(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 heterogeneous benefits across locations. We evaluate the geographical misallocation of RES associated with the uniform nature of subsidies. We estimate the dispersion of marginal benefits from solar production in Germany and compute the social and private benefits from optimal reallocations of residential solar installations keeping total capacity fixed. We find that total value of solar would increase by 6.4% relative to the current allocation using conservative values for solar penetration. Reallocating all solar and taking into account transmission would yield considerably larger gains.

JEL codes: H23, Q42, Q48, Q51

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

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1 Introduction

Climate change mitigation policies largely rely on the adoption of renewable energy sources (RES). Yet, to many policy-makers, the decision to introduce 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, 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. They have been implemented in a number of jurisdictions including Australia, California, Germany, Ontario, and Spain. Nevertheless, these subsidies do not necessarily account for the costs and benefits of those technologies. Usually the incentives differ by RES technology, i.e. solar versus wind, but do not account for the relative productivity of the technology or their marginal benefits, which largely depend 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-specific 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. 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 across 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 and their benefits.

[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.

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 moving capacity from regions with low marginal benefits into regions with higher marginal benefits taking into account RES productivity. Then we 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.

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.[2] 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.[3] 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 has led to an intense political debate about how to distribute the total

[2] 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.

[3] 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). 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.

cost between different consumer groups (see for instance Gerster and Lamp [2020]). The location of RES also has implications for the dispersion of benefits from new products such as electric vehicles (Holland et al. [2016]) and for electricity storage (Sinn [2017], Zerrahn et al. [2018]). In general, reducing the misallocation of RES can have important implications on the effectiveness of FiT policies and potentially decrease their cost.[4]

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 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. Our results show that although the heterogeneity in average marginal overall benefits across regions ranges only from 40.8 to 44.4 €/MWh, their components contain a large range of variation. The mean avoided production costs across TSOs ranges from 19.3 to 29.4 €/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 3% of the overall marginal benefits, on average, 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 those plants starting in regions with the highest marginal benefits. 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

[4]Other studies have focused on finding a solution to the social planner's cost-minimization problem of allocating production and compare it to the decentralized solution. One example is Carvallo et al. [2020]. This requires to make several assumptions on each specific source. For instance, they allocate the new solar capacity proportionally to the area of the utility and not as a function of the marginal benefits.

system. As the solar penetration increases, more of the existing solar capacity gets allocated to the regions with the highest benefits until all the available solar capacity is placed in one region. Our results show a 6.4% of gains in value (ancillary services, avoided production costs, and avoided emissions combined) relative to the current allocation, assuming a relatively low penetration rate of 20%. These gains reach 10.9% if the maximum penetration rate allowed is 40% instead of 20%. Not surprisingly, in both cases those 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.

An important policy aspect when discussing reallocation of production is the transmission capacity. In order to study the importance of transmission, 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 about 3 gigawatts (GW), which is in line with current projects under construction.[5] 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 approximately 18 to 40% depending on the rate of solar penetration and the transmission capacity. Applying these figures to a benefit-cost analysis for the currrent project under construction, we conclude that the net benefits of the project can be positive, even without accounting for other forms of RES or other interconnections when sufficient capacity is allocated in the region with the highest total benefits.[6]

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

[5]See the German *Network Development Plan* published in 2019, NDP 2030.

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

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.[7] 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]. Similarly to Fell et al. [2020], we also exploit the price spread across regions as evidence of congestion.[8]

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. Stiglitz [2019], for example, identifies conditions for policies with differential pricing to be effective. 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.[9] However, we show empirically that a quota mandate in the form of a fraction of the total capacity that should be RES in the region, 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.[10]

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

[8] 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].

[9] 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.

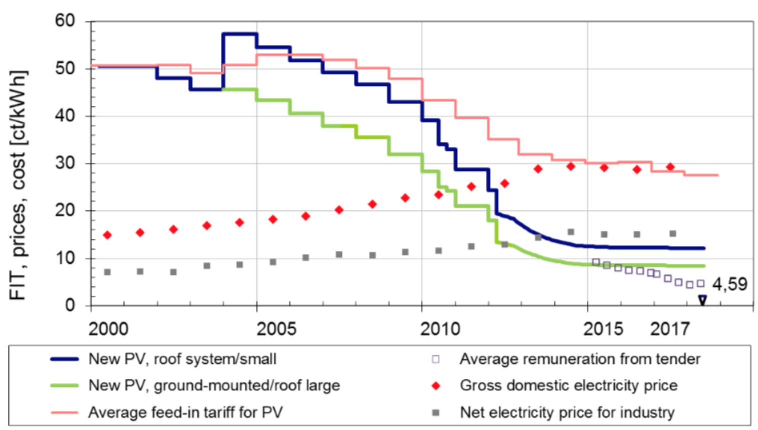
[10] The design of these policies could include a revenue-neutrality constraint in which the tax revenue from

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 estimated marginal benefits. 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.

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

emissions equals the total amount spent in subsidies (for example, see Durrmeyer and Samano [2018]). We abstract from this and focus on the costs/benefits from the geographical dispersion.

from the fact that rates are set at the point in time when the installation is first 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 FiTs even after 2015.[11]

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.[12] 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 and with higher benefits.

3 Data

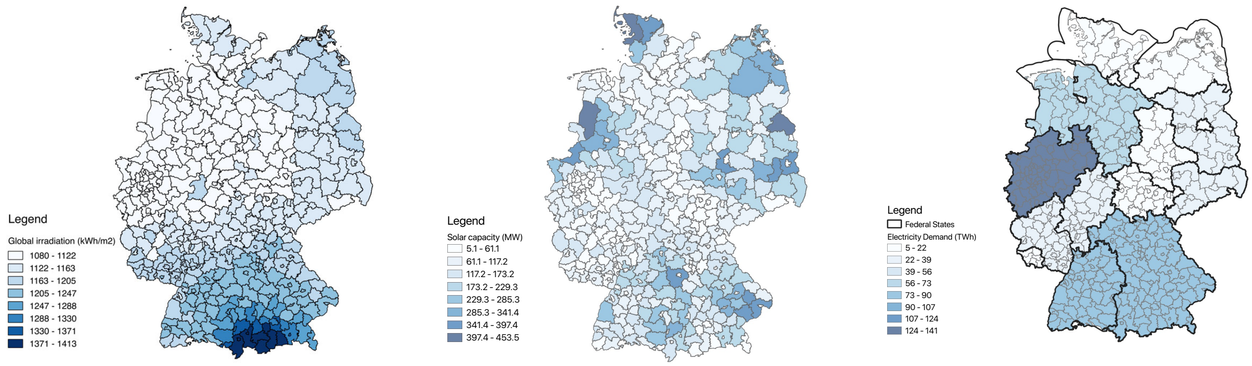
Our primary data sources are publicly available data from the German electricity market. We obtain high-frequency data on load and supply from renewables and non-renewable plants for each of the four regulatory zones that are served by one of the Transmission System Operators (TSOs) in Germany for the 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.

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

[12] We provide the total solar capacity for residential installations ($\leq$ 10kW) in Appendix Figure C.1.

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.

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.[13] 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 in the wholesale segment.

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.[14] While system balancing takes

[13]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. We obtain electricity production (fuel) costs for other technologies that are not defined on the world market, such as lignite and nuclear from ENTSO-E (TYNDP 2018).

[14]http://regelleistung.net We use the "balance exchange energy prices" (ReBap) and calculate our main variable as activated ancillary services times the Germany-wide price (ReBap) for both positive and

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 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.[15] 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 C.2 in the Appendix, on the other hand, plots the average portfolio mix by TSO for the years 2015 and 2016. This graph documents that there is great amount of heterogeneity in the production mix. While 50 Hertz and Amprion have a large share of brown coal plants, TransnetBW has 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.

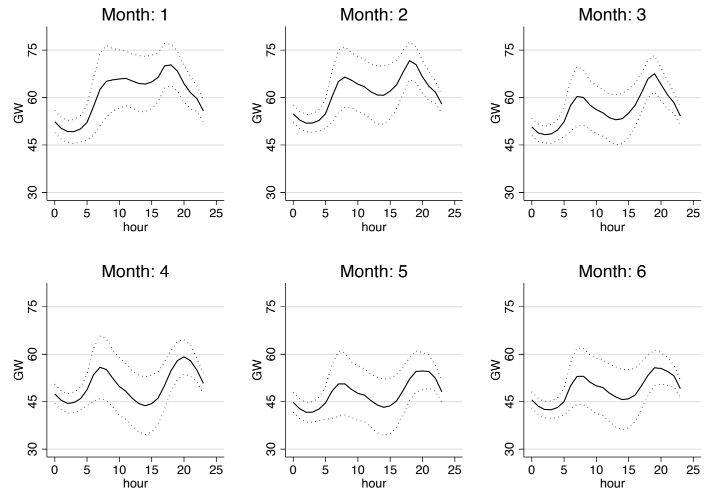
We complement the aggregated data at the TSO level with several disaggregated data sources. First, we obtain disaggregate data on all solar installations in Germany that are subject to FiTs.[16] We complement those data with solar PV production information from individual residential plants available from PV Output that provides us with the power

negative ancillary services. While these figures are labeled as prices by the operator, we will refer to them sometimes as costs in the absence of pure costs measures.

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

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

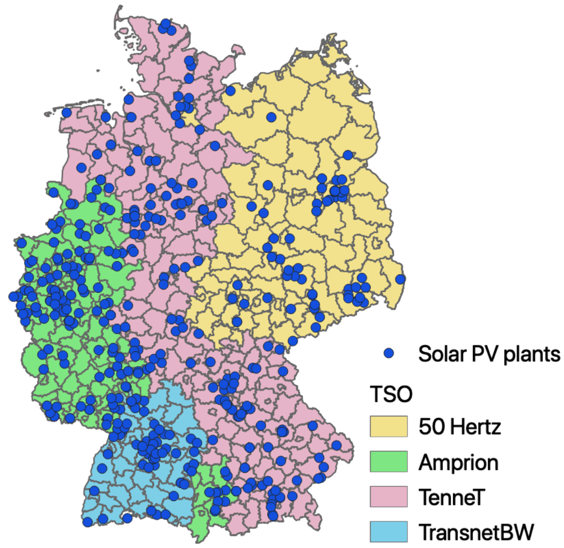
Figure 3: Load Profiles Net of Solar



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).

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.

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`.

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 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.[17]

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 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

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

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 is the average of marginal costs in region j plus 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

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

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 it in subsection 4.2.

[17]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.

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 costs. 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.[18] 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 A. 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 with constraints [see for instance Abrell et al., 2019b], our fully data-driven approach allows us to exploit several years of highly disaggregated data at the 15-minute level.

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.[19] We show the summary statistics of the avoided emissions multiplied by

[18]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.

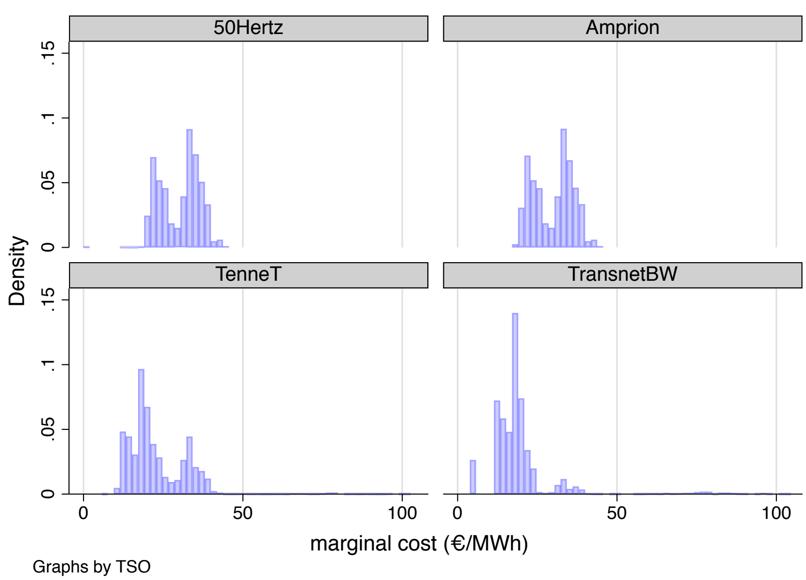
[19]The SCC is designed to measure climate change damages and includes effects on human health, agricultural output, property damages from flood risk, and changes in heating and air-conditioning costs. See EPA fact sheet. We chose the SCC in the US of 36 \$/tCO_2 at a discount rate of 3% annual for year 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

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.

Figure 5: Distribution of Marginal Operating Costs by TSO



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

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.

4.2 Ancillary services costs and renewables

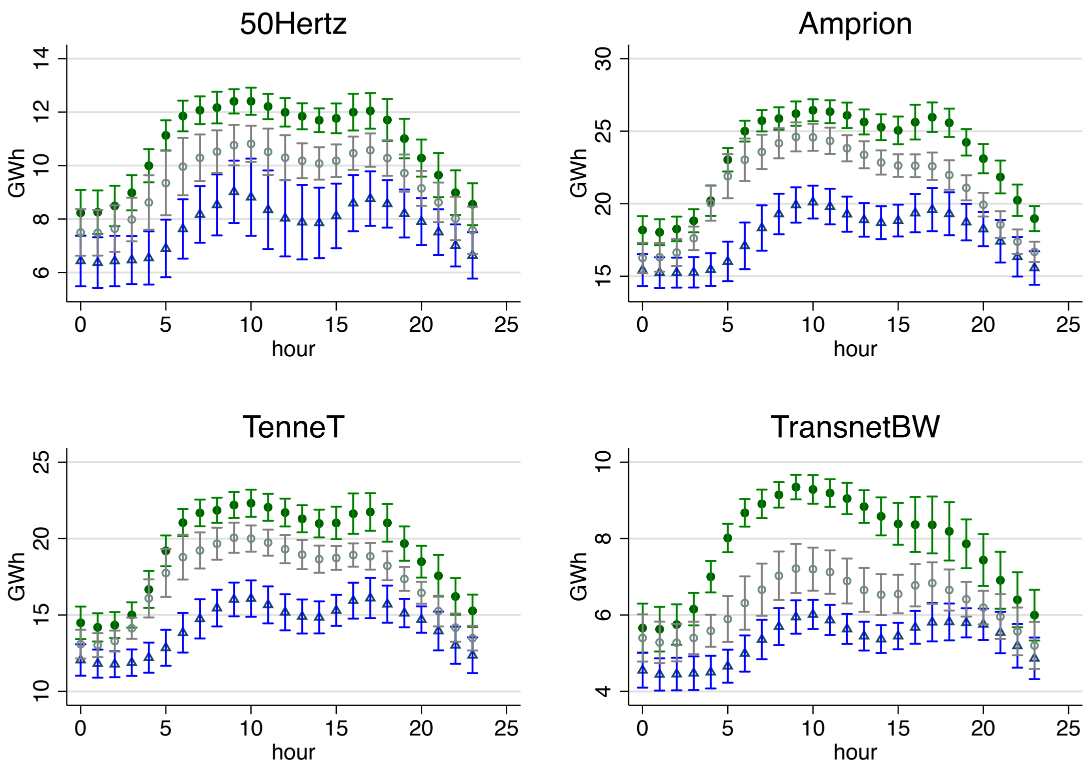
The third component in our marginal benefits calculation has received little attention in the literature. One exception is Tangeras and Wolak [2019] who use a kernel regression to find the effect of renewables output on ancillary costs in California. Their results show that the effect can change signs 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 to increase the differentiation among the load profiles. 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 cluster-TSO pairs we estimate the relationship between the ancillary costs on solar output and load using a polynomial that includes all the terms up to degree (including interactions). Even though our clusters were obtained using all hours of the day

end of March 2020.

Figure 6: Clusters of Load Profiles by TSO



Notes: Each panel shows the mean hourly load profiles grouped into three different clusters and one standard deviation bands for each cluster. 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.

since the objective was to classify daily load profiles, the regression below only uses the time intervals for which there is positive solar output since otherwise the ancillary services are not related to solar production. In addition, we include two-way fixed effects FEs of hour of the day, day of the week, month, and year as follows,

$$\begin{aligned} AS_{jt}(R_{jt}, Q_{jt}) &= a_0 + a_1 R_{jt} + a_2 R_{jt}^2 + a_3 R_{jt}^3 + a_4 Q_{jt} + a_5 Q_{jt}^2 + a_6 Q_{jt}^3 + \\ &+ a_7 R_{jt} Q_{jt} + a_8 R_{jt} Q_{jt}^2 + a_9 R_{jt}^2 Q_{jt} + FE_. \end{aligned}$$

where a_i are the parameters to estimate, R_{jt} is the renewable output and Q_{jt} the total load at time t in TSO j. The marginal effect from an increase in renewable output on expected ancillary services is the derivative of the expression above with respect to R_{jt}. We estimate this equation for each of the different clusters of load profiles.

We present the regression results in Table C.1 and Table C.2 in the Appendix. 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. Figure C.3 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].

We present in the Appendix Table C.3 and Table C.4 the results from a quadratic and a cubic specifications for $AS_{jt}(R_{jt}, Q_{jt})$ 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.

Table 2: Effect of Solar Output on Ancillary Services

	$\partial AS/\partial R$		
TSO	Low demand	Medium demand	High demand
50Hertz	2.42	0.44	−0.06
Amprion	2.32	−0.69	2.34
TenneT	−0.02	−0.65	0.69
TransnetBW	2.54	0.83	−1.05

Notes: Each number, 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 C.1 and Table C.2. Those coefficients were obtained using only observations for which $R_{jt} > 0$. The columns, labeled as "low", "medium", and "high", correspond to each of the three clusters from Figure 6 from low to high demand levels.

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 46% and 72% 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 the average values can be costs or benefits depending on the TSO, but with high volatility. The fact that increasing RES can have a positive impact on ancillary service costs is supported by the overall time trend. 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%.[20] Finally, our results show heterogeneity for the four TOSs as measured by the standard deviations of the marginal benefits.

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

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	-1.05	29.39	12.48	40.82
	(3.15)	(6.35)	(2.09)	(6.85)
TenneT	0.09	21.97	22.34	44.4
	(1.37)	(10.14)	(7.28)	(8.41)
TransnetBW	-0.22	19.34	23.2	42.32
	(4.1)	(13.02)	(7.58)	(16.3)
50Hertz	-0.51	29.37	12.13	40.99
	(2.26)	(6.39)	(1)	(6.78)

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. Negative avoided ancillary costs represent costs, while positive values represent gains. The last column contains the overall average and standard deviation (in parentheses) by TSO.

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 an optimization process. We exploit the heterogeneity in regional solar radiation and marginal benefits to calculate a counterfactual allocation of solar installations in Germany so that every incremental amount of solar capacity to be reallocated is placed where the resulting benefits are the highest. We focus on small scale residential solar installations in subsection 5.1 and on all solar capacity in subsection 5.2, where we also account for transmission. 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 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). We recognize that MB_{jt} is a non-constant function of the solar output, which accounts for the different displacement effects from high and low levels of solar penetration. Then we take the sum over our entire sample period. This is the baseline value used below to compute the gains of each reallocation scenario. Note that this value takes into account both differences in solar productivity and differences in MB across regions and time periods.

Our main policy parameter is the ratio of solar capacity allowed with respect to the maximum feasible total solar capacity that could be installed in residential buildings in a given region. We call this fraction γ. At a value of $\gamma = 1$ (100%), all residential buildings would have solar panels installed in their rooftops. The current value of γ as of 2016 is approximately 5%.[21] In line with the average size of residential solar installations in Germany, we assume a capacity of 6.7 kW per rooftop. The total number of residential buildings varies from 2.2 million in TransnetBW up to approximately 7 million in the largest TSO, TenneT.

For each of the reallocation scenarios we consider a value of γ, greater or equal to the actual value, that determines the maximum fraction of total residential solar capacity that can be installed according to the optimization algorithm we describe below. Each TSO is subject to the same value of γ for any given scenario. Since we are interested only in measuring misallocation of resources, we keep the total solar capacity fixed throughout our different scenarios, the only thing that changes is the location of the components of this capacity. The policy parameter γ can therefore be interpreted as a type of Renewable Portfolio Standard (RPS). However, instead of a mandate on the fraction of load to be covered by RES production, we define γ as a fraction of maximum potential capacity.

We now describe how we optimize the reallocation of solar capacity. Let $\mathcal{S}$ be the total amount of currently installed residential solar capacity in all the TSOs together. Split $\mathcal{S}$ into

[21] We calculate this value at the TSO level for the last month of our sample, December 2016, using the housing stock from the 2011 census. Using county level data, we find a similar average market penetration of 6% with an interquartile range between 3.3% and 8.2%.

discrete blocks of capacity of size s each (for example $s = 1$ MW). For a given value of γ we reallocate $\mathcal{S}$ as follows, starting with zero cumulative capacity in each TSO:

1. Add a block of capacity of size s to the cumulative solar capacity in each TSO.
2. For each TSO separately, compute the expected gains from adding the amount s to the TSO's capacity.
3. Compare the gains in each of the TSOs and permanently allocate the capacity s to the TSO for which total gains are largest if the fraction of the cumulative solar capacity in this TSO with this addition is less or equal to γ.
    - In case no more capacity can be added to the TSO with the highest value, i.e. the capacity constraint is binding, allocate s to the TSO with the second highest gains.
    - Similarly, in case the capacity constraint is binding for the TSO with the second highest gains, move to the TSO with the third highest gains, and so on.
4. If $\mathcal{S}$ has not been completely reallocated, go back to step 1. Otherwise, the process ends since there is no more capacity to reallocate.

In order to determine where to allocate the next block of capacity s, we must compute the gains in each TSO and choose the TSO where those gains are the largest. This process exhausts all the possibilities of allocation, conditional on the size s of the blocks. The configuration we find at the end of this process is optimal because we obtain the configuration by construction.

We use the TSO-specific MB_{jt} and data on residential solar production at the 15-min interval to multiply the newly allocated solar capacity in each TSO at each step of the algorithm to convert capacity (MW) into production (MWh) and ultimately monetary value (€/MWh). The algorithm thus accounts for both regional *differences in solar productivity* and *differences in the marginal benefits* from solar production. As the cumulative amount of solar increases in the TSOs, the value of the marginal benefits changes since it is possible that the conventional technology displaced is of a different nature than when the first block s was allocated. Our three components of marginal benefits can take on different values as the cumulative solar capacity increases or decreases relative to the actual allocation. When the solar capacity in a TSO is lower relative to its initial amount −as it can happen when in a step of the algorithm the marginal benefits for that block are greater elsewhere− we use the value of MB_{jt} from the actual allocation. That is, we assume the MB function to be constant for solar penetration rates that are lower than the initial rate in the TSO. However, if the cumulative solar capacity is greater than its initial amount, there is displacement of conventional sources of production and we invoke our MB function which evaluates the effects from this displacement in terms of avoided operating costs, avoided emissions, and avoided ancillary costs.[22]

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 never occurs during our sample period.[23] When we reallocate also larger solar installations, we introduce the possibility of transmission in subsection 5.2. In this case, the surplus will be valued at the MB of the importer of this excess.

An alternative approach to reallocate capacity could have been to uniquely focus on the TSOs productivity of their solar installations. Table C.6 in the Appendix shows the average solar productivity per TSO obtained through linear regressions of individual solar plant-level production data on installation characteristics. The TSO-specific coefficients measure the average productivity of the PV sites in each TSO. A naive optimization process would allocate as much solar capacity as possible (up to a fraction γ) in the most productive TSO, then it would reallocate the remaining solar capacity in the second most productive TSO (up to a fraction γ), and so on until total initial solar capacity has been reallocated. This process would provide a suboptimal solution because the MB function for the most productive TSO

[22]Using this procedure, we can rely on observed electricity market data as opposed to simulated supply curves.

[23]Even in case all solar was allocated to the TSO with the highest MB, TransnetBW, the production from residential installations only accounts for an average of 15% of total load (maximum of 74%).

might decrease quickly with the addition of solar capacity, and some of the capacity could contribute with more gains if placed in a TSO where the MB is higher even if productivity is slightly lower.[24]

Our results from the full optimization process consist of reallocating residential solar installation plants assuming an average capacity of 6.7 kW per rooftop in line with the data. We set the minimum value for γ to be 5% so that gains from reallocation are approximately zero 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, which would result in an inefficient allocation by construction.

Our main outcome of interest is the ratio

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

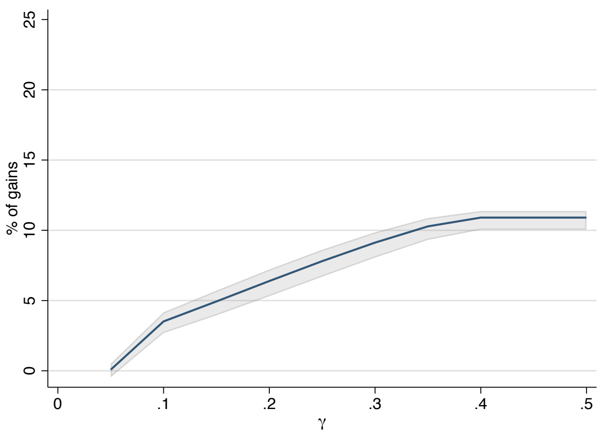
for a given value of γ. Therefore, when γ is small, we should have gains close to 0. Figure 7 shows the reallocation values expressed as percentages and for different values of γ and of the SCC. As the parameter γ increases, more of the existing solar capacity gets allocated to the regions with higher marginal benefits. Interestingly, using larger values of the SCC increases the gains for medium to large values of γ but it results in slightly negative gains for low values of γ. This is due to the particular portfolio mix of the TSOs that are assigned more solar capacity than their initial amounts. 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 a measure of uncertainty of our main results, for each value of γ we compute the gains from reallocation but using load and solar output observations that are increased by two standard deviations each using the joint distribution of residuals of a seemingly unrelated regression of load and solar output. Then we repeat but decreasing each of load and solar output by two standard deviations of the residuals distribution. More specifically, we regress load on its 1-hour lagged value and its 24-hours lagged value together with TSO, hour of the

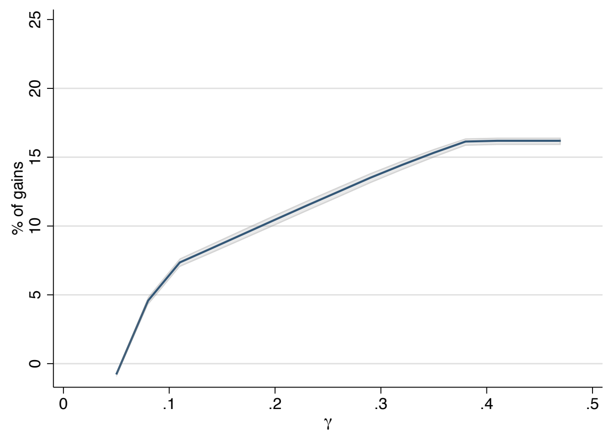
[24]The results from this alternative approach are available upon request.

Figure 7: Value of Reallocation for Different Values of γ

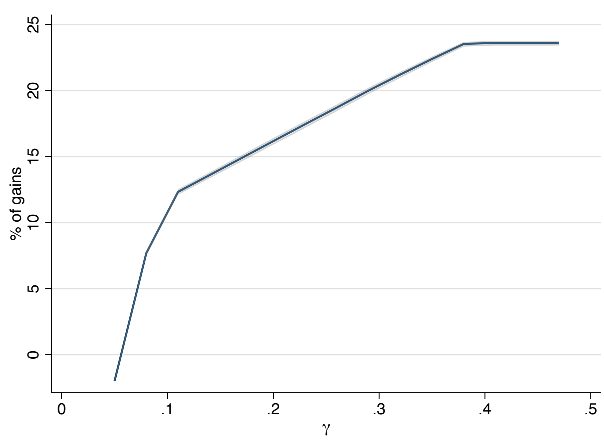
(a) SCC = 31.71 €/tCO_2



(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 also compute the gains when adding and subtracting two standard deviations of the joint distribution of residuals from a seemingly unrelated regression of load and solar output (see main text for details). This produces the bands around the main outcomes and represent the uncertainty in the simulations.

day, day of the week, month, and year dummy variables. Similarly for solar output, where we employ the individual solar PV production data. We recover the residuals from this system of equations and calculate their standard deviations by TSO.[25] The bands around the main line in Figure 7 represent the gains for combinations of an increase or a decrease on solar output or load by the same number of standard deviations of their respective residuals distribution. Consistent with the regressions on average solar productivity from Table C.6, we see almost no uncertainty in the gains. This is mainly driven by the fact that residential installations in a given TSO are rather homogeneous and produce a similar output.

Our results show that a relatively low penetration rate of $\gamma = 20\%$ for reallocation represents 6.4% 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 106 million euros and 148 million euros when $\gamma = 0.3$. The first amount (106 million euros) is roughly equivalent to the production of 266,000 residential PV plants of average size valued at an average wholesale electricity price of 30.30 €/MWh during our sample period, and to 371,000 PV plants of the same capacity when $\gamma = 0.3$.[26] In 2016, there were roughly 950,000 residential installations in Germany, therefore these values from misallocation represent approximately 28% and 39% of the market value of the production of all residential installations, respectively.

Those results use a relatively conservative measure of the SCC. With a higher valuation of 50 €/tCO_2 as in the main specification in Abrell et al. [2019b] who compute the social costs of different policies to incentivize the adoption of RES, the gains from reallocation are 10.5% and 13.5% 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 16 and 20% respectively and as shown in Figures 7b and 7c. The width of the uncertainty bands decreases with the SCC value because there is less uncertainty about the gains when one of the components is

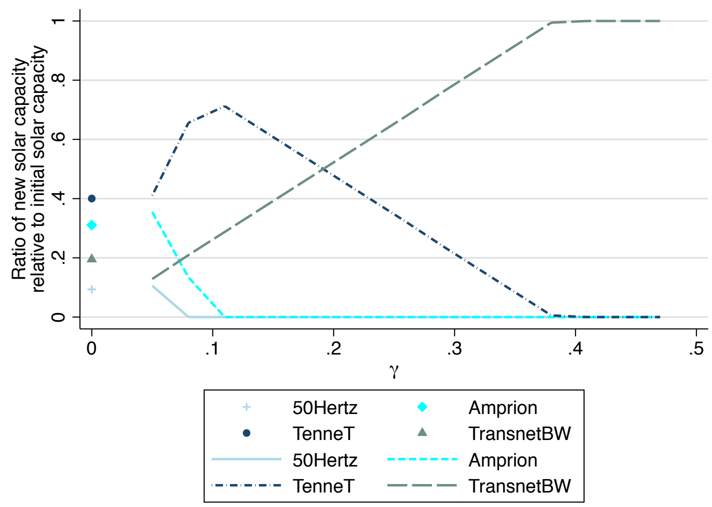
[25] The detailed results from these regressions are available upon request.

[26] To calculate this number we use the average installation size together with the average annual production in Germany from Table C.6 of 984 kWh/kW and the average wholesale electricity price. We find an annual production value of roughly 200 €per installation and year.

highly valued.

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 marginal benefits, some TSOs end up without any RES capacity at all. This is shown in Figure 8, which plots the ratio of new solar capacity relative to the initial amount for each TSO and at different values of γ. For sufficiently high values of the penetration rate γ, there is a TSO with a ratio of 1. The figure also depicts the actual allocation of solar at $\gamma = 0$.

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 residential solar installations ($\leq$ 10kW) 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 9a compares the percentage changes relative to their benchmark values of each of those components at each value of γ. Figure 9b 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 decreases 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 C.2 and with the frequencies of marginal technologies in Table C.5. For example, the marginal technology in TransnetBW is dominated by hard coal, a high-emitting source, and according to Figure 8, at $\gamma = 0.05$ this TSO receives less solar capacity than in the actual allocation. Consequently, at these low levels of γ, other TSOs with a slightly cleaner production mix receive a larger share of solar capacity and the initial "gains" are negative. This, however, changes quickly as more capacity gets allocated to TransnetBW. Recall that the gains do not depend on the average technology mix within each TSO, which is dominated by nuclear in the case of TransnetBW, but on the marginal technologies displaced by adding solar to the system.[27]

Production costs decrease because of the displacement of conventional production even beyond the level of production costs from the baseline. Similarly, we find that ancillary services costs decrease by 40% or more as γ increases. As more solar is reallocated we find that the ancillary services do no longer represent costs, but contribute to the gains (when the change relative to its baseline is lower than 100%). This is a direct consequence of our estimates in subsection 4.2. Recall that these costs are very small.

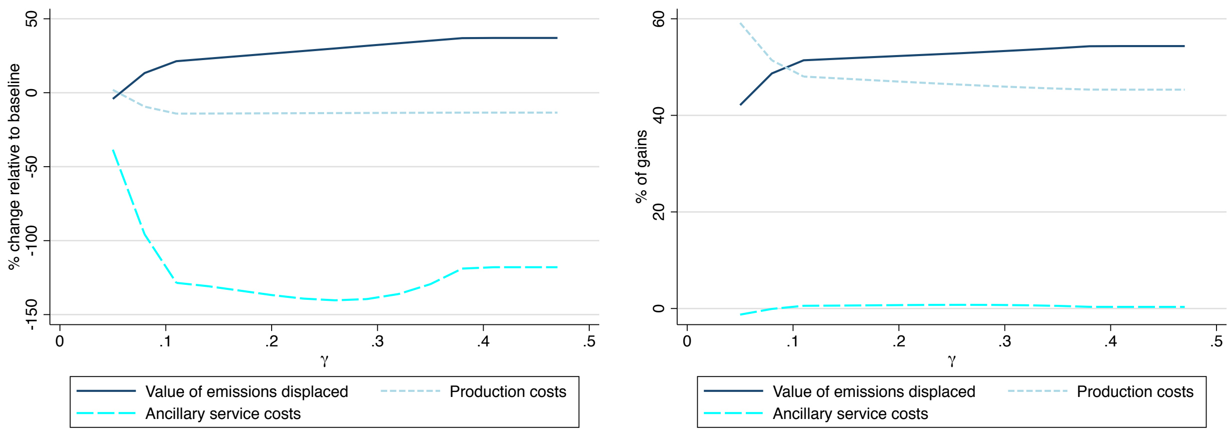
Figure 9a highlights the trade-off a regulator (social planner) would face when reallocating solar capacity between evaluating the misallocation using a global measure of benefits as in our main results versus using only one of the components. For example, if the regulator cares only about maximizing the value of emissions displaced, the best value for γ would be the maximum value considered for this parameter, as Figure 9a suggests. Similarly if the objective function was to decrease production costs only, the policy would require γ to be at least approximately 14% and higher values of this parameter would have almost no

[27]Similarly, 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 C.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 Relative to Baseline and Decomposition of Gains

(a) Changes in each component relative to its baseline value

(b) Decomposition of gains



Notes: Panel (a): For each component we compute the difference of its value for each level of γ and expressed it as a percentage relative to the value of that component before any reallocation. Panel (b): 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.

additional impacts. For the ancillary services, any value of γ considered decreases the costs, some of those values even beyond its initial amount. The optimal value in this case would be around 28%.

Figure 9b shows the changes in the contribution of each component to the total gains. The figure makes evident that the two main drivers of the benefits are the value of emissions displaced and the savings in production costs, consistent with Table 3. Each of these components account for roughly 40 to 60% of total gains. The savings in ancillary services costs are much smaller. For low values of γ, their share is negative because production costs are greater than their initial level but after $\gamma = 0.09$ all three components positively contribute to the total gains.

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* (NDP) in 2012.[28] Key projects discussed in the NDP are several high-voltage direct current lines between North and South Germany (see Appendix Figure C.4) with the objective to increase interchange capacity for electricity from RES production across regions. In particular, the NDP 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 cost and potential environmental and aesthetic impacts.[29] 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, which stretches from North to South Germany and that has large heterogeneity in solar productivity. 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.[30] In a final step, we compare the additional benefits from the interconnection to the total investment cost for different cost scenarios.

We split TenneT based on administrative boundaries in a North and South region.[31] We

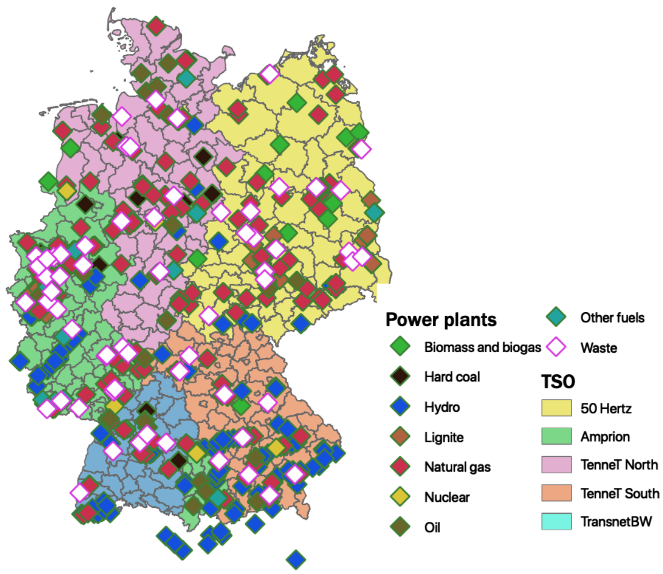
[28]Several revisions to the original NDP have been made in recent years. We consider here the 2019 version, which focuses on the electricity market in 2030, NDP 2030. The NDP is an integral part of the German climate change objectives to produce 80% of all electricity from renewable resources by 2050.

[29]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 730 km and 580 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 5 billion euros for SuedOstlink. Source: TenneT, last accessed 7 September 2020.

[30]We focus on 'all' solar capacity rather than purely residential installations in this subsection to highlight the role of the transmission constraint, which is mainly relevant when there is excess energy production in one subregion.

[31]To split the TSO, we overlap 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.

Figure 10: TSO Service Areas and Conventional Power Plants



Notes: TenneT is split into North and South region, defined by the administrative boundaries of Bavaria. 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.

start our analysis by constructing the expected marginal benefits for solar in the two regions. As load and electricity production data are only available at the TSO level, we construct demand and supply in the two subregions as follows.[32] 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 10 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, allows 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 for 'important' changes in capacity (changes of

[32]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 ≥ 100 MW.

100 MW or more in actual availability) for all technologies at high frequency. 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 that show that the split leads to values that are comparable with those in the previous section.

Similar to the residential reallocation, for a given value of γ, we optimize for each MW of reallocated capacity according to the maximum expected benefit calculated as solar production $\times$ MB_{jt}, where both solar productivity and MB_{jt} can change over time and by region. We use the observed MB_{jt} in case less solar is allocated to a TSO than in the benchmark (observed) case, but allow for lower marginal costs and different marginal emissions - in line with the observed supply curves - in case more solar gets allocated to any given region. Finally, while in the residential reallocation exercise we defined γ as the share of total residential buildings that can be covered with solar panels, this classification no longer applies when using all solar, including large roof-mounted as well as ground-mounted installations. Therefore, we define γ as the share of total generation capacity that is covered by solar in each TSO. In our data, this value ranges from 14% in Amprion to 31% in TenneT South in 2016.

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

$$E[\lambda_N] = a_N + b_N(R_N - Q_N) + b_N Q + FEs$$
$$E[\lambda_S] = a_S + b_S(R_S - Q_S) + b_S Q + FEs$$

only using time intervals for which the transmission constraint is binding: $\lambda_N \neq \lambda_S$. In the expressions above, $R_j - Q_j$ is the residual load and Q is the quantity traded. 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 and since we do not have data on trade between the two regions, we use $Q = Q_S$ in the first regression and $Q = Q_N$ in the second. This exogenous covariate serves as a valid supply shifter in the estimation of an otherwise endogenous regression. Table 4 shows the results. The expressions above are supply functions since as $Q = K$ (the size of the capacity constraint) increases, exports increase and more expensive technologies need to be used: higher λ_S.[33] Our regressions use the spread in the marginal costs of electricity across the two regions as evidence of congestion similarly to Fell et al. [2020]. However, we use this spread to define the eligible set of observations to include in our regressions, as opposed to including a function of the spread as a regressor.

Based on the results in Section B in the Appendix, we find that

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

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 11 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 3,487 MW, which is roughly equivalent to twice the capacity of the TenneT transmission

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

Table 4: 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
$R_N - Q_N$	-0.000932**		-0.000984**		-0.000480	
	(0.000301)		(0.000298)		(0.000418)	
Q_S	-0.00118		-0.00127		-0.00128	
	(0.000820)		(0.000814)		(0.00101)	
$R_S - Q_S$		-0.00634***		-0.00653***		-0.00730***
		(0.000586)		(0.000606)		(0.000675)
Q_N		0.00196*		0.00217*		0.00329**
		(0.000878)		(0.000889)		(0.00102)
N	4,461	4,461	4,398	4,398	3,787	3,787
R^2	0.820	0.708	0.823	0.711	0.834	0.708

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

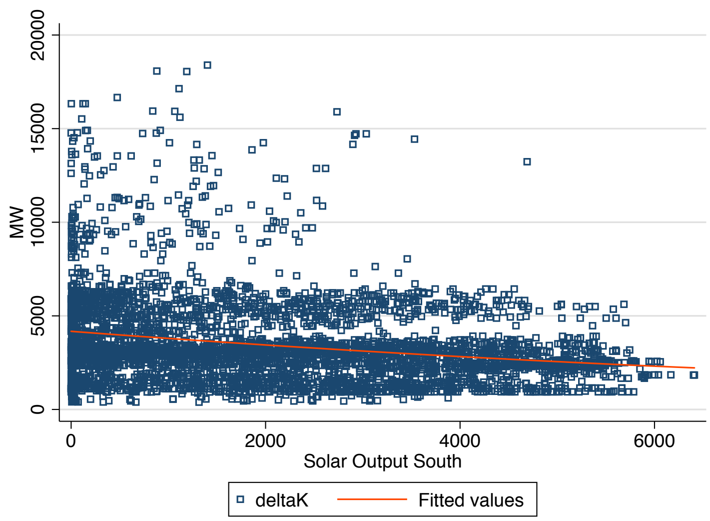
line to Norway or about four times the capacity of a new projected interconnection to the Netherlands.[34] Similarly, the SuedOstlink project between TenneT and 50 Hertz is designed for a capacity of 2,000 MW with possibility of an expansion to 4,000 MW.[35] Those projects indicate that our estimates are well within reasonable values in the industry for this market.

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 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 higher than total 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. Given our transmission model, we focus on the additional

[34] https://www.tennet.eu/our-grid/international-connections/nordlink/
[35] https://www.50hertz.com/en/Grid/Griddevelopement/Onshoreprojects/SuedOstLink.

Figure 11: Implied Transmission Capacities



Notes: Each square represents one of the values obtained using Equation 2. The overall mean is 3,487 MW.

benefits from displaced production costs and abstract from additional effects on emissions in the North region, as highlighted by Fell et al. [2020].[36] In the absence of the new transmission capacity, the surpluses in the South would be valued at 0. Since this transmission line can 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. In addition, given that most observations fall within a range of 6,000 MW in Figure 11 and the projected line capacities in the NDP, we limit the amount of additional transmission capacity to be no more than 6,000 MW.

Figure 12 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.[37] For relatively low levels of γ the gains are increasing as in the case without transmission, i.e. when optimizing the solar

[36]As we simulate the marginal cost for the North region as a function of ΔK, there exists no direct mapping from marginal costs to emissions.

[37]Note that the minimum γ is set at 0.2, which results in approximately zero gains from reallocation. We allow γ to increase up to 55% of each TSO's capacity, i.e. up to 55% of each TSO's capacity can be solar capacity.

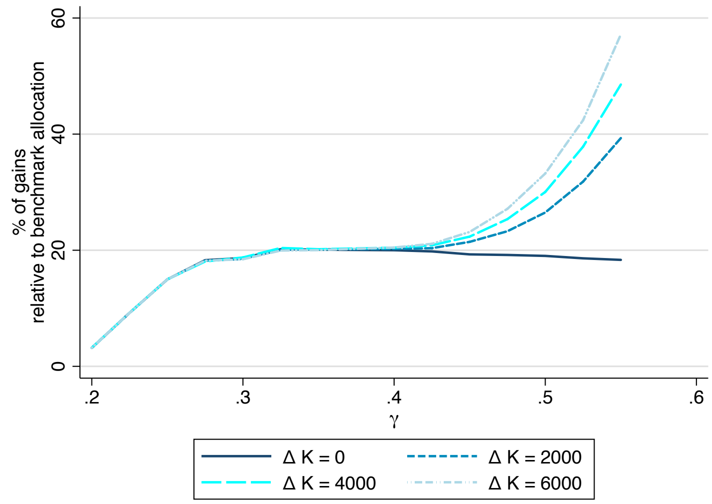
allocation total gains increase as long as the capacity constraint in the TSO is not binding (solar production$_j \leq$ load$_j$).

Once solar output is placed in high-productivity regions, particularly in South TenneT, the excess can be exported to the North region provided there is sufficient transmission capacity available. If there is no additional capacity in transmission ($\Delta K = 0$), 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 become considerably larger, i.e. a capacity constraint of 2,000 MW evaluated at $\gamma = 0.55$ leads to approximately double the gains compared to the case without interconnection. The increasing gains, reflect the fact that the excess of solar production in the South valued at its corresponding marginal benefits value in the North more than offsets the losses in benefits in the regions where solar capacity has been decreased. Appendix Figure C.5 shows the allocation shares with and without interconnection capacity ΔK, and highlights that at high levels of γ, more capacity will be allocated to TenneT South in case capacity is available, as the gains in this region are larger. For completeness, Appendix Figure C.6 shows the gains from reallocation for residential solar installations allowing for heterogeneous solar productivity in TenneT North and South.

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 5. 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 $\gamma = 0.5$ are 364.54 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 are biased upwards.

We compare those gains to the tentative investment cost of the underground transmission

Figure 12: Gains from Expanding Transmission Capacity



Notes: Each curve depicts the gains from reallocation if the transmission capacity between regions North and South is expanded by the amount indicated in the legend. We show the allocation for the example of $\Delta K \in \{0, 2000\}$ in Appendix Figure C.5.

lines that are currently under construction in Germany (SuedOstlink) with that same capacity (2,000 MW) and a total length of 580 km. This cost is estimated to be approximately 5 billion euros, which has an annualized value of approximately 151 million euros when using a lifetime of 40 years in line with the official amortization period of this project, and an annual discount rate of 1% as in Davis and Hausman [2016].

For the realized underground cables, the benefit-cost (BC) ratios are greater than one only in the case where we consider large values of γ. At 35%, close to, but above the observed solar-to-capacity share in TenneT South, we show that investment is not beneficial. On the other hand, once we allow for larger reallocation values of 50%, the BC ratios are positive (2.4 and 2.2, depending on the size of the tranmission line).[38] 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.[39] The BC analysis shows that additional

[38] To calculate the expected cost for the 4,000 MW interconnection with underground cables, we rely on cost estimates per km from *Suedlink*, a similar project with 4,000 MW capacity. We find a total investment cost of 7.9 billion euros.

[39] See industry report by Xcel Energy. For our calculation, we assume a cost factor of 8%, the midpoint between the two cost estimates.

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.

Table 5: Benefit-Cost Analysis for Power Line Investment

Planned interconnection, ΔK [MW]		2,000			4,000	
Annualized investment costs [m€]						
Overhead lines		12.06			19.93	
Underground lines		150.77			249.14	
Capacity share, γ	.35	.4	.5	.35	.4	.5
Annual gains						
from reallocation [m€]	3.30	11.05	364.54	3.80	21.20	536.75
Benefit-cost ratio						
Overhead lines	0.27	0.92	30.22	0.20	1.11	28.00
Underground lines	0.02	0.07	2.42	0.02	0.09	2.24

Notes: Change in gains from reallocation for given γ comparing case of no interconnection ($\Delta K = 0$) with interconnection scenarios of 2,000 and 4,000 MW, respectively. Annualized investment costs for underground lines based on *SuedOstLink* project, with estimated total costs of 5 billion (bn) euros (Source: TenneT). For the 4,000 MW transmission, we assume a total cost of 7.94bn euros, using the cost per kilometer from the alternative *Suedlink* project, a transmission line with 4,000 MW capacity. For overhead lines we assume that total investment cost represents approximately 8% of the underground cables. For both type of high-voltage lines we consider furthermore a 40 year lifespan and a 1% annual discount rate.

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 of the social cost of carbon. We find economically relevant gains relative to the current allocation if solar panels had been allocated according to their solar productivity and marginal benefits. In addition, if a new transmission line were built between the North and the South regions, this would increase the gains from reallocating solar PV plants for medium-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 only be 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 economic incentives for technology adoption.

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A Details on Data and Simulation Procedure

A.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, this is usually not the case for brown coal (lignite) and uranium (nuclear energy). We therefore rely on energy market modelling data from ENTSO-E (TYNPD 2018) for these type of fuels, and complement this information with emission factors for lignite in Germany from 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 onshore and offshore, solar, hydro (reservoir, run of river, pumped storage), geothermal, and other renewables), 2) nuclear, 3) biomass and waste, 4) lignite, 5) hard coal, 6) gas, and 7) oil. In the specific case of 50 Hertz we furthermore make the assumption that oil is always infra-marginal, as electricity production from 'oil' is linked to an oil refinery (IKS Schwedt) that produces electricity as a by-product in its main production process. We verify this information in our data by plotting the electricity production profile for this plant, which 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.2 Reallocating RES

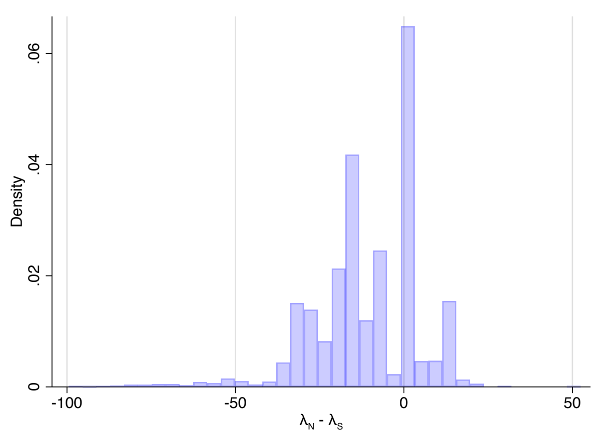
For the reallocation exercise in subsection 5.1, we take as given total residential solar capacity on the last day of our sample (31 December 2016). Similarly, we obtain data for total installed capacity (all generating units) per TSO. We calculate the total residential solar output per time interval, using total solar output by TSO and multiply it by the fraction of residential to total solar capacity. We complement these data by using individual solar PV production data, obtained from PVOutput. These data allow us to account for heterogeneity in residential solar output within each TSO. 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).

A.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 4 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 in TenneT South, we allow this region to export energy to the TenneT 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.

B 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,

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

C Additional Tables and Figures

Table C.1: Ancillary Costs on Solar and Load by Cluster of Load Profile (part 1)

	50 Hertz			Amprion		
	(1)	(2)	(3)	(1)	(2)	(3)
solar	4.843	17.96***	6.985	67.11	-63.46*	65.40*
	(5.628)	(3.804)	(4.616)	(116.6)	(27.61)	(29.43)
solar^2	-0.00219*	-0.00544***	-0.000453	0.00419	0.000305	0.00524***
	(0.000942)	(0.000877)	(0.000845)	(0.00566)	(0.00182)	(0.00121)
solar^3	-3.53e-08	0.000000535***	-2.49e-08	0.000000140	0.000000414***	4.71e-08
	(3.22e-08)	(7.35e-08)	(4.22e-08)	(0.000000117)	(7.13e-08)	(3.20e-08)
load	11.00**	9.647**	10.12**	-256.3***	-4.513	7.495
	(3.627)	(3.184)	(3.503)	(76.41)	(3.619)	(27.21)
load^2	-0.00161***	-0.00166***	-0.00190***	0.00972***	0.000302	-0.000183
	(0.000432)	(0.000484)	(0.000466)	(0.00285)	(0.000326)	(0.00129)
load^3	6.86e-08***	8.78e-08***	0.000000106***	-0.000000122***	-6.08e-09	1.19e-09
	(1.61e-08)	(2.53e-08)	(1.99e-08)	(3.52e-08)	(8.64e-09)	(2.02e-08)
solar × load	0.000464	-0.00266***	0.000133	-0.00495	0.00623*	-0.00640*
	(0.000798)	(0.000702)	(0.000620)	(0.00892)	(0.00296)	(0.00263)
solar × load^2	-7.62e-08*	0.000000179***	-7.56e-08**	9.89e-08	-0.000000142	0.000000154**
	(3.52e-08)	(5.07e-08)	(2.60e-08)	(0.000000171)	(8.07e-08)	(5.92e-08)
solar^2× load	0.000000204**	0.000000146	5.65e-08	-0.000000233	-0.000000129	-0.000000238***
	(7.86e-08)	(9.19e-08)	(7.37e-08)	(0.000000220)	(8.86e-08)	(5.40e-08)
N	16,096	7,206	14,426	8,459	10,527	17,649
R^2	0.115	0.111	0.0936	0.0900	0.0958	0.0810

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

Notes: Dependent variable: ancillary costs. First three columns correspond to the three clusters of load profiles for 50 Hertz and last three columns for Amprion. Each regression includes two-way fixed effects of 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 C.2: Ancillary Costs on Solar and Load by Cluster of Load Profile (part 2)

	TenneT			TransnetBW		
	(1)	(2)	(3)	(1)	(2)	(3)
solar	379.7***	-3.003	37.45**	103.8***	48.99	102.7***
	(43.06)	(5.676)	(14.38)	(28.02)	(31.69)	(31.05)
solar^2	0.000249	0.00109**	0.00184***	0.00750**	0.0193***	0.0138***
	(0.00127)	(0.000417)	(0.000498)	(0.00241)	(0.00361)	(0.00346)
solar^3	3.14e-08	-3.96e-10	-1.65e-08	3.28e-08	0.00000146***	-0.000000209
	(1.96e-08)	(1.49e-08)	(9.38e-09)	(0.000000131)	(0.000000252)	(0.000000293)
load	-138.6**	-15.78	-20.48	-147.3***	44.95	-96.64
	(43.23)	(14.93)	(21.16)	(26.05)	(78.80)	(79.00)
load^2	0.00731***	0.00136	0.00150	0.0200***	-0.00449	0.0154
	(0.00213)	(0.00104)	(0.00124)	(0.00321)	(0.0152)	(0.0119)
load^3	-0.000000125***	-3.63e-08	-3.31e-08	-0.000000861***	1.21e-08	-0.000000789
	(3.50e-08)	(2.40e-08)	(2.41e-08)	(0.000000131)	(0.000000975)	(0.000000594)
solar $\times$ load	-0.0348***	-0.000223	-0.00471**	-0.0277***	-0.0265*	-0.0309***
	(0.00394)	(0.000730)	(0.00158)	(0.00647)	(0.0121)	(0.00938)
solar $\times$ load^2	0.000000797***	2.58e-08	0.000000140**	0.00000179***	0.00000335**	0.00000222**
	(9.04e-08)	(2.52e-08)	(4.38e-08)	(0.000000377)	(0.00000119)	(0.000000730)
solar$^2 \times$ load	-2.63e-08	-6.55e-08**	-8.23e-08**	-0.000000873**	-0.00000443***	-0.00000157**
	(5.85e-08)	(2.47e-08)	(2.69e-08)	(0.000000275)	(0.000000674)	(0.000000538)
N	10,546	10,575	16,489	23,442	7,474	5,869
R^2	0.161	0.0650	0.0774	0.0743	0.125	0.126

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

Notes: Dependent variable: ancillary costs. First three columns correspond to the three clusters of load profiles for TenneT and last three columns for TransnetBW. Each regression includes two-way fixed effects of 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 C.3: Ancillary Costs on Solar and Load by Pooling All Observations

	(1)	(2)
solar	0.305	-0.772
	(0.157)	(0.398)
solar^2	0.0000352^{*}	0.000405^{***}
	(0.0000141)	(0.0000702)
load	0.509^{***}	0.680^{**}
	(0.112)	(0.246)
load^2	0.00000526	-0.00000594
	(0.00000309)	(0.0000169)
solar × load	-0.0000411^{***}	-0.0000557
	(0.00000815)	(0.0000413)
solar^3		$-1.12\text{e-}08^{*}$
		(4.87e-09)
load^3		1.65e-10
		(3.60e-10)
solar × load^2		$2.56\text{e-}09^{*}$
		(1.18e-09)
solar^2 × load		$-1.25\text{e-}08^{***}$
		(2.89e-09)
FE	✓	✓
N	148,758	148,758
R^2	0.0475	0.0478

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

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

Table C.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 C.3 and evaluated at the mean solar output and the mean load.

Table C.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/`).

Table C.6: Ranking of TSOs by Output per Unit of Capacity Installed

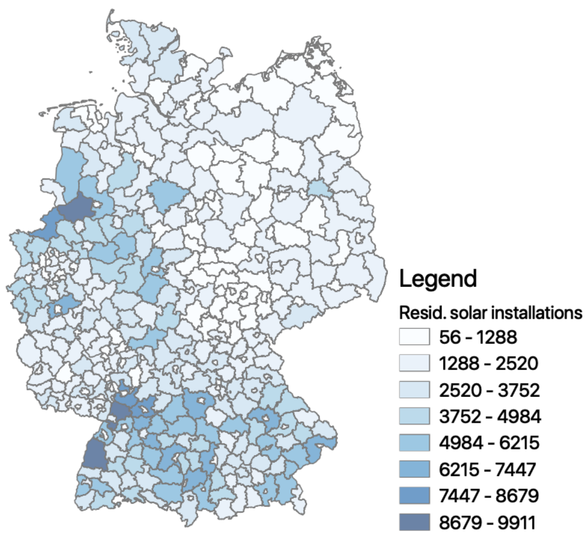
	(1)	(2)	(3)
TransnetBW	907.331***	988.127***	1037.727***
	(31.821)	(35.940)	(38.489)
Amprion	818.864***	927.586***	971.994***
	(22.174)	(30.437)	(32.935)
50 Hertz	820.226***	912.942***	966.330***
	(33.770)	(37.201)	(41.332)
TenneT	806.680***	894.915***	965.630***
	(22.579)	(28.738)	(33.769)
Controls:			
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
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

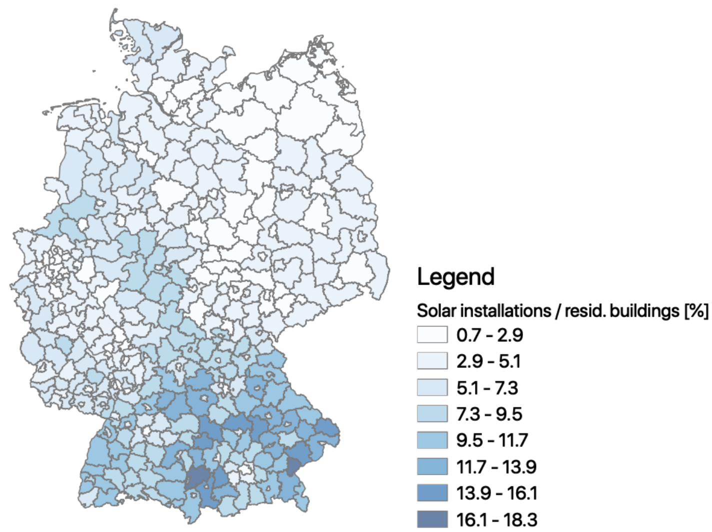
Notes: Dependent variable: output in kWh per kW of capacity installed. Control variables are included as categorial variables. The reference (omitted) category in column 2 are South facing solar plants with no shading and a large inverter size (> 7 kW). Column 3 additionally conditions on tilt (15-40 degrees as omitted category). For each column, the magnitude of the coefficients define the ranking in solar productivity.

Figure C.1: Residential Solar Installations

a: Cumul. Solar Uptake

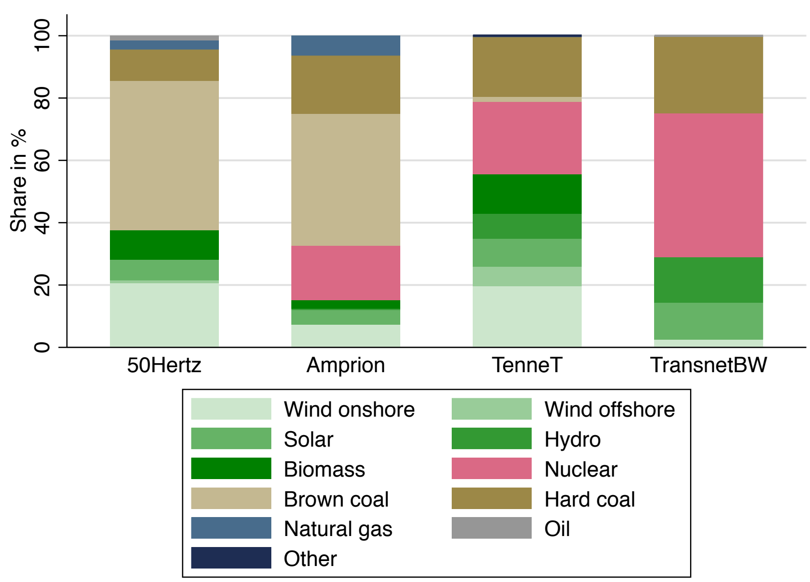


b: Cumul. Solar Uptake / Resid. Bldgs.



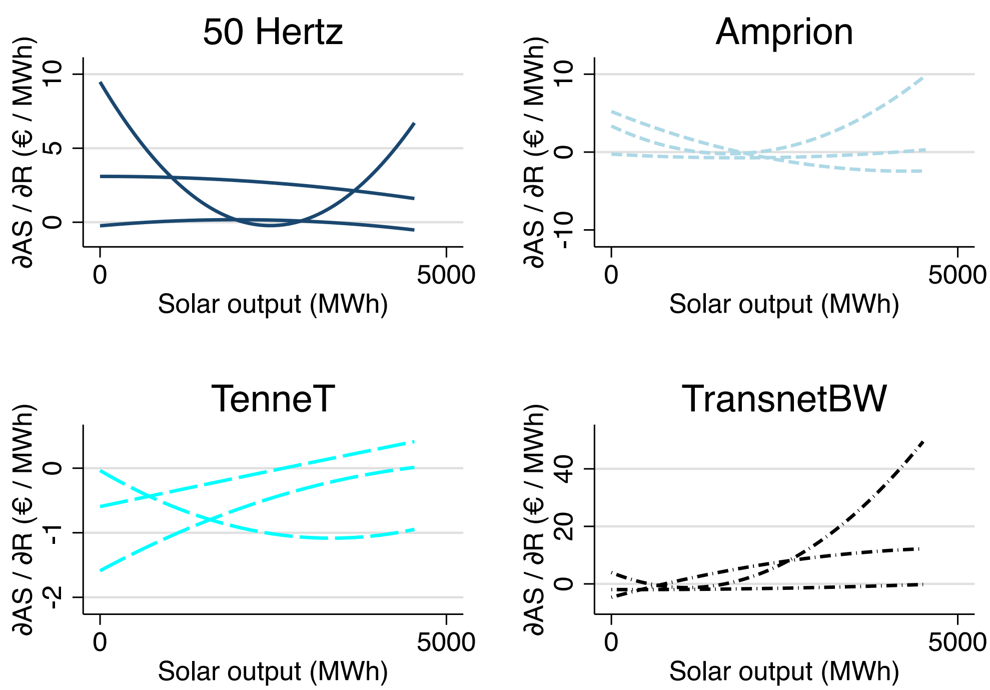
Notes: Cumulative residential solar installations (Dec 2016), with a maximum installed capacity of 10 kW (Panel a). Cumulative solar installations over residential buildings in Panel b. Darker areas represent more installed solar and higher penetration rates, respectively.

Figure C.2: Technology Portfolio Mix by TSO, Production 2015-16



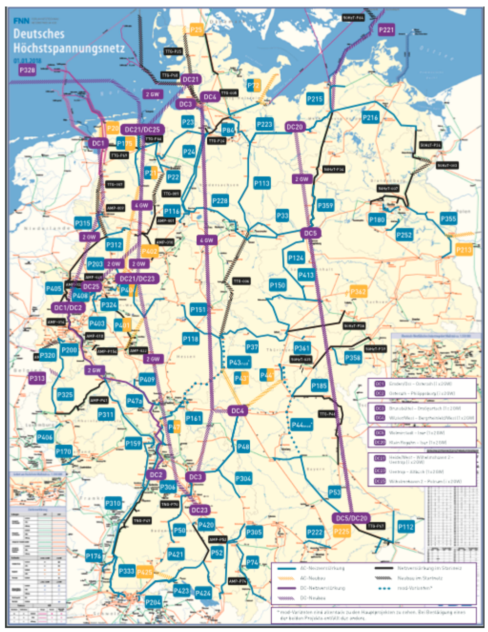
Notes: Average technology shares in electricity production 2015-16. Source: ENTSO-E.

Figure C.3: Effect of Solar Output on Ancillary Services Prices



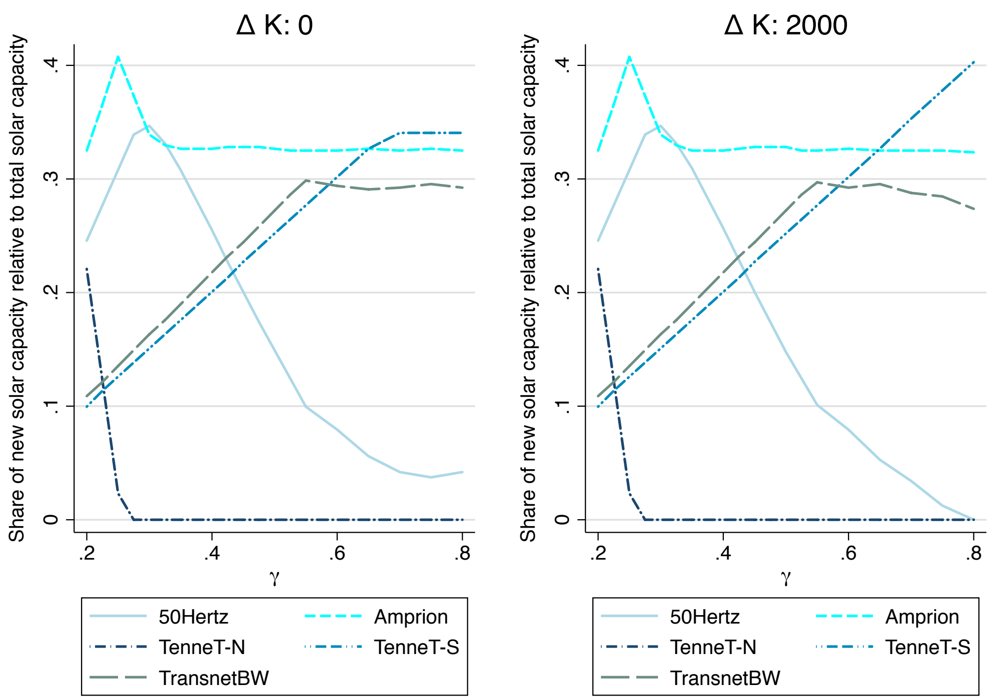
Notes: Functions obtained using the coefficients from the main specification of the ancillary services costs regressions evaluated at the mean of load in the TSO and in each cluster of load. The three lines for each TSO correspond to each of the clusters of load profiles. The maximum value in the horizontal axis is the 90th percentile of the Germany-wide distribution of solar output, which is greater than the maximum solar output observed for TransnetBW.

Figure C.4: Planned Extension of High Voltage Network



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

Figure C.5: 5 TSO with Transmission: Solar capacity allocation by TSO

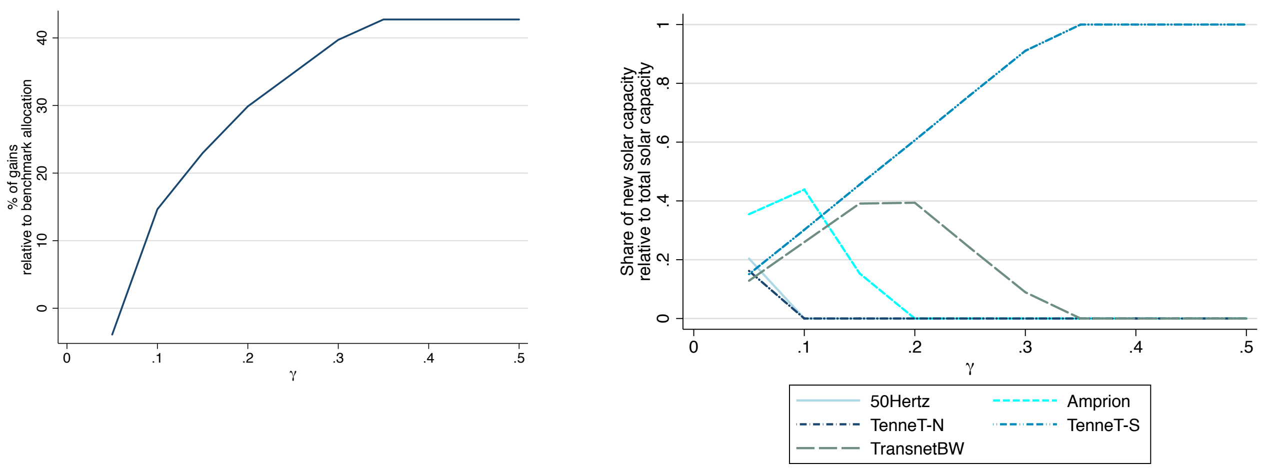


Notes: Solar capacity allocation as function of γ with and without interconnection between TenneT South (export region) and TenneT North.

Figure C.6: Reallocation of Residential Solar with 5 TSOs

a: Gains from Reallocation

b: Solar Capacity Allocation



Notes: Gains from reallocation and solar capacity shares when allowing for heterogeneous solar productivity in TenneT North and TenneT South but relying on the same MB_{jt} mapping in the two subregions. Residential installations only. No interconnection capacity assumed.