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International cross-listing and price discovery under trading concentration in the domestic market: Evidence from Japanese shares

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ABSTRACT

This study examines the role for the Tokyo and the New York Stock Exchange in price discovery for Japanese shares. A structural approach is employed to investigate the efficiency and contribution in price discovery separately. We find that the speed of incorporating information into prices is faster in New York than in Tokyo. Three approaches are taken to control the size of information and confirm that New York is the efficient side in information assimilation. We also find that the observable liquidity measures such as trade frequency, bid–ask spread, volume per trade and return variance, explain the price discovery efficiency.

1. Introduction

Since 1970, when Sony listed its shares on New York Stock Exchange (NYSE), Japanese companies have been listing their shares in U.S. markets and traded as American Deposit Receipts (ADR). There exist many explanations for cross-listings, but in this paper we focus on its effect on price informativeness. Literatures suggest that cross-listing enhances price informativeness.[1] But is this also the case for two markets not having overlapped trading hours such as the case of Tokyo and New York?

Literatures of price discovery across markets are initiated by studies on U.S. stocks cross-listed in central and regional markets. Articles in that line of studies include Hasbrouck (1995), Harris et al. (1995) and Harris et al. (2002) for example.[2] Studies of price discovery across international markets have been increasingly shown its presence. Kleidon and Werner (1996) analyze intraday patterns for U.K. and U.S. trading of British cross-listed stocks. They focus on studying price volatility, volume and liquidity during overlapping period of New York and London market. Menkveld (2008) extends the model of Chowdhry and Nanda (1991) to analyze British and Dutch ADRs. Eun and Sabherwal (2003) examine the price discovery of Canadian stocks listed on both the Toronto Stock Exchange and U.S. exchange. The markets examined in those studies share their trading hours.

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[1] Foucault and Gehrig (2008), Foucault and Fresard, 2013 and Fernandes and Ferreira (2008) for example.

[2] Hasbrouck (1995) and Harris et al. (2002) introduced the widely used reduced model methods. Baillie et al. (2002) show that the two measures can be obtained by estimating a vector error correction model.

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In contrast, this paper examines the price discovery between two markets without overlapped trading hours.[3] If the two markets' operating hours do not at all overlap, trading period of the cross-listed stocks would be simply doubled (or more), which would increase the opportunity of incorporating information to its price. However during the NYSE trading hours, it is midnight in Tokyo and the business operations of the Japanese firms are inactive and changes in the value of the firms would be moderate. In fact, the trading volume of Japanese shares in NYSE amounts only for 3% of trading volume in Tokyo. Despite the small trading volume, is New York still an exchange worth cross-listing for Japanese firms? Does the price informativeness of Japanese shares enhanced? The present paper attempts to answer these questions by investigating the efficiency of price discovery and the magnitude of information arrival in the two markets.

Despite their strong presence in the global market, price discovery of cross listed stocks in the two markets has been little studied in the literature. Lau and David Diltz (1994) use the opening and closing stock prices of seven Japanese cross-listed firms and find bidirectional causality but a stronger impact of NYSE returns on Tokyo returns than the reverse. Karolyi and Stulz (1996) use open-to-close and close-to-open returns of eight Japanese ADRs to investigate the determinants of U.S. and Japanese stock return comovements.

This article is the first to study the dynamic aspect of the price discovery of cross listed stocks in the Tokyo Stock Exchange (TSE) and NYSE using high-frequency data. We extend the price discovery literature by distinguishing the two aspects of the price discovery, the efficiency (or speed) and the magnitude of information arrival. The distinction of the two features is crucial in a non-overlapped trading hours setting, such as the case of TSE and NYSE. When two markets do not share their trading hours, faster information assimilation does not necessary mean a larger size of information incorporation. Even a market is efficient in information assimilation, if the size of the change in the fundamental, i.e., the magnitude of information arrival, is small, the ultimate size of information incorporated during its trading hours may be limited. On the other hand, even if a market is less efficient in information assimilation, if the magnitude of information arrival during its trading hours is large, the ultimate size of information incorporated may be large. The reduced model approaches widely employed in existing literatures do not, and do not need to, consider the potential difference in the magnitude of information arrival as their subject markets under study share their trading hours.

We develop a methodology based on a state space model to explore the speed of price discovery and the magnitude of information arrival. The unobserved efficient price process is modeled as a random walk with deterministic, market-dependent volatility. We model the observed traded price as the adjustment to the efficient price plus temporal microstructural noises. Microstructural noises include errors in analysis or interpretation of information, transitory liquidity needs of traders and asymmetric information. The price adjustment term captures the tendency of the reaction of market participants. The observed price may adjust partially to information or it may overreact to news. Hence even there is no stochastic noise, by this under- or over-reaction of traders, prevents market prices from immediate adjustment on the new information. The model is estimated using by numerically maximizing the likelihood evaluated by the Kalman filter.

The state space model is estimated based on the intraday data of cross-listed Japanese stock in TSE and NYSE over the period September 2007–April 2008. Our findings indeed suggest that the difference in the magnitude of information arrival must be considered. The estimated price discovery measure shows that the speed of incorporating information into prices is faster in New York than in Tokyo. More than 80% of the information arrived in New York is immediately incorporated into prices while it is only 17% in Tokyo. On the other hand, we find that the magnitude of information arrival observed at Tokyo is four times greater than in New York.

As the magnitude of information arrival greatly differs between the two markets, we attempt to control it and obtain a standardized measure of efficiency of information assimilation.[4] Three approaches are taken to control the size of information arrival. The first approach uses the estimates of the speed of information incorporation in order to derive the size of information incorporated per hour. The results imply that price discovery in New York is three times faster than Tokyo.

The second and third approach estimate regressions to test whether the price discovery inefficiency measure is significantly smaller in New York when the size of information is controlled. The results also confirm the informational efficiency of New York. The last approach also allows us to consider whether the observable liquidity measures, such as trade frequency, bid–ask spread, volume per trade and return variance, explain the price discovery efficiency. We find that the measures explain the price discovery efficiency up to 68%.

The benefit for Japanese firms of cross-listing from the improvement in price informativeness seems to be very limited. However, although the direct contribution is restricted, trade activities in the foreign market may indirectly contribute by enhancing the efficiency of the domestic market's price discovery process. Thus, lastly, we ask whether liquidity measures of New York explain efficiency in price discovery of Tokyo. The results show that the provision of liquidity in the foreign market contributes to enhance the price discovery process in the domestic market. The liquidity measures for New York explain 43% of the price discovery efficiency of Tokyo.

The rest of this paper is organized as follows. Section 2 introduces the structural model employed in the present study followed by the methods to measure efficiency in price discovery and the magnitude of information arrival. Section 3 describes

[3] Wang and Yang (2011) examine the FX markets in non-overlapping markets setting. Their structural VAR approach with open-to-close returns does not capture the dynamic aspect of the price discovery. The study applying the most similar approach to the present research is done by Menkveld et al. (2007). Based on partial price adjustment model, they investigate around-the-clock price discovery for Amsterdam–New York cross-listed stocks.

[4] The terms “price discovery,” “information assimilation” and “information incorporation” will be used interchangeably.

the applied data, including the observable liquidity measures and conducts preliminary analysis based on variance ratio test. Section 4 presents the Estimation results and Section 5 concludes.

2. Methodology

The price discovery measures which are widely used in the literature, the Information share (Hasbrouck, 1995) and the Component share (Harris, McInish and Wood 2002), are computed from coefficient estimates of a vector error correction model. This implies that to apply the methods, the trading hours of the two markets in interest must be overlapped. The measures are not capable to examine the price discovery in a non-overlapping trading hour setting, such as the case of TSE and NYSE. Thus we suggest a structural model approach which is able to overcome the limitation of the commonly used reduced model approach. The model we utilize in the paper is a variant of the partial price adjustment model used by Amihud and Mendelson (1987).[5]

Suppose that there exists a financial asset traded at two markets. Let m_t denote the log efficient price of that asset and $p_{i,t}$ denote its log observed price at market i,

$$\begin{aligned}\Delta p_t &= D_t\left(\delta_1\left(m_t - p_{1,t-1}\right) + w_{1,t}\right) + (1-D_t)\left(\delta_2\left(m_t - p_{2,t-1}\right) + w_{2,t}\right),\\ m_t &= m_{t-1} + D_t v_{1,t} + (1-D_t) v_{2,t}\end{aligned} \tag{1}$$

where

$$\begin{aligned}E\left(v_{i,t}\right) = 0,\; E\left(v_{i,t}v_{i,\tau}\right) &= \begin{cases} 0 & t \neq \tau \\ \sigma_{vi}^2 & \text{otherwise}\end{cases}\\ E\left(w_{i,t}\right) = 0,\; E\left(w_{i,t}w_{i,\tau}\right) &= \begin{cases} 0 & t \neq \tau \\ \sigma_{wi}^2 & \text{otherwise}\end{cases}.\end{aligned}$$

$v_{i,t}$ is the innovation to the efficient price, the information shock. $w_{i,t}$ is the noise innovation, the microstructural shock. This stochastic noise pushes the transaction price of the stock away from its fundamental value. Microstructural noises include errors in analysis or interpretation of information, transitory liquidity needs of traders and asymmetric information. $D_t = 1$ when home market is open and $D_t = 0$ when foreign market is open.

δ_i is the price adjustment coefficient. It captures the tendency of the reaction of market participants. If $\delta_i < 1$, transaction prices adjust partially to information, whereas $\delta_i > 1$ implies overreaction to news. Thus, even there is no stochastic noise, by this under- or over-reaction of traders, prevents market prices from immediate adjustment on the new information. Market under-reaction may be caused by strategic trading by informed investors who split their order across time for example. A possible cause of market over-reaction is the liquidity suppliers who are compensated for their services. If price adjusts to the fundamental immediately, $\delta_i = 1$, the adjustment is a full price adjustment.

Recognizing that the partial price adjustment model has state space representation, Kalman filter can be employed to estimate the parameters. Kalman filter also gives estimates for unobserved efficient prices, information shocks, and microstructural noises. Using Kalman filter to the state space model, measures for the speed of incorporating information and the size of information incorporated are estimated.

2.1. Efficiency in price discovery: speed of incorporating information

Model (1) shows explicitly that the market has two types of shocks, noise and information. The method suggested by Yan and Zivot (2007) to measure the efficiency of price discovery, the price discovery impulse response function (PDIRF), is based on the idea of impulse response on the latter shock. To derive PDIRF, represent the transaction price process as follows[6]:

$$p_{i,t} = \sum_{j=1}^{t}\left\{(1-\delta_i)^{t-j}\delta_i\sum_{l=1}^{j} v_{i,l}\right\} + \sum_{j}^{t}(1-\delta)^{t-j} w_{i,j}, \qquad i = 1,2 \tag{2}$$

and then PDIRF is given by

$$f_{i,k} = \frac{\partial p_{i,t}}{\partial v_{i,t-k}} = \sum_{l=0}^{k}\delta_i(1-\delta_i)^l \qquad i = 1,2, k = 0,1,\cdots. \tag{3}$$

[5] Menkveld et al. (2007) and Frijns and Schotman (2009) also use structural approach to examine price discovery. Menkveld et al. model the efficient price process with market-wide shocks. The model by Frijns and Schotman suits for an analysis of the dynamics of the quote change. Those features, market-wide shocks and quote change dynamics, are beyond the scope of the present paper. Thus we keep the model as parsimonious as possible.

[6] See Appendix for derivation.

Table 1
List of sample stocks.

US Ticker	JPN Code	Name	ADR ratio
ATE	6857	Advantest Corp.	1
CAJ	7751	Cannon Inc.	1
HIT	6501	Hitachi Ltd.	0.1
HMC	7267	Honda Motor Co. Ltd.	1
IX	8591	ORIX Corp.	2
KNM	9766	Konami Corp.	1
KUB	6326	Kubota Corp.	0.2
KYO	6971	Kyocera Corp.	1
MC	6752	Matsushita Electric Industrial Co. Ltd.	1
MFG	8411	Mizuho Financial Group Inc.	500
MTU	8306	Mitsubishi UFJ Financial Group Inc.	1
NJ	6594	Nidec Corp.	4
NMR	8604	Nomura Holdings Inc.	1
NTT	9432	Nippon Telegraph and Telephone Corp.	200
SNE	6758	Sony Corp.	1
TDK	6762	TDK Corp.	1
TM	7203	Toyota Motor Corp.	0.5

The table contains company names of 17 cross-listed stocks. While ticker symbols are used in NYSE, code numbers are used in Tokyo. ADR ratio is the relationship between the ADR and the underlying share. For instance, 10 shares of Hitachi traded in New York is equivalent to 1 share of its underlying traded in Tokyo.

Since it is the innovation of intrinsic value of the stock, information shock has to be a permanent effect, i.e., the impulse response $f_{i,k}$ converges to one:

$$\lim_{k\to\infty} f_{i,k} = 1 \qquad i = 1,2 \tag{4}$$

To suffice this condition we have to restrict δ_i in the range of [0, 2]. Hence, a fast convergence of PDIRF means a fast full-incorporation of information shock into the transaction price. PDIRF is function of only one variable, δ_i. And the equation above implies that the closer the δ_i to one, the faster the PDIRF converges to one.

We measure the efficiency of price discovery by how close δ_i is to one by its quadratic loss function:

$$Loss_i = (1-\delta_i)^2. \tag{5}$$

As it measures the loss of informational efficiency, greater $Loss_i$ implies less efficient price discovery process. Further in order to compare price discovery efficiency between two markets, $Loss_i$ can be used as:

$$LR = Loss_1/Loss_2 = (1-\delta_1)^2\Big/(1-\delta_2)^2. \tag{6}$$

If the loss ratio, LR, is smaller than one, market 1 is more efficient in incorporating price information into the transaction price.

The partial price model has state space representation. The unobserved efficient prices m_t are states and the observed transacted prices $p_{i,t}$ are observations. By assuming all $v_{i,t}$ and $w_{i,t}$ are normally distributed with mean zero, mutually and serially uncorrelated, Kalman filter and its associated algorithm obtains the efficient price series $\{m_t\}_{t=0}^{T}$, information shocks $\{v_{i,t}\}_{t=0}^{T}$, microstructural noises $\{w_{i,t}\}_{t=0}^{T}$ and missing values.[7] Parameters δ_i, σ_{vi} and σ_{wi} for $i = 1, 2$ are estimated by numerically maximizing the log-likelihood evaluated by the Kalman filter. Then, PDIRF $f_i = \sum_{l=0}^{k} \delta_i(1-\delta_i)^l$ and $Loss_i = (1-\delta_i)^2$ can be calculated with estimated δ_i.

2.2. Magnitude of information arrival and microstructural noise

During the NYSE trading hours, it is midnight in Tokyo and the business operations of the Japanese firms are inactive and changes in the value of Japanese companies would be moderate.[8] The model (1) considers this by allowing the magnitude of information shocks, σ_{vi}^2, to be different between the two markets. If $\sigma_{v1}^2 > \sigma_{v2}^2$, information arrived during the home market

[7] If there is no trade during the five-minute interval, the traded price is interpolated by Kalman filter.
[8] Menkveld et al. (2007) found larger efficient price volatility in home market (Amsterdam) opening hours than in foreign market (New York) opening hours.

Table 2
Liquidity of the Tokyo and New York markets.

Ticker	Number of trades			Number of shares traded					Bid–ask spread		
	Tokyo	New York		Tokyo		New York			Tokyo	New York	
	Daily	Daily	Ratio	Per trade	Med.	Per trade	Med.	Ratio	Mean	Mean	Ratio
ATE	1196.41	66.34	18.03	2638.41	700	230.95	100	7.0	0.0031	0.0064	0.48
CAJ	1733.06	1295.51	1.34	3586.11	500	216.37	100	5.0	0.0023	0.0011	2.06
HIT	1244.23	173.37	7.18	13634.92	5000	1767.76	1000	5.0	0.0020	0.0024	0.80
HMC	1677.76	1056.71	1.59	4950.41	500	252.67	100	5.0	0.0035	0.0014	2.45
IX	2370.69	122.03	19.43	284.94	120	81.68	50	2.4	0.0015	0.0051	0.29
KNM	745.77	21.49	34.70	1483.39	400	195.55	100	4.0	0.0037	0.0066	0.56
KUB	1007.88	205.26	4.91	7053.73	3000	978.36	500	6.0	0.0020	0.0047	0.43
KYO	1092.54	76.79	14.23	1087.80	400	176.57	100	4.0	0.0020	0.0049	0.40
MC	931.53	776.15	1.20	8603.87	2000	269.45	100	20.0	0.0028	0.0018	1.53
MFG	2691.79	369.28	7.29	53.51	8	0.73	0.4	20.0	0.0027	0.0056	0.49
MTU	3126.76	2077.66	1.50	18227.85	4700	550.05	200	23.5	0.0024	0.0025	0.96
NJ	97.44	123.06	0.79	499.41	200	58.69	25	8.0	0.0037	0.0045	0.81
NMR	2526.57	870.10	2.90	5382.03	1900	295.65	100	19.0	0.0017	0.0018	0.93
NTT	1260.73	1028.19	1.23	23.50	4	1.34	0.5	8.0	0.0025	0.0017	1.50
SNE	2062.09	2048.80	1.01	4139.82	500	234.25	100	5.0	0.0024	0.0013	1.80
TDK	1155.37	39.55	29.22	1134.82	400	165.54	100	4.0	0.0021	0.0056	0.38
TM	2409.34	1467.60	1.64	4751.78	600	396.22	200	3.0	0.0022	0.0012	1.87
Mean	1607.64	695.17	8.72	4560.96	1231	345.40	169	8.76	0.0025	0.0035	1.04
Std.Dev.	810.53	703.35	10.67	5039.38	1582	432.97	242	7.00	0.0007	0.0020	0.69

This table presents summary statistics of trade frequency, trading volume and bid–ask spread for sample stocks for the period September 17, 2007 to April 7, 2008. All statistics are computed using all trades between 19:00 Eastern Standard Time(EST) and 1:00 EST (break from 21:00 to 22:30) for Tokyo and from 9:30 EST to 16:00 EST for New York. The 1st and 2nd columns report the daily average of trade frequency calculated as the average number of trades a day in Tokyo divided by that in New York. The 3rd column reports the ratio of the two metrics. The 4th to 7th columns report average number of shares per trade and median. The 8th column reports the ratio of the median volume per trade. Average bid–ask spreads are reported in the 9th and the 10th columns. They are computed using the best bid and ask prices observed every 5 min. For comparison purpose, the reported bid–ask spreads are divided by the mid-quote. The last column reports the ratio of the average spread.

trading hours has larger magnitude of change in efficient price, and vice versa. Using the estimated σ^2_{v1} and σ^2_{v2}, we measure the proportion of information arrival, information arrival share, in the home market as

$$IAS = \frac{\sigma^2_{v1}}{\sigma^2_{v1} + \sigma^2_{v2}}. \tag{7}$$

The variance of microstructural noise, σ^2_{wi}, provides us a measure to study the magnitude of the noise. We use its relative variance to the information innovation, $\sigma^2_{wi}/\sigma^2_{vi}$, to compare the two market's price noisiness.

3. Overview of the Tokyo and New York markets

In this section we provide an overview of the Tokyo and New York markets. We start from the data description followed by a provision of statistics of liquidity measures to summarize the two markets' trading activity. The last section conducts a variance ratio test to give a preliminary analysis of price discovery of the two markets.

3.1. Data description

The cross-listed Japanese shares studied in this paper are ADRs. Each ADRs is issued by a U.S. depository bank, the biggest depository bank is Bank of New York Mellon. ADRs are traded in U.S. dollars, pay dividends in U.S. dollars, hence they can be traded like U.S. domestic shares.[9]

This study uses 5 minute trading prices of 17 Japanese stocks listed both in Tokyo and in New York. The data is obtained from Thomson Reuters Tick History database managed by SIRCA. Our sample covers from September 17, 2007 to April 7, 2008.[10] Table 1 lists the sample Japanese stocks studied in the paper.

While New York uses the ticker symbol, Tokyo uses “meigara-kohdo,” which means “trading code” to recognize them. Hereafter we use the ticker to abbreviate the company name. The table also reports the ADR ratio. It tells the relationship between the ADR and the underlying share. For instance, 10 shares of Hitachi traded in New York is equivalent to 1 share of its underlying traded in Tokyo.

During the observation period Tokyo market had 134 business days and New York had 140 business days. TSE operation hours are 4.5 h, it opens at 19:00 Eastern Standard Time(EST) and closes at 1:00 EST (they have break from 21:00 EST to 22:30 EST)

[9] We use daily average of Japanese yen–U.S. dollar exchange rates to convert all prices to USD.
[10] During that period, there were 19 ADRs listed in NYSE. NTT DoCoMo and NIS Group are excluded since the data was not available for the former stock and observation days for the latter stock were only half of the others.

Table 3
Variance ratio.

Ticker	Daily			Hourly		
	V^T	V^{NY}	Ratio	V^T	V^{NY}	Ratio
	$\times 10^{-3}$	$\times 10^{-3}$		$\times 10^{-3}$	$\times 10^{-3}$	
ATE	0.7329	0.2116	3.66*	0.0362	0.0050	7.64*
CAJ	0.2445	0.1832	1.40	0.0121	0.0043	2.92*
HIT	0.2882	0.1424	2.11*	0.0142	0.0034	4.41*
HMC	0.1970	0.1543	1.36	0.0097	0.0037	2.84*
IX	0.8926	0.3026	3.10*	0.0441	0.0072	6.46*
KNM	0.5592	0.1323	4.34*	0.0276	0.0031	9.06*
KUB	0.5245	0.2024	2.72*	0.0259	0.0048	5.67*
KYO	0.2250	0.1191	2.04*	0.0111	0.0028	4.26*
MC	0.3471	0.1302	2.79*	0.0171	0.0031	5.83*
MFG	0.6879	0.3582	2.00*	0.0340	0.0085	4.17*
MTU	0.5708	0.3291	1.87*	0.0282	0.0078	3.90*
NJ	0.4416	0.1633	2.83*	0.0218	0.0039	5.91*
NMR	0.3929	0.2622	1.56*	0.0194	0.0062	3.26*
NTT	0.2442	0.1973	1.29	0.0121	0.0047	2.70*
SNE	0.3452	0.1936	1.88*	0.0170	0.0046	3.92*
TDK	0.4245	0.2169	2.02*	0.0210	0.0051	4.22*
TM	0.2423	0.1450	1.75*	0.0120	0.0034	3.66*
Mean	0.4330	0.2026	2.28	0.0214	0.0048	4.75
Std.Dev.	0.2021	0.0718	0.85	0.0100	0.0017	1.77

This table presents summary statistics of return variance for sample stocks for the period September 17, 2007 to April 7, 2008. All statistics are computed using the open-to-close returns. Return variance for Tokyo,V^T and New York, V^{NY}, are reported for daily variance and hourly variance separately. The hourly variance is scaled by the number of operating hours, 4.5 h and 6.5 h for Tokyo and New York, respectively. The variance ratio is calculated as the return variance of Tokyo divided by that of New York. The individual ratio with asterisk is statistically significant at the 5% significance level.

while NYSE operation hours are 6.5 h, opens at 9:30 EST and closes at 16:00 EST.[11] Thus, there is no overlapping period in these two markets. Each stock has 7236 and 10,920 observations from Tokyo and New York, respectively.

3.2. Liquidity

In this section we describe the liquidity measures of the Tokyo and New York markets. It is well documented in the literature that a market's price discovery efficiency is determined by its liquidity.[12] In the paper we consider trading frequency, trading volume and bid–ask spread. In Section 4.3.3 we confirm that these liquidity variables can explain our price discovery efficiency measure. Table 2 presents descriptive statistics of the three liquidity variables.

3.2.1. Trading frequency

The first three columns of Table 2 report the trading frequency measure of the two markets.

During the whole 134 day observation period, approximately 215 thousand transactions were occurred on average in Tokyo. The first column calculates the average number of trades a day. It ranges from 97.44 of NJ to 3126.76 of MTU. The cross sectional mean is 1607.64 per day which implies that approximately 30 trades has occurred every 5 min on average.

The same statistics for New York are reported in the second column in the table. The average trading frequency for each stock during the 140 days in NYSE was approximately 97 thousand, which is around 45% of Tokyo. Its daily average is slightly less than 700, which ranges from 21.49 of KNM to 2077.66 of MTU. We observe 5 trades in every 5 min in New York on average. The correlation between the daily average of Tokyo and New York is 0.45, significantly different from zero with the conventional 5% level.

The third column calculates the Tokyo to New York ratio of the average trading frequency a day. The ratio varies widely, it ranges from 0.79 of NJ to 34.70 of KNM. Ratios of seven stocks are between 1 and 2, and five stocks are greater than 10. NJ is the only stock which is more frequently traded in New York than in Tokyo. The trade frequency in Tokyo is 8.72 times more than New York on average.

3.2.2. Trading volume

The fourth to the eighth columns of Table 2 present summary statistics on the number of shares traded. The number for New York is adjusted using the ADR ratio in Table 1.

[11] Japan does not apply Daylight Saving Time (DST). Time difference between Tokyo and New York changes from 14 h to 13 h when DST employed in U.S. We have 7302 observed prices for TSE and 10,870 for NYSE.

[12] Eun and Sabherwal (2003) and Mizrach and Neely (2008) find a significant effect of liquidity variables on the price discovery in US–Canada cross listed stocks and the US Treasury market, respectively.

The total number of shares traded in Tokyo during the sample period varies very widely from 3.97 million shares of NTT to 7409.24 million shares of MTU. The same statistics for New York exhibits substantially smaller size. The difference of the volume between the two markets is much larger than what we have seen for the trading frequency. On average, the volume traded in New York is 31.16 million shares, which is approximately only 3% of the 1128.33 million shares of Tokyo.

4560.96 shares are traded per trade on average in Tokyo while 345.40 are traded in New York. The number of shares for each trade largely varies and its distribution skewed largely to the right. Therefore the median would represent better the typical volume of a trade. The eighth column calculates the ratio of the medians. It implies that the typical volume per trade in Tokyo is 8.76 times larger than New York. In summary, both of the volume measure, the number of shares in particular, show large trading concentration in the domestic market.

3.2.3. Bid–ask spread

The last three columns of Table 2 present the bid–ask spread measures. To calculate the spread, we use the best bid and ask prices observed every 5 min. For comparison purposes the spreads are divided by the mid-quote, the average of the best bid and ask prices. The numbers reported in the table are based on these standardized spreads.

On average the bid–ask spreads are 0.25% and 0.35% of the mid-quote in Tokyo and New York, respectively. Given the previous trading volume comparison, we may expect Tokyo would have much narrower spread than New York. However, as the ratio in the table shows, there are six cases that the spread is wider in Tokyo than in New York. On average the ratio is just slightly above one.

3.3. Preliminary analysis: variance ratio test

As a preliminary analysis of price discovery, we conduct the commonly used variance ratio test (e.g., Amihud and Mendelson, 1991; French and Roll, 1986). We compute the return variance of each stock in the two markets separately and test the variance ratio using daily return. Namely, we test:

$$V^T/V^{NY} = 1 \tag{8}$$

where V^T and V^{NY} denote the Tokyo and New York open-to-close return variability, respectively. The variances are calculated from returns measured as the change in the log of the price. Assuming the returns are i.i.d. normally distributed, the sample statistic, $\hat{V}^T/\hat{V}^{NY}$, is $F_{nT-1,nNY-1}$ distributed, where nT and nNY are the number of observations used for calculation for Tokyo and New York, respectively.

3.3.1. Results

Table 3 provides the comparison of the computed variances and the resulting variance ratio.

The average daily variance in the Tokyo trading period is 0.43×10^{-3}, which corresponds to a standard deviation of 2.08%. The average daily variance in the New York trading period is 0.20×10^{-3} which corresponds to a standard deviation of 1.42%. The daily variance ratio is statistically significantly different to one with 5% level for 14 stocks. The exceptions are CAJ, HMC and NTT. The daily variance ratio implies that the Tokyo trading period is a factor of 2.28 more informative than New York trading hours on average which ranges from 1.29 of NTT to 4.34 of KNM. The variance ratios are much smaller than the ratio of volumes we observed above.

The table also reports the results from the daily variance and the hourly variance. The latter variances are scaled by the number of operating hours for each markets, 4.5 h and 6.5 h for Tokyo and New York respectively. The average hourly variance in the Tokyo trading hours is 0.21×10^{-4}, which corresponds to a standard deviation of 46 basis points. The average hourly variance in the New York trading period is 0.05×10^{-4}, which corresponds to a standard deviation of 22 basis points. The hourly variance ratios for all stocks are significantly different to one with 5% level. Having the variances scaled by the operating hours, the relative price informativeness of Tokyo to New York doubles from its daily counterpart. It is a factor of 4.75 more informative than New York on average which ranges from 2.70 of NTT to 9.06 of KNM.

Table 4
Pairwise correlation of liquidity and variance ratios.

	Volume	Spread	Variance
Frequency	−0.3730	−0.6204*	0.6467*
Volume		−0.0406	−0.1556
Spread			−0.5657*

The table reports the pair wise correlation coefficient estimates of the three liquidity ratios and the variance ratio. The average number of trade per day, the median number of shares per trade, and the average standardized spread from 5 minute observation are used to calculate the frequency, volume and spread ratio, respectively. The variance ratio is computed using the open-to-close returns. The individual correlation coefficient with asterisk is statistically significant at the 5% significance level.

The preliminary variance ratio test suggests that Tokyo is the dominant side in price informativeness. However, the test does not take in account the dynamic aspect of the price discovery process. Later we confirm that the variance ratio result is consistent with the magnitude of information arrival but not with the speed of information assimilation.

3.3.2. Variance vs. liquidity. Lastly we test the pairwise correlation of the three liquidity ratios and the variance ratio. Table 4 presents the results.

The average number of trade per day, the median number of shares per trade, and the average standardized spread from 5 minute observation are used to calculate the frequency, volume and spread ratio, respectively. The table provides two interesting results. First, it shows that the bid–ask spread ratio is significantly correlated with the trading frequency while it does not with the size of the trade. Second, the table shows that the variance ratio is significantly correlated with the trading frequency and the bid–ask spread while it does not with the size of the trade. The results imply that the volume per trade does not determine the relative liquidity or price informativeness of the two markets.

4. Estimation results

We proceed the analysis by decomposing the price changes into information and noise using the structural partial price adjustment model. The model is estimated as introduced in Section 2.

4.1. Efficiency in price discovery

Table 5 shows the estimated partial adjustment parameters of the state space model including the quadratic loss function and its ratio, *LR*.

The first and fifth columns report the partial adjustment coefficients of Tokyo and New York, respectively. The standard errors are presented between parentheses. All estimates are statistically significant. The cross sectional average of δ_1 is 0.171 which ranges from 0.006 of MC to 0.852 of CAJ. The value of δ_1 less than one implies that the domestic market tend to under-react to the information arrival. The cross sectional average of δ_2 is 0.838 which ranges from 0.005 of CAJ to 1.119 of NMR. KYO and NMR are the only case with an adjustment coefficient of greater than one, which implies an over-reaction to the information arrival.

The quadratic loss function, $Loss_i$, measures the inefficiency in information assimilation. The quadratic loss averages to 0.829 and 0.177 for Tokyo and New York, respectively. We confirm that with the loss ratio, *LR*, reported in the last column of the table. *LR* is greater than one in almost all of the shares, i.e., the price discovery process is more efficient in New York. The average *LR* implies that Tokyo is eighteen times inefficient than New York. The exception is CAJ which is accompanied by a *LR* of 0.15.

Fig. 1 plots the PDIRF of Tokyo and New York using the cross sectional average of δ_1 and δ_2.

In one hand, more than 80% of the information is immediately incorporated into prices observed in New York. On the other hand, the immediate incorporation of the information to the prices amounts only 17% in Tokyo. The domestic market takes more than 10 min to reflect the 50% of the new information on its transaction prices. The time needed for Tokyo and New York to incorporate half of the size of information is respectively computed as $half_1$ and $half_2$ in third and sixth columns of Table 7. Except CAJ, 50% of an information shock is incorporated into observed price immediately in New York. In contrast, Tokyo needs 80 min on average, which ranges from 0 min of CAJ to 575 min of MC.

Our finding that the market oversea is more efficient in information assimilation process, in terms of speed, than the home market is not to be anticipated as one may naturally presume that the home market participants know more about the domestic stocks. We have to recall that during the NYSE trading hours, it is midnight in Tokyo and the business operations of the Japanese firms are inactive and changes in the value of the firms would be moderate. Even a market is efficient in information assimilation, if the size of the change in the fundamental, i.e., the magnitude of information arrival, is small, the ultimate size of information incorporated during its trading hours may be limited. On the other hand, even if a market is less efficient in information assimilation, if the magnitude of information arrival during its trading hours is large, the ultimate size of information incorporated may be large. The distinction of the two features is crucial in a non-overlapped trading hours setting, such as the case of TSE and NYSE. We conduct a comparison of the magnitude of the information arrival in the following section.

4.2. Magnitude of information arrival and microstructural noise

If one looked only at the findings from the partial adjustment coefficient estimates, then it would be natural to conclude that the New York is much faster and more efficient in incorporating the new information than Tokyo. However a comparison of the magnitude of the variance of efficient price innovation, i.e., the size of the information, shows a need of careful interpretation of the results.

4.2.1. Information arrival

The first column in Table 6 reports σ_{v1}/σ_{v2}, the ratio of the size of information arrival.

The standard errors for the ratio are presented between parentheses. All are statistically significant. The average variance is 4.78×10^{-5} during the Tokyo trading hours and 0.27×10^{-5} during the New York trading period, which corresponds to a standard deviation of 69 basis points and 16 basis points, respectively. All σ_{v1}/σ_{v2} are larger than one, which implies that the size

Table 5
Efficiency in price discovery.

	Tokyo			New York			
Ticker	δ_1	$Loss_1$	$half_1$	δ_2	$Loss_2$	$half_2$	LR
ATE	0.034	0.966	100	0.979	0.021	0	46.74
	(0.005)			(0.007)			
CAJ	0.852	0.148	0	0.005	0.995	690	0.15
	(0.052)			(0.003)			
HIT	0.034	0.966	100	0.829	0.171	0	5.65
	(0.004)			(0.013)			
HMC	0.363	0.637	5	0.727	0.273	0	2.33
	(0.021)			(0.024)			
IX	0.056	0.944	60	0.764	0.236	0	4.01
	(0.008)			(0.013)			
KNM	0.023	0.977	145	0.975	0.025	0	39.67
	(0.004)			(0.007)			
KUB	0.051	0.949	65	0.877	0.123	0	7.69
	(0.006)			(0.014)			
KYO	0.046	0.954	70	1.010	0.010	0	100.40
	(0.004)			(0.024)			
MC	0.006	0.994	575	0.935	0.065	0	15.25
	(0.004)			(0.013)			
MFG	0.225	0.775	10	0.970	0.030	0	25.68
	(0.020)			(0.010)			
MTU	0.158	0.842	20	0.829	0.171	0	4.91
	(0.014)			(0.024)			
NJ	0.037	0.963	90	0.926	0.074	0	12.94
	(0.004)			(0.010)			
NMR	0.138	0.862	20	1.119	0.119	0	7.22
	(0.025)			(0.008)			
NTT	0.043	0.957	75	0.960	0.040	0	23.90
	(0.005)			(0.012)			
SNE	0.221	0.779	10	0.860	0.140	0	5.58
	(0.020)			(0.029)			
TDK	0.290	0.710	10	0.672	0.328	0	2.16
	(0.021)			(0.014)			
TM	0.330	0.670	5	0.810	0.190	0	3.52
	(0.021)			(0.024)			
Mean	0.171	0.829	80.00	0.838	0.177	40.59	18.11
Std.Dev.	0.211	0.211	134.73	0.242	0.231	167.35	25.17

The table shows the partial adjustment coefficient estimates for the model (1). $Loss_i$ is the quadratic loss function. $half_i$ are half-lives, the expected number of minutes for 50% of an information shock to be incorporated into the price, computed from the PDIRF in Eq. (3). Standard errors are in parentheses. LR is the quadratic loss ratio in the Eq. (6).

of information arrived in Tokyo is greater than in New York regardless of company. The result is consistent with the finding from the variance ratio test in the previous section. On average the magnitude of information arrival is four times larger in Tokyo.

The second column in the table reports the information arrival share of Tokyo computed by the Eq. (7). The cross-sectional average of the information arrival share is 91.28%, which ranges from 66.67% of KYO to 97.95% of HMC. In other words the proportion of the magnitude of information arrival in NYSE is only 8.72%. This could be explained by the fact that the New York trading hours are during midnight in Tokyo local time (23:30–06:00). As domestic businesses are not active during the New York trading hours, changes in efficient price of the stocks would be moderate. Hence despite its efficiency, the role for NYSE in price discovery for Japanese stocks is quite restricted. This result is in line with the finding in Menkveld et al. (2007) that the variance of efficient price innovation in home market opening hours is larger than foreign market opening hours.

As the size of information arrival greatly differs between the two markets, the speed of information assimilation estimates in Table 5 must be reconsidered. Our finding that the Tokyo market is accompanied by a larger quadratic loss function, $Loss_i$, might be because the magnitude of information arrival during its trading hours is much greater than that during New York trading period. We attempt to obtain a standardized measure of efficiency of information assimilation considering the size of the information in the next section.

4.2.2. Microstructural noise

The table provides the estimates for the microstructural noise variance in the third and fifth columns for Tokyo and New York respectively. The result implies that noises are larger in Tokyo for most of the stocks, which is consistent with Chelley-Steeley (2003) who describes that home market has larger noise than in foreign market. The average size of the noises in Tokyo is 1.52×10^{-5} which corresponds to a standard deviation of 39 basis points while the metric for New York is 17 basis points.

The table also provides the noise to information ratio, $\sigma^2_{wi}/\sigma^2_{vi}$. The ratio shows that the magnitude of the noise is 55% of the size of the information in Tokyo on average. In the case of New York, it is slightly larger than the information on average while the

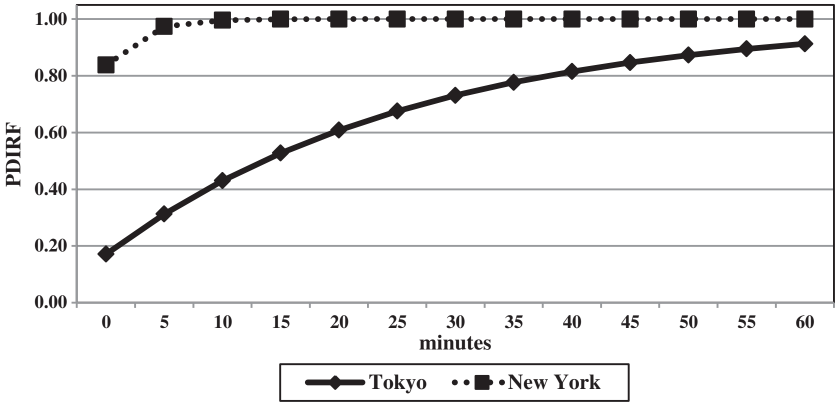

Fig. 1. Price discovery impulse response functions. The figure plots the PDIRF for Tokyo and New York up to 60 min. PDIRF are calculated from the cross sectional average of the partial adjustment coefficient.

median is 47% of MTU. The last column of the table calculates the ratio of the noise to information ratios, $\sigma^2_{w1}\sigma^2_{v2}/\sigma^2_{v1}\sigma^2_{w2}$. Although the median of the metric is slightly above one, it varies largely by stock. It seems that the role of the location as a determinant of the relative size of the microstructural noise is limited.

Table 6
Magnitude of information arrival and microstructural noise.

Ticker	σ_{v1}/σ_{v2}	*IAS*	Tokyo σ^2_{w1}	Tokyo $\sigma^2_{w1}/\sigma^2_{v1}$	New York σ^2_{w2}	New York $\sigma^2_{w2}/\sigma^2_{v2}$	$\sigma^2_{w1}\sigma^2_{v2}/\sigma^2_{v1}\sigma^2_{w2}$
		%	$\times 10^{-5}$		$\times 10^{-5}$		
ATE	5.33	96.60	2.329	0.248	0.074	0.222	1.114
	(0.62)						
CAJ	3.23	91.25	0.317	0.107	3.112	10.936	0.010
	(0.43)						
HIT	3.00	90.03	1.155	0.800	0.112	0.702	1.139
	(0.34)						
HMC	6.92	97.95	1.226	0.167	0.089	0.582	0.287
	(0.41)						
IX	3.03	90.15	3.043	0.619	0.495	0.922	0.671
	(0.31)						
KNM	2.86	89.10	2.119	0.494	0.056	0.107	4.642
	(0.38)						
KUB	3.04	90.24	1.773	0.825	0.138	0.594	1.389
	(0.25)						
KYO	1.41	66.67	0.936	2.112	0.007	0.032	65.377
	(0.13)						
MC	3.07	90.43	1.255	0.786	0.050	0.297	2.649
	(0.29)						
MFG	6.82	97.90	2.063	0.161	0.184	0.666	0.242
	(0.52)						
MTU	6.39	97.61	2.136	0.168	0.146	0.470	0.357
	(0.56)						
NJ	3.08	90.45	1.287	0.712	0.104	0.548	1.300
	(0.32)						
NMR	3.02	90.13	1.703	0.562	0.000	0.000	20915.983
	(0.33)						
NTT	2.94	89.62	0.871	0.632	0.057	0.359	1.760
	(0.50)						
SNE	3.02	90.11	1.065	0.467	0.047	0.188	2.487
	(0.19)						
TDK	6.30	97.54	1.114	0.123	0.278	1.224	0.101
	(0.45)						
TM	4.94	96.06	1.424	0.374	0.056	0.357	1.045
	(0.33)						
Mean	4.02	91.28	1.519	0.550	0.294	1.071	1235.327
Std.Dev.	1.70	7.25	0.663	0.476	0.736	2.562	5071.613

The table shows the parameter estimates for the model (1). σ^2_{vi} and σ^2_{wi} are the parameters from the state space model. Standard errors are in parentheses. *IAS* is the proportion of the magnitude of information arrival in Tokyo market, calculated with the Eq. (7).

4.3. Efficiency in price discovery with the size of information considered

In this section we examine whether New York is still efficient in information assimilation after the size of information is considered. The magnitude of the change in the efficient price, σ_{v_i}, is used as the proxy of the typical size of information arrived. Indeed the correlation between efficient price variance and loss function is 0.61 which is statistically significant with 1% level.

Three approaches are taken to control the size of information arrival. The first approach uses the estimates of the speed of information incorporation in order to derive the size of information incorporated per hour.

The second and third approach estimate regressions to test whether the price discovery inefficiency measure is significantly smaller in New York when the size of information is controlled. The former utilizes the estimated magnitude of information arrival while the latter employs the observed liquidity variables to control the size of information.

4.3.1. Information size adjusted speed of price discovery

In the previous section, with PDIRF estimates, we compute the speed of incorporating half of the information into the price, $half_i$. Our first approach uses the results and attempts to derive the size of information incorporated per hour, $\omega_{i,j}$, by

$$\omega_{i,j} = 60 \times \frac{\sigma_{vij}/2}{half_{i,j}} \qquad \text{for } i = 1,2 \text{ and } j = 1,2,\ldots,17 \tag{9}$$

where i indicates the market, 1 for Tokyo and 2 for New York, and j identifies the stock. $half_{i,j}$ is the time needed to incorporate half of the information into the price of stock j in market i. Their estimates are reported in Table 5. σ_{vij} denotes the standard deviation of the efficient price, the proxy of the typical size of information of stock j in market i. Thus, $(\sigma_{vij}/2)/half_{i,j}$ measures the typical size of information incorporated in a minute.

While $half_{i,j}$ measures the speed of information assimilation regarding the *proportion* of the size of information, $\omega_{i,j}$ measures the speed regarding the *level*. Table 7 presents the computed $\omega_{i,j}$.

As for many cases in New York, more than half of the information is incorporated *immediately*, or in less than 5 min. We first compute the $\omega_{i,j}$ considering the immediate incorporation as 1 min. The speed of information assimilation in Tokyo is 217 basis points per hour on average. As we have CAJ as extreme case, the table also reports the median. The median for Tokyo is 35 basis points per hour. On the other hand, the speed in New York is 450 basis points per hour on average. The median of the ratio is 0.0533 of ATE, which implies that New York is approximately twenty times faster in information assimilation than Tokyo. The average ratio excluding CAJ is 0.30, implying New York is around three times faster than Tokyo. When we consider an immediate incorporation as 5 min, the slowest possible assumption, we see seven cases associated with faster information assimilation is in Tokyo. The median of the ratio increased to 0.27 and the mean excluding the outlier becomes 1.49.

In summary, the results suggest that if same size of information has arrived at the two markets, New York will be the faster side in incorporating it into the price. It is noteworthy that the results we observe here largely differ to variance ratios reported in Table 3. The variance ratio does not exclude noise while the $\omega_{1,j}/\omega_{2,j}$ does. The contradicting results from the two metrics imply

Table 7
Size of information incorporated per hour.

	Immediate = 1 min			Immediate = 5 min		
	Tokyo	New York	Ratio	Tokyo	New York	Ratio
	$\omega_{1,j}$	$\omega_{2,j}$	$\omega_{1,j}/\omega_{2,j}$	$\omega_{1,j}$	$\omega_{2,j}$	$\omega_{1,j}/\omega_{2,j}$
ATE	0.0029	0.0545	0.0533	0.0029	0.0109	0.2666
CAJ	0.1634	0.0001	2228.1480	0.0327	0.0001	445.6296
HIT	0.0011	0.0379	0.0300	0.0011	0.0076	0.1502
HMC	0.0514	0.0371	1.3839	0.0514	0.0074	6.9197
IX	0.0035	0.0695	0.0504	0.0035	0.0139	0.2522
KNM	0.0014	0.0687	0.0197	0.0014	0.0137	0.0986
KUB	0.0021	0.0458	0.0468	0.0021	0.0092	0.2339
KYO	0.0009	0.0447	0.0202	0.0009	0.0089	0.1010
MC	0.0002	0.0390	0.0053	0.0002	0.0078	0.0267
MFG	0.0340	0.0498	0.6823	0.0340	0.0100	3.4115
MTU	0.0169	0.0529	0.3195	0.0169	0.0106	1.5976
NJ	0.0014	0.0414	0.0342	0.0014	0.0083	0.1710
NMR	0.0083	0.0546	0.1511	0.0083	0.0109	0.7553
NTT	0.0015	0.0379	0.0392	0.0015	0.0076	0.1959
SNE	0.0143	0.0475	0.3018	0.0143	0.0095	1.5090
TDK	0.0285	0.0452	0.6302	0.0285	0.0090	3.1509
TM	0.0371	0.0375	0.9882	0.0371	0.0075	4.9409
Mean	0.0217	0.0450	131.3473	0.0140	0.0090	27.6124
Median	0.0035	0.0452	0.0533	0.0035	0.0090	0.2666
Std.Dev.	0.0397	0.0153	540.3333	0.0164	0.0030	107.7392

The table reports the size of information incorporated per hour, $\omega_{i,j}$, computed from the Eq. (9). $\omega_{i,j}$ is calculated considering the immediate information incorporation as 1 min and 5 min separately.

Table 8
Regressions of price discovery inefficiency on size of information.

	c	b_1	b_2	$\overline{R}^2$
[1]	15.36*	1.31*		0.48
	(2.73)	(0.23)		
[2]	2.18*		−4.06*	0.53
	(0.46)		(0.65)	
[3]	6.54	0.42	−2.95*	0.53
	(4.96)	(0.48)	(1.42)	

The table reports estimates of the Eq. (10). The dependent variable is a transformation of the quadratic loss function. Standard errors are given in parentheses under the coefficients. The individual coefficient is statistically significant at the *5% significance level.

that the noises in Tokyo market are greater than New York. We indeed confirm that by observing greater noise of Tokyo, σ^2_{w1}, than that of New York, σ^2_{w2}, in previous section.

4.3.2. Linear regression with the size of information

Next, we test whether the quadratic loss function is significantly smaller in New York when the size of information is controlled. We estimate the regression,

$$\ln\left(\frac{Loss_{i,j}}{1-Loss_{i,j}}\right) = c + b_1 \ln\sigma^2_{vij} + b_2(1-D_i) + \varepsilon_{i,j}, \tag{10}$$

for $i = 1$ and 2 and $j = 1, 2, \ldots, 17$, where σ^2_{vij} denotes the variance of the efficient price, proxy of the typical size of information of stock j in market i. The quadratic loss, $Loss_{i,j}$, in left hand side is transformed as it is bounded between zero and one.[13] We use the estimated $Loss_{i,j}$ reported in Table 5.

b_1 is expected to have a positive sign as larger average size of information arrival would delay the price discovery process. If the price discovery inefficiency measure is significantly smaller in New York, the coefficient of the dummy variable, b_2, should exhibit significant negative sign. Table 8 presents the estimation results.

It shows that the estimates of b_1 and b_2 have the expected positive and negative sign, respectively. As $Loss_{i,j}$ measures the inefficiency, not the efficiency, of information assimilation, negative b_2 implies that the New York market is more efficient in price discovery than the home market in Tokyo. Thus the statistically significant b_2 of the regression (10) confirms our earlier finding that the speed of information incorporation in New York is faster than in Tokyo with size of information arrival controlled.

4.3.3. Linear regression with the observable liquidity measures

Our third approach utilizes the observable liquidity measures. The purpose of using the measures is not only to proxy the size of information, but also to consider whether they explain the price discovery efficiency.

We estimate the regression,

$$\begin{aligned}\ln\left(\frac{Loss_{i,j}}{1-Loss_{i,j}}\right) &= c + b_1 \ln N_{i,j} + b_2 \ln\left(\frac{S_{i,j}}{1-S_{i,j}}\right) + b_3(1-D_i)\ln\left(\frac{S_{i,j}}{1-S_{i,j}}\right) \\ &\quad + b_4 \ln Vol_{i,j} + b_5 \ln V_{i,j} + b_6(1-D_i) + \varepsilon_{i,j}\end{aligned} \tag{11}$$

where $N_{i,j}$ is the number of trade per day and $S_{i,j}$ denotes the standardized average bid–ask spread we have defined in Section 3.1. $S_{i,j}$ is transformed as it is bounded between zero and one. $Vol_{i,j}$ measures the median number of shares per trade, reported in Table 3. $V_{i,j}$ measures the hourly adjusted variance we computed in Section 3.2.

We expect that a greater liquidity, i.e., number of trade, enhances the price discovery process, $b_1 < 0$. We consider whether narrower bid–ask spread contributes to a smaller loss, $b_2 > 0$. Trades with larger volume should convey more information, thus we further expect $b_4 < 0$. Moreover, noisy trades should diminish the informational efficiency and arrival of large size of information should slow down the price discovery process, thus $b_5 > 0$ is anticipated. Finally, we hypothesize that the New York market is more efficient in information assimilation, $b_6 < 0$.

We find a negative correlation between the quadratic loss and the spread in Tokyo while the opposite relationship in New York. Thus, the fourth term of the right hand side of Eq. (11) is to distinguish the effect of the spread in Tokyo from that in New York. Hence we anticipate $b_3 > 0$.

Table 9 provides the estimation results. It illustrates that the observable market structure variables strongly explain the price discovery estimates. The $\overline{R}^2$s from the two regressions are 66% and 68%, respectively. While the second regression involves the product of the spread and dummy variable, the first does not. The shift of the sign of b_2 from negative to positive suggests the need of the interaction term. An increase in the trade frequency decreases the quadratic loss measure, b_1 is significant at the 10%

[13] In their regression analysis of information shares on liquidity measures, Mizrach and Neely (2008) also apply the transformation.

Table 9
Regressions of price discovery inefficiency on liquidity measures.

	c	b_1	b_2	b_3	b_4	b_5	b_6	$\bar{R}^2$
[1]	1.94	−0.57*	−1.65*		0.14	1.62*	−1.97	0.66
	(4.49)	(0.26)	(0.61)		(0.15)	(0.74)	(1.34)	
[2]	16.97†	−0.49†	0.90	−2.91†	0.17	1.75*	−19.06†	0.68
	(9.52)	(0.25)	(1.55)	(1.64)	(0.15)	(0.71)	(9.73)	

The table reports estimates of the Eq. (11). The dependent variable is a transformation of the quadratic loss function. Standard errors are given in parentheses under the coefficients. The individual coefficient is statistically significant at the †10% or *5% significance level.

level. Although not statistically significant, we estimate that an increase in the bid–ask spread increases the quadratic loss for Tokyo. An increase in the price volatility also significantly lowers the efficiency of price discovery process. Finally, we confirm again that the New York market is more efficient in price discovery process as $b_6 < 0$, significant at the 10% level.

4.3.4. Trading system and trading rules

Overall, our findings from the three approaches suggest that New York is faster in information assimilation than Tokyo. Possible explanations can be drawn from the difference in the market structure such as trading system and trading rules which determine latency, tick size, trade size and price variation.

4.3.4.1. Latency. Trading systems determine latency, which directly affects the speed of information assimilation. Recent empirical studies find that the lower latency improves liquidity and price discovery (e.g., Hasbrouck and Saar, 2013; Riordan and Storkenmaier, 2012). While NYSE introduced its Hybrid market at the end of 2006, resulting in a reduction of the execution time to less than one second (Hendershott and Moulton, 2011), the matching speed in TSE was only once every few seconds.[14] The longer latency in the Tokyo market would reduce its price discovery efficiency.

4.3.4.2. Tick size. The difference in minimum tick size between the two markets may also contribute in the difference in price discovery efficiency. Beaulieu et al. (2003) document a significant effect of the minimum tick size reduction on price discovery in the Canadian stock market. The minimum tick size in NYSE is $0.01 for all stocks. On the other hand, the minimum tick size in Tokyo depends on the price of the stock. For example, the minimum tick size of a stock priced less than 2000 Japanese yen (JPY) is 1 JPY, approximately $0.01, while that of a stock priced between 5000 JPY to 30,000 JPY is 10 JPY. In our sample, the tick size of TSE stocks is 10 times greater than the NYSE stocks on average. The smaller tick size in New York may enhance the price discovery.

4.3.4.3. Trade size. The trade size constraint in the TSE could also disturb its price discovery process. A recent empirical study by Gozluklu et al. (2013) find a substantial improvement in liquidity after the removal of the minimum trade unit constraint at Borsa Italiana. In the Tokyo market, the minimum trade unit depends on the company while the minimum for New York traded ADRs is identically 100 shares. The minimum trade size of TSE is 60% greater than that of NYSE. The large trading unit might lower its price discovery efficiency in Tokyo.

4.3.4.4. Price variation. The TSE utilizes maximum price variation and daily price limit system while the NYSE does not have such price stabilization mechanisms. The maximum price variation and price limit in Tokyo depends on the price of the stock. For instance, the daily price limit of a stock priced 5000 JPY to 7000 JPY is 1000 JPY and its maximum price variation is restricted to 100 JPY. Kim and Ghon Rhee (1997) examine the price limit system of the Tokyo market, confirming that its price discovery process is delayed due to the restriction. The absence of limited price variations may better off the New York market's informational efficiency.

4.4. The effect of liquidity in New York on the price discovery in Tokyo

We find that the magnitude of information arrival is quite small during the New York trading hours. Hence the benefit for Japanese firms of cross-listing from the improvement in price informativeness seems to be very limited. However, although the direct contribution is restricted, trade activities in the foreign market may indirectly contribute by enhancing the efficiency of the domestic market's price discovery process.[15] Thus, we ask whether liquidity measures of New York explain efficiency in price discovery of Tokyo.

[14] TSE introduced the new trading system "arrowhead" on January 4, 2010. The new system substantially lowered the latency. It responds to an order in 1 ms on average and updates market information in 2.5 ms frequency.

[15] Becker et al. (1990) and Lau and David Diltz (1994) find that the U.S. market performance greatly influences the Japanese market while the Japanese market has very small impact on U.S. side.

Table 10
Regressions of price discovery inefficiency of Tokyo on liquidity measures of New York.

	c	b_1	b_2	$\overline{R}^2$
[1]	4.95*	−0.48†		0.14
	(1.51)	(0.25)		
[2]	11.24*		(1.55*)	(0.36)
	(2.91)		(0.49)	
[3]	12.46*	−0.36	1.40*	(0.43)
	(2.82)	(0.21)	(0.47)	

The table reports estimates of the Eq. (12). The dependent variable is a transformation of the quadratic loss function. Standard errors are given in parentheses under the coefficients. The individual coefficient is statistically significant at the †10% or *5% significance level.

The question is considered by estimating the regression,

$$\ln\left(\frac{Loss_{1,j}}{1-Loss_{1,j}}\right) = c + b_1 \ln N_{2,j} + b_2 \ln\left(\frac{S_{2,j}}{1-S_{2,j}}\right) + \varepsilon_j \tag{12}$$

where $Loss_{1j}$ is the quadratic loss measure of the home market, N_{2j} is the number of trade per day, and S_{2j} denotes the standardized average bid–ask spread of the foreign market. We hypothesize that a higher trade frequency and smaller bid–ask spread in the market oversea have spill-over effect enhancing price discovery efficiency in the domestic market, thus we anticipate $b_1 < 0$ and $b_2 > 0$.[16]

Table 10 summarizes the results of regressions of the quadratic loss measure of Tokyo on liquidity measures of New York. The $\overline{R}^2$ amounts 43% when both liquidity measures are involved in the regression. An increase in the liquidity in the foreign market enhances the price discovery process in the domestic market. We estimate that an increase in the trade frequency in New York decreases the quadratic loss measure in Tokyo. A smaller bid–ask spread in the market oversea significantly enhances the information assimilation in the home market. From the findings we conclude that the spill-over effect of the trading activity in New York is not negligible. The provision of liquidity in the foreign market contributes to enhance the price discovery process in the domestic market.

5. Conclusion

If the two markets' operating hours do not at all overlap, trading period of the cross-listed stocks is extended, which would increase the opportunity of incorporating information to its price. However the business would be inactive and changes in the value of companies would be moderate during midnight in home country. In fact, the trading volume of Japanese shares in NYSE amounts only for 3% of trading volume in Tokyo. The present paper considers the efficiency of price discovery and the magnitude of the information arrival of the two markets by analyzing intraday data of cross-listed Japanese stocks.

The structural approach employed in the study allows us to examine the two features, the speed of price discovery and the magnitude of information arrival. When two markets do not share their trading hours, faster information assimilation does not necessary mean a larger size of information incorporation. The induced model approaches widely employed in existing literature have not, and do not need to, distinguish the two aspects of price discovery.

We find that the speed of incorporating information into prices is faster in New York than in Tokyo. More than 80% of the information arrived in New York is immediately incorporated into prices while in Tokyo it is 17%. We find that the size of information incorporated in prices observed at Tokyo is four times greater than in New York. Three approaches are taken to control the size of information and confirm that New York is the efficient side in information assimilation.

We also find that the observable liquidity measures, such as trade frequency, bid–ask spread, volume per trade and return variance, explain the price discovery efficiency up to 68%. Finally, we show that the provision of liquidity in the foreign market contributes to enhance the price discovery process in the domestic market. The liquidity measures for New York explain 43% of the price discovery efficiency of Tokyo.

Overall, we conclude that Tokyo is the dominant side in the magnitude of the information arrival while New York market is more efficient in information assimilation. Moreover, although the size of information assimilated during the NYSE trading hours is very limited, its trading activities indirectly contribute by enhancing the efficiency of the domestic market's price discovery process.

The first conclusion that the home market dominates the size of information arrival is expected from observing the large dominance of trade activity in domestic side. However the second conclusion that the market oversea is more efficient in information assimilation process than the home market is not to be anticipated as one may naturally presume that the home market participants know more about the domestic stocks. Possible explanations can be drawn from the difference in the market structure, such as trading system and trading rules. Indeed, the actions such as the introduction of the "arrowhead" and

[16] *Vol* is not included in this analysis, as the estimation results of Eq. (11) suggest that it is not a significant factor of determining price discovery.

consideration of the change to smaller tick size are intended to enhance the market efficiency of TSE.[17] What exact characteristics of market structure explain the difference in informational efficiency is beyond the scope of the paper, and we leave this interesting question for future research.

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Appendix. Derivation of the price discovery impulse response function

Start from the equation:

$$\Delta p_{i,t} = \delta_i \left(m_t - p_{i,t-1} \right) + w_{i,t} \qquad i = 1, 2 \tag{A.1}$$

and rewrite it in level price form:

$$p_{i,t} = (1-\delta_i) p_{i,t-1} + \delta_i m_t + w_{i,t}. \tag{A.2}$$

Then assuming $p_{i,0} = 0$ and $m_{i,0} = 0$, for $t = 1$:

$$\begin{aligned} p_{i,1} &= (1-\delta_i) p_{i,0} + \delta_i m_1 + w_{i,1} \\ &= \delta_i v_{i,1} + w_{i,1} \end{aligned} \tag{A.3}$$

and for $t = 2$:

$$\begin{aligned} p_{i,2} &= (1-\delta_i) p_{i,1} + \delta_i m_2 + w_{i,2} \\ &= (1-\delta_i) \left[\delta v_{i,1} + w_{i,1} \right] + \delta_i \left(v_{i,1} + v_{i,2} \right) + w_{i,2}, \end{aligned} \tag{A.4}$$

hence recursively, for $t \geq 1$:

$$\begin{aligned} p_{i,t} &= \delta_i v_{i,t} + [\delta_i + (1-\delta_i)\delta_i] v_{i,t-1} + \cdots + \left[\sum_{l=0}^{t-1} (1-\delta_i)^l \delta_i \right] v_{i,1} \\ &\quad + (1-\delta_i)^{t-1} w_{i,1} + (1-\delta_i)^{t-2} w_{i,2} + \cdots + w_{i,t} \\ &= \sum_{j=1}^{t} \left\{ (1-\delta_i)^{t-j} \delta_i \sum_{l=1}^{j} v_{i,l} \right\} + \sum_{j}^{t} (1-\delta)^{t-j} w_{i,j}. \end{aligned} \tag{A.5}$$

Desired result as in equation is obtained and we have the PDIRF $f_{i,k} = \sum_{l=0}^{k} \delta_i (1 - \delta_i)^l$ for $i = 1$ and 2.

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