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ANALYSIS OF FORECASTING MODELS IN AN ELECTRICITY MARKET UNDER VOLATILITY

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Abstract

Short-term electricity price forecasting has received considerable attention in recent years. Despite this increased interest, the literature lacks a concrete consensus on the most suitable forecasting approach. This study reports an extensive empirical analysis that we conducted to evaluate the short-term price forecasting dynamics of different regions in the Swedish electricity market (SEM). We utilized several forecasting approaches ranging from standard conditional volatility models to wavelet-based forecasting. In addition, we performed out-of-sample forecasting and back-testing, and we evaluated the performance of these models. Our empirical analysis indicates that an ARMA-GARCH framework with the Student's t-distribution significantly outperforms other frameworks. We only performed wavelet-based forecasting based on the MAPE. The results of the robust forecasting methods are capable of displaying the importance of proper forecasting process design, policy implications for market efficiency, and predictability in the SEM.

Keywords: forecasting, Swedish electricity market, GARCH modeling, multi-scale analysis

JEL Classifications: C53, G17

Contents

1.	INTRODUCTION	1
2.	SWEDISH ELECTRICITY MARKET.....	2
3.	METHODOLOGY.....	3
3.1	ARMA-GARCH Forecasting Models	3
3.2	Wavelet-Based ARMA-GARCH Forecasting Models	5
4.	DATA AND SUMMARY STATISTICS	6
5.	EMPIRICAL ANALYSIS.....	7
6.	CONCLUSION AND IMPLICATIONS.....	10
	REFERENCES	11
	APPENDIX	15

1. INTRODUCTION

Many countries are developing new energy policies to secure their energy systems, sustain the development of their economy, and reduce the negative environmental impact. Over the past few decades, Sweden, like many other European countries, has largely promoted renewable energy to produce green electricity while reducing the output from nuclear power. This has not only affected the electricity price in the long run but also increased its volatility in the market since the electricity production profile has shifted from a relatively reliable mixture of nuclear and hydraulic sources to an intermittent supply using wind and solar power (Tang and Rehme 2017). Therefore, understanding the short-term electricity price becomes more important for all the players in the market. Furthermore, reliable forecasting is significant in developing bidding strategies for electricity-generating firms alongside traders, distributional firms, and large consumers.

On the other hand, the electricity industry is becoming more complicated. Energy conservation programs and energy efficiency improvements have changed the demand. New technologies, such as batteries for electric vehicles, have the potential to transform the demand pattern of electricity in the market extensively. Other energy alternatives, such as hydrogen, also alter the demand and shift the timing of the electricity demand via the storage capability. On the supply side, as previously mentioned, the electricity-generating profile changes depending on the energy policies in a country, which again embeds uncertainty from a long-term perspective. In addition, the electricity price typically has long- and short-term seasonal cycles. Therefore, many possibly interrelated factors could have an influence on electricity.

In the increasingly competitive electricity market, forecasting the day-ahead price is fundamental for all stakeholders. Accurate forecasting of such prices enables power generators to adapt their bidding tactics and consumers to derive a plan to protect themselves from increasing prices. Unlike the fundamentals of other commodities, the electricity market exhibits a unique characteristic; specifically, it is not possible to store electricity in significant amounts. The non-storability feature hinders the utilization of inventories in smoothing the shocks in the demand and supply, thereby resulting in increased volatility of electricity prices. Furthermore, such shocks add uncertainty to electricity prices. For instance, during periods of relatively low demand, power generators with lower marginal costs may be sufficient to accommodate the demand; however, an increase in the demand necessitates the utilization of additional generators to compensate for the demand deficit. Accurate forecasting may therefore enable production houses to utilize their resources better to cope with the dynamic demand from various regions.

Previous studies have utilized different approaches to forecast the prices of underlying assets, for instance ordinary least squares (OLS) (Aye et al. 2015; Birkelund et al. 2015; Botterud, Kristiansen, and Ilic 2010; Danese and Kalchschmidt 2011; Van Donselaar et al. 2016; Haugom et al. 2011; Junttila, Myllymäki, and Raatikainen 2018; Mosquera-López and Nursimulu 2019; Weron and Zator 2014), the error correction model and cointegration (Eksoz, Mansouri, and Boursakis 2014; Fantazzini and Toktamysova 2015; Kalantzis and Milonas 2013; Mjelde and Bessler 2009; B. Zhu et al. 2019), vector autoregression (Bunn and Chen 2013; Girish, Rath, and Akram 2018; Junttila et al. 2018; Nakajima and Hamori 2013; Park, Mjelde, and Bessler 2006), the autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedasticity (GARCH) type (Bowden and Payne 2008; Charwand, Gitizadeh, and Siano 2017; Ferbar Tratar 2015; Furió and Chuliá 2012; Loi and Jindal 2019; Rostami-Tabar et al. 2015; Tratar, Mojškerc, and Toman 2016),

machine learning approaches (Lolli et al. 2017; Nikolopoulos, Babai, and Bozos 2016; Tang and Rehme 2017; Y. Zhu et al. 2019), optimization and networks (Hasni et al. 2019; Le, Ilea, and Bovo 2019; Mirza and Bergland 2012; Tande 2003; Zhu, Mukhopadhyay, and Yue 2011), quantile smoothing (Bruzda 2019), and generalized additive models (Serinaldi 2011). Despite significant literature having evaluated the forecasting accuracy of various approaches, there is no concrete consensus regarding which framework is best suited to encapsulating the dynamics of the electricity markets. We extend the previous literature by utilizing a wavelet-based forecasting approach. In addition, we determine the robustness of the forecasting performance of our proposed framework by varying the window sizes.

Short-term electricity price forecasting is interesting from many aspects. Understanding the price mechanism will enhance the investment decision, both for investors in the energy sector and for electricity users. Short-term electricity price forecasting has received considerable attention in recent years (Bowden and Payne 2008; Liu and Shi 2013). Nevertheless, the literature lacks a concrete consensus on the most suitable forecasting approach to capture the dynamics of electricity markets, possibly due to the aforementioned challenges. We therefore conducted an extensive empirical analysis to evaluate the short-term price forecasting dynamics using data from four different regions in the Swedish electricity market (SEM). More specifically, we utilized several forecasting approaches, ranging from standard conditional volatility models to wavelet-based forecasting, to investigate their performance and applicable conditions. In addition, we performed out-of-sample forecasting and back-testing and assessed the performance of these frameworks by utilizing the root mean squared error (rMSE) and symmetric mean absolute percentage error (sMAPE). Our results could provide guidelines for policy makers, operations managers, and investors related to the electricity market.

The contribution of this study is twofold. First, to the best of our knowledge, this is the first study to incorporate multiresolution-wavelet-based decomposed series into OLS modeling to forecast electricity prices in the Swedish market context. This is essential to capture the hierarchical structure of the original time series and to obtain the optimal predictions at all levels. Second, the expansion of renewable electricity production in Norway and Sweden has led to increased volatility in electricity prices (Serinaldi 2011; Tang and Rehme 2017). The increased employment of renewables in electricity generation further necessitates the examination of forecasting performance due to abrupt adjustments in the electricity markets.

Our empirical analysis suggests that the ARMA-GARCH models significantly outperform the other underlying models based on the rMSE and MAPE. Although we utilized the Student's t-distribution to capture the prospective extreme movement, we gained no significant improvement by changing the marginal distributional framework. Furthermore, the wavelet-based forecasting framework only outperformed the MAPE framework.

The remainder of this paper proceeds as follows. Section 2 presents an overview of the Swedish electricity market (SEM). Section 3 outlines the methodological frameworks that we employed. Section 4 provides the data and preliminary statistics. Section 5 discusses the empirical findings of this study. Finally, section 6 presents the concluding remarks and the implications of the findings.

2. SWEDISH ELECTRICITY MARKET

The electricity market clearing price is the junction between the supply curve and the demand curve, which the sell bids from generator companies and the buy bids from

retailers/buyers establish (Serinaldi 2011). For the Swedish market, this settlement price is based on the Nord Pool Elspot and Elbas (Pool 2018a, 2018b). The Nord Pool Elspot is the physical market that establishes short-term contracts based on the short-term available generation capacity and the forecasted demand for the next day. Elspot contains hourly contracts, 12–36 hours in advance every day, which it bases on seller participants' operational generation capacities and buyer participants' demand. This price is reliant on a number of factors, such as the hydro, wind, and cloud situations as well as the level of economic activity and the temperature (Barthelmie, Murray, and Pryor 2008; Tande 2003). Elbas is an hour-ahead market for hourly contracts that adjusts the actual capacity and demand. Continuous contracts and the balancing market then resolve the final adjustment balancing, which is the responsibility of the transmission system operator (TSO).

On the supply side, the volatility characteristics of new renewable electricity generation, such as wind and solar power, create additional challenges in balancing the electricity grid (Tande 2003; Tang and Rehme 2017). The larger the proportion of new intermittent renewable capacity that a power system has installed, the greater the uncertainty about the supply of electricity and consequently the price (Serinaldi 2011). Therefore, a robust forecast model for electricity prices performs an increasingly important role for both sellers and buyers in the electricity market (Barthelmie et al. 2008; Bowden and Payne 2008; Serinaldi 2011).

The electricity markets in essence balance the supply and demand with a) the day-ahead balance, the *Elspot market* and b) the hour-ahead balance, if something occurs, the *Elbas market*; c) during the operating hours, the TSO is responsible for the final balance to keep the frequency between 49.9. and 50.1 Hertz. A better forecast can aid in making this balancing more efficient but can also be beneficial for other operational aspects, such as planning the maintenance of wind power or gauging when to switch to hydrogen production instead of dispatching to the grid (Barthelmie et al. 2008; Tande 2003). Forecasts are more valuable when the balance markets are part of a competitive electricity trading system and not only treated with long-term bilateral contracts as such markets provide more financial incentives to generators and dealers for accurate production forecasts (Barthelmie et al. 2008).

3. METHODOLOGY

ARMA-GARCH forecasting models are able to capture serial correlation both in mean and in volatility equations and therefore provide a framework in which returns' distribution of forecast. Including time dependency for returns' first and second moments enables these models to estimate and preserve the effect of asymmetric shocks. Owing to the existence of autocorrelation, seasonality, and non-stationarity in electricity markets, ARMA-GARCH models are potentially suitable modeling approaches. However, the electricity markets also show non-linearity and complex behavior that can affect the forecast accuracy. Hence, we used wavelet analysis to transform the return series into details and smooths. This provides a forecasting procedure with a well-behaved decomposed series (Uddin et al. 2019; Zhang, Gençay, and Ege Yazgan 2017). We examined a wavelet-based approach for forecasting electricity market returns using multi-resolution analysis and ARMA-GARCH models.

3.1 ARMA-GARCH Forecasting Models

ARMA-GARCH models the expected returns through an autoregressive moving average process and derives them from a recursive heteroscedastic volatility process. Let $r =$

$\{r_1, r_2, \dots, r_T\}$ be the discrete return vector from the observed electricity market prices. The mean equation based on ARMA (p, q) is

$$r_t = c + \sum_{i=1}^p \varphi_i r_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (1)$$

where c represents the constant term, φ_i is the autoregressive coefficient and represents the effects from past observation, θ_i is the moving average component, and ε_t corresponds to the error term.

Assuming that the variance of the error term ε_t is not constant and homoscedastic, we used the standard GARCH (p, q) model, which captures time-varying conditional variance:

$$\begin{aligned} \varepsilon_t &= h_t^{1/2} z_t \\ z_t &\approx i.i.d. \\ h_t &= \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^q \beta_i h_{t-i} \end{aligned} \quad (2)$$

where z_t is a vector of standardized residuals, h_t denotes the conditional variance at time $t \in \{1, 2, \dots, T\}$, with parameter restrictions, $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\sum_{i=1}^p \alpha_i + \sum_{i=1}^q \beta_i < 1$. As Engle and Bollerslev (1986) suggested, imposing $\sum_{i=1}^p \alpha_i + \sum_{i=1}^q \beta_i = 1$ results in the persistence of conditional variance forecasts in finite samples and infinite-variance unconditional distribution. The authors referred to this framework as integrated GARCH (IGARCH), and it enables the modeling of conditional forecasts with persistent shocks. Glosten, Jagannathan, and Runkle (1993) introduced the GJR-GARCH model, which assumes that negative and positive shocks are asymmetric:

$$h_t = \omega + \sum_{i=1}^p (\alpha_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2) + \sum_{i=1}^q \beta_i h_{t-i} \quad (3)$$

where γ_i denotes the leverage parameter and $I_{t-i} = \{0: \varepsilon_t > 0, 1: \varepsilon_t \leq 0\}$. Hentschel (1995) demonstrated how to decompose the error terms in the variance equation. This decomposition includes different powers for the standardized residuals and conditional variance. Studies refer to this model as the family GARCH (FGARCH):

$$h_t = \omega + \sum_{i=1}^p \alpha_i h_{t-i}^\lambda [|z_{t-i} - \eta_{1i}| - \eta_{1i}(z_{t-i} - \eta_{2i})]^\delta + \sum_{i=1}^q \beta_i h_{t-i}^\lambda \quad (4)$$

where $\lambda = \delta$ results in the full FGARCH model.

Another GARCH model is the component GARCH (CGARCH) that Engle and Lee (1999) suggested, which imposes the conditional variance that a permanent and transitory component drives. The CGARCH models short- and long-term volatility by introducing ϑ_t , a parameter that captures the permanent part of the conditional variance:

$$\begin{aligned}
h_t &= \vartheta_t + \sum_{i=1}^p \alpha_i (\varepsilon_{t-i}^2 - \vartheta_{t-i}) + \sum_{i=1}^q \beta_i (h_{t-i} - \vartheta_{t-i}) \\
\vartheta_t &= \omega + \rho \vartheta_{t-1} + \phi (\varepsilon_{t-1}^2 - h_{t-1})
\end{aligned} \tag{5}$$

where ρ is the first-order autoregressive coefficient for the time-varying intercept.

3.2 Wavelet-Based ARMA-GARCH Forecasting Models

To construct wavelet-based models, we combined multi-resolution analysis (MRA) with the ARMA-GARCH models and OLS regression. We utilized MRA to transform the returns into “details” and “smooths.” Utilizing the ARMA-GARCH model presented in section 3.1, Eq. (1)–(4), we obtained “first-round forecasts,” including step-ahead forecasts of the original and transformed series. Hyndman et al. (2011) and Zhang et al. (2017) indicated that it is possible to regard each variable at various scales as a linear mixture of the lowest-level variables. To preserve the hierarchical structure of the original signal and obtain the optimal projections for all the hierarchical layers, we followed Zhang et al. (2017) and regressed the first-round predictions on a “summing” matrix, which presents the linear relationship in the hierarchical structure.

Using MRA for the training sample $r_t, t \in [1, T]$, we obtained the wavelet details, $D_{j,t}$, and smooths, $S_{j,t}$. We used a maximal overlap discrete wavelet transform (MODWT) to obtain the j th-level MODWT wavelet $W_{j,t}$ and scaling V_j coefficients (Durai and Bhaduri 2009) as follows:

$$W_{j,t} = \sum_{l=0}^{L_1-l} \tilde{k}_{j,l} r_{t-l \bmod N} \quad V_{j,t} = \sum_{l=0}^{L_1-l} \tilde{g}_{j,l} r_{t-l \bmod N} \tag{6}$$

$$D_{j,t} = \sum_{l=0}^{N-l} \tilde{k}_{j,l} W_{j,t+l \bmod N} \quad S_{j,t} = \sum_{l=0}^{N-l} \tilde{g}_{j,l} V_{j,t+l \bmod N} \tag{7}$$

$$r_t = \sum_{j=1}^J D_{j,t} + S_{j,t} \tag{8}$$

where $\tilde{k}_{j,l} = k_{j,l}/2^{j/2}$ and $\tilde{g}_{j,l} = g_{j,l}/2^{j/2}$ denote the wavelet and scaling filters, respectively. $j \in [2, J]$ and J is the decomposition level. We set $J = 2$ and obtained the two-level MRA-wavelet-based transformed series, $D_{j,t}$, and $S_{j,t}$. We further utilized the ARMA-GARCH models that we presented above and obtained “first-round forecasts” $\hat{Y}_{T+h} = [\hat{r}_{T+h}, \hat{D}_{1,T+h}, \hat{D}_{2,T+h}, \hat{S}_{1,T+h}, \hat{S}_{2,T+h}]'$ for horizon h . Following Zhang et al. (2017), we then created a “summing” matrix, Z , with zero and one entries, which encapsulated the linear connection in the hierarchical structure. Contemplating the base-level variables, $\beta_t = [S_{2,t}, D_{2,t}, D_{1,t}]'$, we can convey the linear relationship as

$$Y_t \equiv \begin{bmatrix} r_t \\ S_{1,t} \\ D_{1,t} \\ S_{J,t} \\ D_{J,t} \end{bmatrix} = \begin{bmatrix} S_{2,t} + D_{2,t} + D_{1,t} \\ S_{2,t} + D_{2,t} \\ D_{1,t} \\ S_{2,t} \\ D_{2,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} S_{2,t} \\ D_{2,t} \\ D_{1,t} \end{bmatrix} \equiv Z\beta_t \quad (9)$$

Utilizing an OLS, we regressed the first-round forecasts $\hat{Y}_{T+h} = [\hat{r}_{T+h}, \hat{D}_{1,T+h}, \hat{D}_{2,T+h}, \hat{S}_{1,T+h}, \hat{S}_{2,T+h}]'$ on the summing matrix Z . This offered the optimal base-level forecasts $\tilde{\beta}_{T+h} = [\tilde{S}_{2,T+h}, \tilde{D}_{2,T+h}, \tilde{D}_{1,T+h}]'$. By incorporating the optimal base-level forecasts from the OLS, we assessed the best possible forecasts at all the hierarchical levels:

$$\tilde{Y}_{T+h} = Z\tilde{\beta}_{T+h} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tilde{S}_{2,t} \\ \tilde{D}_{2,t} \\ \tilde{D}_{1,t} \end{bmatrix} = \begin{bmatrix} \hat{r}_{T+h} \\ \tilde{S}_{1,T+h} \\ \tilde{D}_{1,T+h} \\ \tilde{S}_{2,T+h} \\ \tilde{D}_{2,T+h} \end{bmatrix} \quad (10)$$

4. DATA AND SUMMARY STATISTICS

This study analyzed SEM data that the authors obtained from Nord Pool. The data include the daily prices of four Swedish markets from 2 November 2011 to 17 October 2019, resulting in 2076 daily returns.

Table 1: Descriptive Statistics

	NP1SEAV	NP2SEAV	NP3SEAV	NP4SEAV
Mean	0.002	0.002	0.012	0.003
Std dev.	14.235	13.973	19.278	21.068
Min.	-120.91	-120.92	-183.47	-183.47
Max.	102.6	102.6	233.43	238.46
Skewness	0.17	-0.07	0.62	0.51
Kurtosis	11.91	12.38	26.47	20.19
J-B	12,306***	13,297***	60,866***	35,429***
ARCH	317***	374***	206***	210***
Q(10)	131***	126***	211***	213***

Notes: This table provides descriptive statistics for the daily returns of four Swedish electricity markets. The total number of observations for each market is 2076. The sample period is from November 2, 2011 to October 17, 2019. JB is the result of the Jarque–Bera normality test. The table reports the test statistic for the Ljung–Box Q (with 10 lag) and ARCH (with 1 lag) tests. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 1 presents the descriptive statistics of the electricity market returns. It reports the highest average return (0.012%) for NP3SEAV and the highest volatility for NP4SEAV (21.07%). The table contains both the minimum and the maximum returns for NP3SEAV and NP4SEAV. However, the first two markets, NP1SEAV and NP2SEAV, show lower minimum and maximum returns. All the series report positive skewness except for NP2SEAV. According to positive kurtosis and the results of the Jarque–Bera normality test, all of the series follow a non-normal distribution. The significant statistics for Engle's

ARCH test with one lag indicate the existence of ARCH effects and volatility clustering for all the series. Furthermore, the results of the Ljung–Box test with 10 lags suggest serial correlation for most of the series. These results indicate the possibility of using ARMA-GARCH models, which take advantage of existing serial correlation and ARCH effects for forecasting electricity market returns.

5. EMPIRICAL ANALYSIS

To assess the performance of the forecasting models, we forecast the one-step-ahead electricity market returns using rolling window estimation. We set the training sample size to 15, 30, and 50 days and forecast the market returns over the out-of-sample period. We then analyzed the forecasting models using the rMSE and sMAPE measures. The rMSE assumes a normal distribution for forecast errors and penalizes error variance by assigning more weights to larger errors. The sMAPE is a common accuracy measure when the relative error is of interest, particularly when forecasting returns, as these are relative values. Furthermore, we used paired t-tests and the Diebold–Mariano test (Diebold and Mariano 1995). The latter compared wavelet-based and simple forecasting models to understand better which frameworks are more appropriate for the Swedish electricity market.

Table 2: Improvements in Forecast Accuracy

Forecasting Model	rMSE				sMAPE			
	NP1SEA V	NP2SEA V	NP3SEA V	NP4SEA V	NP1SEA V	NP2SEA V	NP3SEA V	NP4SEA V
<i>Panel (A) Window Size = 15 Days</i>								
MRA-AR	2.68	2.72	3.54	2.66	1.57	1.09	1.28	1.02
MRA-ARMA	8.18	7.67	10.91	6.05	1.94	1.46	1.00	1.45
MRA-ARMA-GARCH	2.88	2.86	2.38	2.52	0.77	0.55	1.01	1.40
MRA-ARMA-IGARCH	3.02	3.19	3.28	3.15	0.20	0.06	0.87	0.39
MRA-ARMA-GJRGARCH	2.36	2.62	2.42	2.99	1.09	1.14	0.69	0.71
MRA-ARMA-FGARCH	2.89	2.90	2.26	2.00	0.79	0.51	1.17	1.61
MRA-ARMA-CSGARCH	4.87	5.78	2.25	2.92	1.04	0.82	1.32	1.00
<i>Panel (B) Window Size = 30 Days</i>								
MRA-AR	−0.97	−0.57	15.14	16.19	1.77	1.40	1.22	0.33
MRA-ARMA	1.79	2.39	22.17	21.74	0.87	0.77	1.43	0.80
MRA-ARMA-GARCH	−0.89	−0.36	15.07	9.43	−0.12	−0.02	−0.51	−0.75
MRA-ARMA-IGARCH	−0.97	−0.49	14.28	15.72	−0.68	−0.77	−0.80	−0.91
MRA-ARMA-GJRGARCH	−1.76	−1.92	−2.93	−2.65	−0.05	−0.18	−1.29	−0.37
MRA-ARMA-FGARCH	−1.65	−1.84	−1.99	−1.75	0.30	0.35	−0.71	0.17
MRA-ARMA-CSGARCH	−0.62	−0.71	−2.08	−0.18	0.21	−0.01	0.40	0.00
<i>Panel (C) Window Size = 50 Days</i>								
MRA-AR	−2.63	−3.31	−0.62	−0.79	3.97	2.78	2.86	2.70
MRA-ARMA	−1.24	−2.24	0.63	0.33	0.95	0.22	1.18	−0.26
MRA-ARMA-GARCH	−3.40	−5.24	−2.63	−2.61	−0.13	0.15	−0.47	−1.65
MRA-ARMA-IGARCH	−2.31	−3.92	−2.53	−2.05	−0.35	0.03	−0.04	−2.10
MRA-ARMA-GJRGARCH	−2.73	−3.77	−2.07	−2.37	−1.24	−0.34	−0.37	−2.06
MRA-ARMA-FGARCH	−3.21	−4.99	−2.44	−2.56	−0.08	0.21	−0.44	−1.69
MRA-ARMA-CSGARCH	0.49	−0.27	−1.63	−1.84	0.43	0.32	−0.27	−1.49

Note: This table provides improvements in the root mean squared error (rMSE) and symmetric mean absolute percentage error (sMAPE) for the Sweden Electricity Market data calculations, including daily returns. Each value represents the percentage change (reduction) in forecast accuracy from the wavelet-based forecasting model to its simple counterpart model. Panels A–C report the results based on 15, 30, and 50 days as training sample sizes.

Since the objective of this study was to examine and assess wavelet-based forecasting for Swedish electricity markets, we considered the improvements that we obtained from the ARMA-GARCH models based on MRA compared with the benchmarks, which are simple ARMA-GARCH models. To show improvements, we obtained forecast accuracy measures (rMSE and sMAPE) for each wavelet-based and simple forecasting model and computed the corresponding percentage change. We also used autoregressive (AR) and ARMA models with lag models. For the other models, we used lag 1 for the GARCH and ARCH terms.

Table 3: Paired t-Test for Forecast Accuracy

Forecasting Model	rMSE				sMAPE			
	NP1SEA V	NP2SEA V	NP3SEA V	NP4SEA V	NP1SEA V	NP2SEA V	NP3SEA V	NP4SEA V
<i>Panel (A) Window Size = 15 Days</i>								
MRA-AR	1.17	1.13	1.53	1.32	2.21**	1.55	1.80*	1.46
MRA-ARMA	2.35**	2.12**	2.73***	2.71***	2.34**	1.75*	1.17	1.69*
MRA-ARMA-GARCH	2.16**	2.05**	1.51	1.65*	0.91	0.64	1.19	1.65*
MRA-ARMA-IGARCH	2.10**	2.10**	1.74*	1.79*	0.25	0.07	1.07	0.47
MRA-ARMA-GJRGARCH	1.99**	1.99**	1.06	1.42	1.27	1.29	0.81	0.82
MRA-ARMA-FGARCH	2.16**	2.08**	1.43	1.35	0.93	0.59	1.38	1.87*
MRA-ARMA-CSGARCH	2.20**	2.51**	1.37	1.779*	1.23	0.96	1.57	1.18
<i>Panel (B) Window Size = 30 Days</i>								
MRA-AR	-1.01	-0.58	0.90	0.91	2.39**	1.85*	1.66*	0.46
MRA-ARMA	1.53	1.97**	1.19	1.09	0.96	0.83	1.58	0.86
MRA-ARMA-GARCH	-0.91	-0.37	1.45	1.17	-0.13	-0.02	-0.56	-0.81
MRA-ARMA-IGARCH	-1.02	-0.53	0.99	1.02	-0.74	-0.85	-0.89	-1.00
MRA-ARMA-GJRGARCH	-1.62	-1.67*	-1.01	-1.00	-0.05	-0.19	-1.39	-0.39
MRA-ARMA-FGARCH	-1.36	-1.48	-1.47	-1.35	0.33	0.37	-0.77	0.18
MRA-ARMA-CSGARCH	-0.54	-0.68	-1.41	-0.16	0.22	-0.01	0.43	0.00
<i>Panel (C) Window Size = 50 Days</i>								
MRA-AR	-4.41***	-5.38***	-0.32	-0.49	5.10***	3.47***	3.52***	3.39***
MRA-ARMA	-1.18	-2.15**	0.28	0.17	0.98	0.23	1.24	-0.27
MRA-ARMA-GARCH	-2.22**	-3.24***	-1.93*	-2.07**	-0.14	0.16	-0.52	-1.83*
MRA-ARMA-IGARCH	-1.88*	-3.02***	-1.84*	-1.42	-0.38	0.03	-0.05	-2.34**
MRA-ARMA-GJRGARCH	-1.90*	-2.50**	-1.88*	-2.15**	-1.32	-0.36	-0.40	-2.27**
MRA-ARMA-FGARCH	-2.25**	-3.32***	-1.83*	-1.99**	-0.09	0.22	-0.50	-1.87*
MRA-ARMA-CSGARCH	0.50	-0.26	-1.18	-1.48	0.47	0.34	-0.30	-1.66*

Note: This table provides test statistics for the difference in mean of forecast accuracy measures between simple forecasting models and wavelet-based models. For the rMSE (sMAPE), the null hypothesis is that the difference in the mean of squared errors (absolute percentage errors) is not greater than zero. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2 reports the improvements in the forecast accuracy measures. As we can see, there are gains from utilizing wavelet-based decomposition in forecasting electricity markets when the rolling window size is small (e.g., 15 days). According to Panel (A), all the MRA-based models outperformed the benchmarks in reducing the rMSE and sMAPE. For instance, considering NP1SEAV, there is an 8.18% (6.05%) improvement (decrease) in the rMSE (sMAPE). However, there are limited improvements from wavelet-based models when using longer horizon training sample sizes (30 and 50 days). Panels (B) and (C) show improvements from MRA when using AR and ARMA models. In general, when using larger rolling window sizes and modeling the dynamics of conditional volatility with GARCH models, there are no gains from wavelet-based

decomposition in forecasting SEM. Table 3 presents the results of statistical significance in forecast accuracy improvements using the two-tailed paired t-test.

Table 4: Diebold–Mariano Test for Wavelet-Based Models

Forecasting Model	MRA-AR	MRA-ARMA	MRA-ARMA-GARCH	MRA-ARMA-IGARCH	MRA-ARMA-GJRGARCH	MRA-ARMA-FGARCH	MRA-ARMA-CSGARCH
MRA-AR	0.00	−1.53	−2.20	−1.41	−2.22	−2.20	−2.34
MRA-ARMA	1.53*	0.00	−1.06	−0.02	−1.03	−1.05	−1.12
MRA-ARMA-GARCH	2.20**	1.06	0.00	1.47*	−0.72	0.04	−0.70
MRA-ARMA-IGARCH	1.41*	0.02	−1.47	0.00	−1.43	−1.46	−1.42
MRA-ARMA-GJRGARCH	2.22**	1.03	0.72	1.43*	0.00	0.72	0.07
MRA-ARMA-FGARCH	2.20**	1.05	−0.04	1.46*	−0.72	0.00	−0.70
MRA-ARMA-CSGARCH	2.34***	1.12	0.70	1.42*	−0.07	0.70	0.00

Note: This table provides the Diebold–Mariano test statistics for improvements of forecast errors between the forecasting model in each row and the forecasting model in each column. We obtained the results using the daily returns of NP1SEAV and an estimation window of 15 days. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Diebold–Mariano Test for Simple Models

Forecasting Model	AR	ARMA	ARMA-GARCH	ARMA-IGARCH	ARMA-GJRGARCH	ARMA-FGARCH	ARMA-CSGARCH
AR	0.00	−0.55	−1.94	−2.19	−2.01	−1.96	−1.78
ARMA	0.55	0.00	−1.68	−1.80	−1.56	−1.68	−1.51
ARMA-GARCH	1.94**	1.68**	0.00	0.71	0.28	−0.81	0.88
ARMA-IGARCH	2.19**	1.80**	−0.71	0.00	−0.37	−0.79	−0.07
ARMA-GJRGARCH	2.01**	1.56*	−0.28	0.37	0.00	−0.38	0.38
ARMA-FGARCH	1.96**	1.68**	0.81	0.79	0.38	0.00	0.98
ARMA-CSGARCH	1.78**	1.50*	−0.88	0.07	−0.38	−0.98	0.00

Note: This table provides the Diebold–Mariano test statistics for improvements of forecast errors between the forecasting model in each row and the forecasting model in each column. We obtained the results using the daily returns of NP3SEAV and an estimation window of 50 days. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Tables 4 and 5 provide the results of the Diebold–Mariano test for improvements in forecasting accuracies for the wavelet-based and simple models, respectively. All the forecasting models significantly outperform MRA-AR(1), which indicates the benefits of including the moving average term in the mean equation. In particular, the MRA-ARMA-CSGARCH model achieves higher test statistics (2.341) and shows better outperformance of the MRA-AR than the other frameworks. This suggests the existence of permanent and transitory effects in the conditional volatility process. The results in Table 5 indicate that there are gains from modeling the dynamics of conditional volatility using GARCH models. All the simple ARMA-GARCH models perform better than both the AR and the ARMA model. This shows the presence of heteroscedasticity in the error terms. In addition, both Table 4 and Table 5 show that there is not much improvement from the different GARCH models. In general, these results for electricity markets indicate that the choice of variance equation does not result in a better point forecast for both wavelet-based and simple models.

To summarize, our empirical analysis revealed four aspects of SEM forecasting. First, MRA and wavelet decomposition led to more accurate forecasts with smaller estimation windows. This result is applicable when fewer observations are available for forecasting. Second, in almost all cases, including the dynamics of conditional volatility produced

better forecasts. Third, there was not much improvement from changing the GARCH models. Finally, there were differences between the four Swedish districts in terms of forecasting one-day-ahead electricity prices.

6. CONCLUSION AND IMPLICATIONS

The forecasting of electricity prices is complex. In the increasingly competitive electricity market, forecasting the one-day-ahead prices is essential for all market participants. Accurate forecasting of such prices facilitates power suppliers' modification of their bidding tactics and, in the meantime, enables consumers to devise a plan to hedge themselves against high prices. The non-storability characteristic of electricity hinders the exploitation of inventories to smooth supply and demand shocks, thereby causing increased uncertainty in electricity prices. Therefore, accurate price forecasting may enable electricity generators to allocate their resources optimally to manage the dynamic demand from various regions.

Using data from four regions in the SEM, this study investigated and compared several short-term forecasting models. Our empirical analysis showed that the ARMA-GARCH models significantly outperformed the other frameworks when they used the rMSE and sMAPE as the performance measures. In addition, wavelet-based forecasting outperformed the sMAPE. The MRA-based models outperformed the benchmarks in reducing the rMSE and sMAPE in forecasting electricity prices when the rolling window size was small (e.g., 15 days). However, with longer horizon training sample sizes (30 and 50 days), there were limited improvements from the wavelet-based models.

The empirical findings are significant for policymakers, power suppliers, electricity generators, and general consumers. In particular, accurate forecasting may enable power generators to offset the uncertain demand and supply from different regions, which may eventually lead to a reduction in electricity prices' variability. In addition, these findings are important with regard to the stability of grids and the economic profitability of market participants. Specifically, with a better understanding of the variations in electricity prices, grid operators may be better able to avoid the grid disparities that large variations in electricity prices exemplify. An improved understanding of accurate forecasting contributes significantly to the economic benefits of market agents. In addition, these findings are of significant interest for policymakers given the increased diversion of resources toward clean energy production. An accurate forecasting framework may enable policymakers to devise a roadmap for better integration of grid systems and electricity prices across different regions. This can lead to a decrease in the supply and demand disparity and eventually a reduction in the uncertainty of electricity prices.

As understanding and capturing the price dynamics are important in the electricity market, the numerical results that the robust forecasting methods generated are capable of displaying the importance of a proper forecasting process design, policy implications for market efficiency, and predictability in SEM. Nevertheless, this study only focused on the data statistics of the electricity market and did not include the important operational factors, such as the profile of electricity production sources and seasonal influence. A combined method will be interesting for exploring the principal factors influencing electricity prices (compare Tande 2003; Barthelmie, Murray, and Pryor 2008). This also represents a direction for future research.

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APPENDIX

Table A1: Literature Review

Authors	Data	Methods	Results
Mosquera-López and Nursimulu (2019)	Spot and futures data of German electricity markets (daily data from 2010 to 2017)	Linear, non-linear, and threshold regression	There are different time-varying short- and long-run price drivers. The electricity demand influences the spot market, while the gas, coal, and carbon prices affect the futures.
B. Zhu et al. (2019)	European data on carbon price, oil, coal, gas, electricity, STOXX, and GSCI (daily data from 2009 to 2016)	Multiscale decomposition, cointegration, and error correction model	A long-term equilibrium relationship exists among carbon, coal, electricity, and the stock index. In the short run, the electricity and stock markets significantly affect the carbon market.
Kalantzis and Milonas (2013)	Electricity futures and spot prices of French and German electricity markets (daily data between 2002 and 2011)	Bivariate VECM-GARCH model	The introduction of futures lowers the spot price volatility in France. The German market dominates and leads the long-run relationship.
Birkelund et al. (2015)	Implied and realized volatility indexes in the Nordic power forward market (daily data between 2005 and 2011)	Ordinary least squares (OLS)	There is a positive volatility risk premium in options prices.
Nakajima and Hamori (2013)	Electricity, gas, and crude oil prices (daily data from 2005 to 2009)	Lag-augmented VAR, Granger causality, cross-correlation	Gas prices Granger-cause electricity prices in mean.
Bunn and Chen (2013)	Electricity spot and futures (daily data from 2007 to 2010)	MSVAR model	Undertaking various regimes is important for forecasting.
Botterud, Kristiansen, and Ilic (2010)	Nord Pool electricity market spot and futures prices (daily data from 1996 to 2006)	Regression analysis	Differences between supply and demand explain the short-term price variation.
Mjelde and Bessler (2009)	US spot prices, natural gas, uranium, coal, and crude oil (weekly data from 2001 to 2008)	Cointegration analysis	Contemporaneous peak electricity prices move natural gas prices. Fuel source markets are weakly exogenous in the long run.
Charwand, Gitizadeh, and Siano (2017)	Electricity retailers	SARIMA	SARIMA helps the retailer to identify a procurement strategy and evaluate its policy against risk.
Van Donselaar et al. (2016)	Perishable items data from retailers	Regression analysis, moving average forecast	Modeling threshold and saturation effects leads to worse forecasting performance.
Eksoz et al. (2014)	Seasonal, perishable, promotional, and newly launched products	Conceptual framework	Forecasting strategies of manufacturers and retailers are fundamental to consensus forecasts. The forecast horizon and frequency should not be neglected.
Ferbar Tratar, Mojškerc, and Toman (2016)	M3 competition (quarterly and monthly)	Four-parameter exponential smoothing	Their proposed method produces a more accurate short-term out-of-sample forecast.
Loi and Jindal (2019)	Wholesale and retail electricity prices in Singapore (daily data from 2012 to 2017)	ARIMA-GARCH	Supply competition and retail liberalization led to a decrease in electricity prices.
Aye et al. (2015)	Aggregate retail sales (monthly data from 1970 to 2012)	Linear and non-linear models, time recursion estimation schemes	Combination forecast models provide better forecasts and are unaffected by business cycles and time horizons.

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Table A1 *continued*

Authors	Data	Methods	Results
Fantazzini and Toktamysova (2015)	German car sales (monthly data from 2001 to 2014)	Multivariate cointegration tests, VECMX, VAR, AR	Multivariate models outperform the competing models in terms of forecast horizons.
Ferbar Tratar (2015)	Noisy demand data	Multiplicative HW method, seasonal ARIMA	HW methods (additive and multiplicative) are appropriate for demand with trend and seasonality.
Y. Zhu et al. (2019)	SMEs' credit risk in supply chain finance (46 SMEs' and 7 enterprises' data from 2014 to 2015)	Machine learning approaches	Random subspace multiboosting has good performance in dealing with small samples.
Nikolopoulos, Babai, and Bozos (2016)	Supply chain sporadic demand data	Nearest-neighbor approaches	The nearest-neighbor approach picks up patterns in short series.
Le, Ilea, and Bovo (2019)	Case study	Optimization model and network constraints	The model can evaluate current and future integration.
Rostami-Tabar et al. (2015)	Demand dataset of European grocery stores (weekly data of 103 observations)	IMA and SES	There is increased benefit resulting from cross-sectional forecasting in a non-stationary environment.
Hasni et al. (2019)	Demand information data of 9000 stock-keeping units (monthly data with 84 observations)	Two bootstrapping methods	The proposed adjusted methods result in higher service cost efficiency.
Mirza and Bergland (2012)	Wholesale electricity in the Norwegian electricity market (weekly data from 2000 to 2010)	Partial adjustment model	Dominant retailers may be exercising power in the retail electricity market.
Furió and Chuliá (2012)	Spanish electricity, crude oil, and natural gas forward market	VECM-MGARCH	Crude oil and natural gas forward prices play a prominent role in the Spanish electricity price. Causation flow from crude oil and natural gas forward markets to the Spanish electricity forward market.
Park, Mjelde, and Bessler (2006)	11 US spot market electricity prices (daily data between 1998 and 2002)	VAR	A time-varying relationship exists among assets. The separations among markets disappear in longer time frames.
Junttila, Myllymäki, and Raatikainen (2018)	Finnish electricity futures (monthly data from 2006 to 2016)	OLS, VAR, Granger causality	There is a significant positive excess futures premium in the Finnish market. The speculative and hedging-based strategy is increasing in the Nordic markets.
Bruzda (2019)	Monthly, quarterly, and annual sales data from M3 forecast competition	Quantile smoothing	The suggested procedure leads to a better quantile forecast of logistic data. Conditional median and mean modeling is able to provide the best forecasting in time series data.
Haugom et al. (2011)	Daily data of the Nord Pool electricity forward market	OLS	There is a strong degree of persistence in realized volatility and a significant impact of market measures in predicting.
Weron and Zator (2014)	Spot and futures prices in the Nord Pool electricity market (weekly data from 1998 to 2010)	Regression models with GARCH residuals	The impact of the water reservoir level on the risk premium is positive.
Zhu, Mukhopadhyay, and Yue (2011)	Single selling season manufacturers	Different forecast scenarios	Forecast accuracy is costly.

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Table A1 *continued*

Authors	Data	Methods	Results
Lolli et al. (2017)	Intermittent demand forecasting	Single-layer neural network	The employed framework provides superior performance in terms of back-propagation. The forecast accuracy of the models doubled with the augmentation of increased frequency horizons.
Girish, Rath, and Akram (2018)	Spot electricity prices in the Indian electricity sector (hourly price data from 2014 to 2015)	Granger causality and VAR model	No causality exists among the electricity markets. Short- and long-run causality exists between peak and off-peak prices.
Serinaldi (2011)	Electricity markets (CalPX and IPEX)	GAMLSS	The GAMLSS framework is a flexible alternative to various linear and nonlinear stochastic models.
Tang and Rehme (2017)	Swedish electricity industry	System dynamic approach	There is complex and nonlinear interaction of various factors in the electricity sector. Energy policy should incorporate incentives to use renewables with other decisions.
Bowden and Payne (2008)	MISO hubs	ARIMA-EGARCH	The model demonstrates the presence of an inverse leverage effect in electricity prices. ARIMA-EGARCH-M outperforms in terms of out-of-sample forecasting.
Tande (2003)	Wind farms	Grid integration	The use of reactive compensation may relax the short-term voltage and allow the integration of wind power.
Danese and Kalchschmidt (2011)	343 manufacturing firms from six different regions	Hierarchical regression	The structured forecasting process can improve the operational performance.

Notes: Generalized autoregressive conditional heteroscedasticity (GARCH), vector error correction model (VECM), Markov switching vector autoregressive (MSVAR), seasonal autoregressive integrated moving average (SARIMA), non-stationary integrated moving average (IMA), single exponential smoothing (SES), generalized additive models for location, shape, and scale (GAMLSS), California Power Exchange (CalPX), Italian Power Exchange (IPEX), and Midwest Independent System Operator (MISO).