Electricity Consumption Patterns and Price Volatility In Türkiye:

A Wavelet Analysis

Erhan Uluceviz[a]

Harald Schmidbauer[b]

Angi Rösch[c]

Abstract

For two decades, the now decentralized Turkish electricity market has been undergoing liberalization, similar to other electricity markets worldwide, and has essentially adopted the European market structure. Hourly electricity prices are determined by maximizing market surplus. These prices fluctuate wildly, owing to the nature of electricity as a commodity. Hourly electricity consumption data, on the other hand, exhibit a strong periodic pattern resulting from consumers' daily routines. These may be disturbed on "non-regular" days, such as weekends and holidays, making the pattern of electricity consumption less regular.

We hypothesize that a low level of regularity of consumption translates into elevated price volatility. The empirical basis for this study consists of hourly electricity consumption and price data for Türkiye during 2017–2022. We perform a wavelet analysis of the consumption data in order to capture the strength, or wavelet power, of periodic patterns across time, and investigate the effect of holidays and weekends on wavelet power. These wavelet power series, quantifying consumption regularity, serve as input to regression models explaining intraday price volatility. With this novel approach, we can show, for example, that an interruption of daily routines (on "non-regular" days) leads to higher electricity price volatility.

Keywords: Electricity consumption, price volatility, holidays, Türkiye, wavelet analysis.

JEL Classification: C32, C55, Q41

a Department of Economics, Gebze Technical University, 41400, Kocaeli, Türkiye. E-mail: erhan@uluceviz.com, ORCID: 0000-0002-4496-8756.

b Department of Statistics, Shanxi University of Finance and Economics, Taiyuan, China. E-mail: harald@hs-stat.com, ORCID: 0000-0002-4209-0601.

c FOM University of Applied Sciences, Munich, Germany. E-mail: angi@angi-stat.com, ORCID: 0000-0002-7058-1002.

Boğaziçi Journal Review of Social, Economic and Administrative Studies, Vol. 37, no. 2 (2023), pp. 92-117, doi: 10.21773/boun.37.2.3 Research Article | Received: 20.06.2023- Accepted: 25.12.2023

Türkiye'de elektrik tüketim örüntüleri ve fiyat oynaklığı: bir dalgacık dönüşümü analizi

Özet

Yaklaşık yirmi yıldır; artık merkezi olmayan Türkiye elektrik piyasası, dünyadaki diğer elektrik piyasalarına benzer şekilde serbestleşme sürecinden geçmiş ve esasen Avrupa tipi piyasa yapısını benimsemiştir. Saatlik elektrik fiyatları, piyasa fazlasını maksimize edecek şekilde belirlenmektedir ve elektriğin bir emtia olarak doğası gereği, bu fiyatlar yüksek ölçüde dalgalanır.

Öte yandan saatlik elektrik tüketim verileri, tüketicilerin günlük rutinlerinden kaynaklanan güçlü bir periyodik örüntü sergiler. Bu örüntü, hafta sonları ve tatiller gibi "düzenli olmayan" günlerde bozulabilir ve daha az düzenli hale gelebilir.

Bu çalışmada, düşük düzeydeki bir tüketim düzenliliğinin yüksek fiyat oynaklığına yol açtığını varsayıyoruz. Bu çalışmanın ampirik temeli, 2017-2022 döneminde Türkiye için saatlik elektrik tüketimi ve fiyat verilerinden oluşmaktadır. Tüketim verilerinin dalgacık analizi ile tüketimdeki periyodik örüntünün gücünü (dalgacık gücünü) hesaplıyor ve tatillerin ve hafta sonlarının dalgacık gücü üzerindeki etkisini araştırıyoruz. Tüketim düzenliliğini ölçen bu dalgacık gücü serileri, gün içi fiyat oynaklığını açıklayan regresyon modellerinde açıklayıcı değişken olarak kullanılmaktadır. Bu yeni yaklaşımla, örneğin günlük rutinlerin kesintiye uğramasının ("düzenli olmayan" günlerde) daha yüksek elektrik fiyatı oynaklığına yol açtığını gösterebiliriz.

Anahtar Kelimeler: Elektrik tüketimi, fiyat oynaklığı, tatiller, Türkiye, dalgacık analizi.

JEL Sınıflandırması: C32, C55, Q41

1. Introduction

The liberalization of electricity markets has been one of the top agenda items of politicians in the last 30 years. The electricity industry, usually comprised of vertically integrated national monopolies, used to be owned by national or regional governments, see Leautier and Crampes (2016). This resulted in the liberalization of generation and distribution monopolies to the effect that economic forces could determine electricity prices through supply and demand.

Certain characteristics of electricity make it a unique type of good: It cannot be stored economically in large quantities. Supply and demand should match closely at all times to keep the system in balance and operational. While this is accomplished by the transmission system operator (TSO) on the technical side, centralized as well as decentralized day-ahead markets are established to align financial incentives with technical requirements and to determine financially binding day-ahead prices and quantities (on an hourly basis) on the financial side.

In a centralized day-ahead market (e.g. as in the U.S.), a system operator decides which generators should produce given "... detailed knowledge about costs, ramp-rates, and locations of plants to make technically feasible and efficient decisions in real-time", see Ahlqvist et al. (2022). In a decentralized market (e.g. as in Europe), market participants make commitments to produce the amount of electricity they are willing to trade the next day. These committed quantities can be met from their own production or from other participant(s) as a result of bilateral agreement(s).

The Turkish electricity market has been closely following the trends prevailing in the rest of the world, and especially the European market structure. Privatization of the sector began in 2001. As of 2022, generation, transmission and distribution are owned and run by private and state-owned enterprises and supervised by The Energy Market Regulatory Authority (EPDK).

The state-owned Turkish Electricity Transmission Company (TEİAŞ) is a monopoly in transmission activities. It operates the real-time balancing and transmission of electricity from production to distribution networks that supply electricity to final consumers.[1]

The distribution infrastructure is owned by the state-owned Turkish Electricity Distribution Company (TEDAŞ). The Electricity Market Law, passed by the parliament in 2013, has had a significant impact on the sector. As a result, electricity distribution is divided into 21 regional monopolies, and following privatization, licenses were handed over to private companies. In 2013, the Energy Exchange Istanbul (EPİAŞ) was granted a license to operate wholesale day-ahead and intraday electricity markets. It also runs a forward electricity market. The Turkish day-ahead electricity market operates in a decentralized

[1] "[Since 2010], the Turkish electricity system has been operating in synchronous parallel mode with the European Network of Transmission System Operators for Electricity (ENTSO-E)". Source: https://www.teias.gov.tr/en-US/about-us, accessed on 2022-11-21.

fashion. In 2018, 40% of electricity trade passed through EPİAŞ; the rest was carried out by bilateral contracts, (see IEA 2021b).

In the Turkish day-ahead market, the market operator EPİAŞ collects market participants' bids (using EPİAŞ terminology in their documentation), which can represent both demand and supply, and solves an optimization problem so that the sum of consumer and producer, i.e. market, surplus is maximized. The optimization result determines hourly market clearing prices (MCPs), as well as matching prices and quantities for each bid (see the EPİAŞ website for the day-ahead electricity market clearing algorithm.[2] For the European day-ahead electricity market clearing model, see e.g. Chatzigiannis et al. (2016).

The demand side of the (day-ahead) electricity market is driven by the (day-ahead) electricity consumption at the national level. On the supply side, at the time supply decisions are submitted by the market participants, day-ahead (hourly) electricity consumption is still unrealized. Hence, day-ahead (hourly) MCPs are determined while both (hourly) day-ahead demand and supply are unknown. This, in practice, leads to highly volatile MCPs arising from uncertainties in demand due to, e.g., human behavior and everyday activities, and supply due to, e.g., ramp-rate constraints and unplanned outages.

The present study is an effort to investigate how and to what extent demand uncertainty, emerging from consumption pattern uncertainty, translates into MCP volatility. The focal point is not to forecast prices or price volatility, a topic which already spans a large portion of literature; see, e.g., the extensive review in Weron (2014).

Electricity consumption is usually quite regular, following a superposition of periodic (daily, weekly, etc.) patterns. There are, however, intermittent phases when these patterns are weakened, e.g., at holidays when consumers are free not to follow their usual routines. Another consumption pattern will also appear when many consumers, especially those who service Islamic fasting prayer during Ramazan ayı, follow their special daily schedule. In this study, we hypothesize that a strong periodic (or regular) electricity consumption pattern will lead to a decreased volatility in electricity prices. To test this hypothesis, we identify cycles in electricity consumption and measure their strength (or power). To that end, we apply wavelet analysis of hourly consumption data in Türkiye.[3]

This project has a potential for practical implications. Financial experts in this field may appreciate using fine-tuned methods of time series analysis rather than black-box methods such as machine learning, which sacrifice explainability for predictability. It could also support technical experts' efforts

---

[2] EPİAŞ document, https://www.epias.com.tr/wp-content/uploads/2016/03/public_document_eng_v4.pdf, accessed on 2022-11-27

[3] Wavelet decomposition has already been applied to electricity markets, see, e.g. Kristjanpoller et al. (2018), Magazzino et al. (2021) and Rana and Koprinska (2016).

to plan the capacity by adding another dimension of consumption regularity through the use of wavelets.

We performed wavelet analysis in this research in the R environment using the R package *WaveletComp* (Rösch and Schmidbauer, 2018; R Core Team, 2021); the R package *tseries* was useful for further time series analyses (Trapletti and Hornik, 2023).

This paper is organized as follows. Section 2 is about wavelet decomposition methodology, Section 3 discusses the data we use, and the applied transformations. Section 4 provides information about our methodological approach in detail. Section 5 reports empirical findings, which are briefly discussed in Section 6. Finally, Section 7 summarizes and concludes the paper.

2. Wavelet Analysis

This study rests essentially on exploiting the wavelet power spectrum of the hourly series of electricity consumption in Türkiye. Wavelet analysis is a tool for detecting which period (or its reciprocal, frequency) is important in a given time (or, synonymously, signal) series (x_t), where the periodic properties of (x_t) may, in contrast to Fourier analysis, be time-dependent. The first step in wavelet analysis is to compute the complex-valued wavelet transform of the series:

$$\mathrm{Wave}(\tau, s) = \int_{-\infty}^{\infty} x_t \ \psi_t^*(\tau, s)\, dt, \tag{1}$$

where ψ_t is an analyzing function, a wavelet, we use the Morlet wavelet in this study, τ is a time shift parameter, and s is a scale parameter linked to period p via $p = s \cdot (2\pi/6)$. The asterisk denotes conjugation of a complex number. The real-valued wavelet power is defined as

$$\mathrm{Power}(\tau, s) = \frac{1}{s} \cdot |\mathrm{Wave}(\tau, s)|^2. \tag{2}$$

Intuitively, a high value of $\mathrm{Power}(\tau, s)$ indicates that period $p = s \cdot (2\pi/6)$ (or, equivalently, frequency $f = 6/(s \cdot 2\pi)$) is an important additive component of (x_t) at time τ.

As an example, the upper plot of Figure 1 shows a simulation of the model

$$x_t = 0.8 \cdot \sin\left(2\pi \frac{t}{100}\right) + \left(1 - \frac{t}{1000}\right) \cdot \sin\left(2\pi \frac{t}{40}\right) + \epsilon_t, \quad t = 1, \ldots, 1000, \tag{3}$$

where (ϵ_t) is Gaussian white noise with standard deviation 0.2. Series (x_t) is an additive superposition of a series with period 100 and another series with period 40, with some noise added on. This means there are two important periods in (x_t), namely period 100 and period 40. In the course of time, the structure of the time series changes, and period 40 fades away. This is clearly visible in the heat map of the wavelet power in the lower plot of Figure 1. The time series plot and the heat map both share the same time axis (the abscissa axis). The ordinate axis of the heat map is the period axis. Without knowing model (3), and without wavelet analysis resulting in the heat map, it will be difficult to identify the structure of the series in Figure 1 from mere eyeballing.

The existence of the time axis in the heat plot corresponds to the idea that wavelet transformation allows for the detailed analysis of signals with time-varying characteristics. The information given in a heat plot of the wavelet power can be reduced by computing the arithmetic mean of the wavelet power series at a given period across time. The time-specific information about (x_t) will then be lost, of course. The average power, in this sense, for the example above is plotted in Figure 2. This is similar to the Fourier transform of (x_t) and corresponds to the idea that time is integrated out in the Fourier transform, which cannot reveal transient characteristics of a time series. This is the reason why the present study is based on wavelet analysis and not on Fourier analysis: the pattern of electricity consumption is time-dependent (for example, workdays are different from weekends).

The following remarks are crucial as they explain how we use wavelet analysis in the present study. Suppose we have observed the series (x_t) up to time $t = 200$, and we have to forecast the next 50 observations. Such a forecast will typically be based on the periods 100 and 40, which are both very strong in this part of (x_t). In contrast, having observed the series up to $t = 1000$, a forecast beyond $t = 1000$ will, owing to the now simpler structure of the series, use only period 100, and forecasting (x_t) will be even easier. Now, however, suppose that the task is *not to forecast* future observations of the series. We assume that (x_t), $t = 1, \dots, 1000$, has been sent to a recipient as a signal, and the recipient will react in some way to the signal. We further assume that this recipient was expecting a signal composed of periods 100 *and* 40, and not only period 100. This situation is very similar to dual-tone multi-frequency signaling,[4] where the signal is lacking the second frequency it is supposed to have. In such a situation, forecasting future observations is simply not the point: the recipient will perceive the absence of period 40 as a flaw in the signal structure. Confusion ensues. In this sense, a high wavelet power at distinct frequencies can make a series more regular and reduce the uncertainty in a signal.

We shall see later that the situation of the recipient in this example is similar to the situation of an electricity provider. Predominant periods in the electricity consumption pattern turn out to be twelve hours, one day, and one week. This pattern may be weakened, for example, during holidays, increasing the uncertainty in the consumption pattern. This study investigates the consequences on electricity price volatility.

[4] Dual-tone multi-frequency signaling is a telecommunication system where each digit (0, 1, …, 9) is acoustically encoded using a mixture of two (out of seven) sine wave sounds; see https://en.wikipedia.org/wiki/Dual-tone_multi-frequency_signaling, accessed on 2023-02-27. A signal with only one sine wave sound is therefore ambiguous.

Put Figure 1 about here

Put Figure 2 about here

3. Data, and their Transformation

The data basis for this study covers the years 2017 through 2022 (2191 days = 52584 hours).[5] Three sources of information were used: (1) hourly Turkish electricity market consumption data (MWh) in real time,[6] (2) hourly electricity market clearing prices (MCP, USD per MWh), and (3) a calendar of public holidays in Türkiye.

Consumption and price data are provided by Enerji Piyasaları İşletme A.Ş. (EPİAŞ, the Energy Markets Operator Company) as published on the EPİAŞ Transparency Platform.[7]

Figure 3 displays the daily extremes of hourly consumption (MWh) in Türkiye. Extremes are bounded; the series' stationarity was confirmed (ADF test, p-value<1%). Daily consumption was obtained by simply adding up the 24 hourly consumption readings for that day. The hourly electricity price series (MCP, USD per MWh), on the other hand, is far more shaky and has recently become quite ragged, see Figure 4. This series had to be processed for further analysis: sporadic zero prices (the original data set has 79 hours with zero prices) were replaced by means of interpolation, and the series of hourly price changes (hourly returns) was calculated, the stationarity of which was confirmed (ADF test, p-value<1%). The target variable in our study is the daily realized volatility of hourly electricity price changes. Frequent spikes in this series, however, heavily distort the usual measure of volatility, the daily standard deviation. In order to achieve a high degree of model robustness, we decided to use the daily median absolute deviation (MAD)[8] of hourly price changes as a more suitable proxy for daily realized volatility. The actual input to the models below is then the logarithm of the series values plus 2; this monotonous transformation mitigates the skewness. Figure 5 demonstrates the effect.

---

[5] In 2016, Türkiye switched to summer time, and by decree seasonal time zone change was repealed. This is why we chose to start with the year 2017. See Turkish Republic Official Gazette on 2016-09-08, no. 2016/9154, https://www.resmigazete.gov.tr/eskiler/2016/09/20160908-2.pdf, accessed on 2022-09-23.

[6] The time stamp used in this study is Turkish time, i.e. UTC+3.

[7] EPİAŞ Şeffaflık Platformu: Consumption, https://seffaflik.epias.com.tr/transparency/tuketim/gerceklesen-tuketim/gercek-zamanli-tuketim.xhtml, accessed on 2023-01-24.

Market prices, https://seffaflik.epias.com.tr/transparency/piyasalar/gop/ptf.xhtml, accessed on 2023-01-24.

[8] For a sample $x_1, \ldots, x_n$ of observations the MAD is defined as the median of the absolute deviations from the observations' median: MAD = median $(|x_i - \text{median}\ (x_i)|)$.

Put Figure 3 about here

Put Figure 4 about here

Put Figure 5 about here

The central idea of the present study is that daily electricity consumption in Türkiye is calendar-driven, and that ultimately, through the channel of consumption, holidays and weekends drive daily realized volatility of electricity prices. Türkiye has nine occasions of holidays in the course of one year, among which seven are non-religious holidays, two are religious.[9]

While the dates of non-religious holidays are fixed according to the Gregorian calendar, the two religious holidays follow the Islamic (or *Hijri*) calendar which is based on the shorter lunar year. As a consequence, the latter are floating with respect to the Gregorian calendar, shifting around 11 days earlier each year: the end of Ramazan ayı (the month of Ramazan) is celebrated with a floating three-day holiday, Ramazan Bayramı (the Ramazan holiday); Kurban Bayramı, the four-day "festival of the sacrifice", is celebrated about 68 days later. Table 1 summarizes holidays in Türkiye and their respective lengths in days. In our study, we neglect half-day holidays on the eve of any festival; these are sometimes declared full-day for civil servants, but not for other workers. Figure 6 displays the calendar of full-day holidays in Türkiye covering years 2017 through 2022. Also flagged is Ramazan ayı, spanning 28-29 days (depending on the year), which, because of the practice of fasting from dawn to sunset, may exhibit different behavior in electricity consumption as well. For a similar reason, we discriminate between weekends (Saturday and Sunday) and other weekdays (Monday through Friday) in this study.

Put Table 1 about here

Put Figure 6 about here

4. Approach in Three Steps

Our goal is to study the effect of demand uncertainty, emerging from a blurred consumption pattern, on the daily realized volatility of electricity prices. To this end, modeling proceeds in three steps.

(A) As a proxy for the daily realized price volatility, we use the MAD series of hourly electricity price changes. To begin with, we hypothesize that price volatility is higher during Ramazan ayı, holidays and weekends (all of which are "non-regular" days, possibly driving

[9] See "Law on National and General Holidays", no. 2429 ("Ulusal Bayram ve Genel Tatiller Hakkında Kanun"), https://www.mevzuat.gov.tr/MevzuatMetin/1.5.2429.pdf, accessed on 2023-01-26.

demand uncertainty). A multiple linear regression (shifted, logarithm taken) of MAD values on daily consumption (again logarithmic values) and on holiday and weekend indicators, will shed some first light on this hypothesis, and serve as a benchmark model, to be specified as Model (A) in Section 5.1. (This step does not use wavelet analysis.)

(B) In the next step, we scrutinize the regularity of electricity consumption patterns and relate it to Ramazan ayı, to holidays and weekends. We hypothesize that the regularity is diminished during Ramazan ayı, holidays and weekends. To gauge the regularity of consumption, the hourly series of consumption was subjected to wavelet analysis. The hourly series of wavelet power is retrieved for various bands of period lengths: around 12 hours (half-day), 24 hours (one day), and 168 hours (one week). For each of these period bands, we compute the series of daily average wavelet power (a proxy for regularity on that day), and regress each member of this series suite (consisting of three series) on Ramazan ayı, holiday and weekend indicators, resulting in three Models of type (B). Wavelet power plots and regression results will be given in Section 5.2.

(C) Finally, we hypothesize: The less regular electricity consumption, the higher the price volatility. To this end, we revisit Model (A). We estimate a multiple linear regression, again with the daily MAD series (shifted, logarithmic values) as dependent variable, on daily consumption (log values) and, as a substitute for holiday and other indicators, on the suite of daily wavelet power average series (again shifted, logarithmic values) obtained in Step (B). Logarithmic values on either side of the equation establish a Cobb-Douglas style model of multiplicative effects of consumption and wavelet power on the realized volatility of electricity prices. Section 5.3 shows our final results for Model (C).

Table 2 shows the set of variables used in this study and their time base. To avoid spurious effects, all non-religious holidays (single-day each) are summarized into one indicator variable, while religious holidays are considered individually.

When on March 11, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a pandemic, confinement measures across Europe and India triggered a plunge in electricity demand (IEA, 2021a). Figure 3 confirms a similar behavior for the Turkish market. The structural break on the demand side suggests splitting the whole era 2017–2022 into two sub-eras, the first era ending with 2020-03-10, i.e. right before the WHO's declaration, see Table 3. This argument is supported by an analysis for structural breaks in the series of market clearing prices as well.[10]

Put Table 2 about here

Put Table 3 about here

5. Empirical Results

The following three sections report our findings for the models introduced in steps (A), (B), and (C). Robustness checks of results are reported in the final section.

5.1 Price Volatility, Consumption, and Holidays

The results in Table 4 provide insight into the relationship between price volatility and consumption along with Ramazan ayı, holiday and weekend dummies. For Era I as well as for Era II, as electricity consumption increases, price volatility decreases significantly at the 0.1% level of significance. A possible interpretation is: given increased electricity demand, suppliers will be less uncertain about the available amount of excess generation capacity and hence less uncertain about their supply decisions and thus about the next day's prices. Among the dummy variables, Ramazan ayı had a significant (at the 0.1% level) positive impact on price volatility in Era I. This may be due to the fact that during Ramazan ayı, a varying part of people in Türkiye abandon their daily routines, thereby leading to a less predictable overall daily consumption pattern and, as a result, higher price volatility. This effect is not observed in Era II, probably due to COVID-19 pandemic countrywide curfews and disrupted industrial activities, leading to a generally diminished intraday predictability.

The above narrative (demand uncertainty boosting price volatility) reflects general economic knowledge. Using wavelet analysis permits us to put the link between consumption regularity and price volatility on a firm empirical basis. This is the subject of the following two sections.

Put Table 4 about here

5.2 Wavelet Power of Consumption, and Holidays

Wavelet analysis of the hourly series of electricity consumption enables us to identify local patterns of periodicity and their strength across time. The heat maps in Figure 7 display the wavelet spectra in the time-period domain, period measured in hours, for the whole sample of years. Vertical lines

[10] It would be tempting to further split the time range considered according to levels of human mobility and industrial activity. However, the timeline of the COVID-19 pandemic in Türkiye, lacking clear-cut stop-start cycles in activities leading to decreased energy consumption, as well as, a lockdown lasting less than two months, would adversely diminish the data sets.

indicate the dates of holidays in Türkiye according to Figure 6, as well as Ramazan ayı (the "curtain" in light green). The red line in 2020 flags the onset of Era II, when the WHO declared the COVID-19 outbreak a pandemic.

Throughout the calendar, a 24-hour pattern can be identified and related to daily peaks and troughs of electricity consumption, the corresponding ridge of power following a sawtooth due to weekend effects.[11] Consequently, a weekly (168-hour) periodicity is also visible. Yet another, even though less prominent feature is a 12-hour pattern, often discontinued and not as strong as the daily pattern. Interestingly, half-day periodicity is interrupted during Ramazan ayı and disappearing altogether in 2020 after the beginning of the Covid-19 pandemic. An obvious explanation is that people adopt less regular, and hence more complex, daily schedules in extraordinary times. In stark contrast to the consumption series, no consistent pattern of periodicity can be found in the price series, (see Figure 8), resulting from wavelet transformation of the hourly price series.

For any given period, wavelet transformation yields an hourly power series. In our approach we assume that wavelet power at each identified period (12, 24, 168 hours) can be interpreted as a measure of regularity in electricity consumption at the respective, period-driven, pace. Daily averages at period bands around 12 hours, 24 hours, and 168 hours were computed from the respective hourly series. These series are displayed in Figure 9. They will be used as input to Model (C) in Section 5.3. In order to reduce skewness and render positive values, we use logarithmic values of each series to which 1 was added.

Put Figure 7 about here

Put Figure 8 about here

Put Figure 9 about here

Finally, the regression results in Table 5, confirm the (B) part of our research hypotheses, stating that wavelet power of consumption, and thus the strength of consumption regularity, is reduced during Ramazan ayı, holidays and weekends. The results are given for each of the three series of daily power averages (see Figure 9) separately. All regression dummies significantly (at the 10% level) decrease the strength of 12-hour regularity, as well as that of 24-hour regularity, in both eras. In the 168-hour case, results are mixed, but Ramazan ayı consistently has a significant positive impact. So, during

[11] On most working days, consumption peaks at 11–12 am, just before noon, while the lowest consumption is observed in the early morning hours, 4–6 am. Sundays are usually different: The trough is at 6–8 am, and the peak is shifted to the evening hours, 6–10 pm, thereby slightly increasing the period length.

Ramazan ayı weekly regularity of electricity consumption tends to increase, though daily and half-day regularity are decreased. An explanation may be that consumers constitute a heterogeneous set with respect to daily routines during Ramazan ayı, but are more uniform with respect to pursuing their weekly routines, to the effect that weekly regularity is upheld.

Put Table 5 about here

5.3 Price Volatility Revisited, Consumption, and Wavelet Power of Consumption

Having confirmed that wavelet power, at least in the 12 and 24-hour period band, is reduced on the occasion of holidays, religious practice, and on weekends, we go one step further to test the final part of our research hypothesis: Reduced regularity in terms of reduced wavelet power boosts the daily volatility of prices. The results reported in Table 6 are ambiguous, however. Coefficients of daily average power are highly significant for both the 12-hour and 24-hour period band only in Era I, and not all of them are negative as hypothesized. In Era II, there is a strong and positive impact of the 168-hour band. However, the scatterplots[12] in Figure 10 between the variables involved (log of shifted values) provide some clarification, suggesting a compensation effect among the set of wavelet power series in Model (C): It is found that for both eras, wavelet power in the 24-hour band does have a significant and negative impact on price volatility: when seen in isolation (and thus excluding compensation effects), lack of daily regularity indeed tends to increase price volatility. The 12-hour wavelet power has a compensating (minor) positive impact in Era I, but a significant and negative impact in Era II. The opposite is observed for the 168-hour wavelet power which reveals a strong negative (positive) effect in Era I (Era II). In this line of arguments, there is confirmation for both eras: Uncertainty in the consumption pattern, in terms of low wavelet power, leaves prices more volatile.[13]

Consumption coefficients are similar to those in Model (A) (see Table 4). This means that periodic characteristics of the consumption series are hidden to such a degree that there is room for wavelet power of consumption to improve the model: a part of the periodic characteristics does not take direct effect on price volatility, but through wavelet power. Inserting the wavelet

[12] The red line in each scatterplot of Figure 10 is the regression line of daily volatility with respect to the respective wavelet power.

[13] Following the suggestion of an anonymous referee, an alternative to Model (B) could use electricity consumption, instead of wavelet power, as a dependent variable, with the same independent variables. It turns out that all regression coefficients are negative, similar to Model (B). We refrain from further exploring this alternative model, as it does not allow for breaking down the impact of the independent variables on distinct consumption periods.

power series instead of holiday and weekend dummies into the regression model for daily price volatility, we observe a small increase in R^2 and a small decrease in residual standard error compared to Model (A).

Put Table 6 about here

Put Figure 10 about here

5.4 Robustness of our Results

In order to test the robustness of our results in Sections 5.1 through 5.3 we implemented a series of sensitivity checks.

Different wavelet parameter settings. The crucial part in our line of arguments is the output from a wavelet analysis of hourly consumption data. Fine tuning a wavelet analysis requires carefully setting a number of parameters. In the R package *WaveletComp*, these parameters are $loess.span$, the degree of detrending the input series, and dj, the number of voices per octave determining the granularity of results. The significant periods once identified, further decisions concern the selection of a surrounding band of m periods to reduce possible noise by averaging the extracted wavelet power series across periods within this band. Even if these settings have been carefully selected, results should be robust w.r.t. small changes in the settings of the analysis. Table 7 reports the parameter settings implemented for the sake of robustness tests; settings referring to the final results are in bold. For both eras, regression results from these settings turned out to be very similar w.r.t. levels of significance and of estimates.

Put Table 7 about here

Data subsampling. Several runs with only 70% of the days, sampled randomly from the entire set of days, showed only slight differences in results whenever the selection did not distort the pattern of consumption heavily.

Random dates. To exclude spurious effects of holidays on price volatility and wavelet power of consumption, we introduced an indicator of five randomly selected dates per year as an additional regressor into models (A) and (B). No consistent results concerning random indicators could be found in reruns. Rare observations of significance could be explained by overlaps with holidays and weekends. Apart from this, the significance pattern of nonrandom indicators was preserved.

Alternative measures of daily price volatility. The MAD of hourly price changes lended itself to measure intraday price volatility as it avoids spurious effects due to outliers. As explained earlier, the standard deviation of hourly price changes was not suitable. A suitable MAD alternative is the interquartile range of hourly price changes, and using these instead of MAD values leads to similar results, again confirming the robustness of our results.

6. Discussion

In this paper, we are interested in understanding a certain kind of determinant of electricity price volatility. Specifically, we ask whether regularity in the electricity consumption series, measured in terms of wavelet power, can contribute to explaining electricity price volatility, measured in terms of the MAD of hourly price returns. We are now in a position to answer this question with a firm “YES”. In particular, we found evidence for our research hypothesis that lack of consumption regularity tends to increase price volatility. It was shown that holidays tend to reduce consumption regularity, so that we obtain, as a by-product, insight into the channel through which holidays lead to increased price volatility.

These insights could be obtained without resorting to the time-series structure of price volatility. If we insist on exploiting the latter, we find that daily price volatilities (again computed as MAD of daily returns) are highly autocorrelated. A GARCH model can be hardly expected to adequately account for the erratic nature of the data, but the volatility series, in the form of MADs, is smooth enough to allow for an ARMA-X-style generating process. In line with the regression lines depicted in Figure 10, it turns out that the coefficients of the 12 and 24-hour wavelet power series as external regressors are negative in both eras (and the 168-hour series also in Era I), which again confirms our hypothesis from a completely different perspective. This type of model might be helpful in forecasting future price volatility. A typical forecasting exercise may then opt to revert to Machine Learning (ML) algorithms, which are known to outperform traditional time-series methods in many cases.[14]

The purpose of this paper, however, is not to forecast price volatility, or offer a comparison of pertinent models. The focus is on understanding what triggers the creation of volatility in the price process, and we found evidence for one important source: the amount of irregularity in the consumption pattern, measured through wavelet transformation.

7. Summary and conclusions

In line with daily human behavior, electricity consumption data usually exhibit a strong periodic pattern. This regularity, however, may receive a setback when human routines are paused: for example, weekends and holidays may trigger non-routine, and hence less regular, electricity consumption behavior. Wavelet analysis can reveal periodic constituents of consumption data and measure the inherent amount of regularity across time. This is the

[14] As put forth in Makridakis et al. (2022) concerning “the superiority of ML methods”: “This finding is aligned with that of the M5 ‘Accuracy’ challenge, indicating that ML methods can provide better forecasts than standard, statistical approaches, both point and probabilistic ones.”.

basic concept of our research, which prepares the ground to test our working hypothesis: Lack of regularity in electricity consumption is a source of uncertainty in electricity prices, and hence a source of elevated price volatility.

We investigated the daily interplay of two variables: electricity consumption and price volatility in the Turkish electricity market. The empirical basis consists of hourly data from 2017 through 2022. Daily realized price volatility in our research was proxied by the median absolute deviation (MAD) of hourly price changes (in the following, referred to as "(daily) price volatility"). As for consumption, our main focus is on the strength of its regularity, operationalized by a set of daily average wavelet power series resulting from a wavelet analysis of hourly consumption data. The original data set was split into two eras, Era I: before the Covid-19 pandemic (before 2020-03-11), and Era II: during the pandemic (beginning 2020-03-11).

A superposition of three periodic components was found to characterize the electricity consumption data, namely 12-hour (half-day), 24-hour (one day), and 168-hour (one week) periodicity, though at varying wavelet power, or strength of regularity, across time. A negative correlation was found between daily price volatility and each of the three wavelet power series in both eras, with one exception (the correlation between price volatility and the 168-hour wavelet power series is positive in Era II). This essentially confirms our working hypothesis.

Multivariate regression models served to study the effect, direct and indirect, via consumption regularity at the three periods mentioned above, of non-routine-day indicators (holiday, weekend, and Ramazan ayı) on daily price volatility. While apart from consumption, only Ramazan ayı, in Era I, turned out to be significant as direct regressor (Model (A)), non-routine-day indicators were found to significantly decrease the level of consumption regularity (in terms of wavelet power; Model (B)), and, via consumption regularity, to affect daily price volatility (Model (C)). In particular, it was found that in Era I, lack of daily regularity indeed increases price volatility significantly, though a part of the effect is absorbed by half-day regularity. A strong even though positive impact of weekly consumption regularity on price volatility was found in Era II, thus contradicting our working hypothesis but in line with Ramazan ayı's and religious holidays' positive effect on weekly regularity.

Our insights in this study are threefold: (i) The wavelet transformation of electricity consumption yields wavelet power, measuring the regularity of consumption and decreasing on days of "non-routine" consumer behavior; (ii) wavelet analysis, a methodology fitted for the analysis of periodic phenomena, here, consumption, can contribute to explaining a nonperiodic phenomenon, here price volatility, even though the original consumption series is already among the regressors; (iii) wavelet analysis can provide detailed empirical evidence that a lack of consumption regularity tends to boost price volatility.

We found that electricity consumption and its price volatility in Türkiye can be explained through a channel which is readily comprehensible as well as statistically highly significant. Practical implications also arise; for example our findings could support the regulation and control of technical requirements in electricity production.

References

Ahlqvist, Victor, Par Holmberg, and Thomas Tangeras (2022), "A survey comparing centralized and decentralized electricity markets." *Energy Strategy Reviews,* 40, 100812.

Chatzigiannis, Dimitris I., Grigoris A. Dourbois, Pandelis N. Biskas, and Anastasios G. Bakirtzis (2016), "European day-ahead electricity market clearing model." *Electric Power Systems Research,* 140, 225–239.

IEA (2021a), "Covid-19 impact on electricity." Tech. rep., International Energy Agency.

IEA (2021b), "Turkey 2021, Energy Policy Review." Tech. rep., International Energy Agency.

Kristjanpoller, Werner, Alejandro Sierra, and Javier Scavia (2018), "Dynamic comovements between energy consumption and economic growth. A panel data and wavelet perspective." *Energy Economics*, 72, 640–649.

Leautier, Thomas-Olivier and Claude Crampes (2016), "Liberalisation of the European electricity markets: a glass half full." https://web.archive.org/web/20230313132721/https://fsr.eui.eu/liberalisation-european-electricity-markets-glass-half-full/, accessed on 2022-12-11.

Magazzino, Cosimo, Mihai Mutascu, Marco Mele, and Samuel Asumadu Sarkodie (2021), "Energy consumption and economic growth in Italy: A wavelet analysis." *Energy Reports*, 7, 1520–1528.

Makridakis, Spyros, Evangelos Spiliotis, Vassilios Assimakopoulos, Zhi Chen, Anil Gaba, Ilia Tsetlin, and Robert L. Winkler (2022), "The M5 uncertainty competition: Results, findings and conclusions." *International Journal of Forecasting*, 38, 1365–1385.

R Core Team (2021), *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria.

Rana, Mashud and Irena Koprinska (2016), "Forecasting electricity load with advanced wavelet neural networks." *Neurocomputing*, 182, 118–132.

Rösch, Angi and Harald Schmidbauer (2018), *WaveletComp: Computational Wavelet Analysis*, R package version 1.1.

Trapletti, Adrian and Kurt Hornik (2023), *tseries: Time Series Analysis and Computational Finance*, R package version 0.10-53.

Weron, Rafal (2014), "Electricity price forecasting: a review of the state-of-the-art with a look into the future." *International Journal of Forecasting*, 30, 1030–1081.

Figure 1 A Time Series (a) and a Heat Map of its Wavelet Power (b)

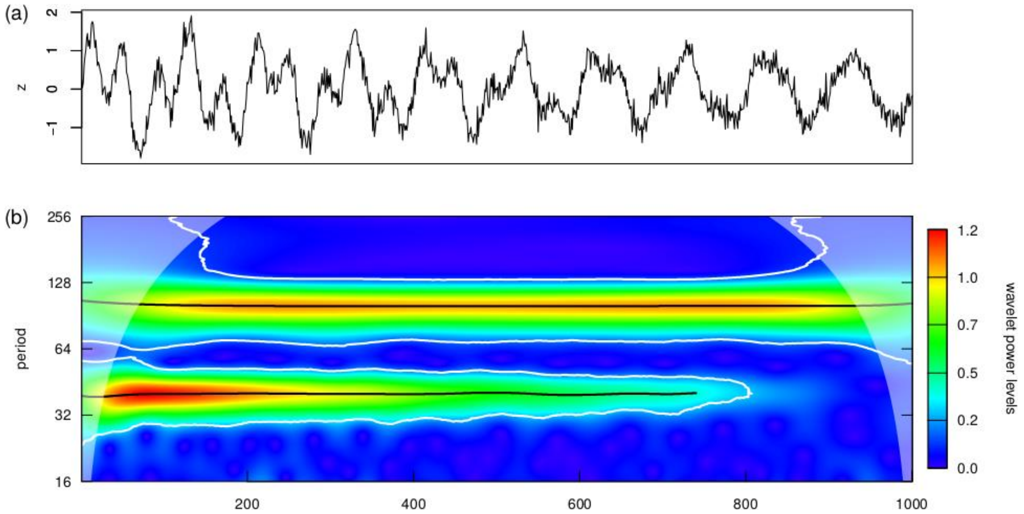

Figure 2 Average Wavelet Power across Time

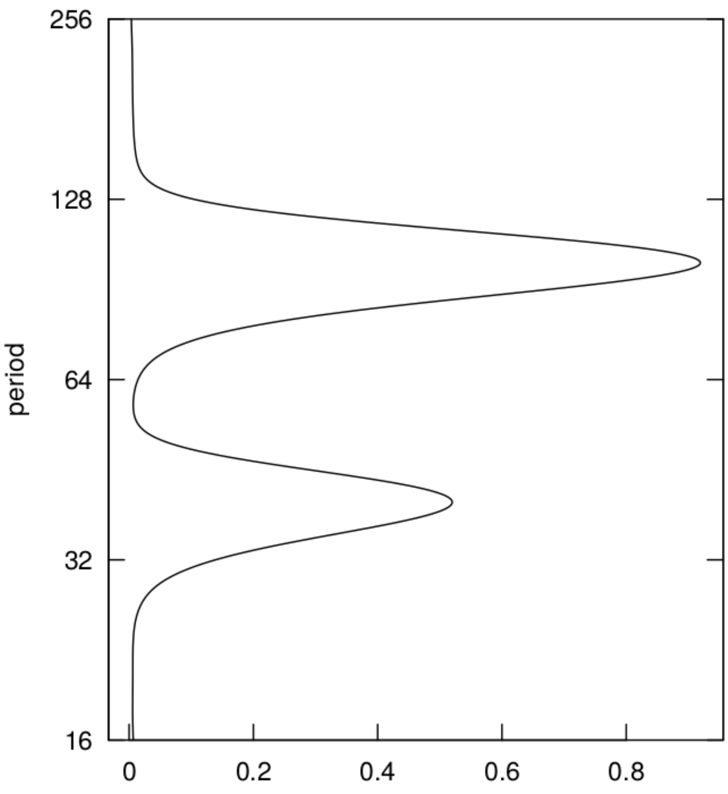

Figure 3 Daily Extremes of Hourly Electricity Consumption, MWh

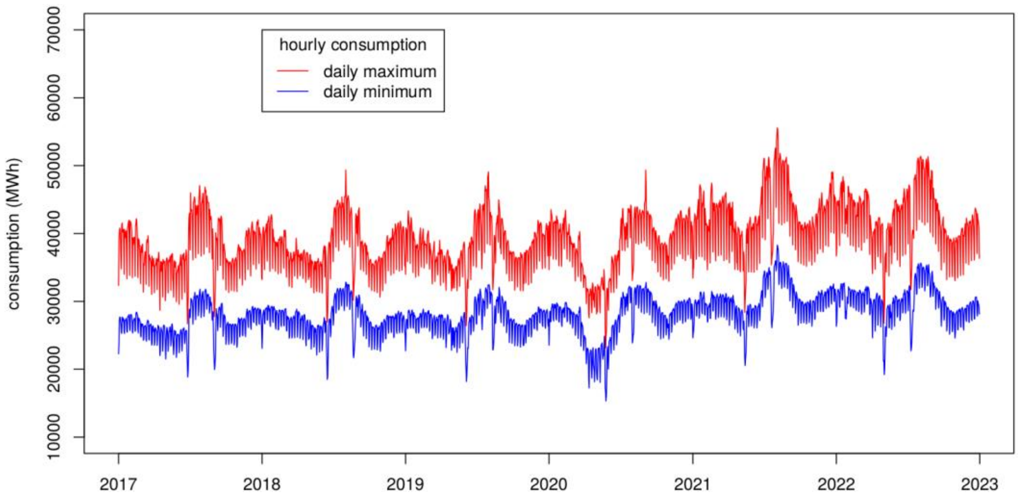

Figure 4 Daily Extremes of Hourly Market Clearing Prices, USD per MWh

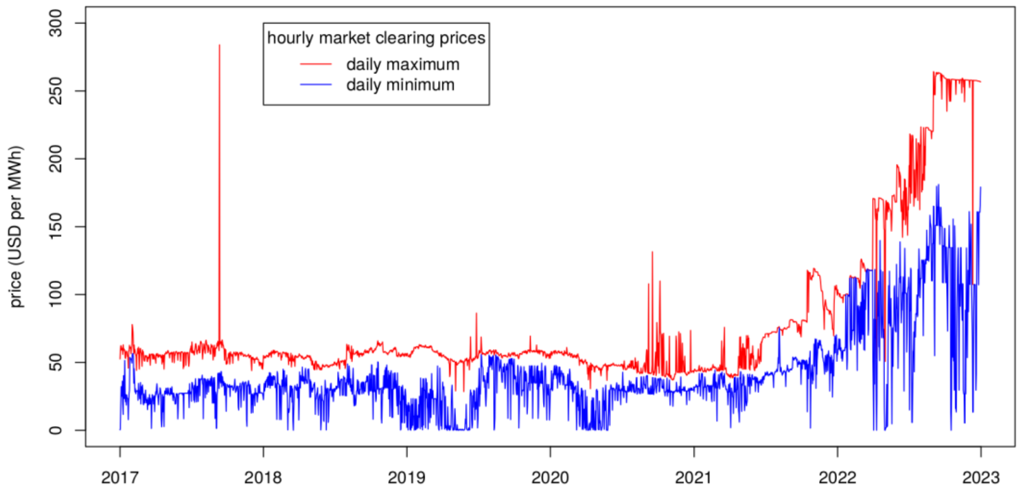

Figure 5 Two Measures of Daily Realized Volatility of Electricity Price Changes – A Comparison

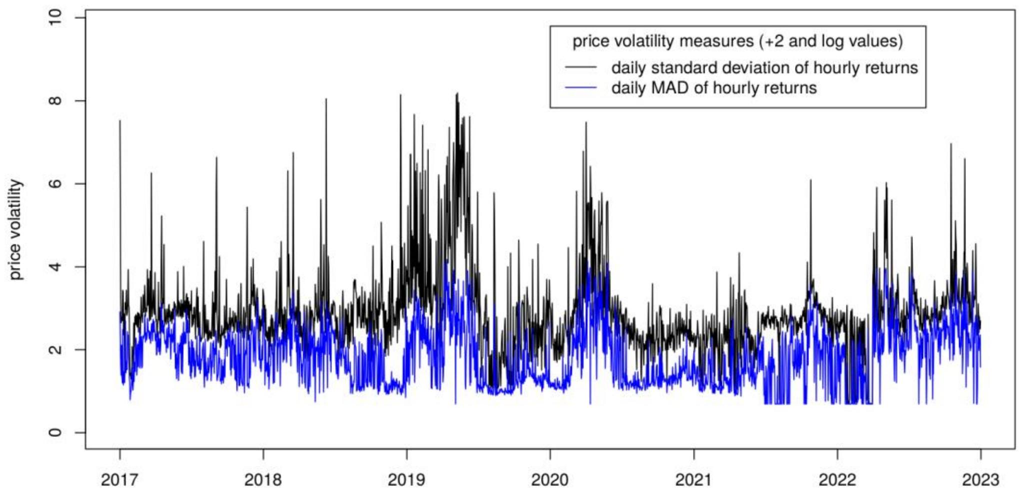

Figure 6 Calendar of Full-Day Holidays in Türkiye, 2017–2022

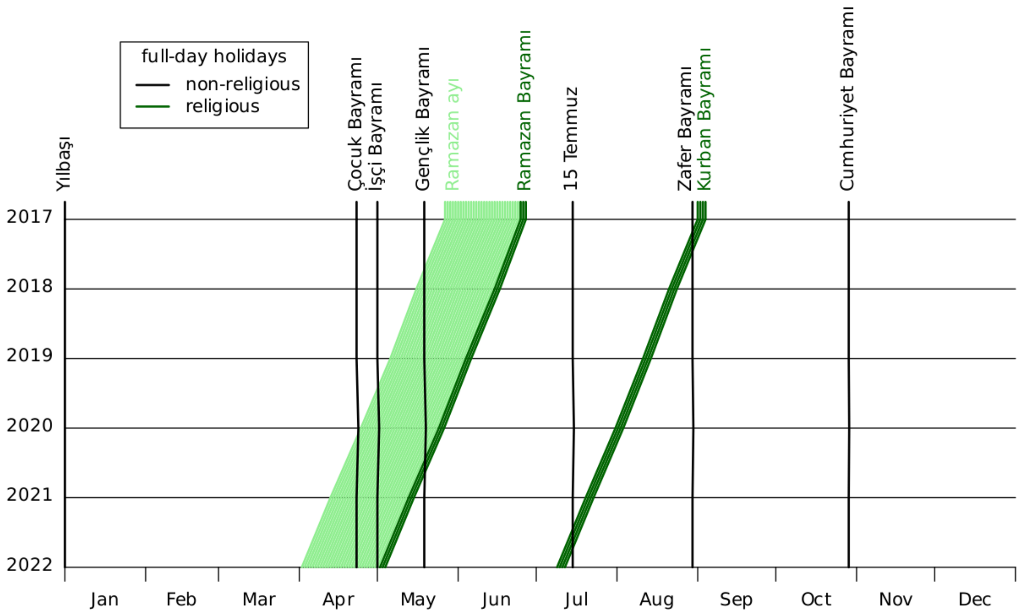

Figure 7 Wavelet Power Spectra of Hourly Electricity Consumption Data in Türkiye, 2017–2022

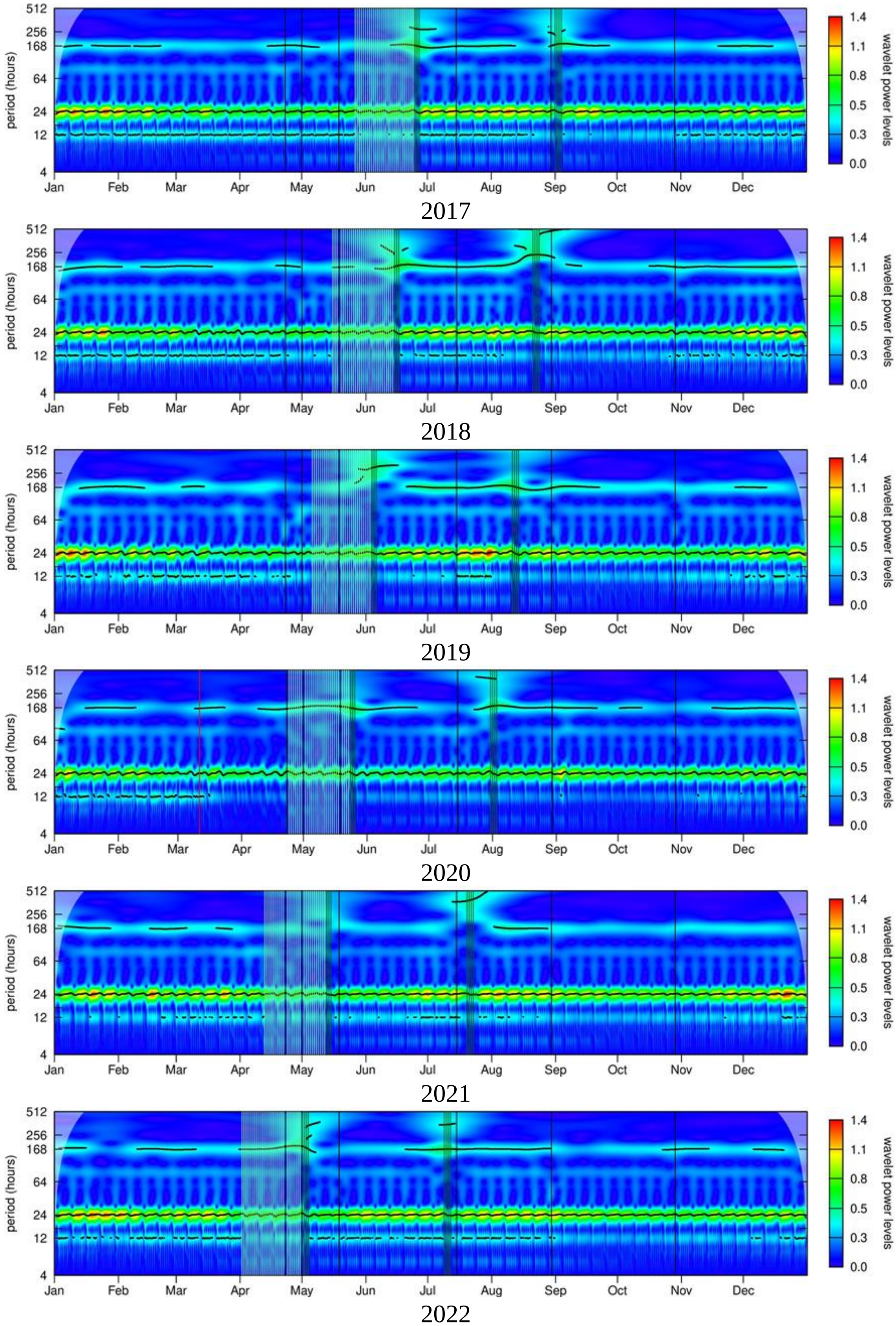

Figure 8 Wavelet Power Spectra of Hourly Electricity Price Data in Türkiye, 2017–2022

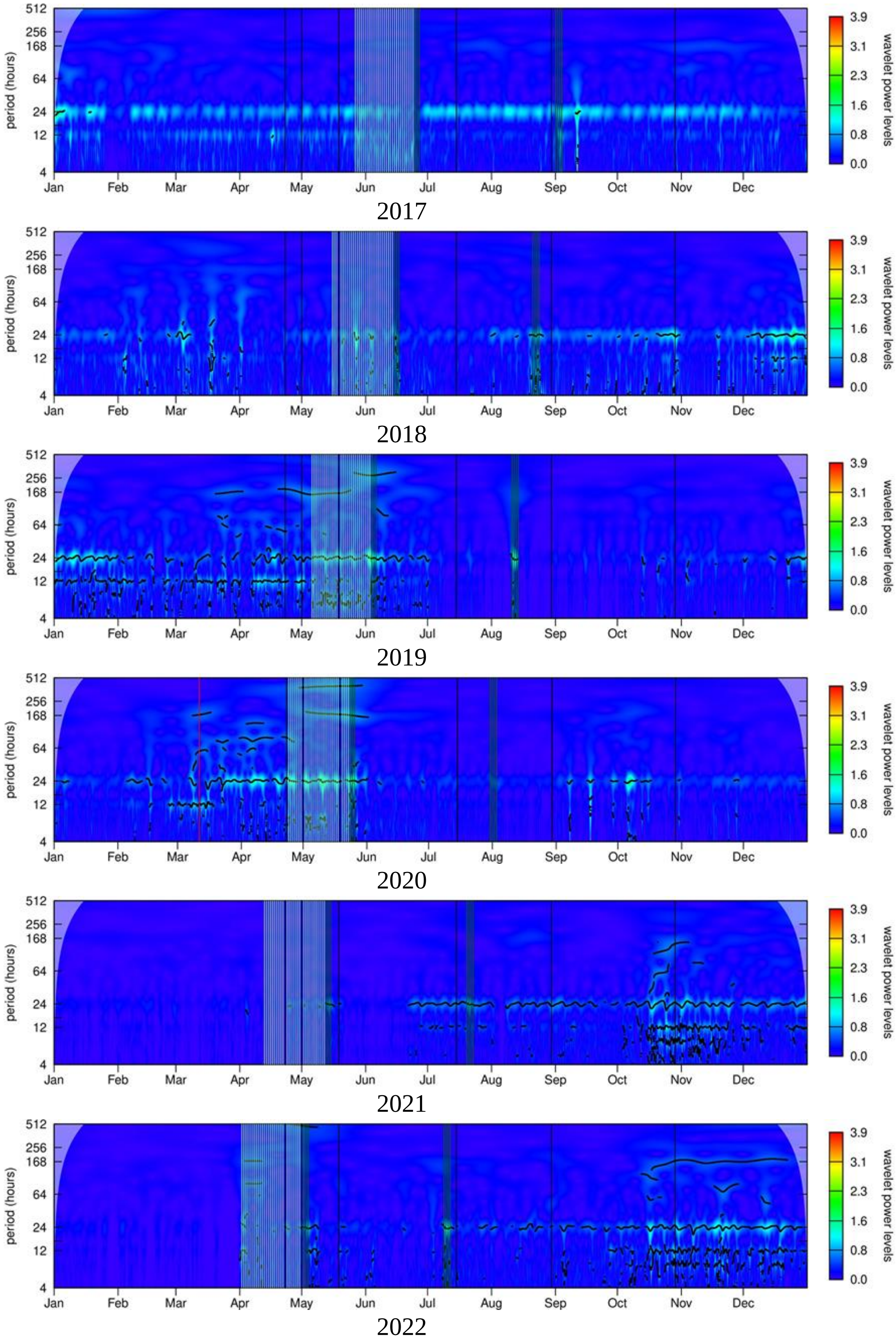

Figure 9 Daily Average Wavelet Power of Electricity Consumption at Periods of 12, 24, and 168 Hours (processed data)

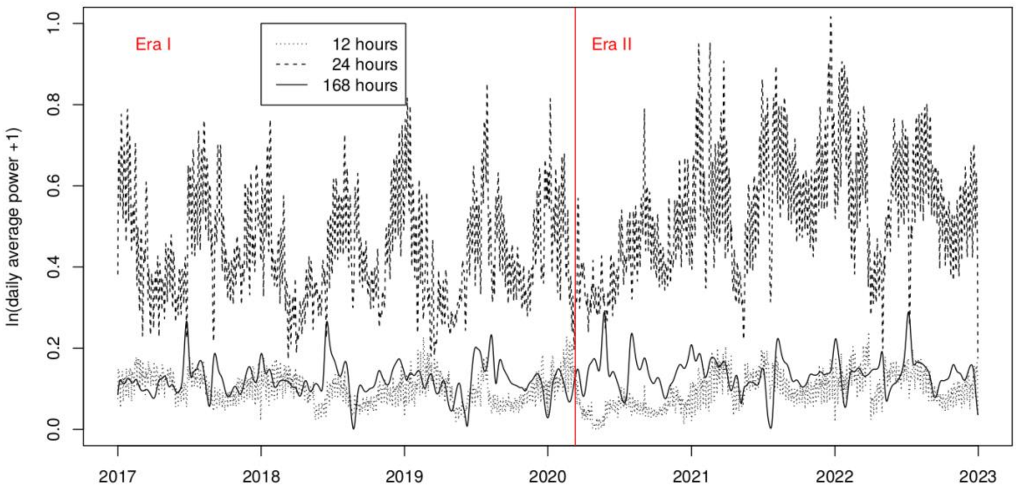

Figure 10 Daily Volatility vs. Daily Average Wavelet Power

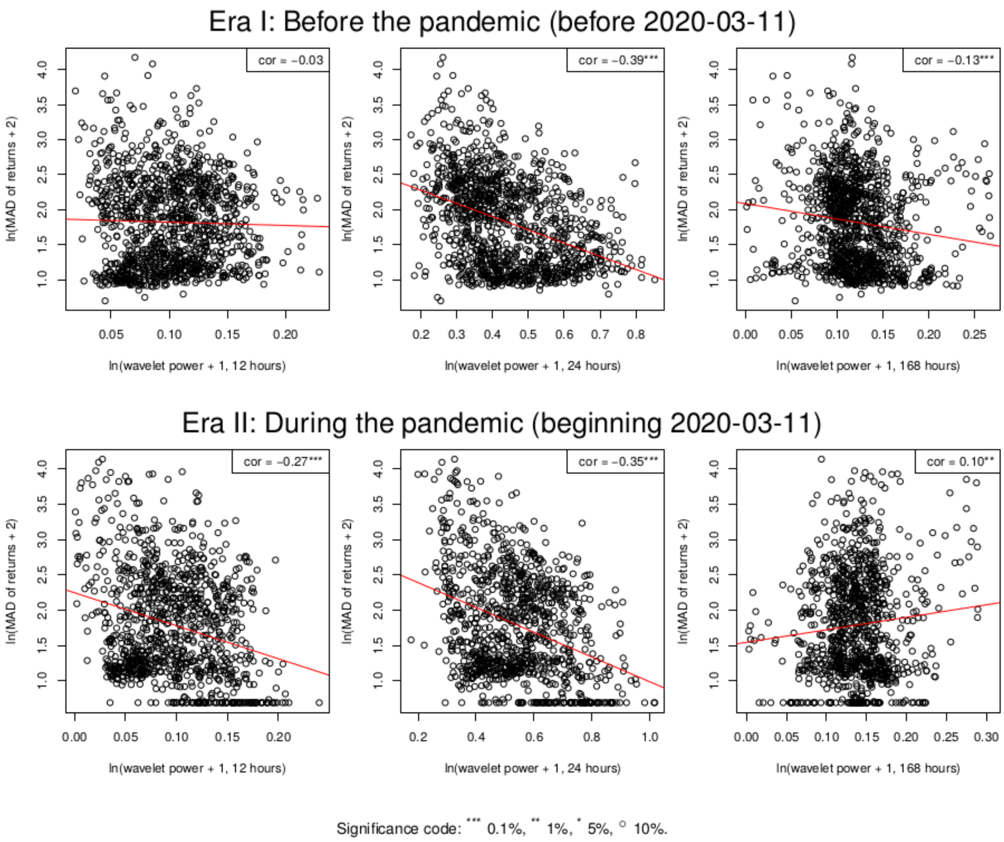

Table 1 Holidays in Türkiye

Holiday name (shorthand in Turkish)	Meaning	Date	Length (days)
Yılbaşı	New Year's Day	01 Jan	1
Çocuk Bayramı	National Sovereignty & Children's Day	23 Apr	1
İşçi Bayramı	International Workers' Day (May Day)	01 May	1
Gençlik Bayramı	Commemoration of Atatürk, Youth & Sports Day	19 May	1
Demokrasi ve Milli Birlik Günü (alias: 15Temmuz)	Democracy & National Unity Day	15 Jul	1
Zafer Bayramı	Victory Day	30 Aug	1
Cumhuriyet Bayramı	Republic Day	29 Oct	1.5*
Ramazan Bayramı	Holiday of Breaking the Fast (Ramazan Feast)	Floating	3.5*
Kurban Bayramı	Holiday of Sacrifice	Floating	4.5*

* starts at 1pm in the previous day

Table 2 Variables Used in this Study and their Time Base

Variable	Interpretation	Time base
Return	electricity price changes (simple returns in percent)	hourly
Daily Volatility	MAD of hourly electricity price changes	daily
Consumption	electricity consumption (MWh)	hourly & daily
Daily Average Wavelet Power	average wavelet power of hourly electricity consumption (retrieved for three different period bands)	daily
Ramazan ayı	Ramazan ayı indicator	daily
Ramazan Bayramı	Ramazan Bayramı indicator	daily
Kurban Bayramı	Kurban Bayramı indicator	daily
any other holiday	any non-religious holiday indicator	daily
Weekend	Sat & Sun indicator	daily

Table 3 Two Eras

Splitting 2017–2022	
Era I:	Before the pandemic (before 2020-03-11)
Era II:	During the pandemic (beginning 2020-03-11)

Table 4 Estimation Results, Model (A)

	Dependent variable ln(MAD of Returns + 2)	
Regressor	Era I	Era II
(Intercept)	37.5592 *** (3.0374)	35.2483 *** (2.7489)
ln(Consumption)	-2.6329 *** (0.2229)	-2.4516 *** (0.2006)
Ramazan ayı	0.3209 *** (0.0655)	0.0860 (0.0790)
Ramazan Bayramı	-0.1104 (0.2090)	0.2314 (0.2452)
Kurban Bayramı	-0.2895 ° (0.1754)	-0.1499 (0.2008)
any other holiday	0.1745 (0.1268)	0.2650 ° (0.1552)
Weekend	0.0334 (0.0432)	0.0540 (0.0512)
R^2	0.2023	0.2045
Residual Std Error	0.5764	0.6796
df	1158	1019

Standard errors in parentheses.

Significance code: *** 0.1%, ** 1%, * 5%, ° 10%.

Table 5 Estimation Results, Model (B)

	Dependent variable ln(Daily Average Wavelet Power + 1)					
	12-hour period		24-hour period		168-hour period	
Regressor	Era I	Era II	Era I	Era II	Era I	Era II
(Intercept)	0.1158 ***	0.1123 ***	0.4821 ***	0.5983 ***	0.1208 ***	0.1367 ***
	(0.0011)	(0.0015)	(0.0043)	(0.0049)	(0.0014)	(0.0016)
Ramazan ayı	-0.0448 ***	-0.0426 ***	-0.1181 ***	-0.2041 ***	-0.0074 °	0.0102 *
	(0.0034)	(0.0043)	(0.0132)	(0.0140)	(0.0043)	(0.0045)
Ramazan Bayramı	-0.0481 ***	-0.0402 ***	-0.1942 ***	-0.3222 ***	0.0633 ***	0.0507 ***
	(0.0102)	(0.0129)	(0.0399)	(0.0423)	(0.0129)	(0.0136)
Kurban Bayramı	-0.0608 ***	-0.0238 ***	-0.1528 ***	-0.2310 ***	0.0137	0.0321 **
	(0.0088)	(0.0112)	(0.0346)	(0.0367)	(0.0112)	(0.0118)
any other holiday	-0.0278 ***	-0.0237 ***	-0.0557 *	-0.0484 °	-0.0053	0.0061
	(0.0065)	(0.0088)	(0.0257)	(0.0287)	(0.0083)	(0.0093)
Weekend	-0.0342 ***	-0.0353 ***	-0.0944 ***	-0.1154 ***	-0.0001	-0.0000
	(0.0020)	(0.0027)	(0.0077)	(0.0087)	(0.0025)	(0.0028)
R^2	0.3247	0.2287	0.1901	0.3218	0.0247	0.0247
Residual Std Error	0.0304	0.0385	0.1192	0.1263	0.0386	0.0407
df	1159	1020	1159	1020	1159	1020

Standard errors in parentheses.

Significance code: *** 0.1%, ** 1%, * 5%, ° 10%.

Table 6 Estimation Results, Model (C)

	Dependent variable ln(MAD of Returns + 2)	
Regressor	Era I	Era II
(Intercept)	36.5512 ***	38.1129 ***
	(3.6565)	(3.8628)
ln(Consumption)	-2.5532 ***	-2.6738 ***
	(0.2752)	(0.2897)
ln(Daily Average Wavelet Power + 1)		
. . . 12-hour period	2.6992 ***	0.9511
	(0.5029)	(0.6662)
. . . 24-hour period	-0.5932 **	-0.1621
	(0.1934)	(0.2349)
. . . 168-hour period	-0.4368	1.4023 **
	(0.4439)	(0.5204)
R^2	0.2127	0.2067
Residual Std Error	0.5721	0.6780
df	1160	1021

Standard errors in parentheses.

Significance code: *** 0.1%, ** 1%, * 5%, ° 10%.

Table 7 Wavelet Parameter Settings for Robustness Tests

loess.span	**0**, 0.01, 0.05, 0.10, 0.20
dj	1/50, **1/100**, 1/200
m	1, **5**, 9, 13