data at the plant level for conventional power plants. However, in the case of Germany, these data are available only for large plants with an installed capacity of $\geq$ 100 MW.

comparable with those in the previous section.

Before elaborating on the impact of the transmission constraint, we need to find the updated ranking of the average solar productivity now that there is a total of five TSOs. We follow the same methodology than in the case before the split and find the correlations of productivity and the location of the PV sites. Table 5 shows the results. Similarly to the analysis in the previous section, we use the ranking implied by the coefficients of the indicator variables for the location of the panels in their corresponding TSO. For consistency with the results from the previous section, we use the ranking from the specification that includes all the observed characteristics, column (3). We find that the South region within TenneT is the second most productive region for PV sites while TenneT-North remains in the last place. Note that the ranking is robust across all specifications except for small differences between Amprion and 50Hertz.

To determine the implied transmission capacities, we follow Joskow and Tirole [2005] and LaRiviere and Lu [2017] and estimate the following regressions (see section A.2 for further details),

$$\begin{aligned} E[\lambda_N] &= a_N + b_N(R_N - Q_N) + c_N Q_S + FEs \\ E[\lambda_S] &= a_S + b_S(R_S - Q_S) + c_S Q_N + FEs \end{aligned}$$

only using time intervals for which the transmission constraint is binding: $\lambda_N \neq \lambda_S$. FEs represent year-month-hour and day fixed-effects. By using only the hours for which the λs are different in each region we guarantee that the transmission constraint is binding. Therefore, any increases in load in N should not affect the scheduling of sources in S and viceversa. This exogenous covariate serves as a valid supply shifter in the estimation of an otherwise endogenous regression. The expressions above are supply functions since as K (the size of the capacity constraint) increases, exports increase and more expensive technologies need to be used: higher λ_S.[29]

Based on the results in section A.2 in the Appendix, we find that

$$\text{capacity imbalance}_t = \Delta K_t = \frac{\Delta z_t}{b_N - b_S}, \tag{2}$$

[29]Notice that even though LaRiviere and Lu [2017] write *price*, they are using marginal costs.

Table 5: Ranking of TSOs by Output per Unit of Capacity Installed When TenneT is Split

	(1)	(2)	(3)
TransnetBW	907.477***	987.803***	1035.926***
	(31.778)	(35.904)	(38.583)
TenneT - South	844.045***	927.582***	981.457***
	(33.269)	(36.912)	(39.836)
Amprion	819.011***	927.587***	969.952***
	(22.144)	(30.405)	(33.064)
50 Hertz	820.374***	912.519***	964.834***
	(33.724)	(37.164)	(41.400)
TenneT - North	782.975***	873.537***	951.631***
	(27.373)	(32.476)	(38.600)
Controls:			
Year	✓	✓	✓
Panel orientation		✓	✓
Panel shading		✓	✓
Inverter size		✓	✓
Panel tilt			✓
N	485	485	464
R^2	0.920	0.928	0.930

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: output in kWh per kW of capacity installed. Control variables are included as categorial variables. The reference (omitted) category in column 2 are South facing plants with no shading and a large inverter size ($>$ 7000 Watts). Column 3 additionally conditions on tilt (15-40 degrees as omitted category). For each column, the magnitude of the coefficients define the ranking in solar productivity. More details in the main text.

Table 6: Estimates of Shadow Costs of Transmission

	(1)	(2)	(3)	(4)	(5)	(6)
	Gap = 2 €/ MWh		Gap = 5 €/ MWh		Gap = 8 €/ MWh	
	λ_N	λ_S	λ_N	λ_S	λ_N	λ_S
$R_N - Q_N$	−0.000737		−0.000761		−0.000434	
	(0.000481)		(0.000491)		(0.000505)	
Q_S	−0.00110		−0.00126		−0.00152	
	(0.00117)		(0.00118)		(0.00124)	
$R_S - Q_S$		−0.00769***		−0.00783***		−0.00791***
		(0.000616)		(0.000632)		(0.000687)
Q_N		0.00260**		0.00274**		0.00340**
		(0.000984)		(0.000996)		(0.00104)
N	4,282	4,282	4,190	4,190	3,867	3,867
R^2	0.779	0.709	0.787	0.711	0.815	0.732

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

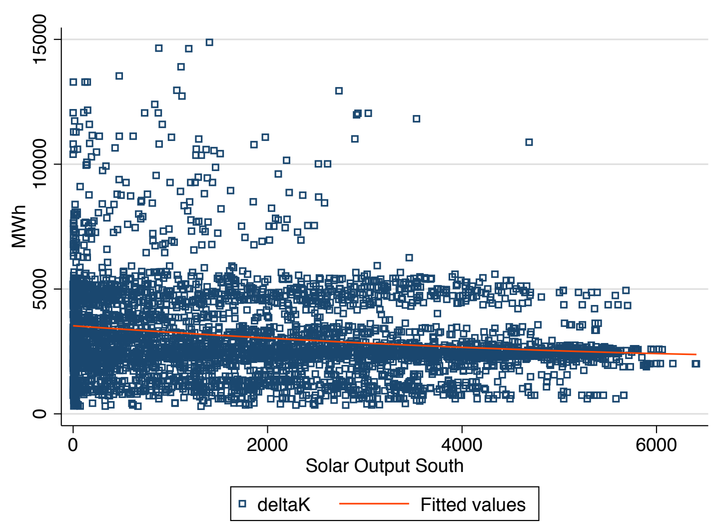
Notes: Dependent variable: as indicated on top of each column. Columns (1) and (2) correspond to a gap of 2 €/ MWh, columns (3) and (4) to a gap of 5 €/ MWh, last two columns to a gap of 8 €/ MWh. Standard errors clustered at the date level.

which is in units of MWh and where $z_t \equiv \lambda_{N,t} - \lambda_{S,t}$ and $\Delta z_t = z_t - z_{t-1}$. Let $\overline{\Delta K}$ be the mean of the distribution of ΔK_t. Then, the imputed marginal cost in region N can be written as

$$\lambda_{N,t} = \lambda_{S,t} + z_{t-1} + (b_N - b_S)\overline{\Delta K}. \tag{3}$$

Figure 12 shows the implied transmission capacities for each of our feasible data points as a function of the solar output in the South region using Equation 2. The mean of these values is 3,089 MWh, which is roughly equivalent to twice the capacity of the TenneT transmission line to Norway or about four times the capacity of a new projected interconnection to the Netherlands.[30] Similarly, the SuedOstlink project between TenneT and 50 Hertz is designed for a capacity of 2 GW with possibility of an expansion to 4 GW.[31] Those projects indicate that our estimates are well within reasonable values in the industry for this market.

Figure 12: Implied Transmission Capacities



Notes: Each square represents one of the values obtained using Equation 2. The overall mean is 3,089 MWh.

With Equation 3 in hand, we can re-do the reallocation simulation for different values of the transmission capacity that replace the value of $\overline{\Delta K}$ in that same equation. For low values

[30] https://www.tennet.eu/our-grid/international-connections/nordlink/

[31] https://www.50hertz.com/en/Grid/Griddevelopement/Onshoreprojects/SuedOstLink.

of this capacity, the marginal cost differential z_t is similar in value to the marginal cost in the previous period. Therefore, we expect that for capacities close to 0, the misallocation of RES will remain similar to the case of no increase in transmission capacity.

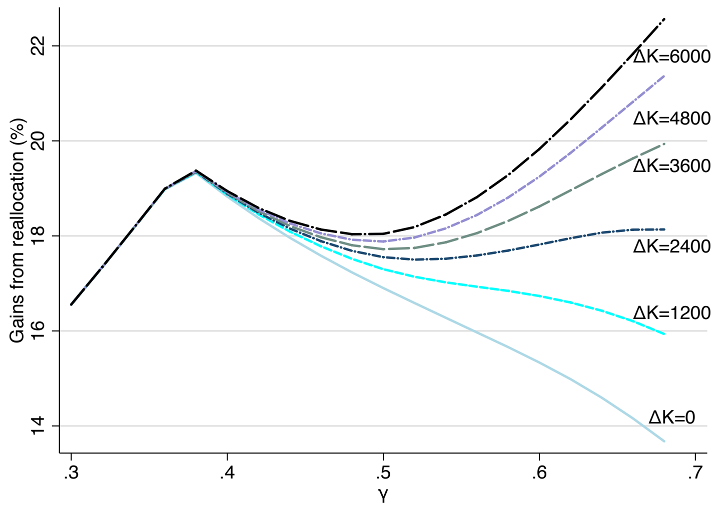
If production in the South is above the load in that region, the excess amount is then exported to the North whenever this amount is less or equal than the size of the added transmission capacity. This quantity is valued at the corresponding marginal benefit in the North at that given point in time. In the absence of the new transmission capacity, the surpluses in the South would be valued at 0. Since this transmission line could carry electricity from any source, and is particularly relevant for large RES plants, we use the total amount of solar capacity installed in Germany in 2016 to conduct our reallocation counterfactuals instead of only the 10-kW solar capacity as before. In addition, given that most observations fall within a range of 6,000 MWh in Figure 12 and the projected line capacities in the NEP, we limit the amount of additional transmission capacity to be no more than 6,000 MW.

Figure 13 shows the gains from reallocating solar as a function of γ for different values of the capacity constraint ΔK. We find that the gains from reallocating solar capacity are larger than without this additional transmission capacity.[32] For relatively low levels of γ the gains are increasing as in the case without transmission, i.e. when allocating more solar in the most productive areas total gains increase as long as the capacity constraint in the TSO is not binding (solar production$_j \leq$ load$_j$). Once solar output is placed in high-productivity regions, particularly in South TenneT, the excess can be exported to the North region in case there is sufficient transmission capacity available. If there is no additional capacity in transmission (the line $\Delta K = 0$), the surplus in solar output from the South cannot displace further conventional plants and the gains decrease because the reallocation takes solar capacity from other regions that could have utilized it. As ΔK increases, the gains exhibit a U-shaped curve. The decreasing part occurs because of the same reasons that explain the curvature of the $\Delta K = 0$ case. The increasing gains however, reflect the fact that the excess of solar production in the South valued at its corresponding marginal benefits

[32]Note that the minimum γ is set at 0.30, which is the maximum of the current total solar capacity in TSO_j divided by total capacity in that TSO. We allow γ to increase up to 0.70, i.e. up to 70% of each TSO's capacity can be solar capacity.

value in the North more than offsets the losses in benefits in the regions where solar capacity has been decreased.

Figure 13: Gains from Expanding Transmission Capacity



Notes: Each curve depicts the gains from reallocation at if the transmission capacity between regions North and South is expanded by the amount indicated to the right of the graph. We show the complete distribution of gains for different values of ΔK in Appendix Figure A.6.

We now turn to a back-of-the-envelope calculation to compare the costs and benefits of a new transmission line using our misallocation estimates. We report different scenarios in Table 7. In line with the above findings, the table shows that additional gains from reallocation for relatively low levels of γ are small. As γ increases, the interconnection capacity becomes more valuable. The additional benefits from a capacity expansion of $\Delta K = 2,000$ MW and with a solar installation rate of $\gamma = 0.66$ are 173 million euros relative to the case where there was no interconnection between the regions but at the same installation rate. We do not take into account the installation costs of the PV plants that would need to be subtracted from those gains. The main reason is that we do not have information on how many years are left in the lifespan of each panel. As a consequence, the benefits-costs ratios below will be biased upwards.

We compare those gains to the tentative investment cost of the underground transmission lines that are currently under construction in Germany (SuedOstlink) with that same capacity

(2,000 MW) and a total length of 530 km. This cost is estimated to be approximately 4.5 billion euros[33], which has an annualized value of 135 million euros when using a lifetime of 40 years[34] and an annual discount rate of 1% as in Davis and Hausman [2016]. The benefit-cost ratios are barely greater than one (1.275), which shows that the investment is not overwhelmingly beneficial even at large values of γ. On the other hand, if there was a larger capacity interconnection available ($\Delta K = 6,000$), this ratio increases to approximately 1.6.[35] Not surprisingly, the project would lead to larger benefits if traditional overhead lines were used that are considered to be 10 to 15 times cheaper as underground cables.[36] The benefit-cost analysis shows that additional transmission can be beneficial if there is sufficient RES capacity reallocated across regions. This is especially important if we were to consider different types of RES technologies that are more abundant in different regions, as it is the case for wind and solar in the North and South of Germany.

6 Conclusion

We develop a comprehensive framework to measure misallocation of RES. This is inspired by the existing rigidity of incentives used to accelerate the adoption of RES. In this paper we concentrated on the uniform nature of feed-in-tariffs. Our framework consists of three steps: measuring the marginal benefits from an additional unit of output from RES, using those valuations to measure the potential gains had an efficient allocation of solar PV installations existed, and accounting for further gains if expansions in transmission capacities are built.

We apply our framework to the case of Germany and we find evidence of heterogeneous marginal benefits from increasing renewable capacities even when using a conservative value

[33]TenneT estimates the total costs between 4 to 5 billion euros. See Sueddeutsche Zeitung, 4 October 2016; last accessed 24 April 2020.

[34]See industry reports, for instance Xcel Energy Information Sheet on Overhead vs. Underground high-voltage transmission lines; last accessed 24 April 2020.

[35]We assume that the three-fold capacity expansion would result in an approximately 77% increase in total costs, reaching a total investment volume of 8 billion euros, as many of the original investment costs are fixed and would not need to be scaled up by the same factor. The upper bound for the total cost of the line would be 3×4.5bn euros = 13.5bn euros.

[36]See Xcel Energy. We assume a cost factor of 1/15 for overhead lines as the delays in planning coupled with regional protests and lawsuits likely led to an increase in total investment cost.

Table 7: Benefit-Cost Analysis for Power Line Investment

	(1)	(2)	(3)	(4)	(5)	(6)
ΔK (MW)		2,000			6,000	
γ	0.37	0.50	0.66	0.37	0.50	0.66
Annual gains from reallocation [m€]	0.630	29.650	173.075	1.500	58.590	394.070
Annualized investment costs 40 years, 1% annual discount						
Overhead lines [m€]	9.046	9.046	9.046	16.082	16.082	16.082
Underground lines [m€]	135.693	135.693	135.693	241.232	241.232	241.232
Benefit-cost ratio						
Overhead lines	0.070	3.278	19.132	0.093	3.643	24.504
Underground lines	0.005	0.219	1.275	0.006	0.243	1.634

Notes: Change in gains from reallocation for given γ comparing case of no interconnection ($\Delta K = 0$) with interconnection scenarios of 2,000 and 6,000 MW, respectively. Annualized investment costs for underground lines based on SuedOstLink project, with estimated total costs of 5 billion euros (TenneT). We assume a total cost of 8 billion euros for the 6,000 MW interconnection. For overhead lines we assume that total investment cost represents approximately 1/15th of the underground cables. For both type of high-voltage lines we consider furthermore a 40 year lifespan and a 1% annual discount rate.

of the social cost of carbon. We find non-negligible gains relative to the current allocation of solar panels if they had been allocated according to a ranking of the regions by their solar productivity. In addition, if a new tranmission line were built between the North and the South regions, this would increase the gains from reallocating solar PV plants for high levels of solar penetration.

As any economics analysis, ours does not go without caveats. We focused on solar installations but a more comprehensive study would include wind installations as well. In the best case scenario, there is no misallocation of wind plants in Germany and the total gains from misallocation would be only caused by misalignments in incentives for solar plants. Therefore, we can see our results as a lower bound on the gains from potential misallocation. Another avenue for future research is to include transmission constraints across the different regions to be able to value surpluses if they exist. Once again, our results can be seen as a lower bound for the true gains since we are implicitly valuing excess solar production, if any, at a marginal benefit of zero. In either of those two cases our framework can be easily extended if more data were available.

The efficiency of the allocation of resources is a core paradigm in economics. Our paper quantifies this efficiency and puts in perspective the costs of simple economics incentives for technology adoption.

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Appendix

A.1 Details on Data and Simulation Procedure

A.1.1 Simulated frequencies of marginal technologies

To obtain the simulated frequencies presented in Table 1, we rely on fuel price data to establish a ranking of the different technologies. While there is a world market price for hard coal, crude oil, and natural gas, lignite is usually not a traded commodity. Rather, lignite production is part of an integrated supply chain of electricity companies, such as RWE and Uniper in the case of Germany. To obtain cost estimates for lignite (fuel costs and emission factors), we rely on a background report published by the German Environmental Ministry in 2017. The simulated merit-order supply curve therefore has the following order, listed from cheapest to most expensive source: 1) renewables (wind offshore and onshore, solar, hydro (reservoir, run of river, pumped storage), geothermal, biomass, waste, and other renewables), 2) nuclear, 3) lignite, 4) hard coal, 5) gas, and 6) oil. In the case of 50 Hertz we furthermore make the assumption that oil in this TSO is always infra-marginal, as electricity production from 'oil' is linked to oil refinery (IKS Schwedt) that produces electricity as a by-product in its main production process. In line with this information, the electrictiy production profile for this plant shows no variation over time.

In our analysis, we do abstract from CO_2 prices from the European Union Emission Trading Scheme (EU-ETS). While electricity production in Europe is subject to the EU-ETS, CO_2 prices during the time of our analysis (2015-16) have been at an all-time low. This was likely due to oversupply of emission certificates. In 2015, the average price per tCO_2 was less than 10 €. In 2016, the price decreased further to approximately 5 €/ tCO_2. Given the price differentials in marginal costs in electricity production (fuel input prices), the low CO_2 prices should not have lead to changes in the aggregate merit-order cost curve (see for instance the industry analysis "What is the minimum CO2-price in order to affect the merit-order?"). We therefore refrain from modeling CO_2 prices.

A.1.2 Reallocating RES

For the reallocation exercise in subsection 5.1, we take as given total residential solar capacity on the last day of our sample (31 December 2016). Similarly, we obtain data for total installed capacity (all generating units) per TSO. In a next step, we use the individual solar PV production data, obtained from PVOutput, and multiply them with daily weights that are TSO specific, in order for the PVOutput data to be representative for the total TSO production of all 10-kW plants.

We calculate the baseline value (marginal costs + marginal emissions + change in ancillary service costs) of actual solar PV production using these data. In a next step, we use the algorithm described in the main text to reallocate solar capacity in line with total allowed capacity shares (γ). Table Table A.1 shows the proposed reallocation of solar capacity for the example of $\gamma = 0.1$. With these values, the maximum share of solar that can be allocated to TransnetBW, the TSO with the highest solar productivity, is 2,210 MW ($0.1 \times$ 22,096 MW). This means that the total remaining solar capacity for redistribution to the other TSOs is 3,518 MW. As Amprion has a large total capacity, it can absorb all the remaining residential solar capacity. In this example 50 Hertz and TenneT remain without solar capacity after the reallocation.

Table A.1: Solar Reallocation with $\gamma = 0.1$

TSO Ranking	TSO Name	Total TSO capacity [MW]	Total installed res. solar [MW]	Reallocated solar capacity [MW]
1	TransnetBW	22,096	1,118	2,210
2	Amprion	66,049	1,780	3,518
3	50 Hertz	22,096	537	0
4	TenneT	64,577	2,294	0

Notes: Total residential solar capacity in Germany 5,728 MW as of December 2016. We assume $\gamma = 0.1$ and reallocate solar according to the TSO ranking of average productivity. Total TSO capacity [MW] refers to total installed capacity (all technologies) in 2016 and total installed residential solar to all small scale solar in a given TSO.

We calculate the gains from solar PV reallocation for each iteration of γ, adjusting the impact that solar has on ancillary service costs at each iteration. We take the marginal benefits from avoided emissions and avoided operating costs constant within each 15-min interval. We believe this is a reasonable assumption as we focus on small scale solar capacity that represents only a small fraction of total demand in each TSO.

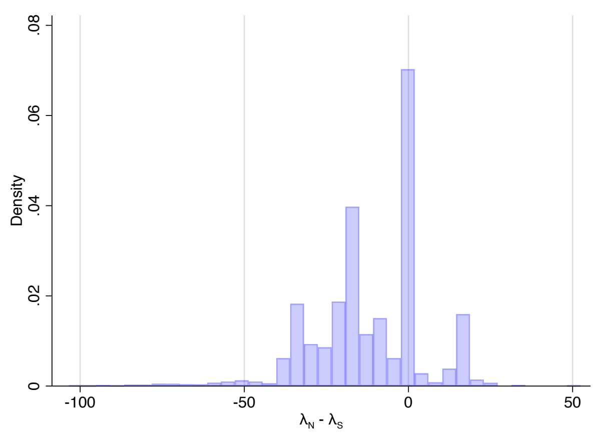
To obtain standard errors for our main results in Figure 7, we bootstrap individual solar PV stations with a fixed number of observations (drawn with replacement). This takes into account the variability of solar production within the TSO. In addition, in each bootstrap iteration we add and subtract one standard deviation to the load, which is calculated using the residuals from projecting load on lagged values and fixed effects to account for uncertainty in demand.

A.1.3 The value of transmission

We construct simulated supply curves for both North and South TenneT following the approach described in subsection 5.2, using the following capacity factors for conventional power plants obtained from the EIA: geothermal: 0.72; hydro: 0.37; nuclear: 0.92; biomass & waste: 0.63; hard coal & lignite: 0.53; natural gas: 0.55; oil: 0.13; and other fuels: 0.5. For wind (offshore and onshore) as well as solar, we can rely on observed production data as these technologies are always inframarginal. In a next step, we obtain high frequency data on plant outages and planned shutdowns for maintenance from ENTSO-E and combine these data with total installed capacity. We take total installed capacity of conventional power plants by TSO at the beginning of 2015. This modeling choice is especially relevant for the production capacities in Bavaria, where a large nuclear plant has been shut down during 2015 and has been replaced by increasing imports through the Austria and Czech interconnections. As we do not model imports/exports to neighboring countries, this assumption guarantees that there is sufficient installed capacity in Bavaria to meet demand. We furthermore obtain detailed (15-min) data on total solar PV production in Bavaria, available from TenneT, which allow us to have realized solar production data for both the North and South regions.

Based on these data, we construct an aggregate supply curve by TSO that we intersect with aggregate load. We split load for North and South TenneT based on its population share. These data allow us to construct the marginal costs (λ_N and λ_S) as well as marginal emissions, for both regions. We report here how the newly calculated λ's compare to the main section (Table 3). As North TenneT has more production capacities, we find that the median cost is lower (17.38 €/MWh) compared to the South region (24.24 €/MWh). Nevertheless, the two values are highly comparable to the other TSOs. We plot the differences between λ_N and λ_S in Figure A.1. Note that there is a large amount of observations for which the absolute value of this gap is greater than zero, the exact number of those observations at different levels of the gap are as described in Table 6 in subsection 5.2.

Figure A.1: Differences in Marginal Costs of Electricity Production: North vs. South TenneT



Notes: Differences of λ_N and λ_S based on simulated supply and demand in the two regions.

Finally, with these data at hand, we can simulate the reallocation for different values of γ and the transmission constraint ΔK. As the reallocation is based on the entire solar capacity, we rely on aggregate TSO $\times$ 15-minute data, with a total of five TSOs. We use the simulated data on marginal costs and marginal emissions for North and South, as well as observed solar production in the two entities to calculate the baseline value (assuming all TSOs are independent). As before, we recalculate changes in the impact on ancillary service costs, but assume constant gains from marginal costs and marginal emissions. We evaluate solar production in each TSO at its marginal benefit as long as total solar production is smaller or equal to total load. If there is excess production in one region, but no possibility to export, we cap the gains at the load level. Note that this assumption is not as restrictive as it looks at first sight given current levels of grid congestion in Germany. When there is excess production at South, we allow this region to export energy to the North region, in line with the transmission capacity ΔK. This energy surplus is valued at the simulated λ_N, which is computed following Equation 3.

A.2 Model of Transmission Capacity

This section closely follows Joskow and Tirole [2005] and LaRiviere and Lu [2017]. To ease the exposition, we suppress the time index. Assume region S is a net exporter to region N and it exports a quantity Q. Also assume that the marginal costs in each region (λ_N and λ_S) are linear functions of the residual load $R_j - Q_j$ and Q,

$$\lambda_N = a_N + b_N(R_N - Q_N) + b_N Q$$

and

$$\lambda_S = a_S + b_S(R_S - Q_S) + b_S Q.$$

Note that the coefficient on Q is the same as that of the residual load, this is because the quantity traded does not change the slope of the supply or the demand for exports, it simply shifts the curves in a parallel manner to the left or to the right. This is also useful because we do not observe quantities traded between region N and S.

In the absence of transmission contraints, $\lambda_N = \lambda_S$ because any arbitrage opportunity can be mitigated by buying or selling electricity from or to the other region. If there is a binding transmission constraint of size K we can evaluate the two expressions above at that transmission level and write the price gap as

$$\lambda_N - \lambda_S = a_N - a_S + b_N(R_N - Q_N) - b_S(R_S - Q_S) + (b_N - b_S)K.$$

Now we add the time index, let $z_t \equiv \lambda_{N,t} - \lambda_{S,t}$ and $\Delta z_t \equiv z_t - z_{t-1}$. Then, the change of the price gap with respect to the capacity of the transmission line is

$$\frac{\partial z_t}{\partial K} = b_N - b_S$$

and an interpretation of such derivative is that

$$\Delta K_t = \frac{\Delta z_t}{b_N - b_S},$$

from which we can infer the size of the capacity constraint given a change in the marginal cost difference between the two regions and the slopes of demand and supply of net exports. This process gives a distribution of the increments in the transmission capacity at each t for which z_t is above a pre-determined threshold.

Observe that $\Delta K_t = 0$ if either $z_t = z_{t-1} > 0$ or if $z_t = z_{t-1} = 0$. Therefore, by using the expression for ΔK_t it is not possible to distinguish whether a value of 0 for the transmission capacity is due to observing the same price gap in two consecutive periods or because the price gap was indeed zero in two consecutive periods. This calls for using an aggregation of the different values of ΔK_t, let $\overline{\Delta K}$ be the mean of that distribution. Then, the imputed marginal cost in region N can be written as

$$\lambda_{N,t} = \lambda_{S,t} + z_{t-1} + (b_N - b_S)\overline{\Delta K}.$$

To estimate the parameters b_N and b_S we need exogenous variation and fixed-effects that solve the natural endogeneity problem between residual demand $(R_j - Q_j)$ and the marginal costs (λ_j). To that end we use the load in region k to estimate the slope in region j since once the transmission constraint is being used at full capacity, any additional load in k has no effect on the production costs in region j. Note that since we do not observe the quantities traded, we omit the terms $b_N Q$ and $b_S Q$ from the estimation equations. This discussion motivates the following equations that we estimate in the main text,

$$\begin{aligned} E[\lambda_N] &= a_N + b_N(R_N - Q_N) + c_N Q_S + FEs \\ E[\lambda_S] &= a_S + b_S(R_S - Q_S) + c_S Q_N + FEs. \end{aligned}$$

A.3 Additional Tables and Figures

Table A.2: Ancillary Costs on Solar and Load by Cluster of Load Profile

	(1) cluster 1	(2) cluster 2	(3) cluster 3
solar	-4.153***	6.756***	0.553
	(0.946)	(0.967)	(0.708)
solar^2	0.000564***	0.000187	0.000678***
	(0.000124)	(0.000174)	(0.000125)
solar^3	1.06e-08	-6.33e-08***	-1.54e-08*
	(1.12e-08)	(1.08e-08)	(6.54e-09)
load	-0.259	0.782	-0.930*
	(0.974)	(0.930)	(0.449)
load^2	0.000106	0.000110	0.000177***
	(0.0000647)	(0.0000736)	(0.0000385)
load^3	-2.11e-09	-5.08e-09**	-4.05e-09***
	(1.24e-09)	(1.84e-09)	(9.01e-10)
solar $\times$ load	0.000186	-0.00120***	-0.000331***
	(0.000126)	(0.000127)	(0.0000726)
solar $\times$ load^2	1.81e-09	3.77e-08***	1.10e-08***
	(3.67e-09)	(4.78e-09)	(2.34e-09)
solar$^2 \times$ load	-3.94e-08***	4.84e-08***	-2.12e-08***
	(6.07e-09)	(9.78e-09)	(5.55e-09)
FE	✓	✓	✓
N	58,555	43,008	47,218
R^2	0.0750	0.0651	0.0653

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: ancillary costs. Each column corresponds to one of the clusters and each regression includes two-way fixed effects of TSO, hour of the day, day of the week, month, and year. In all regressions we use only time observations for which the solar output is positive.

Table A.3: Ancillary Costs on Solar and Load by Pooling All Observations

	(1)	(2)
solar	0.0166	-1.423***
	(0.155)	(0.391)
solar^2	0.0000492***	0.000613***
	(0.0000138)	(0.0000690)
load	0.354**	0.537*
	(0.110)	(0.241)
load^2	0.00000909**	3.76e-08
	(0.00000303)	(0.0000166)
solar $\times$ load	-0.0000315***	-0.0000803*
	(0.00000801)	(0.0000406)
solar^3		-2.03e-08***
		(4.78e-09)
load^3		6.13e-11
		(3.54e-10)
solar $\times$ load^2		4.25e-09***
		(1.16e-09)
solar $^2\times$ load		-1.67e-08***
		(2.84e-09)
FE	✓	✓
N	148,781	148,781
R^2	0.0463	0.0468

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Using observations for which there is positive solar production.

Table A.4: Effect of Solar Output on Ancillary Services Pooling All Observations

	$\partial AS/\partial R$	
TSO	quadratic	cubic
50Hertz	-0.14	-0.60
Amprion	-0.51	-0.56
TenneT	-0.30	-0.61
TransnetBW	-0.11	0.82

Notes: Each number is the value of $\partial AS/\partial R$, in €/ MWh, obtained using the coefficients in Table A.3 and evaluated at the mean solar output and the mean load.

Table A.5: Simulated Frequencies of Marginal Technologies (by TSO)

TSO: 50 Hertz

Source	Freq.	Percent
Natural Gas	69,954	99.68
Hard Coal	152	0.22
Hydro: River	46	0.07
Hydro: Pumped storage	24	0.03

TSO: Amprion

Source	Freq.	Percent
Natural Gas	68,868	98.14
Hard Coal	1,308	1.86

TSO: TenneT

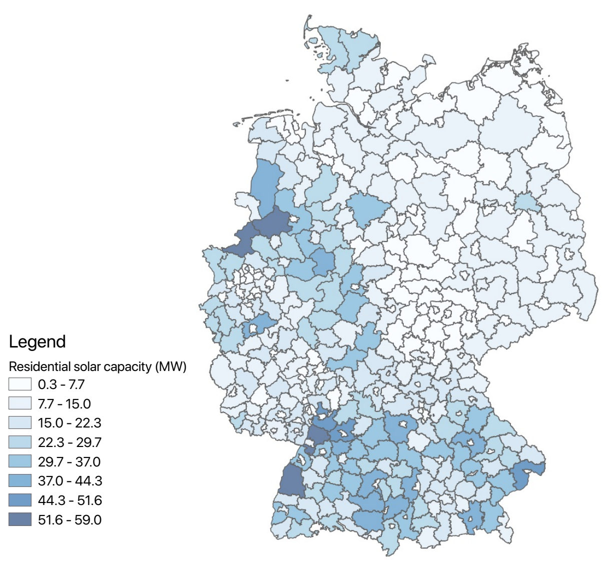
Source	Freq.	Percent
Hard Coal	41,330	58.89
Natural Gas	27,157	38.70
Oil	1,030	1.47
Brown Coal / Lignite	655	0.93
Biomass	4	0.01

TSO: TransnetBW

Source	Freq.	Percent
Hard Coal	57,975	82.61
Natural gas	6,522	9.29
Nuclear	3,522	5.02
Oil	2,157	3.07

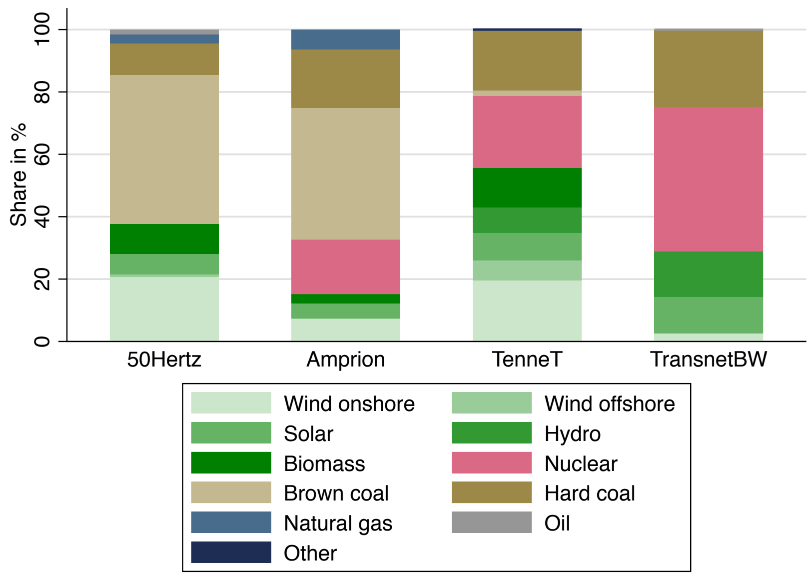
Notes: For each 15-minute interval we compute the marginal cost of each of the technologies shown in the tables and sort them from lowest to highest marginal cost to obtain the system's marginal cost curve. Notice that the marginal cost for fossil fuels can change over time as we use fuel prices to construct this curve. Finally, we select the technology that corresponds to the point in the marginal cost curve that intersects the net load in that time interval. TenneT and TransnetBW display large frequencies for hard coal being the marginal technology. This has been observed also by market analysts (see https://timera-energy.com/german-recession-power-prices-generation-margins/).

Figure A.2: Installed Solar Capacity (< 10 kW installations)



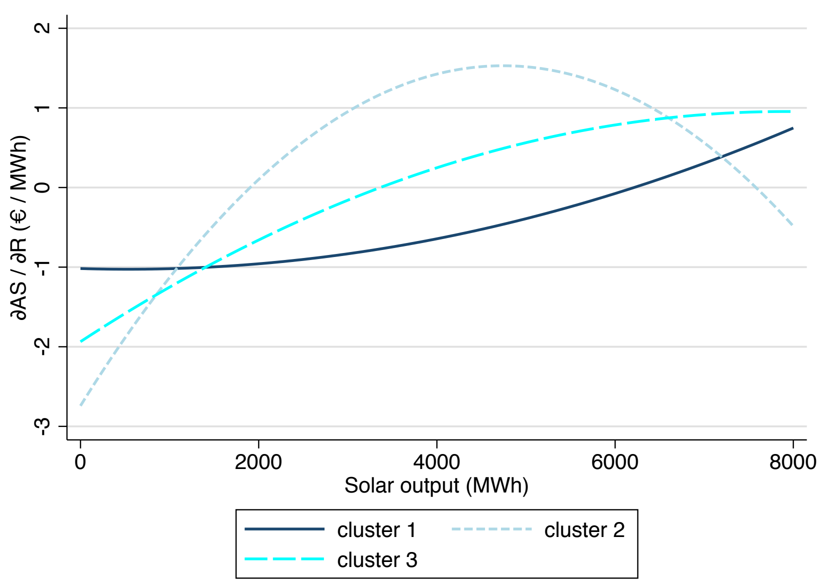
Notes: Cumulative solar capacity (Dec 2016) for residential solar installations, with a maximum installed capacity of 10 kW. Darker areas represent more installed solar capacity.

Figure A.3: Technology Portfolio Mix by TSO, Production 2015-16



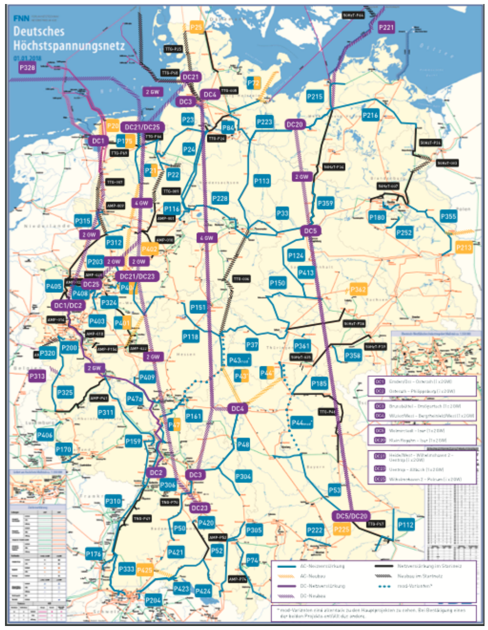
Notes: Average technology shares in electricity production 2015-16. Source: ENTSO-E.

Figure A.4: Effect of Solar Output on Ancillary Services Costs



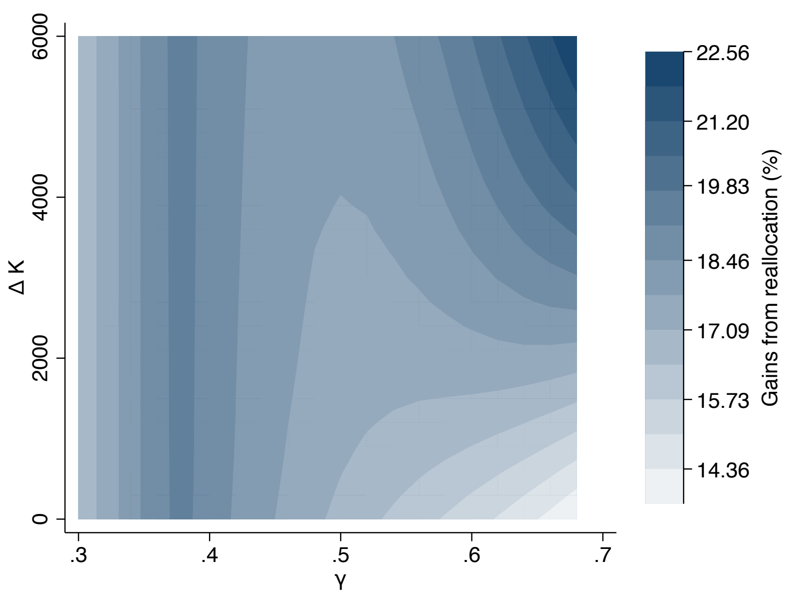
Notes: Functions obtained using the coefficients from the main specification of the ancillary services costs regressions.

Figure A.5: Planned Extension of High Voltage Network



Notes: Net Development Plan Germany (2030). Source: https://www.netzentwicklungsplan.de/de/projekte/projekte-nep-2030-2019

Figure A.6: Gains from Expanding Transmission Capacity



Notes: The surface depicts the gains from reallocation if the transmission capacity between regions N and S is expanded by the amount indicated by ΔK.