

Subsidized Renewables' Adverse Effect on Energy Storages and Carbon Pricing as a Potential Remedy

Mario Liebensteiner^{a,*} Adhurim Haxhimusa^b Fabian Naumann^c

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Abstract: Large-scale energy storage is viewed as a key complementary technology in a power system fed by a large share of intermittent renewable energies (RE). However, subsidies for RE – a well-intended market intervention – may distort price signals, thereby adversely undermining the profitability of energy storages and thus adequate investment incentives. We provide novel causal estimates supporting this notion, using an econometric instrumental-variables framework and data on Austrian pumped storages, operating in the German-Austrian electricity market, characterized by a large share of generously subsidized RE. We find that RE significantly depress storage profitability and that further deployment of RE will intensify this effect. This may pose an obstacle against adequate investment in bulk energy storage capacity. Moreover, we estimate that intensifying carbon pricing would significantly counteract the problem via a market-based price signal. Our paper contributes to the general debate on the design and effects of environmental regulation and particularly shows that a non-market-based policy for a green technology may adversely affect complementary technologies.

Keywords: Carbon pricing; Decarbonization; Energy transformation; Energy storages; Renewable energies

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Abbreviations: 2SLS, two-stage least squares; AT, Austria; DE, Germany; EEX, European Energy Exchange; ETS, emission trading system; IV, instrumental variables; EU, European Union; GW, Gigawatt; MW, Megawatt; HPS, hydroelectric pumped storage; RE, renewable energies; tCO₂, ton of carbon dioxide

^a*Corresponding author:* Friedrich-Alexander-Universität (FAU) Erlangen-Nürnberg, Lange Gasse 20, 90403 Nuremberg, Germany, mario.liebensteiner@fau.de

^bUniversity of Applied Sciences of the Grisons, Comercialstrasse 20, 7000 Chur, Switzerland, adhurim.haxhimusa@fhgr.ch

^cTechnische Universität Kaiserslautern, Gottlieb-Daimler-Str. 42, 67663 Kaiserslautern, Germany, fabian.naumann@wiwi.uni-kl.de

1 Introduction

Many countries around the globe have implemented ambitious support schemes for renewable energies (RE) to tackle anthropogenic greenhouse-gas emissions. However, the most important RE technologies, wind and solar, pose severe challenges to the energy system, because of their weather-dependent, volatile electricity production, which is decoupled from demand. As a result, network operators are often obliged to undertake undesirable steps, such as partial curtailments of renewable electricity infeed and redispatch measures to keep grid stability, eventually reducing the effectiveness of climate policies. In expectation of an energy system fed by a large share of RE, there is widespread consensus that *energy storage* will be essential to balance RE's production volatility [1; 2; 3; 4], thus sustaining electricity supply security, supporting the system integration of renewables [3; 5], as well as ensuring a smooth and effective decarbonization transition [6; 7].

Hydroelectric pumped storages (HPS) are currently the only economically viable utility-scale electricity storage technology, representing almost the entire global storage capacity (about 96% in 2018) [8]. The basic business model of HPS relies on differences in the electricity price over time. At low prices (e.g., at night), water is pumped uphill and then used to produce and sell electricity at peak prices. However, if subsidized RE decreased the electricity price and/or curbed price peaks (e.g. solar power may reduce the price peak around noon), the profitability of HPS could be affected – with potentially long-lasting investment effects [9]. Our idea is that subsidies for RE (guaranteed feed-in tariffs, as in our case) represent a form of state intervention into the electricity market, which boosts RE deployment independently of free-floating market signals arising from the interplay between demand and supply.

This study's objective is thus to assess a potential adverse effect of subsidizing RE on energy storage via an electricity price distortion. We apply an econometric two-stage least squares model with high-frequency data for the hourly period 2015/01/01–2018/06/30 to estimate the *causal chain effect* of subsidized RE via the wholesale spot price (the market distortion) on the profitability of HPS. We exploit the exogenous variation in electricity from wind and solar, subject to prioritized and guaranteed infeed at a-priori set feed-in tariffs, to disentangle the

causal partial effect of RE on HPS profits via the wholesale price. Our data are for Austrian HPS plants, operating in the common German-Austrian (DE/AT) electricity market. Austria has a large fleet of HPS plants, which is often referred to as the “battery of Europe”. Germany is the country with the highest per-capita support payments for RE and the largest installed intermittent RE capacity (predominantly wind and solar power) in the European Union [10]. This setup makes it a relevant case for investigation, because HPS are in constant interaction with substantial, volatile electricity infeed from RE. We find that subsidized RE erode the profitability of HPS via lowering the peak/off-peak price spread. We also estimate that carbon pricing countervails this adverse effect. Several robustness tests support our findings’ validity.

The neoclassical economic theory argues that exogenous market interventions, such as subsidizing RE, would deter otherwise undistorted price signals, needed for optimal investment (in our case, in energy storage capacity). Since Pigou’s seminal work in 1920 [11], neoclassical economics views carbon pricing as an efficient (and thus first-best) solution to greenhouse-gas emissions, with some recent empirical studies [12; 13] supporting this notion. The mainstream economics literature argues that carbon pricing sets *market-based incentives* for all economic agents (producers and consumers) to change their behavior according to their individual abatement costs. A carbon price would thus internalize the emissions externality efficiently, thereby avoiding any adverse effects on other technologies (e.g. energy storage). However, policy-makers seem to be reluctant against implementing “meaningful” carbon pricing, because most global CO₂ emissions are not covered by a carbon price or, if covered, are often subject to a relatively low price [14]. Moreover, despite the efficacy arguments, there is still a debate that carbon pricing may not suffice, but that a mix of climate policies would be necessary [15; 16], with some scholars even arguing for climate policies other than carbon pricing [17]. Yet, other policies than pricing the externality may result in an inefficient market outcome, going back to the “general theory of second best” [18]. Financial support for RE may thus be viewed as less efficient [19] and may create undesirable market distortions. Examples for this are “winner picking” of technologies to be subsidized based on imperfect information of policy-makers [20] or that RE subsidies may adversely drive less pollutant gas-fired power

plants out of the market, while highly pollutant lignite plants remain [21; 22]. This discussion highlights the need for further empirical research on the effects of RE subsidies and carbon pricing to guide the political progress towards successful climate-change policies. This study contributes by showing that generous subsidies for RE may disincentivize investment in storage capacity and that carbon pricing can counteract this adverse effect.

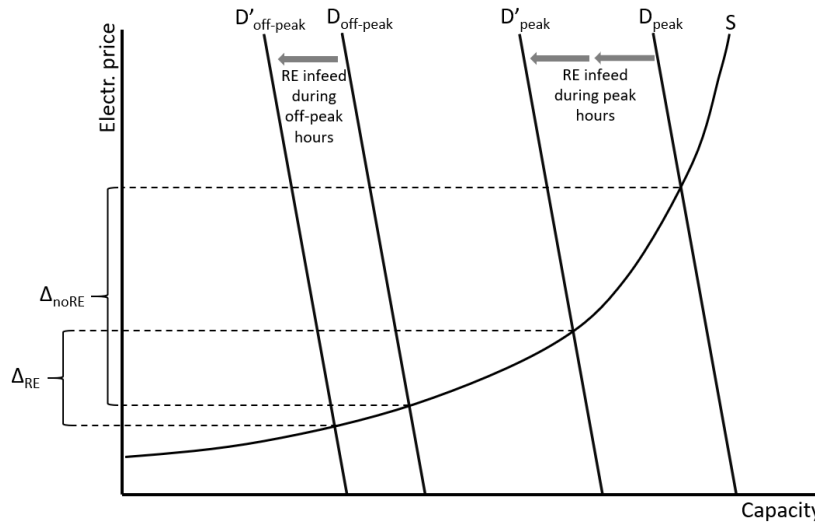
Our study is novel and relevant in several dimensions. Firstly, while there is already a large body of empirical literature on the dampening effect of RE on the electricity wholesale price (the so called “merit-order effect”; e.g. [23; 24]), the adverse effects of subsidized renewables on other complementary technologies (e.g., storages) are largely under-researched. We contribute in this regard. Secondly, we apply rigorous causal econometric analysis of how subsidized RE disincentivize energy storages, while many related studies merely use descriptive statistics or simulations based on stringent assumptions. For example, Hildmann et al. [25] merely discuss (but do not estimate or model) the idea based on descriptive statistics that a vast share of intermittent RE may undermine the business model of HPS. Gaudard [26] simulates the economic performance of a Swiss HPS unit, using assumptions about plant size, efficiency, and other technical aspects, finding that the unit is not economically viable under current market circumstances. RE are, however, not part of the modeling. Wilson et al. [27] use simple descriptive statistics of wholesale electricity price data from Germany and Britain to conclude that lower prices and lower price volatility depress the operating revenues of a simulated HPS plant. In contrast, the influence of RE is not modeled. Kougias and Szabó [9] provide descriptive evidence of uneven (increasing and decreasing) utilization rates of HPS units over time in select European countries, although RE do not enter the modeling. None of these studies establishes causality between RE and storage profits, for example, based on econometric modeling, or disentangles the effect of interest from potentially confounding factors. Thirdly, this is, to the best of our knowledge, this first study to find evidence on a profit-decreasing effect of subsidized RE on energy storage. Liu and Woo [28] apply a sophisticated econometric model and control for potentially confounding factors, yet find no profit-decreasing effect of RE on HPS in California. One potential explanation could be the rather low share of RE dur-

ing their sample period (12/2012–04/2015) and that operational profits of HPS were merely approximated by differences in the wholesale prices during typical pumping and generation hours. In contrast, we investigate a market with a significant share of RE and also employ data on storages' actual pumping and electricity production. Finally, a novel result of our study is that carbon pricing can counteract the adverse effect of subsidizing RE.

The aforementioned publications provide a valuable background for our analysis, by either relying merely on descriptive evidence and economic reasoning or on a more sophisticated methodology (such as [28]), but cannot establish credible evidence for a negative effect of RE on storage profits. To the best of our knowledge, we are the first to identify a significantly negative causal effect of subsidized RE on pumped-storage profits via a distortion of the electricity wholesale price, relying on sophisticated econometric modeling. Moreover, our study is novel in showing that carbon pricing supports the business model of pumped storage and can thus alleviate the problem.

We can derive rich policy implications based on our results. HPS operators often demand for state aid as a potential relief to losing profitability. Yet, this study indicates that intensifying carbon pricing can solve the current situation based on market incentives. An emissions price lifts the wholesale price of electricity and thus maintains the profitability of energy storage. Since there is still a debate among scholars about which climate policy measures would be necessary to decarbonize the economy (e.g., carbon pricing or direct financial aid for RE), our study provides another argument in favor of carbon pricing. The reason is that carbon pricing would not only abate emissions effectively via market-based incentives, but also maintain investment incentives for energy storages (and thus potentially also for other complementary storage facilities).

Figure 1: Schematic effect of subsidized RE on the electricity price spread (Δ_p)



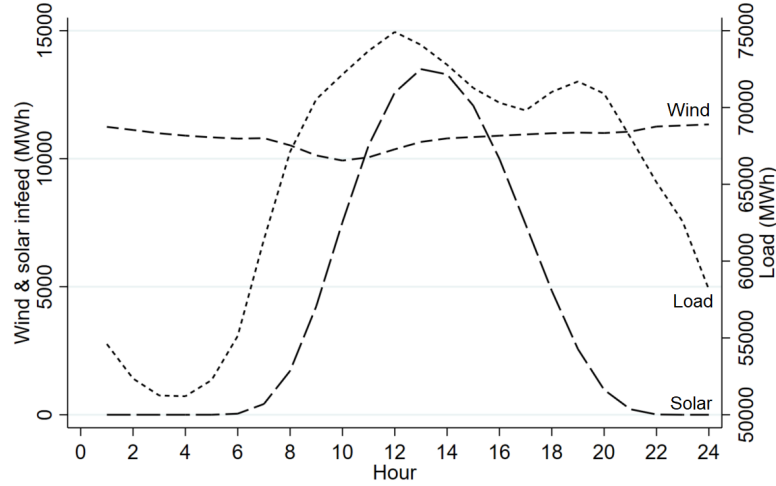
RE infeed reduces the residual demand (D'). While wind power has a rather flat generation profile across the hours of a day, solar power's peak at noon coincides with peak demand, indicated by the second arrow during peak hours. RE infeed diminishes the price spread (Δ_p) between peak and off-peak demand for a typical convex electricity supply curve.

2 Background

2.1 Potential effect of RE on HPS profits

It is worth discussing how RE may affect the price spread between pumping and generating, to infer about potential profitability impacts. Any price distortions, for example through stochastic supply shocks arising from intermittent RE infeed, will affect storage profits. Figure 1 provides a simple stylized illustration of how RE infeed may impact the price spread between peak and off-peak hours. Due to the typical convexity of the supply curve (as determined by increasing fuel costs from the base- to peak-load plants), the divergence between low demand during off-peak times and high demand during peak times results in a price spread. The residual electricity demand curve is shifted to the left whenever RE feed into the system. While in Germany wind infeed exhibits, *on average*, a rather flat infeed profile across the hours of a day, solar infeed peaks at around noon, which coincides with peak demand (see Figure 2). Hence, while there is evidence that *average* solar infeed is load-following, this hides significant stochastic

Figure 2: Profiles of load and wind & solar infeed, sample averages



volatility of weather-driven infeed across hours. As a result, a high and increasing share of *intermittent* RE would require storage facilities to avoid ever-increasing needs for balancing measures or import dependency.

Two aspects are noteworthy in Figure 1. First, even for a flat RE feed-in profile, as with wind power, which would approximately equally shift the residual demand during peak (D'_{peak}) and off-peak ($D'_{off-peak}$) times, the convexity of the supply curve would lead to a reduced price spread ($\Delta_{RE} < \Delta_{noRE}$). Second, the coincidence that solar energy mostly impacts peak demand implies that the shift is stronger during peak times, which means that the price spread gets even further reduced. Wozabal et al. [29] underpin our argument that RE reduce the price spread by empirically estimating that RE infeed reduced the electricity price variance in Germany during 2007–2013. However, electricity markets around the globe are heterogeneous. How peak and off-peak prices respond to wind and solar infeed, depends strongly on the supply structure and RE infeed profiles. In contrast to our setting, which finds that subsidized RE shave peak prices more than off-peak prices, Bushnell and Novan [23] (for California) and Jha and Leslie [30] (for Australia) find that RE depress off-peak prices relative to peak prices, leading to a somewhat different setting than ours.

Hence, before presenting our econometric model's main findings, this is stylized evidence

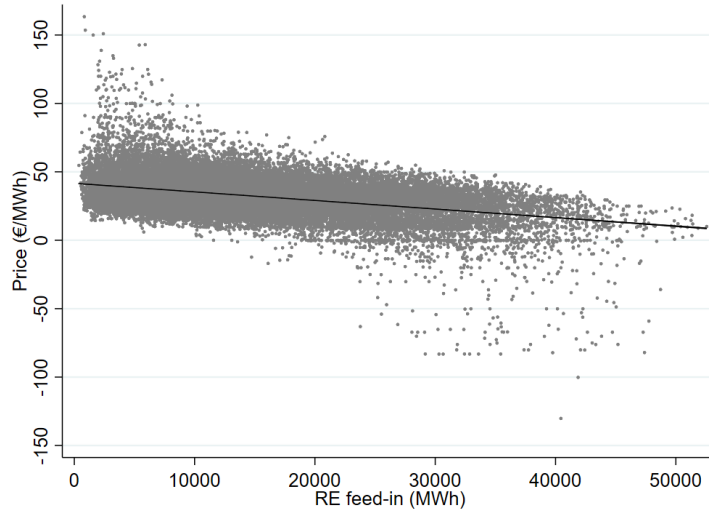
that subsidized RE may deter the business model of HPS via distortions of the wholesale electricity price (and its spread during peak off-peak times). To further underline this argument, Figure 3 shows for our data sample that RE and day-ahead wholesale electricity prices are negatively correlated and that price peaks cannot be observed during high levels of RE feed-in. Moreover, the Online Appendix presents a simple theoretical model to guide our empirical analysis. It shows that the peak/off-peak price spread is indeed the profitability driver of storages (and that the price spread must be large enough to even exceed efficiency losses of storage cycles).

2.2 Additional information

European HPS plants' installed capacity amounted to 45,622 MW in 2018, with a low mean annual growth rate of around 1% during 2006–2018 [31]. This low storage capacity growth rate cannot support the system integration of vastly expanding RE [3; 5; 6; 32]. Despite its small size, Austria has 10% (i.e. 4,420 MW) of this capacity [31]. It is thus often called the “battery of Europe.” HPS plants require specific geographical peculiarities (e.g. an upper and lower water reservoir and a sufficient height difference), limiting its capacity expansion, potentially explaining the slow growth rate. On the other hand, several sources indicate that HPS capacity investment in Austria could have been profitable [33; 34] and technically feasible (i.e., unexploited sites meeting HPS requirements) [34; 35] during our sample period in Austria. Moreover, [33] lists HPS projects in Austria, which were at the planning stage or under construction in 2017, with a total turbine capacity of 3,779 MW. This shows that investors expected storage investment to be profitable at that time.

Germany's share of renewable energies in total electricity production has increased steadily from 6.3% in 2000 to 37.8% in 2018 [36]. It is expected to grow further to at least 80% by 2050 [37]. The roll-up of Germany's RE is largely financed by substantial financial support via guaranteed feed-in tariffs [10]. This development is likely to impact on the wholesale price of electricity severely. Based on our data sample, Figure 3 provides descriptive evidence that renewables are negatively correlated with the wholesale electricity price and that price peaks vanish

Figure 3: Wholesale electricity price & RE feed-in



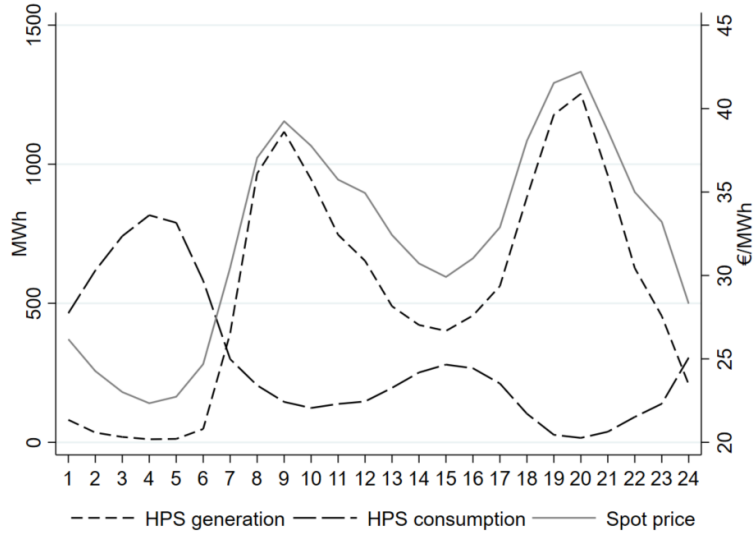
The graph shows combinations of hourly day-ahead forecasts of renewables infeed and day-ahead electricity prices.

for moderate to high RE feed-in.

One caveat of our study is that we only observe data on wholesale electricity prices from the DE/AT day-ahead spot market. We acknowledge that HPS operators may also serve other markets, such as reserve or balancing markets. In contrast, the day-ahead market represents the most relevant market and may thus be viewed as the opportunity market (see section 3.3 for more details). Figure 4 depicts hour-of-day sample averages of production and consumption of Austrian HPS plants, together with the day-ahead spot price, showing strong correlations, which indicate that the day-ahead spot price is indeed relevant for the HPS activity.

Power plants operating in the DE/AT market are subject to the EU ETS, which puts a price on tradable emission permits. Yet, the emissions price was low since its establishment in 2005 (mostly because of an abundance of permits and a generous policy of crediting low-carbon investments in third countries for permits [38]). Figure 5 shows the development of the carbon price for our sample period. It was not until January 19, 2018, that the carbon price exceeded its historic local maximum of only €8.7/tCO₂. Such a low price may not send proper incentives to invest in renewable energies or induce significant emissions abatement [39]. However,

Figure 4: HPS production & consumption by hour of day



The graph shows sample averages of HPS electricity production and consumption in MWh (left y-axis), as well as the electricity day-ahead spot price in €/MWh (right y-axis).

Figure 5: Carbon price (€/tCO₂) in the EU ETS



European Emission Allowances (EUA) price, daily closing value in €/tCO₂. The dashed line is for the local maximum carbon price of 8.7 €/tCO₂ before 2018.

during the last six months of our sample the carbon price climbed up to about €16/tCO₂ (most likely induced by a reduction in the emissions cap). As we argue later, political action towards a significantly higher carbon price may be a viable strategy to relieve the depressing effect of subsidized renewables on the HPS profits.

3 Material and Methods

3.1 Baseline model: causal effect of RE via P on π

Our goal is to estimate the causal chain effect of RE on the profitability of HPS plants, where the causal link is via the wholesale electricity price. We thus apply an econometric two-stage least squares (2SLS) model. The first-stage regression estimates the effect of RE on the wholesale price:

$$P_t = \alpha_{RE}^{1st} RE_t + X_t' \alpha^{1st} + \epsilon_t^{1st}, \quad (1)$$

where RE is the day-ahead forecast of RE infeed, X is a vector of control variables (i.e. load, temperature, temperature squared, price of coal, price of gas, price of CO₂; c.f. data description in section 3.5) including seasonal fixed effects (i.e. fixed effects per year, month, day-of-week, and hour-of-day;), and ϵ_t is the error term. The subscript t is a running time indicator for each sample hour.

In the second stage, we estimate the effect of the predicted price, \hat{P} , on the variable HPS profit (π):

$$\pi_t = \alpha_P^{2nd} \hat{P}_t + X_t' \alpha^{2nd} + \epsilon_t^{2nd}. \quad (2)$$

The first stage (eq. (1)) estimates the merit-order effect, where $\hat{\alpha}_{RE}^{1st}$ measures how much the wholesale price decreases for a marginal increase in the feed-in of RE. Together with the estimates from the second stage (eq. (2)), we can estimate the *causal chain* of a change in RE on the wholesale price and further on the HPS profit as $\hat{\alpha}_{RE}^{1st} \times \hat{\alpha}_P^{2nd}$ [40].

3.2 Price spread

At first sight, the application of the price *level* may not seem to align with our reasoning that the *price difference* between peak and off-peak hours (i.e. Δ_p in our theoretical model in the Online Appendix) is the main profitability driver of HPS. Since we use high-frequency data at the hourly resolution, this is no contradiction, because the prediction of the price series (\hat{P}_t) incorporates the effect of RE on the electricity wholesale price in each hour of the sample, including the effect on price peaks. One way of proofing this is to substitute the price level P for an hourly measure of the price spread (Δ_p) in equation (1), which we define as the price difference between the actual price per hour (P_t) and the daily mean spot price (\bar{P}): $\Delta_p = P_t - \bar{P}$. By definition, the results must be congruent with the baseline model's. The results (see Table 2) and are indeed consistent.

3.3 Identifying assumptions

Our just presented research design uses some important assumptions that deserve attention. First, the 2SLS analysis rests on the exclusion restriction, which requires the instrument (forecasted RE infeed) to impact the outcome variable (storage profits) only through the endogenous variable (spot price). Otherwise, the error term would be correlated with the endogenous variable, leading to estimation bias. The exclusion restriction is not testable, but using economic rationale, it is likely to hold, because RE are determined by wind speed and solar radiation, which may not influence storage operations. There are good reasons that wind and sunshine are unrelated to storage operations. For example, wind and sunshine may not have a pronounced effect on the water levels of the upper or lower storage basins, as to significantly influence the short-run business of HPS. Moreover, to be a valid instrumental variable, forecasted RE infeed must be correlated with storage profits, which is testable: the first-stage statistics show a statistically significant partial coefficient estimate and the Kleibergen-Paap first-stage F statistic, testing for weak instruments, is sufficiently high.

Second, storage operations may not significantly influence electricity prices. This is because storage infeed makes up only a small fraction of the DE/AT electricity mix, so market

power should be fairly limited. According to our data, the average electricity infeed of HPS makes up 0.77% of the load. In any case, our baseline econometric model treats the wholesale electricity price as endogenous to storage profits. By applying an instrumental-variable (IV) approach we circumvent any problems of endogeneity or reverse causality.

Third, as we state in Section 2.2, our measure of storage profitability is derived from the day-ahead spot market: the costs of observed pumping activity and the revenues of observed production activity are evaluated for day-ahead electricity prices, because from the data we cannot distinguish in which markets (e.g. day-ahead spot, intraday, balancing) the storage plants operate. For this reason, we employ the day-ahead spot price as the *reference price*, essentially assuming that there is no arbitrage across markets. This assumption is necessary to conduct our analysis. However, it also seems evident that the day-ahead spot market, as by far the largest and most relevant market, represents the opportunity market for all other markets. Industry experts also told us that Austrian HPS plants accrue most of their revenues from the day-ahead market. Moreover, many academic studies follow a similar avenue. Analyzing revenue streams of HPS in Germany and Britain, Wilson et al. [27] also use day-ahead spot prices. [41] and [42] are further examples of studies of electrical storages in day-ahead markets. Analogously, [22] and [43] assume that the day-ahead market serves as the reference market for electricity-generating power plants, which may also participate in other markets (e.g. intraday). Ortner and Totschnig [44] show quantitatively that Germany's and Austria's day-ahead markets are the most relevant markets in terms of revenues and traded volumes (e.g. balancing markets' monetary volume is less than 3% of day-ahead markets' volume in these countries). However, we acknowledge that our profitability measure is a proxy for actual profitability, representing a lower bound of actual profits (because prices tend to be higher at subsequent markets).

Fourth, there may be the suspicion that owners of storage capacity, who also own RE capacity, may jointly optimize RE generation and storage. This way, RE would be endogenous to storage operations. However, RE enjoy prioritized feed-in at guaranteed, subsidized tariffs in Germany. This way, RE plants will feed into the system whenever the wind blows or the

sun shines. To rule out doubts about the exogeneity assumption, in Section 5.7 we will discuss this issue further and run regressions using wind speeds and solar radiation as instrumental variables.

Finally, our paper investigates *short-run* profitability. We measure short-term variable profits, which disregard output-independent fixed costs. We do not have access to data on fixed or investment costs and can thus not infer the general profitability of capacity investments. Our assumption is that short-run profits are significantly distorted by exogenous market intervention in the form of subsidized feed-in tariffs for RE. This way, wholesale price signals are not (anymore) driven solely by free market forces of demand and supply, thereby sending distorted price signals for investments in other (complementary) technologies, such as HPS. Hence, our detailed data about short-run variable profits allow for claims about profitability shifts in the pumped-storage industry as a response to changes in subsidized renewable energies and their effect on electricity spot prices. If short-run profits decrease, this means that the amortization period becomes delayed or that the investment becomes unprofitable. Moreover, our analysis cannot deliver estimates to infer any longer-run implications, such as learning and innovation, which would nevertheless be among the important elements in understanding the impact of high shares of RE.

3.4 Effect of RE on peak vs. off-peak prices

We may also show that RE have not only a negative average effect on the electricity wholesale price, but that the effect is stronger during peak times (as suggested by Figure 1), thereby dampening the peak/off-peak price spread. To do so, we extend the first-stage equation (1) by an indicator for peak hours and its interaction term with RE:

$$P_t = \beta_{RE}RE_t + \beta_D D_t + \beta_{RE \cdot D} RE_t \cdot D_t + X_t' \beta + \epsilon_t, \quad (3)$$

where D is a binary indicator, which takes up a value of one during peak hours (i.e. 8h–20h) and zero otherwise. Following the same procedure as above, we can then obtain the price prediction (\hat{P}_t) and re-estimate the second stage (equation (2)), which should yield qualitatively

similar results as the above procedure. While the estimate of $\hat{\beta}_{RE}^{1st}$ measures the effect of *RE* on *P* during off-peak hours, $\hat{\beta}_{RE}^{1st} + \hat{\beta}_{RE \cdot D}^{1st}$ measures the effect during peak hours. We expect RE's effect to be more negative during peak than off-peak hours: $\hat{\beta}_{RE}^{1st} + \hat{\beta}_{RE \cdot D}^{1st} < \hat{\beta}_{RE}^{1st}$.

3.5 Data

This analysis combines high-frequency (i.e. hourly and daily) data from several sources for 2015/01/01,01h–2018/06/30,24h. Our sample thus ends before the common German-Austrian electricity market was split on 1 October 2018 into two national price zones (during hours of cross-border electricity flows exceeding a capacity limit of 4.9 GW).

We calculate the hourly variable HPS *profits* at the aggregate (i.e., industry) level as the revenue of generating electricity minus the costs of pumping water uphill: $\pi_t = (q_{Gen,t} - q_{Pump,t}) \cdot p_t$, where q_{Gen} and q_{con} represent generation and consumption, p the spot price, and the subscript t the hour of our sample. Data on electricity production and consumption of HPS plants in Austria are obtained from the European Network of Transmission System Operators for Electricity [45]. Unfortunately, consumption data were missing for most other European countries, which eventually narrowed our analysis to Austrian HPS, for which the data were comprehensively available.

As the reference price of wholesale electricity, we use the hourly day-ahead price for the common DE/AT EPEX spot market, as obtained from the Transparency Platform of the European Energy Exchange (EEX) [46]. It is worth noting that the spot price can be negative for the rare events of feed-in of renewable energies (which is guaranteed and prioritized) exceeding the demand for electricity (less must-run electricity production from base-load power plants).

Regarding RE infeed, we use data on hourly *day-ahead forecasts*, because we analyze the day-ahead spot price of electricity. The data comprise onshore wind, offshore wind, and solar for Germany and Austria, as provided by [45]. Please note that day-ahead *forecasted* and *actual* wind and solar electricity generation are highly correlated (i.e. 98%). The same source provides hourly data on the joint electricity demand (load) in Germany and Austria.

Data on the input prices of coal and natural gas are obtained from S&P Global Platts [31],

Table 1: Sample statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Dependent variable</i>					
Variable profit (€) ^a	30,592	18,557	42,940	-88,345	445,249
<i>Variables of Interest</i>					
RE infeed (MWh) ^{a,c}	30,592	15,072	9,563	372	52,550
RE infeed, 8–20h (MWh) ^{a,c}	16,571	18,415	9,594	372	52,550
RE infeed, 20–7h (MWh) ^{a,c}	14,021	11,121	7,869	524	44,404
Wind infeed (MWh) ^{a,c}	30,592	10,825	8,212	241	44,404
Solar infeed (MWh) ^{a,c}	30,592	4,247	6,456	0	29,484
<i>Control variables</i>					
Electr. price (€/MWh) ^a	30,592	32.19	14.77	-130.09	163.52
Electr. price, 8–20h (€/MWh) ^a	16,571	35.66	16.00	-130.09	163.52
Electr. price, 21–7h (€/MWh) ^a	14,025	28.08	11.92	-83.06	109.92
Load (MWh) ^a	30,592	62,661	10,901	33,951	86,408
Price of coal (€/MWh) ^b	30,592	7.61	1.77	4.62	11.32
Price of gas (€/MWh) ^b	30,592	17.50	3.17	10.83	43.86
Price of CO ₂ (€/tCO ₂) ^b	30,592	7.12	2.57	3.93	16.28
Temperature (°C) ^a	30,592	10.20	7.42	-11.68	35.59
<i>Instrumental variables</i>					
Wind speed (m/s) ^a	30,592	3.97	1.65	1.09	14.08
Sunshine (min) ^a	30,592	11.88	17.02	0.00	60.00

Sample period: 2015/01/01,01h–2018/06/30,24h. ^aHourly resolution. ^bDaily resolution. ^cDay-ahead forecast.

a major independent data and information provider for the energy and commodities markets. We use the Europe CIF ARA price of coal, converted from US\$ per ton to €/MWh, which is available for the daily frequency. We use the daily exchange rate from the European Central Bank for currency conversion. The price of natural gas is derived from Gaspool Germany in €/MWh. The price of CO₂ is obtained from EEX [46], representing the daily closing value of the EUA Primary Spot Auction, in €/tCO₂.

Hourly data on the temperature (in °C) stem from the German Weather Service (“Wetterdienst”) for many weather stations. For our purposes, we chose 16 stations, each located in a city approximately in the center of a German federal state and took the mean values.

Table 1 provides descriptive statistics of our sample. Comparing means with standard deviations suggests that our main variables of interest (variable profits, RE infeed, electricity price) have sufficient variation. It is worth noting that, on average, the HPS industry makes positive profits of €18,557 per hour. The average electricity spot price is €32.18 per MWh, whereas it is significantly higher during peak hours from 8–20h (€35.66) compared to off-peak hours

(€28.08). Renewables have an average infeed of 15,072 MWh, with a significantly higher infeed during peak hours (18,415 MWh) than during off-peak hours (11,121 MWh). Moreover, Online Appendix Table A2 shows correlations of our main variables, indicating that multicollinearity is no issue in our regressions.

4 Results

4.1 Baseline model

Table 2 summarizes the estimates of our baseline two-stage model, the model using the price spread (instead of price) as the endogenous variable, and the model on peak versus off-peak prices. Full regression output tables of all regressions are provided in the Online Appendix. Apart from the main coefficients of interest, all control variables (except for the price of natural gas in some specifications) are statistically significant (see Online Appendix Table A1) and have the expected signs. All IV regressions yield high Kleibergen-Paap first-stage F statistics (the critical value is about 10), rejecting the null hypothesis of weak instruments.

Column (1) of Table 2 reports the estimates of the first-stage model, which gives a negative and statistically significant effect of RE on P . We estimate that a partial increase in the feed-in of RE by one MWh depresses the electricity wholesale price by 0.105 cents per MWh. Evaluated at the means of the respective variables, we can calculate an elasticity: a 10% increase in RE (i.e. 1,507 MWh) leads to a decrease in the electricity wholesale price by 4.90% (i.e. -1.58 €/MWh) – an economically sizable effect.

Evaluated at the mean feed-in of RE of 15,072 MWh, the wholesale price already dropped by 15.77 €/MWh, relative to the counterfactual of no RE feeding into the system. Against a sample mean price of 32 €/MWh, this effect is considerable. Our estimate is also in line with [24], who estimate that one MWh of RE decreases the DE/AT electricity spot price by 0.103 cents per MWh during 2010/07/01–2012/06/30 (when the share of RE was not as pronounced as during our sample).

As presented in column (2), the second stage shows that a marginal change in electricity

Table 2: Main regression results

	Baseline model		Price spread		Peak vs. off-peak	
	(1) IV: 1st stage Price (P)	(2) IV: 2nd stage Profit (π)	(3) IV: 1st stage Price spread (Δp)	(4) IV: 2nd stage Profit (π)	(3) IV: 1st stage Price (P)	(4) IV: 2nd stage Profit (π)
RE	-0.00105*** (1.13e-05)		-0.000317*** (6.32e-06)		-0.00101*** (1.57e-05)	
Price		1,701*** (44.59)				1,736*** (44.73)
Price spread				5,621*** (143.9)		
D^{peak}					0.8778** (0.360)	
RE · D^{peak}					-5.29e-05** (2.09e-05)	
Control variables	yes	yes	yes	yes	yes	yes
Seasonal FE	yes	yes	yes	yes	yes	yes
Observations	30,592	30,592	30,592	30,592	30,592	30,592
R ²	0.788	0.558	0.550	0.222	0.789	0.552
First-stage F stat.	8,612		2,511		2,908	
Effect 10% Δ RE on P	-4.90%					
– during 8–20h (peak)					-5.00%	
– during 21–7h (off-peak)					-4.75%	
Effect 10% Δ RE on π		-14.46%		-14.46		-14.31%

Notes: Standard errors in parentheses are robust to heteroskedasticity and allow for first-order serial correlation (Newey-West SE). *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Sample period: 2015/01/01,01h–2018/06/30,24h. Columns 1: instrumented for price by RE. Column 3: instrumented for the price spread by RE. Column 5: instrumented for the price by RE, D & $D \cdot \text{RE}$. At the bottom of the table, we present changes in P and π for a 10% partial change in RE , evaluated against the mean values of all variables. Control variables: load, temperature, temperature squared, price of coal, price of gas, price of CO₂. Seasonal fixed effects: annual, monthly, day-of-week, and hour-of-day.

wholesale price by one €/MWh is associated with a statistically significant increase in HPS profits by €1,701 per hour. Assessing the causal chain, an 10% increase in subsidized RE leads to a decrease in HPS profitability by 14.46%, via a distortion of the electricity wholesale price (i.e., -4.90% or -1.58 €/MWh), evaluated at mean values of the respective variables. Thus, subsidized RE indeed have a significantly negative effect on HPS profits.

4.2 Price spread

Importantly, investigating the price *level* at a high data frequency (hourly resolution), including all peaks and lows, is qualitatively similar to analyzing the price *spread*, which we identified as the profitability driver of HPS in the theoretical model (see the Appendix). The price-spread model in Table 2 shows that the estimated effect of *RE* via Δ_p on π (following the estimation procedure described in section 3.2) delivers fully robust results. Our findings also support the notion that RE have a depressing effect on the price spread between peak and off-peak hours (i.e., -0.032 cents per MWh), as shown in a stylized manner in Figure 1.

4.3 Peak vs. off-peak

Table 2 estimates another first-stage regression (c.f. eq. (3)), which includes an interaction term of RE with a dummy for peak hours (8–20h). We estimate price effects of -0.105 cents and -0.106 cents per MWh during off-peak and peak hours, respectively, which is again in line with expectations. Also, the second-stage regression (column (4)) delivers qualitatively similar results as our baseline regression: a 10% increase in RE deters HPS profits by 14.3%.

5 Threats to identification, robustness & additional results

In this section, we present additional estimation results and robustness regressions to rule out threats to identification. Table 3 summarizes these estimates. Moreover, full regression output tables are provided in Online Appendix.

Table 3: Summary of alternative regressions

	(1) Red. form	(2) Wind vs. solar	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Wind vs. solar		Inclusion of RE lags			Daily frequency		Non-linear effect	
	Profit (π)	IV: 1st stg Price (P)	IV: 2nd stg Profit (π)	Lag: 1h Profit (π)	Lags: 1h & 24h Profit (π)	Lags: 1h–24h Profit (π)	IV: 1st stg Price (P)	IV: 2nd stg Profit (π)	IV: 1st stg Price (P)	IV: 2nd stg Profit (π)
RE	-1.780*** (0.0414)						-4.33e-05*** (1.76e-06)		-0.000783*** (3.09e-05)	
RE ²									-6.95e-09*** (8.97e-10)	
Wind		-0.00103*** (1.19e-05)								
Solar		-0.00116*** (2.25e-05)								
$\sum_{t=-24}^{t=0} RE_t$				-1.795*** (0.0417)	-1.691*** (0.0467)	-1.252*** (0.0482)				
Price			1,731*** (44.68)					1,176*** (124.8)		1,643*** (45.87)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Seasonal FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	30,592	30,592	30,592	30,587	30,560	30,472	1,275	1,275	30,592	30,592
R ²	0.550	0.789	0.557	0.550	0.551	0.584	0.829	0.539	0.791	0.560
First-stage F stat.		4,377					2,001		641	
Effect 10% ΔRE on P							-4.87%		-3.67%	
Effect 10% ΔRE on π	-14.46%			-14.58%	-13.74%	-10.17%		-9.93%		-10.45%
Effect 10% ΔW on P		-3.47%								
Effect 10% ΔS on P		-1.53%								
Effect 10% ΔW on π			-10.41%							
Effect 10% ΔS on π			-4.58%							

Notes: Standard errors in parentheses are robust to heteroskedasticity and allow for first-order serial correlation (Newey-West SE). *** p < 1%, ** p < 5%, * p < 10%. Sample period: 2015/01/01,01h–2018/06/30,24h.

5.1 Reduced-form model

We can also estimate the reduced-form model, which measures the *direct* effect of RE on HPS profits:

$$\pi_t = \delta_{RE} RE_t + X_t' \delta + \epsilon_t. \quad (4)$$

The results of this model should be qualitatively similar to the baseline model as long as the electricity wholesale price is indeed the main channel through which RE affect π . Indeed, the results, as presented in Column 1 of Table 3, are fully robust: a marginal increase in subsidized RE by one MWh depresses HPS profits by €1.78 per hour, which is equivalent to a drop in profits by 14.46% evaluated for a 10% increase in RE.

5.2 Wind vs. solar

The above discussion already points to the differential effects of wind and solar power. Moreover, recent studies support this notion, showing that solar power decreases the electricity price during the daytime, whereas prices increase during non-daylight hours for California [23] and for Western Australia [30]. Similarly, Novan [47] argues for Texas that wind and solar follow different feed-in patterns during the hours of the day, thus having significantly heterogeneous effects on emissions abatement. Moreover, Linn and Shih [48] show for Texas that wind and solar have contrasting relationships with demand. In the DE/AT electricity market, the feed-in profile of wind is rather flat during the 24 hours of a day. In contrast, solar's peak at noon partly overlaps with high electricity demand during the day (see Figure 2).

Against this backdrop, we quantify the separate effects of wind and solar power. We follow our baseline approach, but replace RE with day-ahead forecasts of wind and solar in-feed. Columns 2 and 3 of Table 3 provide the regression estimates. The first-stage estimates are, as expected, that solar's coefficient estimate (-0.00116) is more pronounced than wind's (-0.00103) (a t-test rejects the H_0 of equal coefficients at the 1% level). However, in the DE/AT electricity market, the sample mean hourly infeed of wind (10,825 MWh) is significantly higher than that of solar (4,247 MWh). Hence, we find a stronger profit-decreasing effect for a 10% in-

crease in the wind infeed (-10.41%) compared to that of solar infeed (-4.58%).

Our estimates indicate that both forms of subsidized renewable energies, wind and solar power, have significantly negative effects on the electricity wholesale price and the profitability of HPS plants. While solar's marginal effect is more pronounced than wind's, the higher feed-in level of wind is eventually more responsible for the decreasing HPS profits. Our results may be true for any electricity market that is somehow comparable to the common German-Austrian electricity market. That is, the electricity supply is a roughly convex function and renewable energy infeed-profiles are that they reduce the price spread between peak and off-peak times. However, it is also possible to have electricity markets where renewable infeed is much less pronounced during peak hours than during off-peak hours or where renewables even increase off-peak prices (e.g. [23] find for California that solar electricity increases the wholesale price during shoulder hours). This calls for further empirical research on this topic.

5.3 Data frequency & level of aggregation

There has been a discussion around the appropriateness of our approach using hourly data. For example, it was argued that our regressions would only be informative about the effect of a within-hour change in RE generation on HPS profits within the same hour. However, an incremental change in RE generation within an hour may likely affect storage profits in other subsequent hours. For example, if renewables caused a price decrease in one hour, this might lead a storage facility to pump (i.e., reduce profits in that hour), while the storage plant may earn a higher profit in a later hour, when it releases the stored water to produce electricity. This way, our econometric model at the hourly level would not capture the full effect of a change in RE on storage profits due to the dynamic incentives of storage operators. One way of addressing across-hour effects would be to run regressions at a higher aggregation level (e.g. at the daily level) [23; 49] or to stay with the hourly specification and add lags of RE generation to control for dynamic effects [30].

Despite these arguments, we believe that our so-far analysis has been valid, because we use of hourly observed data on actual pumping and generation activity of HPS and actual

wholesale electricity prices. This way, we know exactly how much energy used for pumping and for which electricity price, as well as how much electricity was generated and for which price. Hence, even if changes in RE infeed led to a change in the pumping-production behavior of HPS (such as delaying production to later hours when solar depresses the price peak at noon), we observe and can analyze these patterns in our data. This reassures us that there are no profit leakages arising from the data aggregation level that we chose in our empirical approach.

One may think that adaptations of pumping or production activity to supply shocks through changes in RE infeed might take time (as is the case with base-load power plants, such as lignite plants), which would justify the inclusion of lags in RE infeed. HPS are, however, designed to react fast to changing market circumstances, mitigating this concern. Nevertheless, we also present econometric regressions addressing this issue.

Hourly frequency with lags of RE — Given that using several lagged variables of RE infeed would lead to over-identification issues (even the inclusion of only one one-hour lag already gives a p-value of the Hansen J statistic of 0.000), we run the reduced form and additionally include lags of RE infeed. In the first specification, we include a lag of one hour. Both coefficients enter statistically significant. Their composite coefficient estimate is -1.795 and statistically significant (p-value of 0.00). In relative terms, this means that an increase in RE by 10% relative to the mean decreases storage profits by 14.58%. This is a qualitatively robust result. In another specification, we add both a one-hour lag and a 24-hour lag (i.e., the same hour during the previous day). The results are again robust: the composite coefficient estimate is -1.691 and statistically significant (p-Value of 0.00), implying that a 10% increase in RE leads to a decrease in profits by 13.74%. Finally, we include the whole series of all 24-hour lags, resulting in a statistically significant composite coefficient estimate of -1.252. This yields a drop in profits by 10.17% for an increase in RE by 10%. This result is somewhat less pronounced but still suggests a strong profit-decreasing effect of RE on storage profits.

Aggregation at the daily frequency — Turning now to the daily aggregate level, we should emphasize that we do not think this is an adequate approach to identify our effect of interest.

This is because daily mean values take out a lot of variation coming from price peaks and lows within a day, which may result from intra-day changes in RE generation. With daily aggregates, we cannot observe during which hours (e.g., peak vs. off-peak) and by how much RE infeed influenced the electricity price. Thus, our first-stage regression based on daily averages may come to different results than using hourly data (and eventually also influencing our second-stage estimates).

Nevertheless, we run the regressions, as presented in columns 7 and 8 of Table 3. The results again show pronounced and statistically significant effects of subsidized RE infeed on the daily mean price of electricity and HPS profits: a 10% change in RE infeed reduces the daily price by 4.87% and further reduces HPS profits by 9.93%. We can conclude that even for daily averages, which smooth the variation within a day, we find econometric evidence for a significant distortion of the wholesale price of electricity by subsidized RE, which translates into a significant profit distortion of HPS. The less pronounced estimated elasticity (compared to the baseline estimates for hourly data) may be explained by averaging out variation within a day.

5.4 Storage electricity generation as the dependent variable

The storage profits are in part a function of the electricity price, so that our main regression approach may seem tautological. The suspicion could be that storage profits are simply a linear function of the price and that thus price changes due to variations in subsidized RE infeed would translate linearly into profit changes. However, it is likely that this is not the case, because storage operations (electricity generation output) may also respond to price changes, which is something that we can test empirically. We run the baseline regression model, but use the storage electricity generation output as the dependent variable in the second stage instead of the profits. The full regression output is provided in Table A7 the Online Appendix. The estimates yield that a 10% increase in subsidized RE infeed decreases storage electricity generation by 8.27%, which corroborates our hypothesis that storage operations respond significantly to the price distortion created by subsidized RE.

5.5 Nonlinear effect

A potential threat to credibility may be that our applied model assumes a constant linear effect. It may be that the effect is different for higher than for lower RE levels. We thus relax this assumption by introducing a second-order polynomial of RE (RE and RE^2) in our regression. The results (see columns 9 and 10 in Table 3 show that our results stay qualitatively robust, whereas the effect of a 10% increase in RE on π of -10.45% is slightly lower than in the baseline regression.

5.6 Effects of RE on P by hour of day

A similar approach as investigating the hourly price spread or the effect during peak and off-peak times is to estimate the effect of RE on P *per hour of day*, as to show that wind reduces the price across all hours, but that the additional effect of solar particularly dampens peak prices:

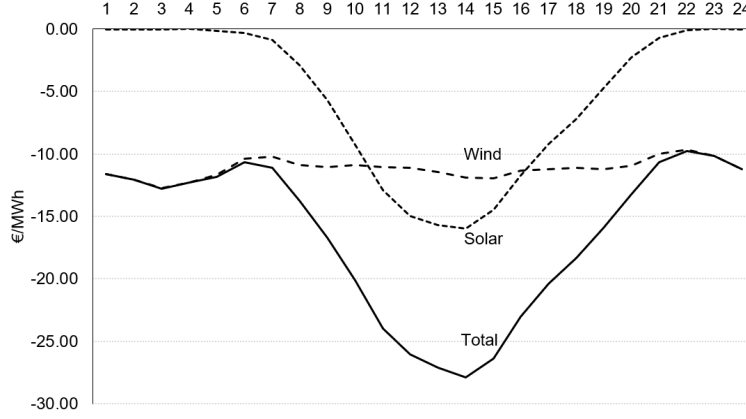
$$P_t = \sum_{h=1}^{24} \gamma_{RE,h} RE_t \cdot \psi_h + X_t' \gamma + \epsilon_t, \quad (5)$$

where ψ_h are hour-of-day fixed effects. $\gamma_{RE,h}$ captures the marginal effects of wind and solar infeed by the hour of day. This then allows for measuring the partial change in the electricity price (Δ_p) for a marginal change in RE, evaluated for the mean RE infeed by the hour of day (\overline{RE}_h):

$$\Delta_p = \hat{\gamma}_{RE,h} \cdot \overline{RE}_h. \quad (6)$$

This approach yields price effects by the hour of day for average wind and solar infeed, evaluated at sample means of all variables. Figure 6 visualizes the results. We can see that the decrease in the wholesale price is most pronounced during noon, when solar feeds into the system, in addition to the rather flat feed-in profile of wind, which eventually causes a decrease in the peak/off-peak price spread.

Figure 6: Effect of mean RE infeed on P by the hour of day



The graph shows the estimated effects of RE on P by the hour of day (c.f. equation (6)) evaluated for average RE infeed (in MWh) by the hour of day. These effects are to be interpreted as effects relative to the counterfactual scenario of no RE in place.

5.7 Exogeneity of RE

So far, we assumed RE to be exogenous. Our discussion above already suggests that RE feed into the system whenever the wind blows or the sun shines (due to prioritized feed-in at guaranteed feed-in tariffs), supporting the notion that RE are exogenous. However, to rule out any concerns, we also run a robustness estimation based on a two-stage instrumental variables (IV) approach with hourly wind speed (W), sunshine (S), and their squared terms (W^2 , S^2) as instruments for RE .¹ The first stage of this procedure is:

$$RE_t = \zeta_w^{1st} W_t + \zeta_{ww}^{1st} W_t^2 + \zeta_s^{1st} S_t + \zeta_{ss}^{1st} S_t^2 + X_t' \zeta^{1st} + \epsilon_t^{1st}. \quad (7)$$

Then, the second-stage regression includes the prediction of RE , \widehat{RE}_t , from the first stage:

$$\pi_t = \zeta_{RE}^{2nd} \widehat{RE}_t + X_t' \zeta^{2nd} + \epsilon_t^{2nd}. \quad (8)$$

Similar estimates of α_{RE} (standard OLS) and β_{RE}^{2nd} (IV) would indicate the exogeneity of RE .

¹We include W and S in levels and squared terms, because this specification yields the highest first-stage F statistic. However, the results stay robust when we omit W^2 and S^2 as instruments.

With this approach, we can rule out any concerns about the exogeneity of RE infeed. The findings, as provided in the Online Appendix Table A9, are robust: a 10% increase in RE decreases HPS profits by 12.77%.

6 Discussion

Our results are economically and politically relevant, because we find that renewable energies undermine the competitiveness of HPS plants. This effect will intensify with higher levels of RE infeed following the ambitious RE targets by the German and Austrian governments, as part of their national climate agendas. Germany, for example, plans to increase its share of RE from 38% in 2018 to 65% by 2030 and 80%–95% by 2050 [50]. However, our estimates warrant caution as a high share of subsidized wind and solar power may significantly negatively affect the short-run profitability of HPS. Ironically, on the one hand the very intermittency of RE would require a vast deployment of large-scale storage capacity to decouple generation and demand and to secure grid stability. On the other hand, the rollout of wind and solar power counteracts the HPS competitiveness.

A potential countermeasure to this dilemma would be a "meaningful" carbon price, which would increase the marginal costs of fossil-fueled technologies relative to carbon-free technologies, such as hydro power plants. A carbon price would set market-based incentives and avoid subsidized renewables' electricity price distortion, which undermines the business model of HPS. Moreover, a carbon price may lead to significant emissions abatement [15], foster R&D and investment in RE [51], while at the same time avoiding the problem that the state has to choose which technologies to subsidize based on imperfect information ("winner picking").

We may use the estimates of our baseline model (columns (1) & (2) of Table 2) to test our hypothesis. The first-stage coefficient estimate of P_{CO_2} is 1.198, implying that a change in the carbon price by one euro per ton of CO_2 increases the electricity wholesale price by around 1.2 euro per MWh (in line with [52]). The second-stage result shows that for a marginal change in the carbon price by one €/t CO_2 , HPS profits increase by €1,670 per hour. Evaluated at the

relatively low sample mean carbon price of 7.12 €/tCO₂, a 10% increase in the carbon price increases the wholesale electricity price by 2.65% (or 85 cents per MWh) and further elevates storage profits by 7.67%. This already shows that the carbon price counteracts the negative impact of subsidized RE on storage profits. Our results are fully robust to an alternative specification, which uses both RE and P_{CO_2} as instruments for P , as shown in the Online Appendix Table A10.

These estimates are economically significant and suggest that carbon pricing can counteract the negative adverse effect of directly subsidized RE. Altogether, this analysis underlines the importance of carbon pricing as a climate policy, supporting the business model of electricity storage.

7 Conclusions

There is a broad consensus among scientists that energy storage is needed to support both the integration and effectiveness of intermittent RE, thereby enhancing social welfare. This study tests if RE, which enjoy generous support payments, destroy large-scale energy storages' competitiveness. The argument is that subsidies for RE are a form of market intervention to foster the deployment of wind and solar power independently of an otherwise undistorted price signal arising from the interplay between demand and supply. The suspicion was that subsidized wind and solar power might depress the wholesale price of electricity, especially during peak load, which may eventually undermine the business model of HPS plants (i.e. price arbitrage).

We estimate the causal chain of RE via the electricity wholesale price on HPS profits, employing a two-stage IV model. For this purpose, we use data on Austrian HPS plants, which operate in the common German-Austrian electricity market. The vast share of heavily subsidized wind and solar power in Germany, together with the substantial HPS capacity installed in Austria, make it a relevant case for investigation, which also bears relevance for other countries with similar RE ambitions and for other settings where market interventions, although well-meant, may adversely impact market outcomes. We estimate that subsidized RE signif-

icantly distort the electricity wholesale price and depress the price spread between peak and off-peak periods. This price distortion eventually reduces HPS profits. With a further deployment of RE via subsidy payments, as planned by the German government according to its climate agenda, HPS profits will likely be strongly influenced (and may even turn negative) in the near future (*ceteris paribus*). It seems a paradox that the weather-dependent volatility of renewables requires system flexibility enabled by energy storage, whereas the distortionary effect of subsidies for renewables on the electricity price counteracts the success of energy storage.

Our results call for political action. State aid for HPS plants could relieve this situation. However, based on our results, we argue and estimate that a market-based policy in the form of carbon pricing would counteract the adverse effect of subsidized RE. As there is still a debate among scholars, which policy measures would be necessary to decarbonize the economy, our study provides another argument in favor of carbon pricing, as a market-based policy, to abate emissions efficiently and also maintain investment incentives for energy storages.

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