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Illiquidity in the Japan Electric Power Exchange

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Abstract

Historical data of system prices and traded volume of electric power over the 48 half-hour intra-daily intervals in the Japan Electric Power Exchange (JEPX) from August 2005 to March 2015 are analyzed. The data allow computation of two representative measures of economic illiquidity, namely, Amihud's price-impact measure and Roll's implied spread cost measure. Based on a dynamic panel regression framework allowed by a panel reinterpretation of the data, I establish that (a) these illiquidity measures comove to some extent, (b) a positive contribution of the price-impact measure to returns is stronger than that of the spread cost, (c) a higher traded volume of electric power does not lower the spread cost, and (d) a great earthquake might disturb the risk-return tradeoff.

Keywords: Market microstructure, Price impact, Spread cost, Day-ahead electric power market.
JEL classification: L94, C23

[1]This study is conducted as a part of the project "Study on Markets and Policies in the Power System Reform" undertaken at the Research Institute of Economy, Trade and Industry (RIETI).

1 Introduction

The Japan Electric Power Exchange (JEPX) was launched in April 2005 in the process of electric power wholesale liberalization led by the Ministry of Economy, Trade and Industry (METI) in Japan. The trading activity in the JEPX is supposed to provide a benchmark for power producers' investment on a variety of power sources and to help producers find their counterparties to trade in case of a huge demand-supply mismatch. An important premise for these objectives is that the JEPX is sufficiently "liquid". However, the amount of traded electric power through the JEPX system is only 0.6% of the total amount of wholesale electric power in the fiscal year of 2010 (Cabinet Office, 2012). Moreover, the JEPX heavily relies on the help of regionally monopolistic power generators for its smooth operation. Recall that the devastating tsunami following the great earthquake centered near the northeastern coast of Japan on 11-March-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, and the government terminated all nuclear power plants in the country for urgent inspections under the political pressure. Amid the extreme disruption in the supply and demand of power, TEPCO temporarily stopped their additional business of power transmission associated with any contracts in the JEPX and triggered the exit of several members from the exchange because of shrinking benefits relative to membership costs. This anecdote raises the research question in this study, namely, if the JEPX can avoid any adverse impact of illiquidity on its functioning.

Illiquidity in a power exchange is often identified with a small amount of trade of electric power. However, the ill-functioning of a power exchange as a *market* may be reflected more in some *economic illiquidity*. Kyle (1985) gives three components of economic liquidity, such as: (a) "depth" to measure the size of an order flow innovation required to change prices a given amount, (b) "tightness" to measure 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" to measure the speed with which prices recover from a random, uninformative shock. Let me focus on (a) and (b): (c) may be relevant for a continuously trading market, but the JEPX is not designed as such. Moreover, I will partially account for a resilient aspect of liquidity by controlling the return volatility in Section 4.4. If we focus on the "depth" aspect of liquidity, an illiquid market should be characterized by a large value of the inverse depth variable, which is often called a price-impact measure. As a first measure of economic illiquidity, I adopt Amihud's (2002) price impact measure, i.e., a time-series average of absolute changes of the log-price relative to the daily traded volume in a monetary unit. The first contribution of this study is to apply the Amihud's measure to the JEPX transaction data, for the first time to my best knowledge, and to document that the price-impact aspect of illiquidity in this exchange may be similar to the average situation in emerging financial markets from 1987 to 2000. In this sense, the JEPX may not be terribly illiquid so long as the price impact is concerned.

Many financial markets are quote-driven, in which mutually competing market makers publicly post ask and bid quotes. Then, a natural measure of illiquidity in terms of tightness is a bid-ask spread because it measures a concession in switching a participant's position between a buy-side and a sell-side. As exploited by Roll (1984), the first-order serial covariance in returns is informative about this spread, because the presence of a positive spread tends to imply a bouncing up and down of transaction prices even when no information has arrived. However, as explained later in Section 2, the JEPX employs a call-auction mechanism without any officially designated market makers to post ask and bid quotes. Several studies document and justify the presence of negative autocorrelations of returns in financial markets without officially designated market makers nor posted quotes, thereby supporting the use of an autocovariance-based spread measure indirectly: see, e.g., Campbell, Grossman and Wang (1993), Haller and Stoll (1989), Amihud and Mendelson (1991), Roll (1984), Stoll and Whaley (1990a), and Hasbrouck (2007). Recently, Brünner (2012) identifies an implicit spread cost in an actual transaction price under the call auction mechanism.[1] Moreover, one can estimate this cost by a standard autocovariance-based technique. The second contribution of this study is to estimate this implicit spread cost for weekly transactions in the JEPX, and reveal that it is about 15 % of the intrinsic value of electric power. This number is comparable to the highest spread costs in emerging markets in 1987-2000 reported for Hungary and Russia. In this sense, the incumbents in the JEPX may have paid a very high transaction cost.

Given two illiquidity measures along with the traded volume measure, I can ask how they are related with each other, and with the functioning of the JEPX. Regarding this question, I establish several results. First, the price-impact measure positively and significantly correlates with the spread cost measure even after controlling the traded volume, fixed effects of individual half-hour contracts and of time, and persistence of the dependent variable. Second, two illiquidity measures are significant risk factors in the sense that they are positively correlated with returns, again in a dynamic panel regression framework. Such relations are not fully confirmed by OLS or static fixed-effect approaches. Third, the cross-sectional patterns of the estimated cost are quite parallel to those of the system price and traded volume. If we used the traded volume as a measure of *liquidity*, it would interfere with the pattern of *illiquidity* in terms of the implicit spread cost measure. Nevertheless, the volume does not explain the variations of the spread cost in a dynamic panel regression with additional controls of the traded volume and the idiosyncratic volatility of returns. Fourth, the great earthquake might disturb the tradeoff between the illiquidity risk and returns.

Let me make a distinction between this study and several earlier ones. Freire, Neves, Tsunechiro, Cabral and Souza (2012) attempt to assess liquidity in the Brazilian electric power market by a churn rate and a liquidity-relative rate. The former is a turnover ratio, but the amount of final energy consumption is used in the denominator; and the latter is a relative volume-weighted number of transactions of a particular contract. Frestad (2012) focuses on liquidity in the Nord Pool, which is a quote-driven market with many market makers. Unfortunately, their results are less informative for this study because the JEPX adopts a call auction mechanism with a single trading in the end without market makers. Earlier works on the JEPX, e.g., Kawamoto and Sakanashi (2010) attempt to forecast the system price, but offer little policy implications.

2 Institutional Details about the JEPX

The participants in the JEPX are classified into three types: (i) general electricity suppliers ("GES") as regional monopolies, (ii) independent power producers ("IPP") with their own power generators and trading with GES, and (iii) power producers and suppliers ("PPS") with their own power generators and selling electric power to large-scale customers via the power transmission system exclusively owned by GES. PPS may need to buy electric power from GES to meet a required power demand by their own customers.

Among several types of contracts in the JEPX, this study focuses on those in the day-ahead market for the delivery of electric power because they account for more than 97% of all trades in this exchange (METI, 2012). Any participant submits an order schedule composed of several limit prices to the JEPX

[1] I appreciate Tobias Brünner for providing his latest manuscript. An earlier version is available at the webpage of the EFMA 2011 Meeting Braga. The main theoretical part has been unchanged.

trading system between 10:00 and 16:00 from six to two business days before the delivery day, and between 8:30 and 9:30 on the last business day before the delivery day from Tuesday to Saturday. Because the JEPX does not open in the weekends, the contracts for Sunday- and Monday-delivery are traded in the last Friday sessions closing at 11:30 and 13:30, respectively. The system aggregates the posted schedules of the demand and supply for each contract into the market-wide demand and supply, and their intersection determines the system price and the traded volume of electric power to deliver in the corresponding half-hour interval in a day. This clearing mechanism is called the Itayose method, which is a version of the periodic, blind, and single-price call auction with batch trading, without formally designated market makers. The system prices and traded volumes of electric power over the 48 half-hour intervals in a particular delivery day are simultaneously determined in a single closing session. Therefore, we should view them as those of 48 different commodities rather than an intra-daily time-series record of those of a single commodity.

The basic unit of electric power in the JEPX is 1,000 kilowatt-hour per hour (kWh/h) or 1 megawatt-hour per hour (MWh/h) and the minimum monetary unit is 1/100 of one Japanese yen per kilowatt-hour (JPY/kWh).

3 Data

3.1 Characteristics of the Data

The data on transactions in the JEPX day-ahead market consist of system prices and traded volumes as described in Section 2. The original sample begins from 02-April-2005, but I eliminate an initial portion of it until 08-August-2005 to avoid any confounding effects due to scarce trading. The final sample spans the period from Tuesday 09-August-2005 to Monday 30-March-2015 with 3,521 days, or 503 weeks of the complete 7-day cycle of delivery dates of Tuesday, Wednesday, ..., Sunday, and Monday. For the vast majority of cases, each cycle corresponds to the outcomes of weekday trading sessions from Monday to Friday. The data are available at the website of the JEPX.[2]

3.2 Seasonalities within a day, a week, a year, and the sample

Figure 1 depicts the 503-week averages of system prices in real blue lines scaled in the left axis (JPY/kWh) and of raw volumes in breaking green lines scaled in the right axis (MWh/h), in each day of a week and each half-hour interval of a day. The title of each panel shows the pair of the day of closing session and the delivery day. We can see a clear M-shaped pattern, especially for the prices of contracts of weekday delivery. This is intuitive as the electric power demend by PPS, such as railway and subway companies, metal processors, automobiles makers, etc., should be higher in that period. The first peak of an intra-weekday volume plot comes earlier (around 8:30) and the second peak comes later (around 21:30) than the system price plot in the same panel. The percentage volatility measures (standard deviations and absolute values) of weekly returns in Figure 2 show a similar M-shaped pattern as the price level, while the plot for the volume returns is stable and flat.

Figure 3 collects the quarter-wise scatterplots of the pairs of traded volumes for the horizontal axis and system prices for the vertical axis from 1-January-2006 to 30-March-2015. The title of each panel shows the first and last days of each quarter. The bodies of a major mass grossly trace upward-sloping supply curves until the great earthquake. In the third quarters and in the post-earthquake period, the

[2]Visit `http://www.jepx.org/market/index.html` (accessed 01.08.2015.)

mass has become more stretched vertically, probably because of the hot weather and power shortage for the TEPCO caused by the halt of all nuclear power plants.

3.3 Time-series patterns of weekly data

Figure 4 records the first-order autocovariance of weekly returns estimated over the whole sample in each day of a week and each half-hour interval of a day, and their 95% confidence bands under the null hypothesis that the weekly returns follow a white-noise process. All of the bands stay below zero, so that the first-order autocovariances of returns are likely to be negative. Those of weekday delivery are more negative and W-shaped, like a flipped image of the M-shaped pattern in Figure 1. The autocovariances for the contracts of weekday delivery tend to take the least-negative values marked by $\circ$ in the midnight and the most-negative values marked by $*$ in the mid-day, especially after the lunch-time break. Subsequently, I will use 4:30-5:00 and 14:30-15:00 as two representative half-hour intervals with the least and greatest autocovariances in returns.

There are two additional issues regarding the persistence of returns. First, returns may be serially correlated in higher orders. However, the plots of autocorrelation functions of weekly returns with the error bands under the white-noise null in Figure 5 show no compelling evidence in favor of this concern. Second, an implicit spread cost may be confounded with the price discreteness. Crack and Ledoit (1996) show that daily returns plotted against their first-order lags produce a "compass-rose" diagram with many straight rays from the point of origin due to the rounding of prices to nearest grids in the minimum tick, and this rounding may induce a mechanical first-order autocorrelation in returns. However, such diagrams in Figure 6 for two representative half-hour intervals show no clear rays from the origin.

The top, middle and bottom panels in Figure 7 respectively show the time-series of the system prices, raw volumes and price returns of contracts for delivery in 4:30-5:00 (left) and in 14:30-15:00 (right). All panels contain three partitions to divide the entire sample into four subperiods: (S1) the pre-quake period from 09-August-2006 to 14-Mar-2011,[3] (S2) the aftershock period from 15-March-2011 to 31-May-2011, (S3) the post-earthquake period from 1-June-2011 to 24-February-2013, and (S4) the period of more involvement by GES from 25-February-2013 to 30-March-2015. The top and bottom panels show greater variations of prices and returns for the contracts in 14:30-15:00 than for those in 4:30-5:00, as is consistent with Figures 1 and 2. The middle panels indicate that the raw traded volume has increased linearly until the great earthquake, dropped in S2, gradually recovered in S3, then increased yet varied so much in S4. The last phenomenon is mainly driven by a greater supply of residual power to the JEPX by GES from the beginning of S4 (METI, 2012).

4 Methodology

Clear intra-daily and intra-weekly regularities in data motivate me to adopt the finest intra-weekly partition of data by distinguishing all of the $48 \times 7 = 336$ half-hour contracts as the cross-sectional units. Accordingly, the time-series sampling frequency is weekly, with 503 weeks as the maximum number of time-series observations. Let $i = 1, \ldots, 48$ be the index for the i-th half-hour interval within a day; $d = 1, \ldots, 7$ be the index for the d-th day of a week representing Sunday ($d = 1$), Monday ($d = 2$), ..., and Saturday ($d = 7$); and $w = 1, \ldots, 503$ be the index for the w-th week in the

[3] The contracts for the delivery on 14-Mar-2011 were determined in the last Friday session on 11-March 2011 closing at 13:30 before the great earthquake hit the northeast coast of Japan at 14:46.

entire sample. (i, d) indicates a specific cross-sectional unit. Therefore, P_{idw} (JPY/kWh) and V_{idw} (MWh/h) represent the system price and the raw volume of electric power to be delivered at i-th half-hour period within d-th day of w-th week.

4.1 A spread-cost measure of illiquidity

Suppose the efficient log price, $\ln P^*_{idw}$, follows a random walk process:

$$\ln P^*_{idw} = \ln P^*_{id,w-1} + \sigma_{id}\epsilon_{idw} \tag{1}$$

where ϵ_{idw} is independent and identically distributed (i.i.d.) with respect to w as a standard normal variable, and σ_{id} is the volatility, i.e., the instantaneous standard deviation of returns common to all ϵ_{idw}'s in an estimation window.[4] Suppose an observed transaction price, P_{idw}, is subject to a percentage deviation from the efficient counterpart:

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

where S_{idw} is another i.i.d. variable representing the implicit spread cost, i.e., the cost associated with a buy-sell roundtrip. Let me assume that S_{idw} is independent of P^*_{idw} and takes a value of either $s_{id} > 0$ or $-s_{id} < 0$ with probabilities π_{id} and $1 - \pi_{id}$, respectively. By taking the natural logarithm and the first-difference Δ with respect to the weekly index w in both sides of (2), we have the main model to work out:

$$\begin{aligned} \ln P_{idw} &= \ln P^*_{idw} + U_{idw} && (3) \\ \Delta \ln P_{idw} &= \Delta \ln P^*_{idw} + \Delta U_{idw} && (4) \end{aligned}$$

where $U_{idw} = \ln(1 + S_{idw}/2)$ represents the gap between the actual transaction price in logarithm and its efficient counterpart. (3) and (4) abstract an essence of the previous literature on financial market microstructure and volatility estimation using noisy high frequency data, e.g., Stoll and Whaley (1990b), Hasbrouck (2007), Bandi and Russell (2008), and Brünner (2012). In particular, the last work justifies the decomposition (3) even in a call auction mechanism.[5] Let me assume that π_{id} enforces $E[U_{idw}] = 0$ rather than $E[S_{idw}] = 0$, as is consistent with Bandi and Russell (2008). By assuming that S_{idw} is i.i.d. with respect to w and independent of P^*_{idw}, I exclude the possibility that the spread is autocorrelated or correlated with the intrinsic value, as predicted by some models of asymmetric information with heterogeneous traders (Copeland and Galai, 1983; and Glosten and Milgrom, 1985). However, Brünner's model indicates that s_{id} incorporates investors' heterogeneous valuations, and asymmetric information between the insider and other investors: see Footnote-5.

A simple measure of the spread is given by Roll (1984) based on the first-order serial covariance of transaction returns. Given (1), the efficient return $\Delta \ln P^*_{idw} = \sigma_{id}\epsilon_{idw}$ has no serial covariance with

[4] Xiu (2010) shows that even when the spot volatility is varying over time, one can estimate the integrated volatility consistently by assuming as if it were constant in the estimation window.

[5] A close inspection of Brünner (2012, Proof of Theorem 1) reveals that there is no loss of generality of his result if we reinterpret his "price", "personal valuation", etc. as log-price, log-valuation, etc.; and if the insider submits a limit order, given a certain condition on parameters. The last point ensures that Brünner's results are appropriate for the JEPX, in which any participant submits a limit-order schedule. Brünner (2012) derives the half spread as $S/2 = \underline{k} + \alpha(\bar{k} - \underline{k}) + (2/\pi)^{1/2}\lambda\sigma$, in which α is the market order volume by the insider (i.e., the informationally superior participant who knows the true value of electric power more likely), $\underline{k}$ and $\bar{k}$ are the lower and upper bounds of the uniform distribution of trader's heterogeneous valuations, λ is the likelihood for the insider to know the sign of $\nu_t - E_{t-1}[\nu_t] \sim N(0, \sigma^2)$, ν_t is an intrinsic asset value following a random walk, and $E_{t-1}[\nu_t]$ corresponds to my $\ln P^*$.

respect to w. However, (3) induces a first-order negative autocovariance of $\Delta \ln P_{idw}$, because

$$Cov(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1}) = Cov(\Delta U_{idw}, \Delta U_{id,w-1}) = -Var(U_{idw}) < 0. \tag{5}$$

Using $E[U_{idw}] = 0$ and the approximation $\ln(1 \pm s_{id}/2) \approx \pm s_{id}/2$,

$$Var(U_{idw}) = E[U_{idw}^2] = \pi_{idw}\{\ln(1 + s_{id}/2)\}^2 + (1 - \pi_{id})\{\ln(1 - s_{id}/2)\}^2 \approx s_{id}^2/4. \tag{6}$$

From (5) and (6), we have $s_{id} \approx 2\{-Cov(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}$ so that a sample analog should be $2\{-\widehat{Cov}(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}$, where $\widehat{Cov}$ is the sample covariance over a period of 13-week estimation window: given $\mu_w := \sum_{h=0}^{12} \Delta \ln P_{id,w-h}/13$,

$$\widehat{Cov}(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1}) = \sum_{h=0}^{11} (\Delta \ln P_{id,w-h} - \mu_w)(\Delta \ln P_{id,w-h-1} - \mu_w)/12. \tag{7}$$

I will always truncate a positive value of $\widehat{Cov}$ at zero to avoid the square root of a negative value. I will apply a finite sample bias-correction proposed by Shultz (2000):

$$SC_{idw} = 2\{-\widehat{Cov}(\Delta \ln P_{idw}, \Delta \ln P_{id,w-1})\}^{1/2}/(1 - 7/96). \tag{8}$$

4.2 A price-impact measure of illiquidity

Here is the definition of a price-impact measure in this study:

$$PI_{idw} = \sum_{h=0}^{12} |\ln P_{id,w-h} - \ln P_{id,w-h-1}|/(13 P_{id,w-h} V_{id,w-h}), \tag{9}$$

which is based on Amihud (2002) as a measure of the inverse depth. It captures an average absolute rate of change of the price relative to the monetary value of a traded volume. Let me justify the application of (9) to the JEPX data by three reasons. First, the Amihud measure has been verified as a sufficiently strong positive covariate of more accurate measures of the inverse depth using intra-daily data (Amihud, 2002, p.35; and Goyenko et al., 2009, Tables 4 and 5). Second, (9) is practical because it uses only the public data of system prices and raw volumes, which are usually available even in a newly established power exchange. Third, a widely applied nature of the Amihud measure brings it a benchmark status: we can compare the JEPX with other financial markets in terms of their liquidity conditions.

There are two issues to overcome regarding (9). First, I use the absolute return in the numerator, according to the original construction by Amihud. However, Lou and Shu (2014) replace this absolute return by unity to show that their version captures a large part of the cross-sectional variations of the original version. To account for this possibility, I will use (9) along with the 13-week average monetary volume

$$MV_{idw} = \sum_{h=0}^{12} P_{id,w-h} V_{id,w-h}/13 \tag{10}$$

in any subsequent statistical framework. Second, in contrast to the implicit spread cost, the Amihud measure of illiquidity lacks a solid theoretical backup (Chordia, Huh and Subramanyam, 2009). This issue is addressed in the next subsection.

4.3 Interactions of Three Measures

In order to see if the Amihud price-impact measure really captures some aspect of illiquidity, I will estimate the next panel regression model for each $\tau = 1, \ldots, 13$, inspired by Amihud (2002, p.35):

$$\begin{aligned} \ln PI_{id,\tau+13t} &= \beta_{lag} \ln PI_{id,\tau+13(t-1)} + \beta_{sc} \ln SC_{id,\tau+13t} + \beta_{mv} \ln MV_{id,\tau+13t} \\ &\quad + \alpha_{id} + \delta_{\tau+13t} + \epsilon_{id,\tau+13t}, \end{aligned} \tag{11}$$

where (i, d) is the cross-sectional index; $t = 1, 2, \ldots, \lfloor (503 - \tau)/13 \rfloor$ is the time-series index; α_{id} is the contract-specific fixed effect to capture any time-of-a-day and day-of-a-week effects unchanged over time with respect to $w = \tau + 13t$, as suggested by Figure 1; δ_w for $w = \tau + 13t$ is the time effect common to all of 336 contracts in the w-th week due to, e.g., a weather condition or natural disaster, as indicated by Figure 7; and ϵ_{idw} is zero-mean, serially uncorrelated unobserved heterogeneity. Let me assume that $\ln PI_{idw}$, $\ln SC_{idw}$ and $\ln MV_{idw}$ have no correlation with ϵ_{idw} after controlling α_{id} and δ_w. The monetary volume is included in the right hand side as a response to the skepticism by Lou and Shu (2014). (11) includes the lagged dependent variable to control the persistence of $\ln PI$ over time.

Note that there are 13 different subsamples with slightly different time-series dimensions for 13 different initial points $\tau = 1, \ldots, 13$ to start this "skip 13-week" subsampling. Accordingly, I compute PI, SC, and MV in each of the 13-week non-overlapping windows: see Figure 8 for how PI is computed. I employ this subsampling scheme to avoid an adverse impact of persistent variables on estimates due to overlapped sampling. I estimate (11) for each of these 13 subsamples separately, then take the averages of 13 subsample-based estimates as the final estimates to avoid any loss of data points. I will use the maximum of 13 subsample-based standard errors for a conservative inference on these final estimates, and the minimum of the subsample-based adjusted R^2 and the maximum of subsample-based standard errors of regressions (SER) as conservative measures of the model fit.

I estimate (11) by three methods: the ordinary least squares (OLS) given $\beta_{lag} = \alpha_{id} = \delta_w = 0$; the static fixed effect (FE) given $\beta_{lag} = 0$; and the GMM-based dynamic panel (DP) according to Arellano and Bond (1991). In estimating (11) by DP, I use all of the available second-order lags and onward, $PI_{id,\tau+13(t-2)}, PI_{id,\tau+13(t-3)}, \ldots$, for instrumenting the latest lag $\ln PI_{id,\tau+13(t-1)}$ in the right hand side. I use the orthogonal forward deviation (Arellano and Bover, 1995) to eliminate α_{id}, because the GMM estimates based on it tend to perform better than those based on the first difference (Hayakawa, 2009). The standard errors of estimates in each subsample are robust to arbitrary cross-sectional dependence. In the DP approach, I use the 1-step rather than a multiple-step update of the GMM weighting matrix in estimating the standard errors, because the multi-step update may assign a downward bias on the standard errors (Windmeijer, 2005).

Figures 1 and 4 indicate that higher volume may not imply a lower spread cost in the JEPX. To check this possibility, I estimate the next model by three methods as above:

$$\ln SC_{id,\tau+13t} = \gamma_{lag} \ln SC_{id,\tau+13(t-1)} + \gamma_{mv} \ln MV_{id,\tau+13(t-1)} + \alpha_{id} + \delta_{\tau+13t} + \epsilon_{id,\tau+13t}. \tag{12}$$

I exclude the price impact measure from the right hand side of (12) to avoid endogeneity due to reverse regression (Hausman, 2001), so long as (11) is a correct specification of data. I apply the same subsampling operations as above, i.e., estimating the model for each of 13 skip subsamples, averaging

13 estimates, etc.

4.4 Returns and Risk Factors

Many studies of empirical finance have verified that illiquidity measures and financial returns correlate positively because investors require a higher return as a compensation for bearing a greater illiquidity risk: see, e.g., Amihud and Mendelson (2008). It is important to check if a similar result holds in the JEPX, because this exchange is supposed to provide a benchmark for power producers in their investment decisions on a variety of power sources, and such decisions should be based on the risk-return tradeoff. For this purpose, I estimate the next model for returns $R_{id,\tau+13t} = \ln P_{id,\tau+13t} - \ln P_{id,\tau+13(t-1)}$ in τ-th "skip 13-week" subsample ($\tau = 1, \ldots, 13$):[6]

$$\begin{aligned} R_{id,\tau+13t} &= \theta_{lag} R_{id,\tau+13(t-1)} + \theta_{pi} \ln PI_{id,\tau+13(t-1)} + \theta_{sc} \ln SC_{id,\tau+13(t-1)} \\ &+ \theta_{iv} \ln IV_{id,\tau+13(t-1)} + \theta_{pv} \ln MV_{id,\tau+13(t-1)} + \alpha_{id} + \delta_{\tau+13t} + \epsilon_{id,\tau+13t}. \end{aligned} \tag{13}$$

There are two justifications for this subsampling-based approach. First, it is important to avoid an adverse impact of persistent variables on estimates.[7] Second, the 13-week window may be more realistic for potential power producers' investment decisions than a shorter, say weekly, window, because the generation of electric power may take some time due to, e.g., the need for installing, modifying and maintaining a large plant. A different timing of subsampling may generate unbalanced panel data, so that it is important to employ the forward orthogonal deviation for eliminating the individual fixed effects because it avoids a data loss (Roodman, 2009). I follow the same subsampling-related operations as in Section 4.3. Inspired by Figure 2, I control the volatility of returns σ_{id} in Equation (1) by a realized measure of the integrated volatility using "skip 13-week" subsampling returns:[8]

$$IV_{id,\tau+13(t-1)} := \left(\sum_{h=1}^{13} R^2_{id,\tau+13(t-h)}\right)^{1/2}. \tag{14}$$

5 Results and Discussion

5.1 The cross-section and time-series of the extracted measures

In Figure 9, the blue dotted lines and red breaking lines show the 503-week means of the Amihud price-impact measures in (9) multiplied by 10^6 as a conventional unit for the Amihud measure, and of the inverse monetary volumes multiplied by 10^5, both scaled in the left axis; and the green starred lines describe the implicit spread cost measures in (8) multiplied by 10^2 for percentage representations, scaled in the right axis. Overall, the liquidity condition, as captured by a small value of the price impact measure, is stable from Tuesday to Friday, improves on Saturday, and worsens toward the opening of a new week. The price-impact aspect of liquidity worsens in every morning from 7:30 to

[6] Amihud (2002, Equation (2)) runs a similar model in an annual scale but relies on a Fama-MacBeth approach, i.e., estimating the cross-sectional regression at each point in time and averaging the estimated coefficients over time. This approach cannot remove the individual fixed effects: see Petersen (2009).

[7] I estimate (13) using the full sample without any skip subsampling by DP, but it is likely to mis-specify the structure of data because the J-statistic is virtually null.

[8] The realized measure of integrated volatility using all successive returns is upwardly biased if the observed log price is subject to (3). The version in (14) based on the the skip subsampling is less biased, as documented by Zhang et al. (2005), and I expect the fixed effects to absorb any remaining bias. A bias-corrected estimator (e.g., Ikeda, 2013) requires a huge amount of high frequency observations.

9:00 and every evening from 22:00 to 0:00 in weekdays. This pattern is consistent with the different timing of two peaks of intra-daily plots of prices and volumes, as addressed in Section 3.2, and more complex than the U-shaped curve of the inverse monetary volume as displayed. For instance, Monday 8:30-18:00 look very liquid as the inverse monetary volume hits the lowest level, but the price impact measure recognizes it as the most *illiquid* period. This is more obvious for the weekday spread costs, as their plots are quite parallel to those of the system prices and raw volumes in Figure 1, hence they are flipped images of the inverse monetary volume. These seemingly contradictory implications may be compatible if there is a large potential demand for electric power in the market during such period: even though the traded volume looks large then, the potential demend for electric power at prices in a reasonable range may be much larger. This possibility suggests the presence of a potential benefit for power producers to enter the JEPX for a profitable transaction of electric power.

Figure 10 collects the time-series plots of the intra-weekly means of the price-impact measures (multiplied by 10^6) and the spread cost measures (in percentages) in 4:30-5:00 and 14:30-15:00. The price-impact measures in 4:30-5:00 tend to be larger than those in 14:30-15:00; and both of them become lower and stabilized since November 2011. Recall that the traded volume drifts upward in this period, as suggested by the middle panels in Figure 7. In contrast, the spread cost measures in 14:30-15:00 interval are higher than those in 4:30-5:00 interval constantly, and both are not stabilized nor lowered in the later sample period. Because the raw traded volume has increased over time, the last point suggests that the traded volume may not affect the implicit spread cost.

5.2 A comparison with emerging financial markets

To gain a sense of the magnitudes of these economic illiquidity measures, I divide the weekly price-impact measures by 5 (the number of trading days in a week), and multiply them by the beginning-of-month contemporaneous JPY-USD exchange rates corresponding to the latest date of observations for the spread measure, or by the the average JPY-USD exchange rate in 1987-2000.[9] These operations convert the weekly spreads in the JEPX to daily U.S. dollar-valued numbers. Then, I multiply the numbers by 10^6, and take the grand mean of these transformed measures over the entire sample. The resulting number is 1.437 based on contemporaneous exchange rates, and 1.687 based on the average exchange rate in 1987-2000. They are similar to 1.427 as the mean daily Amihud measure for 23 emerging financial markets in 1987-2000 as documented by Lesmond (2005, Table 2); or to 1.553 for Thailand.[10] Therefore, the JEPX may not be terribly illiquid so long as the price impact is concerned.

The implicit spread cost in (2) roughly corresponds to the proportional spread in a quote-driven financial market. The grand mean of the extracted spread costs in the JEPX is about 15.72% of the intrinsic value of electric power. This number is worse than the second highest proportional spread cost in the Hungarian financial market (11.14%), and only next to the worst number in the Russian financial market (47.22%), as reported by Lesmond (2005, Table 2). Therefore, the participants in the JEPX may have paid a very high cost of illiquidity in terms of the implicit spread. They suggest why the JEPX struggles to attract many potential power producers and customers, even though there may be a large potential demand for electric power as suggested in Section 5.1: a potentially huge spread cost may be an implicit entry barrier for those outside the exchange, or a strong disincentive

[9]The historical data of USD-JPY exchange rate is retrieved from the website of Federal Reserve Bank of St. Louis. Visit `https://research.stlouisfed.org/fred2/series/DEXJPUS/`

[10]Lesmond (2005, Table 2) covers Argentina, Brazil, China, Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Portugal, Russia, Singapore, South Africa, Taiwan, Thailand, and Venezuela.

for less-profitable incumbents to stay. The last possibility is consistent with the anecdote in Section 1.

5.3 Results of Estimating (11)

Table 1 summarizes the results of estimating (11). "# CS", "# TS" and "# Panel" indicate the number of observations in the displayed dimension, followed by the number of subsamples with the displayed size in parentheses. Recall that the standard errors are designed to err on a conservative side. Nevertheless, all estimates are significant at the 1% level. A significantly positive coefficient of the spread cost suggests that two illiquidity measures do capture a common aspect of illiquidity in the JEPX. A significantly positive coefficient of the monetary volume indicates that a greater volume of electric power trades may improve liquidity in terms of the tightness in the JEPX. Relative to the FE approach, the lack of controlling the fixed effects in the OLS approach may lead to biased estimates. The estimate of the lagged dependent variable is small but significantly positive, suggesting the importance of controlling this factor to make all other estimates more reliable and to improve the model fit by reducing the Nickell bias (Nickell, 1981). Indeed, the DP approach attains the smallest SER among three methods. The degree-of-freedom-adjusted coefficient of determination ($Adj\ R^2$) is at least 80% for the OLS and FE approaches, which is much greater than about 30% obtained by Amihud (2002, p.35) in his cross-sectional OLS regression of his measure onto intra-daily measures of the price impact and the spread cost. Therefore, the displayed significance of coefficients may not be a statistical artifact because a large value of R^2 makes an attenuation bias due to measurement errors smaller (Hausman, 2001), the standard errors are designed to be more conservative, and the SER for the DP approach suggests a better fit than the OLS and FE approaches attain.

5.4 Results of Estimating (12)

Table 2 summarizes the results of estimating (12). The integers in the square brackets below the standard errors in parentheses show how many times the subsampling-based estimates take positive values. Consistent with the discussions in Sections 5.1 and 5.2, the DP estimate of the monetary volume coefficient is not significant even at the 10% level nor uniform over subsamples. However, OLS or FE would judge it as significantly and uniformly positive. This striking contrast suggests that we should rely on DP rather than OLS or FE, even though the lagged dependent variable is not significant.

5.5 Results of Estimating (13)

Table 3 summarizes the results of estimating (13). Let me first discuss the results based on three methods, using the skip subsamples which cover the entire sample period, as indicated by "full" in the headers of the second to fourth columns. First, the final estimates share the same signs. The price-impact measure and the spread cost measure are positive correlates of returns, and the former is greater in magnitude. It suggests that the participants in the JEPX view the price impact as a stronger risk factor than the spread cost and require a higher risk compensation. This may sounds at odds with a potentially huge spread cost as indicated in Section 5.2, but they are compatible if the implicit spread cost is a hidden entry barrier for potential power producers outside the JEPX, while the returns are driven by the behavior of incumbents in this exchange. The monetary volume has a negative impact on returns, suggesting that the participants feel safer if they observe a large traded volume and require less risk compensation. The strongly negative association of the volatility measure with returns is consistent with Amihud (2002, Table 2) and Ang et al. (2006, 2009).[11] Despite these common features of estimates, we should prefer DP to OLS or FE for reasons discussed in Section 5.4. In fact, OLS and FE miss the significance of some explanatory variables, and their SERs are larger than that of DP.

Let me check if the liquidity condition in the JEPX changed before and after the great earthquake. The fifth and sixth columns in Table 3 summarize the DP estimates of a similar subsampling-based model, using only data points in S1 and in S3+S4. They suggest that the full-sample results in the fourth column are mainly driven by properties of data in the pre-earthquake period. In the sixth column for the estimates in S3+S4, economic measures loose their significance. I further estimate (13) in S3 and S4 separately, as summarized in the last two columns. The displayed numbers indicate that the JEPX might be totally disturbed in S3, as suggested by a counter-intuitive negative association of these illiquidity measures with returns and a higher SER. The results in S4 hint the recovery of the tradeoff between the illiquidity risk and returns, as the estimate of the price-impact coefficient becomes positive.

6 Conclusions and Policy Implications

The empirical strategies and results in this study have rich implications for how to design, operate, monitor and reform a day-ahead electric power exchange. First, we should attempt to assess various aspects of illiquidity in a power exchange. Even though a traded volume may be informative about the liquidity condition in the market, some economic measures may show different pictures. The approach in this study is practical for that purpose, because I use only the historical data of prices and volumes. Second, the regulatory authority should pay more attention to the implicit spread cost in the exchange, because a high trading cost may be an implicit entry barrier for potential power producers outside the exchange. Third, the measurement of the implicit spread cost requires a caution in relation to the market-clearing mechanism. If a newly established power exchange adopts a call auction mechanism, the assessment of an implicit spread cost needs justifications as I give in Section 1, because the majority of works in empirical finance rely on the bid-ask spread, which is valid only in a quote-driven market. Fourth, returns in the JEPX may reflect the price-impact aspect of illiquidity more than the spread cost aspect, hence the incumbents in the JEPX view the former as a more risky factor. This is surprising because the magnitude of the spread cost is comparable to the most illiquid emerging markets in 1990s. One way to reconcile these results is to assume that the implicit spread cost is linked to the entry decision of potential power producers, while the price impact measure is related to the concerns of incumbents in the JEPX. Fifth, any statistical analysis requires a careful control of confounding factors, especialy fixed effects, market-wide time effect, persistence of the dependent variable, etc., all of which are nicely managed in a dynamic panel framework. It seems a novel approach to view those contracts of power delivery in 48 half-hour periods within a day and within a week as cross-sectional units.

The most crucial policy implications from this study are (a) the JEPX is very illiquid in terms of the spread cost, but (b) a larger volume does not help reducing it. Recall that the spread cost in Brünner's model depends on trader's heterogeneity and asymmetry of information between the insider

[11] The negative correlation is puzzling, according to a risk-return tradeoff even in a market with frictions (Merton, 1987), and dubbed as an idiosyncratic volatility puzzle in the field of empirical finance. It is interesting to observe a similar puzzle in the JEPX, which is not a standard financial market.

who knows the true value of electric power in some contingency and general traders. Resorting to more indirect but numerous justifications of the spread cost in a call auction mechanism as introduced in Section 1, the spread cost can additionally include (i) the order-processing cost of traders who choose to stay continually in the market, such as the clearing fees and per trade allocation of fixed costs for computers, telephones, and high-speed servers and (ii) the inventory cost of such traders in preparation for a random large-order imbalance (see Hasbrouck, 2007, and references therein for these aspects of the spread cost). The managers and regulartory authority of the JEPX should continually improve these aspects of the spread cost. As a monitoring tool in doing so, the authority should keep an eye on the serial covariance of weekly returns because they are very informative about how the spread cost may change.

Finally, it is difficult to deal with GES in the JEPX: they are almost indispensable for a newly established power exchange to ensure the minimum amount of liquidity in the market for a smooth operation and to guarantee a stable transmission of electric power. On the other hand, they may have little or negative incentives for the power exchange to grow in its activities because they can always bi-laterally sign a contract with PPS. In addition to this disincentive for the GES to let the JEPX improve, its behavior as the informationally superior market participant may hinder the reduction in the JEPX's implicit spread cost. Recall that a shift of the entire demand or supply curve by the insider is the main culprit, thus a wedge for the identification of, the implicit spread cost in Br unner's model. The JEPX's spread cost seems large and stable even though the monetary volume condition has improved over time. Indeed, Agency for Natural Resources and Energy (2017, p.318) as a branch of the METI reports one anecdote that TEPCO might bid at a price much higher than their marginal cost of power generation, thereby raising the equilibrium price. It is unclear to me if this seemingly strategic bidding might stem from TEPCO's desire not to let the market function, from their rational behavior to exploit its informational superiority, from the lack of internal adjustment time for planning and generating electric power and for coordinating operations by different sections inside it, or from any other factors. A further academic investigation about this incidence is quite valuable from a regulatory perspective.

The nexus of a market microstructure analysis in this study and a political economic analysis of regulation of electric power industry may provide a convincing argument about how to let these regionally monopolistic power producers involve in the progress of a power exchange.

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Table 1: The Estimation Results for (11) (Dependent: $\ln PI_{id,\tau+13t}$)

Variables	OLS	FE	DP
$Const$	6.1272^{***}	2.7448^{***}	
	(0.0586)	(0.1744)	
Lag			0.1040^{***}
			(0.0075)
$\ln SC$	0.3804^{***}	0.2967^{***}	0.2935^{***}
	(0.0109)	(0.0095)	(0.0093)
$\ln MV$	-1.0469^{***}	-0.6797^{***}	-0.6321^{***}
	(0.0058)	(0.0200)	(0.0182)
$Adj.R^2$	0.8076	0.8992	
SER	0.5074	0.3673	0.3645
$\#CS$	336	336	336
$\#TS$	38 (9)	38 (9)	36 (9)
	37 (4)	37 (4)	35 (4)
$\#Panel$	12768 (9)	12768 (9)	12096 (9)
	12432 (4)	12432 (4)	11760 (4)

***: significant at the 1% level (two-sided).

Table 2: The Estimation Results for (12) (Dependent: $\ln SC_{id,\tau+13t}$)

Variables	OLS	FE	DP
$Const$	-4.0283^{***}	-3.1404^{***}	
	(.0.1063)	(.0.3399)	
	[0]	[0]	
Lag			0.0080
			(.0.0132)
			[7]
$\ln MV$	0.1315^{***}	1.2207^{***}	0.0546
	(.0.0119)	(.0.0399)	(.0.0401)
	[13]	[13]	[9]
SER	1.034	0.884	0.878
$\#CS$	336	336	336
$\#TS$	38 (9)	38 (9)	36 (9)
	37 (4)	37 (4)	35 (4)
$\#Panel$	12768 (9)	12768 (9)	12096 (9)
	12432 (4)	12432 (4)	11760 (4)

***: significant at the 1% level (two-sided).

Table 3: The Estimation Results for (13) (Dependent: $R_{id,\tau+13t}$)

Variables	OLS (full)	FE (full)	DP (full)	DP (S1)	DP (S3&S4)	DP (S3)	DP (S4)
$Const$	0.1558***	1.2311***					
	(0.1479)	(0.0832)					
	[6]	[13]					
Lag			−0.3806***	−0.3168***	−0.4202***	−0.4219***	−0.4082***
			(0.0094)	(0.0117)	(0.0159)	(0.0208)	(0.0235)
			[0]	[0]	[0]	[0]	[0]
$\ln PI$	0.0092	0.0864***	0.0587***	0.0802***	0.0214	-0.0170	0.0199
	(0.0207)	(0.0130)	(0.0116)	(0.0148)	(0.0195)	(0.0386)	(0.0287)
	[9]	[13]	[13]	[13]	[8]	[5]	[7]
$\ln SC$	0.0130***	0.0040	0.0071***	0.0093***	−0.0093*	−0.0117	−0.0111
	(0.0042)	(0.0028)	(0.0026)	(0.0030)	(0.0050)	(0.0085)	(0.0086)
	[8]	[10]	[11]	[11]	[3]	[3]	[4]
$\ln MV$	−0.0200	−0.1343***	−0.1364***	−0.1599***	−0.3429***	−0.4837***	−0.5011***
	(0.0215)	(0.0113)	(0.0102)	(0.0133)	(0.0320)	(0.0644)	(0.0635)
	[7]	[0]	[0]	[0]	[0]	[0]	[1]
$\ln IV$	−0.0439*	−0.1254***	−0.1077***	−0.1435***	−0.0068	0.0121	0.0180
	(0.0225)	(0.0147)	(0.0142)	(0.0171)	(0.0243)	(0.0455)	(0.0377)
	[5]	[0]	[0]	[0]	[7]	[8]	[9]
SER	0.325	0.196	0.174	0.176	0.164	0.211	0.159
$\#CS$	336	336	336	336	336	336	336
$\#TS$	37 (9)	37 (9)	36 (9)	20 (6)	14 (5)	5 (13)	7 (5)
	36 (4)	36 (4)	35 (4)	19 (7)	13 (8)		6 (8)
$\#Panel$	12432 (9)	12432 (9)	12096 (9)	6720 (6)	4704 (4)	1680 (9)	2352 (5)
	12096 (4)	12096 (4)	11760 (4)	6384 (7)	4656 (1)	1679 (2)	2064 (8)
					4368 (8)	1632 (2)	

***: significant at 1% level (two-sided). *: significant at 10% level (two-sided).

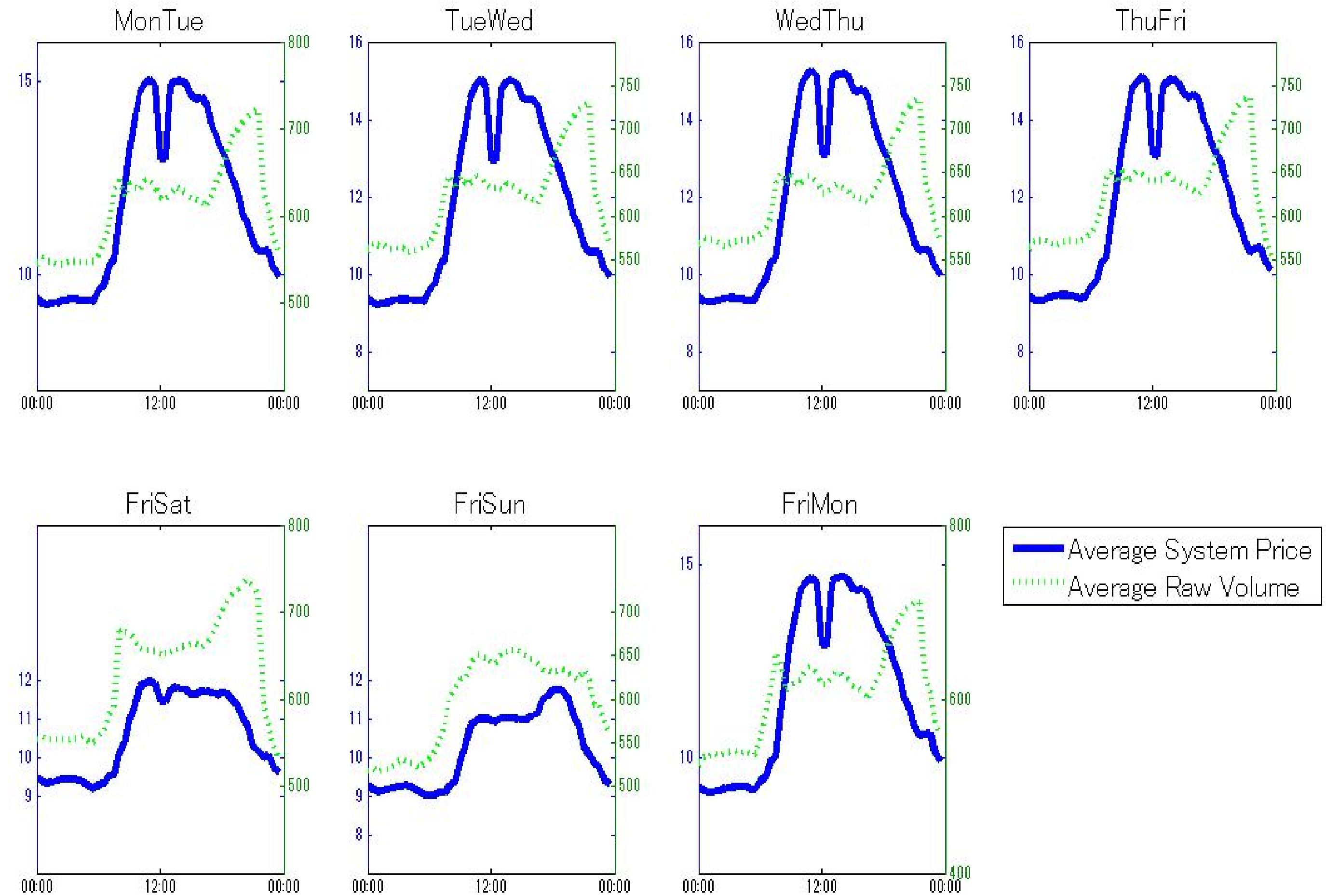

Figure 1: The intra-daily and -weekly plots of average prices and volumes.

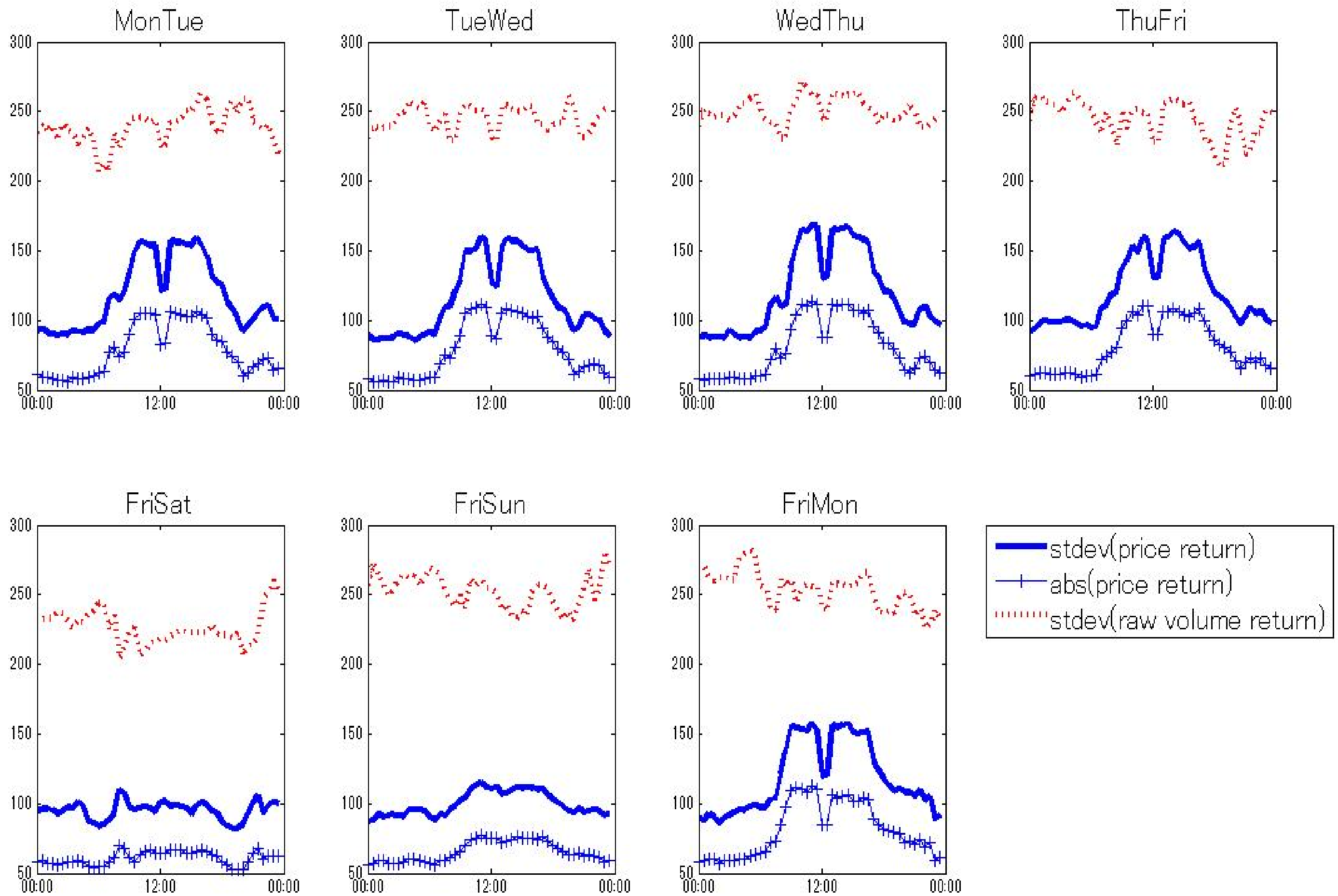

Figure 2: The intra-daily and -weekly plots of volatility measures.

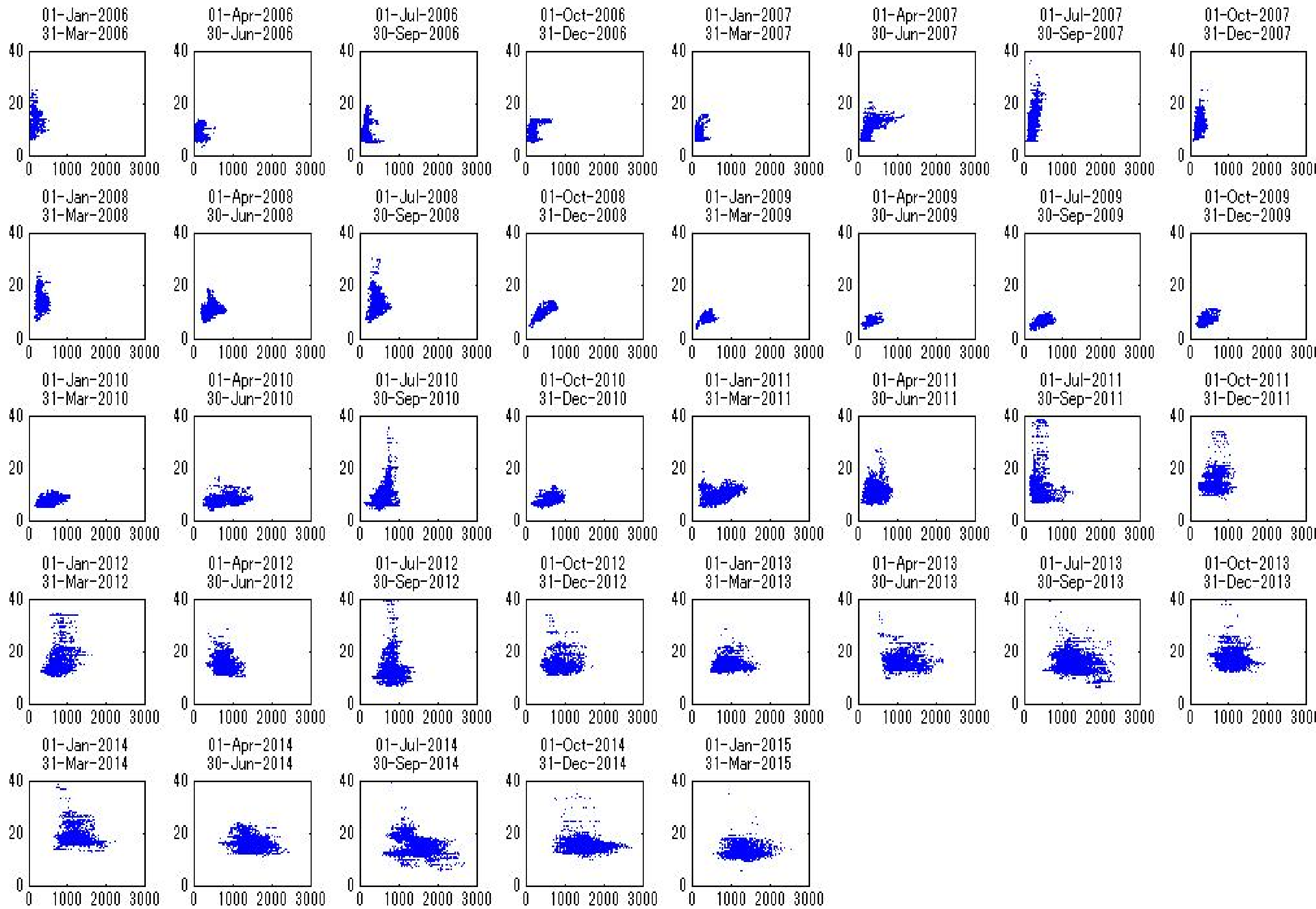

Figure 3: The quarterly scatterplots of prices against volumes.

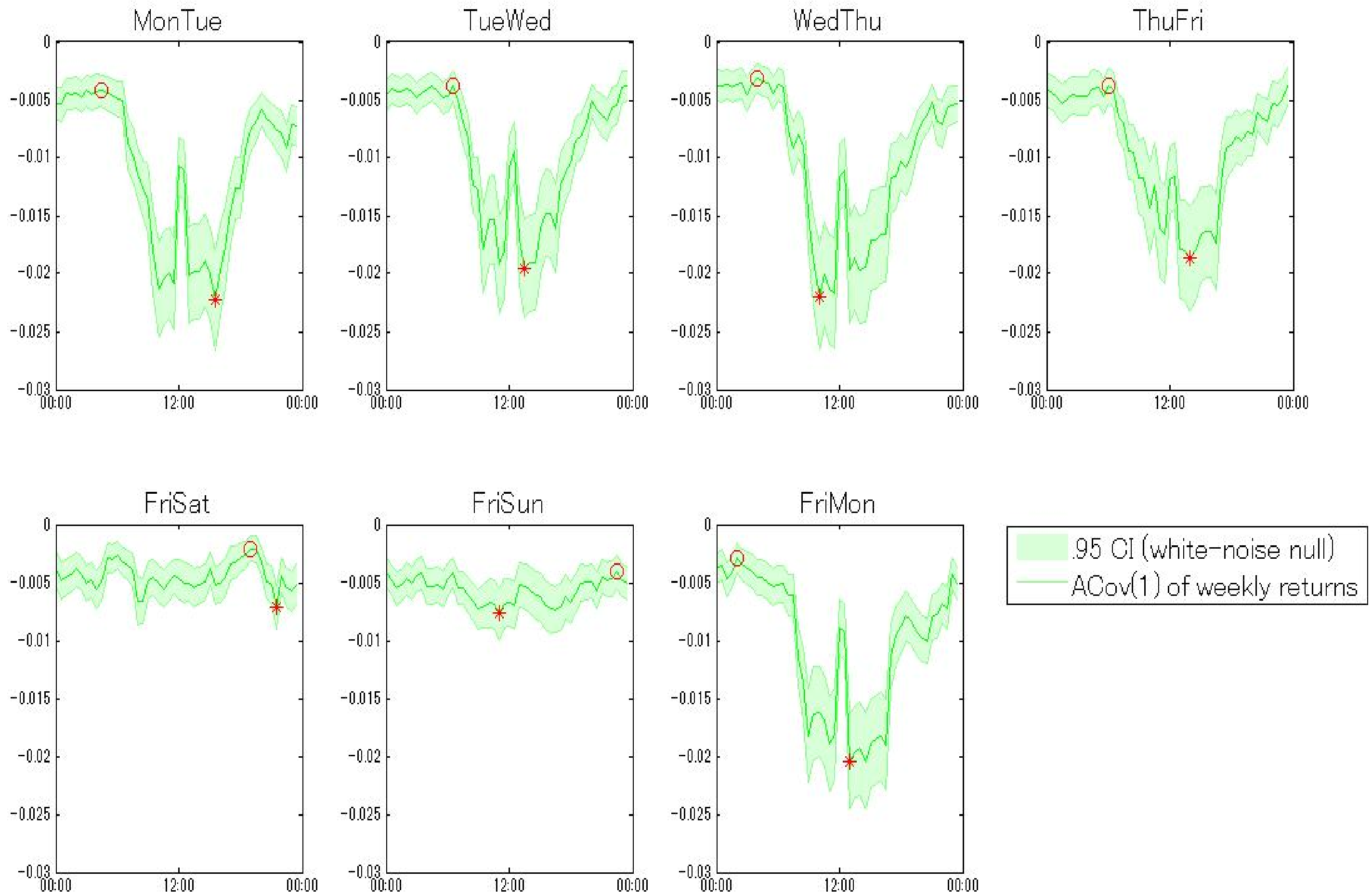

Figure 4: The intra-daily and -weekly plots of the first-order autocovariances of returns and 95% confidence bands.

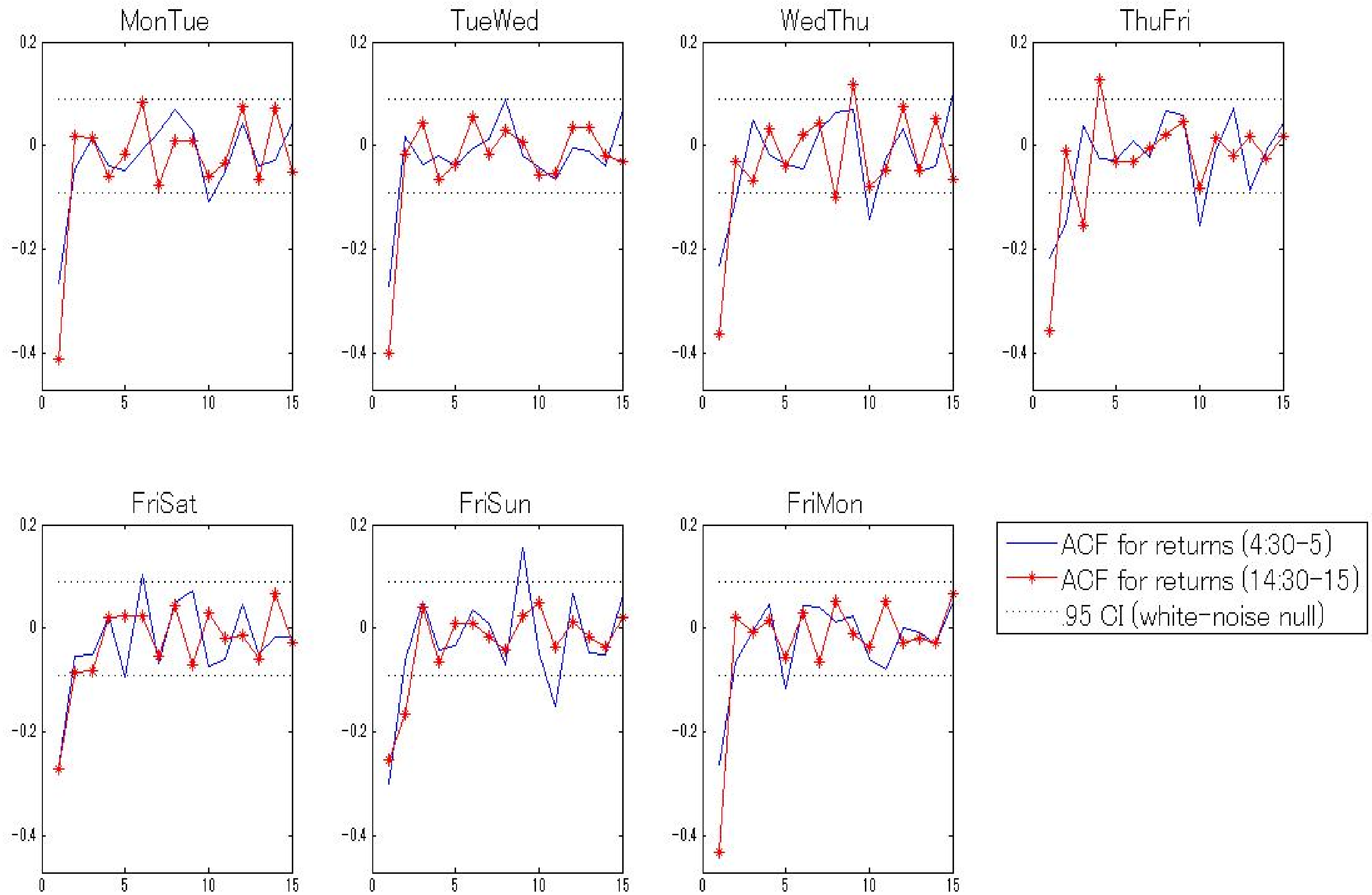

Figure 5: The intra-daily and -weekly plots of autocorrelation functions of returns and the white-noise band.

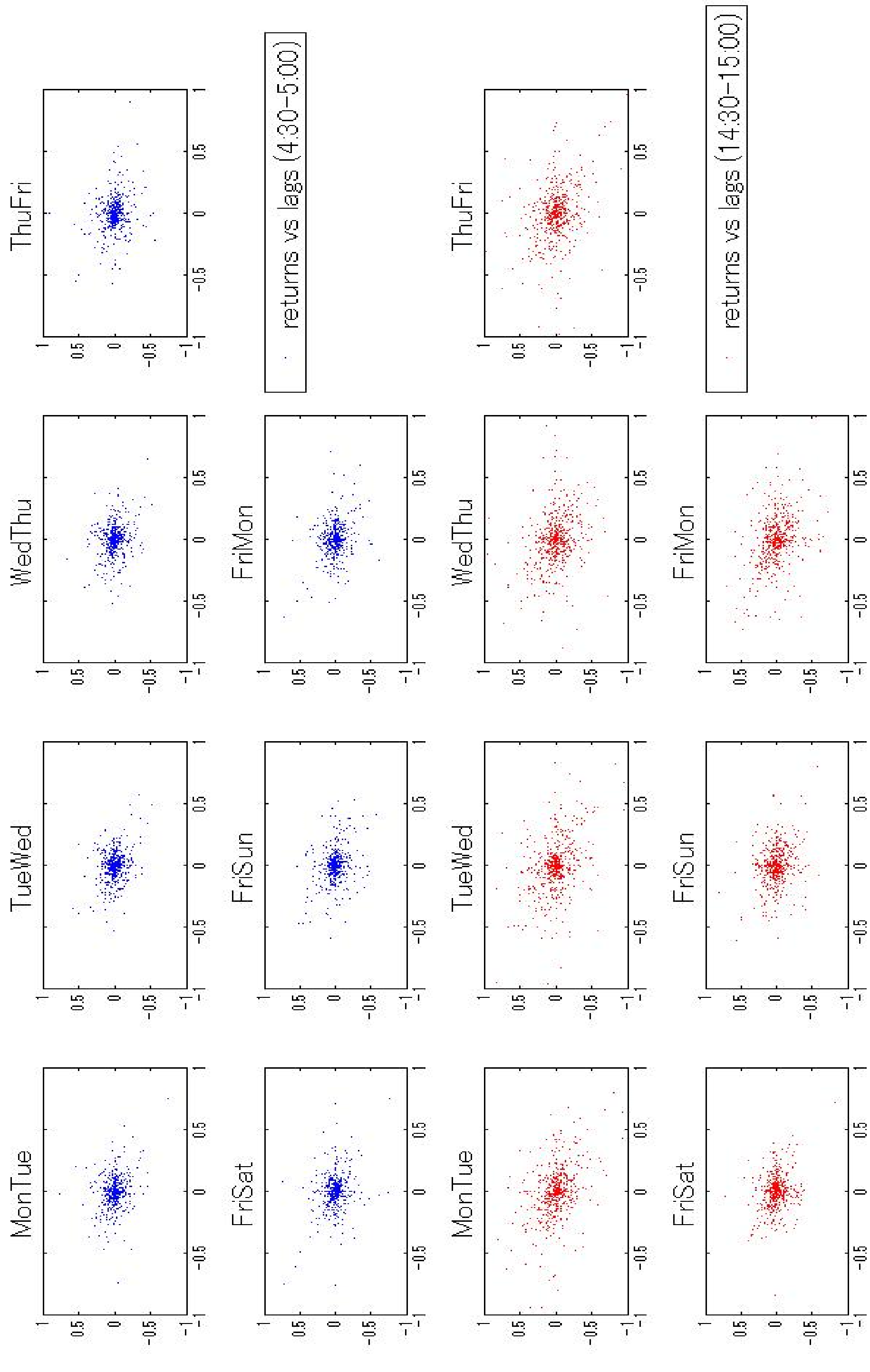

Figure 6: The compass-rose diagrams.

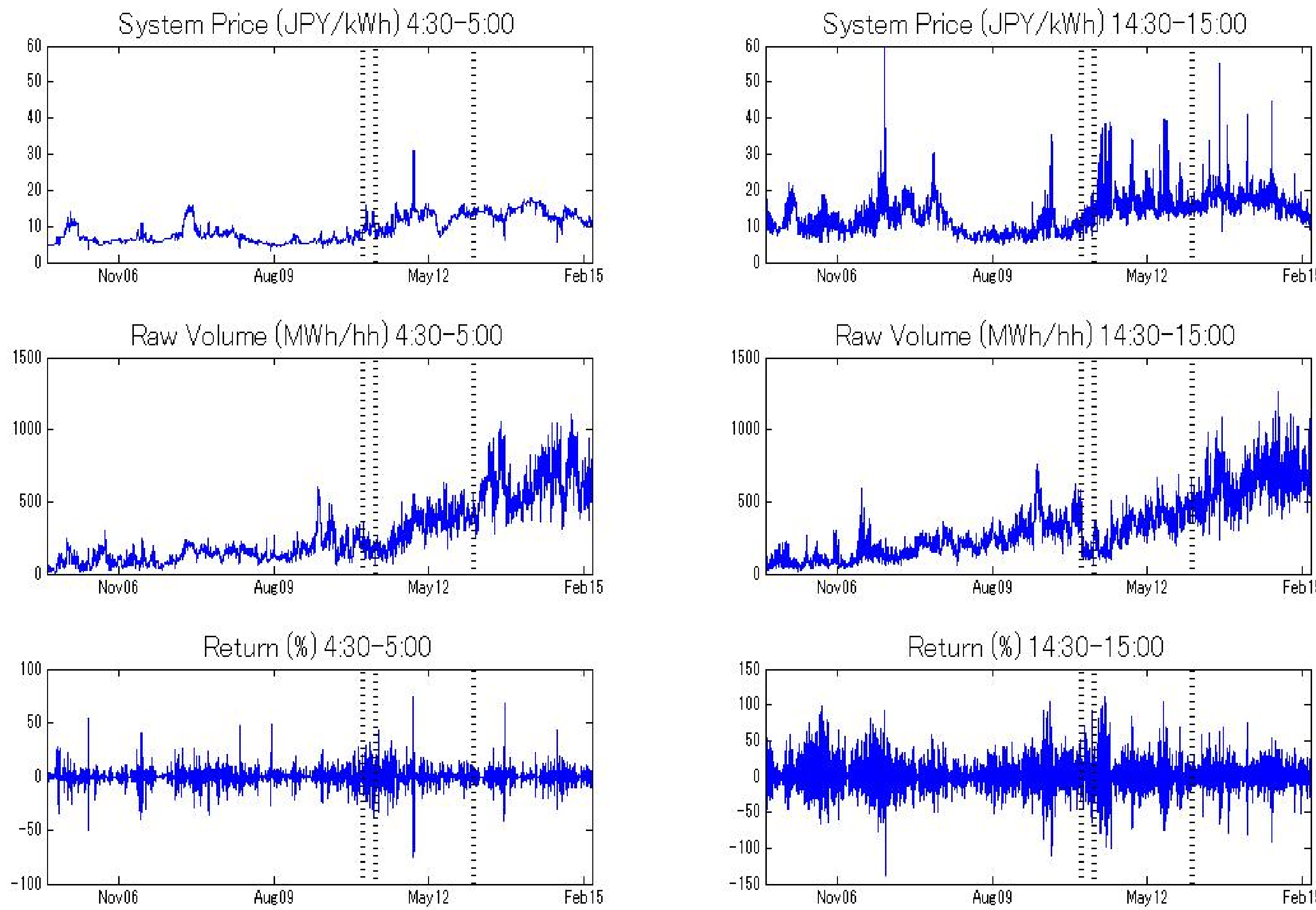

Figure 7: The time-series plots of prices, volumes and returns.

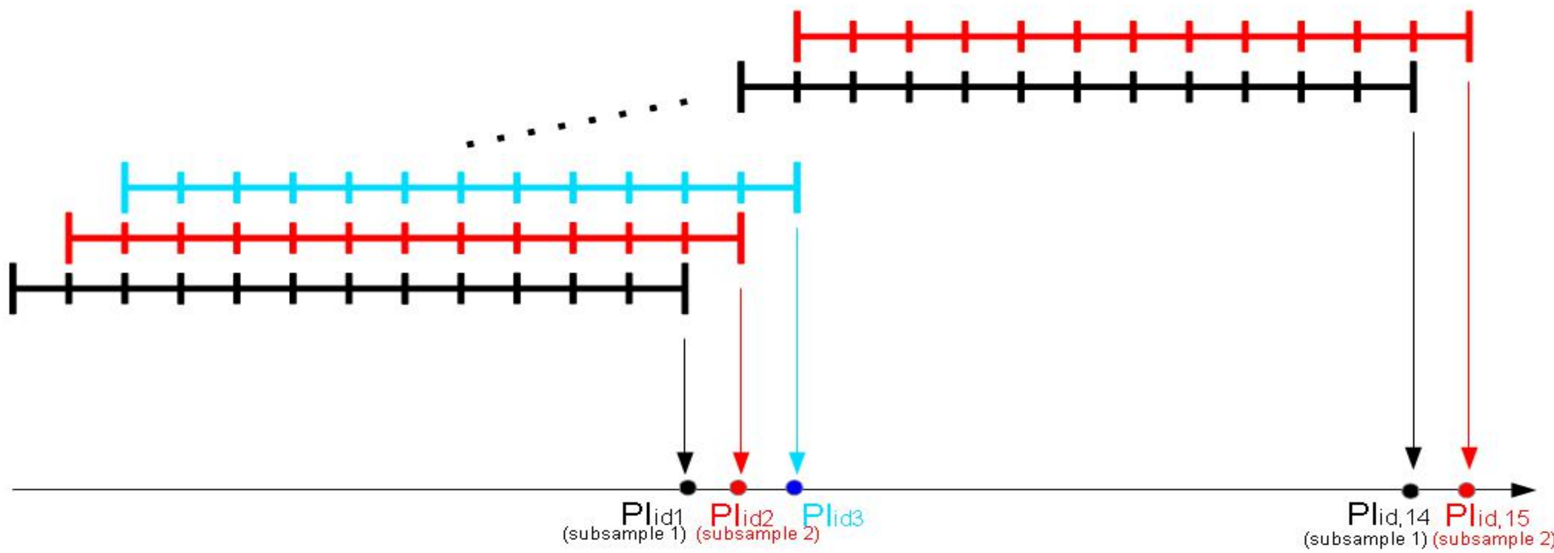

Figure 8: The “skip 13-week” subsampling scheme.

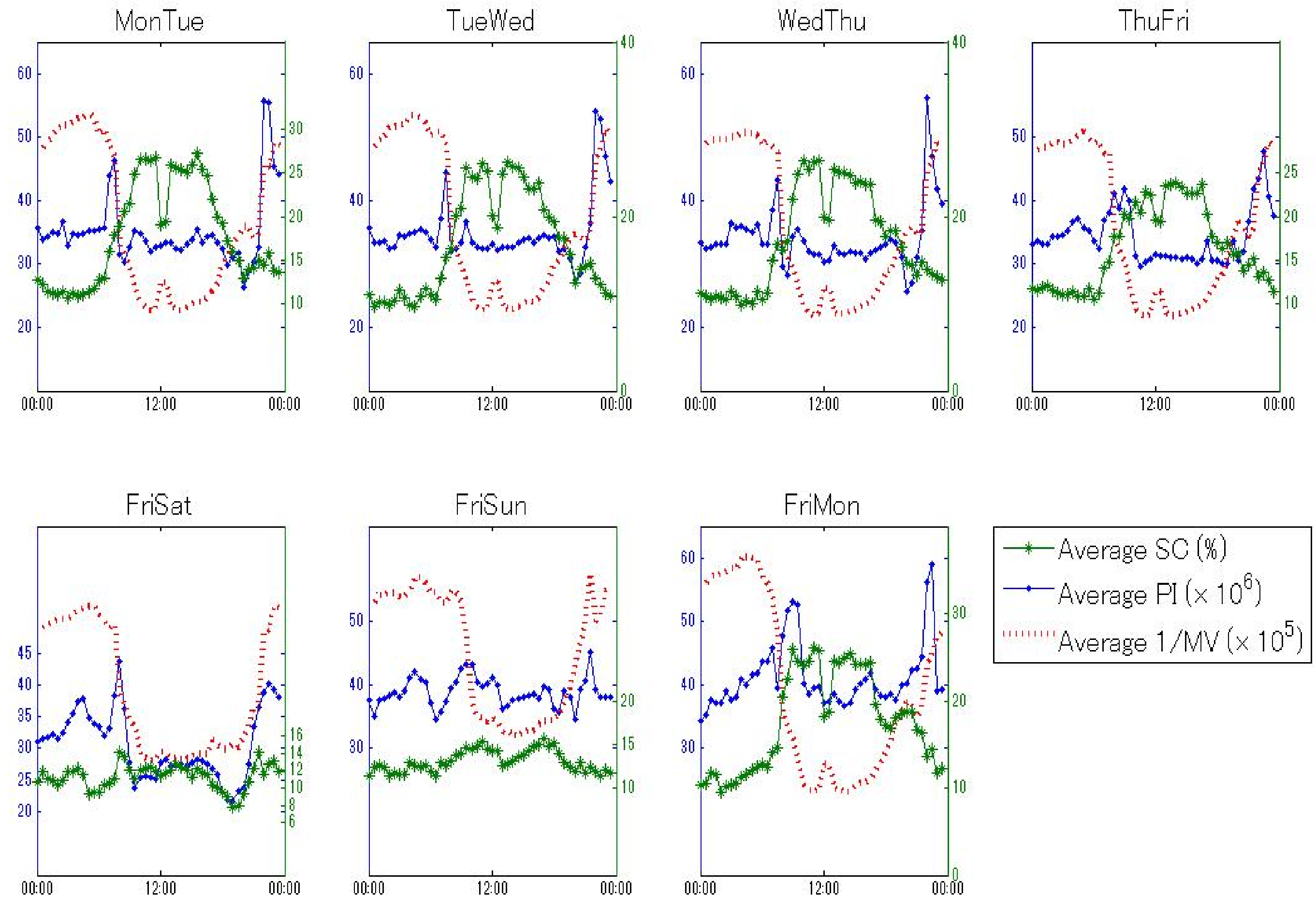

Figure 9: The intra-daily and -weekly plots of the extracted illiquidity measures and inverse monetary volumes.

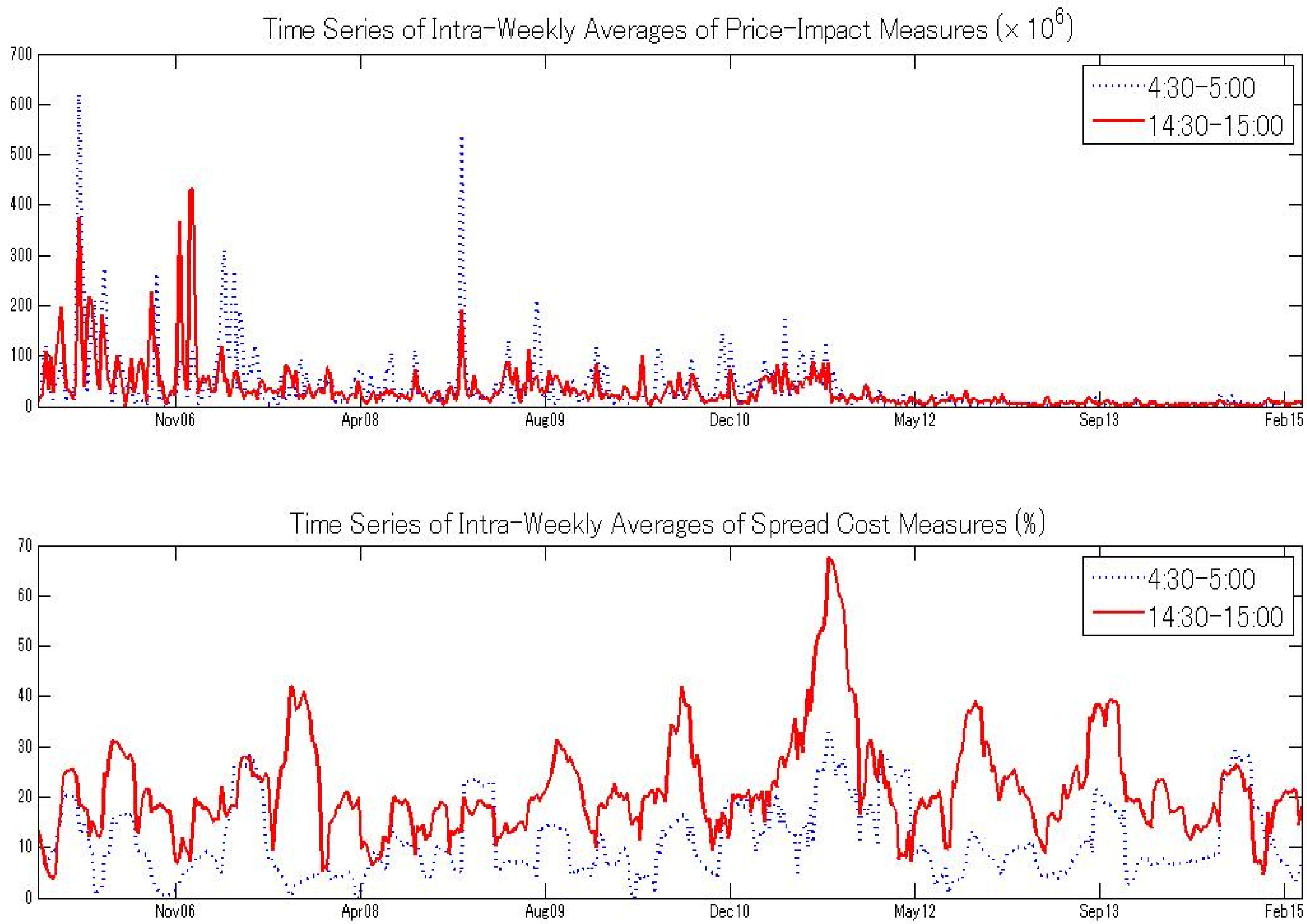

Figure 10: The time-series plots of the extracted illiquidity measures.