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Abstract

How to balance supply and demand have become a long-term question in the electricity market, and anomalies related to calendar issues are critical factors to affect the resource allocation. This paper introduces a test method to control all potential calendar anomalies, and assess the significance of all possible calendar effects in different time frequencies. We implement our test method to the largest electricity trading platform in the United States. Using the high-frequency intraday trading data, we assess the calendar effects in different time frequencies (Day-of-the-week, Hour-of-the-day, Month-of-the-year, Day-of-the-month and season). Our results confirm that calendar effects exist in every dimension of time frequency, and specify those calendar effects with statistical significance. Moreover, this study discovers commonalities between electricity markets and financial markets, which makes it feasible to apply the management of financial markets to electricity markets. Besides, the detected calendar effects depict periodic patterns of market inequilibrium and facilitate the implementation of corresponding technical solutions in electricity markets.

Key Words

Calendar effects; PJM electricity market; Electricity price; Price volatility

JEL: C12; C22; G19; Q49

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1. Introduction

The goal of electricity market reform in all major countries of the world is to secure long-term and reliable electricity supply, break monopolies, introduce competition mechanism, and consequently realize the marketization of electricity price and improve market efficiency. Electricity supply is not only energy-related, but has become an important issue related to the environmental sustainability, development of circular economy and worldwide life standard [1].

Electricity cannot be stored in large quantities. Therefore, the electricity market is widely viewed as the most difficult market to balance between supply and demand [2-4]. The power generators, especially those with unstable output, encounter more challenges in order to maintain an efficient supply to fulfill the prospective consumption which fluctuates by diverse factors. Under this circumstance, maintaining the electricity market with fewer price swings is not only an achievement of the market efficiency, but also the resource efficiency [5-7]. Previous studies observe the price swings in the electricity markets and claim that the price volatility is one of the distinct characteristics for electricity markets. For example, [8, 9] estimtate the price volatility in the wholesale electricity market with respect to geographical and seasonal conditions. [10-12] respectively examine electricity markets in the United States and Canada with empirical datasets on electricity prices, and find different performance on price volatility across markets. Some studies focus on the extreme price records, and investigate the reason of the occurrence of these price records in the electricity market from different aspects. For example, [13, 14] study prices during the peak load periods using stochastic analyses, while [15, 16] use empirical data from the State of New York to investigate the price volatility. [17-19] summarize the problems of peak load prices in 1970s and point out the necessarity of market stability. However, in order to maintain a stable market, we need to evaluate, summarize and forecast the pattern of price volatility in the electricity market. Therefore, calendar effects will be a critical content to test and study.

Calendar effects refer to anomalies in security prices or returns related to the calendar, and depict that certain days, months or times of year are subject to different behavior and performance of markets. Calendar effects are widely investigated in types of financial markets (e.g. stock markets and derivative markets) to signal good or bad time to trade. The wholesale electricity markets, where power producers trade electricity with power-marketing and power-distribution parties, serve with equivalent functions like financial markets. The aim of this study is to examine the significance of calendar effects in the electricity market. Calendar effect is a popular term appeared in empirical studies that investigate the anomalous price movement of financial markets. In this study, we construct a powerful test to examine calendar effects appeared in the electricity prices. We make an empirical analysis and use a dataset from the wholesale Pennsylvania, New Jersey and Maryland (PJM) electricity market between 2013 and 2015. The dataset includes over 12,000 transmission lines, and for each transmission line the real-time pricing (RTP) records update hourly across 26,280 hours (24 hours×365 days×3 years). We test the significance of calendar effects in different dimensions of time frequencies (Day-of-the-week, Hour-of-the-day, Month-of-the-year, Day-of-the-month and season).

Our results confirm the existence of calendar effects in different dimensions of time frequencies, and specify those calendar effects with statistical significance. First, we find significant weekday effects on Tuesdays with higher electricity prices and larger volatility. Second, we observe significant hour-of-the-day calendar effects between 6pm and 8pm in the evening. Third, we find significant January effect and winter effect in the monthly dimension. Fourth, we find significant day-of-the-month effects at the beginning of each month. These results are consistent with findings from existing literature.

The contribution of this study can be summarized into three points. First, this study introduces a test method through which we can make a batch test of all suspicious calendar effects, and instantly apply the test outcomes to market supervision. Second, this study discovers commonalities between electricity markets and financial markets, and points out the feasibility to apply the management of financial markets to electricity markets. Third, the detected calendar effects in electricity markets depict periodic patterns of market inequilibrium, which will enhance the effectiveness and efficiency of practical solutions including electrical energy storage (EES) and demand response (DR) program.

The remainder of this paper is organized as follows. Section 2 introduces current literatures and findings. Section 3 describes the methodology and data. Section 4 presents results. Section 5 presents discussions. Section 6 concludes.

2. Literature Review

Calendar effects refer to cyclical anomalies that are related to the calendar and often classified as persistent cross-sectional and time series patterns in prices. Those anomalies are not predicted by extant theory, but popularly observed in financial market through analyses of price-related measures. Representative calendar effects vary in the literature, including weekday/weekend effects, month effects, intramonth effects, intraday effects, holiday effects and so on.

Weekday/weekend effect is the most important and widely-discussed calendar effect. It was first documented by [20]. [21] points out the “weekend effect” to describe the tendency of stocks to exhibit relatively large returns on Fridays compared to those on Mondays. [22] observes weekly and intradaily patterns in common stock prices using transaction data. [23] finds robust evidence on weekend effects to predict common stock returns. [24] uses the weekend effect to evaluate the rationality of the market. Other related works display the significance of weekday/weekend effects, including

[25-30]. For example, [25] discusses the different behavior of stock prices on Fridays and Mondays in the stock market, and finds the appearance of weekday/weekend effects early in 1950s. [26-27] find that there exists the “Monday effect” with higher expected returns of common stocks and treasury bills. Although the satisfactory explanations of these phenomena are still in progress, calendar anomalies have been the patterns which attact market regulators’ attention. [28-30] observe the weekend effects in the stock return by using a longer time period, a cross-sectional analysis among individual stocks, and including both the United States market and international markets.

Month effect focuses on the anomalies across months. The representative is the January effect, first documented by [31] and also known as the turn-of-the-year effect. Many follow-up studies discuss the month effects in financial markets [32-35]. For example, [32-33] examine, month-by-month, the empirical relation between abnormal returns and market value of common stocks in New York Stock Exchange (NYSE). They find evidence on abnormally high returns in January by contrast of the other months. [34] uses a ninety-year dataset to test the significance of month effects in the Dow Jones Industrial Average Index, and finds a persistent anomalous return in specific months. [35] summarizes these monthly calendar anomalies as the indication of market inefficiency or inadequacies in the underlying asset-pricing model.

Intramonth effects, also called turn-of-the-month (TOM) effect, focus on the sequence of days in one month and their difference in terms of prices. Intramonth effects specify that the last day of one month and the first three of the next are particularly high, as discussed by [36-38]. For example, [36] tests the surge in stock returns at the turn of each calendar month during 1969 and 1986. [37] examines the daily price return patterns in the Standard & Poor's (S&P) 500 Index from 1928 to 1993 to investigate the TOM phenomenon. The results show that the mean returns in the U.S. stock market were significantly positive during TOM (trading days -1 to +4) and first half of the month (trading days -1 to +9) and significantly negative in the rest of the month. Similarly, [38] also finds evidence on TOM phenomenon by using a 55-year dataset on stock market indexes, which is highly related to the distribution of earnings news disclosure on the certain days.

Intraday effects have become more and more important along with the increase of studies using intraday data. For example, [39] observes a large mean price change on the last daily NYSE transaction and consequently infer that closing prices may not consistently represent stock values and the intraday analyses are necessary. [40] examines weekend effects, holiday effects, intramonth and intraday effects, and his results confirm the importance of intraday effects on capturing seasonal movements in security prices. [41-42] study the intraday effects in terms of profitability, and find strong evidence on profit opportunities through intraday-level data in Australian security markets. Similar intraday effects are also found in the other financial markets, such as the foreign exchange market for Japanese Yen [43], and Korean Index Futures Market [44].

Holiday effects are also popularly discussed on prices and their seasonal movement. They refer to the tendency of the market to do well on any day which precedes a holiday. Although the number of holidays is not comparable to weekends, there are still a series of studies that explore these anomalies [34, 45-48] and find a global trend. For example, [45] studies the pre-holiday effects on stock returns and find that they are significant in Canada, Japan, Hong Kong, and Australia, countries whose holidays are different. [46] examines the US market between 1963 and 1986, and finds the holiday effects display as a surge of stock returns on the trading day prior to holidays. [47-48] focus on the investor behavior and find that the holiday effects in the stock markets are highly related to the willingness to invest of investors prior to holidays. They find these holiday effects in Spanish Stock Exchange, New York Stock Exchange and Frankfurt Stock Exchange.

In summary, the existing studies show that various types of calendar effects exist and have become prevalent phenomena in worldwide financial markets. In this study, we extend the exploration of calendar effects into the electricity market. This is reasonable. Some classical studies [49-50] consider electricity as a commodity equivalent to financial securities, and correspondingly consider the electricity markets as similar as the regular financial markets.

The electricity markets convey the similar functions and missions to financial markets. As stated by [35], the mission of the market is to maintain the market efficiency and adequacy. Since calendar anomalies are the signal of inefficiency and inadequacy, it is critical to observe and investigate the calendar anomalies from the perspectives of both academics and practitioners. Therefore, the analyses of calendar effects are beneficial to the management and operation of electricity markets and smart grid systems.

In the electricity markets, some emerging studies have used calendar effects in load forecasting captures weekly and seasonal energy consumption patterns [51] and facilitates the prediction of peak demand [52]. They confirm the value of calendar effects in the analyses of electricity markets. Unfortunately, these studies fail to achieve an ideal predictive power by using the regular methods of calendar effects [53]. Therefore, an efficient analytical test is needed. In the following section, we introduce a new method to explore calendar effects.

3. Methodology

3.1 Statistical Analysis of Calendar Effects

In this section we introduce a statistical analysis for calendar specific anomalies by Hansen, Lunde and Nason (H-L-N), which we will extend as a method in this study [54]. This method uses the correlation structure of the returns of specific calendar effects to create a generalized-*F* test, and checks the joint hypothesis of all calendar effects listed. This method has advantages by contrast to the traditional Bonferroni bound type test which checks each potential calendar effect individually.

This method is initially to address the calendar effects in the stock market indices. Let $r_t \equiv \log P_t - P_{t-1}$ be the log returns in which *t* represents one particular hour of a day, *t-1* represents the previous hour, and *n* represents the total number of periods. A sequence of returns are assumed to be uncorrelated: cov(r_s, r_t) = 0 for $s \neq t$. The expected return is denoted by $\mu_t \equiv E[r_t]$ and the variance is denoted by $\sigma^2 \equiv var(r_t)$.

The period of each calendar effect k is an element of a set $S_{(k)}$, where a subscript in parentheses refers to a calendar effect. A subscript without parentheses is a time reference. Let *m* be the number of calendar effects and the number of elements in $S_{(k)}$ be $n_{(k)}$. For example, k = 1 could represent legal US holidays, so $S_{(1)}$ represents all the hours during the holidays, and $n_{(1)}$ represents the number of total hours of US holidays. The full sample of all hours is represented by $S_{(0)}$, which has all *n* elements, in other words, $n_{(0)} = n$. The expected value and average return for calendar effect k are given by $\xi_{(k)} \equiv E\left[\bar{r}_{(k)}\right] = n_{(k)}^{-1} \sum_{t \in S_{(k)}} \mu_t$ and $\bar{r}_{(k)} \equiv n_{(k)}^{-1} \sum_{t \in S_{(k)}} r_t$ respectively.

This H-L-N method has two types of hypotheses tests. The first type of hypothesis is that there are no calendar specific anomalies:

$$H_0: \xi_{(0)} = \cdots = \xi_{(m)} \tag{1}$$

where $\xi_{(n)}$ represents the expected return for each calendar effect.
The second type of hypothesis is that there are no calendar specific anomalies in standardized expected returns:

$$H_0': \rho_{(0)} = \cdots = \rho_{(m)} \tag{2}$$

where $\rho_{(n)}$ represents the expected standardized return for each calendar effect.

The test of these hypotheses is in the form of a χ^2 test (3):

$$T = X' \boldsymbol{B}_\perp (\boldsymbol{B}'_\perp \boldsymbol{\Omega} \boldsymbol{B}_\perp)^+ \boldsymbol{B}_\perp \boldsymbol{X} \tag{3}$$

where **X** is a normally distributed vector with mean λ and covariance matrix **Ω**, let **B** be a known matrix full column rank and θ a vector with proper dimension such that λ = **B**θ, $\boldsymbol{B}_\perp$ is the orthogonal matrix to B and where $(\boldsymbol{B}'_\perp \boldsymbol{\Omega} \boldsymbol{B}_\perp)^+$ is the Moore-Penrose inverse of $\boldsymbol{B}'_\perp \boldsymbol{\Omega} \boldsymbol{B}_\perp$. This χ^2 test is distributed with f = rank$(\boldsymbol{B}'_\perp \boldsymbol{\Omega} \boldsymbol{B}_\perp)$ degrees of freedom.

The parameters used in the test can be estimated by the bundle of equations below in (4).

$$\begin{cases} \hat{\xi}_{(k)} = \bar{r}_{(k)} \\ \widehat{\omega}^2_{(k),n} = n^{-1}_{(k)} \sum_{t=s_{(k)}} \left(r_t - \bar{r}_{(k)}\right)^2 \\ \hat{\rho}_{(k)} = \hat{\xi}_{(k)} / \widehat{\omega}_{(k),n} \\ \widehat{\boldsymbol{\Sigma}}_n = \mathbf{A}' \operatorname{diag}(\widehat{\sigma}^2_1, \dots, \widehat{\sigma}^2_{1n})\mathbf{A} \\ \widehat{\boldsymbol{\Omega}}_n = \widehat{\boldsymbol{\Lambda}}_n^{-1} \widehat{\boldsymbol{\Sigma}}_n \widehat{\boldsymbol{\Lambda}}_n^{-1} \end{cases} \tag{4}$$

where $\widehat{\boldsymbol{\Lambda}}_n = \operatorname{diag}(\widehat{\omega}_{(0),n} \dots, \widehat{\omega}_{(m),n})$.

The test statistics will be

$$F_\xi = \hat{\xi}' \boldsymbol{\iota}_\perp \left(\boldsymbol{\iota}'_\perp \widehat{\boldsymbol{\Sigma}}_n \boldsymbol{\iota}_\perp\right)^+ \boldsymbol{\iota}'_t \, \hat{\xi} / q_\xi \tag{5}$$

which is asymptotically $F(q_\xi, \infty)$ distributed under H_0, and

$$F_\rho = \rho' \boldsymbol{\iota}_\perp \left(\boldsymbol{\iota}'_\perp \widehat{\boldsymbol{\Omega}}_n \boldsymbol{\iota}_\perp\right)^+ \boldsymbol{\iota}'_t \, \hat{\rho} / q_\rho \tag{6}$$

which is asymptotically $F(q_\rho, \infty)$ distributed under H'_0. The degrees of freedom q_ξ and q_ρ equal the rank of $\boldsymbol{\iota}'_\perp \widehat{\boldsymbol{\Sigma}}_n \boldsymbol{\iota}_\perp$ and $\boldsymbol{\iota}'_\perp \widehat{\Omega}_n \boldsymbol{\iota}_\perp$, respectively. $\boldsymbol{\iota}_\perp$ is not unique, and is given by the matrix that has ones in and right below the diagonals and zeroes elsewhere.

3.2 Selection of Calendar Effects

This section presents the universe of possible calendar effects that we consider in our following analyses. In order to have a comprehensive investigation, we test possible calendar effects from different dimensions of time frequencies, as described below.

1. Day-of-the-week: as we mentioned before, weekday/weekend effect is the most important and widely-discussed type of calendar effects among related studies. In this study we consider effects from different days of the week. We include all the seven days and categorize them into seven groups, in order to evaluate the difference of price movement across days of the week.
2. Hour-of-the-day: we include the 24 hour-of-the-day effects. Compared with existing studies, this type of calendar effects is new. As the advantage, our data updates hourly the electricity prices, so we can further observe and explore the price anomalies from an intraday level. In practice, we categorize price records by hours, and observe each hour's price movement for the test of hour-of-the-day effects.
3. Month-of-the-year: we include the twelve candidate month-of-the-year effects, to evaluate the difference of price movement across months.
4. Season: due to the seasonality of some specific power provider, we also consider and evaluate the difference of electricity price movement across seasons. We classify the seasons with equal number of months: winter (December, January and

February), spring (March, April and May), summer (June, July and August) and fall (September, October and November).

5. Day-of-the-month: in order to test the intramonth effects, we include 31 day-of-the-month effects.

3.3 Data

We use the dataset from the PJM electricity market. As a Regional Transmission Organization (RTO), PJM coordinates the movement of power within its region and is responsible for the operational and planning functions of the PJM bulk power system on behalf of participant members. In order to lower the energy costs of end users, the PJM system manages and coordinates competition among power suppliers located in multi-state service areas through establishing trading rules and protocols, as discussed by [49-50]. Areas served by PJM are divided by the transmission lines which are referred to as the pricing nodes (Pnode).

As a clearing house, PJM matches bids and offers and thus gives the market-clearing price for each service area. The market-clearing price is referred to as the locational marginal price (LMP) and updated hourly. LMP is the sum of the cost of energy, the marginal cost of transmission loss, and the marginal cost of congestion, which are the leading contributors to volatility in electricity prices. It represents the incremental value of an additional megawatt of power transported to a particular Pnode.

We use the hourly LMP data between 2013 and 2015, which includes 26,280 hours (24 hours×365 days×3 years) for each Pnode. There are 12,350 Pnodes in this PJM dataset. Table 1 presents the descriptive statistics of LMPs. From 2013 to 2015, the overall PJM market has an average LMP equal to 38.56, and a standard deviation equal to 47.86. So the coefficient of variation is 1.24. Both the minimum and maximum of LMP are extreme values (-2,240 and 4,643), which confirms the existence of large price volatility in the electricity market.

Table 1 also presents the descriptive statistics of LMPs across the seven days of the week. We observe that the means of LMPs on Sunday (30.76) and Saturday (34.44) are below the overall average LMP, whereas those means of the remaining five days are above the overall average LMP. By contrast, Tuesday has the highest average LMP among the seven days (44.15). These results imply that the power demand on Tuesday is probably higher, while weekends are not the time with higher demand. Thus, the price anomaly may occur on Tuesdays at a higher probability than on weekends. Similarly, the significant difference across days of the week is also observed on the coefficient of variation (*CV*). Tuesday has the highest value (1.80), while weekends have the lowest *CV*s (0.71 and 0.85), considered as low-variance. These results indicate that prices may have smaller dispersion on weekends and have larger dispersion and uncertainty on Tuesday.

We continue to study the summary statistics in other time frequencies. Table 2 presents summary statistics for LMPs by hour-of-the-day. According to the means of LMPs, we find that on average the highest values are mostly located between Hour 18 (6pm) and Hour 21 (9pm), while lowest LMPs are mostly located between Hour 24 (midnight) and Hour 5 (5am). From Figure 1 we can see the differences of average LMPs across hours more clearly. As an inference, hour-of-the-day effects probably exist during the hours in the evening.

Next we observe LMPs from the monthly time level. Table 3 presents the summary statistics for LMPs classified by month-of-the-year and season. In Panel A, LMPs are classified into twelve sections: 1 = January, ..., and 12=December. From Table 3 and Figure 2, we find that January has the highest LMPs on average (59.07) among twelve months. Additionally, January also has the highest CV (2.01), which is far greater than the other eleven months. As an inference, there probably exist January effects in the price of electricity, which is consistent with [32-35]. In Panel B of Table 3, LMPs are classified into four sections: 1=winter (December, January and February), 2=spring (March, April and May), 3=summer (June, July and August) and 4=fall (September, October and November). We see that winter has both the highest average (47.93) and CV (1.63), implying that winter effects may exist in the electricity market.

Finally, we observe LMPs by day-of-the-month. As described in Table 4, we classify LMPs into 31 sections, corresponding to day 1 to day 31 of the month. We find that the average value of LMPs on Day 7 (54.24) is far greater than average values of LMPs on the other days. Figure 3 depicts the large difference between Day 7 and the others clearly. Furthermore, Day 7 also has the highest CV (2.64) among 31 days of the month, and its CV is almost twice as much as the second highest CV (1.56) on Day 24. The significant differences among these summary statistics across days of the month are symbols of potential calendar effects.

In summary, we observe significance cross-sectional differences appeared in the summary statistics when we classify the electricity price in various time frequencies. These findings indicate that certain types of calendar effects exist in the electricity market at a high probability.

4. **Empirical Results**

In this section, we test the significance of calendar effects on LMPs. Different from other markets, we observe negative electricity prices, implying that power generators may pay demanders to take electricity instead of lowering their output under some certain circumstances. The occurrence of negative prices is a symbol of price volatility, which may further lead to the existence of calendar effects.

We apply the test method in Section 3.1 to our PJM dataset. According to Section 3.2, we investigate the calendar effects in different dimensions of time frequencies (Day-of-the-week, Hour-of-the-day, Month-of-the-year, Season, and Day-of-the-month). In each time dimension, first we sort the LMPs into the groups of time periods described in Section 3.2; second, we test the null hypothesis in Equation (1), to examine whether or not there exist calendar specific anomalies of LMPs across sections; third, we figure out the significant calendar effects out of the candidate pool by their higher expected values.

Table 5 presents the summary of empirical test results for calendar effects in five dimensions of time frequencies (Day-of-the-week, Hour-of-the-day, Month-of-the-year, Season, and Day-of-the-month). The p-value is used to judge the hypothesis test. According to [54], the null hypothesis will not be accepted if p-value is greater than 0.05, and consequently the calendar effects will not exist in the corresponding dimensions of time frequencies.

4.1 the Day-of-the-week Calendar Effects

We start with the day-of-the-week dimension. At the beginning, LMPs are classified into seven sections: 0 = Sunday, 1 = Monday, ..., and 6 = Saturday. As described in Section 3.1, we test the null hypothesis that there are no calendar specific anomalies across the sections of days of the week. The p-value is smaller than 0.0001, so the null hypothesis is rejected and the results confirm the existence of calendar effects in the days of the week with robustness.

After confirming the existence of calendar effects in the day-of-the-week dimension, we figure out the calendar effects with significance. As the key advantage, this analytical test enables us to figure out the significant calendar effects out of the candidate pool. The most significant calendar effects are among Tuesdays, Wednesdays and Mondays. As shown in Figure 4, their average values of LMPs (44.15, 40.99 and 40.61 respectively) are the highest three among the seven groups, and much higher than the overall average value (38.56).

Our results indicate that the electricity market displays significant weekday effects instead of weekend effects. Especially on Tuesdays, the average value of LMPs is much higher than the overall average, and the price fluctuations on Tuesdays (standard deviation as 79.40 in Table 1) are much larger than on the other days. This "Tuesday Effect" differs from those traditional calendar effects appeared in the financial markets. The different performance of significant calendar effects between electricity markets and financial markets is derived from their different operation hours. According to [21-24], the regular financial markets close on Saturdays and Sundays and thus accumulate some weekend influences to reveal on the next Mondays. By contrast, the electricity market is a continuous market. The continuous electricity price movement reflects the market condition instantly. Therefore, the results are obvious to tell the peak demands for electricity are between Mondays and Wednesdays, mostly on Tuesdays, which is critical for the management of the electric power system to prepare.

4.2 the Hour-of-the-day Calendar Effects

We continue with the dimension of the hour-of-the-day. We classify LMPs into 24 sections corresponding to 24 hours of a day, and test the null hypothesis. Our results also show the existence of calendar effects among 24 hours of the day. In Table 5, the *p*-value is still below 0.0001 and the null hypothesis is rejected again.

The most significant hour-of-the-day calendar effects are during 6pm, 7pm and 8pm, with the highest three average values of LMPs among 24 hours (49.35, 47.31 and 47.15). The results indicate that the calendar anomalies appear in the evening at a higher probability than in the other time of a day. As stated before, the study of the intraday calendar effects is none among the existing literature about electricity markets. However, capturing the trend of price movement across hours of a day is meaningful and valuable for the electricity markets, like the importance for the financial markets [39, 40]. Take PJM as the example. As one of the oldest smart grid system for electric transition, PJM is also responsible to provide a stable environment for both producers and consumers by maintaining relatively stable LMPs. The most significant hour-of-the-day calendar effects in our results concentrate in the after-business evening hours. It implies that the power demand from households is the principal driver of the higher LMPs during these hours [9, 11].

4.3 the Month-of-the-year and Season Calendar Effects

Third, we evaluate in the month-of-the-year and season dimensions. In Table 5, the *p*-values of month-of-the-year and season are both below 0.0001, and show the existence of calendar effects across months and seasons. The top three months with the significant calendar effects are January, February and March, and their average values of LMPs are 59.07, 55.38 and 48.35 respectively. The similar results appear at the seasonal level. The winter season has the calendar effects during our test period, and the average LMP is 47.93. Both the January Effect and the Winter Effect are consistent to findings in the financial studies mentioned before [31-33]. For electricity markets, this finding is reasonable because during the winter a large amount of power is used for heating. The fluctuation of temperature is largely reflected by the change of power use and consequently leads to the price fluctuations of electricity markets.

4.4 the Day-of-the-month Calendar Effects

Finally, the test at day-of-the-month level also shows the existence of calendar effects. The *p*-values of day-of-the-month is below 0.0001, so the null hypothesis is rejected.

The days with the significant calendar effects are mainly located at the beginning of a month. The highest three calendar effects are on the 7^{th}, 6^{th} and 3^{rd} day of the month, with average LMPs 54.24, 43.52 and 41.67 respectively. The results suggest that the calendar anomalies occur at the beginning of a month with a larger probability. This finding is consistent to existing literature about financial markets [37, 38]. One potential explanation to these day-of-the-month calendar effects is related to the market mechanism. Like financial markets, the electricity markets are news-driven. The LMPs are probably driven by news disclosure, and the news disclosure mostly occurs at the beginning of the month. Therefore, the significant day-of-the-month calendar effects cluster at the beginning of a month.

In summary, the test results confirm that the calendar anomalies exist in different dimensions of time frequencies. In each dimension, the significance of selected calendar effects is statistically robust, and displays consistence with both prevalent calendar effects in the financial markets, and electricity market practice.

5. Discussion

The issue of how to provide a stable environment and achieve efficiency and adequacy for electricity markets has become one of the most controversial topics facing power producers, regulators, political officials and millions of end consumers. Although the establishment of smart grid systems enhances the efficiency on energy allocation, however, energy load forecasting is still required to protect electricity markets from uncertain risky conditions [53].

However, the capacity of energy load forecasting is still under development and has been considered as a critical condition to facilitate the decision-making process of unit commitment, economic dispatch, and energy market operation [55]. In order to improve the capacity and quality of energy load forecasting, the measurement of calendar effects plays a critical role, which has been confirmed by a number of emerging studies discussed before [51-53].

Thus, the first contribution of this study is to introduce a test method through which we can make a batch test of all suspicious calendar effects. Shown in previous sections, we examine all suspicious calendar effects at one time, and lock those with statistical significance. This test is convenient for use. Meanwhile, as stated in [35, 27, 23], calendar effects are dynamic anomalies that do not hold up in different time periods. Therefore, the convenient advantage of this test ensures to figure out the prevalent calendar effects instantly for market supervision.

The second contribution of this study is to discover commonalities between electricity markets and financial markets. In the process of calendar effect analyses, many findings of our study are in line with those in the literature about financial markets. This is meaningful. These commonalities between electricity markets and financial markets suggest that financial theories and analytical methods can facilitate to explain the inside mechanism of the electricity markets. Therefore, to enhance the management of electricity markets, we can learn from regulations, cases and experience from financial markets.

The third contribution of this study is the practical findings of specific significant calendar effects in electricity markets. These selected calendar effects are prototypes of periodic inequilibrium of power demand and supply. Once we capture these calendar effects, it will be helpful to reduce inequilibrium of power demand and supply, and consequently enhance the market efficiency [56].

In practice, electrical energy storage (EES) has been considered as one potentially effective and technical solution to the power inequilibrium [57-58]. Besides, some countries launch the demand response (DR) program which adjusts the demand of electricity by end-users, so as to reduce electricity use at times of high prices and to relieve the congestion of the power grid [59]. However, in order to ensure these technical solutions to be effective, the premise is to make clear the calendar effects of LMPs and to know the right time to launch the technical solutions. Calendar effects provide evidence on patterns of market inequilibrium, which is the key factor for those solutions.

6. Conclusion

The operation of an electric power grid is a constant balancing act. According to the property of the electric power, maintaining a stable price level is not only the requirement of the electricity market efficiency, but also the requirement of the sustainability. The time-series movement of electric prices indicate the instant change between power supply and demand in the market. In order to improve the market efficiency and environmental sustainability, the assessment of the price volatility in the electricity market is a critical point.

Therefore, we focus on calendar effect, the cyclical anomalies related to the calendar and classified as persistent cross-sectional and time series patterns in prices. We introduce a powerful test to assess the significance of calendar effects. In order to find the calendar effects with significant patterns, we include all possible effects in diverse time frequencies, including hourly, daily, monthly and seasonal frequencies. We use a PJM dataset including hourly updated prices for over 12,000 transmission lines during 3 calendar years.

Our results indicate that significant calendar effects exist in every time frequency that we assess. First, we find significant effects among Tuesdays, Wednesdays and Mondays, implying that the electric consumption has “weekday effect”. Second, we find that at the hourly level, significant calendar effects appear in the evening (6pm to 8 pm), which is consistent to the peak load hours of a day. Third, at the monthly level, the top three months with the significant calendar effects and highest average LMPs are January, February and March. This result is equivalent to the result at the seasonal level, which find winter with the significant calendar effect. Finally, we observe that calendar anomalies appear at the beginning of a month with a larger probability than at the other days of a month.

Our results confirm the existence of calendar effects in different dimensions of time frequencies, and specify those calendar effects with statistical significance. These results are consistent with findings from existing literature. As the contribution, this study introduces a powerful test method to batch detect all suspicious calendar effects, discovers commonalities between electricity markets and financial markets, and shed light on the implementation of technical solutions to reduce power inequilibrium in the electricity market.

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Table 1: Summary Statistics for LMPs by Day-of-the-week

This table presents the summary statistics for LMPs classified by days of the week. The LMPs are classified into seven sections: 0 = Sunday, 1 = Monday, ..., and 6=Saturday. Each section has summary statistics, including mean, standard deviation (sd), median (p50), number of observations (N), minimum, maximum, and coefficient of variation (cv, computed by sd/mean).

day-of-the-Week	**mean**	**sd**	**p50**	**N**	**min**	**max**	**cv**
0	30.76	21.82	27.59	4.14E+07	-981.77	1509.94	0.71
1	40.61	45.04	31.06	4.14E+07	-2216.00	2406.08	1.11
2	44.15	79.40	31.38	4.17E+07	-2240.30	2828.63	1.80
3	40.99	46.36	31.20	4.17E+07	-1547.67	2543.35	1.13
4	40.29	46.69	30.97	4.17E+07	-1390.97	1920.32	1.16
5	38.63	43.49	30.49	4.14E+07	-2219.92	4643.74	1.13
6	34.44	29.30	29.34	4.14E+07	-1917.02	1889.33	0.85
Total	38.56	47.86	30.16	2.91E+08	-2240.30	4643.74	1.24

Table 2: Summary Statistics for LMPs by Hour-of-the-day

This table presents the summary statistics for LMPs classified by 24 hours of the day. Hour 1 refers to 1 am of the day, Hour 2 refers to 2 am, … Each section has summary statistics, including mean, standard deviation (sd), median (p50), number of observations (N), minimum, maximum, and coefficient of variation (cv, computed by sd/mean).

hour	mean	sd	p50	N	min	max	cv
1	28.51	26.50	25.38	1.21E+07	−981.77	1830.55	0.93
2	27.87	29.17	24.98	1.21E+07	−1094.82	2257.45	1.05
3	26.32	30.38	24.00	1.21E+07	−1156.63	1608.66	1.15
4	25.95	30.69	23.73	1.21E+07	−1224.14	1256.15	1.18
5	27.77	31.85	24.72	1.21E+07	−1230.64	1479.73	1.15
6	32.64	46.45	26.73	1.21E+07	−787.47	1452.19	1.42
7	40.98	61.16	29.24	1.21E+07	−1041.99	2321.24	1.49
8	42.37	71.53	30.04	1.21E+07	−1078.63	2207.25	1.69
9	40.14	63.58	31.46	1.21E+07	−1310.04	2280.58	1.58
10	41.94	62.33	32.97	1.21E+07	−1599.36	2237.50	1.49
11	44.34	63.77	34.05	1.21E+07	−1917.02	2103.56	1.44
12	43.84	55.17	34.40	1.21E+07	−1547.67	2149.01	1.26
13	42.39	34.98	34.30	1.21E+07	−1943.95	2233.30	0.83
14	43.00	40.85	33.82	1.21E+07	−1407.47	1804.79	0.95
15	40.75	36.91	32.95	1.21E+07	−2099.97	2828.63	0.91
16	42.57	45.15	32.95	1.21E+07	−1757.01	2389.71	1.06
17	44.19	44.44	33.79	1.21E+07	−2041.78	2613.13	1.01
18	49.35	59.28	36.21	1.21E+07	−2117.23	2543.35	1.20
19	47.31	52.80	35.48	1.21E+07	−2216.00	2047.24	1.12
20	47.15	57.63	35.73	1.21E+07	−2240.30	3373.69	1.22
21	45.68	50.13	35.26	1.21E+07	−1966.36	4643.74	1.10
22	39.38	36.54	31.71	1.21E+07	−858.56	3997.30	0.93
23	31.82	27.45	28.07	1.21E+07	−688.07	2446.90	0.86
24	29.14	25.85	26.25	1.20E+07	−848.69	1269.16	0.89

Table 3: Summary Statistics for LMPs by Month-of-the-year and Season

This table presents the summary statistics for LMPs classified by Month-of-the-year and Season. In Panel A, LMPs are classified into twelve sections: 1 = January, ..., and 12=December; in Panel B, LMPs are classified into four sections: 1=winter (December, January and February), 2=spring (March, April and May), 3=summer (June, July and August) and 4=fall (September, October and November). Each section has summary statistics, including mean, standard deviation (sd), median (p50), number of observations (N), minimum, maximum, and coefficient of variation (cv, computed by sd/mean).

Panel A: Month-of-the-year

month	mean	sd	p50	N	min	max	cv
1	59.07	118.48	30.80	2.44E+07	-1156.63	2321.24	2.01
2	55.38	55.62	36.79	2.20E+07	-1917.02	4643.74	1.00
3	48.35	52.39	34.48	2.44E+07	-1224.14	1536.83	1.08
4	35.02	16.56	32.02	2.36E+07	-1390.97	1568.01	0.47
5	36.49	30.31	30.96	2.45E+07	-1147.84	1548.79	0.83
6	34.75	24.92	29.76	2.40E+07	-2240.30	2421.70	0.72
7	36.78	35.85	29.24	2.49E+07	-1106.26	2828.63	0.97
8	30.95	18.29	28.03	2.49E+07	-639.25	1458.10	0.59
9	33.53	44.48	27.72	2.41E+07	-1102.15	1920.32	1.33
10	32.03	19.73	28.39	2.49E+07	-1005.21	1307.95	0.62
11	31.77	20.72	28.57	2.41E+07	-1230.64	1362.11	0.65
12	30.50	21.57	28.10	2.50E+07	-535.52	2613.13	0.71

Panel B: Season

season	mean	sd	p50	N	min	max	cv
1	47.93	77.94	31.17	7.14E+07	-1917.02	4643.74	1.63
2	40.00	36.86	32.41	7.25E+07	-1390.97	1568.01	0.92
3	34.15	27.46	28.96	7.37E+07	-2240.30	2828.63	0.80
4	32.44	30.43	28.26	7.31E+07	-1230.64	1920.32	0.94

Table 4: Summary Statistics for LMPs by Day-of-the-month

This table presents the summary statistics for LMPs classified by 31 days of the month. Each section has summary statistics, including mean, standard deviation (sd), median (p50), number of observations (N), minimum, maximum, and coefficient of variation (cv, computed by sd/mean).

day	mean	sd	p50	N	min	max	cv
1	34.58	23.78	29.31	9552409	-1106.26	2828.63	0.69
2	33.87	23.57	29.94	9552432	-1390.97	2543.35	0.70
3	41.67	52.44	30.3	9552432	-597.1	1692.78	1.26
4	38.66	45.99	29.67	9552432	-415.17	1430.42	1.19
5	36.60	28.75	30.18	9552432	-1230.64	1536.83	0.79
6	43.52	57.31	31.12	9552432	-1005.21	1889.33	1.32
7	54.24	143.22	30.51	9552432	-1224.14	2280.58	2.64
8	40.66	35.46	31.51	9552432	-613.19	1568.01	0.87
9	34.59	21.50	30.6	9543155	-2216	2047.24	0.62
10	36.82	47.57	30.25	9546959	-2240.3	2048.07	1.29
11	38.30	54.53	29.88	9558768	-967.84	2613.13	1.42
12	37.29	35.01	29.55	9558768	-627.35	1920.32	0.94
13	36.63	33.10	30.48	9558768	-2219.92	2024.49	0.90
14	34.66	27.38	29.63	9558768	-848.69	4643.74	0.79
15	36.74	33.30	29.76	9558768	-1917.02	1509.94	0.91
16	38.24	34.54	30.56	9558768	-981.77	1836.48	0.90
17	38.66	35.28	31.09	9558768	-755.26	2421.7	0.91
18	38.81	42.00	31.12	9559824	-1547.67	1824.41	1.08
19	38.82	37.88	30.94	9559941	-646.4	1462.97	0.98
20	41.24	43.34	30.85	9562080	-1044.26	1190.78	1.05
21	39.49	33.72	31.06	9562080	-798.63	1116.33	0.85
22	40.25	52.19	30.8	9563112	-1156.63	1881.03	1.30
23	40.61	53.98	29.49	9563592	-817.59	1383.24	1.33
24	40.78	63.51	29.63	9563592	-836.65	2321.24	1.56
25	38.40	44.96	29.82	9563592	-696.94	1188.35	1.17
26	35.20	25.23	30.01	9564696	-408.58	1759.55	0.72
27	36.76	32.41	29.88	9564816	-1147.84	1704.77	0.88
28	40.28	46.47	30.16	9564816	-1639.91	2107.79	1.15
29	35.52	34.51	28.54	8779985	-829.57	2257.45	0.97
30	37.66	46.38	29.17	8746310	-804.55	2406.08	1.23
31	33.35	20.08	29	5525462	-793.68	1399.18	0.60

Table 5: Performance of Calendar Effects

This table presents the performance of calendar effects in different time frequencies (Day-of-the-week, Hour-of-the-day, Month-of-the-year, Season and Day-of-the-month. For each time frequency, this table provides the most significant calendar effects, and corresponding average LMPs.

Time Frequency	***p*-value**	**Most Significant Calendar Effects and Average LMPs**		
Day-of-the-week	<0.0001	Tuesday 44.15	Wednesday 40.99	Monday 40.61
Hour-of-the-day	<0.0001	6pm 49.35	7pm 47.31	8pm 47.15
Month-of-the-year	<0.0001	January 59.07	February 55.38	March 48.35
Season	<0.0001		Winter 47.93	
Day-of-the-month	<0.0001	7th 54.24	6th 43.52	3rd 41.67

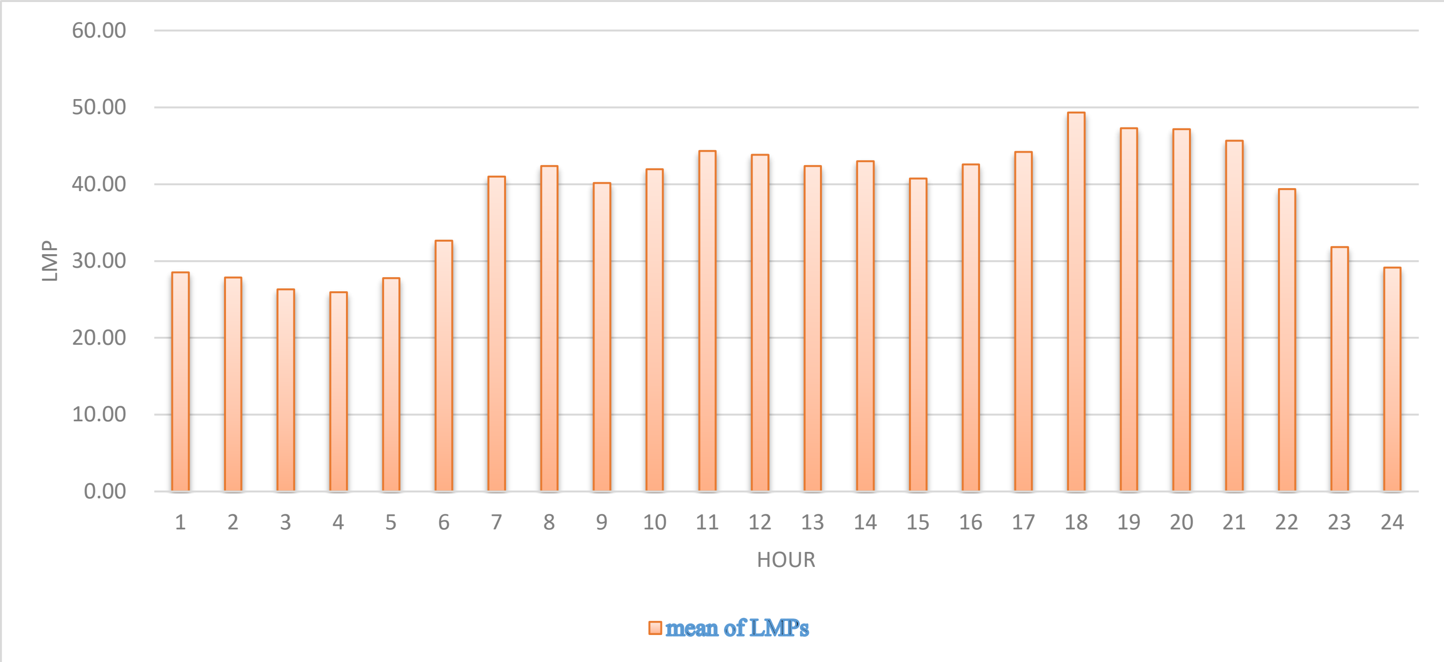

Figure 1: Mean of LMPs by Hour-of-the-day

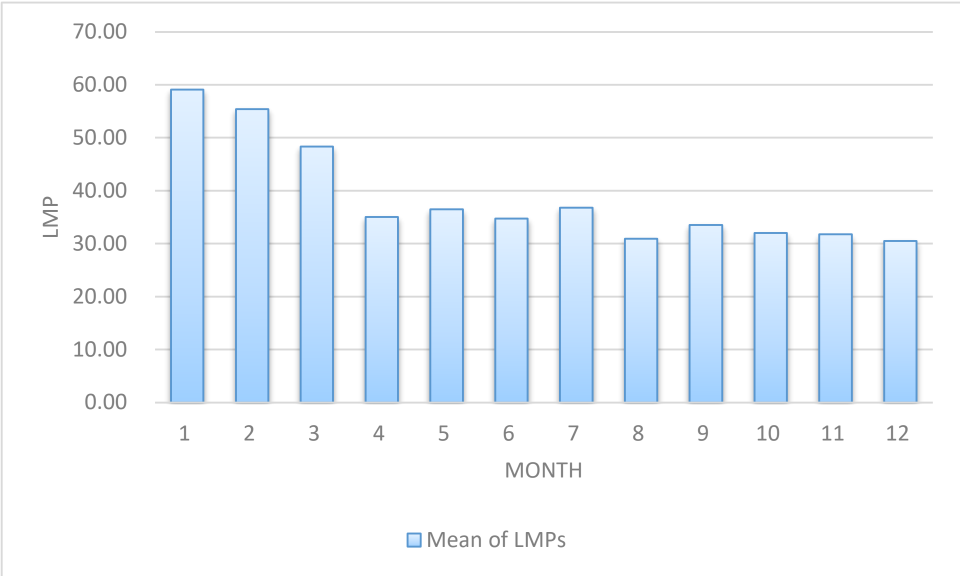

Figure 2: Mean of LMPs by Month

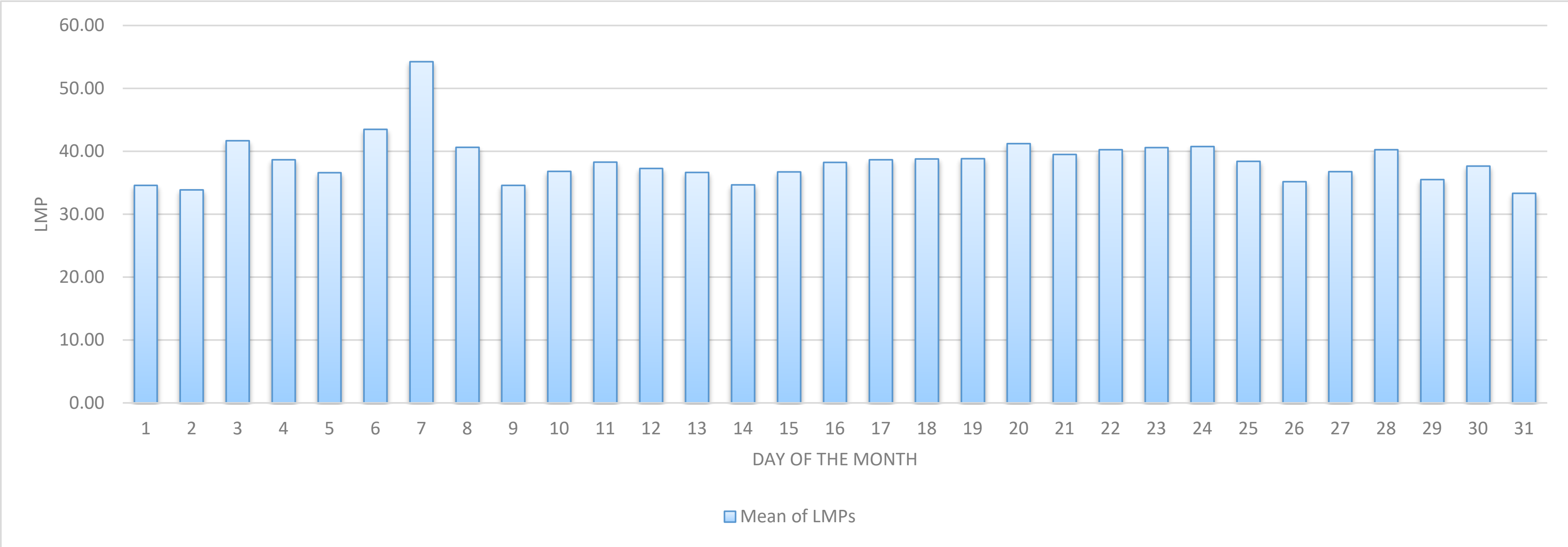

Figure 3: Mean of LMPs by Day-of-the-month

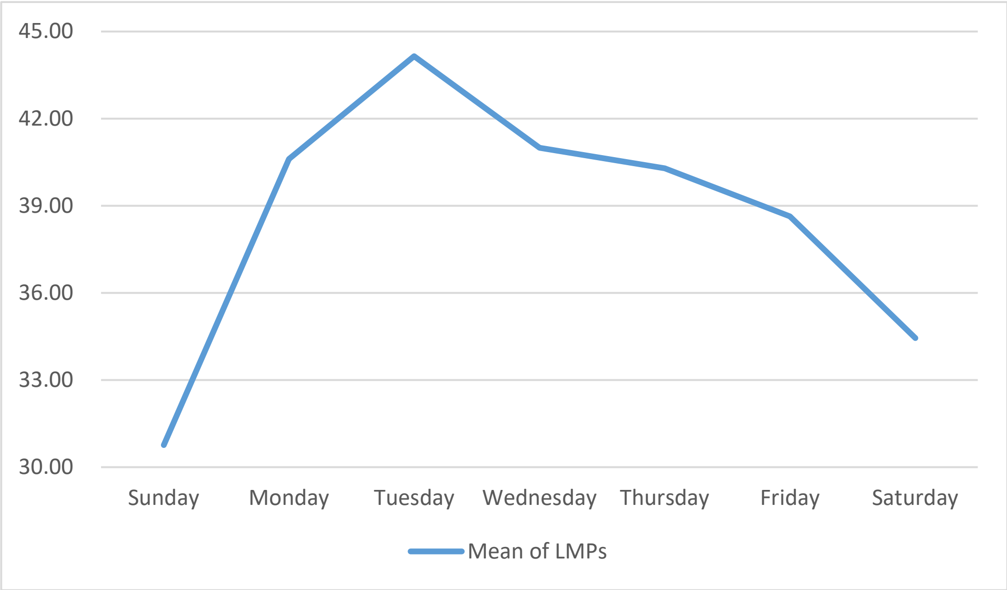

Figure 4: Mean of LMPs by Day-of-the-week