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The hedging effectiveness of electricity futures in the Spanish market

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This paper studies the year-by-year and month-by-month (the same month in all years) hedging effectiveness of futures contracts in the Spanish electricity market from 2007 to 2022. We compare the in-sample and out-of-sample hedging ability of naïve, minimum variance, partially predictable, non-parametric, and BEKK_T hedge ratios. Hedging effectiveness varies over time and across months because of unstable correlations between spot price changes and futures price changes. Some methods present meaningful in-sample performance, but the out-of-sample hedging effectiveness is limited. The hedging effectiveness of the naïve ratio on a year-by-year (month-by-month) basis, with monthly differences, is 16% (40%).

1. Introduction

This paper studies the hedging effectiveness of electricity futures contracts in the Spanish market from 2007 to 2022 over the years and month-by-month. The importance of this topic stems from the problems faced by the current EU's pay-as-clear marginal-price design as a foundation for the wholesale electricity market. This design is under stress because of immediate challenges, such as the oil and natural gas shortage due to the Ukrainian war. Still, the design also faces long-term challenges caused by growing generation shares of non-dispatchable, zero-marginal cost technologies, Peña et al. (2022). Consequently, many authors suggest alternative formats, such as reinforcing the role of the forward and futures markets and auctions of long-term contracts, Fabra (2021). Therefore, understanding whether extant futures markets provide desired results regarding risk sharing and hedging effectiveness is crucial. This paper contributes to the literature by presenting empirical evidence on whether exchange-traded futures contracts help mitigate electricity price risk in the Spanish market. To the best of our knowledge, this is the first paper presenting empirical evidence on this issue in this market. Literature on the effectiveness of hedging strategies in electricity markets includes Byström's (2003) study of the variance reduction performance of electricity futures on Nordpool, reporting out-of-sample hedging effectiveness from 9% to 18%. Malo and Kanto (2006) report hedging effectiveness of 21% in-sample and 17% out-of-sample in NordPool. In the case of California futures traded in the NYMEX, Moulton (2005) documents risk reductions between −2% and 20%. Zanotti et al. (2010) estimate hedging efficacy for Nord Pool, EEX, and Power Next and report risk reductions between −7% and 3%. Martínez and Torró (2018) report risk reduction between −3.7% to 60% in Germany, the Netherlands, and the UK. Most evidence suggests that futures contracts have modest effectiveness in hedging electricity spot price risk. We organize the rest of this paper as follows. After describing the methods in Section 2, we present the data in Section 3. Section 4 discusses the empirical results. Section 5 concludes.

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2. Methods

We analyze hedging effectiveness year-by-year and month-by-month, meaning the same month in all years. We consider five hedging strategies. Detailed explanations of the methods of the five strategies are in the Appendix. The first is the naïve (N) hedging strategy with a hedge ratio equal to one.[1] Second, the OLS minimum variance hedge ratio (MV), Ederington (1979). Third, the Ederington and Salas (2008) (EDS) hedge ratio. The fourth specification (NP) is a non-parametric time-dependent hedge ratio. The fifth specification (BEKK_T) is an extension of the BEKK model, Engle and Kroner (1995), as McAleer et al. (2009)given in . Let $S(t_i)$, be the baseload electricity spot (day-ahead) price[2] corresponding to day t_i, $i = 1,\ldots,$ T, and let $F(t_i, t_j, t_m)$ be the baseload futures price observed at time t_i with delivery over the period $[t_j, t_m]$, $m > j > i$, we shall denote $F(t_i)$ for convenience. A short position in such a derivative commits the seller to deliver an amount of MWh of electricity for every hour of the contracted delivery period, from day t_j to day t_m, at the corresponding futures price. Let the change in spot and futures prices during k days be

$$\Delta_k S(t_i) = S(t_i) - S(t_{i-k}) \tag{1}$$

$$\Delta_k F(t_i) = F(t_i) - F(t_{i-k}) \tag{2}$$

We compute the time series of (1) and (2) using equal nonoverlapping time intervals. The length k of each time interval should be the same as the length of the interval for which the hedge is in effect. We consider $k = d, w, m$ to correspond to daily (one day), weekly (five days), and monthly (around twenty days) changes. The k-period payoff to a firm with a long position in the spot market is

$$PS(t_i, k) = \Delta_k S(t_i) \tag{3}$$

Let $H(t_{i-k})$ be the hedge ratio set at time i-k. The k-period payoff to a firm with a long position in the spot market and a short position in the futures market is

$$PH(t_i, k) = \Delta_k S(t_i) - H(t_{i-k})\Delta_k F(t_i) \tag{4}$$

As a baseline specification for $H(t_{i-k})$ we use the naïve ratio $H^*_{k,N}$

$$H^*_{k,N}(t_{i-k}) = 1 \tag{5}$$

The second specification comes from Ederington (1979), and the optimal hedge ratio $H^*_{k,MV}$ that minimizes the variance of the hedged portfolio (4) is

$$H^*_{k,MV}(t_{i-k}) = \frac{\mathbb{C}OV(\Delta_k S(t_i), \Delta_k F(t_i))}{\mathbb{V}AR(\Delta_k F(t_i))} \tag{6}$$

The third specification is based on Ederington and Salas (2008), and the EDS minimum variance hedge ratio $H^*_{k,EDS}$ is

$$H^*_{k,EDS}(t_{i-k}) = \frac{\mathbb{C}OV([\Delta_k S(t_i) - E(\Delta_k S(t_i))], \Delta_k F(t_i))}{\mathbb{V}AR(\Delta_k F(t_i))} \tag{7}$$

The fourth specification allows for time-varying variances and covariances in (6).[3] We consider the following non-parametric specification $H^*_{k,NP}$ for the optimal hedge ratio,

$$H^*_{k,NP}(t_i, t_{i-k}) = \frac{\mathbb{C}OV(t_i)(\Delta_k S(t_i), \Delta_k F(t_i))}{\mathbb{V}AR(t_i)(\Delta_k F(t_i))} \tag{8}$$

Notice that (8) computes the optimal time-dependent hedging ratio for time t_i using sample variances and covariances data up to t_{i-k}. The fifth specification is a parametric threshold diagonal BEKK(1,1) model (BEKK_T henceforth) to consider asymmetric effects in variances and covariances.[4] We estimate the BEKK_T optimal hedge ratio $H^*_{k,BEKK\_T}$ as

$$H^*_{k,BEKK\_T}(t_i, t_{i-k}) = \frac{h_{k,S,F}(t_i)}{h_{k,F}(t_i)} \tag{9}$$

When calculating out-of-sample hedge ratios, we apply a rolling window. The rolling window size is $n = 240$ (daily differences), $n = 52$ (weekly differences) and $n = 12$ (monthly differences). Using the data in the window up to t_{i-1}, we generate a one-step-ahead conditional variance $h_{k,F}(t_i)$ and covariance $h_{k,S,F}(t_i)$forecast for t_i. We investigate the hedging effectiveness of the futures contracts by looking at the magnitude of variance reduction. To compare the efficiency of the hedging position ($EHP_{k,Z}$) in a period of size k with hedge ratio Z, we utilize a metric, Ederington and Salas (2008), comparing the variance of the hedged position $PH_Z(t_i,k)$to the variance of the unhedged case $PS(t_i,k)$.

[1] This strategy is cost-efficient because there is no need to rebalance hedging positions, so transaction costs are minimal.
[2] This price is the simple average of hourly electricity prices.
[3] Escribano et al. (2011) and Peña et al. (2020) report that the distributions of electricity spot and futures prices and returns are time-varying. Therefore, it is more realistic to expect the optimal hedge ratio to be time-dependent
[4] We present the specification of the BEKK_T model in the Appendix.

$$EHP_{k,Z} = 1 - \frac{\mathbb{V}AR(PH_Z(t_i,k))}{\mathbb{V}AR(PS(t_i,k))};\ Z = H^*_{k,N},\ H^*_{k,MV}, H^*_{k,EDS}, H^*_{k,NP}, H^*_{k,BEKK\_T} \quad (10)$$
$$;i = 1,\ldots,T; k = d,w,m$$

The closer $EHP_{k,Z}$ is to zero, the lower the efficiency of the hedging position.

3. Data

The daily (Monday to Friday) day-ahead[5] power prices source is Eikon, series identifier OMELRTRB, and from now on, we refer to them as "spot prices." The front-month futures continuous price time series[6] source is Eikon series identifier OMIPFTBMc1. The sample goes from July 7, 2007, to August 12, 2022 (3945 data points). Table 1 provides descriptive statistics of the daily (five days a week) spot and futures prices (in €/MWh) in levels and differences with Δ_k and $k = d, w, m$ corresponding to daily, weekly (Friday to Friday), and monthly (last day of the month) differences. Panel A shows summary statistics. Spot price differences are more volatile than futures price differences.[7] The Jarque-Bera JB statistic rejects the null of normal distribution in all cases. The Ljung-Box QLB statistic suggests significant autocorrelation in most series, except the monthly differenced series. Therefore, most series are partially predictable from their lagged values. Engle's ARCH test statistics indicate heteroskedasticity in all cases.

Panel B reports year-by-year correlation coefficients between price change variables. In the total sample 2007–2022, the correlation between spot and futures price changes is 0.38, 0.50, and 0.67 for *d, w,* and *m*, respectively. However, the year-by-year correlation wanders. With daily price changes, the correlation varies from −0.03 (2015) to 0.47 (2022); with weekly changes, the variation is from −0.20 (2015) to 0.66 (2022), and with monthly changes is from −0.01 (2011) to 0.88 (2021). Panel C reports month-by-month correlations. With daily price changes, the correlation varies from −0.04 (June) to 0.71 (March); with weekly changes, the variation is from −0.07 (June) to 0.66 (March), and with monthly changes is from −0.18 (July) to 0.98 (September). Although not stable, the correlations tend to be higher from August to December.

4. Results

In the year-by-year analysis, we divide the data set into yearly estimation periods from 2007 to 2022. Then, we calculate nonoverlapping daily, weekly and monthly differences. We compute hedging ratios (5), (6), (7), (8), and (9), and the hedge effectiveness measure (10) in-sample and out-of-sample. In-sample in (6) and (7) means we compute the hedging ratio for year Y using data from year Y. Out-of-sample in (6) and (7) means we calculate the hedging ratio for year Y using data from year Y-1. With (8) and (9), we report out-of-sample results. In both cases, the estimation window is rolled forward by sequentially dropping the first observation in the window each time and including one new observation up to t_{i-1}. So, the length of the estimation window remains fixed at n observations.[8] When calculating out-of-sample hedge ratios, we apply a rolling window. Using the data in the window up to t_{i-1}, we generate a one-step-ahead conditional variance and covariance forecast[9] for t_i. The Appendix shows a Table with the hedge ratios and the annual effectiveness measure. We summarize the key results. The average values of the hedge ratios for all strategies are around 0.7, 0.8, and 1 for daily, weekly, and monthly differences. But the yearly values of the hedge ratio and the year-by-year hedging performance are erratic. The average hedge effectiveness of the naive strategy is 0.03, 0.04, and 0.16 for daily, weekly, and monthly differences. The average in-sample hedge effectiveness of the MV and EDS is 0.05, 0.11, and 0.26 and 0.19, 0.37, and 0.59 for daily, weekly, and monthly differences. But in both cases, the out-of-sample performance is not significant. The average hedge effectiveness of the out-of-sample non-parametric strategy is 0.06, 0.09, and −0.10 for daily, weekly, and monthly differences. The BEKK_T approach presents average out-of-sample hedge effectiveness of 0.0, −0.06, and −0.43 for daily, weekly, and monthly differences. Table 2 shows the *t*-test and p-values for the average values of hedge ratios, hedge effectiveness measures, and 99% bootstrap confidence intervals computed employing 50,000 samples. The null hypothesis in hedge ratios is that the ratio equals one, and in the case of the hedge effectiveness measure, it is that the measure is zero. Panel A shows the results for the naïve strategy, Panel B the minimum variance, Panel C the partially predictable, Panel D the non-parametric, and Panel E, the BEKK_T.

Regarding the naïve strategy, the *t*-test statistic for the null of zero effectiveness gives p-values of 0.07, 0.16, and 0.01 for daily, weekly, and monthly differences, respectively. The 99% bootstrap confidence intervals contain the zero value in all cases. In the case of the MV and EDS in-sample, the *t*-test statistic for the null of zero effectiveness in-sample gives p-values of 0.00 in all cases. However, the *t*-test statistic for the null of zero effectiveness out-of-sample does not reject the null of no effectiveness. The 99% bootstrap

[5] This series is the average of the twenty-four hourly prices.

[6] This futures contract traded in OMIP is a purely financial instrument with no physical delivery. This series contains the price of the front-month futures baseload (24/7) contract. For instance, on August 16, 2022, the OMIPFTBMc1 price is the price of the futures contract ES BASELD SEP22, which is the monthly futures baseload contract delivered 24/7 during September 2022. Although OMIP offers daily, weekend, weekly, monthly, quarterly, and yearly contracts, more than 95% of trading volume corresponds to contracts with monthly or longer maturity. In terms of monthly-equivalent trading volume, on average, monthly contracts supposed the 53% of total long-term trading volume, followed by quarterly contracts with 36% and yearly contracts with 11%, CNMC (2020). Therefore, in this paper we employ the most liquid futures contract available.

[7] All differenced series are stationary as suggested by the Dickey-Fuller test statistic (not shown).

[8] We report results for $n = 240$ (daily differences), $n = 52$ (weekly differences) and $n = 12$ (monthly differences).

[9] With (8) the forecast for t_i is the ratio estimated at t_{i-1}. With (9) and using the data in the window up to t_{i-1}, we generate a one-step-ahead conditional variance $h_{k,F}(t_i)$ and covariance $h_{k,S,\,F}(t_i)$forecasts

Table 1
Descriptive statistics. Spain spot and front-month (M1) futures electricity prices (€/MWh). Daily data, five days a week. Sample Period July 7, 2007, to August 12, 2022.

Panel A. Summary statistics

	Obs.	Mean	Median	Max.	Min.	SD	Skew.	Kurt.	JB	p-val.	QLB(5)	p-val.	ARCH	p-val.
$S(t_i)$	3945	57.6	49.0	545.0	0.0	42.0	3.8	22.1	6.95E+04	0.00	1.72E+04	0.00	1.74E+04	0.00
$F(t_i)$	3945	59.3	49.5	460.0	20.0	41.4	4.0	22.3	7.21E+04	0.00	1.88E+04	0.00	4.38E+04	0.00
$\Delta d\ S(t_i)$	3944	0.0	−0.1	178.4	−122.1	10.7	1.0	57.3	4.85E+05	0.00	2.01E+02	0.00	7.46E+02	0.00
$\Delta d\ F(t_i)$	3944	0.0	0.0	94.5	−100.0	4.9	−1.4	180.7	5.19E+06	0.00	1.48E+02	0.00	5.04E+02	0.00
$\Delta w\ S(t_i)$	788	0.1	0.3	123.4	−120.5	16.0	−0.1	22.1	1.19E+04	0.00	1.25E+02	0.00	4.25E+02	0.00
$\Delta w\ F(t_i)$	788	0.1	−0.1	169.0	−139.3	11.2	0.4	123.0	4.73E+05	0.00	7.01E+01	0.00	1.26E+02	0.00
$\Delta m\ S(t_i)$	181	0.6	−0.2	122.7	−124.6	24.0	0.0	12.2	6.35E+02	0.00	5.66E+00	0.34	3.80E+02	0.00
$\Delta m\ F(t_i)$	181	0.6	0.5	91.3	−90.4	14.0	0.5	26.1	4.05E+03	0.00	2.88E+00	0.71	1.31E+01	0.00

Panel B. Year-by-year Correlation D: Corr($\Delta_d S(t_i)$, $\Delta_d F(t_i)$),W: Corr($\Delta_w S(t_i)$, $\Delta_w F(t_i)$),M: Corr($\Delta_m S(t_i)$,$\Delta_m F(t_i)$)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2007–22**
D	0.09	0.07	0.09	0.29	0.15	0.12	0.31	0.11	−0.03	0.03	0.20	0.04	0.03	0.15	0.43	0.47	0.38
W	0.29	0.05	0.01	0.41	0.33	0.28	0.49	0.03	−0.20	0.28	0.26	0.45	0.19	0.18	0.58	0.66	0.50
M	0.84	0.24	0.08	0.59	−0.01	0.36	0.65	0.48	0.32	0.24	0.64	0.62	0.26	0.27	0.88	0.57	0.67

Panel C. Month-by-month correlation

Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Mean**
D	0.33	0.11	0.71	0.18	0.09	−0.04	0.05	0.29	0.41	0.25	0.22	0.49	0.26
W	0.47	0.65	0.76	−0.05	0.04	−0.07	0.04	0.42	0.25	0.44	0.34	0.65	0.33
M	0.38	0.64	0.06	0.61	0.65	0.87	−0.18	0.94	0.98	0.94	0.95	0.85	0.64

Table 2
Test statistics and 99% upper (BUL) and lower (BLL) bootstrap intervals for Hedge ratios Naïve (N), Minimum Variance (MV), Partially Predictable (EDS), Non-parametric (NP), and BEKK Threshold (BEKK_T) Hedge effectiveness measure EHP. Sample Period July 7, 2007, to August 12, 2022.

Panel A: Naïve	Average	S.D.	t-Test	P-value	99%BUL	99%BLL
EHP_d	0.03	0.07	1.47	0.07	0.08	−0.01
EHP_w	0.04	0.15	0.98	0.16	0.13	−0.06
EHP_m	0.16	0.28	2.24	0.01	0.34	−0.01
Panel B: MV	**Average**	**S.D.**	**t-Test**	**P-value**	**99%BUL**	**99%BLL**
In-Sample						
$H_{d,MV}$	0.74	0.70	−1.50	0.07	1.21	0.36
EHP_d	0.05	0.07	2.65	0.00	0.10	0.01
$H_{w,MV}$	0.77	0.82	−1.13	0.13	1.28	0.26
EHPw	0.11	0.12	3.73	0.00	0.19	0.04
$H_{m,MV}$	1.05	0.78	0.27	0.39	1.55	0.60
EHPm	0.26	0.24	4.26	0.00	0.41	0.12
Out-of-sample						
$H_{d,MV}$	0.74	0.72	−1.42	0.08	1.12	0.41
EHP_d	0.03	0.07	1.62	0.05	0.08	−0.01
$H_{w,MV}$	0.77	0.84	−1.04	0.15	1.19	0.36
EHPw	0.03	0.21	0.60	0.27	0.15	−0.12
$H_{m,MV}$	1.07	0.80	0.36	0.36	1.48	0.70
EHPm	−0.16	0.68	−0.93	0.18	0.17	−0.69
Panel C: EDS	**Average**	**S.D.**	**t-Test**	**P-value**	**99%BUL**	**99%BLL**
In-Sample						
$H_{d,EDS}$	0.78	0.57	−1.52	0.06	1.18	0.47
EHP_d	0.19	0.07	10.56	0.00	0.24	0.15
$H_{w,EDS}$	0.81	0.64	−1.21	0.11	1.23	0.43
EHP_w	0.37	0.13	11.08	0.00	0.44	0.28
$H_{m,EDS}$	1.10	0.58	0.66	0.26	1.47	0.75
EHP_m	0.59	0.22	10.58	0.00	0.74	0.46
Out-of-sample						
$H_{d,EDS}$	0.78	0.59	−1.44	0.07	1.09	0.51
EHP_d	0.03	0.07	1.81	0.04	0.09	0.00
$H_{w,EDS}$	0.81	0.66	−1.11	0.13	1.15	0.50
EHP_w	0.05	0.19	1.00	0.16	0.16	−0.08
$H_{m,EDS}$	1.11	0.60	0.72	0.24	1.41	0.83
EHP_m	−0.01	0.31	−0.16	0.44	0.18	−0.22
Panel D:NP	**Average**	**S.D.**	**t-Test**	**P-value**	**99%BUL**	**99%BLL**
$H_{d,NP}$	0.74	0.55	5.41	0.00	1.11	0.41
EHP_d	0.06	0.13	1.78	0.04	0.17	0.00
$H_{w,NP}$	0.76	0.79	3.87	0.00	1.26	0.23
EHP_w	0.09	0.18	1.86	0.03	0.20	−0.03
$H_{m,NP}$	0.95	0.68	5.54	0.00	1.43	0.54
EHP_m	−0.10	0.66	−0.60	0.27	0.29	−0.56
Panel E	**Average**	**S.D.**	**t-Test**	**P-value**	**99%BUL**	**99%BLL**
$H_{d,BEKK\_T}$	1.19	0.41	11.57	0.00	1.46	0.93
EHP_d	0.00	0.08	−0.17	0.43	0.05	−0.05
$H_{w,BEKK\_T}$	1.23	0.42	11.83	0.00	1.50	0.97
EHP_w	−0.06	0.37	−0.69	0.25	0.11	−0.35
$H_{m,BEKK\_T}$	1.29	0.45	11.54	0.00	1.59	1.01
EHP_m	−0.43	1.12	−1.56	0.07	0.14	−1.26

confidence intervals contain the zero value. The p-values of hedge effectiveness of the NP are 0.04, 0.03, and 0.27 for daily, weekly, and monthly differences, and the 99% bootstrap confidence intervals contain the zero value.

Regarding the BEKK_T strategy, the *t*-test statistic for the null of zero effectiveness gives p-values of 0.43, 0.25, and 0.07 for daily, weekly, and monthly differences, respectively. The 99% bootstrap confidence intervals contain the zero value in all cases, and the optimal hedge ratio is above one on average. In summary, the size of the futures position wanders. In some years, a negative hedge ratio is indicated; in others, a tiny futures position seems optimal, while in other years, the size of the hedge ratio is almost three. Besides, the empirical evidence suggests a limited ability of futures contracts to hedge a spot position out-of-sample. Several authors, Furió and Torró (2020) and Matsumoto and Yamada (2021), suggest the existence of seasonal patterns in energy commodity demand and spot and futures prices due to climate oscillation throughout the year. These seasonal patterns may impact the design of optimal hedging strategies. Therefore, we analyzed the hedging effectiveness on a month-by-month basis with N, MV, EDS, and NP methods.[10] That is the same month from different years. We include full results in the Appendix but summarize the key results. The hedging effectiveness of the naïve ratio on a month-by-month basis is not different from zero with daily and weekly differences. However, with monthly differences, the average effectiveness is 40% and statistically significant. The hedging effectiveness varies, from 0.95 in September to

[10] We do not apply BEKK_T because of data limitations.

−0.15 in July. The strategy yields negative effectiveness in March and July and is null in April. Overall, this strategy gives better results in June and from August to December. MV and EDS strategies present significant in-sample effectiveness (similar to yearly) but negative out-of-sample performance. The hedging effectiveness is not statistically different from zero with the NP method.

The sample period we analyze, 2007–2022, contains many crisis periods. For instance, the global financial crisis of 2007–2009, the Eurozone crisis of 2009–2012, the Covid pandemic 2020–2022, and the current Ukrainian crisis. Following the insights of Pan et al. (2022), we test for structural changes by running a robust regression to estimate the MV hedge ratio allowing for changes in yearly coefficients. We may see significant changes in the hedge ratio over time, suggesting structural changes. During the 2007–2009 global financial crisis, the optimal ratio was not different from zero. Howfrom 2010–2011 the ratio was higher than one and above two in 2013. From 2014 to 2019, the ratio was zero again. However, the ratio was near one during the three years of the Covid-19 pandemic 2020–2022. The Wald test rejects the null of coefficient equality, thus suggesting structural changes. Detailed results are in the Appendix.

5. Conclusions

This paper studies the year-to-year and month-to-month hedging performance of exchange-traded electricity futures in the Spanish market from 2007 to 2022. The empirical results, based on five different specifications of the hedge ratio, suggest that although the in-sample performance may be helpful, the out-of-sample performance is limited. Hedge ratio estimates indicate a volatile and sometimes counterintuitive hedge position due to unstable correlations between spot and futures price changes. Although hedging effectiveness varies over time, some methods present significant in-sample hedging effectiveness from 2007 to 2022. But in the out-of-sample evaluation, the hedging effectiveness of most strategies is not substantial. On a positive note, the hedging effectiveness of the naïve ratio on a year-by-year (month-by-month) basis, with monthly differences, is 16% (40%) and statistically significant. As other studies suggest, Moulton (2005), electricity futures are of limited use for hedging electricity price risk because of the wandering correlation between spot and futures price changes. This situation contrasts with the one observed in other energy markets where futures contracts present hedging efficiencies of up to 90% (e.g., Furió and Torró, 2020; Bai and Kavussanos, 2022, Li et al., 2021).

CRediT authorship contribution statement

Juan Ignacio Peña: Conceptualization, Methodology, Investigation, Writing – original draft, Software.

Data Availability

Data will be made available on request.

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Supplementary materials

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References

Bai, X., Kavussanos, M.G., 2022. Hedging IMO2020-compliant fuel price exposure using futures contracts. Energy Econ. 110, 10629.
Byström, H.N.E., 2003. The hedging performance of electricity futures on the Nordic power exchange. Appl. Econ. 35 (1), 1–11.
CNMC, 2020. Acuerdo Por El Que Se Emite Informe Relativo a La estructura, Liquidez y Profundidad De Los Mercados De Electricidad a Plazo En España. Expediente n°: INF/DE/016/20.
Ederington, L., 1979. The hedging performance of the new futures markets. J. Financ. 34, 157–170.
Ederington, L., Salas, J., 2008. Minimum variance hedging when spot price changes are partially predictable. J. Bank. Financ. 32, 654–663.
Escribano, A., Peña, J.I., Villaplana, P., 2011. Modeling electricity prices: international evidence. Oxf. Bul.l Econ. Stat. 73 (5), 622–650.
Engle, R., Kroner, K., 1995. Multivariate simultaneous generalized ARCH. Econ. Theory 11, 122–150.
Fabra, N., 2021. The energy transition: an industrial economics perspective. Int. J. Ind. Organ. 79, 102734.
Furió, D., Torró, H., 2020. Optimal hedging under biased energy futures markets. Energy Econ. 88, 104750.
Li, J., Huang, L., Li, P., 2021. Are Chinese crude oil futures good hedging tools? Finance Res. Lett. 38, 101514.
Martínez, B., Torró, H., 2018. Hedging spark spread risk with futures. Energy Policy 113, 731–746.
Malo, P., Kanto, A., 2006. Evaluating multivariate GARCH models in the nordic electricity markets. Commun. Stat.—Simul. Comput. 35 (1), 117–148.
Matsumoto, T., Yamada, Y., 2021. Simultaneous hedging strategy for price and volume risks in electricity businesses using energy and weather derivatives. Energy Econ. 95, 105101.
McAleer, M., Hoti, S., Chan, F., 2009. Structure and asymptotic theory for multivariate asymmetric conditional volatility. Econom. Rev. 28, 422–440.

Moulton, J.S., 2005. California electricity futures: the NYMEX experience. Energy Econ. 27, 181–194.
Pan, Z., Xiao, D., Dong, Q., Liu, L., 2022. Structural breaks, macroeconomic fundamentals and cross-hedge ratio. Financ. Res. Lett. 47, 102633.
Peña, J.I., Rodríguez, R., Mayoral, S., 2020. Tail risk of electricity futures. Energy Econ. 91, 104886.
Peña, J.I., Rodríguez, R., Mayoral, S., 2022. Cannibalization, depredation, and market remuneration of power plants. Energy Policy 167, 113086.
Zanotti, G., Gabbi, G., Geranio, M., 2010. Hedging with futures: efficacy of GARCH correlation models to European electricity markets. J. Int. Financ. Mark. Inst. Money 20, 135–148.