Illiquidity in the Japanese Day-Ahead Electricity Market

Shin S. Ikeda

May 2015

Illiquidity in the Japanese Day-Ahead Electricity Market

Shin S. Ikeda[*]

May 7, 2015

Abstract

Historical data of system prices and traded quantities of electricity over the 48 half-hour intra-daily intervals in the Japan Electric Power Exchange are analyzed. Viewed as a panel dataset of the 48 different commodities in 7 different markets (days of a week) or 336 different contracts over 288 weeks, the data allow me to compute two representative measures of illiquidity, namely, Amihud's price-impact measure and Roll's implied spread cost measure from November 2006 to April 2012. These measures are based on the absolute weekly returns of each of 336 contracts divided by the corresponding volume of traded electricity, and on the first-order serial covariance of weekly returns, respectively. Two measures closely comove but they contribute to the returns in different magnitudes, suggesting that each of them captures both common and distinctive aspects of illiquidity in the JEPX market. Once the lagged returns are controlled for in a dynamic panel framework, the influence of price-impact measures on returns dominate that of spread measures. The price-impact measure and traded volume contribute the return variations in opposite signs, i.e., positively and negatively. It suggests that the assessment of illiquidity requires a careful treatment of these confounding factors.

1   Introduction

The Japan Electric Power Exchange (JEPX) was launched in April 2005. As a part of the process of electricity wholesale liberalization, the JEPX was established to provide a benchmark for power producers' investment on a variert of power sources and to help producers counterparties to trade in case of demand-supply mismatch. An important premise for these objectives is that the JEPX is sufficiently "liquid". However, the amount of traded electricity through the JEPX system is only 0.6% of the total amount of wholesale electricity in the fiscal year of 2010. The majority of the remaining quantity is bi-laterally traded among regionally monopolistic power generators[1]. Moreover, the devastating tsunami following the great earthquake centered near the northeastern coast of Japan on March 11, 2011, caused the breakdown of the swamped Fukushima nuclear power plant operated by the Tokyo Electric Power Company (TEPCO), a regional monopoly franchised in Tokyo. Amid the extreme disruption in the supply and demand of electricity, TEPCO temporarily stopped supplying electricity to the JEPX system, triggering the exit of several members from the exchange because of shrinking benefits relative to membership costs. This anecdotal evidence raises the question about whether the JEPX system can provide sufficient liquidity to avoid an excess demand for electricity, which was the original motive for the creation of the system. Sometimes the liquidity of electricity market is viewed as glossly equivalent to the amount of electricity supplied or traded in the market. However, the well-functioning of a power exchange *market* should be measured by the *market liquidity* associated with some peculiar units. This study primarily aims

---

[*]e-mail: *s-ikeda@grips.ac.jp*. The first version: April 1, 2015.
[1]http://www.cao.go.jp/sasshin/kisei-seido/meeting/2011/energy/120112/item5-2_5.pdf

at highlighting economic measures of illiquidity based onhistorical data of the prices and quantities of traded electricity, and their implications for assessing the function of the JEPX market.

I assess the economic illiquidity in the JEPX by a version of Amihud's (2002) price impact measure, i.e., the absolute change of the log-price relative to the daily trading volume averaged over a certain period of time. The first contribution of this study is to apply the Amihud's measure to the JEPX transaction data for the first time, and to document that the JEPX market is liquid in the weekend but illiquid in weekdays, especially on Monday, and in the daytime covered by the interval from 8:30 to 18:00 in each day of the week. This result might be perceived with no surprise if we recalled the greater economic activity and a tighter demand condition for electricity during such periods. However, such a pattern of illiquidity resembles that of the actually traded volume of electricity. If we used the raw traded volume as a measure of *liquidity*, it interferes with the pattern of *illiquidity* as illustrated by the Amihud's measure.

Another dimension of the market illiquidity is the transaction cost. A natural candidate for measuring such a cost in a quote-driven market is the bid-ask spread, i.e., the discrepancy between the best ask quote (the lowest seller's price) and the best bid quote (the highest buyer's price), because it measures a concession associated with switching one's position between a buy-side and a sell-side. However, it is not relevant for the analysis of JEPX because this exchange adopts a call-auction mechanism without any ask- and bid-quotes posted by market makers. Even if interpreted broadly as a price impact of order imbalance and modifying the definition of spread by the second-best unexcuted limit buy- and sell-prices, no data on limit orders are available in this study. However, Brünner (2012) justifies the decomposition of an actual transaction price into a semi-martingale price component and another component, the latter of which is a price-impact of an order imbalance. Because of the discrepancy of the actually observed transaction prices from the semi-martingale counterpart, we can interpret the order-imbalance term as an *implicit spread cost*. Therefore, we can estimate it by a standard technique such as Roll's (1984) measure based on the first order serial covariance of a series of transaction returns or its modifications according to a set of assumptions on the order flow process. The second contribution of this study is to give estimates of this implicit spread cost in the JEPX market, and to document that the implicit spread cost may be quite large: about 10% of the efficient counterparts.

Given two inverse-measures of the market quality, it is important to ask how they are related with each other, and with the (in)efficiency of the JEPX system. Regarding this question, I establish two results. First, the price-impact measures positively and significantly correlate with the spread measures even after controlling for the individual fixed effects of contracts over all of half-hour intervals and the traded volume. Therefore, the lack of sufficient liquidity may lead to a larger implicit spread cost, as is consistent with Chordia, Hirshlifer and Subramanyam (2008, Section 4). Second, both measures are significant risk factors for participants in the JEPX after controlling for the lagged weekly returns, traded volume, idiosyncratic volatility, contract-specific fixed effects and the time effect. The significance of both measures indicates that they do measure different aspects of the market quality in the JEPX system. Third, the price-impact measure exhibits a positive and greater impact on return variations than the spread measure, while the traded volume influences a negative impact on return variations. As we will see later, the intra-daily and intra-weekly patterns of these illiquidity measures and traded volume are quite resemble, yet their impacts on returns differ both in magnitudes and in directions, suggesting the importance of controlling for these counfounding factors to assess (il-)liquidity in the JEPX market.

2 Background and Literature Review

2.1 Institutional Aspects of the JEPX Market

The participants in the JEPX are classified into three types: (i) general electricity suppliers as regional monopolies (henceforth, "regional monopolies"), (ii) independent power producers (henceforth, "IPPs") with their own power generators and selling and buying electricity to or from the regional monopolies, and (iii) power producers and suppliers (henceforth, "PPSs") with their own power generators and selling electricity to large-scale customers via the electricity transmission system owned by the regional monopolies. PPSs may need to buy electricity from the regional monopolies to meet the required power supply for their own customers.

It is very difficult to store electricity as a commodity. Therefore, the generated electricity should be consumed within a very short period of time. An excess demand for electricity causes lower voltage, unstable frequency and, in the worst case, power blackouts over a broad area. To avoid such disastrous events, the Japanese regulatory board dictates that all regional monopolies instantaneously match the supply and demand of electricity. However, the PPSs are allowed to match the demand and supply up to a $\pm 3\%$ deviation from the perfect match within each half-hour interval. Perhaps to be consistent with this allowance and to encourage more entry of new PPSs for a greater amount of electricity transaction, the JEPX offers trades of electricity at 48 half-hour intervals over the course of a day. Although the JEPX offers several contracts to trade each of 48 commodities, this study focuses on the contracts in the spot market for the delivery of electricity in the next business day because it constitutes the vast majority of the transaction of all contracts.

The clearing mechanism in the JEPX spot market is the Itayose method, a version of the periodic, blind, and single-price call auction with batch trading. There are no formally designated market makers (also known as "dealers" or "specialists") in the JEPX spot market, so that all participants can be market-making to some extents. Participants in the spot market submit their orders to buy (positive) and sell (negative) for the delivery of electricity over a half-hour interval within a specific day to the JEPX system between 10:00 AM and 4:00 PM from six to two business days before the day in question, and between 8:30 AM to 9:30 AM on the last business day prior to the day in question. An order schedule is composed of several limit prices. On the demand (supply) side, a limit price is the maximum (minimum) price acceptable for buying (selling) a certain amount of electricity. The individual demand and supply schedules are not smooth curves but an assembly of semi-open, vertical segments corresponding to several discrete amounts of electricity as seen in Figure 1. The unit of electricity is one megawat-hour per hour (mWh/h) or 1,000 kilowat-hour per hour (kWh/h), and the unit of currency is Japanese yen (JPY). The half-hour interval for electricity transaction indeed implies that the essential unit for each spot contract is 0.5 mWh/h. If the transaction of 5.5 mWh/h of electricity were agreed upon for the price of 4 JPY/kWh, it means that the electricity of 5,500 kWh per hour would be transmitted from one party to another through the transmission network owned by regional monopolies in exchange for the opposite flow of money worth of 4*5,500=22,000 JPY/h. All schedules are aggregated into the market schedules of supply and demand, and their intersection determines a single, market-clearing price for all feasible quantities. The transaction prices and quantities of electricity for all of the 48 half-hour intervals withinin a specific day are simultaneously determined in a single trading day, and the delivery of electricity specified in all contracts takes place in the next business day. Therefore, contracts for these 48 half-hour intervals should be viewed as 48 different commodities rather than an intra-daily time-series record of prices of a single commodity. This viewpoint is important when conducting a dynamic panel analysis of extracted spreads in Section 4.5. Because the spot contracts for the delivery of electricity on Saturday, Sunday and

3

Monday are determined in the Friday session, any customers for transaction of electricity on Monday should rely on informatoin available until the closing time on the last Friday.

2.2 Motivation for Measuring Illiquidity

The participants in the JEPX market are likely to face order imbalances (Liu et al., 2004), or psychological bias such as over-confidence (Daniel, Hirshlifer and Subramanyam, 1998) because (a) the participants are not professional investment bankers but more or less non-financial producers or power generators, and (b) the underlying asset for exchange is non-storable electricity so that the supply and demand schedules in this market crucially rely on the stable operation of participants' power-generating processes and accurate forecasts of weather and energy conditions. The demand or supply schedule may shift suddenly due to any unexpected breakdown of the turbin, the holt of factory operation due to union-led strikes, historically hot or cold weather, any disconnection of fuel logistics, or natural disaster. Therefore, there is some meaning to measure the discrepancy between the price that would prevail in the ideal market condition and the actual price, which I call "the implied spread cost".

The episodes about the ill-functioning of the JEPX system in Introduction may be owed to "illiquidity", i.e., the lack of "liquidity", in general. Several variants of illiquidity measure have been confirmed as effective risk factors for returns, i.e., the return of an asset with higher illiquidity tends to be higher as a compensation for holders to bear such risk after controlling for other relevant characteristics and sources of risk- see, e.g., Amihud and Mendelson (2008). How about the spot contract in the JEPX? To answer this question, we need to specify an appropriate concept of liquidity. Kyle (1985) gives three components in the concept of economic liquidity, such as: (a) "depth" as a measure of the size of an order flow innovation required to change prices a given amount, (b) "tightness" as a measure of the cost of turning around a position (from buy-side to sell-side or vice versa) over a short period of time, and (c) "resiliency" as a measure of the speed with which prices recover from a random, uninformative shock. If we focus on a depth component of liquidity, an illiquid market should be characterized by a larger value of reciprocal of any measure of depth, referred to as a price-impact measure. A popular intra-daily estimate is given by Kyle's λ (lambda), which is the slope coefficient from regressing absolute returns (rates of price changes) onto volume over some stretch of time. Amihud's (2002) measure is a daily counterpart to Kyle's λ using the daily prices and volume, hence appropriate for our purpose because no intra-daily continuous trading takes place in the JEPX market.

The JEPX is an example of an order-driven market. In contrast, a large part of the market microstructure analysis in the financial sector focuses on a quote-driven market mechanism. In the latter, mutually competing market makers publicly post ask and bid quotes, namely, the candidates for seller's and buyer's prices, respectively, and typically transaction prices bounce between them. In this sense, the bid-ask spread is a natural measure of tightness. There are at least three different components in this spread cost for market participants with three different economic principles behind them: (i) the order-processing cost of market makers such as the clearing fees and per trade allocation of fixed costs for computers, telephones, and high-speed servers (Demsetz, 1968; Tinic, 1972; and Roll, 1984), as well as the mispricing caused by investor misreaction (French and Roll, 1986); (ii) the inventory cost of market makers in preparation for a random large-order imbalance (Garman, 1976); and (iii) the cost of adverse selection (Copeland and Galai, 1983; and Glosten and Milgrom, 1985). Because of the ease of data availability and natural interpretation, the majority of literature using the bid-ask spread as a measure of illiquidity focuses on the quote-driven market. A rare exception is Lee, Liu, Roll and Subramanyam (2004) on the market efficiency of the Taiwan Stock Exchange in which no formally designated market makers exist. However, they rely on (a) the second-best bid and ask prices from the limit order prices after the executed ones as a measure

4

of the trade imbalance, and (b) the presence of successive auctions within a day, while we cannot access to data on limit-order schedules in the JEPX and all of the contract in a specific day are determined simultaneously at once.

Because of the absence of clear market makers nor of bid-ask spreads in the order-driven clearing mechanism, and of the specific non-storable nature of electricity as the basis for any contracts in the day-ahead spot market, it seems harder to apply many inventory models for financial markets. However, Brünner (2012) justifies the decomposition of an actual transaction price into a (semi-)martingale price component and another component, the latter of which is a price-impact of an order imbalance. Given a model of order strategies by risk-neutral buyers and sellers, and a potential insider, he derives their equilibrium strategies. The implied transaction price consists of the random-walk component and an additively-separable component reflecting a "difference in valuations" of buyers and sellers and an "asymmetric information" component (see Brünner, 2012, Corollary 1). In addition to this direct theoretical justification, Haller and Stoll (1989) and Amihud and Mendelson (1991) empirically document significantly negative, first-order autocorrelations of some types of security returns in Germany and Japan under some call-auction methods for clearing without dealers. Roll (1984, p.1129-1130) emphasizes that his constant bid-ask half spread is measuring the average absolute value of the price change when the price does change and yet no information has arrived. Madhavan (1992) gives a similar argument as the previous view by Roll:

> ... even in an auction system with one price, an analogous measure or effective bid-ask spread can be constructed because buy orders raise prices while sell orders lower prices. (p. 615)

This remark basically means that the auction system adopted in several financial markets do allow for some players to have market power. Stoll and Whaley (1990) introduce the notion of an implied spread regarding the price reversal phenomena:

> Price reversals reflect the compensation of suppliers of immediacy for taking the other side of transactions initiated by active traders... In an auction market, similar reversals are observed even though no bid-ask spread is quoted because suppliers of immediacy back away from active traders. (p. 54-55.)

Hasbrouck (2007, Section 11.5) reinterprets Garman (1976) as follows:

> Garman's view of dealers as smoothers of buy/sell order imbalances continues to be useful... the perspective also applies when temporary order imbalances arise in the aggregate. Dealers are agents who ... accommodate these imbalances... At the same time, the lines between dealers and customers in many markets have blurred... if inventory control is more broadly interpreted as position management, the issues are as pertinent as ever. (p. 116-117)

Figure 1 illustrates the following rule on how the transaction price and quantity are determined:

$$P^* = \inf\{P \geq 0 : D(P) \geq S(P)\}, \quad Q^* = \min\{D(P^*), S(P^*)\}.$$

P^* is defined by the infimum and not the minimum. Figure 1 explains why this is the case. Note that the line segment for demand includes the upper-end point but not the lower-end point, as it reflects a buyer's worst limit price, namely, the maximum acceptable price for a certain amount of electricity delivery. In contrast, the line segment for supply shows the opposite pattern, reflecting a seller's limit price. In this case, there is no minimum where $D = S$ because the lower-end point is not included in the demand schedule. The indicated equilibrium price will induce the potential

demand $D(P^*)$. On the other hand, the supply schedule does include the lower-end point so that it induces the potential supply $S(P^*)$. Because $S(P^*) < D(P^*)$ in this case, only $Q^* = S(P^*)$ is feasible for transaction. If the supply decreases slightly or the demand increases slightly, while the counterpart is fixed, a deviation from the top left panel in Figure 1 occurs. It may cause a sharp price increase, as shown by the top right panel. A change in equilibrium prices is then a conservative measure of the length of this segment; namely, the local inelasticity of the supply schedule at the old equilibrium quantity. This measure resembles the marketable order imbalances in Lee et al. (2004) as a measure of illiquidity.

The above illustration shows that price discreteness is a real-world complication. The issue of a price discreteness is raised by Crack and Ledoit (1996) who show an impressive regularity of daily returns plotted against their first-order lagged values. The plots show the so-called "compass-rose" pattern where many straight rays emanate from the point of origin. The cause of this pattern is the discreteness of a price rounded to the nearest grid determined by the minimum tick. Fang (2002) shows by simulations that some representative random-walk tests suffer from a size inflation if the rounded grid is in dollars rather than one-eighth of a dollar or cents because the serial covariance may be more exaggerated than the case of a finer grid. The possible effect of discreteness appears as a part of the implicit spread around the efficient log price. Therefore, the measurement of implied spreads is important for checking if the JEPX market is well functioning in terms of informational and institutional efficiency and liquidity provision.

2.3   Studies on Electricity Exchange Markets

Several earlier studies on the liquidity of electricity markets may not give us a clear guidance for studying the JEPX market. For instance, Freire, Neves, Tsunechiro, Cabral and Souza (2012) attempt to assess the liquidity in the Brazilian electricity market by employing (a) the churn rate, which is basically a turnover ratio but using the amount of final energy consumption rather than the total share outstandings for the denominator as in the financial definition; and (b) the liquidity relative rate, which is a relative volume-weighted amount of a particular traded contract. Both measures aim at describing the number of transactions in the electricity market. Given the one-shot, rather than continuous, nature of trading in the call auction mechanism, these measures of transaction in the market are not so relevant for our purpose. Moreover, they do not pay attention to the price responsiveness for a unit of trade in the market, as one of the major issues in assessing liquidity in the market. Frestad (2012) focuses on the liquidity in the different segments of the Nord Pool. Because the Nord Pool is a quote-driven market with many market makers, he can adopt the bid-ask spread capturing the lack of depth as a measure of illiquidity. As mentioned above, the order-driven mechanism and the lack of data in the JEPX do not allow us to use any official bid and ask quote prices. Sklavos et al. (2013) attempts to give a microstructure analysis of liquidity of energy stocks. There are two stark differences between our study and theirs. First, participants in the JEPX trade electricity but not electricity-related shares. Second, the JEPX is an order-driven market without market makers. Therefore, the relevance of their results to ours is limited. Earlier works on JEPX data (Ofuji and Yamaguchi, 2008; Kawamoto and Sakanashi, 2010) focus on forecasting the system price, with little implications for any economic policy recommendations for the improvement of the JEPX market operation. If the transaction price contained a martingale component, the best forcast would be the current value and no room for a sensible forecasting. In this sense, it seems more appropriate for using returns rather than prices as inputs to the regression framework.

3 Methodology

As seen later, the autocorrelation functions of the 48 half-hour commodities' returns in the JEPX show a clear 7-day periodicity corresponding to the day-of-week effect. Given this stylized fact, we should view the contracts at the same half-hour interval but on different days of a common week as different contracts, rather than time-series data of the contract at that half-hour interval. Consequently, we have $48 * 7 = 336$ contracts within a week as a cross-sectional dimension, and 288 weeks as a time-series dimension.

3.1 The Illiquidity Measure

Let P_{idw} (JPY/kWh) be the system price prevailed for the transaction of electricity at i-th half-hour period ($i = 1, \ldots, 48$) within the d-th day ($d = 1, \ldots, 7$ for Sunday, Monday, ..., Saturday) in the w-th week, and let V_{idw} (kWh/h) be the traded volume of electricity at the same timing. The illiquidity ratio is given by the ratio of weekly return for the same i and the same day of two adjacent weeks to the trading volume of that commodity now, i.e.,

$$PI_{idw} = |\ln P_{idw} - \ln P_{id,w-1}|/V_{idw}. \tag{1}$$

If necessary, I will take the average over several weeks as a measure of illiquidity of electricity trade for the i-th commodity in the d-th day over that period of time, say T weeks from $(w - T + 1)$-th to w-th week:

$$ILQ_{idw} = \sum_{i=0,\ldots,T-1} PI_{id,w-i}/T. \tag{2}$$

Note that the definition in (1) involves the raw trading volume of electricity. In contrast, the original version of Amihud's (2002) measure divides the absolute return by the trading volume in value terms (total number of shares converted into a pecuniary value). In case of a standard financial security market, the purpose of investment is the risk management or speculation, so the volume in value terms seems more informative as a summary of the activity in the market. In contrast, the raw volume of transaction matters in the electricity market.

3.2 A Model of the Log Price and the Implied Spread Cost

Here is a list of structural assumptions in this paper.

Assumption 1 *(The data-generating mechanism)*

1. *$t \in [0, 1]$ is a point in time over a unit interval corresponding to one month. The efficient log price of the (i, d)-th electricity commodity $\ln P_{id}^*(t)$, $i \in \{1, \ldots, 48\}$, $d = 1, \ldots, 7$, follows*

$$d \ln P_{id}^*(t) = \sigma_{id} dW_{id}(t), \tag{3}$$

   where $W_{id}(t) \sim N(0, t)$ is the Brownian motion representing the market risk and σ_{id} is a contract-specific constant parameter for the instantaneous standard deviation of returns.

2. *Define $P_{idw}^* := P_{id}^*(t_w)$ where t_w is the time point of w-th week in the period of 288 week-long time series dimension normalized as unity. The transaction price of the (i, d)-th commodity P_{idw} is subject to a percentage deviation from the efficient counterpart:*

$$P_{idw} = P_{idw}^*(1 + S_{idw}/2) \tag{4}$$

S_{idw} is the i.i.d. round-trip spread for the (i,d)-th commodity price in week-w, and is independent of P_{idw}^*. $S_{idw} = \pm s_{idw}$ with respective probabilities p_{idw} and $1 - p_{idw}$. By taking the natural logarithm,

$$\ln P_{idw} = \ln P_{idw}^* + \ln(1 + S_{idw}/2) =: \ln P_{idw}^* + U_{idw}. \tag{5}$$

The actual transaction price in logarithm deviates from its efficient counterpart by U_{idw} in (5). This modelling strategy tracks several models in the literature of market microstructure and volatility estimation using noisy high frequency data (Hasbrouck, 2007; Bandi and Russell, 2008; Corwin and Schultz, 2012). U_{idw} in (5) is a concave transformation of S_{idw} in (4). S_{idw} is the implied spread cost for any participant changing from a seller to a buyer. The half spread $S_{idw}/2$ is more directly linked to the marginal cost of order executions. Note that $p_{idw} \neq 1/2$ in general. Let me assume that p_{idw} enforces $E[U_{idw}] = 0$ rather than $E[S_{idw}] = 0$, as is consistent with Bandi and Russell (2008). Assuming S_{idw} as i.i.d. with respect to w and independent of P_{idw}^* rejects the possibility that the spread per se is autocorrelated or correlated with the intrinsic price, as predicted by Copeland and Galai (1983) and Glosten and Milgrom (1985). However, the lack of data on quotes or order directions hinders an investigation of this possibility.

A simple measure of the spread is given by Roll (1984) based on the first-order serial covariance of transaction returns. If the efficient log price follows (3), the efficient return series $\Delta \ln P_{idw}^* := \ln P_{idw}^* - \ln P_{id,w-1}^*$ has no serial correlation, owing to the independent-incremental property of the Brownian motion process. However, (5) induces the first-order autocorrelation of $\Delta \ln P_{idw}$:

$$Cov(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1}) = -Var[U_{idw}]. \tag{6}$$

Applying the approximation $\ln(1 \pm s_{idw}/2) \approx \pm s_{idw}/2$,

$$Var[U_{idw}] = E[U_{idw}^2] = p_{idw}\{\ln(1 + s_{idw}/2)\}^2 + (1 - p_{idw})\{\ln(1 - s_{idw}/2)\}^2 \approx s_{idw}^2/4. \tag{7}$$

From (6) and (7), we have $s_{idw}/2 \approx \{-Cov(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}$. A sample analog should be $\hat{s}_{idw}/2 = \{-\widehat{Cov}(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}$. For a real-valued measure, we will always truncate $\widehat{Cov} > 0$ at zero. A general consensus about this measure is that it underestimates the implied spread (Harris, 1990). Shultz (2000) mitigates a finite sample bias by

$$\tilde{s}_{idw}^*/2 = \frac{\{-\widehat{Cov}(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}}{1 - 7/\{8(n-1)\}}, \tag{8}$$

which is the version we use.

There are two cautions about this estimator of the spread. First, Jegadeesh and Titman (1995) recognize that Roll's method may over-estimate the spread at a weekly frequency. I will conduct a robustness check later by using a method recently proposed by Corwin and Schultz (2012) based on maximums and minimums, or highs and lows, of transaction prices over two consecutive periods of time. Suppose we have two adjacent periods of the same length, say A and B, with data of highs and lows. Assuming that high and low prices are associated with positive and negative spreads, respectively, Corwin and Schultz (2012, Eq. 18) derive the following formula for s:

$$\hat{\beta}_j = \left\{\ln\left(\frac{\max_{t_i \in A}\{\ln P_j(t_i)\}}{\min_{t_i \in A}\{\ln P_j(t_i)\}}\right)\right\}^2 + \left\{\ln\left(\frac{\max_{t_i \in B}\{\ln P_j(t_i)\}}{\min_{t_i \in B}\{\ln P_j(t_i)\}}\right)\right\}^2,$$

$$\hat{\gamma}_j = \left\{\ln\left(\frac{\max_{t_i \in A \cup B}\{\ln P_j(t_i)\}}{\min_{t_i \in A \cup B}\{\ln P_j(t_i)\}}\right)\right\}^2,$$

$$\hat{s}_{j,CS}/2 = (e^{2.4142(\beta_j^{1/2} - \gamma_j^{1/2})} - 1)/(e^{2.4142(\beta_j^{1/2} - \gamma_j^{1/2})} + 1). \tag{9}$$

For a small spread, we have a simpler approximation $\hat{s}_{j,CS}/2 \approx 2.4142(\beta_j^{1/2} - \gamma_j^{1/2})$. This enables us to interpret $\hat{s}_{j,CS}$ as a range-based measure of the spread with a jackknife-type bias correction. By definition, it is less biased given sufficient variations in data. Otherwise, an empirical range underestimates the population counterpart and so does this measure. Corwin and Schultz (2012) use daily highs and lows based on intra-daily variations. If we only have daily transaction prices, we calculate highs/lows at a lower frequency, particularly the ten-day interval for A and B or the twenty-day period for the estimation, and let this window roll day by day to obtain approximately ten estimates per month. The monthly spread is measured by the average of these estimates. Any negative measure is truncated at zero.

Second, participants' overconfidence may imply the existence of the first-order negative auto-correlation of returns (Daniel, Hirshleifer and Subramanyam, 1998). In case of the JEPX trade, investors may be over-confident about the potential ability of power generation by their company's industrial plant or the prediction on the weather forecast on temperature of the delivery time of electricity. The investigation of this possibility is left for a future research.

4   Data and Results

4.1   Characteristics of the Data

The JEPX calculates and reveals the system price as an integrated benchmark over different areas in Japan. Our original data consist of all system prices and traded amounts of electricity. In an earlier stage of the JEPX, transactions were so infrequent for a very small volume; sometimes no buys or sells were posted. The last day of zero postings in our original sample is October 16, 2006. Therefore, we use the sample period from October 17, 2006 to April 30, 2012, leaving 2,027 days or 288 weeks.

The dotted lines in Figure 2 represent the autocorrelation functions of daily returns, namely, the difference of log prices recorded at the same half-hour itnervals in two adjacent sample days. I select eight different intra-daily, half-hour intervals displaced by 3 hours. The two parallel horizontal broken lines represent the boundaries of the 95% confidence intervals under the null hypothesis that the returns follow a white noise process. For all half-hour intervals, the first-order autocorrelation is significantly negative. These functions show a clear seven-day cycle corresponding to the day-of-week effect. Therefore, this study treats delivery of electricity at the same half-hour period but in different days of the same week as different commodities. Consequently, we have $48 \times 7 = 336$ commodities within a week as the cross-sectional sample size against 288 weeks as the time series dimension.

Figure 3 shows the autocorrelation functions of weekly returns for contracts in 4:30-5:00 and 13:00-13:30 periods. Note that the first order autocorrelation of all of 336 contracts are negative. The most visible pattern is a large negative value of the first order autocorrelation. Moreover, its magnitude differs in different half-hour periods within a day. The largest and smallest negative first-order autocorrelations in all autocorrelations of weekly returns of 366 contracts are given by -0.4684 and -0.1642 for Monday 4:30-5:00 and 13:00-13:30 periods, respectively. As indicated in Section 2.2, the price discreteness may induce a serial correlation in returns. However, a collection of compass-rose diagrams in Figure 4 defies this possibility. Both for 4:30-5:00 and 13:00-13:30 intervals, no clear rays from the origin are visible. The large negative first-order serial correlations of weekly returns should be associated with some economic mechanism generating a price reversal. Figure 5 shows the time-series plots of system prices and traded volume of electricity over 288 weeks and weekly returns over 287 weeks. The bottom panels for returns indicate that the volatility of returns are clustering. Figure 6 exhibits the time-series averages over 288 weeks of system prices and traded volume for each day-of-the-week. They show a clear time-of-the-day effect, especially

9

in weekdays. These patterns of prices and volume are intuitively appealing because they seem coincident with the greater economic activity of those companies participating in the JEPX, such as the gas companies, power generators, trains and subway companies, metal processors, etc.

4.2 Extracting Measures of the Price Impact and Spread Cost

Figure 7 shows the time-series averages over 287 weeks of Amihud's price-impact measures for each day of the week by the blue dotted lines. It is evident that the liquidity condition is stable from Tuesday to Friday, substantially relaxed during the weekend, then tightened again on Monday. The patterns of illiquidity measures as displayed in Figure 7 resemble those of the trading volume in Figure 6. In other words, using the trading volume as a measure of *liquidity* conflicts with the Amihud's price-impact measure, which is supposed to capture some aspect of *illiquidity* in the market. For instance, Monday 8:30-18:00 is the period of the most active transaction of electricity in the market on one hand; but Amihud's measure of illiquidity recognizes it as the period of the least liquidity provision. If the traded volume does not meet a potentially high demand for electricity in this period of time, such a discrepancy suggests the presence of excess demand and therefore further room for entries of electricity suppliers. In Figure 7, I superimpose the inverse of the raw trading volume on the price-impact measure. The displayed patterns show that our measure of illiquidity captures something more than the reciprocal of the amount of traded electricity in the market. Recently, Lou and Shu (2014) replace the absolute return in the numerator of the original definition of Amihud's measure by unity (constant) and confirm that the variation of their new measure captures a large part of that of the original version, thereby casting a skeptical view on a common treatment of the latter as a price impact measure. However, Figure 7 suggests that the version of Amihud measure based on the raw traded volume of electricity in the JEPX does capture a price impact of the traded quantity beyond the variation in trading volume.

The blue dotted lines in each panel of Figure 8 summarizes the time-series averages of the extracted half spreads in each day of a week. The spreads are calculated based on the first-order autocovariance of weekly returns as in (8) over the 13-week rolling window. Weekly spreads are high during the daytime in weekdays, which is seen repeatedly for the system price, traded volume and estimated price-impact measures so far. Indeed, reproduced patterns of price-impact measures in this figure show that two measures of illiquidity are comoving very closely in any day of a week and at any time of a day.

4.3 Relationship among Price-Impact Measures, Spread Measures, Returns, and Volume

Figure 8 revealed a remarkable comovement of price-impact measures and spread measures. They suggest that the liquidity condition is inversely related to the transaction cost emerging in the form of a serial covariance of weekly return of 336 contracts. To test this formally, I run the next dynamic panel regressions with (i, d)-specific fixed effect and w-specific time effect by Arellano-Bond method:

$$(I) \qquad ILQ_{id,13w} = \beta_{lag}ILQ_{id,13(w-1)} + \beta_s \tilde{s}^*_{id,13w} + \beta_v V_{id,13w} + \alpha_{id} + \delta_{13w} + \epsilon_{id,13w}$$

$$(II) \qquad \ln ILQ_{id,13w} = \beta_{lag} \ln ILQ_{id,13(w-1)} + \beta_s \ln \tilde{s}^*_{id,13w} + \beta_v \ln V_{id,13w} + \alpha_{id} + \delta_{13w} + \epsilon_{id,13w}$$

for $i = 1, \ldots, 48$, $d = 1, \ldots, 7$, and $w = 1, 2, \ldots, \lfloor 287/13 \rfloor$ and see if the estimate of β_s is positive so that illiquidity and spread measures point toward the same direction, and if the estimate of β_v is negative or not so that higher transaction volume still induces a relaxed condition for

liquidity in the JEPX market. The models with the enforcement of $\beta_0 = 0$ are denoted by (I_0) and (II_0), respectively. To avoid any contrived serial correlation, I compute ILQ and the Roll spread measure over 13-week non-overlapping windows. Instruments for $PI_{id,13(w-1)}$ and $\ln PI_{id,13(w-1)}$ are given by $\{PI_{id,13(w-2)}, PI_{id,13(w-3)}, \dots\}$ and $\{PI_{id,13(w-2)}, PI_{id,13(w-3)}, \dots\}$, respectively. I also instrumented $\tilde{s}^*_{id,13w}$ and $V_{id,13w}$ by $\tilde{s}^*_{id,13(w-1)}$ and $V_{id,13(w-1)}$ and similarly for log-transformed versions, but the results are qualitatively similar, with larger magnitude of the estimate of β_s. The standard errors are robust against arbitrary cross-sectional clustering.

The estimation results in Table 1 confirm my conjectures. All estimates are significant even at 1% level. The estimate of β_s is significantly positive, indicating that both of the price-impact and spread measures capture some aspects of illiquidity in the JEPX market. The estimate of β_v is significantly negative, suggesting that the relaxation of tight liquidity condition is associated with the increased volume of electricity transaction. Although the estimate of β_{lag} is small, controlling for thit factor makes the magnitude of the estimate of β_v smaller. For the first specification, the coefficient of determination is about 60%, which is almost the double of Amihud's (2002, p.35) from cross-sectional OLS regression of the illiquidity measure onto the intra-daily measures of price impact and spread. The results for the log specification suggests that the traded volume still plays a significant role of governing the overall liquidity condition in the JEPX market.

Table 1: Illiquidity Regression (Dependent: ILQ_{idw})

	β_{lag}	β_s	β_v	$R^2(\%)$	SER
I_0	n/a	1.724	-0.001	69.0	0.131
		(0.029)	(0.000)		
I	-0.031	1.691	-0.001	n/a	0.147
	(0.001)	(0.006)	(0.000)		
I_f	-0.034	1.620	-0.001	n/a	0.110
	(0.001)	(0.006)	(0.000)		
II_0	n/a	0.063	-0.609	56.5	0.387
		(0.002)	(0.039)		
II	0.049	0.066	-0.262	n/a	0.508
	(0.002)	(0.000)	(0.008)		
II_f	0.038	0.061	-0.414	n/a	0.373
	(0.002)	(0.000)	(0.007)		

Note: This table presents the estimated coefficients. All estimates are significant at 1% level.

4.4 Returns and Risk Factors

Let me infer the importance of illiquidity as a risk factor by checking whether the illiquidity measures thus obtained can predict the cross-sectional variation of returns of 336 contracts. I will estimate the dynamic panel regression model with variables of one-week lags, individual fixed effects and time effects:[2]

$$R_{idw} = \theta_{lag}R_{id,w-1} + \theta_{PI}PI_{id,w-1} + \theta_s\tilde{s}^*_{id,w-1} + \theta_{IV}IV_{id,w-1} + \theta_V V_{id,w-1} + \alpha_{id} + \delta_w + \epsilon_{idw}, (10)$$

_____

[2]Amihud (2002) adopts a Fama-MacBeth approach, i.e., estimating the cross-sectional regression at each point in time and averaging the coefficients in the time dimension. This approach is effective in controlling the time effect, but silent about the individual fixed effect (α_{id} in above specification).

and see if the signs, significance and magnitudes of the estimates of θ_{PI} and θ_s are as expected.[3] Inspired by the bottom panels in Figure 5, I control the volatility of returns

$$IV_{id,w-1} := (\sum_{h=1}^{13} R_{id,w-h}^2/13)^{1/2},$$

which is a realized measure of σ over the previous 13 weeks. The estimation results are summarized in Table 2. I also estimate the same model, with the regressors except for the lagged returns are in logarithm scales in the bottom panel (given by rows with $(\ln X)$), so that the estimated coefficients of variables other than the lagged returns can be comparable as semi-elasticities.

Table 2: Returns Regression (Dependent: R_{idw})

Model	θ_{lag}	θ_{PI}	θ_s	θ_V	θ_{IV}	$R^2(\%)$	SER
I_0	n/a	0.015	0.075	-0.000	-0.175	28.8	0.153
		(0.002)	(0.011)	(0.000)	(0.011)		
I	-.0192	0.590	$0.048^{\dagger}$	-0.001	-1.613	n/a	0.230
	(0.008)	(0.033)	(0.062)	(0.000)	(0.118)		
$I_0(\ln X)$	n/a	0.018	0.001	$0.001^{\dagger}$	-0.031	28.8	0.153
		(0.002)	(0.000)	(0.002)	(0.002)		
$I(\ln X)$	-.191	0.256	0.002	-0.304	-0.257	n/a	0.230
	(0.008)	(0.016)	(0.001)	(0.028)	(0.018)		

Note: Estimates with † are NOT significant even at the 10% level.
R^2 and SER take different values in lower digits.

A few important features emerge from Table 2. First, controlling for the one-week lags of returns is important. Because the spread measure is extracted from the first-order negative serial covariance of transaction returns, inclusion of the spread measure as a regressor naturally induces the need for controlling persistence of the weekly return series. Regardless of the raw or logarithmic scales, the coefficients of the price-impact measure and the spread measure become much larger and smaller, respectively, than otherwise. The estimate of θ_{lag} is a small yet significant, and it successfully controls the endogeneity in eliminating the individual fixed effect by differencing both sides of the equation (10) over time given persistence of the dependent variable. Second, the coefficient of the price-impact measure is positive and significant in the dynamic panel result, suggesting that it is a priced risk in the JEPX market, while the spread measure accounts for a smaller portion of the return's variations. Therefore, the returns in the JEPX spot market are driven by the price-impact measure more than the spread measure. Third, the volume measure has a negative impact on returns, suggesting that it is counteracting with the risk factors such as the price-impact measure. This is interesting, given the fact that the time-series averages of the volume and price-impact measures show very similar patterns within each day of the week in Figures 6 and 7, yet they influence weekly returns in opposite fashions. To obtain this result, we need to control for all of the contract-specific fixed effects, common time effect, and persistence of weekly returns of 336 contracts. Fourth, the volatility measure is negatively related to the return variations. The signs and significance of the price-impact measure and the volatility measure are consistent with Amihud (2002, Table 2).

4.5 Discussion and Connection to Market Microstructure Models

Based on the argument in Section 2.2, the estimated half spreads are potentially combinations of (i) the transaction cost and investors' mispricing, (ii) the inventory cost, and (iii) the adverse-

---

[3]I use the two-week lags $R_{id,w-2}$ for instrumenting $R_{id,w-1}$ in the EViews Dynamic Panel wizard. Using all of the possible lagged dependent variables makes dimensions of the data matrix too large.

selection cost. Note that the analysis in Section 4.1 excludes the discreteness of price ticks as a major factor. Furthermore, as noted in the end of Section 3.2, we cannot investigate the possibility of investors' over-confidence given a limited scope of our dataset. Therefore, let me give potential explanations according to (i), (ii), and (iii).

(i) may be associated with order processing, commission fees, and deposits specific to JEPX membership, as explained in Section 2.1. PPSs have to pay some fees for using the electricity transmission system owned by a regional monopoly. It is an additional contribution to the marginal cost of trades in the JEPX. Moreover, because the JEPX system price is determined as the intersection of aggregated market demand and supply schedules, there are multiple players for a specified amount of electricity to be traded. If the breakdown of a power generator causes the non-fulfillment of an agreed quantity for delivery, the compensation scheme involves multiple participants and, therefore, the transaction cost can become quite large. The multiplicity of participants also causes the so-called "hanuke yakujou" (intermittent bids, in Japanese). Suppose a steel company wants to sell the electricity that is generated by steam power in the process of cooling the heated iron during its operations from 9:00 AM to 5:00 PM. However, suppliers and customers are assigned with some randomness by the system. The system may assign the steel company to 10:30-11:00 and 15:00-15:30 where there is a long duration between intervals for selling its electricity. This intermittent generation and available supply of electricity may not be efficient from a seller's viewpoint.

Regarding (ii), we can reinterpret the classical inventory model by Garman (1976) as a model for an immediate supplier in the face of large order-imbalances, as is noted in Section 2.2. This is more pertinent to the JEPX market because, first, the market has no dealers, and, second, the commodity to be traded is electricity, which cannot be stored so that immediacy of trade agreements is crucial to avoid the loss of supply and demand. A hockey stick shaped supply curve by Kanamura and Ohashi (2007) implicitly relies on a similar argument where a higher marginal cost is associated with a larger supply. Jegadeesh and Titman (1995) show that a price reversal and its strength at different sampling frequencies are consistent with the inventory model.

If (iii) is a valid hypothesis as in Copeland and Galai (1983) and Glosten and Milgrom (1985), it implies, even in a dealer market, that the ask-bid quotes are given by conditional expectations. Because the transactions always occur either at the ask or bid quote for a particular mechanism, the actual series of transaction prices is a sequence of conditional expectations or a martingale sequence (Hasbrouck 2007, p. 48). In other words, actual transaction returns follow a martingale-difference sequence allowing no serial correlation. However, the model by Brünner (2012) indicates that the additively-separable spread cost does reflect the asymmetric information component. The fundamental assumption by his model is that buyers and sellers have heterogeneous evaluations about the fundamental values of the asset (electricity in our case). The wider the range of this evaluation heterogeneity, the higher the implied spread cost. This seems consistent with the time series pattern of transaction prices in Figure 5.

5 Robustness Analyses

5.1 Robustness of Weekly Spread Measures

Jagadeesh and Titman (1995) suggest that the Roll measure tends to under-estimate the true spread based on the daily returns and to over-estimate based on the weekly returns. Figure 8 shows the calculated measures of the implied spread cost based on half-hour intervals for each of the 65 months from November 2006 to March 2012 and using the daily returns as inputs to (8). The left panel shows the time-series plot of the measures for the 48 commodities, with the bold black and green trajectories representing their mean and median, respectively. The right panel is

an assembly of the cross-sectional patterns of intra-daily spreads for 48 different commodities by month, with the bold black and green lines representing the time-series mean and median values of the extracted spreads, respectively.

To see if the magnitude of the estimated half spreads is dominated by a bias component associated with the specific combination of the Roll measure using daily returns, we also calculate the spread on the basis of the Roll measure using weekly returns and the Corwin-Schultz method. Figure 9 summarizes the time-series averages of the three spread measures over the entire sample period. The three trajectories based on half-spread estimates are largely in line with each other during the daytime period. Our discussion in Section 3.2 indicates that the true spread for an active day-time period should lie between the daily and weekly Roll measures, and a similar magnitude is shared by the Corwin-Schultz measure. When there are insufficient variations in the data, such as the nighttime period, the Corwin-Schultz measure is expected to underestimate the spread. The overall pattern of plots in this figure is consistent with the statistical features of several measures, and the general shapes are quite parallel with each other.

6   Conclusion

I assess the liquidity issues in the JEPX market using data of the system prices and traded volume only. The extractedt price-impact measures and spread cost measures are positively yet imperfectly correlated contemporaneously after controlling for the traded volume, fixed and time effects, suggesting that they capture common and distinctive features of illiquidity in the JEPX market. As risk factors for return variations, the price-impact measure show much larger influence on returns than the spread measure in the dynamic panel framework given controlling for the lagged weekly returns and instrumenting appropriately, in conjunction with other covariates such as the traded volume, idiosyncratic volatility, contract-specific fixed effects and time effect. The intra-daily and intra-weekly patterns of the price-impact measure and traded volume are similar, yer they exhibit opposite signs of influence on return variations, suggesting the importance of controlling for several confounding factors to make any statemenets about the liquidity and efficiency issues in the JEPX spot market.

Appendix: More Institutional Details about the JEPX

There are two electricity networks in Japan, roughly corresponding to the east-west geographical division. The most stark difference in terms of electricity between the eastern and western parts of Japan is the frequency: it is 50Hz in the easten part of Japan including Tokyo, while 60Hz in the western part of Japan including Osaka. This subdivision dates back to the earliest stage of regional monopolistic electricity companies who separately imported power generators either from Germany (in the east) or from the U.S. (in the west).

JEPX provide 48 commodities for 9 different locations in Japan, associated with 9 different regional monoploistic electric companies. Although it is possible to have 9 different price patterns for these areas, prices in Hokkaido and Tohoku are the same as the one in Tokyo (the eastern part of Japan), while the prices in Chubu, Hokuriku, Chugoku, Shikoku and Kyushu are the same as the one in Kansai (area including Osaka). Essentially, we only have two areas: east and west.

All participants must pay the commission fee, which is the 0.03 JPY/kWh for each unit of kWh/h transaction of electricity, and the consumption tax is also levied on. Using the above example with the consumption tax rate at 0.05, both sides must pay the 1.05*0.03*5500=173.25JPY per hour to the JEPX, so the revenue for the JEPX is 173.25*2=346.50 JPY per hour.

All participants must pay the deposit, too. The deposit covers the cost of non-fulfillment of the agreed-upon demand or supply of electricity. For a buyer, it limits the total amount of payment required when bidding for electricity within the demand schedule. For a seller, it covers the potential compensation to a buyer if it cannot deliver the agreed amount of electricity (e.g., due to the breakdown of a power generator). The deposits for all trades in one month are held in reserve until the next month when they are paid back to each participant after subtracting these compensations. A foregone interest incurs an opportunity cost of the transaction. Moreover, the power transmission line system is owned by regional monopolies. Whenever the PPSs wish to deliver electricity to their customers, they must pay a fee for using the transmission line to a regional monopoly. Finally, the multiple suppliers and customers involved in the agreed amount of electricity make the negotiations in the case of non-fulfillment of a contract more complex than a bilateral contract between a single participant and a regional monopoly.

References

Amihud, Y. and H. Mendelson (1991). Volatility, Efficiency and Trading: Evidence from the Japanese Stock market. *The Journal of Finance*, 46(5): 1765-1789.

Bandi, F. M. and J. Russell (2008). Microstructure Noise, Realized Variance, and Optimal Sampling. *The Review of Economic Studies*, 75(2): 339-369.

Brünner, T. (2012). Transaction costs in an electronic call auction in the presence of insider information. Mimeo.

Crack, T. and O. Ledoit (1996). Robust structure without predictability: the 'compass rose' pattern of the stock market. *The Journal of Finance* , 51(2): 751-762.

Copeland, T. E. and D. Galai (1983). Information Effects on the Bid-Ask Spread. *The Journal of Finance*, 38(5): 1457-1469.

Corwin, S. A. and P. Schultz (2012). A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *The Journal of Finance*, 67(2): 719-759.

Demsetz, H. (1968). The Cost of Transacting. *The Quarterly Journal of Economics*, 82(1): 33-53.

Fang, Y. (2002). The compass rose and random walk tests. *Computational Statistics and Data Analysis*, 39(3): 299-310.

Garman, M. B. (1976). Market Microstructure. *Journal of Financial Economics*, 3(3): 257-275.

Glosten, L. R. and P. R. Milgrom (1985). Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics*, 14(1): 71-100.

Harris, L. E. (1990). Statistical Properties of the Roll Serial Covariance Bid/Ask Spread Estimator. *The Journal of Finance*, 45(2): 579-590.

Haller, A. and H. R. Stoll (1989). Market Structure and Transaction Costs: Implied Spreads in the German Stock Market. *Journal of Banking and Finance*, 13(4): 697-708.

Hasbrouck, J. (2007). *Empirical Market Microstructure*. Oxford University Press.

Jegadeesh, N. and S. Titman (1995). Short-Horizon Return Reversals and the Bid-Ask Spread. *Journal of Financial Intermediation*, 4(2): 116-132.

Kanamura, T. and K. Ohashi (2007). A structural model for electricity prices with spikes: Measurement of spike risk and optimal policies for hydropower plant operation. *Energy Economics*, 29(5): 1010-1032.

Kawamoto, K. and K. Sakanashi (2010). Analysis of Wholesale Electricity Market Competition with the Unit Commitment Model, *Journal of Japan Society of Energy and Resources*, 31(2): 25-33 (in Japanese).

Lou, X. and T. Shu (2014). Price Impact or Trading Volume: Why is the Amihud (2002) Illiquidity Measure Priced?

http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2291942

Madhavan, A. (1992). Trading Mechanisms in Securities markets. *The Journal of Finance*, 47(2): 607-641.

Ofuji, K. and N. Yamaguchi (2008). Estimation of Structural Changes in Trade Dynamics of Electricity Exchange using Kalman filter. *Denryoku Chuou Kenkyuujo Houkoku*, Y07016 (in Japanese).

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *The Journal of Finance*, 39(4): 1127-1139.

Schultz, P. (2000). Regulatory and Legal Pressures and the Costs of Nasdaq Trading, *Review of Financial Studies*, 13(4): 917-957.

Sklavos, K., L. Dam and B. Scholtens (2013). The Liquidity of Energy Stocks. *Energy Economics*, 38: 168-175.

Stoll, H. R. and R. E. Whaley (1990). Stock Market Structure and Volatility. *Review of Financial Studies*, 3(1): 37-71.

Tinic, S. M. (1972). The Economics of Liquidity Services. *The Quarterly Journal of Economics*, 86(1): 79-93.

Figure 1: Demand and Supply Schedules.
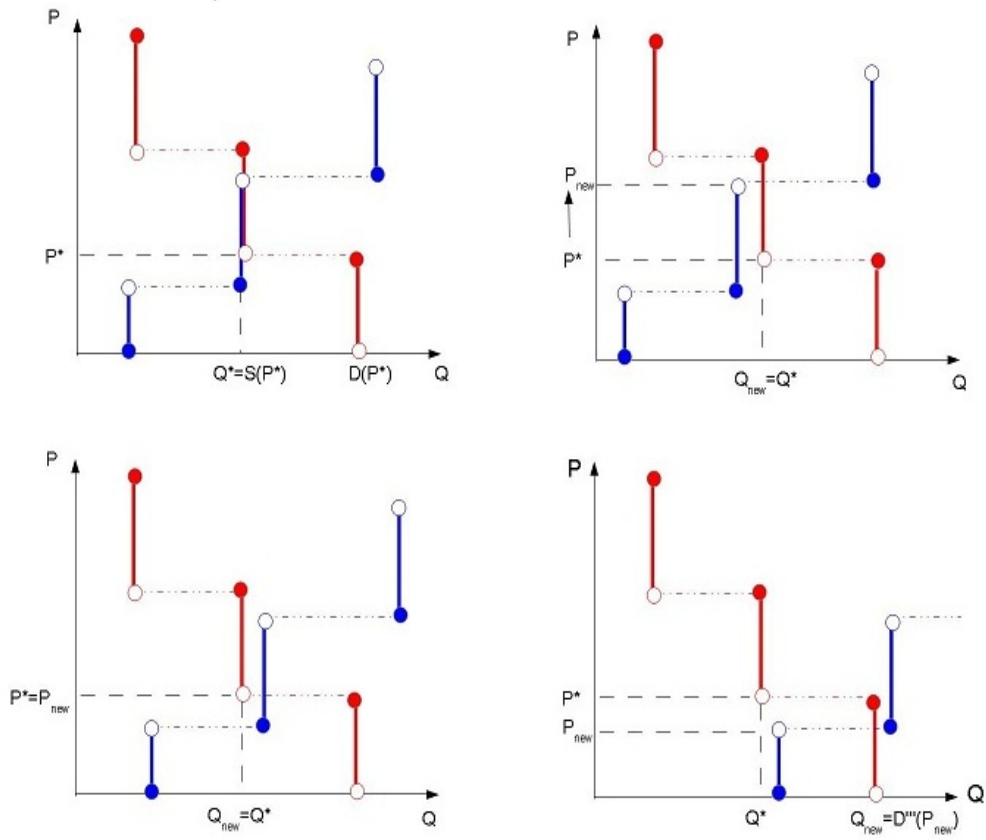
The equilibrium price satisfies $P^* = \inf\{P \geq 0 : S(P) \geq D(P)\}$. Note: At $P = P^*$, $S(P^*) < D(P^*)$ so that P^* cannot be attained by the minimum of P such that $S(P) = D(p)$. Although some investors quote the demand $D(P^*)$ for such a price, it is not executed according to the JEPX limit order rule.

Figure 2: Autocorrelation Functions of Daily Returns in 8 Intervals
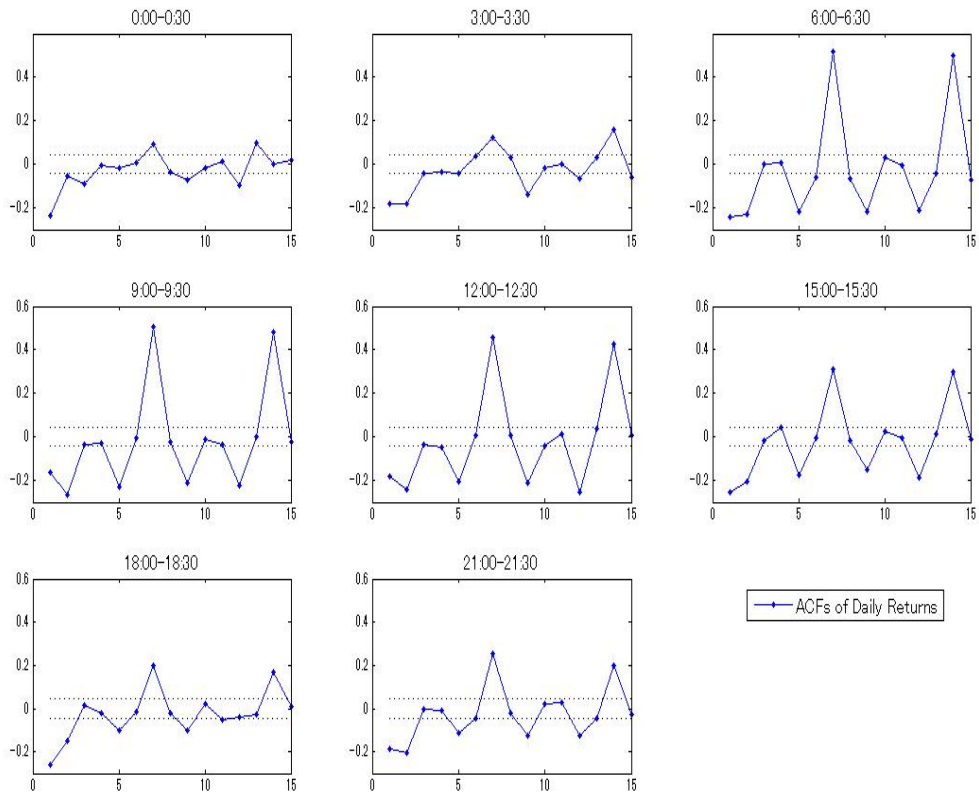
Note: The two parallel broken lines are the boundary of the 95% confidence band under the null hypothesis that corresponding weekly returns follow a white noise process. Blue dotted lines are autocorrelation functions. All of the first-order autocorrelations as displayed are significantly negative. Reflecting the day-of-week effect, every autocorrelation function shows peaks at every seventh displacement.

Figure 3:   Autocorrelation Functions of Weekly Returns
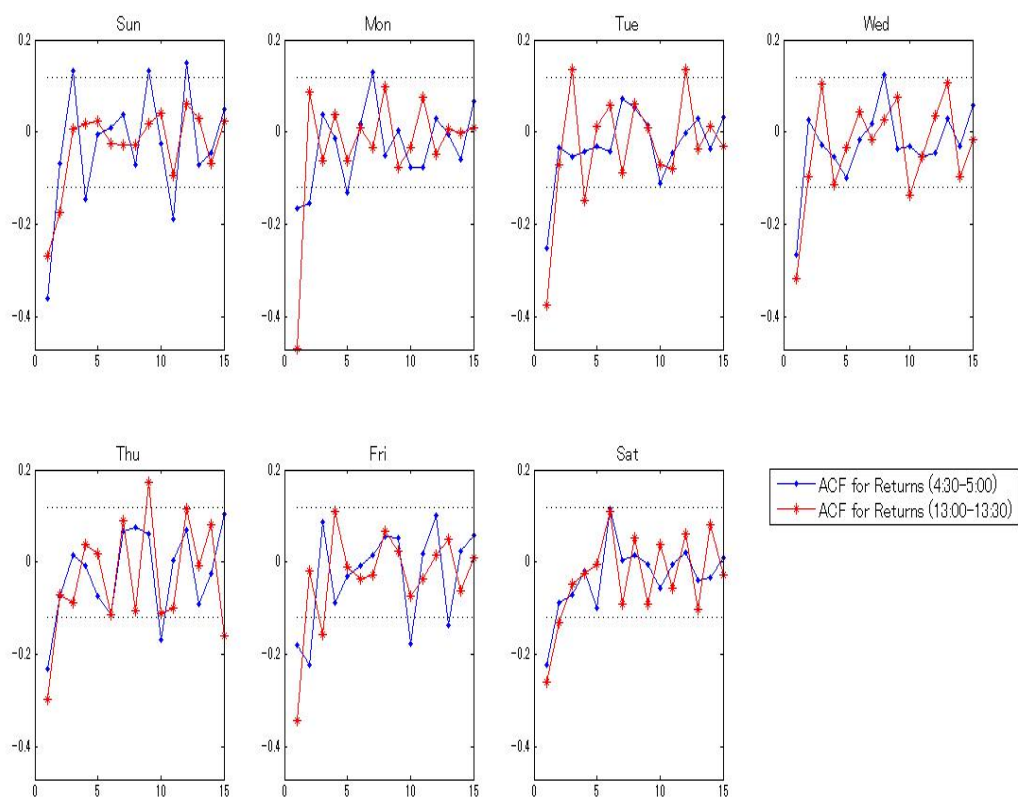
Note: The first order serial correlations are still visible. The magnitude is much greater for weekly returns in 13:00-13:30 periods than for 4:30-5:00 periods.

Figure 4:   Time-Series Averages of System Prices, Traded Volume and Weekly Returns (4:30-5:00 for Left; 13:00-13:30 for Right).
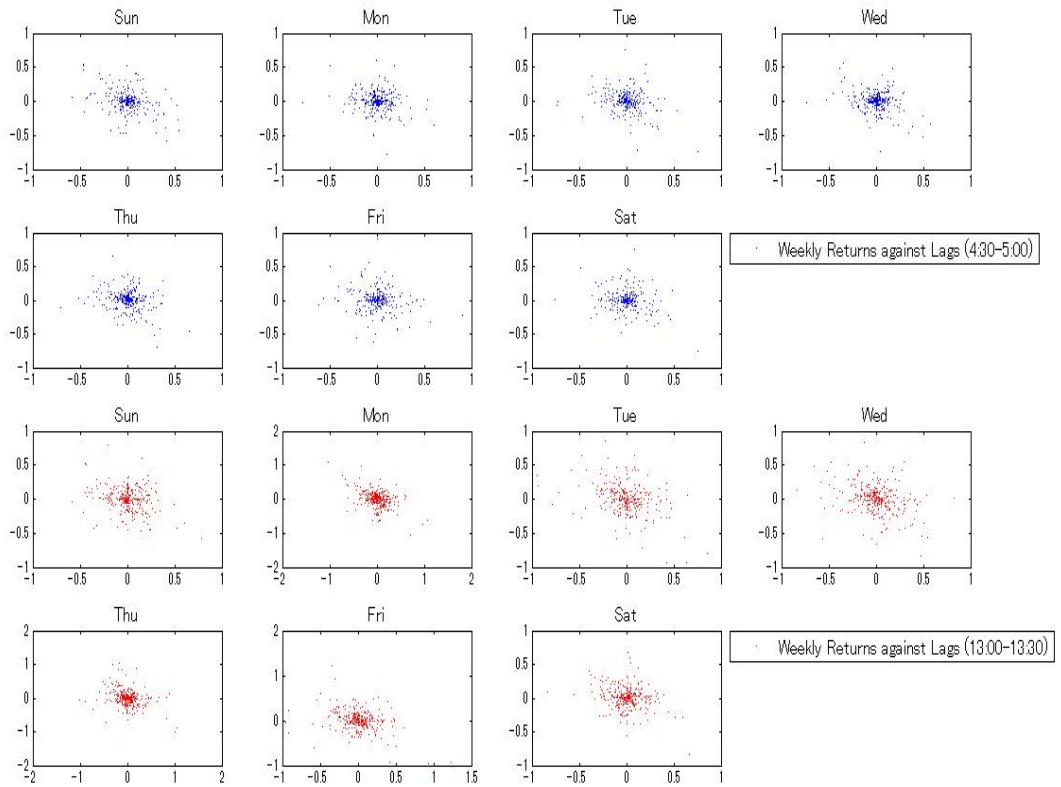

Note: The first seven panels with red dots are the scatterplots of weekly returns in 4:30-5:00 period against their one-week lagged counterparts, and the second seven panels with red dots show similar scatterplots of weekly returns in 13:00-13:30 period. Overall, the price discreteness in the form of clear rays from the origin are not crucially recognized.

Figure 5: Time-Series Averages of System Prices, Traded Volume and Weekly Returns (4:30-5:00 for Left; 13:00-13:30 for Right).
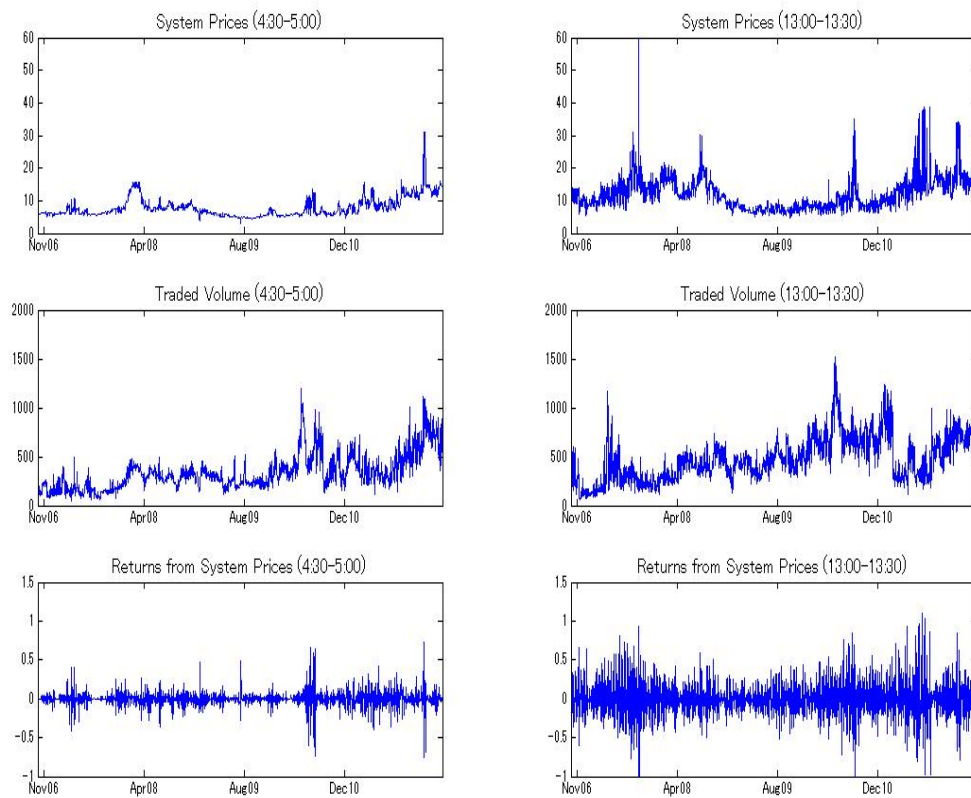

Note: The top panels are the time series plots of system prices in 4:30-5:00 and 13:00-13:30 periods over 288 weeks; the middle panels are for traded volume of electricity over 288 weeks; and the bottom panels are for returns over 287 weeks. The return plots show clear time periods of high and low volatility of returns, and such effects are stronger for prices in 13:00-13:30 period.

Figure 6:   Time-Series Averages of System Prices, Traded Volume and Weekly Returns (4:30-5:00 for Left; 13:00-13:30 for Right).
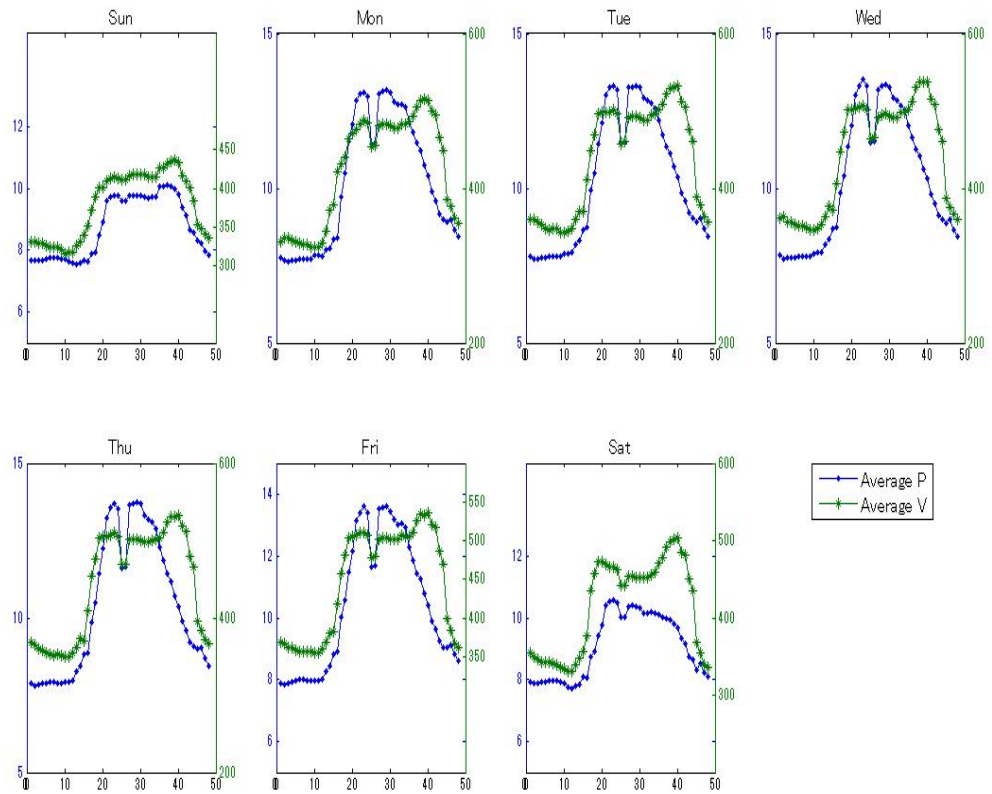

Note: Time-Series Averages of System Prices (Left Scale) and Traded Volume (Right Scale) of 48 Commodities in Each Day-of-Week. The sharp troughs in the middle of the most of panels show the lunch-time break from 12:00 to 13:00. The traded volume identify the daytime period from 8:00 to 22:00, and the nighttime period from 22:30 to 7:30 in the next morning.

Figure 7:   Time-Series Averages of Weekly Price Impact Measures (Left-Scale) and of Reciprocal Volume (Right-Scale).
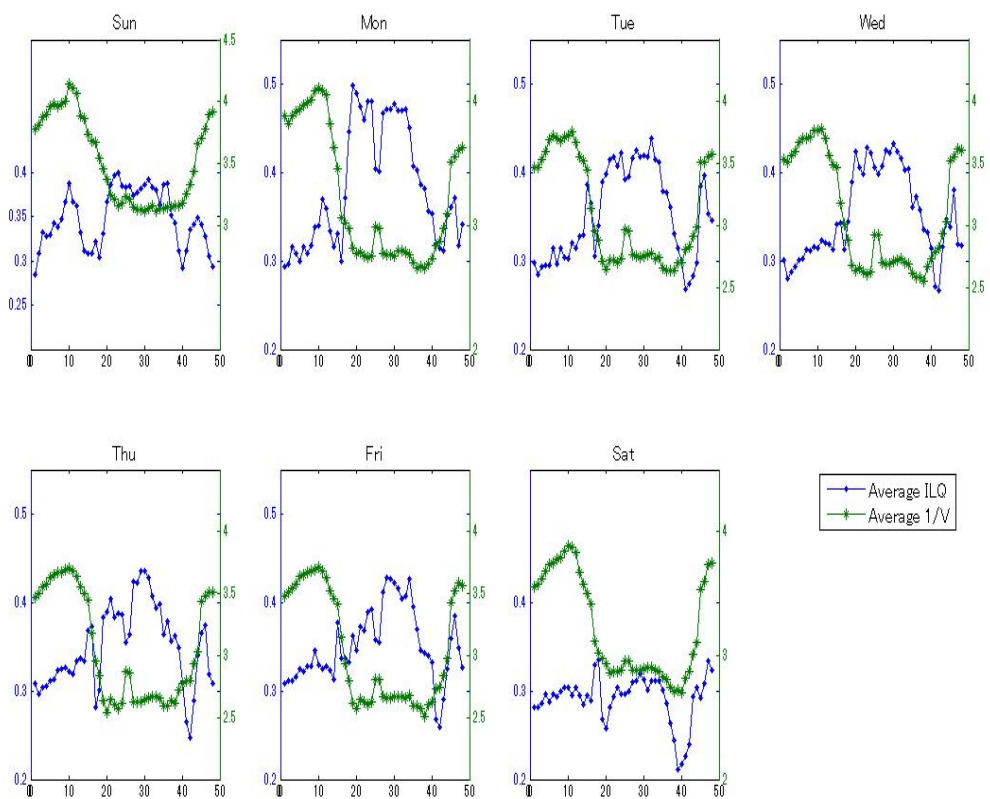

Note: Time-Series Averages over 288 weeks of Amihud Price-Impact Measures (Left Scale) and of the Reciprocals of Traded Volume (Right Scale) of 48 Commodities in Each Day-of-Week.

Figure 8: Time-Series Averages of Weekly Spread Measures (Left-Scale) and of Price Impact Measures (Right-Scale).
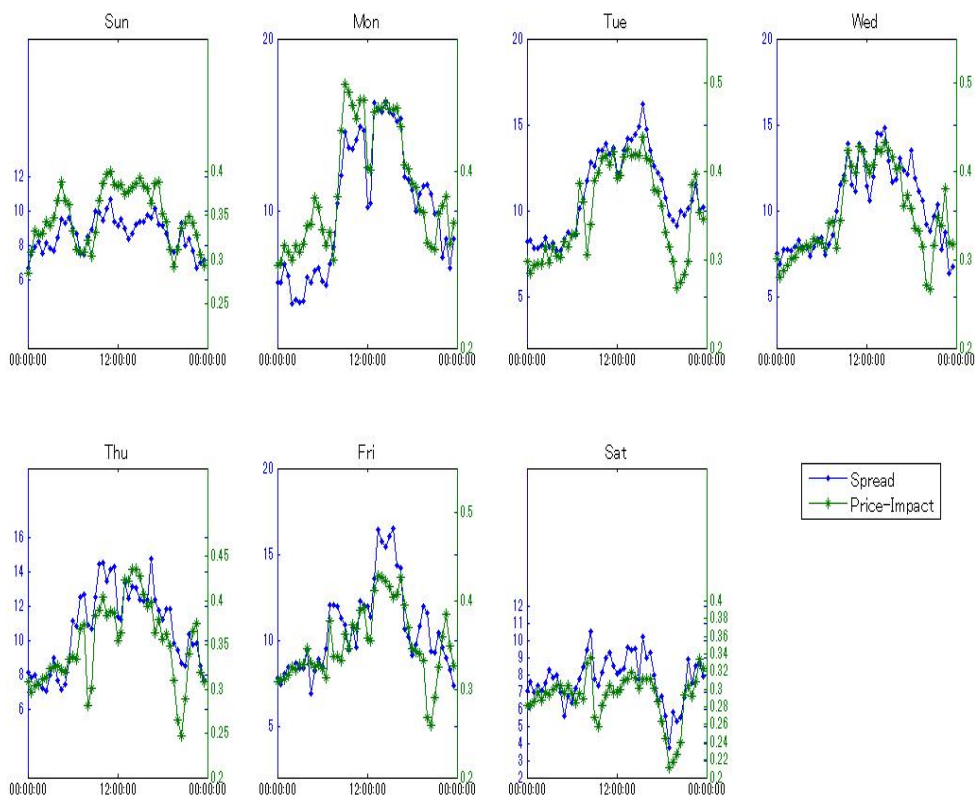
Note: Time-Series Averages over 288 weeks of Roll's implied spread cost measuers of 48 Commodities in Each Day-of-Week.

Figure 9: Alternative Spread Measures. Roll's in Blue Real/Dotted; Corwin-Schultz's in Red.
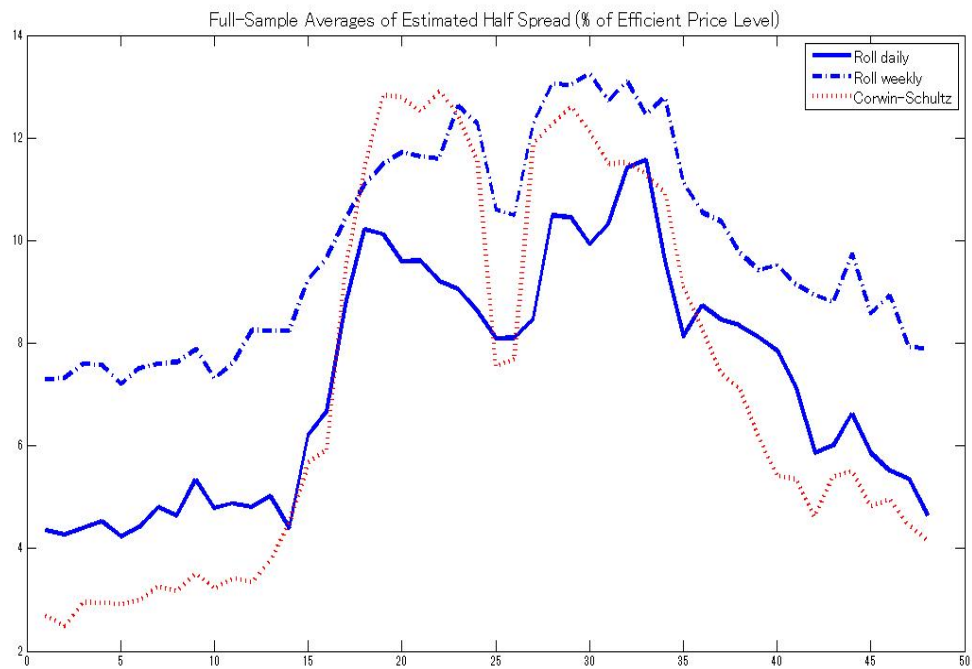
Note: The real and broken lines in blue are the full-sample average of monthly spreads from the bias-corrected Roll method based on daily returns and weekly returns, respectively. The red-dotted line is the full-sample average of monthly spreads estimated by the Corwin-Schultz method as the within-month average of estimates in the 20-day rolling-window. For the daytime period with active trades of electricity, the Corwin-Schultz estimates are roughly in the middle of two versions of Roll measures based on daily and weekly returns, while they are below them in the night-time period, as is consistent with the fact that the accuracy of a range-based estimator requires large variations in data during the period for defining it.