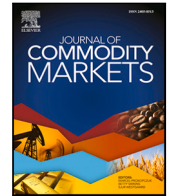


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Trading time seasonality in electricity futures

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ABSTRACT

Trading time seasonality reflects the seasonal behavior of futures prices with the same time of maturity. Hence, it differs from classical seasonality, which reflects seasonal behavior induced by the spot price observed for varying maturities. This type of seasonality is linked to the pricing kernel which in turn accounts for seasonal changes in preferences of agents and tied to risk aversion and thus the demand for hedging. In the present study we empirically examine trading time seasonality in yearly Nordic and German electricity futures contracts. Visual inspection of both average monthly futures prices and the futures backward curves provides strong indications of futures prices systematically varying over the trading year. On average both Nordic and German futures prices are lowest in first quarter and highest in third quarter trading months. This is confirmed by statistical tests of stochastic dominance. Exploiting this insight in a simple trading strategy induces positive and significant alphas in the sense of the capital asset pricing model. We relate the findings to potential seasonal risk preferences and hedging pressure in the electricity futures market.

1. Introduction

It is well known that because of limited storability and transportability, electricity spot prices are highly affected by temporal demand and supply, which in turn is typically affected by seasonal factors, such as weather conditions (e.g., temperature and wind). As electricity futures prices are settled against the actual hourly spot price over the delivery period, any seasonality in the spot price will translate into seasonal variation in the futures prices. However, electricity futures with the same maturity can display another type of seasonality, which is not caused by their maturity time or the underlying spot price, namely seasonality in trading time. Such trading time seasonality has received very little attention in the literature and is more closely investigated in the current study.

The presence of trading time seasonality is linked to the pricing kernel, which in turn accounts for seasonal changes in the preferences of agents. Seasonal risk preferences and securities return seasonality patterns have been addressed by a number of recent studies, e.g., [Kamstra et al. \(2014, 2017\)](#) and [Li et al. \(2018\)](#). However, since preferences of agents are tied to risk aversion and demand for hedging, often referred to as hedging pressure, our results add a seasonal dimension to the important research in this particular field, including studies of [Hirshleifer \(1990\)](#), [Bessembinder \(1992\)](#), [Roon et al. \(2000\)](#), and [Basu and Miffre \(2013\)](#).

Seasonal patterns in electricity futures prices, spot prices, and in the volatility of these, have been well documented in previous studies (e.g., [Bessembinder, 1992](#); [Lucia and Schwartz, 2002](#); [Longstaff and Wang, 2004](#); [Bunn and Chen, 2013](#)). Moreover, a number of previous studies has addressed the presence of a forward premium in the Nordic electricity market (e.g., [Botterud et al., 2010](#); [Lucia and Torr , 2011](#); [Weron and Zator, 2014](#)). Although [Bunn and Chen \(2013\)](#) note that no consensus has yet been reached on the existence and explanation of risk premia in electricity futures, several recent studies on the Nordic electricity market suggest

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the existence of seasonality in risk premia for both weekly (e.g., Haugom et al., 2018) and monthly (e.g., Haugom et al., 2020) futures. Haugom et al. (2018) note that a significant forward premium exists in the Nordic power market for weekly futures and that this premium is highest during the winter and fall. They also suggest that the forward premium is directly related to risk factors in the market, such as inflow level. This finding makes sense given the importance of hydrology in the Nordic power market and can be compared with results from the European power markets where fossil fuels is a major part of the supply stack of electricity generation. Redl and Bunn (2013) find, for example, that underlying fuel commodities explain parts of the market price of risk in electricity in the EEX Market. Many of the same results are found in studies of the U.S. (e.g., Xiao et al., 2015) and Australian (e.g., Thomas et al., 2011; Handika and Trück, 2013) electricity markets. Also, most studies find that risk premia are largest during winter (and in peak periods) and lower during the summer. The results from previous studies highlight that electricity is a derived commodity and that risk, risk preferences, and eventually seasonality in the electricity futures markets to a large extent also might be transferred from the underlying commodities going into the supply stack. The different markets are also interrelated. By analyzing quarterly and annual futures in the Nordic and German markets, Ewald et al. (2022a) show that the difference in risk premia between the two markets is gradually decreasing. However, deterministic variation in the electricity futures market can also be caused by seasonality in the pricing kernel that translates between the pricing measure and the physical measure. Hence, it directly impacts futures and other derivatives prices, but without consequences for the spot price dynamics under the physical measure. Deterministic variations in the risk premia in electricity markets are not necessarily a violation of the no-arbitrage assumption nor the efficient market hypothesis because the risk factors that market players consider when taking positions also vary with the seasons of the year. In fact, Hirshleifer (1991) presents a micro-economic multi-stage model where the resolution of uncertainty at some stage in the cycle reduces the demand for hedging and in this way generates seasonal demand for hedging. This model is an equilibrium model and therefore arbitrage free. However, seasonal demand in hedging does not necessarily lead to trading time seasonality, and in fact Hirshleifer (1991) Proposition 1 explicitly precludes any trading time seasonality. However, Hirshleifer (1991) also writes: “*This “martingale” result is far from being a universal truth about futures pricing; rather, it arises from three stylized features of the current model: additively separable preferences, effectively complete markets, and non-random endowment of the numeraire*”. (p. 308). It is therefore appropriate to assume that under more general assumptions, seasonality in hedging behavior can lead to seasonality in risk premia and therefore trading time seasonality. Our analysis in Sections 4 and 5 demonstrates that this is indeed the case.

Ewald et al. (2022b) identify the presence of such trading time seasonality in the U.S. natural gas and crude oil markets and argue that it might be a violation of the no-arbitrage assumption. Although electricity has different attributes to natural gas and crude oil, including being non-storable, storability in production inputs (see e.g., Douglas and Popova, 2008; Bunn and Chen, 2013) may still cause trading time seasonality.

To the best of our knowledge, the presence of trading time seasonality in markets for electricity futures has not been examined in previous research. The existence of possible arbitrage in the trading of spreads in electricity futures between the Nordic and German power markets is, however, discussed in Ewald et al. (2022a). They find that an intelligently chosen long–short strategy can generate a positive alpha in the capital asset pricing model (CAPM) sense. This is a first piece of evidence that the no-arbitrage assumption may be violated in the market. In our opinion, however, a violation of the no-arbitrage assumption based solely on trading time seasonality is much more severe. To examine this, we use daily closing prices for yearly Nordic- and German electricity futures traded on Nasdaq Commodities (Nasdaq) and the European Energy Exchange (EEX), respectively, for the period 2006 to 2021. The results show that trading time seasonality exists in both Nordic and German electricity futures, and that it is possible to construct a simple long–short strategy that generates positive alphas in the CAPM sense. We discuss the findings in more detail toward the end of the article and relate them to the potential existence of seasonal hedging pressure and risk preferences.

2. Methods

2.1. Theoretical approach

We use $F(t, T)$ to denote the futures price at time t for maturity at time T . Futures prices are determined by supply and demand and in equilibrium the no-arbitrage assumption holds. Mathematically, futures prices are modeled as stochastic processes

$$t \mapsto F(t, T) \quad (1)$$

and well-known results from mathematical finance show that, under some assumptions, the no-arbitrage condition is equivalent to the existence of a so-called martingale measures, under which futures prices are martingales for all maturities T . If the market is complete, there is a unique such martingale measure. However, in the case of market incompleteness, a manifold of martingale measures may exist. In equilibrium, the market adopts one of these and we refer to this measure as the pricing measure \mathbb{Q} . It is also referred to as a risk-neutral measure. The pricing kernel $\frac{d\mathbb{Q}}{d\mathbb{P}}$ translates between the physical measure \mathbb{P} and the pricing measure \mathbb{Q} . Let us use $P(T)$ to denote the underlying spot price and assume that $F(T, T) = P(T)$, i.e., that there is price convergence. Then, the martingale property of (1) under \mathbb{Q} implies that:

$$F(t, T) = \mathbb{E}_t^{\mathbb{Q}}(P(T)) = \frac{\mathbb{E}_t^{\mathbb{P}}\left(\frac{d\mathbb{Q}}{d\mathbb{P}} \cdot P(T)\right)}{\mathbb{E}_t^{\mathbb{P}}\left(\frac{d\mathbb{Q}}{d\mathbb{P}}\right)}. \quad (2)$$

The expectations $\mathbb{E}_t^{\mathbb{Q}}$ and $\mathbb{E}_t^{\mathbb{P}}$ are the conditional expectations under the pricing and physical measures, respectively.

Therefore, seasonality in spot prices $P(T)$ transcends into futures prices. This form of seasonality in contract maturity is reflected in the forward curve $T \mapsto F(t, T)$ for fixed t . However, as Eq. (2) shows, this is not the only possible source of seasonality in futures prices. In fact, any prevalent seasonality in the pricing kernel $\frac{d\mathbb{Q}}{d\mathbb{P}}$ would transcend into futures prices, without impacting on the spot price $P(T)$ under the physical measure. This form of seasonality can be identified through the backward curves under the physical measure, i.e., the realization of $t \mapsto F(t, T)$.¹ Thus, trading time seasonality could be present even if the spot prices were not seasonal at all.

In equilibrium, the pricing kernel $\frac{d\mathbb{Q}}{d\mathbb{P}}$ is equivalent to the marginal utility of agents and, as such, it reflects their preferences. Therefore, seasonality in the pricing kernel is linked to seasonality in preferences, which involves the agent's risk aversion and their demand for hedging. This provides a link between our study and the studies of seasonal risk premia in Shao et al. (2015) and Kamstra et al. (2014). Furthermore, our study adds a seasonal element to the well-known studies on hedging pressure (e.g., Hirshleifer, 1990; Bessembinder, 1992; Roon et al., 2000; Basu and Miffre, 2013). Finally, because in general the pricing kernel can be linked to volatility, our study is related to studies on seasonal changes in volatility (e.g., Ewald and Zou, 2021; Koekebakker and Lien, 2004). Our study also expands on Hirshleifer (1991), providing empirical evidence that his Proposition 1 is violated in the real world under more general assumptions.

Thus, we have identified two channels through which futures prices $F(t, T)$ can inherit seasonal features, the spot price $P(T)$ and the pricing kernel $\frac{d\mathbb{Q}}{d\mathbb{P}}$. We distinguish trading time seasonality as reflected in the backward curve from seasonality in the forward curves. Seasonality in the spot price $P(T)$ can only induce seasonality in the forward curve; it cannot produce seasonal features in the backward curve, as only the pricing kernel can do this. However, the two types of seasonality are not completely independent, as seasonality in the pricing kernel induces seasonality in the forward curves. The reason for this is that the shape of the forward curves $T \mapsto F(t, T) = \mathbb{E}_t^{\mathbb{Q}}(P(T))$ depends on the dynamic properties of the spot price $P(T)$ under the pricing measure \mathbb{Q} and this dynamics reflects the pricing kernel as well.² Therefore, seasonality in the pricing kernel always induces seasonality in both backward and forward curves. An interesting question is whether, in principle, one could have seasonality in the backward curves without any seasonality in the forward curves, and without violating the no-arbitrage assumption. This case is reported in Ewald et al. (2022b) for crude oil. Technically, it might be possible that seasonality in the spot price can offset the seasonal effects in the forward curves caused by a seasonal pricing kernel, and that only the seasonal effects in the backward curves remain. However, it is more likely to be a sign of arbitrage, and so far, no arbitrage-free model has been constructed that features trading time seasonality without seasonality in the forward curves or spot price.

2.2. Statistical tests and empirical specification

Our examination of possible trading time seasonality involves three steps. First, we visually inspect plots from two directions: average trading time prices and futures backward curves. Second, we conduct nonparametric tests to reveal any stochastic dominance by some trading months over others. Third, we search for any arbitrage opportunity by examining parameters obtained from applying the CAPM to a specific trading strategy that is identified based on visual inspection and statistical tests.

2.2.1. Visual inspection

Visual inspection of the data follows a two-step procedure. First, we calculate the average futures price in each month over all years. In this way, we can obtain a first visual impression of whether some months, on average, are traded at a higher or lower price than other months.

Then, to complete the visual inspection, we calculate the backward curves. Here, the maturity horizon is fixed and the trading time varies, i.e., the backward curve includes all contracts traded on different dates in the past that mature on the same period ahead in time, i.e. front year, second front year, and so on. Specifically, the series of contracts that appear in the backward curve can be identified as $F(t_j, T_k)$, where $j = [12(k - 1) + i]$, so that t_1, t_2, \dots, t_N indicates the different trading months prior to the fixed maturity horizon year T_1, \dots, T_M , and for every k , $i = 1$ is the month closest to maturity (i.e., December), $i = 2$ is November and so on, until $i = 12$ is January. Thus, the backward curve, as used in this paper, illustrates a backward-looking view of the prices of those future contracts traded in different months but maturing in the same time horizon, so that $j = 1, \dots, 12$ is future contracts maturing in the front year ($k = 1$), $j = 13, \dots, 24$ is future contracts maturing in the second front year ($k = 2$), and so on. If there is seasonality relating to the trading month, the backward curve should capture this and will show a periodic pattern.

2.2.2. Nonparametric statistical tests

We use the Kruskal–Wallis test (Kruskal and Wallis, 1952) to provide some more formal statistical evidence for trading time seasonality. The Kruskal–Wallis test involves a nonparametric one-way analysis of variance (ANOVA) for testing trading months based on the ranks if there exist any statistical differences. A significant Kruskal–Wallis test indicates the existence of stochastic dominance of (at least) one trading month relative to the others.

Following a significant Kruskal–Wallis test, Dunn's test (Dunn, 1964) tests for stochastic dominance among multiple pairwise comparisons. Consequently, we will test for the existence of stochastic dominance of one trading month over another and, hence, formally test for a plausible long–short strategy as indicated by the visual inspection.

¹ Note that under the pricing measure \mathbb{Q} , the backward curves are tied to the martingale property of (1) but, under the physical measure \mathbb{P} , seasonality can be displayed without violating the no-arbitrage assumption.

² In a continuous time model, this becomes apparent in the corresponding Girsanov transformation, but the same effect appears in discrete time models.

2.2.3. Empirical model

The possible existence of trading time seasonality and the fact that futures contracts with the same maturity are systematically traded at higher prices in some specific months of the year than in others might be exploited by adopting a trading strategy that buys in low-priced months and sells in high-priced months. Over time, this could produce excessive positive trading returns. We formally test this in terms of the CAPM and show that such a strategy can produce positive and significant alphas. A similar line of investigation has been followed in [Basu and Miffre \(2013\)](#) to understand differences in hedging pressure. However, these authors examine Sharpe ratios only and it is generally agreed that alphas provide a better measure of abnormal returns. In any case, this analysis provides another layer of evidence of a possible violation of the no-arbitrage assumption.

Entering a futures contract does not require any initial investment other than a small (relative to the contract's market value) collateral to settle any gain or loss when the position is marked to market on a daily basis. The value of a futures contract is equal to zero on the opening each day. This complicates the calculation of the returns of investments in the futures market. Moreover, for any long position in a commodity future, an equivalent short position must exist, i.e., they are in net-zero supply and, thus, the overall net position of an electricity future must equal zero. [Dusak \(1973\)](#), [Black \(1976\)](#), and [Baxter et al. \(1985\)](#) argue that although the percentage return on the futures contract investment cannot be calculated, given that the initial value is zero, the absolute return of the value of the open position, $\mathbb{E}(R_i) = \mathbb{E}(P_i^1) - P_i^0$, can be used, where P_i^0 and P_i^1 are the value of the asset i at times 0 and 1 respectively. Following this approach, the CAPM can be transformed into:

$$\mathbb{E}(P_i^1) - P_i^0 = r_f P_i^0 + \beta_i^* (\mathbb{E}(R_m) - r_f), \quad (3)$$

where

$$\beta_i^* = \frac{\text{cov}(P_i^1 - P_i^0, R_m)}{\sigma^2(R_m)},$$

R_m is the market return and r_f is the risk-free rate of return. In this case P_i^0 is the value of an asset that reflects a long position in a futures contract. As no initial investment is required to enter such long position at time 0, P_i^0 is zero. Following the setup as in [Dusak \(1973\)](#), which is commonly applied when using the CAPM in the context of futures, the value of this asset at time 1 will then be the difference of the two futures prices so that P_i^1 can be calculated as the change in the futures prices over the period, denoted as Δp_i , as follows:

$$\mathbb{E}(\Delta p_i) = \beta_i^* (\mathbb{E}(R_m) - r_f), \quad (4)$$

and

$$\beta_i^* = \frac{\text{cov}(\Delta p_i, R_m)}{\sigma^2(R_m)}.$$

Thus, the expected price change of a futures contract is equivalent to the product of the expected market premium and the specific β_i^* (i.e., the sensitivity of the futures prices to changes in the market portfolio).

Eq. (4) can be translated into the following testable empirical specification of CAPM:

$$r_i^t = \alpha_i + \beta_i^* (r_m^t - r_f^t) + e_i^t, \quad (5)$$

where r_i^t is the relative change in the futures price between $t - 1$ and t . r_m^t is the corresponding return of the market portfolio and α_i is the excessive return generated from the trading strategy. In theory, any arbitrage opportunity should generate a positive and statistically significant α_i .

3. Description of the data

We use data on daily closing prices for yearly electricity futures with maturities of the front year and up to 5 years from the trading date for the Nordic (Nasdaq Commodities³) and the German market (the European Energy Exchange (EEX)) for the period from June 2006 to February 2021. The data are extracted from the Refinitiv Eikon database.⁴

Our focus is on annual seasonality in terms of monthly price changes. Therefore, for each of the yearly futures contracts, we take the average price of all daily observed futures prices within a trading month as the monthly price. These prices are used throughout this paper unless stated otherwise. Averaging removes any short-term patterns and abnormalities and does not affect the reliability of our results.

The data are organized in three-dimensional arrays,

$$F(i, l, k) \quad (6)$$

³ Until November 2010 the exchange name was Nord Pool.

⁴ It should be noted that until September 2015, the benchmark electricity contract with monthly to yearly maturity on the Nordic market was a "Deferred Settlement Futures" contract, with the same characteristics as forward contracts. However, as this distinction has negligible consequences for our analysis, in the remainder of the paper we use the term futures for all contracts.

where (i, l) denotes the trading month and year with monthly averaging and (k) is the maturity horizon year. Entries in the array where there are no corresponding futures prices are set as void and ignored in all algebraic operations. Then the average

$$\bar{F}_{trd}(i)$$

over all futures prices traded in a particular month is ⁵:

$$\bar{F}_{trd}(i) = \text{avg}\{F(i, l, k) \mid l, k \text{ s.t. } F(i, l, k) \text{ is not void}\} \quad (7)$$

Averaging across years eliminates any long-term trends and emphasizes any systematic seasonal patterns.

We select the OMX Nordic 40 and the DAX indexes as proxies for the market portfolio in the Nordic and German markets, respectively, and the Eurozone 3-month interest rate as the risk-free rate, r_f^e .

In order to account for transaction costs in trading electricity futures we use 1 per cent (approximately 0.3–0.5 Euro/MWh) of the market value as a proxy.⁶

Table 1 shows average prices for the different maturity for both markets in the period analyzed. German electricity futures are traded somewhat higher than Nordic futures and have slightly higher absolute volatility, although the average level is quite stable for years ahead in both markets.

Table 1
Average prices and standard deviations of Nasdaq and EEX contracts.

Commodity	1 yr ahead	2 yr ahead	3 yr ahead	4 yr ahead	5 yr ahead
Nasdaq (6/2006~2/2021)	36.1699 (10.3171)	35.2669 (9.7917)	35.2525 (9.9037)	36.2174 (9.9377)	37.2461 (10.1886)
EEX (6/2006~2/2021)	45.2699 (11.8985)	45.4041 (12.3115)	45.9275 (12.8091)	47.5093 (13.3077)	48.3466 (13.9492)

4. Empirical findings

4.1. Visual inspection

From Fig. 1, we observe that there appears to be a tendency for seasonal effects to be related to trading months. The average prices for both yearly and quarterly contracts reach their minimums when traded in February. The average trading time prices peak in September for the front year and in July/August if we average all contracts. This effect is present in both the Nordic and German markets. Therefore, visual inspections of the trading time plots indicate some sort of trading time seasonality that might be consistent with a strategy of buying in the first quarter and selling in the third quarter of the year.

Inspection of the backward curves of the yearly contracts in the two markets gives the same impression: there is a strong indication of trading time seasonality in Fig. 2. Given that the yearly contracts start to mature in January, the low average prices occurring 11, 23, 35, etc. months before maturity correspond to the trading month of February.

4.2. Statistical test

We provide more formal evidence by conducting a Kruskal–Wallis test. Our samples are split into 12 groups (the number of months in a year), with a degree of freedom of 11. The null hypothesis is that there is no seasonality relating to trading months in our sample. As is evident from Table 2, the null hypothesis is clearly rejected for both markets.

Table 2
Results of Kruskal–Wallis test.

Market	Chi-Square	Sample size (N)
Nasdaq	143.447***	1605
EEX	71.708***	1605

a: Degrees of Freedom: 11.

b: 10% significance *, 5% significance **, 1% significance ***.

⁵ Here, the average is taken for a particular trading month over all contracts traded in that month (but possibly in different years) for all maturities.

⁶ Transaction costs in electricity futures consists of trading and clearing fees, costs of collaterals, as well as indirect costs from trading in the bid–ask spread, which in illiquid products can be a significant part of the transaction costs.

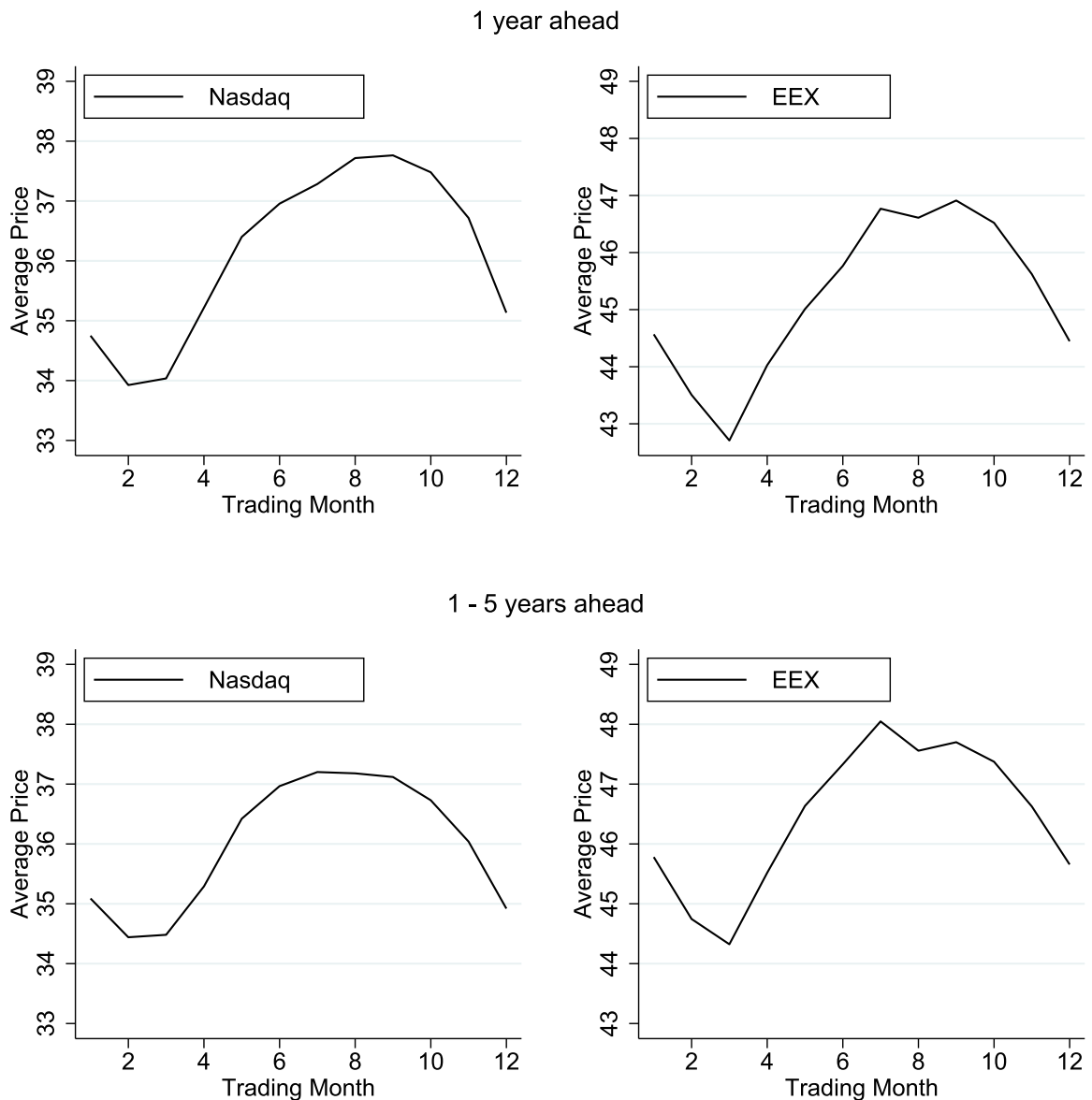


Fig. 1. Average monthly price in different trading months.

The Kruskal–Wallis test does not indicate which trading month or months stochastically dominate others. Therefore, we conduct Dunn’s test among multiple pairwise comparisons of the trading months. As is evident from Tables 3 and 4 for the Nordic and German markets, respectively, February and March are significant stochastically dominated by all other months, whereas the opposite is true for the months July to October. However, differences between the months within the first and third quarters are insignificant.

4.3. CAPM analysis—“Buy low, sell high”

Based on the statistical tests, we choose to further test a naïve strategy where we go long in February and net out the position with a corresponding short position in August. Three panels for each of the two markets are chosen: Panel 1 - trading only front year; Panel 2 - buying futures two and three years ahead; and Panel 3 - buying futures four and five years ahead. Table 5 shows the descriptive statistics of the created annual returns from each strategy as well as for the market portfolio(s).

Table 6 shows the results from the CAPM estimation of a simple “long in February–short in August” strategy. Since the strategy operates on an annual seasonal cycle, the CAPM analysis is based on annual returns from the strategy and corresponding annual returns of the market portfolio. As expected, from an empirical specification of a futures investment model, we are not able to find significant betas from the CAPM (see e.g., Baxter et al., 1985), for any of the panels or markets but panel 3 for Nasdaq which is

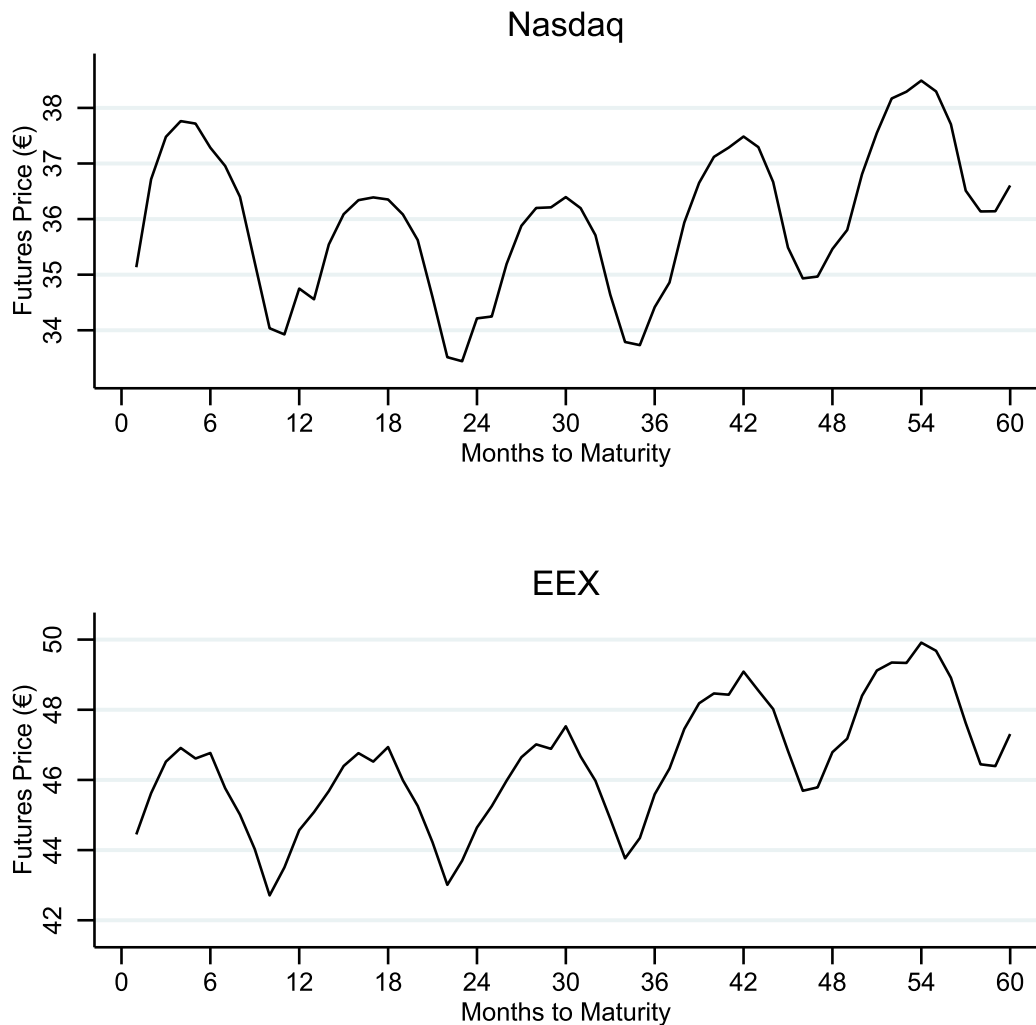


Fig. 2. Aggregated backward curves, Nasdaq and EEX.

significantly positive at the 10% level. However, we find clearly significant positive alphas in all CAPM regressions. Whereas the significant alphas are approximately of the same size for the three panels on the EEX market (ranging from 2.82 to 3.22), the level seems to be lower in the Nasdaq market and there are differences between panels. In the Nasdaq market, the strategy in Panel 3 of buying futures four and five years ahead in February and netting the position out in August yields an alpha of 1.28. However, the strategy in Panel 1, which considers futures one year ahead, yields an alpha of 2.00.

Table 6 also provides results from estimations of Sharpe ratios in which the Sharpe ratio distribution is obtained following a bootstrapping technique (Shen et al., 2007). Following Cheung and Miu (2010) we test if the Sharpe ratio of the trading strategy ($SR_i = \frac{r_i - r_f}{\sigma(r_i)}$) is larger than the Sharpe ratio from the market portfolio ($SR_m = \frac{r_m - r_f}{\sigma(r_m)}$), and the null hypothesis to be tested is $H_0: SR_i = SR_m$. Any significant positive value will, thus, indicate a potential excess profit from the trading strategy relative to the market index. Not surprisingly the sign and significance of the estimated values are similar to the alpha values from the CAPM estimation. The results are in accordance with the ones obtained by Basu and Miffre (2013).

5. Trading time seasonality and hedging pressure

The finding of positive alphas from exploiting the seasonality through a simple trading strategy might in fact be a violation of the no-arbitrage principle that lays the foundation for futures pricing models. A supplementary recursive analysis of the CAPM model (not reported here) did not show any declining pattern or trend of the alphas as we would expect from the revelation of such information when the market matures. So, the question remains, why do the electricity futures markets exhibit trading time seasonality? The explanation might be found in that shifting seasonal uncertainty alters the decision making for risk averse producers.

Table 3Results of nonparametric pairwise monthly comparisons of Nasdaq contracts (pairwise z-test statistics with *p*-values in parentheses below).

Month	Mean	1	2	3	4	5	6	7	8	9	10	11
1	35.08											
2	34.44	1.87 (0.03)										
3	34.48	1.81 (0.04)	-0.06 (0.48)									
4	35.29	-0.32 (0.37)	-2.11 (0.02)	-2.05 (0.02)								
5	36.42	-2.67 (0.00)	-4.43 (0.00)	-4.36 (0.00)	-2.25 (0.01)							
6	36.97	-3.44 (0.00)	-5.24 (0.00)	-5.16 (0.00)	-2.97 (0.00)	-0.67 (0.25)						
7	37.20	-4.71 (0.00)	-6.52 (0.00)	-6.44 (0.00)	-4.16 (0.00)	-1.81 (0.04)	-1.17 (0.12)					
8	37.18	-4.94 (0.00)	-6.75 (0.00)	-6.66 (0.00)	-4.38 (0.00)	-2.03 (0.02)	-1.40 (0.08)	-0.24 (0.41)				
9	37.12	-4.78 (0.00)	-6.57 (0.00)	-6.49 (0.00)	-4.23 (0.00)	-1.90 (0.03)	-1.27 (0.10)	-0.12 (0.45)	0.12 (0.45)			
10	36.73	-4.22 (0.00)	-6.04 (0.00)	-5.96 (0.00)	-3.69 (0.00)	-1.34 (0.09)	-0.68 (0.25)	0.50 (0.31)	0.73 (0.23)	0.61 (0.27)		
11	36.04	-2.94 (0.00)	-4.76 (0.00)	-4.69 (0.00)	-2.47 (0.01)	-0.14 (0.44)	0.54 (0.29)	1.74 (0.04)	1.97 (0.02)	1.84 (0.03)	1.25 (0.11)	
12	34.92	0.48 (0.32)	-1.33 (0.09)	-1.27 (0.10)	0.78 (0.22)	3.03 (0.00)	3.78 (0.00)	5.00 (0.00)	5.22 (0.00)	5.06 (0.00)	4.53 (0.00)	3.30 (0.00)

Table 4Results of nonparametric pairwise monthly comparisons of EEX contracts (pairwise z-test statistics with *p*-values in parentheses below).

Month	Mean	1	2	3	4	5	6	7	8	9	10	11
1	45.78											
2	44.75	2.18 (0.01)										
3	44.32	2.79 (0.00)	0.60 (0.27)									
4	45.52	0.21 (0.42)	-1.88 (0.03)	-2.46 (0.01)								
5	46.64	-0.88 (0.19)	-2.96 (0.00)	-3.53 (0.00)	-1.05 (0.15)							
6	47.33	-1.55 (0.07)	-3.68 (0.00)	-4.27 (0.00)	-1.69 (0.05)	-0.62 (0.27)						
7	48.05	-2.66 (0.00)	-4.82 (0.00)	-5.42 (0.00)	-2.75 (0.00)	-1.66 (0.05)	-1.06 (0.14)					
8	47.56	-2.18 (0.01)	-4.35 (0.00)	-4.95 (0.00)	-2.30 (0.01)	-1.21 (0.11)	-0.59 (0.28)	0.48 (0.32)				
9	47.70	-2.63 (0.00)	-4.77 (0.00)	-5.37 (0.00)	-2.73 (0.00)	-1.64 (0.05)	-1.05 (0.15)	-0.00 (0.50)	-0.47 (0.32)			
10	47.37	-2.38 (0.01)	-4.54 (0.00)	-5.14 (0.00)	-2.48 (0.00)	-1.39 (0.08)	-0.78 (0.22)	0.29 (0.39)	-0.19 (0.42)	0.29 (0.39)		
11	46.63	-1.45 (0.07)	-3.61 (0.00)	-4.21 (0.00)	-1.60 (0.06)	-0.51 (0.31)	0.11 (0.45)	1.19 (0.11)	0.72 (0.24)	1.18 (0.12)	0.91 (0.18)	
12	45.66	0.38 (0.35)	-1.72 (0.04)	-2.30 (0.01)	0.16 (0.44)	1.21 (0.11)	1.86 (0.03)	2.93 (0.00)	2.48 (0.01)	2.91 (0.02)	2.66 (0.04)	1.78 (0.04)

Table 5
Descriptive statistics of the created Annual Returns (AR) from each strategy and the market portfolios.

Variable	Mean	SD	Min	Q25	Median	Q75	Max
Nasdaq							
AR: 1 yr ahead	0.041	0.151	-0.368	-0.054	0.030	0.135	0.362
AR: 2-3 yr ahead	0.033	0.114	-0.239	-0.061	0.034	0.117	0.274
AR: 4-5 yr ahead	0.025	0.099	-0.178	-0.076	0.032	0.106	0.200
Market	-0.003	0.121	-0.345	-0.049	-0.020	0.011	0.371
EEX							
AR: 1 yr ahead	0.053	0.118	-0.177	-0.035	0.052	0.128	0.325
AR: 2-3 yr ahead	0.047	0.114	-0.202	-0.049	0.050	0.150	0.265
AR: 4-5 yr ahead	0.043	0.118	-0.195	-0.050	0.041	0.147	0.265
Market	-0.020	0.104	-0.308	-0.082	-0.028	0.032	0.337

Table 6
CAPM regression parameters and estimated difference between Sharpe ratios for trading strategy (SR_i) and market portfolio (SR_m).

Panel	Nasdaq			EEX		
	α_i	β_i^*	$SR_i - SR_m$	α_i	β_i^*	$SR_i - SR_m$
1	2.004*** (0.340)	0.454 (2.673)	0.315*** (0.001)	3.223*** (0.442)	5.914 (2.841)	0.538*** (0.001)
2	1.487*** (0.181)	1.455 (1.559)	0.311*** (0.001)	2.819*** (0.299)	1.809 (2.147)	0.495*** (0.001)
3	1.275*** (0.183)	3.077* (1.643)	0.278*** (0.001)	2.930*** (0.335)	2.341 (2.367)	0.471*** (0.001)

a: 243 observations in panel 1, 486 observations in panel 2 and panel 3.

b: 10% significance *, 5% significance **, 1% significance ***.

c: Bootstrapped standard errors in parentheses (based on 5000 replications).

Fig. 3, which shows the average monthly change in open interest against average monthly price for the front year futures, shows that growth in open interest is highest during the first months of the year. This corresponds with, on average, the lowest prices. This might be an indication that there are short hedgers building up their positions and thus, an overweight of sales interests are pushing prices down.

Our findings can therefore be related to the literature on the role of hedging pressure (Hirshleifer, 1990). For example, Bessembinder (1992) finds that while there is little evidence that unconditional mean futures differ from zero (meaning that the futures' beta is zero), mean returns are nonzero when conditioned on net hedging. Systematic hedging pressure is found to be a significant determinant of commodity futures risk premia (e.g., Roon et al., 2000; Basu and Miffre, 2013).

This literature argues that supply and demand and, hence, futures prices are determined through hedgers' and speculators' preferences, the size of inventories, access to hedging, and possibilities for diversification. All these elements are reflected in the pricing kernel. Hence, our findings add a seasonal perspective to the well-known results by Hirshleifer (1990), Bessembinder (1992), and Roon et al. (2000). Our analysis provides additional support to the results of Basu and Miffre (2013), who also exploit patterns in price variations to generate abnormal returns, but, in contrast to this paper, use Sharpe ratio's instead of CAPM alphas and do not refer to seasonality.

Bessembinder (1992) argues that the no-arbitrage approach cannot be applied in a traditional manner in electricity futures markets because electricity cannot be stored. Nevertheless, it is possible to store much of the inputs used in electricity generation (e.g., fossil fuels, water and snow reservoirs). Electricity is a derived commodity (Bunn and Chen, 2013), thus the market characteristics of production inputs and prices of these are also reflected in the pricing kernel. For example, Huisman and Kilic (2012) found that futures prices from markets in which electricity is predominantly produced with perfectly storable fuels contained time varying risk premiums. This could also apply to the hydro-dominated Nordic power system. Knowledge about hydro conditions (which also affect the so called water values (see e.g., Reneses et al., 2016)) is far lower during the first quarter than in the third quarter because of uncertainty about for example water content in the snow and how snow melting will develop during the spring. Thus, risk-averse producers might be more inclined toward hedging during the first quarter and less so in the other quarters. This pattern reflects exactly the ideas in Hirshleifer (1991). While the latter predict that this seasonal hedging behavior has no effect on futures prices, their statement hinges on some very specific conditions which we believe are not met in reality. It is far more realistic to assume that producer hedging pressure is ultimately pushing futures prices down.

The findings on trading time seasonality may contradict some of the large body of literature on the risk premium in electricity futures. However, in fact this might be a consequence both of producer risk aversion, but also translation of risk from derived commodities may cause this behavior (see e.g., Bunn and Chen, 2013; Redl and Bunn, 2013). This relation will typically be stronger for long-term futures. Seasonal risk premia in natural gas markets as found by Shao et al. (2015) will then translate into risk premia in long-term electricity futures. Thus, our findings of trading time seasonality in electricity futures markets may then be closely related to the findings of Ewald et al. (2022b) on trading time seasonality for natural gas and oil futures.

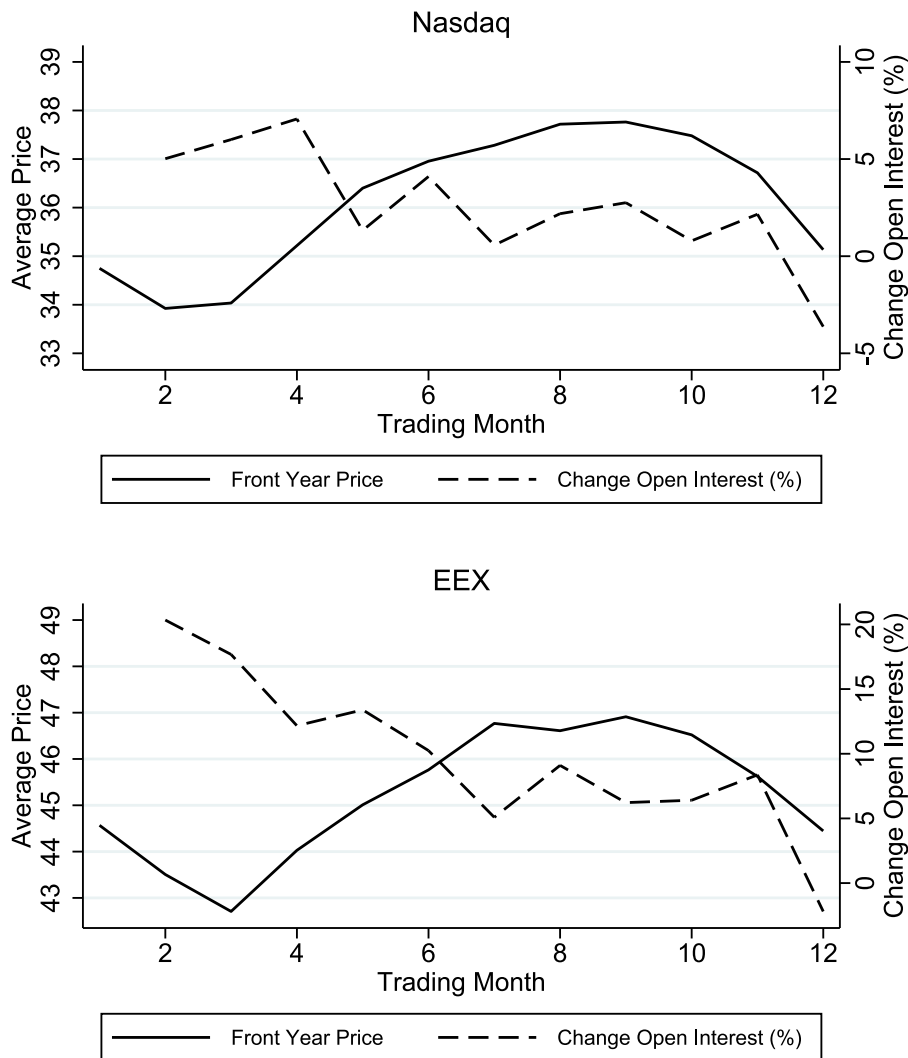


Fig. 3. Average monthly front year price and relative change in open interest.

Our finding of trading time seasonality can thus be related to seasonal risk preferences (Kamstra et al., 2014, 2017; Li et al., 2018). However, these studies link the season and risk preferences to individuals and relate this to behavioral evidence of “winter blues” and seasonal affective disorder, and not to company hedging strategies. However, changing seasonal risk preferences should not be ignored as a possible explanation for lower prices during first quarter. Our finding of trading time seasonality can also be related to seasonal risk preferences.

Additionally, we find higher levels of alphas, though lower variations between the trading panels in the German market compared with the Nordic market. One explanation is that uncertainty concerning snow and water reservoirs is the main explanation for trading time seasonality in the electricity futures market. In turn this results in seasonality to be more prevalent in the hydro-dominated Nordic electricity market, as our CAPM estimates indicate. Nonetheless, the two markets are interrelated. Moreover, our findings of generally higher alpha values in the German market could be explained by market agents here having other risk preferences or being faced with more uncertainty.

6. Concluding remarks

This study addresses a concept that has received very little attention in the literature, namely trading time seasonality. The theoretical discussion reveals that there are dependent seasonal patterns in the forward and backward curves caused by seasonal preference structures reflected in a seasonal pricing kernel.

We empirically examine electricity futures prices in the Nordic and German markets. The study contributes with new knowledge about the structure of these markets as the results suggest that the futures prices exhibit strong seasonal variation in trading time

and significant positive alphas in a CAPM sense from a long–short trading strategy exploiting this insight. While our strategy is not without risk, the CAPM suggests that, relative to the risk, the observed returns are excessive and that our strategy is market beating. We have provided explanations of the peaks in the third quarter and the trough in the first quarter that occur in both markets and show that this is more than a coincidence.

Even though the study presents proofs for the existence of trading time seasonality in Nordic and German electricity futures, the agents' risks preferences and the actual source of trading time seasonality remains unknown. A more rigorous investigation of the possible factors from which the seasonality in the pricing kernel originates from is left for future research.

CRediT authorship contribution statement

Ståle Størdal: Conceptualization, Data curation, Validation, Writing – original draft, Writing – review & editing. **Christian-Oliver Ewald:** Conceptualization, Methodology, Writing – review & editing. **Gudbrand Lien:** Formal analysis, Software, Visualization, Writing – review & editing. **Erik Haugom:** Software, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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