Online Supplement to "Seasonality in transition: Renewables, electricity price shapes and seasonal priors"

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This supplement documents the data (Section S1), reports market-level facts and the comparison with other commodities and with fuel costs (Sections S2-S3), robustness checks of the estimates and the test of the TDS restriction (Section S4), the variability results (Section S5), details of the out-of-sample evaluation (Section S6), of the solar PPA valuation (Section S7) and of the decision analysis (Section S8), the seasonal value factors (Section S9) and the futures benchmark (Section S10). Equation, table and figure numbers without the prefix S refer to the main text.

S1 Data construction

Electricity prices. Hourly day-ahead prices are taken from Ember's European Wholesale Electricity Price Data (release of February 2026; CC BY 4.0), which compiles ENTSO-E transparency data and, for Great Britain and the all-island Irish market, EMR and SEMOpx data. For each market we drop duplicated UTC timestamps, assign hours to local calendar days and months, and compute daily and monthly baseload prices as arithmetic means of hourly prices. Block prices are means of local hourly prices over 00:00-05:59 (night), 10:00-15:59 (midday) and 18:00-21:59 (evening), over all days of the month. Months with fewer than 95% of their hours are incomplete, and only calendar years with twelve complete months enter the analysis. Our monthly averages are close to Ember's published monthly averages: the median of the market-level mean absolute differences is 0.11 EUR/MWh and the correlation exceeds 0.999 in every market.

Multi-zone markets. For countries with several bidding zones Ember publishes one national series without documenting the zone. For Italy its annual averages coincide with the national single price (PUN). For Denmark, Norway and Sweden we regress each national hourly series on the zonal day-ahead prices of the Open Power System Data time series (January 2015 to September 2020; ENTSO-E data), without intercept and with non-negative weights, over hours in which the zonal prices differ by more than 5 EUR/MWh. The fitted weights sum to one: Sweden 0.07 (SE1), 0.11 (SE2), 0.63 (SE3) and 0.18 (SE4); Norway 0.30 (NO1), 0.26 (NO2), 0.19 (NO3), 0.13 (NO4) and 0.12 (NO5); Denmark 0.61 (DK1) and 0.39 (DK2). In those hours the weighted averages reproduce the national series with mean absolute errors of 0.14-0.22 EUR/MWh, against 2.2-9.5 EUR/MWh for any single zone. The national series of these countries are therefore fixed-weight averages of

zonal prices, on which no contract settles; Table S3 reports the estimates without the Nordic markets.

Sample. The 27 markets are Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom. Luxembourg is dropped because its price is identical to Germany's (same bidding zone), Montenegro and North Macedonia because their series start in 2023, and Serbia because the generation data contain no solar series for it. Austria enters in 2019, after the split of the German-Austrian zone in October 2018; Ireland in 2019; Bulgaria and the United Kingdom in 2017 and Croatia in 2018, the first complete years of their series; Switzerland ends in 2024 because its series stops in September 2025. The sample has 281 complete market-years and 3,372 market-months.

Generation and demand. Monthly generation by technology and demand (TWh) come from Ember's monthly electricity data for Europe (CC BY 4.0). Demand is generation plus net imports. Generation refers to countries: the United Kingdom series includes Northern Ireland, whose prices belong to the all-island Irish market, and the Ireland series covers the Republic only. When a technology has no row for a market-month, its generation is set to zero (solar in early years in some markets). Penetration, deviations x^j and the demand deviation d are computed only for years with twelve months of data. Coverage starts in 2016 for Italy and Slovenia, in 2017 for Finland and Switzerland and in December 2018 for Croatia, and ends in September 2025 for Austria, which leaves 3,276 market-months with generation data. European penetration is chain-linked: it starts from the demand-weighted average of 2015 and cumulates the year-on-year changes of the demand-weighted average over the markets observed in both years (weights: demand in the later year), so that markets entering or leaving the data do not create breaks.

Fuel and carbon costs. The World Bank Pink Sheet (release of 3 February 2026; CC BY 4.0) provides monthly prices of European natural gas (USD/mmbtu; the TTF price from April 2015) and of Australian and South African coal (USD/t). They are converted to euros with the monthly FRED series EXUSEU (USD per EUR, inverted); gas is converted to EUR/MWh (thermal) with 3.412 mmbtu per MWh. The EU allowance price is the monthly mean of daily averages of EEX primary auction clearing prices for general allowances (contract T3PA); the compiled file lacks 2016, which we take from EEX's 2016 annual auction report. The cost proxies are $C^G = \mathrm{TTF}/0.50 + 0.37\,\mathrm{EUA}$ for a combined-cycle plant and $C^K = \mathrm{coal}/(6.978 \times 0.38) + 0.90\,\mathrm{EUA}$ for a hard-coal plant (6.978 MWh per tonne), in EUR/MWh of electricity. The main specifications use Australian coal; South African coal is a robustness check.

Variability measures. All measures are in EUR/MWh and use all days: the within-month standard deviation of daily baseload prices, and the monthly means of the within-day standard deviation and of the daily maximum minus minimum of hourly prices.

Neighbours and coupling. Neighbours are interconnected markets: AT (DE, CZ, HU, SI, CH, IT); BE (FR, NL, DE, GB); BG (RO, GR); HR (SI, HU); CZ (DE, AT, PL, SK); DK (DE, SE,

NO, NL); EE (FI, LV); FI (SE, EE, NO); FR (BE, DE, CH, IT, ES, GB); DE (DK, NL, BE, FR, CH, AT, CZ, PL, SE, NO); GR (BG, IT); HU (AT, SK, RO, HR, SI); IE (GB); IT (FR, CH, AT, SI, GR); LV (EE, LT); LT (LV, PL, SE); NL (BE, DE, GB, NO, DK); NO (SE, FI, DK, NL, DE, GB); PL (DE, CZ, SK, LT, SE); PT (ES); RO (HU, BG); SK (CZ, PL, HU); SI (AT, IT, HR, HU); ES (FR, PT); SE (NO, FI, DK, DE, PL, LT); CH (DE, FR, IT, AT); GB (FR, BE, NL, NO, IE). For every pair and month we compute, from hourly prices matched on UTC time, the share of hours in which the two day-ahead prices differ by at most max(1 EUR/MWh, 2%) of their mean. Under flow-based coupling exact equality is rare even when congestion is negligible. The coupled neighbours' deviation of market i is $\sum_n w_{in}\bar{D}_n x_n^j / \sum_n \bar{D}_n$, where w_{in} is the pair's share in the previous year (the same year when the previous one is not observed). Averaged over the years 2015-2025, pair shares range from 0.02 (Norway-United Kingdom) to 0.97 (Latvia-Lithuania), with a mean of 0.33 over the 52 pairs. A market's demand-weighted coupling intensity, $\sum_n w_{in}\bar{D}_n / \sum_n \bar{D}_n$, averages 0.35 over the estimation sample, from 0.09 for Ireland and the United Kingdom to 0.96 for Portugal. Rest-of-Europe deviations are demand-weighted averages over all other markets with twelve months of generation data in the year.

S2 Market-level stylised facts

Table S1: Market-level stylised facts, 2017-2019 versus 2023-2025.

		Solar	Wind	Summer/winter ratio		Amplitude	Permutation p	
Market	Sample	pen. (%)	pen. (%)	Raw	Fuel-netted	(%)	Raw	Fuel-netted
Austria[1]	2019–2025	2.2→9.8	11.5→13.4	0.88→0.75	1.10→0.84	13.7→15.7	0.250	0.250
Belgium	2015–2025	3.8→10.6	7.9→16.5	0.77→0.76	0.84→0.84	15.8→15.3	0.375	0.375
Bulgaria	2017–2025	3.3→13.4	3.4→3.8	0.92→0.83	1.02→0.92	14.0→14.2	0.200	0.250
Croatia[2]	2018–2025	0.5→4.6	8.3→14.9	0.97→0.84	1.04→0.93	13.6→11.9	0.100	0.300
Czechia	2015–2025	3.3→6.1	0.9→1.1	0.93→0.80	1.02→0.88	11.1→12.9	0.036	0.089
Denmark	2015–2025	2.6→9.6	43.2→51.9	1.00→0.85	1.04→0.91	7.5→11.3	0.107	0.161
Estonia	2015–2025	0.0→11.5	8.2→13.8	1.01→0.82	1.09→0.88	7.1→16.7	0.071	0.107
Finland	2015–2025	0.1→1.2	5.8→21.9	1.00→0.65	1.00→0.67	8.2→33.8	0.018	0.018
France	2015–2025	2.1→5.8	5.8→11.1	0.76→0.62	0.81→0.68	17.2→29.9	0.125	0.143
Germany	2015–2025	7.7→15.1	21.0→27.4	0.91→0.84	1.00→0.92	9.1→10.9	0.179	0.268
Greece	2015–2025	7.3→22.4	10.2→21.5	0.94→0.85	1.04→0.94	8.2→12.9	0.214	0.268
Hungary	2015–2025	1.9→19.4	1.6→1.3	0.93→0.82	1.01→0.91	14.5→14.0	0.089	0.196
Ireland[1]	2019–2025	0.0→2.1	29.4→32.8	0.87→0.86	1.05→0.96	16.2→8.7	0.750	0.500
Italy	2015–2025	7.3→12.3	5.8→7.4	0.91→0.91	1.00→1.00	7.8→6.4	0.482	0.625
Latvia	2015–2025	0.0→5.7	1.8→3.3	1.04→0.83	1.09→0.88	7.5→15.3	0.036	0.071
Lithuania	2015–2025	0.5→9.8	10.2→25.5	1.03→0.83	1.11→0.88	7.4→15.4	0.036	0.125
Netherlands	2015–2025	3.1→21.6	9.0→26.7	0.88→0.80	0.97→0.88	7.9→13.0	0.036	0.089
Norway	2015–2025	0.0→0.0	2.8→10.4	0.91→0.66	0.96→0.70	6.5→32.3	0.036	0.054
Poland	2015–2025	0.2→10.5	8.9→14.4	1.06→0.94	1.11→0.99	7.4→6.3	0.054	0.125
Portugal	2015–2025	2.1→13.5	25.4→25.6	0.95→0.84	1.03→0.91	8.3→33.9	0.161	0.232
Romania	2015–2025	2.3→7.1	11.2→12.0	0.93→0.84	1.01→0.92	16.0→14.0	0.214	0.250
Slovakia	2015–2025	1.7→2.1	0.0→0.0	0.93→0.80	1.00→0.88	13.1→13.3	0.054	0.071
Slovenia	2015–2025	2.1→8.4	0.0→0.0	0.92→0.82	1.02→0.91	14.3→11.9	0.089	0.196
Spain	2015–2025	5.2→21.8	19.4→24.5	0.96→0.82	1.03→0.89	8.2→35.5	0.107	0.161
Sweden	2015–2025	0.0→3.1	13.2→29.2	0.94→0.60	0.97→0.63	8.1→35.2	0.018	0.018
Switzerland	2015–2024	2.8→7.9	0.2→0.3	0.72→0.70	0.80→0.79	19.0→21.0	0.619	0.571
United Kingdom	2017–2025	3.8→5.6	18.4→30.5	0.89→0.82	0.98→0.92	6.8→11.4	0.150	0.150

Penetration: annual generation over annual demand, averaged over the years of each window with generation data. Summer/winter ratio: average shape factor of April-September over that of January-March and October-December of the same year, geometric mean over years; fuel-netted: computed from log shapes net of the within-year fuel-cost path times the market's pass-through (column (1) of Table 1). Amplitude: standard deviation across months of the average log shape (%). Permutation p: one-sided p-value for a decline of the log summer/winter ratio, permuting whole years between all available years of 2015-2019 and 2023-2025 (minimum 1/56 with eight years). A superscript gives the number of years in the first window when it is below three; the second window of Switzerland has two years.

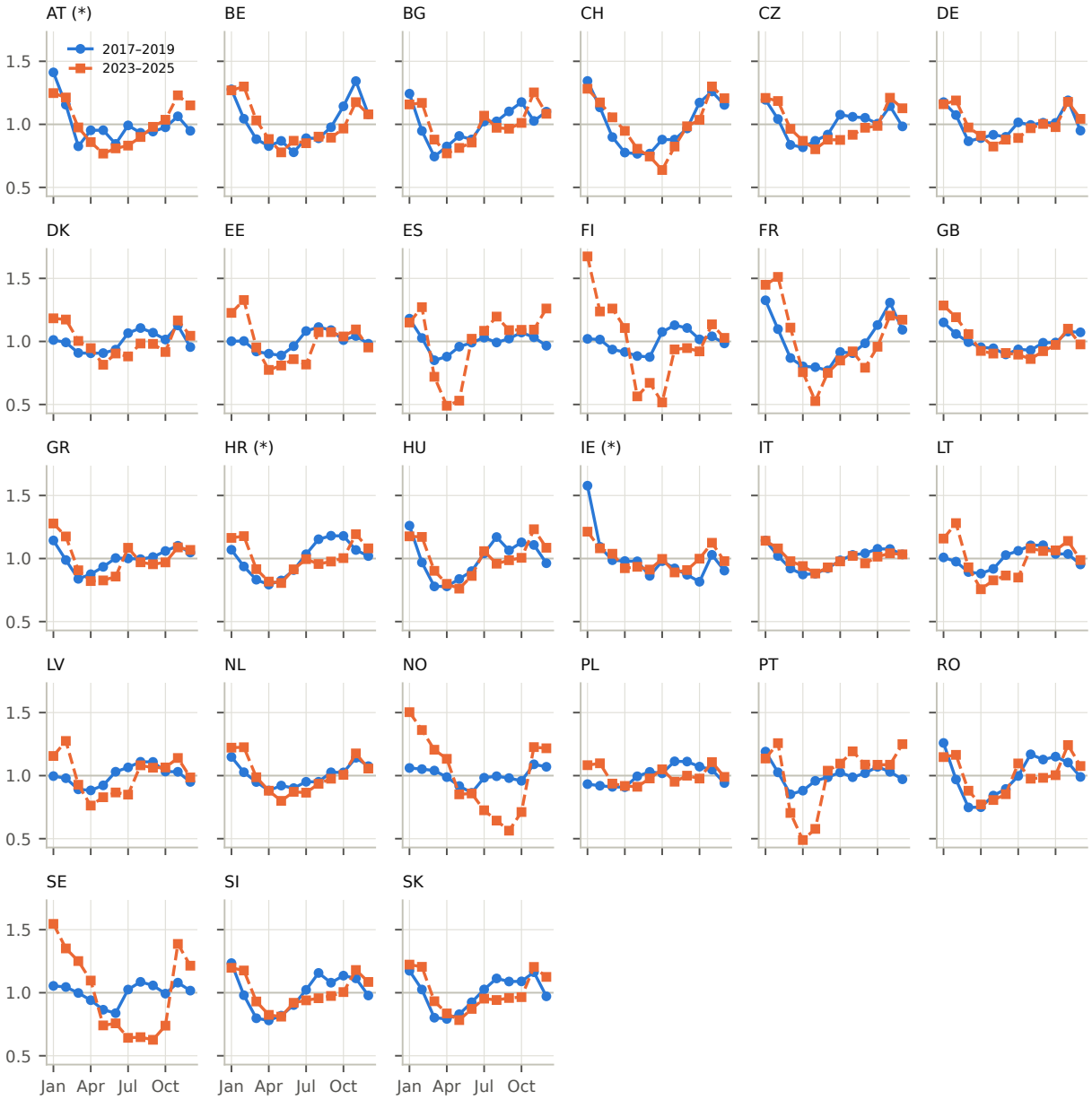


Figure S1: Average monthly shape factors in 2017-2019 and 2023-2025 for all 27 markets (ISO codes). (*) Fewer than three years in the first window.

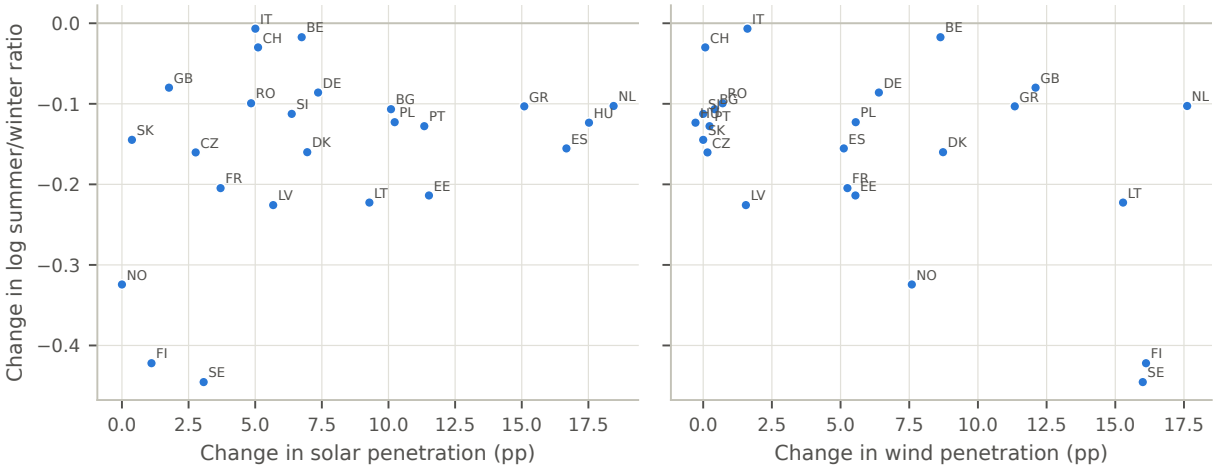


Figure S2: Change in the log summer/winter price ratio between 2017-2019 and 2023-2025 against the change in own solar (left) and wind (right) penetration, 24 markets. Cross-market regression: −0.157 (0.032) +0.0071 (0.0038) ×Δsolar −0.0089 (0.0038) ×Δwind, HC1 standard errors.

S3 Seasonality across commodities and fuel costs

Table S2: Seasonal shape of World Bank commodity prices and of the fuel-cost proxies, 2017-2019 versus 2023-2025.

	Summer/winter ratio		Amplitude (%)		
Series	2017–19	2023–25	2017–19	2023–25	p
Natural gas, Europe (TTF)	0.86	0.87	9.5	8.4	0.514
Natural gas, US	0.93	0.86	6.7	11.7	0.114
LNG, Japan	0.99	0.92	1.6	7.9	0.314
Crude oil, Brent	1.01	1.01	2.8	3.9	0.429
Coal, Australia	0.98	0.95	2.9	7.3	0.629
Maize	1.02	0.96	3.2	6.6	0.029
Wheat, US HRW	1.04	0.99	3.7	5.8	0.257
Soybeans	0.98	0.99	2.0	4.5	0.343
Rice, Thai 5%	1.03	1.01	2.3	3.5	0.114
Coffee, Arabica	0.96	0.97	2.6	5.3	0.429
Sugar, world	0.92	1.01	6.4	3.2	0.800
Palm oil	0.96	0.95	3.7	3.7	0.257
Orange	0.97	0.97	4.7	4.4	0.514
Urea	0.94	0.98	5.8	6.4	0.771
Copper	0.97	1.00	1.7	2.3	0.714
Aluminum	1.01	0.97	1.2	2.3	0.200
Gold	1.00	1.00	1.6	8.1	0.257
Gas-plant cost (TTF + EUA)	0.89	0.89	8.2	6.9	0.464[a]
Coal-plant cost (coal + EUA)	1.01	0.98	4.3	3.6	0.536[a]
Electricity (median of 24 markets)	0.93	0.82	8.2	14.1	0.018[b]

Summer/winter ratio and amplitude defined as in Table S1. p: one-sided exact permutation p-value for a decline of the log summer/winter ratio, permuting whole years between 2016-2019 and 2023-2025 (the Pink Sheet gas series is the TTF price from April 2015). [a]Permuting years between 2015-2019 and 2023-2025. [b]Pooled test over 21 markets (Section 4).

Table S3: Robustness of the estimates of column (1) of Table 1.

Specification	Solar	Wind	Hydro	Nuclear	Demand	N
Baseline [column (1)]	−1.76*** (0.28)	−1.41*** (0.17)	−0.80*** (0.09)	−0.55*** (0.12)	1.23*** (0.17)	3,276
Excluding 2020–2022	−1.61*** (0.30)	−1.08*** (0.17)	−0.76*** (0.10)	−0.46*** (0.13)	0.93*** (0.16)	2,304
Excluding Nordic markets	−1.66*** (0.28)	−1.57*** (0.17)	−0.79*** (0.11)	−0.35*** (0.10)	1.19*** (0.17)	2,772
Excluding hydro-dominated markets	−1.64*** (0.29)	−1.41*** (0.16)	−0.81*** (0.11)	−0.39*** (0.10)	1.20*** (0.15)	2,844
Excluding Iberian gas-cap months (6/2022–12/2023)	−1.82*** (0.28)	−1.37*** (0.15)	−0.69*** (0.09)	−0.55*** (0.12)	1.17*** (0.16)	3,238
South African coal in the coal-cost proxy	−1.73*** (0.28)	−1.32*** (0.15)	−0.75*** (0.09)	−0.55*** (0.11)	1.09*** (0.13)	3,276
Ember's published monthly averages	−1.74*** (0.28)	−1.39*** (0.17)	−0.80*** (0.09)	−0.55*** (0.12)	1.23*** (0.17)	3,276
Shape factor $s-1$ as dependent variable	−1.70*** (0.29)	−1.41*** (0.18)	−0.75*** (0.09)	−0.62*** (0.12)	1.22*** (0.20)	3,276
Driscoll–Kraay with 12 lags	−1.76*** (0.33)	−1.41*** (0.18)	−0.80*** (0.09)	−0.55*** (0.12)	1.23*** (0.17)	3,276
Sample from 2017	−1.94*** (0.30)	−1.35*** (0.17)	−0.78*** (0.10)	−0.50*** (0.13)	1.37*** (0.15)	2,820

Coefficients ×100 with Driscoll-Kraay standard errors in parentheses. Nordic markets: Norway, Sweden, Finland, Denmark. Hydro-dominated markets: Norway, Sweden, Switzerland, Austria. Iberian gas-cap months: Spain and Portugal, June 2022 to December 2023. Ember's published monthly averages instead of our own averages of hourly prices (the two series are nearly identical). Shape factor: $s-1$ instead of the log price as dependent variable. All specifications include market×year and market×month effects and market-specific fuel pass-through.

Table S4: Estimates of column (1) of Table 1 on samples ending in 2019-2025.

Sample	Solar	Wind	Hydro	Nuclear	Demand	N
2015–2019	−0.45 (1.48)	−1.17*** (0.19)	−0.75*** (0.12)	−0.56*** (0.16)	0.83*** (0.28)	1,356
2015–2020	−0.44 (1.15)	−1.23*** (0.15)	−0.70*** (0.11)	−0.59*** (0.15)	1.01*** (0.23)	1,680
2015–2021	−1.19 (0.94)	−1.26*** (0.14)	−0.81*** (0.10)	−0.63*** (0.13)	1.12*** (0.19)	2,004
2015–2022	−0.98 (0.63)	−1.49*** (0.19)	−0.89*** (0.12)	−0.63*** (0.11)	1.28*** (0.23)	2,328
2015–2023	−0.67* (0.38)	−1.49*** (0.18)	−0.75*** (0.12)	−0.63*** (0.12)	1.16*** (0.18)	2,652
2015–2024	−1.37*** (0.33)	−1.41*** (0.20)	−0.77*** (0.09)	−0.61*** (0.13)	1.23*** (0.17)	2,976
2015–2025	−1.76*** (0.28)	−1.41*** (0.17)	−0.80*** (0.09)	−0.55*** (0.12)	1.23*** (0.17)	3,276

Coefficients ×100 with Driscoll-Kraay standard errors in parentheses.

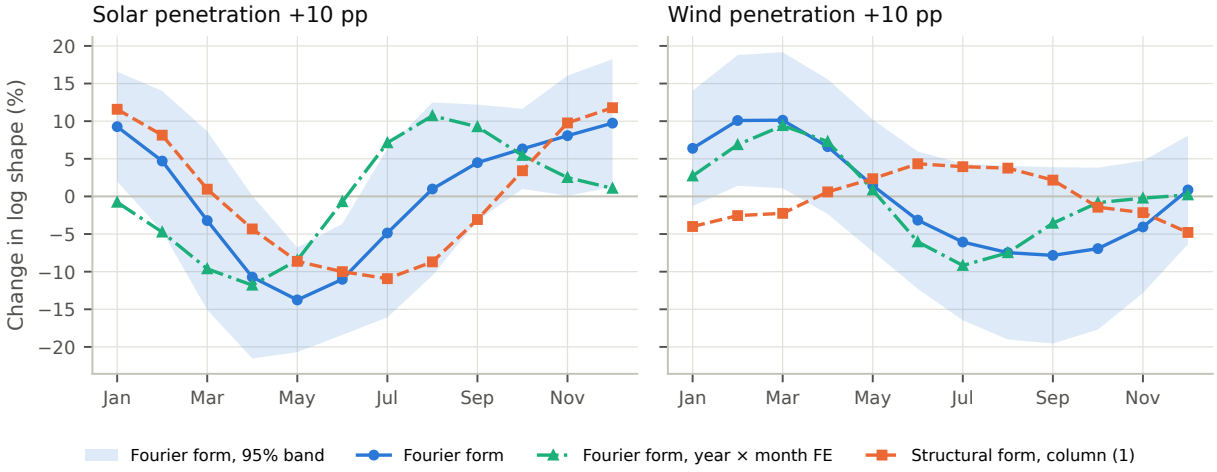


Figure S3: Implied change in the seasonal log shape for a 10 percentage-point increase in annual penetration. Fourier form: penetration interacted with two harmonics (95% Driscoll-Kraay band for the baseline), with and without year×month effects. Structural form: column (1) of Table 1 times the sample-average relative output profile, as in Proposition 1(a).

S4 Robustness of the estimates and the TDS restriction

Reduced form. Figure S3 and Table S5 report the reduced Fourier form. In the full sample, solar penetration reshapes the seasonal cycle (Wald statistic 28.6 on four restrictions, $p < 0.001$), with the trough in May; with year×month effects the pattern is not significant (Wald $p = 0.16$), the trough moves to April and prices from July to October rise. For wind, both versions show a winter rise and a summer fall (contrast −5.5 and −6.0 per ten points, standard errors 3.8 and 3.3; Wald $p = 0.21$ and 0.11). On samples ending in 2017-2020 and in 2023 the solar contrast had the

Table S5: Reduced (Fourier) form: penetration interacted with two seasonal harmonics, by estimation sample.

	Solar penetration			Wind penetration		
Estimation sample	Wald	p	S/W, +10 pp	Wald	p	S/W, +10 pp
2015–2017	9.7	0.047	34.0 (71.1)	7.8	0.100	−8.3 (14.3)
2015–2018	1.0	0.904	15.4 (31.7)	27.4	0.000	3.3 (13.1)
2015–2019	6.6	0.156	27.4 (21.3)	24.4	0.000	8.8 (6.5)
2015–2020	14.9	0.005	11.1 (16.0)	8.1	0.089	9.3 (5.1)
2015–2021	9.7	0.047	−15.1 (13.4)	17.4	0.002	8.1 (4.9)
2015–2022	7.1	0.130	−7.2 (6.5)	8.0	0.093	5.9 (5.7)
2015–2023	6.6	0.157	1.6 (4.7)	10.6	0.032	0.1 (4.6)
2015–2024	8.3	0.080	−4.2 (4.8)	21.7	0.000	−5.8 (5.1)
2015–2025	28.6	0.000	−11.6 (4.4)	5.9	0.209	−5.5 (3.8)
2015–2025, year × month FE	6.5	0.164	2.0 (4.7)	7.6	0.107	−6.0 (3.3)

Wald: joint test (Driscoll-Kraay) that the four penetration-harmonic coefficients are zero. S/W, +10 pp: implied change in the summer/winter contrast of the log shape (log points) for a 10 percentage-point increase in penetration, Driscoll-Kraay standard error in parentheses. The structural form implies a negative contrast for solar and a positive one for wind. Samples ending in 2017-2024 are those available at the forecast origins of Section 6.

opposite sign; it has the structural sign and is significant only when 2025 is included.

Table S6: Season-specific price responses to solar and wind output.

	Winter (DJF)	Spring (MAM)	Summer (JJA)	Autumn (SON)
Solar	−2.08*** (0.45)	−1.45*** (0.42)	−1.41** (0.71)	−2.07*** (0.61)
Wind	−1.61*** (0.22)	−0.79** (0.34)	−1.13*** (0.35)	−1.80*** (0.30)
Equality across seasons, Wald $\chi^2(3)$	Solar: 1.2 (p=0.757)		Wind: 7.0 (p=0.071)	

Column (1) of Table 1 with the solar and wind deviations interacted with season indicators. Coefficients ×100, Driscoll-Kraay standard errors in parentheses; Wald tests use the Driscoll-Kraay covariance.

Further checks. Interacting the solar and wind deviations with annual own penetration (in deviation from its mean, per ten percentage points), the interaction coefficients (×100) are 0.25 (0.19) for solar and 0.20 (0.05) for wind in column (1), and 0.20 (0.20) and 0.19 (0.05) with year×month effects: there is no evidence that the price response steepens with penetration, and wind's flattens. The solar coefficient is stable across seasons ($p = 0.76$ for equality), while wind's is larger in autumn and winter ($p = 0.07$; Table S6). With year×month effects, demand-weighted (uncoupled) neighbours' deviations have coefficients of −0.31 (0.37) for solar, −0.57 (0.29) for wind and −0.67 (0.22) for hydro. Entering both sets, the coupled deviations dominate for wind and hydro: −1.39 (Driscoll-Kraay 0.56, two-way 0.76) and −2.78 (0.82, 0.79) for the coupled ones against −0.09 (0.41, 0.40) and 0.38 (0.32, 0.48) for the uncoupled ones; for solar neither is significant (coupled 0.27, uncoupled −0.97, two-way standard errors 1.35). Coupling weights based on the share of hours with exactly equal prices (mean demand-weighted intensity 0.23 instead of 0.35) give coefficients for coupled neighbours' wind, hydro and solar of −1.44 (Driscoll-Kraay 0.44, two-way 0.63), −2.12 (0.60, 0.83) and −0.74 (0.40, 0.53), close to those of column (6) of Table 1.

The TDS restriction by origin. Estimated on samples ending in 2017-2023, the difference between the penetration and weather coefficients of wind in the log-price regression lies between −0.2 and 1.6, with Driscoll-Kraay p-values between 0.13 and 0.88; it becomes significant only with the 2024 data (3.1, $p = 0.004$). For solar, the difference was positive and significant at the 2020

Table S7: Test of the TDS restriction: penetration-driven and weather-driven parts of the output deviations.

	Weather part	Penetration part	Difference			Wild p	Pen. share (%)
Log monthly baseload price (Table 1)							
Baseline, solar	−0.84 (0.78)	−1.19 (0.43)	−0.35	(1.06)	[1.27]	0.927	88
Baseline, wind	−1.63 (0.16)	1.28 (0.88)	2.91	(0.89)	[1.64]	0.016	10
Year × month FE, solar	0.12 (0.76)	0.32 (0.51)	0.20	(1.13)	[1.43]	0.855	76
Year × month FE, wind	−1.29 (0.18)	1.37 (0.86)	2.66	(0.91)	[1.24]	0.005	7
Midday block shape factor (Table 2)							
Baseline, solar	−3.11 (0.67)	−3.77 (0.42)	−0.66	(0.86)	[1.10]	0.849	88
Baseline, wind	−1.67 (0.17)	2.94 (0.90)	4.62	(0.89)	[1.97]	0.003	10
Year × month FE, solar	−1.47 (0.58)	−1.00 (0.40)	0.47	(0.84)	[1.28]	0.680	76
Year × month FE, wind	−1.33 (0.16)	2.05 (0.83)	3.38	(0.86)	[1.37]	0.002	7

Each deviation $x^j = z^j\kappa^j$ is split into a penetration part $z^j\bar{\kappa}^j$, with $\bar{\kappa}^j$ the market's output-weighted average profile over the sample, and a weather part $z^j(\kappa^j - \bar{\kappa}^j)$. Coefficients ×100 (log price) or in percent of the annual baseload price (midday block), Driscoll-Kraay standard errors in parentheses. Difference: penetration minus weather coefficient, Driscoll-Kraay standard error in parentheses and two-way clustered (market and year) in brackets; Proposition 1 implies zero. Wild p: wild cluster bootstrap by year (Webb weights, null imposed, 9,999 draws). Pen. share: share of the within variation of the deviation (after fixed effects and fuel terms) due to the penetration part. All other regressors as in Table 1.

origin (4.5, $p = 0.02$), when the penetration part had the wrong sign, and insignificant at the other origins. A rule that dropped channels whose restriction was rejected at the origin would therefore have dropped solar in 2020 and kept wind until 2024.

S5 Variability

Table S8: Within-month price variability on seasonal deviations of residual-load components.

	Daily SD		Intraday SD		Intraday range	
	(1)	(2)	(3)	(4)	(5)	(6)
Solar	−0.49	−0.04	3.23***	1.41***	3.50***	1.33***
	(0.62)	(0.37)	(0.51)	(0.28)	(0.52)	(0.29)
	[0.68]	[0.71]	[0.92]	[1.07]	[0.92]	[1.04]
Wind	0.58**	0.73***	0.12	0.20	0.09	0.16
	(0.27)	(0.23)	(0.19)	(0.20)	(0.19)	(0.19)
	[0.43]	[0.30]	[0.28]	[0.25]	[0.27]	[0.24]
Hydro	0.07	0.19*	−0.25*	−0.15	−0.21	−0.11
	(0.16)	(0.11)	(0.15)	(0.11)	(0.15)	(0.12)
	[0.26]	[0.14]	[0.17]	[0.11]	[0.17]	[0.10]
Nuclear	−0.57***	−0.43***	−0.67***	−0.61***	−0.66***	−0.63***
	(0.20)	(0.16)	(0.14)	(0.14)	(0.14)	(0.15)
	[0.21]	[0.19]	[0.32]	[0.27]	[0.33]	[0.28]
Demand	1.01**	0.84**	0.94***	0.93***	0.91***	0.86***
	(0.47)	(0.34)	(0.28)	(0.28)	(0.29)	(0.27)
	[0.51]	[0.45]	[0.39]	[0.39]	[0.39]	[0.37]
Year × month FE		✓		✓		✓
Within R^2	0.259	0.071	0.409	0.084	0.407	0.077
Observations	3,276	3,276	3,276	3,276	3,276	3,276

Dependent variables (logs of EUR/MWh measures): standard deviation of daily baseload prices within the month (daily SD); monthly mean of the within-day standard deviation of hourly prices (intraday SD); monthly mean of the daily max-min range of hourly prices (intraday range). All specifications include market×year and market×month effects and market-specific fuel pass-through. Coefficients ×100; Driscoll-Kraay standard errors in parentheses, two-way clustered (market and year-month) in brackets; significance from Driscoll-Kraay.

A first-order expansion of the merit order within the month makes price variability proportional to the variability of residual load, which solar output drives within the day and wind output from day to day. In Table S8, a solar deviation of 1% of demand raises the intraday range by 3.5% (two-way clustered standard error 0.92), and by 1.3% with year×month effects, where it is significant with Driscoll-Kraay but not with two-way clustered standard errors (1.04). Wind output raises day-to-day variability (0.58% and 0.73%; with year×month effects significant under both estimators). Demand raises all measures and nuclear output lowers them, but these effects vanish when variability is measured relative to the monthly price level (Table S10), so they operate through price levels; relative to the price level, wind's effect on day-to-day variability is larger and robust (1.98 and 1.82, two-way standard errors 0.45 and 0.39), and solar's effect on the relative intraday range is 5.26 (0.99) without and 1.22 (0.90) with year×month effects. With year×month effects, season-specific slopes put solar's effect on the intraday range in April-September (2.1%, against 0.5% in October-March; Driscoll-Kraay $p = 0.08$ for equality) and wind's effect on the daily standard deviation also in April-September (1.3% against 0.4%; $p = 0.07$) (Table S9, Figure S4). Seasonal volatility amplitudes calibrated on history therefore inherit the generation mix of the calibration period.

Table S9: Season-specific responses of within-month price variability.

	Solar		Wind		p: summer = winter	
Dependent variable	Apr–Sep	Oct–Mar	Apr–Sep	Oct–Mar	Solar	Wind
Daily SD	−1.14 (1.22)	0.25 (1.24)	1.25*** (0.43)	0.21 (0.35)	0.512	0.082
Daily SD, year × month FE	0.44 (0.67)	−0.57 (0.86)	1.31*** (0.43)	0.40 (0.24)	0.449	0.070
Intraday SD	2.53*** (0.93)	4.01*** (0.78)	0.56** (0.28)	−0.11 (0.26)	0.292	0.101
Intraday SD, year × month FE	2.14*** (0.47)	0.58 (0.63)	0.60 (0.36)	−0.04 (0.22)	0.100	0.120
Intraday range	2.82*** (0.99)	4.25*** (0.80)	0.43 (0.28)	−0.09 (0.26)	0.336	0.188
Intraday range, year × month FE	2.11*** (0.48)	0.45 (0.64)	0.51 (0.35)	−0.05 (0.22)	0.081	0.154

Specifications of Table S8 with solar and wind deviations interacted with April-September and October-March indicators. Coefficients ×100, Driscoll-Kraay standard errors in parentheses; p-values for equality of the two seasonal coefficients.

Table S10: Variability relative to the monthly price level.

Dependent variable (log)	Solar	Wind	Hydro	Nuclear	Demand
Daily SD / price	1.27** (0.51) [0.68]	1.98*** (0.24) [0.45]	0.87*** (0.17) [0.47]	−0.02 (0.18) [0.26]	−0.22 (0.49) [0.52]
Daily SD / price, year × month FE	−0.15 (0.39) [0.65]	1.82*** (0.20) [0.39]	0.90*** (0.12) [0.36]	0.13 (0.14) [0.16]	0.06 (0.30) [0.40]
Intraday range / price	5.26*** (0.45) [0.99]	1.50*** (0.22) [0.31]	0.59*** (0.15) [0.35]	−0.11 (0.13) [0.16]	−0.32 (0.33) [0.43]
Intraday range / price, year × month FE	1.22*** (0.27) [0.90]	1.25*** (0.21) [0.34]	0.60*** (0.11) [0.29]	−0.07 (0.11) [0.12]	0.08 (0.24) [0.33]

Dependent variables: logs of the daily standard deviation and of the mean intraday range divided by the monthly baseload price. Specifications as in Table S8. Coefficients ×100; Driscoll-Kraay standard errors in parentheses, two-way clustered (market and year-month) in brackets.

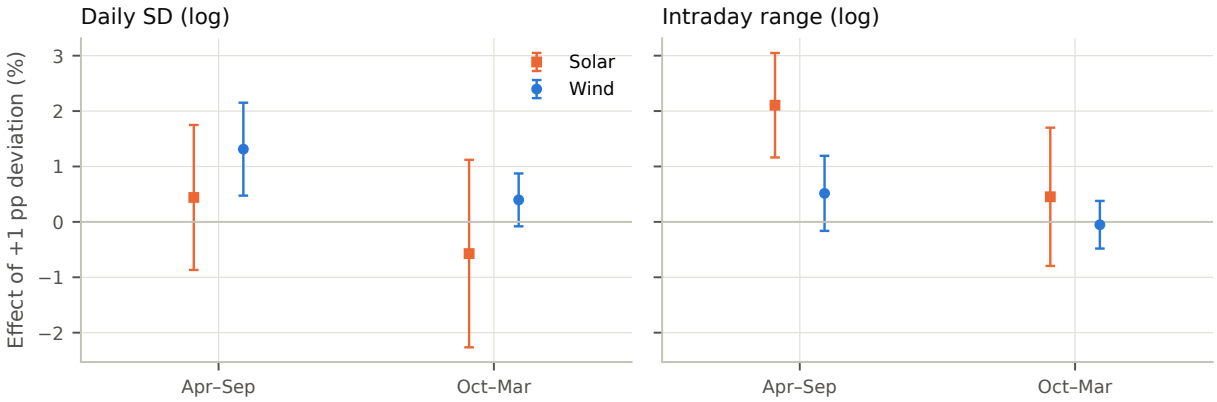


Figure S4: Season-specific effects of solar and wind deviations on log within-month variability, specifications with year×month effects (95% Driscoll-Kraay intervals).

S6 Out-of-sample evaluation: details

Rules. All rules forecast the twelve shape factors of year Y at the end of year $b = Y - h$ with data up to b. HIST5 averages the shape factors of the last five, and at least three, years; HIST5x uses the five most recent years outside 2021-2022 when at least three are available; HIST1 and HIST3 use the last one and three years. SIN5 regresses the log shapes of the last five years on two Fourier harmonics. EWMA weights the shape factors of the last five years by 0.6^{b-y}. TREND-F adds to SIN5 the least-squares linear drift of the market's own log shapes over the window, extrapolated to Y and projected on two harmonics; DRIFT-F uses the cross-market average of these drifts. EUSHIFT adds to SIN5 the cross-market average deviation of the last observed log shape from the window mean, projected on two harmonics. The TDS rules use the coefficients of the specification with own and demand-weighted neighbours' solar, wind and hydro deviations and own nuclear and demand deviations, re-estimated on data up to b (Table S12); profiles $\bar{\kappa}^j$ and deviations $\bar{x}^j$ are averaged over the window years with generation data. Projected penetration is $\hat{z}^j_Y = \max\{0, z^j_b + h(z^j_b - z^j_{b-2})/2\}$, for markets and for the chain-linked European aggregate. TDS-EU uses the change in European penetration between the window and the target year, the market's own profiles (the sample-average profile for markets without own output of a technology) and the sum of own and neighbours' coefficients. The rules adjust for solar and wind; hydro, nuclear and demand deviations enter the estimation as controls only. The solar-only variants keep only the solar term and were chosen after inspecting the results. Clean-history rules subtract $\hat{\gamma}^G_i \widetilde{\ln C^G}_{y,m} + \hat{\gamma}^K_i \widetilde{\ln C^K}_{y,m}$ (pass-through estimated at b, tildes denoting within-year deviations) from past log shapes and add back the average within-year fuel profile of all years from 2015 to b; variants that add nothing back have larger biases. For the fuel-adjusted target, the realised fuel path is removed from both history and target, so that evaluation conditions on the realised path. The midday rules apply the same constructions, in levels, to the seasonal shape of midday prices, with TDS coefficients from the regression of the midday block shape factor on own and neighbours' deviations.

Tests. Paired loss differentials $\ell_{A,iY} - \ell_{B,iY}$ are averaged over market-years. The two-way clustered variance (market and target year) uses $G/(G-1)$ corrections, falls back to the larger one-way variance when negative, and is compared with $t(G_{\min} - 1)$, where $G_{\min}$ is the number of target

years. The wild cluster bootstrap draws Webb six-point weights for the eight target-year clusters, imposes the null and recomputes the same two-way clustered statistic in every draw (MacKinnon, Nielsen and Webb, 2021, Journal of Business & Economic Statistics 39, 505-519; 19,999 draws; 99,999 for the analyses of Section 7). The minimum detectable effect is $(t_{0.975} + t_{0.80})$ times the two-way standard error.

Further results. Excluding 2025, TDS-EU against SIN5 shifts the mean summer/winter error of monthly baseload shapes by −1.0 log points ($p = 0.36$), the mean solar value-factor error by −0.4 points ($p = 0.23$) and the absolute summer/winter error by −0.2 ($p = 0.80$); for the midday block the shifts remain significant (−8.2 points, $p = 0.04$, and −2.7, $p = 0.03$). EUSHIFT, which carries the last common European deviation forward, has an RMSE of 33.4 and an absolute summer/winter error of 23.7, against 27.8 and 18.9 for SIN5 ($p = 0.08$ and 0.37 for the differences).

Channel selection. Table S17 compares TDS-EU with its solar-only version and with an ex ante selection rule that drops a channel at every origin at which the test of the TDS restriction (Table S7, Driscoll-Kraay, 5%) rejects on data up to the origin; the rule uses the log-price test for monthly baseload shapes and PPAs and the midday test for midday shapes. Applied one year ahead, the rule drops solar at the 2020 origin and wind at the 2024 origin with the log-price test, and solar at the 2020 origin and wind at the 2023 and 2024 origins with the midday test; it performs like TDS-EU. Dropping wind throughout, a choice made after seeing the restriction test, lowers absolute errors slightly but insignificantly and overcorrects the mean biases of monthly and midday shapes. Figure S5 shows the summer/winter bias of midday shapes by target year.

Table S11: One-year-ahead shaping accuracy for the seasonal shape of midday prices, 2018-2025.

	One year ahead, 2018–2025 (199)				Origin 2019, 2023–2025 (71)			
Method	RMSE	S/W bias	|S/W|	Solar VF	RMSE	S/W bias	|S/W|	Solar VF
FLAT	35.46	28.52	35.44	9.25	36.29	52.69	52.69	15.80
HIST1	39.75	6.55	28.93	1.84	33.28	44.57	44.57	13.33
HIST5	31.90	11.48	26.07	4.01	32.67	42.93	43.12	13.59
SIN5	30.64	10.51	25.26	3.95	32.67	43.27	43.40	13.64
TDS-F	29.82	−0.08	20.81	0.75	32.01	41.36	41.48	13.04
TDS-EU	29.73	−0.23	20.13	0.49	31.55	40.21	40.40	12.57
TDS-F‡	30.24	−2.71	21.42	−0.02	26.35	19.67	25.37	7.07
TDS-EU‡	30.11	−2.99	20.53	−0.35	24.52	16.79	20.89	5.50
Paired differences, one year ahead: p-values, two-way clustered [wild bootstrap by year]								
TDS-F − SIN5	0.46 [0.41]	0.03 [0.04]	0.28 [0.29]	0.03 [0.03]				
TDS-EU − SIN5	0.43 [0.38]	0.02 [0.02]	0.23 [0.23]	0.02 [0.02]				
TDS-F − SIN5, excl. 2025	0.83 [0.72]	0.06 [0.08]	0.59 [0.58]	0.05 [0.07]				
TDS-EU − SIN5, excl. 2025	0.77 [0.67]	0.04 [0.04]	0.48 [0.46]	0.03 [0.03]				
MDE, TDS-EU − SIN5	3.54	11.83	12.82	3.71				

Seasonal shape of midday prices: monthly mean price of local hours 10:00-15:59 minus its annual average, in percent of the annual baseload price. RMSE of the twelve monthly values; S/W bias: summer (April-September) minus winter mean, forecast minus realised, and its absolute value; Solar VF: solar-output-weighted error, the error in the seasonal component of the capture value of solar output at midday prices. TDS coefficients from the regression of the midday block shape factor on own and neighbours' deviations (market×year and market×month effects, fuel pass-through), re-estimated at every origin. ‡Realised penetration of the target year. Market-years in parentheses. p-values (two-way clustered, wild cluster bootstrap by year in brackets) and MDE as in Table 3.

Table S12: Coefficients of the TDS rules by forecast origin.

	Solar			Wind			Hydro		
Origin	Own	Neighb.	Sum	Own	Neighb.	Sum	Own	Neighb.	Sum
2017	0.44	0.73	1.17 (2.67)	−0.59	−2.38	−2.97 (0.26)	−0.78	−0.34	−1.12 (0.32)
2018	−0.67	−0.71	−1.38 (2.00)	−0.49	−2.07	−2.56 (0.32)	−0.64	−0.70	−1.34 (0.18)
2019	−0.60	−1.17	−1.77 (2.14)	−0.49	−1.65	−2.14 (0.31)	−0.65	−0.62	−1.28 (0.17)
2020	0.02	−2.95	−2.93 (1.86)	−0.80	−1.11	−1.91 (0.25)	−0.64	−0.56	−1.20 (0.18)
2021	−0.57	−3.07	−3.64 (1.68)	−0.79	−1.22	−2.02 (0.26)	−0.72	−0.72	−1.45 (0.17)
2022	−0.85	−1.49	−2.34 (1.17)	−1.00	−1.25	−2.25 (0.27)	−0.79	−0.75	−1.54 (0.17)
2023	−0.45	−1.57	−2.02 (0.59)	−1.04	−1.21	−2.25 (0.26)	−0.68	−0.83	−1.51 (0.20)
2024	−0.69	−2.21	−2.90 (0.43)	−0.98	−1.22	−2.20 (0.27)	−0.71	−0.89	−1.59 (0.21)

Coefficients ×100 of own and demand-weighted neighbours' deviations in the specification used by the TDS rules, estimated on data up to the origin. Sum: own plus neighbours, the coefficient used by TDS-EU, with its Driscoll-Kraay standard error in parentheses.

Table S13: One-year-ahead shaping accuracy on fuel-adjusted shapes, 2018-2025 (conditional on the realised fuel path).

Method	RMSE	Within-quarter RMSE	S/W bias	|S/W| error	Solar VF bias	Wind VF bias
Price history						
FLAT	18.21	11.92	7.21	13.41	2.01	0.14
HIST1	22.26	15.42	3.46	15.27	0.88	0.48
HIST5	17.87	12.07	4.86	13.34	1.41	0.29
HIST5x†	17.87	12.17	5.09	13.56	1.60	0.18
SIN5	17.36	11.70	4.81	12.94	1.52	0.28
EWMA	18.43	12.45	4.57	13.59	1.25	0.35
TREND-F	20.25	13.00	4.12	15.71	1.09	0.45
DRIFT-F	18.06	12.36	3.94	12.28	1.15	0.34
EUSHIFT	17.84	12.33	3.09	12.24	0.87	0.43
Transition-adjusted						
TDS-H	17.69	12.17	2.79	12.63	0.77	0.50
TDS-F	17.08	11.72	2.65	12.18	0.89	0.50
TDS-EU	17.01	11.64	2.72	12.20	0.78	0.53
Conditional on realised penetration						
TDS-EU‡	16.95	11.61	1.67	11.74	0.45	0.66
Paired differences: p-values, two-way clustered [wild bootstrap by year]						
SIN5 − HIST5	0.03 [0.01]	0.12 [0.08]	0.88 [0.88]	0.06 [0.06]	0.01 [0.01]	
TDS-EU − SIN5	0.34 [0.40]	0.44 [0.45]	0.17 [0.17]	0.47 [0.53]	0.12 [0.12]	
MDE, TDS-EU − SIN5	1.09	0.21	4.47	3.13	1.37	
Market-years	200	200	200	200	181	181

As Table 3, with the realised within-year fuel-cost path removed from the target and the history.

Table S14: Horizons and window length on identical target market-years, 2020-2025.

	RMSE, raw			S/W bias, raw			S/W bias, fuel-adjusted		
Method	$h=1$	$h=2$	$h=3$	$h=1$	$h=2$	$h=3$	$h=1$	$h=2$	$h=3$
Last year (HIST1)	41.59	42.65	39.90	4.86	7.78	7.50	6.33	8.38	7.90
3-year average (HIST3)	33.78	33.42	31.53	6.80	5.10	3.93	8.37	7.95	7.82
5-year average (HIST5)	31.91	31.25	30.38	4.93	5.23	4.59	8.42	7.77	7.07
Sinusoidal (SIN5)	30.79	30.49	29.46	6.07	6.42	5.76	8.16	7.83	7.34
SIN5, clean history (SIN5c)	29.71	29.63	28.71	7.13	7.53	6.62			
TDS sinusoidal (TDS-F)	30.81	30.54	29.54	2.57	4.36	4.63	4.68	5.78	6.21
TDS, European penetration (TDS-EU)	30.79	30.60	29.57	2.71	4.36	4.54	4.83	5.79	6.15
TDS-EU, clean history (TDS-EUc)	29.60	29.64	28.68	3.78	5.46	5.40			
TDS-EU, realised penetration‡	30.82	30.67	29.98	1.33	1.58	0.82	3.45	3.01	2.45
Market-years	146						146		

Forecasts made at the end of $Y-h$ for the same target market-years at every horizon. Bias of the log summer/winter ratio in log points.

Table S15: Pre-crisis prior against post-crisis shapes: forecasts made at the end of 2019 for 2023-2025.

	Raw shapes				Fuel-adjusted shapes			
Method	RMSE	S/W bias	|S/W|	Solar VF	RMSE	S/W bias	|S/W|	Solar VF
Flat (baseload)	25.03	23.54	23.94	6.29	20.30	17.68	19.15	4.70
5-year average (HIST5)	22.94	14.13	16.81	3.89	19.26	13.68	17.24	3.85
Sinusoidal (SIN5)	23.17	15.26	17.39	4.16	19.20	14.26	17.45	3.99
SIN5, clean history (SIN5c)	23.17	15.33	17.42	4.17				
TDS sinusoidal (TDS-F)	23.88	18.26	19.73	5.01	19.93	17.24	19.46	4.83
TDS, European penetration (TDS-EU)	23.83	18.27	19.52	4.95	19.92	17.26	19.36	4.77
TDS-EU, clean history (TDS-EUc)	23.83	18.33	19.56	4.96				
TDS-F, realised penetration[‡]	22.85	11.63	15.60	3.29	18.70	10.62	15.89	3.12
TDS-EU, realised penetration[‡]	22.41	10.42	13.84	2.58	18.25	9.43	13.85	2.41
TDS-EU, solar channel only[§]	22.66	12.08	15.19	3.19	18.62	11.09	15.55	3.03
TDS-EU, solar only, realised pen.[§‡]	21.98	4.41	11.99	0.88	17.84	3.42	12.96	0.71
Market-years	71				71			

Window 2015-2019 (at least three years); TDS coefficients estimated on data up to 2019. [‡]Realised penetration of the target year. [§]Solar term only, chosen ex post. A single origin: market-years share common shocks, so differences are descriptive.

Table S16: One-year-ahead RMSE and summer/winter bias by target year, raw shapes.

		RMSE						Summer/winter bias					
Year	*N*	HIST5	SIN5	SIN5c	TDS-EU	TDS-EUc	TDS-EU[‡]	HIST5	SIN5	SIN5c	TDS-EU	TDS-EUc	TDS-EU[‡]
2018	22	17.5	15.5	15.5	14.9	14.9	15.0	−12.7	−11.5	−11.5	−9.1	−9.1	−9.4
2019	22	15.8	16.1	16.1	16.2	16.2	16.2	−3.2	−1.6	−1.6	−0.1	−0.1	0.3
2020	24	21.9	21.1	21.2	21.4	21.5	21.4	12.7	13.8	13.9	15.2	15.2	15.0
2021	25	47.8	47.0	48.7	46.6	48.3	46.4	22.5	22.7	24.3	22.2	23.7	20.6
2022	27	38.1	38.5	37.0	40.0	38.4	40.7	−45.2	−43.5	−40.3	−47.4	−44.2	−49.4
2023	27	32.7	29.9	25.8	30.1	26.0	30.3	9.1	10.2	10.2	6.6	6.5	6.8
2024	27	22.9	22.5	23.0	22.0	22.3	21.8	8.5	9.7	12.1	7.0	9.4	5.1
2025	26	30.3	27.9	24.4	27.0	23.3	26.7	21.5	22.6	22.8	13.0	13.2	10.3
All	200	28.8	27.8	26.9	27.7	26.8	27.8	1.6	2.8	3.8	0.7	1.7	−0.4

Common sample of Table 3. [‡]Realised penetration.

Table S17: Channel selection in the transition adjustment, one year ahead (2018-2025).

	Monthly baseload shapes			Midday shapes			Solar PPAs	
Rule	|S/W|	S/W bias	Solar VF	|S/W|	S/W bias	Solar VF	|Error|	Bias
Baseline[a]	18.87	2.81	1.01	25.26	10.51	3.95	13.02	11.15
TDS-EU	17.78	0.70	0.27	20.13	−0.23	0.49	7.67	2.77
TDS-EU, solar only[§]	17.05	−2.10	−0.53	19.21	−3.32	−0.39	7.32	2.10
TDS-EU, ex ante sel.	18.00	0.78	0.31	20.77	−0.15	0.52	8.66	3.83
Paired differences: p-values, two-way clustered [wild bootstrap by year]								
Solar only − TDS-EU	0.23 [0.23]	0.00 [0.00]	0.00 [0.00]	0.22 [0.22]	0.00 [0.00]	0.00 [0.00]	0.04 [0.04]	0.00 [0.00]
Ex ante sel. − TDS-EU	0.72 [0.83]	0.91 [0.94]	0.87 [0.89]	0.65 [0.89]	0.96 [0.98]	0.95 [0.96]	0.36 [0.83]	0.37 [0.83]

Monthly baseload shapes: absolute and mean summer/winter error (log points) and solar value-factor bias, as in Table 3 (200 and 181 market-years). Midday shapes: as in Table S11 (199 and 181). Solar PPAs: absolute error and bias of the profile capture rate, as in Table 4 (161). [a]SIN5 for shapes, HIST5 for PPAs; PPA *p*-values are for differences from HIST5. Ex ante selection: drops a channel at origins at which the TDS restriction is rejected at 5% on data up to the origin. [§]Chosen ex post.

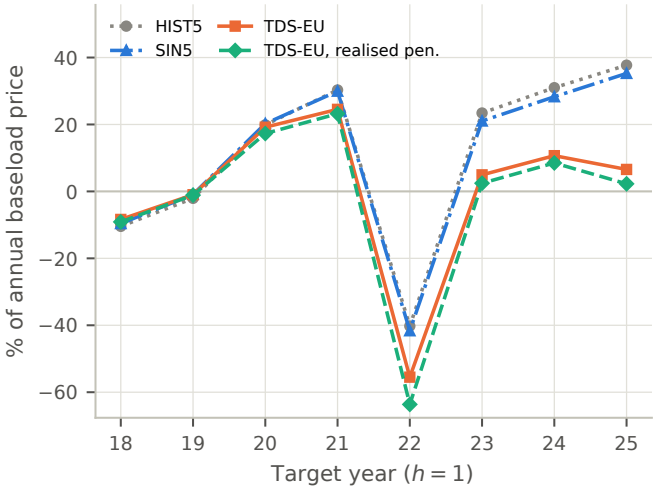


Figure S5: Summer/winter bias of the seasonal shape of midday prices by target year, one year ahead: summer minus winter mean, forecast minus realised, in percent of the annual baseload price. Positive values mean that summer middays are overpriced relative to winter middays.

Table S18: Cross-sectional determinants of the one-year-ahead summer/winter bias.

Target	Prior	Δ regional solar pen.	Δ regional wind pen.	N
Raw	HIST5	−0.33 (0.61)	1.07** (0.46)	200
Raw	SIN5	0.19 (0.60)	0.71* (0.40)	200
Raw	TDS-EU	0.41 (0.60)	0.42 (0.42)	200
Raw	TDS-EU‡	0.45 (0.61)	0.37 (0.43)	200
Fuel-adjusted	HIST5	−0.27 (0.54)	0.85* (0.43)	200
Fuel-adjusted	SIN5	0.05 (0.54)	0.68* (0.39)	200
Fuel-adjusted	TDS-EU	0.28 (0.53)	0.39 (0.41)	200
Fuel-adjusted	TDS-EU‡	0.32 (0.54)	0.33 (0.42)	200

Regression of the market-year bias on the change in regional (own plus neighbours, demand-weighted) solar and wind penetration between the window and the target year, with target-year effects. Market-clustered standard errors in parentheses; significance from $t(G-1)$. Proposition 2 predicts a positive coefficient on solar growth and a negative one on wind growth for historical rules. ‡Realised penetration.

S7 Solar PPA valuation: details

Output profiles. The within-day profile $\nu_{m,h}$ of each market's solar fleet is the mean output at local hour h in month m over all days of the Open Power System Data time series (version 2020-10-06; hourly national solar generation from January 2015 to September 2020), minus the month's smallest hourly mean, which removes most of the night-time output of solar-thermal plants with storage in Spain, divided by the mean of this shifted profile over the 24 hours. Hungary has data from September 2019 only, which cover all months. Croatia and Poland, with too few observations, use the profiles of Slovenia and Czechia, and Estonia, whose series has no diurnal cycle, that of Lithuania. Finland, Ireland, Latvia, Norway and Sweden have no hourly solar data and are not included. In June, the six midday hours (10:00-15:59) account for 56-67% of daily output, against 25% for a flat profile. The profiles are held fixed: they ignore changes in plant orientation and tracking since 2020 and the day-to-day covariance of output and prices, so that the capture rate is that of a contract on a fixed expected profile. The profile defines the contract and enters forecast and realised capture rates alike; that it uses data up to 2020, after the first forecast origins, gives the rules no information about prices.

Hourly rules. Hourly shapes $s_{y,m,h} = P_{y,m,h}/\bar{P}_y$ use the mean price of each local hour over the days of the month and the annual baseload price $\bar{P}_y$, the simple mean of monthly prices; each forecast is normalised to a mean of one over the 288 hour-month cells. HIST5 averages the shapes of the last three to five years with price data; TREND adds the least-squares linear drift of each cell over the same window, extrapolated to the target year and truncated at zero, so that, up to the truncation, it extrapolates the capture rate linearly; TDS-EU multiplies HIST5 by $\exp(a_{m,h})$ with $a_{m,h} = \sum_{j\in\{S,W\}}(\hat{\beta}_j + \hat{\beta}_j^{nb})(\hat{z}_Y^{EU,j} - \bar{z}_W^{EU,j})\,\kappa_{m,h}^j$, where $\hat{\beta}$ are the coefficients of the monthly TDS-EU rule at the origin (Table S12), $\hat{z}^{EU}$ the extrapolated European penetration and $\bar{z}_W^{EU}$ its window mean, and $1 + \kappa_{m,h}^S = \nu_{m,h}(1 + \bar{\kappa}_m^S)\bar{d}/d_m$, $1 + \kappa_{m,h}^W = (1 + \bar{\kappa}_m^W)\bar{d}/d_m$ with window-average monthly profiles measured on monthly output, d_m the days in month m and $\bar{d}$ their mean. TDS-F replaces the European term by the change in own penetration, with the own coefficient, and the demand-weighted change in neighbours' penetration, with their monthly profiles and the neighbours' coefficient, as the monthly TDS-F rule. The seasonal part of TDS-EU replaces $\kappa_{m,h}^S$ by its deviation from the annual mean of each hour. The realised capture rate uses the target year's monthly output shares and the same within-day profile. Three-year contracts are signed at the end of each year 2017-2022 for delivery in the next three years; the forecasts for the three delivery years use horizons $h = 1, 2, 3$, and the contract error is the average of the three annual errors (equal annual volumes). The six-year contract signed at the end of 2019 covers the 19 markets with price history from 2017 and delivery data for 2020-2025: Austria and Croatia have less than three years of prices at the end of 2019 and Switzerland ends in 2024.

Tests. The tests of Table 4 use the statistics of Section S6 with 99,999 bootstrap draws; for three-year contracts the clusters are markets and origins. The mean errors of HIST1, HIST5, TREND, TDS-F and TDS-EU are 5.5, 11.2, 4.1, 2.1 and 2.8 points ($p = 0.18$, 0.03, 0.29, 0.46 and 0.34 for a zero mean; wild bootstrap 0.19, 0.04, 0.29, 0.47 and 0.35). In EUR/MWh, the absolute errors of HIST5 and TDS-EU are 12.5 and 9.2 (difference $p = 0.39$, MDE 12.0); the 2022 errors, with the highest prices of the sample, dominate this comparison. Without 2025, the absolute errors of

TDS-EU and HIST5 differ by 3.8 points ($p = 0.19$).

Calibrating the size of the update. By Proposition 4(c), the share λ of the update that the conditional mean endorses can be estimated from past decisions. For a fixed profile, the analogue is the slope, through the origin, of the realised minus the HIST5 capture rate on the TDS-EU minus the HIST5 capture rate. Estimated recursively on earlier delivery years (one until ten contracts are available) and applied as $\widehat{CR} = \widehat{CR}^{\text{HIST5}} + \hat{\lambda}(\widehat{CR}^{\text{TDS-EU}} - \widehat{CR}^{\text{HIST5}})$, the calibrated update has a mean error of -0.3 points and a mean absolute error of 9.4, against 7.7 for TDS-EU ($p = 0.24$ for the difference); the full-sample slope is 1.30. With eight delivery years, the recursive estimate is too noisy to improve on the unscaled adjustment.

Further results. The European adjustment overcorrects in Italy and the United Kingdom, whose midday prices fell least: in 2023-2025 their mean errors are -10.5 and -10.0 points for TDS-EU against 4.4 and 4.6 for HIST5 (and -7.4 and -3.9 for TDS-F, which uses own penetration), while for the other 20 markets TDS-EU errors range from 4.7 to 13.0 points and HIST5 errors from 18.0 to 32.2. In 2022, when gas prices peaked in August, all rules underpriced solar output, HIST5 by 2.7 points and TDS-EU by 12.5. For the six-year contract signed at the end of 2019, FLAT (pricing solar output at the baseload price) overvalues it by 16.7 points, HIST1 by 19.2, HIST5 by 20.9, TREND by 16.3, TDS-EU by 17.0 and TDS-F by 17.3; with realised European penetration, TDS-EU overvalues it by 7.7 points (4.8 EUR/MWh).

Chronological availability of hourly solar production profiles. The baseline within-day profile $\nu_{m,h}$ is estimated using the fixed 2015-2020 OPSD sample. At forecast origins before the end of 2020, some of these hourly generation observations were not yet available. We therefore rebuild $\nu_{m,h}$ separately at each forecast origin from historical observations available by that date, preserving the baseline preprocessing: local-time hour assignment, subtraction of the month's smallest hourly mean and normalisation to a mean of one over 24 hours. We then recompute both the TDS-adjusted hourly price forecast (whose solar loading depends on $\nu_{m,h}$) and the forecast and realised profile capture rates. Thus, this test removes future information from the within-day solar profile rather than merely changing the weighting of the realised output. The annual baseload price and target-year monthly solar production shares remain at their realised values, by design, so the exercise evaluates price-shape forecasts conditional on those quantities; it is not a fully real-time fixed-price PPA backtest.

Hungary has insufficient historical hourly solar observations for three early one-year origins. The complete 161-market-year comparison uses the Slovak profile observed by the same origin for those three cases, as a neighbouring-market proxy. A conservative alternative drops them, leaving 158 market-years without any borrowed profile. Table S19 reports the resulting values. On the full sample, the TDS-EU-HIST5 difference in mean signed error is -8.38 points (two-way-clustered $p = 0.0095$, wild cluster bootstrap by target year $p = 0.0102$); the reduction in absolute error is -5.35 points ($p = 0.0892$). Against TREND the absolute-error reduction is -2.44 points ($p = 0.0249$). Without the three Hungarian cases, the signed-error difference remains significant ($p = 0.0084$; wild bootstrap $p = 0.0104$), while the absolute-error difference remains marginal ($p = 0.0882$). The 2023-2025 results are unchanged because the profile source is fully historical at those origins.

Table S19: Robustness of solar PPA valuation to the availability of within-day solar profiles (points of the annual baseload price).

Sample and profile	Rule	N	Mean bias	Mean |error|	Bias, 2023-25
One year, original profile	HIST5	161	11.15	13.02	22.23
	TREND	161	4.10	10.11	-
	TDS-EU	161	2.77	7.67	7.47
One year, origin-only profile	HIST5	161	11.15	13.01	22.23
	TREND	161	4.10	10.11	-
	TDS-EU	161	2.77	7.67	7.47
One year, origin-only, no borrowing	HIST5	158	11.25	13.15	-
	TREND	158	4.11	10.19	-
	TDS-EU	158	2.73	7.72	-
Six years, origin 2019, original profile	HIST5	19	20.90	20.90	-
	TREND	19	16.29	16.29	-
	TDS-EU	19	16.99	16.99	-
Six years, origin 2019, origin-only profile	HIST5	19	20.77	20.77	-
	TREND	19	16.20	16.20	-
	TDS-EU	19	16.88	16.88	-

One-year contracts cover 2018-2025; origin-only profiles use no post-origin hourly solar observations. The 161-case variant uses a time-appropriate Slovak profile for three early Hungarian observations; the 158-case variant excludes them. The six-year contract covers 2020-2025 and is valued at end-2019 for 19 markets (including the Slovak proxy for Hungary). For six-year contracts all mean errors are positive, so bias and mean absolute error coincide. All results are conditional on realised annual baseload prices and target-year monthly solar output shares. Values are rounded independently; comparisons for the three-year contracts and for futures-calibrated curves are not recalculated in this check.

Germany: actual output. For Germany, actual quarter-hourly photovoltaic output for 2015-2025 is available from SMARD (Bundesnetzagentur | SMARD.de, CC BY 4.0). Table S20 compares, for each delivery year, the capture rate of actual output, $\sum_t q_t P_t / (\bar{P}_Y \sum_t q_t)$ over the hours of the year; the profile capture rate with the year's own monthly shares and own within-day profile; and the profile capture rate of Section 7.1. The first gap is the within-month covariance of output and prices: sunny days are cheap, so actual output earns less than its average profile, by 0.4 points in 2018 and 3.9 points in 2025. The second gap, from holding the within-day profile at its 2015-2020 average and from small differences between SMARD and Ember monthly output shares, is below 0.1 points in absolute value until 2021, +0.5 and −0.5 points in 2022 and 2023, and −1.6 and −1.1 points in 2024 and 2025, as the fleet's daily profile changed. Because the forecasts do not depend on the realised profile, both gaps shift the errors of all rules by the same amount: against actual output, HIST5 overvalued German solar output by 12.7 points on average over 2018-2025 and TDS-EU by 5.2, against 10.0 and 2.5 with the profile capture rate. A forward curve for actual output would add an expected covariance term, which the rules of Section 7.1 omit.

Table S20: Germany: capture rates of actual and profile output and valuation errors of one-year solar PPAs.

	Capture rate			Gap (points)		Error vs actual		Error vs profile	
Year	Actual	Own profile	Profile	Covariance	Profile	HIST5	TDS-EU	HIST5	TDS-EU
2018	0.988	0.992	0.992	−0.4	0.0	−2.6	−1.0	−3.1	−1.4
2019	0.932	0.945	0.945	−1.3	0.0	3.9	3.4	2.6	2.1
2020	0.811	0.836	0.835	−2.5	0.1	14.9	13.1	12.5	10.7
2021	0.783	0.804	0.805	−2.1	−0.1	14.9	7.5	12.7	5.3
2022	0.952	0.976	0.972	−2.4	0.5	−4.7	−14.5	−6.7	−16.5
2023	0.765	0.794	0.799	−2.9	−0.5	15.8	4.5	12.4	1.1
2024	0.595	0.632	0.648	−3.6	−1.6	29.6	17.0	24.3	11.7
2025	0.519	0.558	0.569	−3.9	−1.1	30.1	11.7	25.1	6.7
Mean	0.793	0.817	0.821	−2.4	−0.4	12.7	5.2	10.0	2.5

Capture rates in units of the annual baseload price. Actual: actual quarter-hourly output aggregated to hours (SMARD) and hourly day-ahead prices. Own profile: profile capture rate with the year's monthly output shares and within-day profile. Profile: profile capture rate of Table 4 (2015-2020 within-day profile, Ember monthly output shares). Covariance gap: actual minus own profile; profile gap: own profile minus profile; in points. Errors: forecast minus realised capture rate, in points, against actual output or against the profile capture rate.

S8 Decision analysis: details

The stylised inflow profile (share of annual inflow by month, January to December) is proportional to (0.35, 0.35, 0.45, 0.9, 2.2, 2.5, 1.9, 1.3, 0.8, 0.55, 0.4, 0.3), a snowmelt regime, normalised to sum to 12. The reservoir has storage capacity $\bar{S} = 6$ (half of annual inflow) and turbine limit $\bar{T} = 2.5$ (the maximum monthly inflow), so that run-of-river operation is feasible without spill; its value is reported as $(s'r - s'\iota)/12$, the premium over run-of-river in percent of the annual baseload price times annual energy. The store has capacity 1, charge and discharge limits $\bar{c} = 1/3$ per month and $\eta_c = \eta_d = \sqrt{0.75}$. Both programmes are cyclic and solved with HiGHS. Under FLAT every schedule is optimal; the static policy runs the reservoir as run-of-river and does not trade the store, and the rolling policy starts from half-full storage.

The rolling-intrinsic policy re-solves, at the start of each month t, the programme over months t to 12 with the storage level inherited from month $t-1$, the terminal level equal to the initial level of the static plan under the prior, the realised shape factor for month t, and for later months the prior rescaled by the ratio of realised to prior shape factors summed over months 1 to t; only month t's decision is implemented. Without the current month's price (rescaling with months before t only), the policy reproduces the static schedule in every market-year for every prior except FLAT, whose ties are broken differently. Knowing the current month's mean price idealises the month-ahead forward price, which differs from it by a forecast error and a risk premium. Table S22 compares this policy with two variants that differ only in the level at which later months are forecast: the prior times last year's annual baseload price (a naive annual forward, available at the decision date), and the prior times the realised annual price (a perfect annual forward, an idealised benchmark that uses information not available at the time). The naive anchor raises the regrets of the averaged and smoothed priors further one year ahead, and those of the store by 8-10 points at the 2019 origin; the perfect anchor cuts them to 11.0-12.5 points for the reservoir and 18.9-22.8 for the store with averaged or smoothed priors, and to 13.3 and 29.8 points even without a seasonal prior (FLAT). Table S21 reports realised values of static and rolling schedules, the optimizer's curse $V(\hat{s}) - s'\hat{x}$ and the shares of market-years in which the store trades and in which it loses money, for all priors. No prior selects the perfect-foresight reservoir schedule, one year ahead or at the 2019 origin; for

the store, priors that do not trade select it in the one market-year in which no cycle is profitable (Italy 2025). Minimum detectable effects for TDS-EU against SIN5 are 2.1 and 3.6 points for the static regret of the reservoir and the store, and 2.2 and 1.9 points for their rolling regret.

The solar-PPA bias uses the realised monthly output shares of the target year, so that it isolates the price-shape error; the run-of-river bias uses the inflow profile. The Jensen benchmark computes, for each market, the intrinsic value of the average realised shape over the target years of Table 3 and subtracts the average perfect-foresight value over the same years; Table 5 reports the mean over the 27 markets.

Value of flexibility over time. Averaged over the 24 markets with three years of data in 2017-2019, the perfect-foresight reservoir premium rose from 17.3% of the annual baseload price in 2017-2019 to 29.5% in 2023-2025 and the store value from 13.5% to 35.0%, with increases in 22 of 24 markets; on fuel-adjusted shapes, the corresponding values rose from 10.6% to 22.1% and from 5.9% to 23.0%, so the rise is not a by-product of the fuel-price path. Across markets and years, it rises with wind penetration (0.91 points per point of penetration for the reservoir premium, two-way clustered standard error 0.32), not with solar penetration. On the market-years of Table 5, the static TDS-EU reservoir premium rose by 5.5 points, from 7.3% in 2018-2019 to 12.8% in 2023-2025, against 12.3 points under perfect foresight (from 16.6% to 28.9%), and the static store lost money in both periods (-4.1 and -6.8, against perfect-foresight values of 13.5 and 33.8).

Updating priors. For each market-year and asset, the analysis of Table 6 computes the static schedules of the incumbent and the candidate prior with HiGHS and keeps the incumbent schedule when it remains optimal under the candidate (tolerance 10^{-7} in shape units). The tolerance t^* is found by bisection on $[0, 1]$ (30 steps), checking at each step whether the incumbent schedule attains the optimal value under $\hat{s}_0 + t\Delta s$. $\hat{\lambda}$ is the least-squares slope of $G + U_0$ on K through the origin over market-years with changed schedules; its two-way clustered standard error (market and target year) uses $t(7)$, and the wild cluster bootstrap by target year imposes the null and recomputes the two-way statistic. Table S23 reports realised gains by the size of the value U_1 claimed for the update, and Table S24 further updates. A recursive rule that updates only when $\hat{\lambda}K > U_0$, with $\hat{\lambda}$ estimated on earlier target years (set to one until ten changed market-years are available), would have earned 1.02 and 1.64 points on average for the reservoir and the store, against 1.10 and 2.15 for always updating. Whenever $\hat{\lambda}$ was at least one, the rule updated every changed schedule, because $U_0/K < 1$; the shortfall comes from the few years with $\hat{\lambda} < 1$: for the reservoir 2024 ($\hat{\lambda} = 0.76$; 1.37 against 1.94 points), and for the store 2021, when $\hat{\lambda} = -0.58$ stopped all updates, which would have gained 4.30 points, while in 2023 ($\hat{\lambda} = 0.81$) skipping some updates helped slightly (1.41 against 1.21).

Sensitivity to physical asset characteristics. We repeat the out-of-sample static scheduling exercise over 200 market-years for nine reservoir and nine seasonal-store configurations, without changing the SIN5 and TDS-EU price forecasts. Reservoir capacity takes values of 3, 6 and 9 months of mean inflow and the monthly turbine limit takes values 1.5, 2.5 and 3.5 times mean inflow. For the store, round-trip efficiency is 0.65, 0.75 or 0.85, and the charging time is 2, 3 or

6 months. Relative to SIN5, TDS-EU reduces mean operational regret in all 18 configurations: by 0.11-1.62 points for the reservoir and by 0.14-2.43 for the store. In the baseline configurations ($\bar{S} = 6$, $\bar{T} = 2.5$; and $\eta = 0.75$, $\bar{c} = 1/3$), the gains are 1.10 and 2.15 points, matching the main-text results up to rounding. The 18 outcomes share the same market-years and price forecasts and are therefore not independent replications. After a Holm correction across the 18 comparisons, none rejects a zero mean gain at the 5% level (smallest adjusted $p = 0.404$). This is qualitative stability of the sign of the average difference over alternative constraints, not evidence of uniformly significant operational gains.

Decision-focused rescaling as a diagnostic. As an exploratory alternative to the structural adjustment, consider $\hat{s}^{DF} = \hat{s}^{SIN5} + \alpha(\hat{s}^{TDS\text{-}EU} - \hat{s}^{SIN5})$. At each target-year origin, we select $\alpha \in \{0, 0.25, 0.50, 0.75, 1, 1.25, 1.50\}$ to minimise the mean static regret over earlier target years only, with a common coefficient across markets but separate coefficients for the reservoir and store. The value $\alpha = 1$ is used before sufficient history is available. In the chronologically evaluated 2020-2025 targets (156 market-years), the reservoir regret is 17.59 under SIN5, 16.40 under TDS-EU and 16.64 under decision-focused rescaling; corresponding store regrets are 49.11, 46.57 and 46.37 points. The paired rescaling-minus-TDS-EU difference is not significant (two-way-clustered $p = 0.316$ for the reservoir and $p = 0.835$ for the store). Hence this scalar decision-focused recalibration does not establish a performance improvement relative to TDS-EU. These diagnostic results are not used to select or retune the baseline TDS model in the main text.

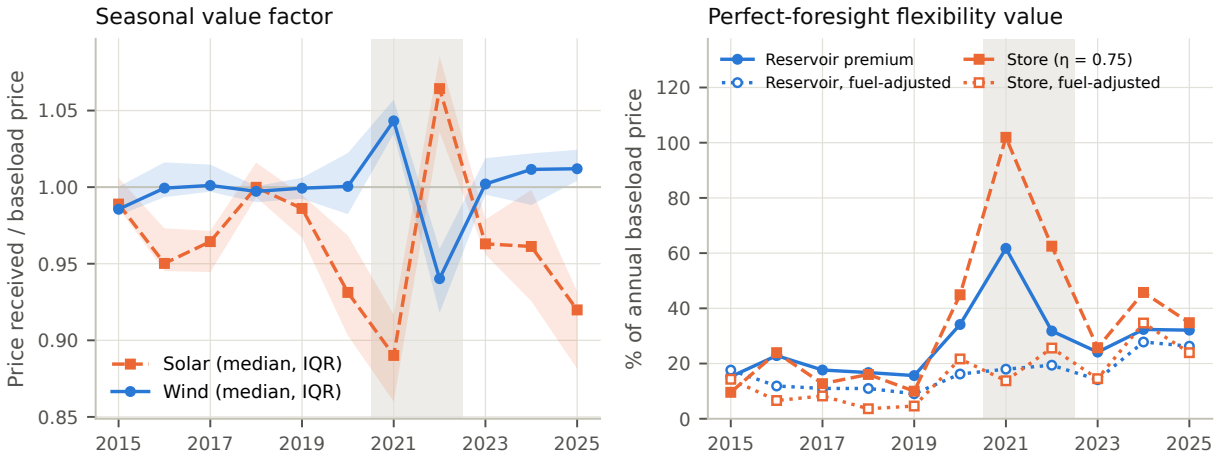


Figure S6: Left: seasonal value factors of solar and wind output (median and interquartile range across markets). Right: perfect-foresight value of the reservoir (premium over run-of-river) and of the store (programme (6) of the main text with $\bar{c} = 1/3$, $\eta = 0.75$), on raw and fuel-adjusted shapes, in percent of the annual baseload price (mean across the 21 markets observed in all years). Shaded: crisis years 2021-2022.

Table S21: Decision outcomes for all priors (percent of the annual baseload price).

	Reservoir			Store				
Prior	Static	Rolling	Curse	Static	Rolling	Curse	Trades (%)	Losses (%)
A. One year ahead, targets 2018–2025								
FLAT	0.00	7.19	0.00	0.00	−10.39	0.00	0	0
HIST1	10.23	7.16	20.00	−12.85	−18.31	54.34	96	74
HIST3	14.47		7.12	−1.77		21.55	90	53
HIST5	14.56	10.76	5.04	−0.37	−2.07	15.37	88	49
HIST5x†	14.89		0.67	2.85		5.21	82	42
EWMA	13.29		8.21	−2.14		21.68	86	52
TREND-F	9.74		14.50	−8.56		38.62	86	56
DRIFT-F	11.51		10.80	−5.19		30.45	82	50
EUSHIFT	11.14		12.60	−3.94		31.68	88	62
SIN5	15.50	12.61	1.39	0.72	1.37	10.59	82	45
SIN5c	15.61	12.09	−1.51	2.45	−0.48	4.16	74	38
TDS-H	14.82		5.93	1.25		15.92	84	47
TDS-F	16.10		1.85	2.63		10.51	79	44
TDS-EU	16.60	13.02	1.49	2.88	1.95	10.60	80	44
TDS-EUc	16.41	12.48	−0.96	3.30	0.23	5.42	75	38
TDS-EU‡	16.23	12.03	2.38	3.43	1.22	10.83	79	43
TDS-EUs‡§	16.31		3.30	4.37		10.85	82	44
Perfect-foresight value	31.44			43.07				
B. Origin 2019, targets 2023–2025								
FLAT	0.00	13.79	0.00	0.00	−2.86	0.00	0	0
HIST1	14.55	16.45	1.62	−3.19	1.87	13.66	100	58
HIST3	13.40		−1.28	2.05		2.23	54	25
HIST5	14.98	15.22	−2.67	2.26	0.60	1.56	54	24
HIST5x†	14.98		−2.67	2.26		1.56	54	24
EWMA	14.75		−2.79	2.32		1.16	49	21
TREND-F	8.59		8.57	−18.30		36.31	93	65
DRIFT-F	12.90		−2.66	−5.26		9.43	73	54
EUSHIFT	17.80		−7.44	3.08		−1.80	37	7
SIN5	13.58	13.61	−2.44	2.80	0.19	−0.34	49	23
SIN5c	13.69	13.56	−2.61	2.62	0.28	−0.20	49	23
TDS-H	14.23		−2.75	1.09		2.63	51	25
TDS-F	11.90		−1.72	2.39		−0.28	44	23
TDS-EU	12.32	12.94	−1.94	0.37	0.17	2.25	45	25
TDS-EUc	12.34	12.88	−2.01	0.30	0.29	2.28	45	25
TDS-EU‡	14.85	14.49	−0.90	4.76	1.32	0.19	68	30
TDS-EUs‡§	16.24		0.88	5.49		2.52	86	42
Perfect-foresight value	29.36			34.93				

Static: realised value of the schedule optimised on the prior. Rolling: realised value of the rolling-intrinsic policy (computed for the priors of Table 5). Curse: value of the optimal schedule under the prior minus its realised value. Trades: share of market-years in which the static store schedule trades; Losses: share in which it loses money. Reservoir values are premia over run-of-river. †Uses hindsight. ‡Realised penetration. §Solar term only, chosen ex post.

Table S22: Operational regret of static schedules and of rolling-intrinsic policies with different level forecasts (percent of the annual baseload price).

	Reservoir				Store			
		Rolling: later months anchored to				Rolling: later months anchored to		
Prior	Static	Prices so far	Last year	Realised year	Static	Prices so far	Last year	Realised year
A. One year ahead, targets 2018–2025								
FLAT	31.44	24.25	27.52	13.28	43.07	53.46	58.74	29.85
HIST1	21.21	24.28	27.38	16.37	55.92	61.38	53.49	30.17
HIST5	16.87	20.68	24.43	12.48	43.44	45.14	50.37	22.80
SIN5	15.94	18.83	23.26	11.31	42.35	41.70	46.60	18.90
SIN5c	15.83	19.35	23.63	11.59	40.62	43.55	47.84	19.50
TDS-EU	14.84	18.42	22.74	11.01	40.19	41.12	46.09	19.16
TDS-EUc	15.03	18.96	23.20	11.06	39.77	42.84	47.13	19.29
TDS-EU‡	15.21	19.40	23.29	11.72	39.65	41.85	46.74	19.90
B. Origin 2019, targets 2023–2025								
FLAT	29.36	15.57	16.70	10.55	34.93	37.79	35.47	20.62
HIST1	14.81	12.91	17.87	9.44	38.12	33.06	36.84	17.99
HIST5	14.38	14.14	15.23	9.75	32.67	34.33	42.84	20.69
SIN5	15.78	15.75	16.40	12.67	32.13	34.74	43.51	20.54
TDS-EU	17.04	16.42	16.40	12.97	34.56	34.75	42.84	20.55
TDS-EU‡	14.51	14.87	16.00	11.69	30.16	33.61	43.16	20.02

Rolling: monthly re-optimisation with the current month's price known and later months forecast by the prior times the level of prices observed so far (the policy of Table 5), last year's annual baseload price, or the realised annual baseload price (anticipative). Regret: perfect-foresight value minus realised value. ‡Realised penetration.

Table S23: Realised gain from updating SIN5 to TDS-EU by the value claimed for the update, one year ahead (percent of the annual baseload price).

	Reservoir				Store			
Claimed value	Share (%)	U_1	Gain G	$G > 0$ (%)	Share (%)	U_1	Gain G	$G > 0$ (%)
$U_1 = 0$ (unchanged)	35.5	0.00	0.00		44.5	0.00	0.00	
$0 < U_1 \leq 0.5$	52.5	0.11	1.59	60.0	33.5	0.20	2.11	56.7
$0.5 < U_1 \leq 2$	10.5	1.08	1.78	76.2	15.5	0.98	4.99	74.2
$U_1 > 2$	1.5	3.37	4.97	100.0	6.5	4.88	10.37	84.6

U_1: value of the update claimed by TDS-EU (Proposition 4); G: realised gain; shares of the 200 market-years. $G > 0$: share of market-years in the bin with a positive realised gain.

Table S24: Further updates of the prior: static schedules (percent of the annual baseload price).

	Reservoir				Store			
Update	Unch. (%)	U_1	Gain G	$\hat{\lambda}$	Unch. (%)	U_1	Gain G	$\hat{\lambda}$
A. One year ahead, targets 2018–2025								
HIST5 → TDS-EU	5.5	1.28	2.03	1.19 (0.26)	16.0	2.55	3.25	1.08 (0.22)
SIN5 → TDS-EU, solar only§	40.0	0.41	0.85	1.59 (0.36)	47.0	1.00	3.65	2.07 (0.22)
SIN5 → TDS-EU, ex ante selection	33.5	0.29	0.72	1.55 (0.26)	40.5	0.73	1.53	1.77 (0.18)
B. Origin 2019, targets 2023–2025								
SIN5 → TDS-EU	21.1	0.22	−1.27		57.7	0.36	−2.43	
SIN5 → TDS-EU‡	19.7	0.53	1.27		46.5	0.57	1.96	
SIN5 → TDS-EU, solar only§	35.2	0.12	0.61		59.2	0.14	1.51	

As Table 6. Unch.: share of market-years in which the incumbent schedule remains optimal under the candidate. $\hat{\lambda}$ is not reported for the single origin of panel B. §Chosen ex post. ‡Realised penetration.

S9 Seasonal value factors

Section 3.1 of the main text defines the seasonal value factor of technology j, $VF^j = \sum_m w_m^j s_m$ with output shares $w_m^j = (1 + \kappa_m^j)/12$, the between-month component of the capture rate.

Proposition S1 (Seasonal value factors)**.** To first order, $VF^j = 1 + \mathrm{Cov}_m(\kappa^j, q)$, where Cov_m is the covariance across months. Under (2) with profiles held fixed,

$$\frac{\partial VF^j}{\partial z^j} = -\theta_j \,\mathrm{Var}_m(\kappa^j) \le 0, \qquad \frac{\partial VF^j}{\partial z^l} = -\theta_l \,\mathrm{Cov}_m(\kappa^j, \kappa^l), \quad l \neq j.$$

The own effect is strictly negative unless the profile is flat.

Proof. Because $\sum_m q_m = 0$, $s_m = e^{q_m}/(\frac{1}{12}\sum_{m'} e^{q_{m'}}) = 1 + q_m + O(q^2)$. Hence $VF^j = \sum_m \frac{1+\kappa_m^j}{12}(1 + q_m) + O(q^2) = 1 + \frac{1}{12}\sum_m \kappa_m^j q_m + O(q^2) = 1 + \mathrm{Cov}_m(\kappa^j, q) + O(q^2)$, using $\sum_m \kappa_m^j = \sum_m q_m = 0$. By (2) with fixed profiles, $\partial q_m/\partial z^l = -\theta_l \kappa_m^l$, so $\partial VF^j/\partial z^l = -\theta_l \frac{1}{12}\sum_m \kappa_m^j \kappa_m^l = -\theta_l \,\mathrm{Cov}_m(\kappa^j, \kappa^l)$, which equals $-\theta_j \,\mathrm{Var}_m(\kappa^j)$ for $l = j$. □

This is the monthly analogue of the covariance form of value factors (Lamont, 2008, Energy Economics 30, 1208-1231). The first term is seasonal cannibalisation; the second is a cross effect, positive between solar and wind because their monthly profiles are negatively correlated in Europe.

Table S25: Seasonal value factors and penetration (percentage points of the value factor per percentage point of penetration).

	Solar value factor				Wind value factor			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own solar	−0.296*	0.028	0.024	0.016	0.080	−0.106	−0.092	−0.092
	(0.152)	(0.131)	(0.118)	(0.111)	(0.073)	(0.086)	(0.080)	(0.080)
Own wind	0.025	−0.100	−0.115*	−0.119	0.057	0.026	0.025	0.027
	(0.135)	(0.060)	(0.059)	(0.067)	(0.101)	(0.070)	(0.070)	(0.069)
European solar			−1.517***	0.353			0.674**	0.078
			(0.343)	(1.638)			(0.230)	(0.809)
European wind			1.171***	1.849***			−0.358**	−0.595
			(0.277)	(0.569)			(0.159)	(0.354)
Fuel-path VF	0.967***	0.805**	1.071***	1.071***	1.025***	0.980***	1.071***	1.060***
	(0.218)	(0.301)	(0.136)	(0.143)	(0.132)	(0.179)	(0.087)	(0.112)
Market FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE		✓				✓		
Quadratic trend				✓				✓
Market-years	222	222	222	222	244	244	244	244

Regressions of the seasonal value factor (in %) on penetration with market effects and the value factor implied by the within-year fuel-cost path; columns (2) and (6) add year effects, (3) and (7) European penetration (demand-weighted, chain-linked), (4) and (8) also a quadratic time trend. Market-years with own penetration of at least 0.5%. Standard errors two-way clustered by market and year in parentheses; significance from t distributions with the number of years minus one degrees of freedom. Proposition S1 with column (1) of Table 1 and market-level profile moments implies −0.49 for solar on own solar penetration, +0.15 for solar on wind, +0.19 for wind on solar and −0.13 for wind on wind.

Table S25 relates the seasonal value factors of Proposition S1, the between-month component of capture rates at monthly baseload prices, to penetration. Without year effects, solar's value factor falls by 0.30 points per point of own solar penetration (two-way clustered standard error 0.15), against −0.49 implied by Proposition S1, and wind's rises with solar penetration (0.08, standard error 0.07), the sign of the predicted cross effect. With year effects, both relations disappear or reverse (0.03 and −0.11): within years, markets with more solar do not have lower solar value

factors. In European aggregates, solar's value factor falls with European solar penetration (−1.52, standard error 0.34) and rises with European wind penetration (1.17, 0.28), and wind's shows the mirror image. With eleven years, however, these are time-series associations: they are roughly three to eight times (2.7-7.6) the slopes implied by Proposition S1, and with a quadratic time trend the European solar coefficient becomes insignificant (0.35, standard error 1.64), while the wind cross effect survives (1.85, 0.57). Monthly value factors thus offer no evidence of seasonal cannibalisation that can be separated from other changes over time; solar's effect on capture values operates within the day (Sections 5 and 7.1 of the main text). Over time (Figure S6), the median seasonal value factor of solar stayed within its pre-2020 range of 0.95-1.00 in 2023 and 2024 and fell to 0.92 in 2025, while that of wind edged above one; fuel-price trends dominated in 2021 and 2022, depressing solar's value factor to 0.89 and then lifting it to 1.06.

S10 Futures benchmark

Data. Daily settlement prices of EEX baseload futures for Germany, France and Italy (monthly, quarterly and annual contracts) from January 2015 (Italy from April 2015) to October 2026, of which the analyses use those up to November 2025. German and French prices are LSEG Datastream exports: Phelix DE futures, listed from April 2017, and Phelix DE/AT futures where a Phelix DE price is missing (on most common days the two differ by less than 1 EUR/MWh). Italian prices are EEX settlement prices in a single file, in which contract identifiers change in April 2025 while prices continue. These data are proprietary. Values of 1 EUR/MWh or less (placeholders in one French yearly series) are dropped; contract-days that appear in several export sheets are combined by their median (they differ on 9 of about 26,000); dates on which every contract of a market repeats the previous settlement, which are exchange holidays padded in the files (157 market-days), and three year-contract settlements recorded after the year had cascaded into quarters and months are dropped; and only settlements before the first delivery day are used.

Futures curves. At an information date, each contract enters with its last settlement in the previous 20 days: quarterly contracts for a first quarter and year contracts stop trading a few days before delivery, when they cascade into months and quarters. The twelve monthly levels of a delivery year are the monthly contracts where listed (at the end of the previous year, the first nine months for Germany and the first six for France and Italy) and, for the other months of a quarter, the quarterly price split across them in proportion to a prior's monthly shape, so that the quarter's hour-weighted average equals the quarterly price. At every origin from the end of 2017 to the end of 2024 all quarters of the next year were priced, and the year contract was never needed.

Seasonal shapes. Table S26 compares the shape implied by year-end futures (monthly levels normalised to a mean of one, months within a quarter split by SIN5) with the priors of Section 6 on the 24 market-years of Germany, France and Italy in 2018-2025, with the metrics of Table 3; splitting by TDS-EU instead changes none of the means in the table by more than 0.02. The futures shape and the priors have similar accuracy. Its summer/winter bias is more negative over the whole period (−4.1 log points, against −0.5 for TDS-EU), in France and Germany (by 8.2 and

5.2 log points relative to TDS-EU) but not in Italy (+2.6); the p-values of the table, clustered by year, do not account for such persistent differences between markets. In 2023-2025 the bias is smaller (7.2, against 12.0 for TDS-EU and 14.4 for HIST5), but in 2023 its near-zero mean (−0.5) hides offsetting errors across markets (−10.9 for France, −5.4 for Germany and +14.9 for Italy), and its absolute error (10.4) exceeds those of HIST5 (6.7) and TDS-EU (5.5). In 2022, like the priors, the futures underpriced summer relative to winter (bias −68.6 log points, against −61.3 for HIST5).

PPAs on futures-calibrated curves. Table S27 reports the valuation errors of one-year solar PPAs on hourly forward curves calibrated to the futures (Section 7.1): monthly levels from the futures at the last trading day before the delivery year, months without a monthly contract split by the rule's own monthly profile, and the rule's within-month hourly shape normalised to a monthly mean of one, so that the curve reprices the monthly and quarterly contracts it uses. The forecast capture rate is relative to the mean of the monthly levels, the forward annual baseload price. In EUR/MWh the error is that of the break-even price and includes the error of the futures level, which was 38% of the realised annual price in absolute value on average, from −52% for 2021 to +109% for 2023 (means over the three markets). TDS-EU lowers the mean error relative to HIST5 by 7.4, 7.1 and 7.9 points in Germany, France and Italy, to +2.2, 0.0 and −5.4 points: in Italy, where the history-based shapes were nearly unbiased (2.5), it overcorrects, and its absolute error (6.7) exceeds that of HIST5 (4.8). Without 2025, TDS-EU lowers the mean error relative to HIST5 by 6.0 points ($p = 0.02$) and the absolute error by 2.4 ($p = 0.31$).

Schedules on futures curves. Table S28 reports the regrets of static schedules optimised on the year-end futures shape and of a rolling-intrinsic policy that re-optimises at the start of every month on the futures curve of the last trading day of the previous month (the front-month contract prices the current month), returns to the initial storage level of the static futures plan, and uses no realised price; for comparison, the static schedules and the rolling-intrinsic policy of Section 7 under HIST5, SIN5 and TDS-EU on the same market-years. Over 2018-2025 the static futures schedules had higher regrets than those on the priors (reservoir 20.7, against 13.1 for TDS-EU, $p = 0.37$; store 45.1 against 37.1, $p = 0.61$), mainly because of 2021; in 2023-2025 they had lower regrets (10.6 against 15.9 for the reservoir and 21.7 against 38.9 for the store), mostly in 2025. Re-optimised monthly on the futures, the schedules did about as well as the rolling-intrinsic policy on TDS-EU over 2018-2025 (reservoir 17.9 against 18.2, store 38.5 against 40.5), and rolling on futures lowers the reservoir's regret relative to the static futures schedule by 2.8 points ($p = 0.10$, wild bootstrap 0.05).

Table S26: Futures-implied seasonal shapes against the priors, one year ahead: Germany, France and Italy, 2018-2025.

	2018–2025 (24 market-years)					2023–2025	
Rule	RMSE	WQ RMSE	S/W bias	|S/W|	Solar VF	S/W bias	|S/W|
FLAT	28.5	12.4	14.8	24.6	3.9	25.1	25.1
HIST5	29.2	12.9	−1.4	21.5	−0.4	14.4	17.4
SIN5	28.2	12.9	0.5	20.8	0.1	16.1	18.1
TDS-EU	28.3	13.0	−0.5	20.0	−0.2	12.0	15.8
TDS-EU‡	28.3	13.0	−1.5	19.7	−0.4	10.6	15.3
Futures (FUT)	28.2	12.7	−4.1	20.3	−0.4	7.2	12.7
Paired differences: p-values, clustered by target year [wild bootstrap by year]							
Futures − HIST5	0.76 [0.77]	0.86 [0.87]	0.17 [0.17]	0.61 [0.63]	0.97 [0.97]		
Futures − TDS-EU	0.97 [0.98]	0.74 [0.74]	0.00 [0.01]	0.85 [0.84]	0.41 [0.39]		
TDS-EU − HIST5	0.14 [0.13]	0.88 [0.87]	0.53 [0.54]	0.14 [0.16]	0.41 [0.42]		

Metrics and units as in Table 3 (WQ: within-quarter; S/W: log summer/winter ratio; VF: value factor). Futures: monthly levels from EEX baseload futures at the last trading day of the previous year, normalised to a mean of one. ‡Realised penetration. *p*-values: standard errors clustered by target year, $t(7)$, ignoring dependence within markets; wild cluster bootstrap by year in brackets.

Table S27: Valuation errors of one-year solar PPAs on hourly forward curves calibrated to EEX futures: Germany, France and Italy, 2018-2025.

	2018–2025 (24 market-years)				2023–2025		Spot-based
Hourly forward curve	Bias	|Error|	RMSE	|Error|, EUR/MWh	Bias	|Error|	|Error|
Futures, flat within months	8.36	11.91	16.04	42.84	20.5	20.5	13.55
Futures + HIST1	2.37	7.02	8.76	39.23	7.6	8.2	9.74
Futures + HIST5	6.39	9.92	12.67	40.95	14.9	14.9	10.12
Futures + TREND	1.66	7.45	9.54	39.27	7.1	7.8	9.84
Futures + TDS-F	−0.11	6.86	9.35	39.11	3.0	8.0	7.03
Futures + TDS-EU	−1.09	7.09	9.73	39.28	1.2	8.2	7.38
Futures + TDS-EU‡	−2.28	7.83	11.05	39.83	0.0	8.7	7.81
Paired differences: p-values, clustered by delivery year [wild bootstrap by year]							
TDS-EU − HIST5	0.01 [0.01]	0.19 [0.19]	0.30 [0.29]	0.69 [0.64]			
TDS-EU − FLAT	0.03 [0.03]	0.14 [0.12]	0.18 [0.21]	0.52 [0.52]			
HIST5 − FLAT	0.16 [0.17]	0.16 [0.16]	0.14 [0.07]	0.22 [0.22]			
TDS-EU − TREND	0.05 [0.04]	0.72 [0.72]	0.85 [0.86]	1.00 [1.00]			

Monthly levels from EEX baseload futures at the last trading day before the delivery year; within-month hourly shape of each rule of Table 4, normalised to a monthly mean of one (flat: none). Errors: forecast minus realised profile capture rate, points of the annual baseload price; |Error|, EUR/MWh: absolute error of the break-even price, including the error of the futures level. Spot-based: absolute error of the same rule in Table 4 on the same market-years. ‡Realised penetration. *p*-values as in Table S26.

Table S28: Regret of static and rolling schedules on priors and on EEX futures curves: Germany, France and Italy (percent of the annual baseload price).

	2018–2025 (24 market-years)				2023–2025			
	Reservoir		Store		Reservoir		Store	
Prior or curve	Static	Rolling	Static	Rolling	Static	Rolling	Static	Rolling
HIST5	16.3	22.5	40.8	45.6	17.5	15.9	42.4	38.5
SIN5	14.9	19.9	39.8	40.3	16.8	15.8	42.0	39.4
TDS-EU	13.1	18.2	37.1	40.5	15.9	15.8	38.9	38.4
Futures (FUT)	20.7	17.9	45.1	38.5	10.6	10.0	21.7	23.4
Perfect-foresight value	32.0		43.2		28.1		30.4	

Regret: perfect-foresight value minus realised value. Static: schedule optimised on the prior or on the futures shape at the end of the previous year. Rolling: for the priors, the policy of Table 5 (current month's price known, later months from the prior rescaled to the level observed so far); for the futures, monthly re-optimisation on the futures curve of the last trading day of the previous month. Reservoir values are premia over run-of-river.