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Spot–Futures Price Adjustments in the Nikkei 225: Linear or Smooth Transition? Financial Centre Leadership or Home Bias?

Jieye Qin [1,*], Christopher J. Green [2] and Kavita Sirichand [2]

[1] Department of Economics, School of Economics and Management, Anhui Jianzhu University, Hefei 230022, China
[2] School of Business and Economics, Loughborough University, Loughborough LE11 3TU, UK
* Correspondence: j.qin@ahjzu.edu.cn

Abstract: This paper studies price discovery in Nikkei 225 markets through the nonlinear smooth transition price adjustments between spot and future prices and across all three futures markets. We test for smooth transition nonlinearity and employ an exponential smooth transition error correction model (ESTECM) with exponential generalised autoregressive conditional heteroscedasticity (EGARCH), allowing for the effects of transaction costs, heterogeneity, and asymmetry in Nikkei price adjustments. We show that the ESTECM-EGARCH is the appropriate model as it offers new insights into Nikkei price dynamics and information transmission across international markets. For spot–futures price dynamics, we find that futures led spot prices before the crisis, but spot prices led afterwards. This can be explained by the lower level of heterogeneity in the underlying spot transaction costs after the crisis. For cross-border futures prices, the foreign exchanges (Chicago and Singapore) lead in price discovery, which can be attributed to their roles as global information centres and their flexible trading conditions, such as a more heterogeneous structure of transaction costs. The foreign leadership is robust to the use of linear or nonlinear models, the time differences between Chicago and the other markets, and the long-run liquidity conditions of the Nikkei futures markets, and strongly supports the international centre hypothesis.

Keywords: price adjustment; smooth transition; price discovery; information transmission; Nikkei 225 futures

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1. Introduction

Price discovery is the process by which markets impound available information and adjust to reach equilibrium (Booth et al. 1999). A critical question for an index futures market is whether spot or futures prices lead price discovery. Theory and early empirical studies suggest that futures prices generally lead the underlying spot prices and therefore perform the price discovery function. This is due to more efficient trading conditions in futures, including lower transaction costs, greater short-sale opportunities, aggregation of the underlying shares within the index futures contract, and higher leverage (Fleming et al. 1996). Subsequent studies indicate that spot–futures price relationships could be more complex. In some markets, futures lead spot prices (Park et al. 2017; Chen and Tsai 2017); in others, spot prices lead futures (Yang et al. 2012; Bohl et al. 2011); still other markets have bidirectional causality (Booth et al. 1999; Guo et al. 2013). However, if futures for the same underlying spot asset are quoted simultaneously on different markets, market frictions, differences in transaction costs, and other market characteristics can induce different adjustment processes and speeds, so that one of these markets may impound information in the price faster than the others; this allows them to act as price-leader, either temporarily or consistently over time. This raises a second critical question of whether a specific futures market is most important in price discovery.

This paper aims to study price discovery for Nikkei 225 futures, which are quoted simultaneously in the Osaka Exchange (OSE), Singapore Exchange (SGX), and Chicago

Mercantile Exchange (CME), with a common spot market in Tokyo. The availability of quotes on three different markets with differences in institutional characteristics offers a broad choice for Nikkei investors and renders the spot–futures price adjustments potentially more interesting than for a single market. We seek to identify the price discovery process for the Nikkei, first between spot and futures prices and second among the different futures markets. We focus on three aspects of price discovery: nonlinearities in price adjustments, price leadership across markets, and the role of liquidity in the adjustment process.

Existing literature suggests that price discovery and information transmission processes can create nonlinearities in price adjustments, especially because of transaction costs and market imperfections. See, for example, McMillan (2005), Fung and Yu (2007), Beckmann et al. (2014), Bekiros et al. (2018), and Chen et al. (2022). The speed of adjustment may change over time depending on the size and sign of price deviations from equilibrium, giving rise to regime-switching error correction behaviour. Allowing for transaction costs, arbitrage is triggered only when price deviations are large enough to cover the transaction costs (Anderson 1997). Interactions between noise traders and fundamental traders contribute to nonlinearities, as small price deviations may be adjusted more quickly for lower capital requirements and risks (McMillan and Speight 2006; Shleifer 2000). Short-sale restrictions also impart asymmetry to price adjustments so that negative and positive price deviations have different market responses (van Dijk and Franses 1997; Tse 2001). In general, price adjustments may vary across regimes and depend on the size and sign of price deviations within each regime. Nonlinear regime-switching in futures has been described by different variants of the smooth transition autoregressive model of Teräsvirta (1994) as it can allow for the effects of transaction costs, heterogeneity, and asymmetry. Evidence for smooth transition behaviour was reported in several futures markets, such as S&P500 (Taylor 2007), FTSE 100 (Taylor et al. 2000), Dow Jones (Tse 2001), Hang Seng (Fung and Yu 2007), and emerging index futures (Sila Alan et al. 2016).

Turning to price leadership, this concerns price adjustments between competing futures markets in the same underlying spot asset. The two main hypotheses in the literature are home-bias and international centre (Fung et al. 2001).[1] The home-bias hypothesis argues that the domestic market leads the price discovery process due to "home advantages", including proximity to the spot market, familiarity with local trading environment and regulation, and fewer trading barriers (Roope and Zurbruegg 2002). In contrast, the international centre hypothesis argues that, if a foreign market is a global financial centre, we might expect it to lead international price discovery because it provides better trading conditions. A global financial centre may have a higher degree of efficiency in processing and sharing information, lower transaction costs, more opportunities for risk management by trading other financial instruments, and access to a wider pool of capital and better informed investors from around the world. Li et al. (2022) reported the offshore CME leading price discovery for cross–listed currency futures and attributed the foreign leadership to a more efficient trading environment including lower transaction costs.

Liquidity also plays an important role in price discovery in a multi-market setting. Admati and Pfleiderer (1988) showed that liquidity (noise) traders who have discretion over the timing of their trading and informed traders who trade on private information both have incentives to trade in thick markets where their price impact is minimal. Insofar as trading concentrates in the most liquid market, its prices tend to reveal information the most quickly. Thus, higher liquidity creates more rapid price discovery, enhancing arbitrage and increasing market efficiency (Chordia et al. 2008). Empirical evidence largely supports that liquidity is positively related to price discovery and efficiency (Chung and Hrazdil 2010; Frijns et al. 2018; Li et al. 2022). In some cases, however, the positive relationship does not hold. One reason is that the bid–ask spread, a measure of illiquidity, is often found to be positively associated with price discovery, and thus an informative market could exhibit wide spreads and slow price adjustments (Hasbrouck 1995). Moreover, market makers who cannot fully remove return predictability may attract other market participants to trade on information about order flows. The adverse selection of these market makers lowers liquidity but improves efficiency as prices can respond more fully to the order flows (Chordia et al. 2008).

Most Nikkei studies look at spot–futures price interactions in just one or two markets (e.g., Tse 1995; Iihara et al. 1996; Shyy and Shen 1997; Fung et al. 2001; Frino and West 2003; Covrig et al. 2004; Tsuji 2007). Evidence supporting the home-bias hypothesis was reported by Covrig et al. (2004), while Fung et al. (2001), Frino and West (2003), and Kao et al. (2015) reported results consistent with the international centre hypothesis. Booth et al. (1996) and Shyy and Shen (1997) could not find support for either hypothesis. Therefore, the question of which Nikkei futures market leads the international price discovery process remains unresolved. Furthermore, these studies mostly fail to consider all three Nikkei futures markets; because of this, they do not provide a complete picture of Nikkei price adjustments. Exceptionally, Booth et al. (1996) and Kao et al. (2015) examined the price transmission among the three Nikkei futures markets, but they used linear error correction models (ECM) and did not test for nonlinearities in price adjustments. Tsuji (2007) estimated a nonlinear threshold autoregressive model to allow for the effect of transaction costs on the Nikkei basis, but the adjustment process implied by the model assumes a single, constant transaction cost threshold for all market participants, which is difficult to justify in practice, and is not consistent with the evidence for the Nikkei that was reported by Brenner et al. (1989). As costs and restrictions may vary among investors, market prices are likely to switch between regimes in a smooth, continuous manner (Anderson 1997; Tse 2001). In summary, there have been no studies of nonlinear price adjustments or the role of liquidity in Nikkei spot and futures dynamics, and therefore, no attention has been paid to the impact of nonlinear price dynamics on price discovery across all three Nikkei futures markets. Our paper is motivated by all of these issues.

Accordingly, in this paper, we study the nonlinear smooth transition price adjustments for the triple-listed Nikkei futures contracts. We test for nonlinearities and employ an exponential smooth transition error correction model (ESTECM) of Tse (2001) with exponential generalised autoregressive conditional heteroscedasticity (EGARCH) of Nelson (1991), allowing for transaction costs, heterogeneity, and asymmetry in Nikkei price adjustments. We establish the presence of smooth transition nonlinearity in the data and justify the use of the ESTECM-EGARCH model. We examine whether price adjustments are essentially simultaneous across all three Nikkei futures markets, or if one market tends to lead price discovery. We also investigate the role of liquidity in the speeds of adjustment and price discovery, especially whether the informativeness of the three Nikkei futures markets is related to their liquidity.[2] Our findings highlight the importance of the international Nikkei futures (CME and SGX) in the cross-border price discovery process. This is robust to the use of linear or nonlinear models, non-synchronous trading times, and the long-run liquidity conditions of Nikkei futures.

Our study contributes to the existing literature in the following ways. First, to the best of our knowledge, nonlinear smooth transition price adjustments for the triple-listed Nikkei futures have not previously been analysed. The ESTECM-EGARCH framework enables us to describe Nikkei price adjustments in the presence of transaction costs, heterogeneity, and asymmetry, and offers new insights into Nikkei price dynamics and information transmission across international markets. For example, it shows the importance of heterogeneity in transaction costs in the information roles of the different Nikkei markets, which have not previously been explored in a nonlinear framework. Second, we study Nikkei price dynamics before and after the 2008 global financial crisis and compare the home-bias hypothesis to the international centre hypothesis for the three Nikkei futures markets. We find that offshore financial centres lead the international price discovery, and that such price leadership is robust to the use of linear or nonlinear models and to the time differences among these markets, which strongly supports the international centre hypothesis. The analysis is useful for exchange regulators as it reveals possible ways through which an offshore exchange can improve its competitive advantage to become more attractive for investors. Third, we shed light on the role of liquidity in influencing Nikkei speeds of adjustment and price discovery, and why the CME leads the international transmission of information despite being relatively less liquid than SGX and OSE. Our results indicate that illiquidity may weaken the short-run Nikkei price adjustments but does not affect the long-run leadership of the CME. This is useful for Nikkei investors who seek to make informed decisions and manage cross-border risks as it implies that trading strategies could differ substantially across different investment horizons. Along with being important areas of research, the characterisation of nonlinear price adjustments and the identification of leadership in price discovery are also practical issues for Nikkei investors seeking to create profitable trading strategies in terms of information interpretation, market opportunities evaluation, and choice of the market through which to invest.

The rest of this paper proceeds as follows. Section 2 explains the institutional differences among the Nikkei markets; Section 3 presents the methodology; the data and preliminary analysis are in Section 4; the results and discussion are in Section 5; and Section 6 concludes the paper.

2. Institutional Differences among Nikkei 225 Markets

The Nikkei 225 is a price weighted index consisting of 225 common stocks listed in the First Section of the Tokyo Stock Exchange. Nikkei futures based on this index are traded domestically in the OSE and internationally in the SGX and CME. The OSE is the largest of the three markets in terms of daily average trading volume (Figure 1). Using trading volume as a measure of liquidity, this suggests that the OSE enjoys the highest liquidity, but that the CME is relatively illiquid. However, the foreign Nikkei markets show higher average growth rates in trading volume than the OSE. A deeper investigation into Nikkei futures liquidity is provided in Section 5.4. In terms of trading hours, Nikkei futures are traded in three different time zones (Table 1). Singapore is one hour behind Japan, so the trading hours of the OSE and SGX largely overlap, but SGX trades for 40 min longer than OSE. The longer trading time may be important to liquidity traders, and research supports that extra minutes contribute to daily price changes in the SGX (Covrig et al. 2004). For the CME, Central Standard Time (CST) in Chicago is 15 h behind Japan Standard Time (JST) in Tokyo. The opening hours of the OSE do not overlap with the opening hours of CME's open outcry system. However, CME Nikkei futures are also traded on the Globex electronic trading platform, which is open almost around-the-clock and therefore does overlap OSE trading.[3] Initially, we assume synchronous trading hours; the differences in trading hours are considered fully in Section 5.3.

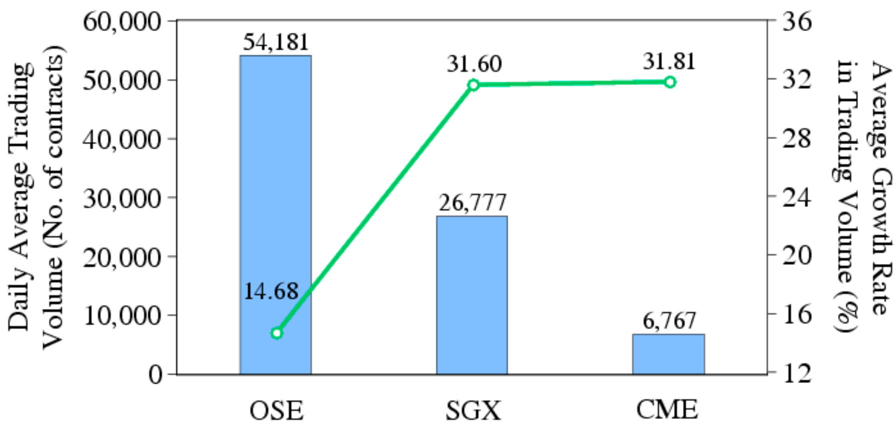

Figure 1. Nikkei futures trading volume. ***Notes:*** The left axis shows the daily average trading volume, calculated as the average number of contracts traded daily. Since the contract size of SGX futures is half that of OSE futures (Table 1), SGX volume is halved to facilitate direct comparison with OSE volume. CME volume is unadjusted due to dollar denomination. The right axis shows the average growth rate in trading volume, calculated as the average percent change in the number of contracts traded daily.

Table 1. The Nikkei futures contracts.

	OSE	SGX	CME
Contract size	Index × ¥1000	Index × ¥500	Index × $5
Tick size	10 index points (¥10,000)	5 index points (¥2500); 1 index point (¥500) for strategy trades	5 index points ($25)
Contract months	Nearest 3 for Mar and Sept; nearest 10 for Jun and Dec	Nearest 6 for serial months; nearest 20 for Mar, Jun, Sept, Dec	Mar, Jun, Sept, Dec
Trading hours (Local time)	9.00–15.15, 16.30–3.00	7.45–14.25, 15.15–2.00	Open outcry: 8.00–15.15 Electronic trading: 17.00–16.15
Trading system	Electronic trading	Open outcry (before 01/11/2004) Electronic trading (since 01/11/2004)	Open outcry and electronic trading [1]
Daily price limits	±8%, ±12%, ±16% of the previous day's settlement price	±7.5%, ±12.5% of the previous day's settlement price	±8%, ±12%, ±16% of a volume weighted average price calculated by CME
Margins	¥720,000	Initial: ¥396,000 Maintenance: ¥360,000	$4000 [2]
Trading fees	¥70 (proprietary) or ¥110 (customer) per contract	0.0075% of traded value	$0.245 (open outcry) or $0.50 (Globex) per contract [3]
Mutual offset	No mutual offset	Mutual offset with CME	Mutual offset with SGX
Final settlement day	Second Friday of the contract month	Second Friday of the contract month	Second Friday of the contract month

Notes: This table presents the contract specifications of the Nikkei 225 futures over the sample period 20/06/1996–31/12/2014 (OSE and SGX), 01/01/1997–31/12/2014 (CME). Data are from the OSE, SGX and CME. [1] CME closed the Nikkei open outcry system on 19/06/2015. [2] Equivalent to ¥430,200 using the sample average yen-dollar middle rate 107.55. [3] Equivalent to approx. ¥26.35 (open outcry) or ¥53.78 (Globex), using the sample average yen-dollar middle rate 107.55.

Table 1 shows key contract specifications and regulatory policies for the Nikkei exchanges. First, the contract size of SGX futures is half that of OSE futures, although both are yen-denominated. Smaller contracts allow lower capital requirements and risks that may appeal to investors with capital constraints and/or risk aversion. CME contracts are transacted and settled in dollars, meaning that the contract size is not comparable with OSE and SGX. This also introduces yen-dollar exchange rate risk to CME arbitrage, which is absent from OSE and SGX.[4] Second, OSE futures have had a computerised trading system since inception, but SGX shifted from open outcry to an electronic trading system on 1st November 2004. The shift in trading was smooth and did not exert a material effect on SGX futures prices.[5] Open outcry and the Globex electronic trading platform were available for CME contracts up until 2015, when open outcry was discontinued. Third, the SGX and CME permit a finer tick size than OSE, which induces smoother price changes and narrower bid–ask spreads. Covrig et al. (2004) estimate the average percent bid–ask spread on OSE contracts to be 0.069% compared to 0.040% for SGX. Fourth, even though all the exchanges use price limits, generally the SGX and CME offer lower margins and trading fees. Their contracts can be traded through the mutual offset, which provides investors with the flexibility of being able to enter a position in either exchange and clear that position in either the SGX or CME without additional cost. Overall, it can be argued that the foreign exchanges offer a more flexible and attractive trading environment for Nikkei investors than the OSE.

3. Methodology

3.1. The No-Arbitrage Conditions

The no-arbitrage condition between spot and futures prices is given by the cost of carry model (Cornell and French 1983):

$$F_t = S_t \exp(r - d)(T - t), \tag{1}$$

where F_t is the futures price, S_t the spot price, r the constant risk-free rate, d the continuous dividend yield on the index, T the maturity date of the futures contract, and $(T - t)$ the time to maturity, i.e., the number of calendar days remaining until expiration of the futures contract. Spot and futures prices should not deviate far from each other for long, as arbitrage would quickly remove the price deviations to restore equilibrium. In principle, there should be a cost of carry relationship between Nikkei spot prices and each of the three futures prices; this implies that spot and futures prices should be cointegrated in individual Nikkei markets, with their relationship given by:

$$f_t = \beta_0 + \beta_1 s_t + b_t, \tag{2}$$

where f_t = lnF_t, s_t = lnS_t, and b_t is a residual that includes the basis spread between the spot and futures prices. It is widely accepted that spot and futures prices are generally cointegrated with cointegrating vector [1, −1]. This requires $b_t = f_t - s_t$, where b_t is the log-basis.

For Nikkei futures, there are further no-arbitrage conditions. As they share the same underlying index and maturity date, Nikkei futures contracts listed on domestic and foreign markets are equivalent assets. Their markets should be linked by spread arbitrage, and their prices should move closely together. Following Board and Sutcliffe (1996), futures price parity can be written as:

$$F_{1t} = F_{2t}, \tag{3}$$

where 1, 2 denote any two Nikkei futures markets. Any departures from futures price parity should be quickly removed, even more quickly than in spot–futures arbitrage, because of the lower transaction costs and risks of trading the futures. Therefore, Nikkei futures prices should also be cointegrated, with the cointegrating relationship between any pair of log futures prices (f_{1t}, f_{2t}) given by:

$$f_{1t} = \beta_0' + \beta_1' f_{2t} + b_t', \tag{4}$$

where $b_t{}'$ is a residual, and the cointegrating vector is expected to be [1, −1].

3.2. The Linear ECM

The Granger representation theorem states that cointegrated time series can be described by an error correction mechanism (Engle and Granger 1987). A linear ECM for spot and futures prices is given by:

$$R_t = k + \sum_{j=1}^{p} \pi_j R_{t-j} + \alpha z_{t-1} + u_t, \tag{5}$$

where R_t is a 2 × 1 vector of log-returns Δs_t, Δf_t (or Δf_{1t}, Δf_{2t}), with lags j = 1, 2, ... , p, and p a positive integer; π_j is a 2 × 2 matrix of short-run adjustment coefficients, with off-diagonal coefficients $\pi_{sf,j}$, $\pi_{fs,j}$ (or $\pi_{12,j}$, $\pi_{21,j}$) measuring cross-market causalities; k is a 2 × 1 vector of constants; u_t is a 2 × 1 vector of white noise; z_{t-1} is the error correction term; and α (=$(\alpha_s, \alpha_f)'$ or $(\alpha_1, \alpha_2)'$) is a 2 × 1 vector of error correction coefficients showing the speed of adjustment to equilibrium. We expect $\alpha_s > 0$ and $\alpha_f < 0$. For example, the greater is α in the spot equation (α_s), the larger is the adjustments in the spot price in response to disequilibrium in the basis, and therefore the slower the spot market price itself reflects information, as it is being driven by basis disequilibrium, and hence, by price discovery in the futures market (Harris et al. 1995).

We estimate the linear ECM for all spot–futures and futures–futures pairs and conduct Granger causality tests on these ECMs.[6] In a spot–futures ECM, futures-to-spot causality (price discovery in futures) requires rejection of H_{01}: $\alpha_s = 0$ (long-run) or H_{02}: $\pi_{sf,j} = 0$, j = 1, 2, ... , p (short-run). Spot-to-futures causality (price discovery in spot) requires rejection of H_{03}: $\alpha_f = 0$ (long-run) or H_{04}: $\pi_{fs,j} = 0$, j = 1, 2, ... , p (short-run). Bidirectional causality (price discovery in both) requires rejection of either H_{01} and H_{03} (long-run), or H_{02} and H_{04} (short-run). The causality tests for the futures–futures pairs are performed analogously. For the OSE-related pairs, long-run causality from the OSE to the other markets (the home-bias hypothesis) requires rejection of H_{05}: $\alpha_{SGX} = 0$ (or $\alpha_{CME} = 0$), while H_{06}: $\alpha_{OSE} = 0$ should be rejected for the international centre hypothesis (Fung et al. 2001).

3.3. The ESTECM

Equations (1) and (3) are perfect market relationships in the absence of transaction costs. In the presence of transaction costs, disequilibria are not corrected until the benefits of arbitrage exceed its costs. The no-arbitrage conditions must be replaced by no-arbitrage bands where the band width is determined by the level of transaction costs:

$$F_t^L \leq F_t \leq F_t^U, \tag{6}$$

where $F_t{}^L$ is the lower bound and $F_t{}^U$ the upper bound. Investors compare futures prices with the transaction-cost bounds, and arbitrage only takes place when price deviations are large enough that arbitrage gains are more than sufficient to pay the transaction costs. The speed of adjustment to large deviations should therefore be quicker than adjustment to small deviations.

One approach to modelling this situation is to distinguish between a middle and an outer regime. The middle regime is the band immediately around the conventional no-arbitrage line, and it corresponds to small price deviations without substantial arbitrage incentives or price adjustments. The outer regime corresponds to large price deviations with active arbitrage and rapid price adjustments. However, a fixed threshold of transaction costs is difficult to justify for all market participants. Transaction costs are likely to be heterogeneous among different investors who have different trading goals, expectations, risks, constraints, and market access (Tse 2001). Aggregating over all investors will blur the boundaries of individual error correction regimes (Anderson 1997), implying that observed price adjustments will tend to be continuous and smooth for the whole market, rather than discontinuous as the price hits a single fixed transaction costs boundary. With heterogeneous transaction costs, there is evidence that the error correction process also depends on the sign of price deviations; negative price deviations induce quicker adjustments than positive deviations of the same size (van Dijk and Franses 1997). Such asymmetry is comparable to the leverage effect, in which bad news tends to have a larger impact on the second moment of asset returns than good news does (Bae and Karolyi 1994).

To allow for nonlinear price adjustments on account of transaction costs, heterogeneity, and asymmetry, we employ an ESTECM (Anderson 1997; Tse 2001):

$$R_t = k + \sum_{j=1}^{p} \pi_j R_{t-j} + (k^* + \sum_{j=1}^{p} \pi_j^* R_{t-j} + \alpha z_{t-1}) \times T(z_{t-d}) + u_t, \tag{7}$$

where k^* is a 2×1 vector of constants; $\pi_j{}^*$ is a 2×2 matrix of nonlinear adjustment coefficients with off-diagonal coefficients $\pi_{sf,j}{}^*$, $\pi_{fs,j}{}^*$ (or $\pi_{12,j}{}^*$, $\pi_{21,j}{}^*$); and the 2×1 residual vector u_t is iid with zero mean and finite variance. For short-run Granger causality tests, $\pi_{sf,j}$, $\pi_{fs,j}$ (or $\pi_{12,j}$, $\pi_{21,j}$) measure the cross-market adjustments in the middle regime, while ($\pi_{sf,j}$ + $\pi_{sf,j}{}^*$), ($\pi_{fs,j}$ + $\pi_{fs,j}{}^*$) (or ($\pi_{12,j}$ + $\pi_{12,j}{}^*$), ($\pi_{21,j}$ + $\pi_{21,j}{}^*$)) measure the cross-market adjustments in the outer regime. $T(\cdot)$ is the smooth transition function bounded between 0 (the middle regime) and 1 (the outer regime), and takes the following exponential form (Tse 2001):[7]

$$T(z_{t-d}) = 1 - \exp\left[-\gamma(z_{t-d} - c^*)^2 \times g(z_{t-d})\right], \tag{8}$$

$$g(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta(z_{t-d} - c^*)]\}, \tag{9}$$

z_{t-d} is the transition variable with delay parameter $d > 0$, $\gamma > 0$ is the smoothness parameter, θ the asymmetry parameter, and c^* is the centrality parameter. Equation (8) is a U-shaped curve with speedier correction for price deviations (z_{t-d}) that are larger in magnitude, which is consistent with the effect of transaction costs. The parameter γ governs the rate of smooth transition between regimes. The higher γ is, the steeper the transition function and the quicker the adjustment between the regimes. As $\gamma \to 0$, $T(\cdot) \to 0$; as $\gamma \to \infty$, $T(\cdot) \to 1$, and Equation (7) becomes linear in either case.[8] Moreover, γ has implications for the level of heterogeneity in market transaction costs (Taylor et al. 2000). Smaller γ indicates greater heterogeneity and higher transaction costs, while larger γ indicates less heterogeneity and lower transaction costs. Equation (9) is the asymmetry function that increases monotonically with θ (Anderson 1997). A negative (positive) θ means that more investors correct negative (positive) price deviations than equally sized positive (negative) ones. If θ = 0, $T(\cdot)$ is symmetric around c^* and investors are indifferent to the sign of deviations. We impose the restriction $k^* = c^* = 0$, because price returns will be demeaned (Section 4) and arbitrage is inactive at a price deviation of zero.

To test for smooth transition nonlinearity, we use the procedure of Teräsvirta (1994) that takes the ECM as null against an ESTECM. The null hypothesis of linearity is H_0: $\gamma = 0$; however, under this hypothesis, the ESTECM contains nonlinear parameters that are not restricted (Teräsvirta 1994; Franses and Dijk 2000). Such a problem is normally circumvented by performing the Lagrange multiplier (LM)-type linearity tests of Saikkonen and Luukkonen (1988) and Teräsvirta (1994). Given d, this involves running the following auxiliary regression (Taylor et al. 2000; McMillan 2005):

$$R_t = \beta_{00} + \sum_{j=1}^{p} \left(\beta_{0j} r_{t-j} + \beta_{1j} r_{t-j} z_{t-d} + \beta_{2j} r_{t-j} z_{t-d}^2 + \beta_{3j} r_{t-j} z_{t-d}^3 \right) + v_t, \tag{10}$$

where $r_t = (\Delta s_t, \Delta f_t, z_{t-1})'$ or $(\Delta f_{1t}, \Delta f_{2t}, z_{t-1})'$; and v_t is the residual. The lag length p is determined by estimating the ECM. H_0: $\gamma = 0$ is equivalent to H_0: $\beta_{1j} = \beta_{2j} = \beta_{3j} = 0$, under which an LM-type test statistic asymptotically follows a $\chi^2(3p)$ distribution. $LM = N(RSS_L - RSS_A)/RSS_L$, where N is the sample size, RSS_L is the residual sum of squares of the linear ECM, and RSS_A the residual sum of squares of Equation (10). To select the value of d, we perform the LM-type linearity tests for different candidates of d and determine d as the one that generates the lowest p-value of the test, because the correct d should have the highest power in the test (Teräsvirta 1994). Information criteria and other evaluation tests can also be used to specify d since a suitable d should have a better model fit (van Dijk et al. 2002).

If linearity is rejected, the ESTECM is estimated by nonlinear least squares (NLS). NLS is equivalent to maximum likelihood if the ESTECM residual is assumed to be normal; otherwise, the NLS estimates can be interpreted as quasi-maximum likelihood (QML) estimates (van Dijk et al. 2002).[9] Following the prevailing practice (Teräsvirta 1994; Anderson 1997), we standardise γ by the sample variance of z_{t-d} and standardise θ by the sample standard deviation of z_{t-d} to provide a scale-free environment for the nonlinear parameters. NLS estimates are conditional on starting values. A two-dimensional grid search over γ and θ is performed to obtain different sets of starting values, which are then used to estimate the same specification to find the global maximum in the likelihood function. The model with the minimal residual variance is selected as the final model.

3.4. The Conditional Variance Models

Preliminary estimates suggest heteroscedasticity in the mean model residuals. Thus, the linear ECM residuals are described by the GARCH (1, 1) model of Bollerslev (1986):

$$u_t = \sigma_t \eta_t, \tag{11}$$

$$\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2 \tag{12}$$

where $\eta_t \sim \text{iid}(0,1)$; $\omega > 0$; $a \geq 0$; $b \geq 0$; $a + b < 1$; σ_t is a time-varying, positive, and measurable function of the information set at time $t-1$.[10] The ECM-GARCH (Equations (5), (11), (12)) is the base model in the subsequent analysis.

The conditional variance of the ESTECM is assumed to follow the EGARCH (1, 1) process of Nelson (1991):

$$ln\sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a|u_{t-1}/\sigma_{t-1}| + bln\sigma_{t-1}^2, \quad (13)$$

The EGARCH model is selected to capture any possible leverage effect and to be consistent with the exponential transition function in the first moment.[11] Evidence for the leverage effect exists if $\lambda < 0$, implying that negative shocks tend to increase the conditional variance more than positive shocks do. Equations (7), (11) and (13) form the ESTECM-EGARCH model.

To estimate the ESTECM-EGARCH, we employ the two-step approach of Chan and McAleer (2002) to estimate the ESTECM by NLS and then the EGARCH by QML using the ESTECM residuals. Assuming a t-distribution for the conditional mean and the variance, the NLS and QML are consistent such that the NLS estimates can be interpreted as QML estimates (van Dijk et al. 2002).[12]

4. Data and Preliminary Analysis

Daily closing prices of the Nikkei index and daily settlement prices of the three Nikkei futures markets during 20/06/1996–31/12/2014 (OSE, SGX) and 01/01/1997–31/12/2014 (CME) are obtained from the respective exchanges and Datastream. Since Nikkei futures expire on the second Friday of the contract months (Table 1), the futures price series is compiled using the nearest futures contracts and rolling over to the next nearest contract at the start of the contract month. Nontrading days are excluded. The whole sample is split two: before the 2008 global financial crisis (sample A) and after it (sample B).[13] This enables us to compare Nikkei price dynamics before and after the crisis. In addition, as the main object of our paper is to model stable nonlinear dynamics in the returns data, observations falling within the extremely turbulent period of the financial crisis are omitted. Specifically, for spot–futures interactions, sample A is 28/06/1996–09/10/2008 (OSE, SGX), 09/01/1997–12/09/2008 (CME); and sample B is 04/11/2008–31/12/2014 (OSE, SGX), 02/12/2008–31/12/2014 (CME). For futures–futures interactions, sample A is 17/01/1997–12/09/2008 and sample B is 02/12/2008–30/12/2014.

Tables A1 and A2 in Appendix A present the descriptive statistics for Nikkei data and Johansen (1988, 1991) maximum likelihood tests for cointegration among the Nikkei spot prices and three futures prices, respectively. Overall, the Nikkei prices are I(1), and the four prices are cointegrated with three cointegrating vectors, or with one common stochastic factor as expected. Therefore, the Nikkei price dynamics can be described by an ECM, and the difference between any two prices can be used as the error correction term. We use the log-basis ($b_t = f_t - s_t$) for spot–futures and the respective log futures spreads for futures–futures: ($f_{OSE,t} - f_{SGX,t}$), ($f_{OSE,t} - f_{CME,t}$) or ($f_{SGX,t} - f_{CME,t}$).

The time to maturity of the futures contracts exerts a significant effect on our data, as may be expected. In addition, nonlinearities in the error correction estimates can be caused by a few outliers in the data (van Dijk and Franses 1997). To remove the time effect as each contract approaches expiration and certain outliers, each of the spot and futures returns and error correction terms are regressed on a constant, the time to maturity, and dummies that represent the outliers. Any trends and outliers removed from one series are removed from all the other series.[14]

5. Results and Discussion

We begin by showing residual diagnostics of the ECM-GARCH and ESTECM-EGARCH models for both spot–futures (Table A3) and futures–futures (Table A4) in Appendix A; these include tests for autocorrelation, any remaining GARCH, asymmetric response, and the information criteria. The results show that both models can represent Nikkei error correction dynamics, but the ESTECM-EGARCH model performs better in terms of the asymmetry tests and model fit.

Table 2 reports the results of the LM-type linearity tests. The LM-type statistics are highly significant, which indicates that the linearity null can be strongly rejected in favour of the ESTECM. The presence of smooth transition nonlinearity in the data justifies the ESTECM. The ECM cannot capture such nonlinearity; hence, the ESTECM is more appropriate for describing the Nikkei price adjustments. Therefore, we analyse the estimation results of both models but place more emphasis on the ESTECM-EGARCH results.

Table 2. LM-type linearity tests.

Panel A: Spot–futures pairs						
	(SPOT, OSE)		**(SPOT, SGX)**		**(SPOT, CME)**	
Market	**SPOT**	**OSE**	**SPOT**	**SGX**	**SPOT**	**CME**
Sample A						
$d = 1$	6.22×10^{-9}	1.94×10^{-9}	8.24×10^{-3}	8.38×10^{-3}	1.70×10^{-4}	2.17×10^{-8}
$d = 2$	3.95×10^{-3}	1.88×10^{-3}	1.21×10^{-1}	6.70×10^{-2}	3.70×10^{-6}	1.12×10^{-1}
$d = 3$	5.66×10^{-4}	1.70×10^{-4}	1.38×10^{-6}	4.87×10^{-8}	8.39×10^{-3}	1.83×10^{-4}
Sample B						
$d = 1$	1.85×10^{-9}	4.37×10^{-11}	2.89×10^{-3}	4.64×10^{-2}	2.97×10^{-9}	1.56×10^{-9}
$d = 2$	4.45×10^{-4}	1.93×10^{-5}	1.49×10^{-2}	2.31×10^{-2}	7.54×10^{-10}	2.03×10^{-7}
$d = 3$	3.91×10^{-9}	2.64×10^{-9}	7.63×10^{-4}	1.98×10^{-2}	1.46×10^{-4}	4.82×10^{-7}
Panel B: Bilateral futures pairs						
	(OSE, SGX)		**(OSE, CME)**		**(SGX, CME)**	
Market	**OSE**	**SGX**	**OSE**	**CME**	**SGX**	**CME**
Default: CME with OSE, SGX						
Sample A	1.19×10^{-9}	5.10×10^{-9}	2.53×10^{-16}	1.16×10^{-15}	9.11×10^{-16}	1.44×10^{-15}
Sample B	1.06×10^{-16}	2.55×10^{-17}	1.81×10^{-15}	1.86×10^{-11}	3.08×10^{-14}	9.56×10^{-12}
Alternative: CME ($t-1$) with OSE, SGX						
Sample A			3.53×10^{-13}	6.31×10^{-15}	4.90×10^{-12}	4.00×10^{-15}
Sample B			5.75×10^{-6}	7.56×10^{-16}	2.81×10^{-5}	1.75×10^{-15}

Notes: This table reports p-values of LM-type linearity tests for Nikkei spot–futures pairs and bilateral futures pairs. The tests are based on estimation of the auxiliary regression (Equation (10)) for each of the price returns. The null hypothesis of linearity is equivalent to H_0: $\beta_{1j} = \beta_{2j} = \beta_{3j} = 0$, under which a LM-type test statistic follows $\chi^2(3p)$ asymptotically. $LM = N(RSS_L - RSS_A)/RSS_L$, where N is the sample size, RSS_L the residual sum of squares from estimating the ECM, and RSS_A the residual sum of squares from estimating Equation (10). Panel A tests linearity for values of the delay parameter: $d = \{1, 2, 3\}$. Panel B tests for linearity based on $d = 1$. Panel B uses a default trading time sequence, where the CME returns on day t are aligned with the OSE, SGX returns on day t; and an alternative trading sequence, where the CME returns on day $t-1$, denoted CME ($t-1$), are aligned with the OSE, SGX returns on day t (Section 5.3).

5.1. Spot–Futures Price Dynamics

Table 3 Panel A presents the results of the ECM-GARCH. Generally, the error correction coefficients $\alpha_s > 0$ and $\alpha_f < 0$ support the error correction adjustments to equilibrium. Long-run causalities are bidirectional as both α_s and α_f tend to be significant. Given a lag length of one, we examined the short-run coefficients ($\pi_{sf,1}$, $\pi_{fs,1}$) directly to test the hypothesis that returns in one market do not Granger-cause returns in the other, and we found that futures led spot prices, especially after the financial crisis.

Table 3. Estimation results: Spot–futures price dynamics.

	(SPOT, OSE)		**(SPOT, SGX)**		**(SPOT, CME)**	
Market	**SPOT**	**OSE**	**SPOT**	**SGX**	**SPOT**	**CME**
Panel A: linear ECM-GARCH						
Parameter estimates						
Sample A						
α	0.3481 **	−0.2665 **	0.4096 **	−0.2090 **	0.7631 **	−0.1049 **
	(3.3224)	(−2.4707)	(3.9760)	(−2.0068)	(19.9597)	(−2.1596)
Sample B						
α	0.0109	−0.3488 **	0.2686 **	−0.2342 *	0.7364 **	0.0246
	(0.0695)	(−2.2769)	(2.0821)	(−1.8797)	(17.6859)	(0.4654)

Table 3. *Cont.*

Market	(SPOT, OSE) SPOT	OSE	(SPOT, SGX) SPOT	SGX	(SPOT, CME) SPOT	CME
Granger causality tests (short-run coefficients)			**Cross-market π**		**p-value**	
Sample A			$\pi_{fs,1}$	$\pi_{sf,1}$		
	SPOT does not cause OSE		0.0165		0.8636	
	OSE does not cause SPOT			0.1222	0.1816	
	SPOT does not cause SGX		−0.0557		0.5517	
	SGX does not cause SPOT			0.2126 **	0.0174	
	SPOT does not cause CME		−0.0476		0.1208	
	CME does not cause SPOT			0.0183	0.5317	
Sample B						
	SPOT does not cause OSE		−0.1947		0.1824	
	OSE does not cause SPOT			0.4014 **	0.0056	
	SPOT does not cause SGX		−0.0625		0.5129	
	SGX does not cause SPOT			0.2227 **	0.0231	
	SPOT does not cause CME		0.0402		0.2896	
	CME does not cause SPOT			0.0723 **	0.0394	

Market	(SPOT, OSE) SPOT	OSE	(SPOT, SGX) SPOT	SGX	(SPOT, CME) SPOT	CME
Panel B: nonlinear ESTECM-EGARCH						
Parameter estimates						
Sample A						
p	2	1	4	2	4	1
α	1.1559	−0.3575 **	0.5400 **	−0.0640	0.6253 **	−0.1068 **
	(1.5269)	(−1.9752)	(3.3099)	(−0.4798)	(7.5587)	(−2.4801)
γ	0.1461	0.7785	1.9356 *	2.3417	4.4606 **	20.2189
	(1.0069)	(1.0618)	(1.8197)	(1.5282)	(2.6413)	(0.2665)
θ	−2.3406	15.0295	0.4863	119.8710	3.5954	30.0258
	(−0.2721)	(0.0101)	(0.2775)	(0.0002)	(0.6950)	(0.0076)
λ	−0.0784 **	−0.0821 **	−0.0792 **	−0.0796 **	−0.0451 **	−0.0603 **
	(−7.1727)	(−7.3079)	(−7.0450)	(−7.1750)	(−3.0222)	(−5.3048)
Sample B						
p	1	1	2	2	4	1
α	0.1631	−0.2918	0.1831 *	−0.2044	0.6120 **	−15.3060
	(0.4695)	(−0.7096)	(1.7592)	(−1.5750)	(9.9129)	(−0.0011)
γ	0.1478	0.1051	1.7694	1.6575	852.7394	0.0001
	(0.4299)	(0.5572)	(1.1857)	(1.4016)	(1.6061)	(0.0011)
θ	−47.7984	−16.2092	−1.4902	−3.0504	1.1110	−1.3540
	(−0.0001)	(−0.0011)	(−0.3643)	(−0.5382)	(0.0215)	(−0.1293)
λ	−0.0910 **	−0.0986 **	−0.0977 **	−0.1043 **	−0.0450	−0.0882 **
	(−5.5864)	(−6.0936)	(−5.7200)	(−6.4223)	(−1.6242)	(−4.4347)
Granger causality tests (short-run coefficients)			**Middle regime**		**Outer regime**	
			Wald statistic	**p-value**	**Wald statistic**	**p-value**
Sample A						
	SPOT does not cause OSE		0.0049	0.9443	0.5617	0.7551
	OSE does not cause SPOT		33.6258 **	0.0000	41.3764 **	0.0000
	SPOT does not cause SGX		7.3938 **	0.0248	12.2442 **	0.0156
	SGX does not cause SPOT		25.0331 **	0.0000	32.0654 **	0.0001
	SPOT does not cause CME		1.0255	0.3112	4.1704	0.1243
	CME does not cause SPOT		7.5797	0.1082	18.4163 **	0.0183
Sample B						
	SPOT does not cause OSE		0.6461	0.4215	0.6588	0.7194
	OSE does not cause SPOT		8.5391 **	0.0035	9.5248 **	0.0085
	SPOT does not cause SGX		6.7064 **	0.0350	14.2367 **	0.0066
	SGX does not cause SPOT		3.4664	0.1767	18.1997 **	0.0011
	SPOT does not cause CME		0.0434	0.8349	0.0442	0.9781
	CME does not cause SPOT		1.9830	0.7389	13.2384	0.1039

Notes: This table presents the estimation results of the linear ECM-GARCH model (Equations (5), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (7), (11), (13)) for Nikkei spot–futures pairs. Panel A: The ECM is estimated by OLS with the model lag $p = 1$ selected by Schwartz information criterion (SIC). The GARCH is estimated by QML with Bollerslev–Wooldridge robust standard errors and covariance (Bollerslev and Wooldridge 1992). For pair-wise Granger causality tests, given the unit model lag, the cross-market π's are the estimated short-run adjustment coefficients $\pi_{sf,1}$, $\pi_{fs,1}$ in the ECM, reported with the associated p-values based on t-statistics. Panel B: The ESTECM is estimated by NLS with the restriction $k^* = c^* = 0$ and the model lags chosen by Akaike information criterion (AIC). The delay parameter $d = 1$. The EGARCH is estimated by QML. The Wald tests for Granger causality are performed in the middle regime (for $\pi_{sf,j}$ and $\pi_{fs,j}$) and the outer regime (for $\pi_{sf,j} + \pi_{sf,j}^*$ and $\pi_{fs,j} + \pi_{fs,j}^*$). The Wald statistics (Wald) and the associated p-values are reported. Numbers in parentheses are z-statistics. ** Significance at the 5% level. * Significance at the 10% level.

To select the delay parameter (d) for the ESTECM, an inspection of Table 2 Panel A finds that the smallest p-values of the LM-type statistics occur when $d = 1$ for OSE spot and futures; $d = 3$ for SGX spot and futures; $d = 2$ for CME spot and $d = 1$ for CME futures. A value of $d > 1$ means that the nonlinear regime switch takes more than one trading day to complete. However, this is probably not plausible, considering the likely arbitrage speed facilitated by electronic trading. Therefore, we decide to estimate the ESTECM first using the value of d whose p-value is the smallest, and then again with $d = 1$ for those markets in which the smallest p-values imply $d > 1$. We then make the final choice of d at the evaluation stage. Our results show that the ESTECM estimates are generally similar across different values of d, but the AIC of the models with $d = 1$ is always smaller than the AIC of the models with $d > 1$. This suggests that models with $d = 1$ do indeed provide a better fit, as well as being intuitively more consistent with what we expect in terms of the speed of arbitrage. Hence, we only reported and analysed estimation results with $d = 1$.

Table 3 Panel B presents the results of the ESTECM-EGARCH. In all cases, $\alpha_f < 0$ supports the error correction adjustments to equilibrium. The bidirectional causality remains in the CME; in the SGX, a significant α_s indicates futures leading spot prices. Comparing speeds of adjustment, futures show a quicker speed of adjustment than spot prices in sample A ($|\alpha_f| < |\alpha_s|$), but the spot market has a quicker speed of adjustment in sample B. This implies that, within a single regime, the futures prices led the price discovery process before the financial crisis, but the spot market led afterwards. The reversal of the price discovery roles is an interesting find and is discussed later in this paper.

The joint significance of the short-run coefficients is checked by pair-wise Granger causality tests, which are performed separately in the middle regime (for $\pi_{sf,j}$ and $\pi_{fs,j}$) and the outer regime (for $\pi_{sf,j} + \pi_{sf,j}{}^*$ and $\pi_{fs,j} + \pi_{fs,j}{}^*$). Short-run causality from spot returns to futures returns is checked using a Wald test to examine if all the lagged spot returns are zero in the futures equation; futures-to-spot causality is correspondingly checked using the lagged futures returns in the spot equation. With few exceptions, the results show futures-to-spot causality in the three Nikkei markets in both regimes, although there is some evidence of a bidirectional relationship in the SGX. There are more significant casual relationships in the outer regime than in the middle regime, which lends support to the transaction-cost argument that large price deviations are adjusted more quickly than small ones.

It is worth mentioning that the insignificance of estimates of γ should not be taken as evidence against smooth transition, as their standard statistics are invalid.[15] Estimates of γ are sensitive to re-scaling, algorithms, and data in the transition region. It is agreed that estimations of γ are generally imprecise (Teräsvirta 1994; Franses and Dijk 2000; Beckmann et al. 2014). To counter this, we examined which market has a relatively larger transition speed rather than a specific value of γ. Table 3 Panel B shows that futures have a relatively larger transition speed in sample A, and that the spot market has a relatively larger speed in sample B. In Figure A1 in Appendix A, the futures (spot) transition functions are steeper than the spot (futures) transition functions before (after) the crisis. When the error correction coefficients are also considered, this implies that, before the crisis, Nikkei futures were both faster to reflect information within a single regime and faster to transition between regimes. However, after the crisis, the spot market played a leading role with a quicker speed of adjustment and quicker rate of regime switch. A possible reason for this reversal of the price discovery roles lies in the relatively low level of heterogeneity (larger estimates of γ) in spot transaction costs among noise and fundamental traders after the financial crisis, compared to futures transaction costs. Noise traders follow market sentiment in rising markets but pay more attention to fundamentals in falling markets, where prices are driven by fundamental traders to equilibrium (McMillan and Speight 2006). As markets fall and recover after the crisis, Nikkei investors sharing the same spot market are more likely to behave in a similarly conservative manner, facing more equal transaction costs. The aggregate market response to price deviations may also be subject to fewer risks of cognitive bias and misprice deepening (Shleifer 2000), giving rise to more rapid error correction behaviour than in the futures.

Estimates of θ are broadly positive in sample A and negative in sample B. They imply that a positive (negative) log-basis is removed more quickly before (after) the crisis. Since basis adjustment is faster in futures before the crisis and faster in spot afterwards, the sign pattern of θ is broadly consistent with the conventional argument that short positions are less costly in the futures market. It would be natural to expect that adjustments to a positive log-basis are more likely to be completed by short-selling futures and to a negative log-basis by reducing long positions in the spot market. The estimates of θ are insignificant; however, imposing $\theta = 0$ in the mean model does affect the lag lengths and estimation of the models substantially, and thus, estimates of θ are retained in the model. The parameter λ is significantly negative, which suggests that negative shocks are associated with greater volatility, giving firm evidence for the leverage effect in individual Nikkei markets.

5.2. Cross-Border Futures Price Dynamics

Table 4 Panel A displays the linear results across the borders. We see that α_{OSE} tends to be significant, and as between the foreign markets, the SGX mainly adjusts to SGX-CME spreads. This suggests that long-run causality runs from the CME to the other markets. Since the lag lengths are generally greater than unity in these estimates, we examine short-run Granger causalities using the augmented lag method of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). This involves estimating a vector autoregressive (VAR) model of order (p + 1) in levels and performing the usual Wald tests on the original p variables, to ensure that the Wald statistics follow a standard asymptotic $\chi^2(p)$ distribution. Between the OSE and SGX, causality runs from the SGX to the OSE, not the reverse. The significant Wald statistics in the other pairs indicate bidirectional causality, but the causalities originating from the CME are much stronger. These provide strong evidence that the CME is the leading market in the cross-border price discovery process, followed by the SGX and then the OSE. The foreign-to-domestic information flows are stronger than the reverse, giving support to the international centre hypothesis.

Table 4. Estimation results: The cross-border futures price dynamics.

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Market	**OSE**	**SGX**	**OSE**	**CME**	**SGX**	**CME**
Panel A: linear ECM-GARCH						
Parameter estimates						
Sample A						
α	−1.0946 *	−0.1595	−0.9659 **	0.0039	−0.9721 **	0.0406
	(−1.9044)	(−0.2909)	(−10.8556)	(0.0518)	(−10.8722)	(0.5257)
Sample B						
α	−0.8340	0.0598	−0.8477 **	−0.0761	−0.8133 **	−0.0731
	(−1.3173)	(0.0958)	(−11.8565)	(−0.7847)	(−11.4988)	(−0.7472)
Granger causality tests (short-run coefficients)			**Wald statistic**		***p*-value**	
Sample A						
	OSE does not cause SGX		7.4347		0.4905	
	SGX does not cause OSE		36.3391 **		0.0000	
	OSE does not cause CME		14.9148 *		0.0608	
	CME does not cause OSE		909.6269 **		0.0000	
	SGX does not cause CME		19.0258 **		0.0147	
	CME does not cause SGX		930.2693 **		0.0000	
Sample B						
	OSE does not cause SGX		3.0781		0.6880	
	SGX does not cause OSE		10.7331 *		0.0569	
	OSE does not cause CME		20.9322 **		0.0008	
	CME does not cause OSE		955.4050 **		0.0000	
	SGX does not cause CME		20.2243 **		0.0011	
	CME does not cause SGX		975.8948 **		0.0000	

Table 4. *Cont.*

Market	(OSE, SGX) OSE	SGX	(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Panel B: nonlinear ESTECM-EGARCH						
Parameter estimates						
Sample A						
p	2	1	1	1	1	1
α	−3.4355 **	−1.0656	−0.8532 **	0.0708	−0.8437 **	0.0819
	(−2.7324)	(−1.1475)	(−22.3866)	(0.4059)	(−22.1564)	(0.3915)
γ	0.3945	0.2535	3024.3838	0.1930	18347.6705	0.1483
	(1.5462)	(0.9728)	(0.7482)	(0.7645)	(0.5265)	(0.6808)
θ	−66.8270	−68.2985	203.2291	−71.9725	−133.0122	−27306.5802
	(−0.0003)	(−0.0001)	(0.1075)	(0.0000)	(−0.1643)	(0.0000)
λ	−0.0732 **	−0.0739 **	−0.0381 **	−0.0594 **	−0.0359 **	−0.0595 **
	(−6.0012)	(−6.0412)	(−3.2108)	(−4.9907)	(−3.0292)	(−4.9871)
Sample B						
p	1	1	2	1	2	1
α	−0.3714	0.3917	−0.8867 **	−0.1731 **	−0.8477 **	−0.0866
	(−0.8084)	(0.7475)	(−16.8463)	(−2.3674)	(−16.0663)	(−1.6029)
γ	5.4304	2.8788	42.7342 *	5.2953	49.0643 *	3331.5697
	(1.0068)	(0.8938)	(1.6484)	(0.6480)	(1.8682)	(0.9340)
θ	−5.1529	−3.8982	43.3605	58.0112	25.8319	42.5430
	(−0.3041)	(−0.2923)	(0.0633)	(0.0017)	(0.2052)	(0.2703)
λ	−0.0912 **	−0.0908 **	−0.0881 **	−0.1098 **	−0.0958 **	−0.1175 **
	(−5.1735)	(−5.0157)	(−4.1879)	(−4.9301)	(−4.2181)	(−5.0784)
Granger causality tests (short-run coefficients)			**Middle regime**		**Outer regime**	
			Wald	***p*-value**	**Wald**	***p*-value**
Sample A						
	OSE does not cause SGX		2.4497	0.1175	4.5126	0.1047
	SGX does not cause OSE		14.1663 **	0.0008	22.3182 **	0.0002
	OSE does not cause CME		2.3839	0.1226	2.6288	0.2686
	CME does not cause OSE		1.7192	0.1898	1.8392	0.3987
	SGX does not cause CME		1.8213	0.1772	2.0069	0.3666
	CME does not cause SGX		0.9182	0.3379	0.9269	0.6291
Sample B						
	OSE does not cause SGX		0.1767	0.6742	0.2041	0.9030
	SGX does not cause OSE		0.0561	0.8128	0.2557	0.8800
	OSE does not cause CME		0.3616	0.5476	2.9971	0.2235
	CME does not cause OSE		3.9428	0.1393	13.4770 **	0.0092
	SGX does not cause CME		5.3791 **	0.0204	7.1097 **	0.0286
	CME does not cause SGX		3.2738	0.1946	12.8173 **	0.0122

Notes: This table presents the estimation results of the linear ECM-GARCH model (Equations (5), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (7), (11), (13)) for bilateral Nikkei futures pairs. Panel A: The ECM is estimated by OLS with the model lags $p = 7$ (sample A), 4 (sample B) in first differences determined by the sequential modified likelihood ratio test and AIC. The GARCH is estimated by QML with Bollerslev and Wooldridge (1992) robust standard errors and covariance. The Wald tests for Granger causality are performed by the augmented lag method of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). The Wald statistics are asymptotically distributed as $\chi^2(8)$ (sample A), $\chi^2(5)$ (sample B), reported with the associated p-values. Panel B: The ESTECM is estimated by NLS with the restriction $k^* = c^* = 0$, and the model lags chosen by AIC. The delay parameter $d = 1$. The EGARCH is estimated by QML. The Wald tests for Granger causality are performed in the middle regime (for $\pi_{12,j}$ and $\pi_{21,j}$) and the outer regime (for $\pi_{12,j} + \pi_{12,j}{}^*$ and $\pi_{21,j} + \pi_{21,j}{}^*$). The Wald statistics (Wald) and the associated p-values are reported. Numbers in parentheses are z-statistics. ** Significance at the 5% level. * Significance at the 10% level.

Table 4 Panel B reports the results of the ESTECM-EGARCH. There are just one or two lags in the ESTECM bilateral futures pairs, less than those of the spot–futures pairs. Since futures trading incurs fewer costs and risks, faster adjustments and shorter price dependencies across the futures markets are not surprising. For price adjustments within a single regime, generally α_{OSE} is significant, and the CME remains the quickest market in the nonlinear adjustment process. This confirms the finding of the linear model, i.e., that foreign Nikkei futures (especially the CME) lead the home market in the cross-border price dynamics.

Wald tests for short-run causal relationships in the middle regime and the outer regime show that patterns of causality are mixed. There is no evidence of causality running from OSE to the other markets, but there is some evidence of causality running from SGX and CME to OSE. There is also evidence of bidirectional causality between SGX and CME after the crisis. These results broadly reinforce the evidence for the information leadership of the foreign markets.

For the rate of smooth transition, we again concentrate on which market has a relatively larger transition speed. The larger estimates of γ are found in OSE for the OSE-related pairs. This suggests that the OSE is the quickest market in smooth transition, probably because of a more uniform structure of transaction costs. The foreign exchanges exhibit a more heterogeneous structure of transaction costs. For instance, the SGX can offer two different levels of tick sizes and more contract months, smaller contract size and margins, and the mutual offset between the SGX and CME (Table 1). The availability of a more diversified range of trading possibilities attracts cost-sensitive and/or capital-constrained investors and constitutes an advantage of the offshore financial centres. For the SGX and CME, the larger estimates of γ are in SGX (sample A) and then in CME (sample B). This implies that, in the CME, there are faster adjustments between regimes and lower transaction costs after the crisis than there were before. Asymmetry is found across the Nikkei futures in the first and second moments. In OSE-SGX arbitrage, the estimates of $\theta < 0$ indicate that more investors respond to negative spreads than to equally sized positive ones. In the arbitrage pertaining to the CME, the estimates of θ are mostly negative in sample A, but positive in sample B. Compared with the corresponding results for spot and futures, the asymmetric behaviour of the futures prices can be different once the spot market is involved. The significantly negative λ confirms the leverage effect in the Nikkei variances.

5.3. Non-Synchronous Trading Times

The above results firmly support the price-leadership role of the international Nikkei futures, especially the CME. However, they are based on same day returns and assume synchronous trading hours among the exchanges. In fact, Central Standard Time (CST) used by the CME is 15 h behind Japan Standard Time (JST), which is used by the OSE.[16] However, since the CME Globex trades around the clock and OSE trades into the night, there are long periods during any day when both markets are open (Figure 2). Moreover, OSE and CME settlement prices are generated on the same day.[17] The use of the same-day returns may therefore be justified on two counts: first, spread arbitrage can be active due to the common trading hours in the time sequence; and second, matching all the returns on day t captures information on the same "nominal" day. Previous research also tends to support this conclusion (Booth et al. 1996).

Nevertheless, it could be argued that using all the returns on day t implies a default time sequence whereby the OSE, SGX are ahead of the CME. We consider next whether the estimated CME leadership is determined artificially by this time sequence. To check this argument, we follow Booth et al. (1996) and re-estimate the models with an alternative time sequence in which the CME is the earliest trading market of the three. We completed this by aligning the CME returns on day $t-1$ with the OSE and SGX returns on day t, so that the CME becomes the earliest trading market, and all the returns reveal information within the same 24-h time interval.

Table 5 shows the linear results using the alternative trading sequence.[18] Though long-run causalities are bidirectional, the OSE and SGX now have faster speeds of adjustment to futures price parity. The Wald tests for short-run causality also indicate stronger influences of the OSE and SGX. Combining this with our earlier finding that the SGX tends to lead the OSE, which is unaffected by the timing issues, we can argue that the SGX may be the leading market, followed by the OSE and the CME. The price leadership of the CME seems to be transferred to the SGX. However, these results are still consistent with the conclusion that it is the last trading market in each time sequence that reflects information the most quickly. The last trading market may have more opportunities to absorb information that already exists in the earlier markets, which contributes to its price leadership. Overall, we find support for the hypothesis that offshore financial centres (the CME and SGX) act as the main price discovery vehicles for information transmission. This is consistent with the Nikkei literature that uses linear models (Kao et al. 2015) and with the network/platform literature that shows information gravitating to the most ubiquitous international platform (Rochet and Tirole 2003).

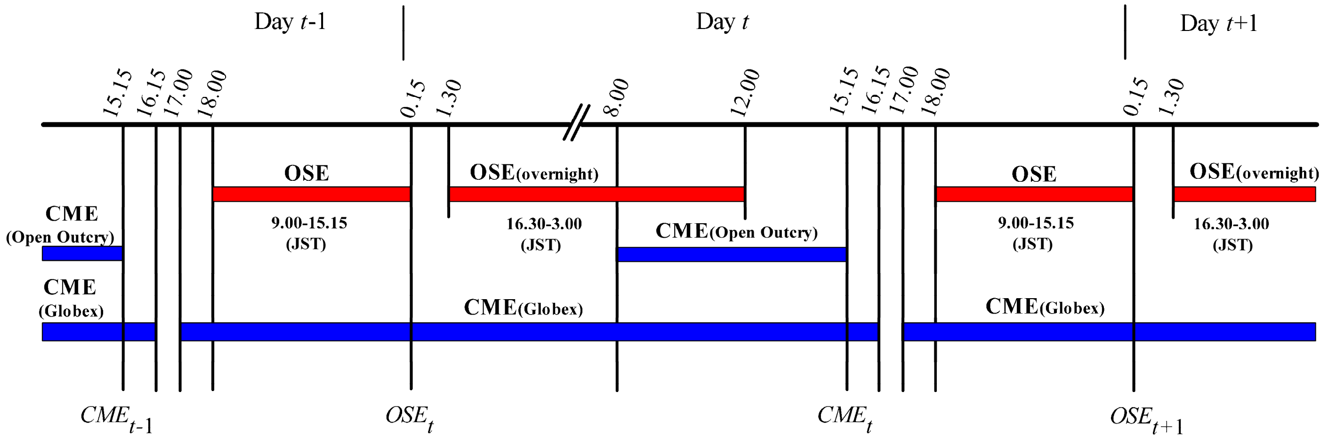

Figure 2. Trading hours of the OSE and CME. ***Notes:*** The time is Central Standard Time (CST) unless otherwise shown. The bottom line shows the time when the OSE, CME settlement prices are generated. For reference, the Nikkei spot market opens 9.00–11.30, 12.30–15.00 (Japan Standard Time, JST), corresponding to 18.00–20.30, 21.30–0.00 (CST).

Table 5. Nonsynchronous trading time tests.

Market		(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Parameter estimates					
Sample A					
α		−0.0876	0.9663 **	−0.0645	0.9987 **
		(−0.8486)	(20.2841)	(−0.5979)	(20.9107)
Sample B					
α		−0.1868 **	0.8573 **	−0.1883 **	0.9195 **
		(−2.1171)	(7.7796)	(−2.1128)	(6.7818)
Granger causality tests (short-run coefficients)				**Wald statistic**	***p*-value**
Sample A					
	OSE does not cause CME			5502.1624 **	0.0000
	CME does not cause OSE			16.0325 **	0.0248
	SGX does not cause CME			5611.5337 **	0.0000
	CME does not cause SGX			16.5222 **	0.0208
Sample B					
	OSE does not cause CME			1495.1841 **	0.0000
	CME does not cause OSE			13.4686 **	0.0194
	SGX does not cause CME			1498.9699 **	0.0000
	CME does not cause SGX			11.8033 **	0.0376

Notes: This table presents the estimation results of the linear ECM-GARCH model (Equations (5), (11), (12)) for bilateral futures pairs (OSE, CME) and (SGX, CME). The model is estimated with the CME returns on day $t-1$ aligned with the OSE, SGX returns on day t. The ECM lags p = 6 (sample A), 4 (sample B) in first differences are determined by the sequential modified likelihood ratio test and AIC. The GARCH is estimated by QML with Bollerslev and Wooldridge (1992) robust standard errors and covariance. The Wald tests for Granger causality are performed by the augmented lag method of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). The Wald statistics are asymptotically distributed as $\chi^2(7)$ (sample A), $\chi^2(5)$ (sample B), reported with the associated p-values. Numbers in parentheses are z-statistics. ** Significance at the 5% level.

5.4. The Role of Liquidity in Nikkei Price Adjustments

From Figure 1, the CME has the lowest average trading volume of the three futures markets. This suggests that the CME is less liquid than the other markets and in principle contradicts the intuitive expectation that greater liquidity encourages higher pricing efficiency. Nevertheless, foreign Nikkei markets, especially the CME, show higher average growth rates in trading volume than the OSE. We also find that the rate of smooth transition in the CME has increased over time compared to SGX, which implies more rapid adjustments between the regimes in the CME in recent years (Section 5.2). As such, the role of liquidity in Nikkei markets deserves a deeper investigation. In this section, we aim to explain such foreign leadership and investigate the role of liquidity in international price discovery for Nikkei futures.

5.4.1. Measuring Futures Illiquidity

Our paper uses daily data covering 19 years; so, for consistency we constructed a daily measure of illiquidity, following Amihud (2002), that uses our full 19-year dataset.[19] Nikkei futures illiquidity, q_t, is defined as the ratio of the daily absolute percent price change to same-day trading volume:

$$q_t = |lnF_t - lnF_{t-1}|/Vol_t, \tag{14}$$

where Vol_t is the yen/dollar trading volume on day t, calculated as the product of the number of contracts traded and the contract size.[20] This ratio gives the daily price response associated with one yen/dollar of trading volume, or the daily price impact of order flow (Amihud 2002). It is then re-scaled by multiplying by 10^6 following Amihud (2002).

We use q_t directly in the spot–futures models but, for bilateral futures pairs, we use excess illiquidity measured as the difference between illiquidity in any two markets. Since CME has the lowest average trading volume but OSE has the highest, the three excess illiquidity variables are defined as: $(q_{CME,t} - q_{OSE,t})$, $(q_{CME,t} - q_{SGX,t})$, and $(q_{SGX,t} - q_{OSE,t})$, ensuring that each excess illiquidity series is positive on average. All six illiquidity variables are adjusted by removing time trends and outliers as specified in Section 4. For consistency, the return series, the error correction terms, and the illiquidity measures are each adjusted by dummying out all the outliers found in any series in each pair and detrending the time effect. Unit root tests show that each illiquidity variable is stationary, so they can be directly incorporated into our specification.[21]

5.4.2. Modelling Nikkei Price Dynamics with Illiquidity

The effect of illiquidity is examined by including q_t in the nonlinear ESTECM-EGARCH model and testing its significance. It is not clear in advance whether illiquidity would affect the adjustment process, the smooth transition process, or both. We therefore re-estimate the linear ECM-GARCH model with the illiquidity variable first to examine whether q_t is significant in the linear adjustment process. For example, the linear ECM for the OSE becomes:

$$R_t = k + \sum_{j=1}^{p} \pi_j R_{t-j} + \delta q_{OSE,t} + \alpha z_{t-1} + u_t, \tag{15}$$

where $\delta = (\delta_{SPOT}, \delta_{OSE})'$ is the coefficient vector of $q_{OSE,t}$ in the linear adjustment process.

Interestingly, we found the effect of illiquidity to be significant in all three markets, especially the CME, in the post-crisis period (Table 6 Panel A and Table 7 Panel A). Moreover, the many positive coefficients of δ indicate that illiquidity positively affects the Nikkei futures returns. For example, excess illiquidity of CME significantly increased the CME market returns, implying that CME returns are higher by a premium due to the higher illiquidity (lower liquidity) of CME. This "illiquidity premium" in the equilibrium price is consistent with Amihud (2002).

For the pairs that exhibit significant illiquidity effects under the linear specification, we proceed by incorporating q_t in both the adjustment process and the smooth transition process of the ESTECM, that is (using OSE as example):

$$R_t = k + \sum_{j=1}^{p} \pi_j R_{t-j} + \delta q_{OSE,t} + (k^* + \sum_{j=1}^{p} \pi_j^* R_{t-j} + \delta^* q_{OSE,t} + \alpha z_{t-1}) \times T(z_{t-d}) + u_t, \quad (16)$$

where $\delta^* = (\delta_{SPOT}{}^*, \delta_{OSE}{}^*)'$ is the coefficient vector of $q_{OSE,t}$ in the nonlinear smooth transition process. For pairs where q_t is insignificant in the linear model, it is incorporated only in the smooth transition process of the ESTECM as (using OSE as example):

$$R_t = k + \sum_{j=1}^{p} \pi_j R_{t-j} + (k^* + \sum_{j=1}^{p} \pi_j^* R_{t-j} + \delta^* q_{OSE,t} + \alpha z_{t-1}) \times T(z_{t-d}) + u_t, \quad (17)$$

The conditional variance of the ESTECM is assumed to follow an EGARCH (1, 1) or EGARCH (2, 1) as necessary. The ESTECM-EGARCH specification is then re-estimated individually for Nikkei spot–futures and bilateral futures pairs. The NLS estimation details are the same as before.

Table 6. Spot–futures price dynamics with illiquidity.

	(SPOT, OSE)		(SPOT, SGX)		(SPOT, CME)	
Market	**SPOT**	**OSE**	**SPOT**	**SGX**	**SPOT**	**CME**
Panel A: linear ECM-GARCH						
Parameter estimates						
Sample A						
α	0.3384 **	−0.2814 **	0.4044 **	−0.2118 **	0.7637 **	−0.1037 **
	(3.2261)	(−2.6090)	(3.9314)	(−2.0421)	(19.9387)	(−2.1133)
δ	−197.1974	−2107.9367	139.6380	−1.2788	−0.8597	−0.9426
	(−0.0622)	(−0.6555)	(0.3985)	(−0.0036)	(−0.8165)	(−0.6758)
Sample B						
α	0.0391	−0.3294 **	0.2656 **	−0.2339 *	0.7358 **	0.0202
	(0.2473)	(−2.1190)	(2.0466)	(−1.8515)	(17.6807)	(0.3856)
δ	4124.7419	2259.8479	555.6569	138.7760	0.7659	4.2394 **
	(1.1893)	(0.5923)	(1.1206)	(0.2095)	(0.9679)	(3.2658)
Granger causality tests (short-run coefficients)			**Cross-market π**		***p*-value**	
Sample A			$\pi_{fs,1}$	$\pi_{sf,1}$		
	SPOT does not cause OSE		0.0065		0.9458	
	OSE does not cause SPOT			0.1305	0.1531	
	SPOT does not cause SGX		−0.0579		0.5367	
	SGX does not cause SPOT			0.2172 **	0.0152	
	SPOT does not cause CME		−0.0462		0.1325	
	CME does not cause SPOT			0.0179	0.5429	
Sample B						
	SPOT does not cause OSE		−0.1978		0.1777	
	OSE does not cause SPOT			0.4056 **	0.0052	
	SPOT does not cause SGX		−0.0623		0.5162	
	SGX does not cause SPOT			0.2281 **	0.0210	
	SPOT does not cause CME		0.0404		0.2870	
	CME does not cause SPOT			0.0720 **	0.0404	

Table 6. *Cont.*

Market	(SPOT, OSE) SPOT	OSE	(SPOT, SGX) SPOT	SGX	(SPOT, CME) SPOT	CME
Panel B: nonlinear ESTECM-EGARCH						
Parameter estimates						
Sample A						
p	2	1	4	2	4	1
α	3.3001	−0.4049 **	2.9406	−0.0691	0.6871 **	0.5237
	(0.4008)	(−2.1373)	(1.5245)	(−0.5319)	(10.1349)	(0.2317)
γ	0.0203	0.7151	0.0877	2.7361	3.3739 **	0.0136
	(0.3539)	(1.1990)	(1.2816)	(1.5086)	(2.9068)	(0.2915)
θ	−18.3518	15.7083	−1.7169	98.6235	3.4451	−43.9446
	(−0.0018)	(0.0107)	(−0.6532)	(0.0004)	(0.7075)	(−0.0002)
λ	−0.0825 **	−0.0832 **	−0.0813 **	−0.0816 **	−0.0445 **	−0.0524 **
	(−7.4164)	(−7.3898)	(−7.2601)	(−7.2321)	(−3.5478)	(−3.7902)
δ *	5180.6540	−9339.2991	−219.3636	−166.4696	−0.7747	44.6965
	(0.1023)	(−1.4337)	(−0.1396)	(−0.3102)	(−0.8195)	(0.3870)
Sample B						
p	1	1	2	2	4	1
α	0.0476	−1.2785	0.1667	−0.1834	0.6855 **	0.0433
	(0.3935)	(−0.1212)	(1.5120)	(−1.4142)	(11.7952)	(0.6314)
γ	9.1023	0.0112	1.1393	1.5431	9.2825 **	0.9851
	(0.7839)	(0.1118)	(1.1481)	(1.4436)	(2.3495)	(0.4616)
θ	10.3011	−26.3139	−17.8785	−36.9457	−26.4214	−12.1269
	(0.1397)	(−0.0001)	(−0.0149)	(−0.0049)	(−0.0445)	(−0.0123)
λ	−0.0969 **	−0.1020 **	−0.0970 **	−0.0947 **	−0.0565 **	−0.0879 **
	(−5.5128)	(−5.9794)	(−5.5615)	(−5.5087)	(−2.8425)	(−4.3116)
δ *	5338.8145 **	32333.3316	491.2193	−836.0924	2.5868	5.6829
	(2.1027)	(0.1165)	(0.5067)	(−1.2293)	(1.1695)	(0.9622)
δ					0.1464	3.0655
					(0.0952)	(1.2444)
Granger causality tests (short-run coefficients)			**Middle regime** Wald	*p*-value	**Outer regime** Wald	*p*-value
Sample A						
	SPOT does not cause OSE		0.0177	0.8941	0.9200	0.6313
	OSE does not cause SPOT		46.2326 **	0.0000	58.9578 **	0.0000
	SPOT does not cause SGX		7.0036 **	0.0301	11.2198 **	0.0242
	SGX does not cause SPOT		71.3739 **	0.0000	80.6378 **	0.0000
	SPOT does not cause CME		2.7859 *	0.0951	3.3167	0.1905
	CME does not cause SPOT		13.1928 **	0.0104	21.2449 **	0.0065
Sample B						
	SPOT does not cause OSE		0.9872	0.3204	1.1024	0.5763
	OSE does not cause SPOT		0.2935	0.5880	11.4576 **	0.0033
	SPOT does not cause SGX		7.9611 **	0.0187	14.1727 **	0.0068
	SGX does not cause SPOT		3.8985	0.1424	18.8842 **	0.0008
	SPOT does not cause CME		0.1953	0.6586	0.5756	0.7499
	CME does not cause SPOT		13.2924 **	0.0099	28.3652 **	0.0004

Notes: This table presents the estimation results of the linear ECM-GARCH model (Equations (15), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (16) or (17), (11), (13)) with illiquidity for Nikkei spot–futures pairs. The futures illiquidity variable q_t in each Nikkei market is defined as the ratio of daily absolute percent price change to same-day trading volume (Equation (14)). Provided that the spot–futures pairs exhibit significant illiquidity effects in the ECM-GARCH, q_t is incorporated in both the adjustment process and the smooth transition process of the ESTECM, i.e., Equation (16) is used. Otherwise, q_t is incorporated only in the smooth transition process of the ESTECM, i.e., Equation (17) is used. Panel A: The ECM is estimated by OLS with the model lag p = 1 selected by SIC. The GARCH is estimated by QML with Bollerslev and Wooldridge (1992) robust standard errors and covariance. For pair-wise Granger causality tests, given the unit model lag, the cross-market π's are the estimated short-run adjustment coefficients $\pi_{sf,1}$, $\pi_{fs,1}$ in the ECM, reported with the associated p-values based on t-statistics. Panel B: The ESTECM is estimated by NLS with the restriction k^* = c^* = 0 and the model lags chosen by AIC. The delay parameter d = 1. The EGARCH is estimated by QML. The Wald tests for Granger causality are performed in the middle regime (for $\pi_{sf,j}$ and $\pi_{fs,j}$) and the outer regime (for $\pi_{sf,j}$ + $\pi_{sf,j}$* and $\pi_{fs,j}$ + $\pi_{fs,j}$*). The Wald statistics (Wald) and the associated p-values are reported. Numbers in parentheses are z-statistics. ** Significance at the 5% level. * Significance at the 10% level.

Table 7. The cross-border futures price dynamics with illiquidity.

Market	(OSE, SGX) OSE	SGX	(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Panel A: linear ECM-GARCH						
Parameter estimates						
Sample A						
α	−1.1588 **	−0.1567	−0.9491 **	0.0356	−0.9541 **	0.0735
	(−2.0651)	(−0.2816)	(−10.8521)	(0.4735)	(−10.8201)	(0.9617)
δ	3.5829	−21.6415	−1.5791	−1.6317	−1.6111	−1.6480
	(0.0088)	(−0.0536)	(−1.4397)	(−1.2047)	(−1.5547)	(−1.2155)
Sample B						
α	−0.8253	0.0708	−0.8630 **	−0.1012	−0.8271 **	−0.0940
	(−1.3037)	(0.1136)	(−12.0270)	(−1.0777)	(−11.7678)	(−0.9940)
δ	887.8163 **	909.0086 **	0.5835	4.4500 **	0.8516	4.4714 **
	(2.0787)	(2.0451)	(0.7461)	(3.6139)	(0.9950)	(3.6674)
Granger causality tests (short-run coefficients)			**Wald statistic**		***p*-value**	
Sample A						
	OSE does not cause SGX		7.4422		0.4898	
	SGX does not cause OSE		36.4347 **		0.0000	
	OSE does not cause CME		15.0894 *		0.0574	
	CME does not cause OSE		908.2400 **		0.0000	
	SGX does not cause CME		19.2558 **		0.0135	
	CME does not cause SGX		928.1152 **		0.0000	
Sample B						
	OSE does not cause SGX		2.7749		0.7346	
	SGX does not cause OSE		10.0362 *		0.0742	
	OSE does not cause CME		18.8425 **		0.0021	
	CME does not cause OSE		948.3163 **		0.0000	
	SGX does not cause CME		18.3181 **		0.0026	
	CME does not cause SGX		967.9434 **		0.0000	
	(OSE, SGX)		**(OSE, CME)**		**(SGX, CME)**	
Market	**OSE**	**SGX**	**OSE**	**CME**	**SGX**	**CME**
Panel B: nonlinear ESTECM-EGARCH						
Parameter estimates						
Sample A						
p	2	1	1	1	1	1
α	−4.3221 **	−1.3997	−0.8576 **	0.0479	−0.8422 **	0.1172 **
	(−2.0155)	(−1.1141)	(−22.7438)	(0.6395)	(−22.4028)	(2.2844)
γ	0.2035	0.1554	281.0000	1.4314	25744.9709	22.0180
	(1.2140)	(1.0040)	(0.5645)	(1.1500)	(0.4681)	(0.7596)
θ	−15.6393	−4.3035	−0.4000	−3.0441	−5812.6910	79.6161
	(−0.0116)	(−0.2843)	(−0.0046)	(−0.3178)	(−0.0001)	(0.0030)
λ	−0.0675 **	−0.0744 **	−0.0395 **	−0.0610 **	−0.0365 **	−0.0621 **
	(−4.7177)	(−6.0392)	(−3.2218)	(−5.0758)	(−2.9964)	(−5.1854)
δ *	−7950.5111	−10237.4848	−3.4014 **	−4.7063 **	−3.6303 **	−3.7872 **
	(−1.3692)	(−1.0741)	(−4.1411)	(−2.1177)	(−4.3460)	(−4.2003)
Sample B						
p	1	1	2	1	2	1
α	−77.2117	−1.7619	−0.8827 **	−0.1891 **	−0.8676 **	−0.1356 *
	(−0.0800)	(−0.2748)	(−17.8023)	(−2.2830)	(−17.7276)	(−1.9017)
γ	0.0020	0.0277	1090.0000	2.9289	4100.0000	4.5398
	(0.0798)	(0.4038)	(0.7234)	(0.7766)	(1.2486)	(0.4920)
θ	514.8777	225.0730	0.9000	147.8629	0.7000	114.6071
	(0.0000)	(0.0000)	(0.0066)	(0.0001)	(0.0053)	(0.0001)
λ	−0.0906 **	−0.0926 **	−0.0853 **	−0.1040 **	−0.0927 **	−0.1032 **
	(−4.5305)	(−4.5146)	(−4.0802)	(−4.6179)	(−4.0884)	(−4.6053)
δ *	126834.9657	22329.2007	5.7032 **	2.5166	7.3026	−1.0341
	(0.0834)	(0.4077)	(2.2960)	(0.9318)	(1.2720)	(−0.4594)
δ	909.2016	917.5998	−3.7275	3.9692 **	−5.2613	4.7557 **
	(1.1918)	(1.2568)	(−1.6084)	(2.8813)	(−0.9245)	(3.8214)

Table 7. *Cont.*

Market	(OSE, SGX) OSE	SGX	(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Granger causality tests (short-run coefficients)			**Middle regime**		**Outer regime**	
			Wald	***p*-value**	**Wald**	***p*-value**
Sample A						
	OSE does not cause SGX		2.3186	0.1278	4.1741	0.1241
	SGX does not cause OSE		11.8084 **	0.0027	14.8913 **	0.0049
	OSE does not cause CME		2.7247 *	0.0988	2.7381	0.2543
	CME does not cause OSE		0.6329	0.4263	0.9301	0.6281
	SGX does not cause CME		0.1479	0.7006	3.0276	0.2201
	CME does not cause SGX		1.2071	0.2719	1.2099	0.5461
Sample B						
	OSE does not cause SGX		0.0169	0.8965	0.1940	0.9076
	SGX does not cause OSE		1.6698	0.1963	1.7253	0.4220
	OSE does not cause CME		0.1438	0.7045	3.0325	0.2195
	CME does not cause OSE		2.2633	0.3225	6.3331	0.1756
	SGX does not cause CME		0.0796	0.7778	1.4618	0.4815
	CME does not cause SGX		1.5937	0.4507	6.2231	0.1831

Notes: This table presents the estimation results of the linear ECM-GARCH model (Equations (15), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (16) or (17), (11), (13)) with illiquidity for bilateral Nikkei futures pairs. The illiquidity variable for these futures pairs is the excess illiquidity measure calculated as ($q_{SGX,t} - q_{OSE,t}$), ($q_{CME,t} - q_{OSE,t}$) and ($q_{CME,t} - q_{SGX,t}$), where q_t is the illiquidity variable in each Nikkei market. Provided that the bilateral futures pairs exhibit significant illiquidity effects in the ECM-GARCH, q_t is incorporated in both the adjustment process and the smooth transition process of the ESTECM, i.e., Equation (16) is used. Otherwise, q_t is incorporated only in the smooth transition process of the ESTECM, i.e., Equation (17) is used. Panel A: The ECM is estimated by OLS with the model lags p = 7 (sample A), 4 (sample B) in first differences determined by the sequential modified likelihood ratio test and AIC. The GARCH is estimated by QML with Bollerslev and Wooldridge (1992) robust standard errors and covariance. The Wald tests for Granger causality are performed by the augmented lag method of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). The Wald statistics are asymptotically distributed as $\chi^2(8)$ (sample A), $\chi^2(5)$ (sample B), reported with the associated p-values. Panel B: The ESTECM is estimated by NLS with the restriction $k^* = c^* = 0$ and the model lags chosen by AIC. The delay parameter $d = 1$. The EGARCH is estimated by QML. The Wald tests for Granger causality are performed in the middle regime (for $\pi_{12,j}$ and $\pi_{21,j}$) and the outer regime (for $\pi_{12,j} + \pi_{12,j}{}^*$ and $\pi_{21,j} + \pi_{21,j}{}^*$). The Wald statistics (Wald) and the associated p-values are reported. Numbers in parentheses are z-statistics. ** Significance at the 5% level. * Significance at the 10% level.

5.4.3. Illiquidity Effects on Nikkei Price Discovery

A significant effect of illiquidity is found in bilateral Nikkei futures pairs (Table 7 Panel B). The illiquidity effects are in a smooth transition process (δ^*) before the crisis and a smooth transition (δ^*) and adjustment (δ) process after the crisis. The post-crisis effect is positive, which suggests that the excess illiquidity of CME tends to increase futures returns as compensation for being relatively less liquid, constituting an illiquidity premium.[22] This reinforces the linear results of an illiquidity premium, especially in the CME during the post-crisis period.

Comparing Table 7 Panel B with Table 4 Panel B, we find that adding illiquidity to the ESTECM-EGARCH does not affect the long-run price adjustments of the Nikkei futures, as identified by α. The CME remains the quickest market in price discovery, followed by the SGX and the OSE. For short-run Granger causalities, adding illiquidity weakens the price leadership of the CME and SGX, especially after the crisis. These results suggest that illiquidity may have a negative impact on the short-run price adjustments to equilibrium for the Nikkei. This is consistent with the empirical evidence in the literature that liquidity is positively related to informational efficiency (e.g., Chordia et al. 2008; Chung and Hrazdil 2010). However, illiquidity does not appear to affect the price leadership of the foreign Nikkei markets in the long run.

When illiquidity is included, the foreign exchanges remain the markets with more heterogeneous transaction costs, as shown by γ. Asymmetry is also found in the first and second moments in the three Nikkei markets, represented by θ and λ, respectively. These results are robust to the inclusion of illiquidity effects. Therefore, our findings firmly corroborate the international centre hypothesis, and the information advantage of the foreign exchanges seems to be clear. Foreign market advantages include their roles as global information centres, their more heterogeneous and lower transaction costs, and their longer trading hours. More importantly, foreign leadership is unaffected by the degree of market illiquidity in the long run, though it may be weaker over shorter horizons.

6. Conclusions

Research on spot–futures interactions has increasingly suggested the presence of nonlinear price adjustments to equilibrium. To our knowledge, this is the first paper that examines nonlinear price adjustments in the information transmission process and price discovery for the triple-listed Nikkei futures contracts. We studied the smooth transition error correction behaviour between Nikkei spot and futures prices and across the three Nikkei futures markets, addressing the question of which Nikkei market leads the price discovery process in international information transmission. The ECM-GARCH is used as a base model, and then the ESTECM-EGARCH is estimated to capture the nonlinear effects of transaction costs, heterogeneity, and asymmetry. Specification tests indicate the presence of smooth transition nonlinearity and suggest that the ESTECM-EGARCH is more appropriate. Our key findings and their implications are as follows.

First, Nikkei price adjustments exhibit smooth transition error correction behaviour, which can be represented by the ESTECM-EGARCH model. Nikkei prices are error-correcting between different regimes and are asymmetric in the first and second moments. The nonlinear dynamics can be explained partly by heterogeneity in transaction costs. For spot–futures price dynamics, we find that futures led spot prices in price discovery before the financial crisis, but that spot prices led afterwards. The reversal of the price discovery roles can be attributed to the relatively low level of heterogeneity in spot transaction costs and the associated interactions between noise traders and fundamental traders in the post-crisis period. For cross-border futures price dynamics, we report quicker adjustments of the OSE and slower adjustments of the SGX and CME in smooth transition, which can again be explained by the different levels of heterogeneity in their transaction cost structures. Our findings underline the importance of allowing for nonlinearities in futures price adjustments in general, and in Nikkei markets in particular. Neglecting nonlinearities in Nikkei prices could result in the loss of important information contained in the prices, such as the level of heterogeneity in transaction costs, which is closely related to the information roles of the markets.

Second, it is the foreign Nikkei markets that take the price leadership in the international price discovery process. This result is robust to the use of linear or nonlinear models, the time differences, and the long-run liquidity conditions of the Nikkei markets, and therefore strongly supports the international centre hypothesis. Foreign leadership in price discovery can be explained by the roles of the CME and SGX as global information centres and their flexible trading conditions, including more heterogeneous and lower transaction costs, and longer trading hours. The informativeness of the foreign Nikkei implies that small, offshore exchanges can compete with a large home market in the globalisation of futures by offering a more attractive trading environment, and thereby increasing market competitiveness. For example, exchange regulators could aim for an improvement in price discovery by increasing the diversity of risk management tools and transaction costs available in the market to enhance the level of heterogeneity in transaction costs.

Third, we investigated the effect of liquidity on Nikkei price adjustments. We found evidence of an illiquidity premium, and we showed that the relative illiquidity of foreign Nikkei markets has a negative impact on Nikkei price adjustments in the short run but does not have a material effect on the foreign leadership or Nikkei price adjustments in the long run. This implies that Nikkei investors who seek to make informed decisions and manage risks across the borders may need to pay more attention to their investment horizons and adjust their trading strategies accordingly. Investors with a long horizon may want to use the information channels provided by foreign Nikkei exchanges as important price discovery vehicles, while short-term investors are more likely to benefit from the greater liquidity of the home market.

As with other studies that use historical data, our work is based on the chosen sample period and therefore cannot capture real-time price interactions in and across the Nikkei markets. Future research could re-visit some of the issues in the paper with an updated intraday dataset, not simply to reflect more recent market conditions but also to release some of the restrictions imposed on the ESTECM—for example, to allow for a time-varying smoothness parameter to describe real price interdependence more accurately. The Nikkei 225 futures have also started to trade on the B3 Exchange (Brazil). It is of interest to study the price discovery role of the emerging Brazilian Nikkei market in the future.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Descriptive statistics.

	SPOT		OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Price returns								
Mean	−0.0003	0.0005	−0.0003	0.0005	−0.0003	0.0005	−0.0001	0.0005
Std. Dev.	0.0147	0.0153	0.0153	0.0154	0.0150	0.0150	0.0149	0.0149
AR(1)	−0.0341 *	−0.0552 **	−0.0712 **	−0.0505 **	−0.0455 **	−0.0371	−0.0729 **	−0.0141
ADF (log-prices) [1]	−1.8208	−1.8860	−1.7740	−1.8810	−1.8641	−1.9030	−1.7527	−1.8133
ADF (returns)	−56.8693 **	−41.4880 **	−59.0176 **	−41.5847 **	−57.4696 **	−41.6747 **	−58.3330 **	−40.4335 **
Panel B: Basis								
Mean			−3.5961	−8.4241	−2.1468	−8.9494	10.6465	37.4029
Std. Dev.			47.3897	34.3022	47.0671	47.6074	129.4377	130.9044
Panel C: Basis change								
AR(1)			−0.4431 **	−0.4614 **	−0.4471 **	−0.4312 **	−0.4311 **	−0.4891 **

Notes: This table presents descriptive statistics for Nikkei price returns, basis, and basis change. The pre-crisis sample A is 28/06/1996–09/10/2008 (SPOT, OSE, SGX), 09/01/1997–12/09/2008 (CME); and the post-crisis sample B is 04/11/2008–31/12/2014 (SPOT, OSE, SGX), 02/12/2008–31/12/2014 (CME). AR(1) is the first-order autocorrelation coefficient. Augmented Dickey-Fuller (ADF) test statistics are computed with constant and trend for log-prices; without constant or trend for returns. The ADF lag length is determined by SIC. Basis is the difference between each Nikkei futures market and the contemporaneous spot price. Basis change is the first–order difference in the basis. ** Significance at the 5% level. * Significance at the 10% level. [1] Zivot–Andrews unit root tests are performed as a robustness check, and the results are qualitatively the same and available on request.

Table A2. Cointegration tests.

Panel A: Tests for the number of cointegrating vectors				
	Trace test		**Maximal eigenvalue test**	
	Statistic	**1% critical value**	**Statistic**	**1% critical value**
Sample A				
None	835.4643	54.4600	346.3023	32.2400
At most 1	489.1620	35.6500	296.8546	25.5200
At most 2	192.3074	20.0400	189.6610	18.6300
At most 3	2.6464	6.6500	2.6464	6.6500
Sample B				
None	642.1812	54.4600	311.2230	32.2400
At most 1	330.9582	35.6500	244.8513	25.5200
At most 2	86.1069	20.0400	85.3596	18.6300
At most 3	0.7473	6.6500	0.7473	6.6500
Panel B: Tests of cointegration restrictions				
	No. of cointegrating vectors		**LR statistic**	***p*-value**
Sample A	3		6.1754	0.1034
Sample B	3		3.2024	0.3615

Notes: This table reports the results of Johansen cointegration tests for the four Nikkei spot and futures prices. The pre-crisis sample A is 17/01/1997–12/09/2008; and the post-crisis sample B is 02/12/2008–30/12/2014. The tests are based on a VAR model in levels with the VAR lag lengths of 8 (sample A), 4 (sample B) chosen by sequential modified likelihood ratio (LR) test and AIC. In Panel B, the LR statistic is for testing the following restriction on the transposed cointegrating matrix beta, which is equivalent to testing the cointegrating vector [1, −1] for every pair of prices. $\beta' = \begin{bmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix}$.

Table A3. Model evaluation for spot–futures pairs.

	(SPOT, OSE)		**(SPOT, SGX)**		**(SPOT, CME)**	
Market	**SPOT**	**OSE**	**SPOT**	**SGX**	**SPOT**	**CME**
Panel A: linear ECM-GARCH						
Sample A			***p* values**			
Q(24) for η_t	0.6953	0.5667	0.4792	0.3000	0.9425	0.9435
Q(24) for ${\eta_t}^2$	0.3413	0.3057	0.5939	0.4673	0.2680	0.9728
Asymmetric tests						
Sign bias test	0.8058	0.5975	0.6125	0.9782	0.5326	0.0960
Negative size bias test	0.9723	0.8283	0.8510	0.6079	0.9351	0.2120
Positive size bias test	0.0002	0.0004	0.0003	0.0008	0.3105	0.4016
Joint test	0.0029	0.0012	0.0061	0.0079	0.1846	0.0307
			Information criteria			
AIC	−5.7547	−5.6923	−5.7593	−5.7208	−6.0463	−5.6845
SIC	−5.7407	−5.6784	−5.7454	−5.7069	−6.0321	−5.6703
Sample B			***p* values**			
Q(24) for η_t	0.9927	0.9956	0.8925	0.9421	0.2993	0.9095
Q(24) for ${\eta_t}^2$	0.3098	0.2517	0.3240	0.3789	0.5422	0.9396
Asymmetric tests						
Sign bias test	0.6771	0.6401	0.5761	0.7278	0.1495	0.7704
Negative size bias test	0.5874	0.9966	0.2475	0.7804	0.8867	0.7939
Positive size bias test	0.4961	0.0225	0.2318	0.0901	0.2365	0.0050
Joint test	0.4079	0.1190	0.3167	0.1916	0.6733	0.1028
			Information criteria			
AIC	−5.7363	−5.7386	−5.7843	−5.8034	−6.2979	−5.6901
SIC	−5.7081	−5.7139	−5.7569	−5.7794	−6.2735	−5.6658

Table A3. *Cont.*

Market	(SPOT, OSE) SPOT	OSE	(SPOT, SGX) SPOT	SGX	(SPOT, CME) SPOT	CME
Panel B: nonlinear ESTECM-EGARCH						
Sample A			***p* values**			
Q(24) for η_t	0.5645	0.4812	0.2366	0.2510	0.9774	0.9307
Q(24) for ${\eta_t}^2$	0.4959	0.4975	0.8622	0.5396	0.2218	0.9683
Asymmetric tests						
Sign bias test	0.1673	0.2289	0.8448	0.7068	0.4002	0.1630
Negative size bias test	0.7356	0.3109	0.3163	0.5905	0.9710	0.1784
Positive size bias test	0.4694	0.2216	0.9853	0.1442	0.8180	0.9151
Joint test	0.3598	0.1098	0.7266	0.3381	0.4380	0.3718
			Information criteria			
AIC	−5.7883	−5.7271	−5.7978	−5.7640	−6.0472	−5.7049
SIC	−5.7525	−5.7013	−5.7460	−5.7302	−5.9964	−5.6784
Sample B			***p* values**			
Q(24) for η_t	0.9939	0.9915	0.9082	0.9625	0.4345	0.9174
Q(24) for ${\eta_t}^2$	0.6513	0.6092	0.1932	0.9482	0.6982	0.9889
Asymmetric tests						
Sign bias test	0.7307	0.2921	0.6884	0.4560	0.4443	0.7734
Negative size bias test	0.4094	0.4463	0.2956	0.3747	0.5206	0.0864
Positive size bias test	0.3525	0.3495	0.4729	0.3684	0.4858	0.0647
Joint test	0.5887	0.3741	0.6004	0.2642	0.8764	0.2382
			Information criteria			
AIC	−5.7606	−5.7689	−5.8130	−5.8409	−6.3081	−5.7454
SIC	−5.7113	−5.7196	−5.7513	−5.7793	−6.2247	−5.7002

Notes: This table shows the evaluation results of the linear ECM-GARCH model (Equations (5), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (7), (11), (13)) for Nikkei spot–futures pairs. The pre-crisis sample A is 28/06/1996–09/10/2008 (OSE, SGX), 09/01/1997–12/09/2008 (CME); and the post-crisis sample B is 04/11/2008–31/12/2014 (OSE, SGX), 02/12/2008–31/12/2014 (CME). Q(24) is Ljung and Box (1978) Q-statistic up to order 24. The asymmetric test of Engle and Ng (1993) includes sign bias test, negative size bias test, positive size bias test, and joint test.

Table A4. Model evaluation for cross-border futures pairs.

Market	(OSE, SGX) OSE	SGX	(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Panel A: linear ECM-GARCH						
Sample A			***p* values**			
Q(24) for η_t	0.9782	0.9847	0.9249	0.9662	0.9367	0.9672
Q(24) for ${\eta_t}^2$	0.1350	0.1471	0.3175	0.9046	0.3488	0.9136
Asymmetric tests						
Sign bias test	0.7731	0.4478	0.9395	0.8409	0.8483	0.7546
Negative size bias test	0.4631	0.6289	0.4455	0.9578	0.4840	0.9084
Positive size bias test	0.1166	0.2262	0.2303	0.2447	0.3896	0.2739
Joint test	0.0521	0.0598	0.2072	0.3050	0.4550	0.3073
			Information criteria			
AIC	−5.6598	−5.6843	−5.9437	−5.6271	−5.9851	−5.6279
SIC	−5.6171	−5.6416	−5.9031	−5.5865	−5.9445	−5.5873
Sample B			***p* values**			
Q(24) for η_t	0.8260	0.8296	0.6116	0.9865	0.7823	0.9864
Q(24) for ${\eta_t}^2$	0.7003	0.7594	0.8349	0.6058	0.9007	0.6203
Asymmetric tests						
Sign bias test	0.6755	0.5554	0.8088	0.3464	0.3284	0.1578
Negative size bias test	0.4975	0.4425	0.5481	0.4620	0.1578	0.2936
Positive size bias test	0.0255	0.0321	0.6175	0.0016	0.8324	0.0007
Joint test	0.0444	0.0546	0.6361	0.0721	0.1038	0.0432
			Information criteria			
AIC	−5.7133	−5.7282	−6.2256	−5.6241	−6.2490	−5.6242
SIC	−5.6657	−5.6807	−6.1745	−5.5766	−6.2015	−5.5766

Table A4. *Cont.*

Market	(OSE, SGX) OSE	SGX	(OSE, CME) OSE	CME	(SGX, CME) SGX	CME
Panel B: nonlinear ESTECM-EGARCH						
Sample A			p **values**			
Q(24) for η_t	0.8606	0.8533	0.8673	0.7066	0.8523	0.7099
Q(24) for $\eta_t{}^2$	0.1790	0.1125	0.1352	0.9711	0.1884	0.9702
Asymmetric tests						
Sign bias test	0.2163	0.2861	0.5144	0.9841	0.4697	0.9875
Negative size bias test	0.8691	0.6958	0.7365	0.6144	0.7450	0.6138
Positive size bias test	0.4882	0.4215	0.1865	0.6515	0.8729	0.6640
Joint test	0.4289	0.4913	0.5046	0.8942	0.7558	0.9009
			Information criteria			
AIC	−5.6968	−5.7284	−5.9703	−5.6485	−6.0170	−5.6480
SIC	−5.6584	−5.6985	−5.9426	−5.6207	−5.9892	−5.6202
Sample B			p **values**			
Q(24) for η_t	0.8439	0.8307	0.3985	0.9734	0.5429	0.9758
Q(24) for $\eta_t{}^2$	0.5630	0.7755	0.8159	0.6326	0.9840	0.8219
Asymmetric tests						
Sign bias test	0.7294	0.8447	0.3969	0.1620	0.2565	0.0541
Negative size bias test	0.9428	0.9573	0.2721	0.9598	0.1822	0.1948
Positive size bias test	0.5561	0.7031	0.5831	0.0043	0.5476	0.0064
Joint test	0.8069	0.9378	0.1252	0.1150	0.1660	0.1298
			Information criteria			
AIC	−5.7470	−5.7658	−6.3091	−5.6943	−6.3398	−5.6980
SIC	−5.6995	−5.7183	−6.2469	−5.6468	−6.2777	−5.6468

Notes: This table shows the evaluation results of the linear ECM-GARCH model (Equations (5), (11), (12)) and the nonlinear ESTECM-EGARCH model (Equations (7), (11), (13)) for bilateral Nikkei futures pairs. The pre-crisis sample A is 17/01/1997–12/09/2008; and the post-crisis sample B is 02/12/2008–30/12/2014. Q(24) is Ljung and Box (1978) Q-statistic up to order 24. The asymmetric test of Engle and Ng (1993) includes sign bias test, negative size bias test, positive size bias test, and joint test.

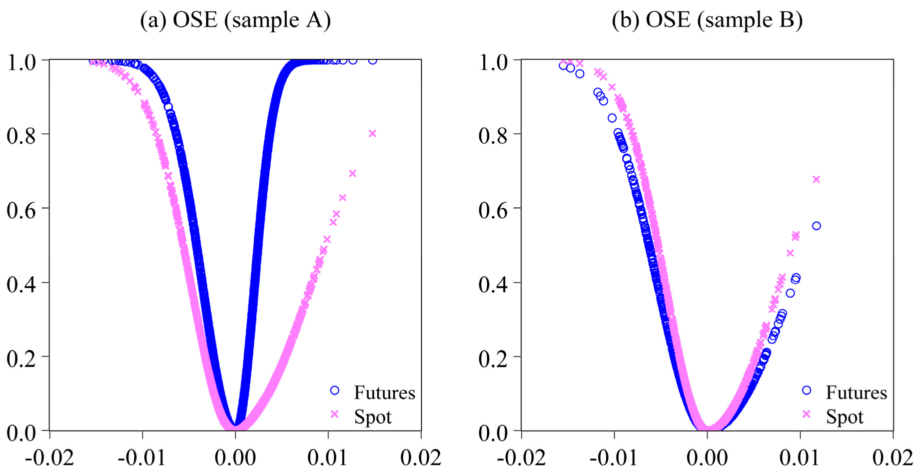

Figure A1. *Cont.*

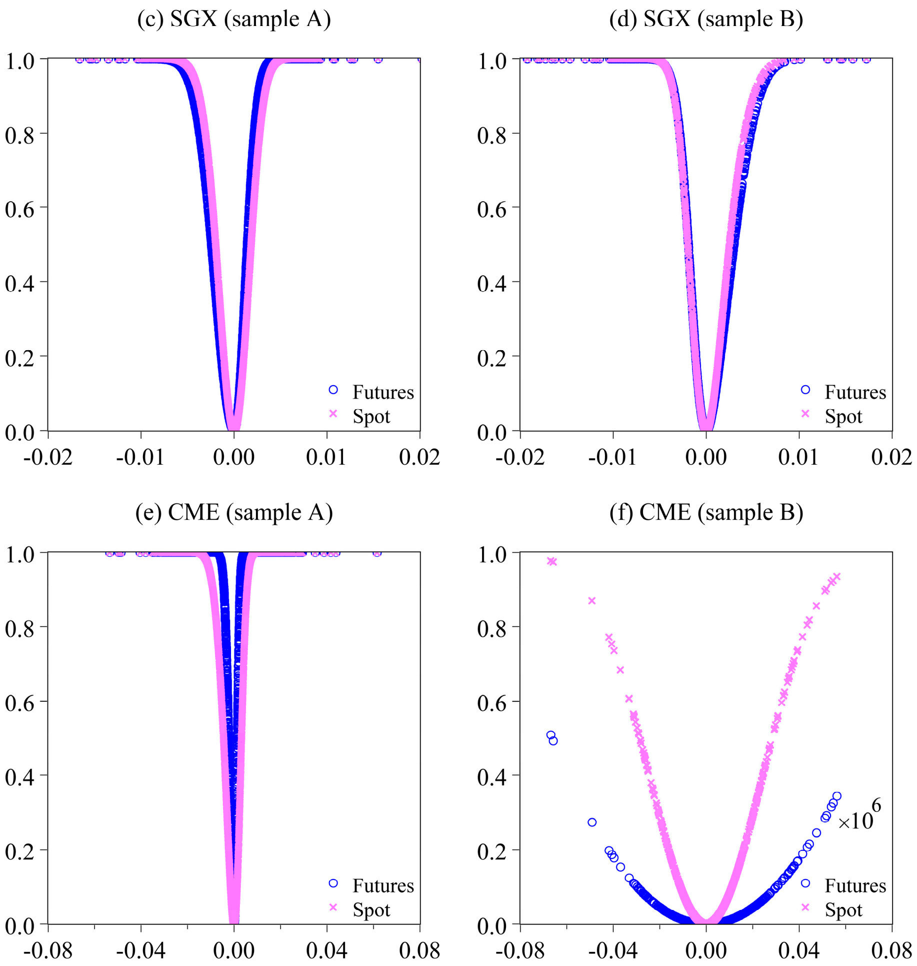

Figure A1. Spot–futures transition functions. ***Notes:*** (**a**–**f**) plot the Nikkei spot–futures transition functions estimated from Equations (8) and (9). $T(z_{t-d})$ on the vertical axis is plotted against z_{t-d} on the horizontal axis. For (**f**) only, since the spot γ is very large in value, the parameters are standardised by dividing γ (θ) by the sample variance (standard deviation) of z_{t-d}; the estimates of the futures transition function are multiplied by 10^6.

Notes

1 Following the existing literature (e.g., Fung et al. 2001; Board and Sutcliffe 1996), we refer to OSE as the home market, and to SGX and CME as the international markets, irrespective of the investors' country of origins.

2 Our research also relates to the literature on the impact of exchange-traded funds (ETFs) on liquidity and price discovery. Several empirical studies show that the introduction of ETFs brings positive effects due to quicker price response to news, lower costs of ETF trading, and enhanced arbitrage across markets (e.g., Poshakwale et al. 2018; Park and Switzer 1995; Chu and Hsieh 2002; Duffy et al. 2021; Box et al. 2021); however, other studies report illiquid markets and little improvement in cross-market price relationships (e.g., Israeli et al. 2017; Hamm 2014; Ackert and Tian 2001). As our data run from 1996 through 2014, and the five major Nikkei ETFs were introduced gradually over 2001–2009, we did not include them in our analysis.

3 The Globex is the first global futures and options electronic trading system that was developed for the CME; it was introduced in 1992.

4 Nikkei futures (spot) prices are expressed as indices, which are pure numerical values without regard to currency denomination. This differs from the actual cost of trading these assets, which is denominated in different currencies (dollars for CME futures; yen for the other Nikkei futures and spot). Estimates of trading costs should consider exchange rate risks, but actual trading costs are not required to study the spot–futures price relationships. For this reason, we do not make exchange rate adjustments for Nikkei prices.

5 SGX investors were given time to adapt to electronic trading in overnight sessions and in a period when both systems were available for trading. In our analysis we use SGX futures prices on the floor before 1st November 2004 and on the electronic system since then. Visual inspection and Quandt–Andrews breakpoint test do not suggest any breaks in the SGX price series around the changeover date.

6 Nikkei price dynamics are studied in pairs (spot–futures pairs and bilateral futures pairs) for two main reasons. First, increasing the number of markets to three would increase the number of parameters to be estimated in the ESTECM-EGARCH model to an unmanageable size. Second, pair-wise estimation makes for more intuitive interpretation of the estimated parameters.

7 Logistic smooth transition ECM (LSTECM) has been used in some studies (e.g., McMillan 2005; Beckmann et al. 2014). The logistic transition function has the following form: $T(z_{t-d}) = \{1 + \exp[-\gamma(z_{t-d} - c^*)]\}^{-1}$, and is monotonically increasing from 0 to 1, implying that the error correction behaviour is independent of the size of price deviations. LSTECM can allow for asymmetric adjustments of positive and negative price deviations, but not for the effect of transaction costs. Hence, the LSTECM is deemed inappropriate for this paper.

8 The error correction term z_{t-1} should be included in both the middle and outer regimes of a complete ESTECM. In that case, when $\gamma = 0$, Equation (7) reduces exactly to Equation (5). However, we retain z_{t-1} only in the outer regime, because arbitrage would be too costly to exploit small price deviations in the middle regime, implying no error correction, while arbitrage should be profitable for large price deviations in the outer regime, implying the existence of error correction dynamics in the outer regime. Thus, as $\gamma \to 0$, Equation (7) reduces to a linear VAR model without the error correction term.

9 Conditions of consistency and asymptotic normality of the NLS estimates are provided by Klimko and Nelson (1978) and Tong (1990).

10 Where necessary we use a GARCH (2, 1) model to remove excessive heteroscedasticity.

11 Where necessary we use an EGARCH (2, 1) model to remove excessive heteroscedasticity.

12 The two–step estimation approach of Chan and McAleer (2002) does not affect the consistency and asymptotic normality of the QML estimates but may incur a loss of efficiency. Joint estimation of the complete ESTECM-EGARCH can be computationally problematic (Chan and McAleer 2002). For comparability, the ECM-GARCH is also estimated in two steps using ordinary least squares (OLS) for the ECM and QML for the GARCH. Occasionally the ESTECM-EGARCH model cannot converge under the *t*-distribution. In those cases, we assume a normal distribution for the conditional mean and the variance, with which the NLS (for the mean) is equivalent to maximum likelihood (for the variance).

13 This is based on an initial inspection of the Nikkei price returns and then on Quandt–Andrews breakpoint tests.

14 Results of tests for time effects are available on request. We define outliers as observations that exceed 6 standard deviations in absolute value from the mean of each series. For spot–futures pairs, we removed 4(OSE), 8(SGX) and 2(CME) outliers; for futures-futures pairs, we removed 4 outliers.

15 The presence of smooth transition nonlinearity should be tested by the LM-type linearity tests (Table 2).

16 The OSE, SGX trading hours are almost overlapping (Section 2). For simplicity, we only compare the time differences between the OSE and CME.

17 This also holds when Central Daylight Time (CDT) is observed by the CME in summer. CDT reduces the OSE, CME time differences to 14 h, so that the OSE settlement price is generated at 1.15 in Chicago on day *t* under the CDT.

18 We do not report the nonlinear results with the alternative time sequence for CME as it generates poorly conditioned estimates with excessive residual autocorrelations. This may be due to the nontrading interval that occurs after the OSE overnight session closes and before the OSE normal session opens, lasting about 6 h, when the CME is open but the other Nikkei markets are all closed (Figure 2). Matching CME on day $t-1$ with the OSE and SGX on day *t* includes this thinly traded period. When markets close and reopen, clustered volatilities are often reported in response to news that arrives during the nontrading gap. Such news in the Nikkei markets can only manifest itself via the CME during the gap when the other markets are closed; and this may vitiate the ESTECM-EGARCH estimates.

19 Some studies calculate illiquidity using high-frequency data. However, such measure requires intraday trading data that are unavailable in the Nikkei for long time periods.

20 The contract size is calculated as the contract multiplier by futures index at the close of the previous trading day. Because the futures price and the trading volume are denominated in the same currency (yen or dollars), Equation (14) is invariant to the currency of denomination.

21 Results are available on request.

22 Amihud (2002) distinguishes between expected and unexpected illiquidity and reports that expected illiquidity has a positive effect on excess stock returns, whereas unexpected illiquidity has a negative effect. However, the distinction between expected and unexpected illiquidity is essentially based on an arbitrary time series model.

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