Determinants of Nikkei Futures Mispricing in International Markets: Dividend Clustering, Currency Risk and Transaction Costs

by

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Abstract

This paper develops a comprehensive modified cost of carry model to study the mispricing of Nikkei 225 index futures contracts traded in Osaka, Singapore and Chicago based on a new 19-year dataset. Using this improved model, we find that dividend clustering, currency risk and transaction costs all play an essential role in the estimation of Nikkei mispricing. An exponential smooth transition autoregressive (ESTAR)-GARCH model is used to describe the international dynamics of Nikkei mispricing. The results indicate that generally mean reversion in mispricing and limits to arbitrage are driven more by transaction costs than by heterogeneous investors.

JEL classification: G13; G14; G15

Keywords: Nikkei 225 futures; mispricing; index arbitrage; ESTAR-GARCH model

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1. Introduction

Many securities are traded simultaneously on different international markets. Differences among markets due *inter alia* to currency of trading, transaction costs, opening hours, supply of liquidity and regulation, can all create different rates of price discovery in separate markets for the same security. This implies that mispricing, arbitrage opportunities and price adjustments may vary among the different markets. This is a particularly important issue for international investors who have the option to trade on these different markets.

Nikkei 225 index futures contracts are a vital investment tool in worldwide trading activities. Nikkei shares are traded in Tokyo, but the corresponding index futures contracts are traded in Osaka, Singapore and Chicago. The triple-listed nature of Nikkei futures and institutional differences among the three markets substantially affect the economic significance of Nikkei mispricing, which is of particular concern for global investors who seek to exploit temporary price deviations around the world. As such, a study accurately estimating the profitability and behaviour of Nikkei mispricing is of crucial empirical and practical importance.

Some previous papers examined mispricing and arbitrage between Nikkei spot and futures markets. Brenner *et al.* (1989a; 1989b; 1990) and Lim (1992) studied Nikkei mispricing in Singapore; Iihara *et al.* (1996) estimated lead-lag relations between the Nikkei index and Osaka futures; Frino and West (2003) and Covrig *et al.* (2004) compared the contributions of Osaka and Singapore to price discovery in the spot Nikkei; Booth *et al.* (1996) and Kao *et al.* (2015) studied information transmission among Nikkei futures; Tsuji (2007) examined the basis dynamics of Osaka futures; Ubukata (2018) studied a conditional hedging strategy to

minimise downside risks for Osaka futures. However, there have been no studies which have specifically compared Nikkei mispricing in all three futures markets. Most importantly, previous studies did not fully consider issues that have a material impact on estimates of Nikkei mispricing, information transmission and market efficiency. These include the clustering of Japanese dividends in the year, the dollar denomination of Chicago Nikkei futures, the impact of transaction costs and differences in market time zones. Board and Sutcliffe (1996) explained the principles of pricing and index arbitrage of the three Nikkei futures, but did not provide empirical evidence. Past empirical papers mostly pre-date the 2008 global financial crisis, which may have affected arbitrage possibilities; and they mostly used limited-time high-frequency datasets.

In this paper, we provide a new and comprehensive analysis of the behaviour and determinants of mispricing in the three main Nikkei futures markets. We contribute to the literature in three ways. First, we estimate and characterise Nikkei futures mispricing in Osaka, Singapore and Chicago using a new daily dataset from 1996 through 2014, providing evidence on the magnitude, sign, persistence, and path dependence of mispricing and the bilateral relationship of mispricing with time to expiration and stock volatility. Second, in view of the complexity of the Nikkei futures we develop a comprehensive modified cost of carry model, which allows for essential factors that have not previously been considered as a whole. These are: (a) the dividend clustering specific to Japanese companies; (b) the currency risk of the Chicago Nikkei futures, given that the Chicago futures contract is a quanto, *i.e.* it is denominated, traded and settled in a currency (US dollars) that is different from the underlying stock index (yen); (c) the different trading hours of the Nikkei markets,

particularly in the context of Chicago's Globex trading system; and (d) the transaction costs of brokers and institutional investors. Hence the present model significantly improves on earlier models such as that of Board and Sutcliffe (1996) used to price Nikkei futures. Third, the ESTAR-GARCH model is employed to examine the effects of transaction costs and heterogeneous investors on the nonlinear adjustments of Nikkei mispricing. ESTAR-GARCH is arguably more satisfactory in describing these nonlinear adjustments than are threshold cointegration models (*e.g.* Tao and Green, 2013), as the former avoids the imposition of potentially arbitrary discontinuities on the aggregate arbitrage process. Recent studies using smooth transition include the Dow Jones (Tse, 2001), FTSE 100 (McMillan and Speight, 2006), S&P 500 (Taylor, 2007), Hang Seng (Fung and Yu, 2007), and emerging index futures (Alan *et al.*, 2016). However, to our knowledge, the ESTAR-GARCH model has not been applied to any of the three Nikkei markets, despite the fact that Nikkei futures contracts are one of the most actively traded derivatives in the world.

The rest of this paper is structured as follows. Section 2 describes the key institutional differences among the Nikkei markets and data. Section 3 modifies the standard cost of carry model for Nikkei futures, allowing for dividend clustering, currency risk, different trading hours and transaction costs. Section 4 reports in detail on our mispricing measures and their behaviour across the markets and over time in relation to time to expiration, stock volatility and path dependence. Section 5 studies Nikkei mispricing dynamics and index arbitrage by the ESTAR-GARCH model. Section 6 concludes the paper.

2. Institutional differences and data

2.1 The Nikkei 225 index and index futures markets

The Nikkei 225 consists of 225 common stocks listed in the First Section of the Tokyo Stock Exchange (TSE).¹ Nikkei 225 index futures contracts are traded on three different markets: the Osaka Exchange (OSE), the Singapore Exchange (SGX) and the Chicago Mercantile Exchange (CME). See Table 1 for details. There are three important differences among these contracts. First, the three futures exchanges are located in different time zones and the futures contracts are traded within different time periods. Second, trading and settlement on the CME are in US dollars while trading and settlement on the other Nikkei markets involve Japanese yen. Third, OSE futures have had a computerised trading system since inception. SGX futures initially used open outcry, but shifted from open outcry to electronic trading on 01/11/2004. Open outcry and electronic trading were both used for CME Nikkei futures during the sample period of this paper.

Table 1 about here

2.2 Data description

Daily closing prices of the Nikkei 225 index and settlement prices of the corresponding futures are collected from *Datastream*, OSE, SGX and CME, for 20/06/1996-31/12/2014 (OSE and SGX) and 01/01/1997-31/12/2014 (CME). The starting dates are the earliest available with consistent dividend data (OSE and SGX), or sufficient trading volume (CME). We use futures contracts that mature in the quarterly months (March, June, September and

December) in each market. Continuous, synthetic futures price series are compiled using the prices of the nearest contract and rolling over to the next nearest contract at the start of the expiration month.² Non-trading days are excluded and futures and spot prices are matched on each day that all markets are trading. Higher-frequency data have been used in some studies (*e.g.* Lim, 1992; Iihara *et al.*, 1996), but we prefer daily data to study mispricing. Daily marking to market implies that gains or losses on every futures contract that is open overnight must be realised at the end of each trading day with reference to the daily settlement price. Thus, settlement prices will reflect the outcome of open spot-futures arbitrage positions each trading day. Since mispricing is a measure of the deviation of the actual price from the fair futures price, the daily settlement price is the best benchmark to represent the actuals. Intraday data will not necessarily produce better statistical power than daily data (Shiller and Perron, 1985). Instead, we make our daily sample as long as possible, and the 19-year data range should generate reasonable power. Total observations are 4,554 (OSE), 4,603 (SGX) and 4,539 (CME).

The risk-free interest rate is proxied by the Gensaki treasury bill overnight middle rate for the OSE and SGX, as it is an open market rate with treasury bills as collateral, free from price control by the Japanese Ministry of Finance. CME Nikkei futures are denominated in dollars; the corresponding risk-free rate is proxied by the daily effective US federal funds middle rate. The daily yen-dollar exchange rate is the middle rate employed in cable transfers in New York, certified by the New York Fed, and fixed in New York at noon (11.00am in the CME). Exact fixing-time rates represent, more precisely than averaged rates, the actual rates at which investors can trade in any arbitrage activity. The Nikkei 225 index is price-weighted,

and an implied dividend series is computed as the product of the daily dividend yield and the index closing price on the previous trading day rescaled to a daily basis.³

We consider the transaction costs of brokers and institutional investors.⁴ In general, brokers enjoy a lower level of transaction costs than institutional investors, and market participants in the OSE and SGX enjoy a lower level of transaction costs than those in the CME due to costs associated with currency conversions in the CME. Hence, we simplify a multitude of transaction costs incurred in index arbitrage by using a two-tier transaction cost system: 0.5% for brokers and 1.0% for institutional investors in the OSE and SGX; 1.5% for brokers and 2.0% for institutional investors in the CME.⁵ These costs consist of the main elements involved in a typical long or short arbitrage, including the adjustment costs of dividends and the exchange rate.⁶ It is recognised that these estimates might differ from actual transaction costs, and there have been changes in fee schedules in Japan, Singapore and the US during the sample period. However, the main purpose of this paper is to investigate Nikkei mispricing and profitable arbitrage opportunities by identifying the most suitable cost of carry model for each futures contract. Transaction costs act as filters to help examine mispricing net of market frictions; the exact amount of the costs is less important than that they be included in the analysis. The estimated transaction costs provide a reasonable approximation of the hurdles that investors face in the different markets.

2.3 Behaviour of Nikkei 225 index and index futures returns

The log returns of the Nikkei 225 index (S_t) and index futures (F_t) prices are defined as $\Delta S_t = \ln(S_{t+1} / S_t)$ and $\Delta F_t = \ln(F_{t+1} / F_t)$, respectively. Table 2 shows descriptive statistics of

these returns over the whole sample. The means are broadly comparable with one another, while the standard deviations of OSE and CME futures are rather higher than those of the SGX and index markets. The returns exhibit negative skewness and moderate leptokurtosis, and the null hypothesis of normality is decisively rejected by the Jarque-Bera (1980) statistics. There are significant negative first-order autocorrelations in the futures returns, which may result from the bid-ask bounce of the Nikkei futures prices. Higher-order autocorrelations are small but significant, indicating weak linear dependence in the daily returns.

Table 2 about here

3. Mispricing with dividend clustering, currency risk and transaction costs

3.1 Cost of carry and mispricing

Cost of carry gives an equilibrium relationship between index and futures markets and hence a theoretically fair (arbitrage-free) futures price at any point in time:

$$F_t^* = S_t e^{(r_t - d_t)(T-t)} \quad (1)$$

where F_t^* is the fair futures price at time t ; S_t the actual index price; r_t the risk-free interest rate; d_t the continuously compounded dividend yield on the stock index; and T the expiration date of the futures contract (Cornell and French, 1983a; 1983b). Deviations from the fair price constitute “mispricing” and in theory offer profitable arbitrage opportunities. However, it may not be possible to exploit the mispricing profitably if it lies within no-arbitrage bounds determined by transaction costs. MacKinlay and Ramaswamy (1988) propose the following widely-used formula for (proportional) mispricing (Mis_t):

$$Mis_t = \frac{F_t - F_t^*}{S_t} \quad (2)$$

where F_t is the actual futures price.

However, equations (1) and (2) cannot be applied directly to Nikkei futures contracts, because of Japanese dividend procedures, yen-dollar exchange rate fluctuations, different trading hours of the Nikkei markets, and the effect of transaction costs. Previous studies of the Nikkei did not consider all these issues. In developing our modified cost of carry and mispricing formulas we first assume:

- A. *Arbitrage positions are not unwound early but held to maturity.*
- B. *There are no short sales restrictions in the TSE.*
- C1. *There are no transaction costs.* This is relaxed in Section 3.5.
- D. *There are no taxes on gains or losses on the arbitrage positions.*

3.2 Dividend clustering

The early literature noted the low and stable dividend flows of Nikkei 225 firms (Brenner *et al.*, 1989a; 1989b) and that most firms paid out dividends once a year (Kato and Loewenstein, 1995). Regulatory changes in the 1990s made it easier for firms to pay dividends more frequently, and in our sample period most Japanese firms paid dividends twice yearly: the interim and year-end. Under the new Corporation Law of Japan effective 01/05/2006, Japanese firms are permitted to pay dividends at any time during a fiscal year and may choose flexible payments, subject to shareholder approval and to certain limits on retained earnings. Nevertheless, most Japanese firms continue to adopt a conservative attitude towards dividends, making their dividend flows low, stable and predictable. Most firms have March as

the fiscal year-end; they go ex-dividend in March and pay the end-year dividend in June. The other ex-dividend date is in September; and the interim dividend is paid in December. Annual dividends are typically split 50-50 as between interim and year-end payments, and are invariably paid in cash. A further issue is that Japanese firms generally declare the dividend before the annual meeting but up to two months after the ex-dividend date. This means that on the ex-dividend date, investors have to forecast the future dividend to be received on the payment date. This introduces dividend uncertainty into index arbitrage activities.

Apart from assumptions A-D, our analysis of Nikkei dividends is based on the following:

E1. *Dividends are certain; thus, investors can exactly forecast future dividends as of the ex-dividend date.* Although dividends are mostly declared after the ex-dividend date, Japanese firms publish reliable ex-ante dividend forecasts and actual payouts are very stable in our sample. Moreover, since we use the nearest contracts to compile the futures series, dividend uncertainty is likely to be small during the short time to expiration. Investors may make dividend forecasting errors, but the risk of such errors is unlikely to be important (Yadav and Pope, 1994).

E2. *Dividends are only paid in the last 10 trading days in June and the first 10 trading days in December.* Historical dividend payment dates of a random sample of 35 Nikkei 225 firms are traced back as far as possible, including and extending beyond the sample period. The dividend payment dates of these firms are generally clustered in the second half of June and the first half of December. Some companies do amend their payment dates following the implementation of the new Corporation Law of Japan, but E2 holds for most firms in most

years of the sample period. The 10-trading-day range is selected to remove weekends and to allow for any slight changes made by firms in the exact timing of their payouts.

E3. *Dividends are exempt from tax.* 50% of dividends received by corporations are tax-deductible; the remaining 50% are subject to withholding tax at 10% for more than half the sample. Company cross-shareholdings are prevalent in Japan, so the net taxable amount of inter-firm dividends is likely to be relatively small. Given also the low and stable dividend payouts, it is reasonable to treat dividends as tax-exempt.

Following Brenner *et al.* (1989a; 1989b; 1990) and Gay and Jung (1999), we modify the standard cost of carry model for OSE and SGX Nikkei futures as follows:

$$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T D_p e^{r_p(T-p)} \quad (3)$$

where F_t^* , S_t , $(T-t)$ are as before; r_t is the Gensaki rate *per day*; and D_p the aggregate dividend on the Nikkei index paid at time p , $p \in [t, T]$. The second term of equation (3) measures the value at expiration of the accumulated dividend payments on the index. D_p is the product of the annualised dividend yield of the Nikkei index and the index closing price converted to daily following assumption E2. Specifically, we divide the annual dividend by 2 to split into interim and final, and then by 10, to estimate the daily dividend paid on the index in the 10-trading-day window in June or December. The daily dividend amount is then credited to the futures' maturity date on each of the proposed dividend payment dates and summed over time to form total dividends paid between any given day and the expiration date of the futures. For comparison, the standard cost of carry model, equation (1) is also constructed using d_t as the annualised dividend yield of the Nikkei index converted to daily. The standard

model is denoted COC1; the preferred dividend-adjusted model, equation (3) is denoted COC2.

Paired *t*-tests and Wilcoxon signed rank tests are used to compare COC1 and COC2 for OSE and SGX contracts in terms of fair futures price and mispricing (Table 3). The differences are all highly significant, suggesting strongly that it is important to allow for dividend clustering in interpreting cost of carry. As a further test, mispricing calculated from COC1 is regressed on a constant and 20 dummy variables representing the proposed June and December dividend payment dates. These dummies are individually and jointly highly significant (Table 4). If dividends were assumed to be paid uniformly over the year, estimated mispricing on the proposed dividend payment dates would appear significantly higher than on non-payment dates. Restricted versions of the regression are also run to check the joint explanatory power of the June and December dummies, and they too are highly significant.⁷ These results reinforce the conclusion that dividend clustering substantively affects the estimation of Nikkei mispricing; and it is essential to allow for clustering in the pricing of Nikkei futures contracts. We therefore use COC2 as a measure of the fair futures price for the OSE and SGX Nikkei futures, because it does allow for dividend clustering. Figure 1 shows the OSE and SGX mispricing estimates given by COC2.

Tables 3, 4 and Figure 1 about here

3.3 Currency risk

CME Nikkei futures contracts are quantos. They have a contract multiplier of 5 dollars and are denominated, traded and settled in dollars, whereas trading and settlement on the underlying index involve yen. This introduces currency risk to index arbitrage, as CME investors are necessarily exposed to yen-dollar exchange rate fluctuations. As Board and Sutcliffe (1996) explained, the standard cost of carry model has to be further modified to allow for the effect of such exchange rate risk. Thus, we further assume:

F1. *CME investors are US-based and only use US dollar financial markets.* This assumption is relaxed in Section 3.3.2 where we consider arbitrage-free pricing of CME Nikkei futures.

F2. *The trading hours of the CME and TSE are overlapping.* This is relaxed in Section 3.4.

3.3.1 Nearly arbitrage-free pricing

To derive the cost of carry model modified for exchange rate risk, we first distinguish between futures and spot index prices and the cash costs of arbitrage positions. Prices are expressed as indices, which are pure numbers, but the actual cost of a contract is the amount of money invested: equal to the product of the futures price and the contract multiplier, and denominated in dollars on the CME or yen in Tokyo. Let futures and spot prices be F_t and S_t . Their cash costs in the futures and spot markets are denoted G_t and H_t , respectively; and m is the dollar contract multiplier. When futures contracts mature at time T , gains or losses on CME Nikkei futures depend on the difference between G_t and $G_T = mF_T = mS_T$, whereas H_T is the yen equivalent of mS_T .

Following Board and Sutcliffe (1996), suppose that at time t , a CME investor shorts a Nikkei futures contract, with a value of G_t ; borrows money at the dollar-denominated risk-free rate (r_t) and uses it to long a unit of the TSE Nikkei index, at the cost of H_t . Dividends (K_p) received at time p on the index are converted to dollars and invested at the risk-free rate (r_p). The dividend received on the Nikkei is $D_p = K_p/m$. At maturity, the investor repurchases the futures contract at a cost of G_T and sells the stock which pays H_T . She also repays the loan and gains the dividends invested earlier with interest. The no-arbitrage condition requires that this strategy generates zero net cash flows. Let c_t , c_p , and c_T be the yen value of one dollar at times t , p , and T . Then these transactions may be written:

Short futures	Borrowing	Long stock	Dividends	Net payoff at T
$G_t - mS_T$	$-\frac{H_t}{c_t} e^{r_t(T-t)}$	$+\frac{H_T}{c_T}$	$+\sum_{p=t}^T \frac{K_p}{c_p} e^{r_p(T-p)}$	$= 0$

Since $G_t = mF_t$, $H_t = mS_t c_t$, and $H_T/H_t = S_T/S_t$ (Board and Sutcliffe, 1996), the no-arbitrage condition may be rewritten to give the fair price for CME Nikkei futures as:

$$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T \frac{D_p}{c_p} e^{r_p(T-p)} + S_T \left(1 - \frac{c_t}{c_T} \right) \quad (4)$$

The first two terms of equation (4) constitute the cost of carry model adjusted for dividends. In the second term, each yen dividend is divided by c_p to convert to dollars on the proposed payment date. The third term reflects exchange rate gains or losses from holding the yen-denominated Nikkei index between times t and T . The sources of currency risk contained in the CME Nikkei futures prices consist of exchange rate fluctuations between the purchase or sale of a futures contract and its expiration at T , as well as on dividend payment dates, p .

Since these exchange rates are uncertain at time t and cannot be perfectly hedged, index arbitrage in the CME is not risk-free.⁸ Equation (4) gives a “nearly fair” price for CME Nikkei futures. It is a “pseudo-arbitrage” condition, valid only insofar as the exchange rate is perfectly predictable.

3.3.2 Arbitrage-free pricing

The Board and Sutcliffe (1996) approach does not provide a risk-free pricing formula for the CME Nikkei contracts. An alternative method is to use the risk-neutral pricing formula of Baxter and Rennie (1996) which does give an arbitrage-free CME futures price.⁹ This is derived from a basic continuous time model which assumes that the Nikkei index and yen-dollar exchange rate are both governed by (correlated) geometric Brownian motion processes:

$$dS/S = (\alpha_S - d)dt + \sigma_S dZ_S$$

$$dE/E = \alpha_E dt + \sigma_E dZ_E$$

where α_S , σ_S are the mean and standard deviation of Nikkei returns; dZ_S is a standard normal variable; $E_t (= 1/c_t)$ is the dollar price of yen with mean α_E and standard deviation σ_E , and dZ_E is a standard normal variable. ρ is the correlation coefficient between dZ_S and dZ_E , so that $\rho\sigma_E\sigma_S$ is the covariance between the spot Nikkei and the dollar-yen exchange rate.

The risk-neutral no-arbitrage price for a dollar quanto on the Nikkei can then be shown to be (Baxter and Rennie, 1996):

$$F_t^* = S_t e^{(r_t - d_t - \rho\sigma_S\sigma_E)(T-t)} \quad (5)$$

Note that in equation (5) r_t is the yen-denominated risk-free rate rather than the US dollar rate.

Clustering of dividends can be allowed for using the argument that at each dividend payment, the spot Nikkei must fall by the amount of the dividend to rule out arbitrage; and the dividends are immediately reinvested in the safe yen asset. The fair quanto price with dividend clustering is therefore:

$$F_t^* = S_t e^{(r_t - \rho \sigma_S \sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_p - \rho \sigma_S \sigma_E)(T-p)} \quad (6)$$

The intuition behind the covariance term is as follows. The quanto is effectively paid at a fixed exchange rate determined by the contract multiplier. If $\rho > 0$, the yen appreciates with the Nikkei and the cash market investor benefits from the higher exchange rate. If the Nikkei falls so in general does the yen and thus the cash market investor loses less from the yen depreciation than does the futures investor because the spot Nikkei is worth less. Therefore a positive correlation between the Nikkei and the yen benefits the cash investor relative to the futures investor. The reverse is true for a negative correlation. Movements in the Nikkei are partially offset by opposite movements in the yen and this benefits the futures investor who faces a fixed (exchange rate) multiplier for the quanto.

Closer inspection of equations (4), (6) and their derivation reveals some important differences apart from the obvious point that equation (4) is not an arbitrage-free price. First, equation (4) is based essentially on observables, whereas equation (6) requires knowledge of the covariance. This cannot readily be extracted from market data especially over the whole time period of our dataset. The standard quanto model of Baxter and Rennie (1996) assumes a constant covariance, although this can be generalised: there is abundant evidence that conditional variances of asset prices do vary over time, and we also find this to be true for the

Nikkei and yen-dollar exchange rate. Therefore ρ , σ_E and σ_S can be calculated either assuming constant variances and covariance, or by using for example a suitable GARCH model to estimate time-varying variances and covariance. This means that tests of equation (6) are subject to the standard dual hypothesis problem: estimated mispricing could be caused by real mispricing, or it could be an artefact of the method used to calculate the covariances.

Second, the arbitrage-free price (6) is constructed using the yen risk-free rate in Japan, and then converted to dollars at the end of the contract, relaxing assumption F1 for this purpose. However, equation (4) is constructed using the US dollar risk-free rate, with dividends converted to dollars as they arise. In perfect capital markets, it may be immaterial which risk-free rate is used. Indeed proofs of equation (6) sometimes rely on covered interest parity (CIP) in the derivation. However, there is growing evidence, especially after the 2008 financial crisis that CIP has regularly failed in major international markets including dollar-yen (Rime *et al.*, 2017). This suggests a higher degree of market segmentation in practice than is consistent with perfect capital markets, and implies a further dual hypothesis issue for both formulas. Mispricing implied by equation (4) or (6) could be due either to real mispricing or to market segmentation that prevents complete interest arbitrage. However, if market segmentation does exist, as the evidence suggests, then equation (4) may be a more plausible representation for US investors, implying as it does that they arbitrage using US interest rates rather than Japanese rates.

Third, equations (4) and (6) embody somewhat different views about the impact of exchange rate movements. Equation (4) implies that if the yen appreciates relative to dollar over the life

of the CME futures contract, the actual futures price will tend to exceed its theoretical price, in that investors with stock positions would profit from the conversion of yen to dollar at maturity of the futures contract. It follows that futures should be overpriced in the CME to maintain the no-arbitrage condition. Likewise, underpricing should be associated with a depreciation of the yen relative to dollar over the life of the contract. The arbitrage-free price (6) implies that differences between OSE futures and CME futures will be attributable to variations in the covariance between the Nikkei and the exchange rate, as explained above, rather than to the relative movement in the exchange rate.

For comparison purposes, equation (4) is denoted COC3 and equation (6) denoted COC4; both are constructed for CME futures.¹⁰ COC1, COC2 are also calculated for CME futures, converting the cash amounts to US dollars where necessary but ignoring the terms reflecting the exchange rate, $S_T(1 - c/c_T)$ and $\rho\sigma_E\sigma_S$. d_t is converted to its dollar equivalent in COC1 by dividing the dollar-valued implied dividend series by the index closing price; daily dividends received on the index are converted to dollars in COC2 using the corresponding exchange rate on that day.

Table 5 about here

From Table 5, *original* column, the differences between the means and medians of the COC1 and COC2 measures of the fair futures price and mispricing for CME Nikkei futures are very significant, as was true for the OSE and SGX. These differences underline the importance of the adjustments for dividend clustering. The significant differences between COC2 and COC3, and between COC2 and COC4 indicate the substantial effect of the exchange rate on

fair futures prices and mispricing. Ignoring currency exposures may lead to significant biases in the calculation of fair prices and mispricing of CME Nikkei futures. Accordingly, either COC3 or COC4 should be more suitable than COC2 for calculating CME mispricing.

Comparing COC3 and COC4 directly, we see that the differences between the two models are all strongly significant (Table 5). The mispricings calculated using the two models are depicted in Figure 2, which shows clearly that COC4 generates lower mispricing estimates in general and on average. Figure 2 implies that COC4 gives a more accurate estimate of the CME futures price than COC3; and this is supported by the root mean squared error (RMSE) which is 0.0461 for COC3, 0.0113 for COC4. Overall, the arbitrage-free pricing model, COC4 provides a more accurate estimate of the CME price than does COC3; and it is therefore used to study CME Nikkei futures mispricing.

Figure 2 about here

3.4 Different trading hours

So far we have assumed that the TSE and CME have overlapping trading hours. In fact, Central Standard Time (CST) in Chicago is 15 hours behind Japan Standard Time (JST) in Tokyo. The opening hours of the TSE are 9.00-11.30, 12.30-15.00 JST, corresponding to 18.00-20.30, 21.30-0.00 CST, and do not overlap with the opening hours of CME's open outcry system: 8.00-15.15 CST. Alongside open outcry, CME Nikkei futures are traded on the Globex electronic trading platform. This starts at 17.00 CST on day $t-1$ and closes at 16.15 CST on day t . Globex allows the CME investors to arbitrage during 18.00-20.30,

21.30-0.00 CST, when the TSE and CME are open simultaneously (Figure 3). Leaving aside currency fluctuations, this implies that index arbitrage between the two markets could involve essentially simultaneous transactions as required by theory.

Figure 3 about here

However, the different daily settlement times in the two markets still introduce a time lag between the stock closing price and futures settlement price, which may pose an additional risk to investors. From the perspective of the TSE (Figure 3(a)), the index closing price S_t is generated in the afternoon closing auction at 15.00 JST (0.00 CST), whereas the CME futures settlement price F_t is derived by 15.15 CST (6.15 JST on the next day). It is assumed that S_t incorporates spot market information up to 0.00 CST on day t , and F_t incorporates the futures market information up to 15.15 CST on day t . As index arbitrage occurs when both markets are open, if information generated by the arbitrage activities in the common trading hours can be revealed and transmitted by market prices, the information contained in S_t is likely to match the information contained in F_t ; yet the information contained in S_t leads the information contained in F_t by 1 trading day. In addition, dividends are usually paid during Japanese business hours; thus, the dating of D_p should match that of the index market price.

Investors need to convert currencies at the spot exchange rate and invest money at the spot interest rate in the common trading hours. Data on those rates are not available, as c_t is fixed at around 11.00 CST, and r_t is published before 15.15 CST on day t , each of which precedes the time when index arbitrage activities could occur. From the perspective of CME investors (Figure 3(b)), two different views are distinguished as to the choice of rates and prices: past

and future. In the past view investors consult historical rates: they trade in the common trading hours and use the rates released beforehand, although on the same day. Since c_t and r_t become available before arbitrage commences on day t , they are likely to be applied to the index closing price S_t , such that they convey the same kind of information as that in S_t . In contrast, in the future view, investors forecast tomorrow's rates, and arbitrage is based on the perfect foresight assumption: the rates forecasted and used on day $t-1$ equal the actual rates on day t . Thus, c_t and r_t on day t would be known precisely on day $t-1$ in the arbitrage associated with S_{t-1} . Similarly, c_{t+1} and r_{t+1} are used with S_t , and so on. Table 6 compares the theoretical cost of carry models for these two views with the original view that ignores the time lag between the index closing price and the futures settlement price.

Tables 6, 7 about here

The effect of the different trading hours is examined as before using paired t -tests and Wilcoxon signed rank tests for CME fair futures prices and mispricing in each view (Table 5, *past* and *future* columns). The results are qualitatively and in some cases quantitatively the same as those of the CME data in the original view, which strongly suggests that the difference in trading hours may not be important. In Table 7, the three views are compared pairwise by each cost of carry model, and the tests suggest that almost all of the mean (median) differences are insignificant. Overall, the effect of the different trading hours and the consequent timings of prices, interest rate and exchange rate are essentially negligible, due perhaps to the time lag being short. Therefore, we will use COC4 in the original view to estimate CME mispricing.

3.5 Transaction costs

The no transaction costs assumption C1 (Section 3.1) is now replaced with:

C2. *Transaction costs are one-off payments made at the start of each trade.*

Transaction costs create lower and upper limits around the fair futures price, within which arbitrage activities are unprofitable. Let TC_t^U and TC_t^L be the transaction costs of a long and short arbitrage respectively, both of which include costs of dividend reinvestment and currency exchange. Transaction costs are measured in relative terms in *percent* of the index value. Based on Brenner *et al.* (1989a), the lower limit F_t^L and the upper limit F_t^U of the arbitrage-free futures price for the three Nikkei futures can be formulated as:¹¹

$$F_t^L = S_t(1 - TC_t^L)e^{(r_t - \rho\sigma_S\sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_p - \rho\sigma_S\sigma_E)(T-p)} \quad (7a)$$

$$F_t^U = S_t(1 + TC_t^U)e^{(r_t - \rho\sigma_S\sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_p - \rho\sigma_S\sigma_E)(T-p)} \quad (7b)$$

With transaction costs, the mispricing formula (2) becomes (Fung and Draper, 1999):

$$Mis_t = \begin{cases} \frac{F_t - F_t^U}{S_t} & \text{if } F_t^U < F_t \\ 0 & \text{if } F_t^L \leq F_t \leq F_t^U \\ \frac{F_t - F_t^L}{S_t} & \text{if } F_t < F_t^L \end{cases} \quad (8)$$

Mispricing only appears when the futures price moves outside the lower and upper transaction cost limits. Equations (7)-(8) are used to compile the mispricing series of the Nikkei futures in the presence of transaction costs, as shown in Figure 4.

Figure 4 about here

4. Behaviour of Nikkei 225 futures mispricing

4.1 Summary statistics

Following Brenner *et al.* (1989a; 1989b; 1990), we provide separate summary statistics for overpricing ($Mis_t > 0$) and underpricing ($Mis_t < 0$) in Table 8. There are somewhat more instances of underpricing on the OSE and SGX and more of overpricing on the CME. As Brenner *et al.* (1989b) note, underpricing in the OSE and SGX may be partly explained by the higher costs related to short-selling the index, due for example to the uptick rule in the TSE.¹² As such, underpricings may not necessarily indicate short arbitrage opportunities in the two markets, even before allowing for transaction costs. With transaction costs, instances of the OSE and SGX mispricing fall sharply. It seems clear that only brokers with a lower level of transaction costs would have been able to profit from short arbitrage in the OSE and SGX. On the CME, most of the mispricings disappear but there are still arbitrage opportunities even with the stricter 2.0% transaction costs.

Table 8 about here

Mispricing persistence is measured by autocorrelation coefficients (Table 9). Moderate values of first-order autocorrelations at the level of mispricing are significantly positive in the OSE and SGX, indicating mild persistence. CME mispricing exhibits weak persistence with small first-order autocorrelations not all significant, and the weak persistence implies difficulties of arbitraging profitably the CME futures. Higher-order autocorrelations diminish gradually but do not disappear. Transaction costs may deter investors from removing mispricing in the OSE

and SGX (Brenner *et al.*, 1989a; 1989b), and exchange rate transaction costs are a further deterrent in the CME. For the first difference in mispricing, the negative first-order autocorrelations are consistent with the hypothesis that mispricing is a mean-reverting process. Mean reversion in mispricing may reflect arbitrage as investors move divergent prices back inside the no-arbitrage bounds (MacKinlay and Ramaswamy, 1988); or it could be due to heterogeneous arbitrage activities (McMillan and Speight, 2006). These different explanations are studied in Section 5.

Tables 9, 10 about here

4.2 Mispricing and time to expiration

In the absence of early unwinding (assumption A), the size of mispricing may be expected to increase with time to expiration, as longer dated contracts carry greater uncertainty about dividends, interest, and the costs of mimicking the index basket (Mackinlay and Ramaswamy, 1988). Dividend uncertainty is unlikely to be significant for the Nikkei but the other two factors are important. This hypothesis is examined using the non-parametric method suggested by Brenner *et al.* (1989b) and Yadav and Pope (1994). Mispricing data are sorted into 5 groups by time to expiration in descending order, with each group covering roughly 20 trading days, and the group means (medians) checked for monotonic orderings.¹³ The null of equal means is tested by running an OLS regression on dummy variables representing each group; the mean ordering is significant if the regression *F*-statistic is significant. The null of equal medians is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952), a non-parametric test for suspicious median ordering among groups, complemented with

Kendall's tau-b coefficient (Kendall, 1938), which helps identify the direction of the median ordering. These tests are performed separately for absolute mispricing (that is, the magnitude of mispricing), underpricing and overpricing.

There are significant monotonically positive relationships between mispricing size and time to expiration in five instances (Table 10). These are particularly located in underpricing on the OSE and SGX, and in overpricing on the CME; consistent with the predominant signs of mispricing in these markets. These results provide new evidence from the Nikkei to support the proposition in the literature that mispricing tends to be greater in size for longer dated contracts.

4.3 Mispricing and stock volatility

Futures mispricing may also be related to the volatility of the underlying stock index. An increase in stock volatility is likely to be associated with increased returns. However, if some investors prefer stocks for tax and dividend purposes, they may respond to increased volatility by short sales of futures instead of the stock index (Chen *et al.*, 1995). Unless arbitrated by other investors, this would increase the underpricing of futures, implying a positive relationship between volatility and the magnitude of underpricing. To examine this relationship, the conditional variance estimated from a constant-mean GARCH (1, 1) model (Bollerslev, 1986) is used to estimate time-varying volatility in the Nikkei index. The mispricing data are again sorted into 5 groups of roughly equal size based on the estimated stock volatility in descending order. We again check absolute mispricing, underpricing and overpricing for monotonic orderings.

Sixteen mispricing statistics have a significant monotonically positive relationship to stock volatility (Table 11). It seems clear that mispricing generally increases in magnitude the more volatile is the stock market. But the evidence for the argument that this is due specifically to underpricing of futures is less clear. Underpricing size is positively related to stock volatility for the OSE and SGX, but some overpricing on the OSE, SGX and CME is also positively related to stock volatility. Overall therefore, the more robust conclusion is that mispricing does tend to be greater in magnitude the more volatile is the stock market, which may be attributable to underpricing or overpricing.

Table 11 about here

4.4 Path dependence in mispricing

This section finally investigates the potential effect of early unwinding on mispricing in terms of path dependence, addressing the following question: what is the probability that mispricing crosses a lower (upper) transaction cost bound on day $t+1$, given that it crosses a lower (upper) bound on day $t-1$ and returns to zero on day t ? If the stochastic behaviour of mispricing does not depend on its past, the probability of hitting a lower (upper) bound should be independent of mispricing history. But if early unwinding prevents mispricing from reversing its direction, then the time series of mispricing is conditional on its history, and the probability of hitting a bound also becomes conditional on the history of mispricing. Following MacKinlay and Ramaswamy (1988) and Kempf (1998), we calculate the conditional probability of each of four scenarios: *lower-lower*, *lower-upper*, *upper-upper* and *upper-lower*. *Lower-upper* describes the case that mispricing hits an upper bound on day $t+1$,

given that it hits a lower bound on day $t-1$ and returns to zero on day t ; the other scenarios are defined analogously (MacKinlay and Ramaswamy, 1988). The narrower transaction cost bounds (0.5% for OSE and SGX; 1.5% for CME) are used to calculate the conditional probabilities as there are more observations to enable valid significance tests.

Table 12 about here

The *lower-lower* and *upper-upper* scenarios have much larger conditional probabilities in all three futures markets (Table 12). χ^2 tests clearly reject the null that there is no association between hitting a lower (upper) bound on day $t+1$ and hitting a lower (upper) bound on day $t-1$, given that mispricing returns to zero on day t . We therefore find strong support for the hypothesis of path dependence in all the Nikkei futures markets. This result on daily data strengthens the argument of previous studies using higher-frequency data (MacKinlay and Ramaswamy, 1988; Kempf, 1998).

5. Index arbitrage in the Nikkei 225 futures markets

5.1 The ESTAR model

We now turn to modelling the mean-reverting behaviour of mispricing. Here the ESTAR model of Teräsvirta (1994) is employed to describe the nonlinear adjustment processes of Nikkei mispricing in the presence of transaction costs. ESTAR is chosen, first because the smoothness parameter in the model provides a parametric estimate of the speed of market reactions to mispricing, and this can be interpreted as the propensity-to-arbitrage of the market, a gauge of how quickly index arbitrage restores prices to equilibrium (Taylor, 2007).

Second, investors may be heterogeneous, with different trading objectives, costs and risks (Tse, 2001), such that in aggregate, the market is likely to adjust to price discrepancies smoothly rather than discontinuously as in a state switching model. The exponential transition function of an ESTAR model can represent such smooth adjustments. Third, the ESTAR model enables us to trace out the profile of market responses to any given mispricing and thus to identify how far observed nonlinear adjustments are due to transaction costs *per se* and how far to the heterogeneity of investors. The ESTAR model can be formulated as follows (Teräsvirta, 1994):

$$y_t = k + \sum_{j=1}^p \pi_j y_{t-j} + (k^* + \sum_{j=1}^p \pi_j^* y_{t-j}) \times T(y_{t-d}) + u_t \quad (9)$$

where $\{y_t\}$ is a stationary, ergodic series; k, k^* are constants; π_j, π_j^* are adjustment coefficients, $j=1, 2, \dots, p$; $u_t \sim \text{iid}(0, \sigma_t^2)$; y_{t-d} is the transition variable with delay parameter $d>0$; $T(\cdot)$ is a continuous smooth transition function, bounded between 0, the middle regime where no investors trade, and 1, the outer regime where all investors trade. The ESTAR model has an exponential $T(\cdot)$ given by:¹⁴

$$T(y_{t-d}) = 1 - \exp[-\gamma(y_{t-d} - c^*)^2] \quad (10)$$

Graphically, $T(\cdot)$ is a U-shaped relationship with quicker (slower) reversion for larger (smaller) mispricings, in agreement with the argument that transaction costs will increase arbitrage activity as the size of mispricing increases. The location parameter c^* gives the centre of $T(\cdot)$. If $k^*=c^*=0$, we have the exponential autoregressive (EAR) model (Haggan and Ozaki, 1981). The smoothness parameter $\gamma>0$ is an estimate of the propensity-to-arbitrage; it controls the steepness of $T(\cdot)$ and measures the rate of transition from one regime to the other, or how quickly investors respond to mispricing. The higher the value of γ , the greater is the

speed of price-adjustment, and hence the more intensive are arbitrage activities. If $\gamma=0$ or $\gamma=\infty$, the model reduces to a linear AR process.

Preliminary estimates of equations (9)-(10) reveal significant ARCH effects in the residuals.

We model this using a GARCH (1, 1) process (Bollerslev, 1986):

$$u_t = \sigma_t \eta_t \quad (11)$$

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

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 function of the information set at time $t-1$.¹⁵ Equations (9)-(12) form the complete ESTAR-GARCH model.

5.2 Estimation method

For modelling purposes, the whole sample is divided into a pre-crisis period (sample A) and a post-crisis period (sample B), excluding a short interval of extreme market turmoil during October-November 2008. Sample A covers 28/06/1996-09/10/2008 (OSE, SGX) and 09/01/1997-12/09/2008 (CME); sample B covers 04/11/2008-31/12/2014 (OSE, SGX) and 02/12/2008-31/12/2014 (CME). We recognise that this is potentially arbitrary. However, it is widely agreed that the crisis is an exceptional period; and the dates of the sample split are based particularly on the Quandt-Andrews unknown breakpoint test.

Given the positive relationship observed between mispricing and time to expiration, the expiration effect is removed by running an OLS regression of mispricing on a constant and time to expiration. The demeaned mispricing series free of expiration effect is denoted Mis_t^* .¹⁶ It follows that the restriction $k=k^*=c^*=0$ can be applied to the ESTAR model, for $\{y_t\}$ is demeaned ($k=k^*=0$) and the transition functions are usually centred at zero ($c^*=0$);

fixing c^* can also improve the accuracy of the remaining estimates (Chan and McAleer, 2002). To check the suitability of Mis_t^* as the transition variable in equation (9), several unit root tests are performed, all of which show that Mis_t^* is $I(0)$,¹⁷ and can therefore act as the transition variable in the model.

To establish the validity of the ESTAR model for these data, we next check if Mis_t^* can be represented instead as a simple linear AR process. The null hypothesis of linearity in equations (9)-(10) can be expressed as $H_0: \gamma=0$. However, under the null, the ESTAR model suffers from the problem of unidentified nuisance parameters: if $\gamma = 0$, k^* , π_j^* and c^* in equations (9)-(10) are unidentified (Teräsvirta, 1994; Franses and van Dijk, 2000). This problem can be circumvented using the Lagrange multiplier (LM)-type linearity test proposed by Saikkonen and Luukkonen (1988) and Teräsvirta (1994). Given a value of the delay parameter (d), run the following auxiliary regression by OLS:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^p (\beta_{0j}y_{t-j} + \beta_{1j}y_{t-j}y_{t-d} + \beta_{2j}y_{t-j}y_{t-d}^2) + v_t \quad (13)$$

where $\hat{u}_t$ is the estimated residual from the linear model; v_t the residual from the auxiliary regression. The null hypothesis of linearity $H_0: \gamma=0$ corresponds to $H_{01}: \beta_{1j}=\beta_{2j}=0$, under which a LM-type test statistic has an asymptotic $\chi^2(2p)$ distribution. The alternative is an $ESTAR(p)$ model. The linearity test is repeated for different candidates of d , and d is selected as the one that generates the smallest p -value of the test, because a correct d should have the highest power in the test (Tsay, 1989; Teräsvirta, 1994). With the restriction $k^*=c^*=0$, it is useful to test two additional hypotheses, $H_{02}: \beta_{1j}=0$ against the alternative hypothesis of an $ESTAR(p)$ model, and provided that H_{02} is not rejected, $H_{03}: \beta_{2j}=0 \mid \beta_{1j}=0$ against the

alternative hypothesis of an $\text{EAR}(p)$ model (Michael *et al.*, 1997). Ordinary F -statistics approximate the LM-type statistics, and for data with relatively large p and small sample, the F -statistics are more powerful and without size distortions (Teräsvirta, 1994).

Table 13 about here

Table 13 reports the results of the linearity tests. Panel A shows the results of H_{01} for different delay parameters $d = \{1, 2, 3, 4, 5\}$. The smallest p -values occur when $d=1$ for OSE and SGX (sample B); $d=2$ for SGX (sample A), CME (sample A); and $d=3$ for CME (sample B). Panel B shows the results for H_{01} - H_{03} . Linearity is decisively rejected in each market in each sample. The CME (sample A) does not reject H_{02} , but its strong rejection of H_{03} reveals the presence of nonlinearity. Therefore, the null of a linear AR process can be rejected for all markets, in favour of the ESTAR model.

Estimation of the ESTAR model is by nonlinear least squares (NLS). This is equivalent to maximum likelihood if the errors u_t are normal; otherwise NLS can be interpreted as quasi-maximum likelihood (van Dijk *et al.*, 2002). The NLS estimates are consistent and asymptotically normal provided that $\{y_t\}$ is stationary and ergodic and $u_t \sim \text{iid}(0, \sigma_t^2)$ (Klimko and Nelson, 1978; Tong, 1990). We apply the two-stage procedure of Chan and McAleer (2002) to estimate the ESTAR-GARCH model: first estimate equations (9)-(10), and then estimate equations (11)-(12) separately using the residuals from equations (9)-(10).¹⁸ The separate estimation of mean and variance processes does not affect the consistency and asymptotic normality of the estimates (Chan and McAleer, 2002). The exponential transition function is standardised by dividing its exponent by the sample variance of the transition

variable to make γ scale-free and to facilitate searching for starting values (Teräsvirta, 1994; van Dijk *et al.*, 2002). The lag order p is determined by the Akaike Information Criterion. Starting values are obtained by a grid search over γ . Since there may be several local maxima in the likelihood function, various sets of starting values are used. Among the models whose algorithms converge, the final model is that which generates the lowest residual variance. Model adequacy is checked in terms of residual autocorrelation, ARCH and nonlinearity.

5.3 Empirical results

5.3.1 Propensity-to-arbitrage

The ESTAR-GARCH estimates are provided in Table 14. The diagnostics for the estimated model are broadly satisfactory. The lag order p indicates that linear dependence in Nikkei mispricing lasts for about a week. This is less than found in earlier studies of the Nikkei (Brenner *et al.*, 1989b) and could be attributable to the longer sample as well as the more precise method of estimation provided by the ESTAR approach. The (standardised) smoothness parameter γ is quite small in sample A, but becomes larger in sample B in all three markets. This change in γ is evident in Figure 5 where the U-shaped transition functions reveal the mean-reverting behaviour of mispricing, with the tails depicting quicker movements to equilibrium for larger mispricings (note the differences in scales of the vertical axes). The steeper transition functions in sample B suggest a higher propensity-to-arbitrage in the post-crisis years. Given that volatility and mispricing are positively related, this change could be partly due to the appreciably lower persistence of market volatility in the Nikkei markets in the post-crisis period, according to the estimated GARCH coefficients. The CME γ

is found to be lower than those of the OSE, SGX in both samples. This indicates that there is a slower market response to mispricing in the CME than in OSE or SGX. This could be because of residual exchange rate risk in arbitraging the Nikkei and also higher transaction costs associated with the additional foreign currency transactions required by hedging the Nikkei on the CME.

Table 14 and Figure 5 about here

5.3.2 Heterogeneous arbitrage activities

The ESTAR-GARCH model can provide an interpretation of heterogeneity in arbitrage behaviour. Apart from transaction costs, heterogeneous arbitrage activities could contribute to mean reversion in mispricing. If there are heterogeneous investors consisting of noise traders and informed traders, small mispricings are more likely to be arbitrated away because of their low risk and low capital requirements for informed traders, whereas large mispricings may be foregone because informed traders fear that prices will become further misaligned through the activities of noise traders (McMillan and Speight, 2006). The heterogeneity in the Nikkei markets is explored through the adjustment coefficients in the estimated model. Table 15 shows the ESTAR adjustment coefficients in the middle and outer regimes respectively (π_j and $\pi_j + \pi_j^*$). Negative adjustment coefficients, especially in the outer regime, are indicative of mean reversion. Following McMillan and Speight (2006), we report the results of testing two parameter restrictions, $H_{04}: \pi_j = \pi_j + \pi_j^* = 0$ to check the mean-reverting properties of mispricing and the interaction of heterogeneous investors (Panel A), and $H_{05}: \pi_j = \pi_j + \pi_j^*$ to check whether the adjustments in different regimes are symmetric (Panel B).

Table 15 about here

For the OSE and SGX, before the financial crisis (sample A), negative adjustment coefficients in the outer regime help confirm that mispricing is mean-reverting. Moreover, H_{04} is strongly rejected in the two markets, supporting mean-reverting behaviour and heterogeneous investors. The slow adjustments from one regime to the other are evident, up to 6 trading days after a given mispricing appears. The adjustments in different regimes are symmetric, as H_{05} cannot be rejected. After the financial crisis however (sample B), both H_{04} and H_{05} are strongly rejected. The estimated adjustment coefficients suggest that mean reversion is associated with shorter lags in the middle regime, but is not very apparent in the outer regime as prices seem to be driven further away from equilibrium, although the size of the deviations decays over time. Large mispricings are removed more quickly than small mispricings, *i.e.* $|\pi_j| < |\pi_j + \pi_j^*|$ within 2-3 trading days, after which the adjustments in the different regimes become symmetric. Not surprisingly, the CME is different in certain respects. CME mispricing does exhibit mean reversion and heterogeneity with the rejection of H_{04} before and after the financial crisis. However, unlike the OSE and SGX, generally $|\pi_j| > |\pi_j + \pi_j^*|$ after the crisis. This might suggest that small mispricings are being arbitrated more quickly than large. However, this effect is not statistically significant as the test of H_{05} indicates symmetric adjustments in the CME. In summary, we find evidence for heterogeneous investors' arbitrage activity in all three Nikkei markets. In the OSE and SGX, the effect of transaction costs may be stronger than that of heterogeneous investors because larger mispricings create more rapid market responses than do smaller mispricings.

Compared with the OSE and SGX, the CME Nikkei exhibits greater extent of heterogeneity after the crisis which may arise from the more various motivations, costs and risks in trading the quanto, though the effect of heterogeneous investors appears to be as important as that of transaction costs on this market.

6. Conclusions

A comprehensive modified cost of carry model allowing for dividend clustering, currency risk, time differences and transaction costs is developed to study the Nikkei futures mispricing based on a new 19-year dataset since 1996. It is found that dividend clustering, currency risk and transaction costs are all essential in estimating the fair Nikkei futures prices and hence mispricing. The results suggest that institutional investors are likely to find it difficult to arbitrage profitably OSE and SGX mispricing. The relatively large size of CME mispricing may represent profitable arbitrage opportunities, but the higher transaction costs due primarily to currency exposures and the weak persistence of CME mispricing also imply the difficulties of arbitraging the CME futures.

The dynamics of Nikkei mispricing is described by the ESTAR-GARCH model that provides an estimate of the propensity-to-arbitrage in each Nikkei market and provides for smooth adjustments between regimes. The results suggest that market responses to Nikkei mispricing are more rapid after the financial crisis than before. However, market responses are slower on the CME than those on the OSE and SGX, due perhaps to residual exchange rate risk and to higher transaction costs involved in the currency conversions required by CME arbitrage. In general, large mispricings induce more rapid adjustments than small mispricings, meaning

that mean reversion in mispricing and limits to arbitrage are more likely to be driven by transaction costs than by heterogeneous investors.

For investors, this implies that there are more-or-less objective bounds to arbitrage activities, independently of the composition of market participants. The message for academics and policy makers is that modifications of the standard cost of carry formula are important for dual- or triple-listed futures, especially where there are local institutional factors at play. Though based on the same security, contracts can be quite different in specifications, costs, risks, and consequently in mispricing and arbitrage possibilities. These differences should be taken into consideration when pricing these futures contracts, and interpreting estimates of mispricing.

Figure 1 The OSE and SGX Nikkei Futures Mispricing

(a) OSE;

(b) SGX

Mispricing is calculated from equations (2)-(3).

Figure 2 The CME Nikkei Futures Mispricing: Comparison between COC3 and COC4

(a) CME mispricing computed from COC3, equation (4);

(b) CME mispricing computed from COC4, equation (6).

Figure 3 Trading Hours of the TSE and CME

The bottom shows the time when futures settlement price (F) and stock closing price (S) are generated, from the perspectives of the TSE (a) and CME (b). The time is CST unless otherwise marked.

(a) TSE

(b) CME

Figure 4 Nikkei Futures Mispricing with Transaction Costs

(a) OSE (0.5% transaction costs);

(b) OSE (1.0% transaction costs);

(c) SGX (0.5% transaction costs);

(d) SGX (1.0% transaction costs);

(e) CME (1.5% transaction costs);

(f) CME (2.0% transaction costs).

Mispricing with transaction costs is calculated from equations (7)-(8).

Figure 5 Transition Functions in the Nikkei Futures Markets

$T(y_{t-d})$ on vertical axis, y_{t-d} on horizontal axis, have been multiplied by 100.

(c) SGX (sample A);

(d) SGX (sample B);

(e) CME (sample A);

(f) CME (sample B)

Table 1 Nikkei 225 Futures Contracts

	OSE	SGX	CME
Underlying asset	Nikkei 225	Nikkei 225	Nikkei 225
Launch date	03/09/1988	03/09/1986	25/09/1990
Contract size	Index×¥1,000	Index×¥500	Index×\$5
Tick size	10 index points (¥10,000)	5 index points (¥2,500); 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	9.00-15.15, 16.30-3.00 (JST)	7.45-14.25, 15.15-2.00 (SGT)	Open outcry: 8.00-15.15 (CST) Electronic trading: 17.00-16.15 (CST)
Trading mechanism	Electronic trading	Open outcry (before 1/11/2004) Electronic trading (after 1/11/2004)	Open outcry and electronic trading †
Last trading day	The business day prior to the settlement date	The business day prior to the settlement date	The business day prior to the settlement date
Final settlement day	Second Friday of the contract month	Second Friday of the contract month	Second Friday of the contract month
Final settlement price	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date
Settlement procedure	Cash settlement	Cash settlement	Cash settlement

Notes: The table presents details of Nikkei 225 futures contracts traded on the OSE, SGX and CME as of 31/12/2014. JST is Japan Standard Time. SGT is Singapore Time. CST is Central Standard Time. Data are from the OSE, SGX and CME. † The CME closed the open outcry system for Nikkei contracts on 19/06/2015.

Table 2 Descriptive Statistics of Nikkei 225 Index and Index Futures Returns

Assets	Mean (%)	SD (%)	Skewness	Kurtosis	JB	Autocorrelations (Lag)			No. of obs
						1	2	8	
S	-0.0055	1.5524	-0.3149	8.4193	5646.8630**	-0.0430**	-0.0240**	-0.0010**	4553
OSE	-0.0056	1.6139	-0.2398	12.4884	17123.0600**	-0.0800**	-0.0180**	-0.0020**	4553
SGX	-0.0056	1.5760	-0.2319	11.7503	14723.1400**	-0.0570**	-0.0240**	-0.0020**	4602
CME	-0.0023	1.6202	-0.0786	8.0865	4896.7430**	-0.0530**	-0.0470**	0.0110**	4538

Notes: This table gives the descriptive statistics of Nikkei 225 index (S) and index futures (OSE, SGX, CME) returns over the whole sample 20/06/1996-31/12/2014 (OSE and SGX), 01/01/1997-31/12/2014 (CME). Returns are calculated as log changes of the index (futures) prices. The statistics include mean, standard deviation (SD), skewness, kurtosis, Jarque-Bera (1980) statistics (JB) and autocorrelation coefficients. Mean, SD are in percentage. Autocorrelation coefficients are reported at lags 1, 2 and 8. ** denotes significance at the 5% level.

Table 3 Dividend Clustering in Nikkei Futures: the OSE and SGX contracts

		OSE	SGX
Differences in fair futures price (¥)	Mean	-19.5812**	-19.7319**
COC1 vs COC2	Median	-17.9388**	-18.1174**
Differences in futures mispricing (%)	Mean	0.1592**	0.1605**
COC1 vs COC2	Median	0.1376**	0.1387**

Notes: This table compares COC1 and COC2 for the Nikkei futures contracts traded on the OSE and SGX, in terms of differences in fair futures price (equations (1), (3)) and mispricing (equation (2)). Mean differences are tested by paired *t*-tests; median differences are tested by Wilcoxon signed rank tests. The null hypothesis is that the mean (median) differences are zero. ** denotes significance at the 5% level.

Table 4 Dividend Payment Dates and Dividend Clustering

Coefficient	OSE			SGX		
	Unrestricted	Restricted		Unrestricted	Restricted	
		June dummies	Dec dummies		June dummies	Dec dummies
β_0	0.0009**	0.0010**	0.0010**	0.0010**	0.0011**	0.0011**
β_1	0.0027**	0.0026**		0.0029**	0.0028**	
β_2	0.0026**	0.0025**		0.0029**	0.0028**	
β_3	0.0012*	0.0011		0.0013**	0.0012*	
β_4	0.0011*	0.0011*		0.0016**	0.0015**	
β_5	0.0015**	0.0014*		0.0015**	0.0014**	
β_6	0.0006	0.0005		0.0010*	0.0009	
β_7	0.0020**	0.0019**		0.0023**	0.0022**	
β_8	0.0020**	0.0019**		0.0023**	0.0022**	
β_9	0.0018**	0.0017**		0.0016**	0.0015**	
β_{10}	0.0000	-0.0001		-0.0004	-0.0005	
β_{11}	0.0030**		0.0029**	0.0023**		0.0023**
β_{12}	0.0013*		0.0012	0.0014**		0.0014**
β_{13}	0.0029**		0.0028**	0.0029**		0.0028**
β_{14}	0.0020**		0.0019**	0.0015**		0.0014**
β_{15}	0.0024**		0.0024**	0.0028**		0.0027**
β_{16}	0.0023**		0.0022**	0.0022**		0.0021**
β_{17}	0.0029**		0.0029**	0.0026**		0.0025**
β_{18}	0.0012**		0.0012**	0.0014**		0.0013**
β_{19}	0.0022**		0.0022**	0.0022**		0.0021**
β_{20}	0.0025**		0.0024**	0.0022**		0.0022**
<i>F</i> -statistic	7.1521**	9.5780**	5.2105**	6.0785**	7.2182**	5.3713**
No. of obs	4554			4603		

Notes: This table provides the results of the ordinary least squares (OLS) regression of mispricing calculated from COC1 on 20 dummy variables representing the proposed dividend payment dates, *i.e.* the last 10 trading days in June and the first 10 trading days in December, for the OSE, SGX Nikkei futures contracts. The regression model is:

$$Mis_i = \beta_0 + \sum_{p=1}^{20} \beta_p D_p + \varepsilon_i$$

where Mis_i is futures mispricing calculated from equations (1)-(2); $D_p=1$ if the day is the p^{th} dividend payment date, 0 otherwise; β_p is the corresponding coefficient. The proposed dividend payment dates are: $p=1...10$ for the 1st...10th dividend payment dates in June, $p=11...20$ for the 1st...10th payment dates in December. The unrestricted model is estimated with all 20 dummies. The restricted versions are estimated with the 10 June dummies or the 10 December dummies. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table 5 Dividend Clustering and Currency Risk in Nikkei futures: the CME contracts

		original	past	future
Differences in fair futures price (\$)				
COC1 vs COC2	Mean	-0.1994**	-0.1994**	-0.1994**
	Median	-0.1732**	-0.1732**	-0.1736**
COC2 vs COC3	Mean	18.2374*	18.2876**	18.5470**
	Median	29.6363	29.6642	28.3943
COC2 vs COC4	Mean	51.3539**	51.3688**	51.3103**
	Median	23.4391**	23.4567**	23.4772**
COC3 vs COC4	Mean	33.1165**	33.0812**	32.7632**
	Median	-4.0340**	-4.0546**	-4.0115**
Differences in futures mispricing (%)				
COC1 vs COC2	Mean	0.0017**	0.0017**	0.0017**
	Median	0.0013**	0.0013**	0.0013**
COC2 vs COC3	Mean	-0.0967	-0.0970	-0.0991
	Median	-0.2516*	-0.2532*	-0.2451*
COC2 vs COC4	Mean	-0.3292**	-0.3293**	-0.3288**
	Median	-0.1937**	-0.1941**	-0.1932**
COC3 vs COC4	Mean	-0.2324**	-0.2323**	-0.2297**
	Median	0.0373**	0.0380**	0.0376**

Notes: This table compares COC1, COC2, COC3 and COC4 for the CME Nikkei futures contracts, in terms of differences in fair futures price (equations (1), (3), (4), (6)) and mispricing (equation (2)). Mean differences are tested by paired *t*-tests; median differences are tested by Wilcoxon signed rank tests. The null hypothesis is that the mean (median) differences are zero. Results are listed in the order of original view, past view and future view (see Section 3.4 for discussion). ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table 6 The Cost of Carry Model in Different Views for the CME Contracts

	Original view	Past view	Future view
Variables	$S_t, F_t, D_p (d_t), c_t, r_t, \rho\sigma_S\sigma_E$	$S_t, F_{t+1}, D_p (d_t), c_t, r_t, \rho\sigma_S\sigma_E$	$S_t, F_{t+1}, D_p (d_t), c_{t+1}, r_{t+1}, \rho\sigma_S\sigma_E$
COC1	$F_t^* = S_t e^{(r_t - d_t)(T-t)} \quad \dagger$	$F_{t+1}^* = S_t e^{(r_t - d_t)(T-t)} \quad \dagger$	$F_{t+1}^* = S_t e^{(r_{t+1} - d_t)(T-t)} \quad \ddagger$
COC2	$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T \frac{D_p}{c_p} e^{r_p(T-p)}$	$F_{t+1}^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T \frac{D_p}{c_p} e^{r_p(T-p)}$	$F_{t+1}^* = S_t e^{r_{t+1}(T-t)} - \sum_{p=t}^T \frac{D_p}{c_{p+1}} e^{r_{p+1}(T-p)}$
COC3	$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T \frac{D_p}{c_p} e^{r_p(T-p)} + S_T \left(1 - \frac{c_t}{c_T}\right)$	$F_{t+1}^* = S_t e^{r_t(T-t)} - \sum_{p=t}^T \frac{D_p}{c_p} e^{r_p(T-p)} + S_T \left(1 - \frac{c_t}{c_T}\right)$	$F_{t+1}^* = S_t e^{r_{t+1}(T-t)} - \sum_{p=t}^T \frac{D_p}{c_{p+1}} e^{r_{p+1}(T-p)} + S_T \left(1 - \frac{c_{t+1}}{c_T}\right)$
COC4	$F_t^* = S_t e^{(r_t - \rho\sigma_S\sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_p - \rho\sigma_S\sigma_E)(T-p)}$	$F_{t+1}^* = S_t e^{(r_t - \rho\sigma_S\sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_p - \rho\sigma_S\sigma_E)(T-p)}$	$F_{t+1}^* = S_t e^{(r_{t+1} - \rho\sigma_S\sigma_E)(T-t)} - \sum_{p=t}^T D_p e^{(r_{p+1} - \rho\sigma_S\sigma_E)(T-p)}$

Notes: This table compares the cost of carry model in different views as to variable selection and model modifications for the CME futures contracts. The original view ignores the time lag between the index closing price in the TSE and the futures settlement price in the CME. From the perspective of the CME investors, the past view assumes that the historical rates released prior to arbitrage, yet on the same day, are used in arbitrage; the future view assumes that rates on the next day can be known precisely and used in arbitrage today. The first row shows the variables that are required in the cost of carry model in each view. The variables are index closing price (S), futures settlement price (F), exchange rate (c), risk-free interest rate (r) and the Nikkei-exchange rate covariance ($\rho\sigma_S\sigma_E$). Their subscripts t and $t+1$ indicate the timing difference. Since COC1 uses the continuous dividend rate d_t , while COC2, COC3 and COC4 use the aggregate dividend term D_p paid on day p , D_p is followed by d_t which is in brackets, as they both are dividend-related variables. The following rows list the modifications to the four versions of cost of carry model using the variables. $\dagger$ d_t has been converted to its dollar equivalent using c_t . $\ddagger$ d_t has been converted to its dollar equivalent using c_{t+1} .

Table 7 Different Trading Hours for the CME mispricing

Differences in futures mispricing (%)		COC1	COC2	COC3	COC4
Past vs Future	Mean	-0.0005	-0.0005	-0.0026	0.0000
	Median	0.0000	0.0000	0.0000	0.0000*
Past vs Original	Mean	0.0099	0.0099	0.0099	0.0099
	Median	0.0485	0.0485	0.0485	0.0485
Future vs Original	Mean	0.0104	0.0104	0.0125	0.0099
	Median	0.0498	0.0498	0.0512	0.0495

Notes: This table compares the original, past and future views of each cost of carry model for the CME mispricing. Mean differences are tested by paired *t*-tests; median differences are tested by Wilcoxon signed rank tests. The null hypothesis is that the mean (median) differences are zero. * denotes significance at the 10% level.

Table 8 Summary Statistics of Nikkei 225 Futures Mispricing without and with Transaction Costs

Panel A: OSE																	
Year	Without transaction costs							With transaction costs of 0.5%					With transaction costs of 1.0%				
	Mean (%)	SD (%)	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs
1996	0.09	0.21	91	42	0.20	-0.14	133	3	1	0.06	-0.12	4	0	0	0.00	0.00	0
1997	-0.06	0.34	105	140	0.23	-0.27	245	15	20	0.10	-0.28	35	0	2	0.00	-0.37	2
1998	-0.16	0.43	89	158	0.27	-0.40	247	11	48	0.18	-0.29	59	0	11	0.00	-0.22	11
1999	-0.04	0.36	118	127	0.26	-0.31	245	13	20	0.13	-0.26	33	0	3	0.00	-0.12	3
2000	-0.04	0.42	103	145	0.31	-0.29	248	19	26	0.31	-0.21	45	2	3	0.95	-0.37	5
2001	-0.06	0.46	112	134	0.28	-0.34	246	20	24	0.23	-0.41	44	2	4	0.32	-0.95	6
2002	-0.06	0.37	122	124	0.24	-0.35	246	16	34	0.15	-0.17	50	1	2	0.03	-0.09	3
2003	-0.05	0.34	109	136	0.24	-0.28	245	10	21	0.10	-0.22	31	0	2	0.00	-0.30	2
2004	-0.03	0.25	111	135	0.19	-0.21	246	4	7	0.23	-0.07	11	0	0	0.00	0.00	0
2005	-0.04	0.23	116	129	0.15	-0.20	245	2	10	0.07	-0.08	12	0	0	0.00	0.00	0
2006	-0.02	0.26	127	121	0.17	-0.23	248	6	9	0.14	-0.10	15	0	0	0.00	0.00	0
2007	-0.01	0.26	133	112	0.16	-0.22	245	6	10	0.24	-0.15	16	1	0	0.08	0.00	1
2008	-0.06	0.52	102	143	0.34	-0.34	245	21	25	0.41	-0.49	46	6	6	0.50	-0.84	12
2009	-0.07	0.39	109	134	0.23	-0.31	243	11	28	0.22	-0.36	39	1	9	0.15	-0.13	10
2010	-0.09	0.32	90	155	0.19	-0.26	245	9	37	0.19	-0.15	46	0	1	0.00	-0.05	1
2011	-0.08	0.36	103	142	0.19	-0.27	245	9	31	0.24	-0.32	40	1	4	0.00	-0.20	5
2012	-0.09	0.36	99	149	0.19	-0.28	248	10	34	0.31	-0.28	44	1	1	0.21	-0.09	2
2013	0.00	0.37	132	113	0.25	-0.29	245	19	25	0.23	-0.17	44	2	1	0.27	-0.32	3
2014	-0.04	0.31	122	122	0.19	-0.27	244	11	22	0.15	-0.17	33	0	1	0.00	-0.14	1
Overall	-0.05	0.36	2093	2461	0.22	-0.28	4554	215	432	0.22	-0.25	647	17	50	0.38	-0.34	67

Panel B: SGX

Year	Without transaction costs							With transaction costs of 0.5%					With transaction costs of 1.0%				
	Mean (%)	SD (%)	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs
1996	0.09	0.21	93	40	0.19	-0.14	133	3	1	0.14	-0.09	4	0	0	0.00	0.00	0
1997	-0.04	0.36	119	126	0.24	-0.30	245	14	23	0.17	-0.25	37	1	3	0.18	-0.25	4
1998	-0.13	0.44	93	153	0.29	-0.39	246	18	42	0.16	-0.34	60	1	9	0.13	-0.28	10
1999	-0.01	0.37	121	123	0.28	-0.29	244	14	16	0.21	-0.29	30	2	4	0.13	-0.13	6
2000	-0.03	0.38	106	142	0.30	-0.27	248	16	19	0.27	-0.22	35	1	1	1.01	-0.59	2
2001	-0.03	0.45	122	123	0.29	-0.34	245	18	21	0.27	-0.39	39	2	4	0.28	-0.64	6
2002	-0.04	0.39	124	122	0.26	-0.34	246	15	28	0.14	-0.24	43	1	4	0.20	-0.30	5
2003	-0.03	0.34	118	127	0.25	-0.29	245	10	21	0.13	-0.17	31	0	3	0.00	-0.10	3
2004	-0.02	0.26	113	133	0.20	-0.21	246	6	7	0.16	-0.09	13	0	0	0.00	0.00	0
2005	-0.05	0.23	105	139	0.16	-0.21	244	1	12	0.03	-0.08	13	0	0	0.00	0.00	0
2006	-0.02	0.24	128	120	0.16	-0.22	248	5	6	0.15	-0.11	11	0	0	0.00	0.00	0
2007	-0.03	0.26	131	114	0.16	-0.24	245	6	12	0.13	-0.12	18	0	0	0.00	0.00	0
2008	-0.06	0.48	104	140	0.33	-0.35	244	24	39	0.27	-0.29	63	5	6	0.16	-0.53	11
2009	-0.06	0.40	112	131	0.25	-0.32	243	12	26	0.22	-0.39	38	1	10	0.20	-0.17	11
2010	-0.11	0.33	92	153	0.20	-0.29	245	9	36	0.15	-0.19	45	0	0	0.00	0.00	0
2011	-0.11	0.45	101	155	0.23	-0.32	256	15	37	0.26	-0.44	52	2	10	0.17	-0.46	12
2012	-0.10	0.41	99	161	0.25	-0.31	260	13	38	0.39	-0.31	51	3	4	0.26	-0.23	7
2013	0.04	0.55	139	121	0.35	-0.32	260	23	30	0.68	-0.19	53	8	1	1.14	-0.82	9
2014	-0.06	0.46	117	143	0.25	-0.31	260	12	29	0.36	-0.34	41	1	5	2.53	-0.79	6
Overall	-0.04	0.39	2137	2466	0.24	-0.29	4603	234	443	0.27	-0.28	677	28	64	0.58	-0.37	92

Panel C: CME

Year	Without transaction costs							With transaction costs of 1.5%					With transaction costs of 2.0%				
	Mean (%)	SD (%)	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	No. of obs
1997	-0.08	0.92	132	121	0.54	-0.76	253	7	15	0.36	-0.92	22	1	10	0.93	-0.81	11
1998	-0.06	1.05	121	131	0.72	-0.78	252	15	13	0.83	-0.95	28	8	8	0.87	-0.90	16
1999	0.07	0.69	142	111	0.55	-0.55	253	3	7	0.25	-0.32	10	1	2	0.14	-0.38	3
2000	-0.08	0.87	109	143	0.69	-0.67	252	9	11	0.66	-0.39	20	5	2	0.36	-0.81	7
2001	-0.03	1.17	122	130	0.84	-0.85	252	15	20	0.91	-0.80	35	8	9	1.02	-0.97	17
2002	-0.07	1.02	108	144	0.87	-0.77	252	23	13	0.50	-0.42	36	9	3	0.39	-0.25	12
2003	0.12	0.88	136	116	0.75	-0.63	252	18	7	0.37	-0.56	25	5	2	0.22	-0.62	7
2004	0.02	0.80	133	119	0.61	-0.63	252	8	9	0.28	-0.59	17	2	4	0.13	-0.41	6
2005	-0.01	0.57	129	123	0.42	-0.47	252	1	4	0.03	-0.10	5	0	0	0.00	0.00	0
2006	-0.01	0.77	132	119	0.54	-0.62	251	7	7	0.50	-0.54	14	3	3	0.45	-0.47	6
2007	0.01	0.98	142	109	0.64	-0.80	251	11	18	0.80	-0.64	29	8	10	0.53	-0.43	18
2008	0.20	2.38	138	115	1.68	-1.58	253	54	35	1.78	-2.15	89	39	30	1.87	-1.96	69
2009	0.58	1.50	171	81	1.35	-1.04	252	60	21	1.02	-0.82	81	38	16	0.97	-0.51	54
2010	0.13	1.06	156	97	0.77	-0.89	253	17	20	0.44	-0.79	37	6	10	0.47	-0.90	16
2011	-0.03	1.15	130	122	0.78	-0.90	252	15	21	0.54	-0.94	36	4	10	1.07	-1.14	14
2012	0.09	0.77	149	104	0.59	-0.62	253	6	9	0.17	-0.39	15	1	3	0.25	-0.29	4
2013	0.63	1.19	179	73	1.17	-0.69	252	46	7	0.87	-0.79	53	28	4	0.80	-0.72	32
2014	0.16	1.06	150	102	0.79	-0.77	252	19	14	0.71	-0.75	33	9	7	0.85	-0.77	16
Overall	0.09	1.13	2479	2060	0.81	-0.77	4539	334	251	0.88	-0.90	585	175	133	1.00	-0.99	308

Notes: This table presents summary statistics of Nikkei 225 futures mispricing over the sample period. Mispricing without transaction costs is calculated from equations (2), (3) and (6). Mispricing with transactions costs is calculated from equations (7)-(8). Transaction costs are 0.5% for brokers, 1.0% for institutional investors in the OSE and SGX; 1.5% for brokers, 2.0% for institutional investors in the CME. Panel A, B and C display the mispricing in the OSE, SGX and CME, respectively. The mean and standard deviation (SD) of mispricing without regard to sign are in percentage. Signed mispricings without or with transactions costs are divided into overpricing and underpricing; and these are categorised into: number of overpricings (no.of pos), number of underpricings (no.of neg), and their respective means (mean pos and mean neg) in percentage.

Table 9 Autocorrelation Coefficients of Nikkei 225 Futures Mispricing

Panel A: OSE

Autocorrelations (Lag)								
Year	1	2	3	4	1	2	3	4
	Level of mispricing				First difference in mispricing			
1996	0.074	0.118	0.092	-0.030	-0.517**	0.023**	0.059**	-0.118**
1997	0.221**	0.295**	0.236**	0.194**	-0.547**	0.087**	-0.008**	-0.058**
1998	0.281**	0.059**	0.062**	0.149**	-0.335**	-0.161**	-0.047**	0.007**
1999	0.271**	0.156**	0.206**	0.175**	-0.418**	-0.095**	0.046**	0.042**
2000	0.247**	-0.035**	-0.043**	0.117**	-0.319**	-0.188**	-0.097**	0.074**
2001	0.188**	0.254**	0.213**	0.154**	-0.538**	0.062**	0.011**	-0.006**
2002	0.162**	0.008**	-0.060*	0.077*	-0.417**	-0.038**	-0.116**	0.175**
2003	0.136**	0.213**	0.183**	0.164**	-0.544**	0.064**	-0.005**	0.015**
2004	0.241**	0.238**	0.174**	0.173**	-0.499**	0.047**	-0.049**	0.020**
2005	0.488**	0.356**	0.344**	0.317**	-0.362**	-0.114**	0.012**	0.079**
2006	0.511**	0.482**	0.267**	0.313**	-0.473**	0.198**	-0.260**	0.110**
2007	0.494**	0.455**	0.388**	0.307**	-0.448**	0.028**	0.021**	-0.052**
2008	0.118*	0.185**	0.248**	0.178**	-0.538**	0.003**	0.078**	0.034**
2009	0.544**	0.414**	0.496**	0.496**	-0.357**	-0.230**	0.088**	0.161**
2010	0.674**	0.630**	0.557**	0.502**	-0.430**	0.045**	-0.031**	-0.014**
2011	0.646**	0.595**	0.520**	0.498**	-0.427**	0.033**	-0.074**	0.064**
2012	0.771**	0.666**	0.613**	0.515**	-0.271**	-0.114**	0.100**	-0.154**
2013	0.434**	0.357**	0.300**	0.322**	-0.432**	-0.017**	-0.070**	0.052**
2014	0.512**	0.488**	0.341**	0.347**	-0.476**	0.126**	-0.156**	0.042**
Overall	0.357**	0.299**	0.271**	0.270**	-0.455**	-0.023**	-0.021**	0.037**

Table 9 continued

Panel B: SGX

Year	Autocorrelations (Lag)							
	1	2	3	4	1	2	3	4
	Level of mispricing				First difference in mispricing			
1996	0.114	0.268**	-0.014**	0.021**	-0.589**	0.233**	-0.166**	0.019**
1997	0.258**	0.352**	0.151**	0.176**	-0.562**	0.197**	-0.151**	-0.012**
1998	0.313**	0.087**	0.074**	0.222**	-0.336**	-0.155**	-0.116**	0.072**
1999	0.242**	0.156**	0.172**	0.158**	-0.443**	-0.067**	0.028**	0.041**
2000	0.277**	0.024**	0.005**	0.057**	-0.335**	-0.168**	-0.034**	-0.028**
2001	0.217**	0.233**	0.239**	0.170**	-0.504**	0.005**	0.044**	-0.005**
2002	0.132**	0.004	-0.048	0.169**	-0.425**	-0.019**	-0.155**	0.262**
2003	0.220**	0.154**	0.181**	0.137**	-0.449**	-0.057**	0.051**	0.007**
2004	0.340**	0.287**	0.247**	0.178**	-0.467**	0.001**	0.018**	-0.022**
2005	0.448**	0.387**	0.295**	0.318**	-0.431**	0.041**	-0.118**	0.093**
2006	0.518**	0.487**	0.272**	0.313**	-0.469**	0.200**	-0.256**	0.097**
2007	0.447**	0.413**	0.332**	0.291**	-0.456**	0.041**	-0.024**	0.000**
2008	0.203**	0.269**	0.275**	0.185**	-0.534**	0.038**	0.069**	0.004**
2009	0.512**	0.411**	0.423**	0.384**	-0.377**	-0.130**	0.059**	0.054**
2010	0.645**	0.612**	0.527**	0.474**	-0.450**	0.070**	-0.045**	0.011**
2011	0.593**	0.505**	0.452**	0.477**	-0.391**	-0.045**	-0.095**	0.094**
2012	0.572**	0.509**	0.454**	0.377**	-0.424**	-0.009**	0.024**	-0.051**
2013	0.399**	0.137**	0.117**	0.112**	-0.277**	-0.205**	-0.011**	0.033**
2014	0.220**	0.201**	0.233**	0.180**	-0.493**	-0.027**	0.056**	0.005**
Overall	0.358**	0.279**	0.248**	0.247**	-0.439**	-0.037**	-0.023**	0.038**

Table 9 continued

Panel C: CME

Year	Autocorrelations (Lag)							
	1	2	3	4	1	2	3	4
	Level of mispricing				First difference in mispricing			
1997	0.100	-0.102*	0.053	0.134**	-0.388**	-0.196**	0.039**	0.128**
1998	0.319**	0.137**	0.166**	0.122**	-0.364**	-0.157**	0.054**	-0.026**
1999	0.316**	0.153**	0.100**	0.138**	-0.377**	-0.070**	-0.079**	0.032**
2000	-0.029	-0.088	0.075	0.028	-0.472**	-0.107**	0.101**	0.038**
2001	0.111*	-0.042	-0.011	0.066	-0.409**	-0.107**	-0.026**	0.029**
2002	0.038	0.051	-0.025	-0.037	-0.499**	0.041**	-0.038**	-0.019**
2003	0.030	0.029	-0.006	0.055	-0.495**	0.015**	-0.053**	0.089**
2004	0.241**	0.146**	0.126**	0.026**	-0.439**	-0.048**	0.054**	-0.092**
2005	0.127**	0.044*	0.011	-0.029	-0.452**	-0.029**	0.004**	-0.087**
2006	0.073	-0.110	0.009	0.011	-0.402**	-0.163**	0.063**	-0.037**
2007	0.155**	0.040**	0.130**	-0.013**	-0.431**	-0.124**	0.142**	-0.087**
2008	0.053	-0.117	0.090*	0.080*	-0.412**	-0.198**	0.117**	0.024**
2009	0.143**	0.184**	0.094**	0.087**	-0.526**	0.080**	-0.039**	0.016**
2010	0.241**	0.072**	0.023**	0.008**	-0.390**	-0.078**	-0.024**	-0.008**
2011	-0.003	0.138*	0.016	0.122*	-0.570**	0.131**	-0.114**	0.146**
2012	0.223**	0.214**	0.132**	0.054**	-0.487**	0.040**	-0.005**	-0.015**
2013	0.087	0.120*	0.068*	0.181**	-0.522**	0.051**	-0.091**	0.239**
2014	0.183**	0.133**	0.151**	-0.017**	-0.468**	-0.041**	0.113**	-0.121**
Overall	0.144**	0.061**	0.103**	0.098**	-0.452**	-0.073**	0.027**	0.029**

Notes: This table gives the autocorrelation coefficients of Nikkei 225 futures mispricing by year over the sample period. The autocorrelation coefficients are calculated up to the fourth lag for the level of mispricing and for the first difference in mispricing. Panel A, B and C show the autocorrelation coefficients in the OSE, SGX and CME, respectively. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table 10 Nikkei 225 Futures Mispricing and Time To Expiration

	Mispricing (%)		Absolute mispricing (%)		Underpricing (%)		Overpricing (%)		
Time to expiration	Mean	Median	Mean	Median	Mean	Median	Mean	Median	No. of obs
Panel A: OSE									
(80, 105]	-0.1361	-0.1514	0.3976	0.3506	-0.4259	-0.3879	0.3501	0.2825	1071
(60, 80]	-0.0518	-0.0109	0.2615	0.1946	-0.3022	-0.2109	0.2177	0.1742	955
(40, 60]	-0.0248	-0.0106	0.2008	0.1444	-0.2136	-0.1551	0.1866	0.1296	1047
(20, 40]	-0.0036	0.0034	0.1952	0.1502	-0.2015	-0.1522	0.1891	0.1479	1032
[8, 20]	-0.0099	-0.0047	0.1833	0.1443	-0.1861	-0.1348	0.1802	0.1564	449
Test statistics			A: 132.0443**		A: 80.6546**	B: -16.2661** C: -0.2410**			
Panel B: SGX									
(80, 105]	-0.1411	-0.1464	0.4043	0.3442	-0.4323	-0.3846	0.3564	0.3078	1078
(60, 80]	-0.0352	-0.0166	0.2827	0.2039	-0.3062	-0.2190	0.2573	0.1941	967
(40, 60]	-0.0219	-0.0130	0.2145	0.1490	-0.2282	-0.1622	0.1998	0.1407	1060
(20, 40]	0.0096	0.0171	0.2157	0.1654	-0.2191	-0.1641	0.2127	0.1662	1048
[8, 20]	-0.0150	-0.0150	0.1847	0.1332	-0.1856	-0.1303	0.1836	0.1445	450
Test statistics					A: 69.3707**				
Panel C: CME									
(80, 105]	0.1141	0.0865	0.8550	0.6298	-0.7847	-0.6030	0.9178	0.6583	1055
(60, 80]	0.0955	0.0706	0.7723	0.5822	-0.7434	-0.5559	0.7964	0.6109	949
(40, 60]	0.1007	0.1094	0.8072	0.5910	-0.7878	-0.5663	0.8230	0.5970	1057
(20, 40]	0.0953	0.1432	0.7725	0.5472	-0.7878	-0.5275	0.7609	0.5678	1068
[8, 20]	-0.0152	0.0277	0.7004	0.4795	-0.7447	-0.5201	0.6594	0.4699	410
Test statistics								B: 4.5334** C: 0.0669**	

Notes: This table provides tests of the relationship between Nikkei futures mispricing and time to expiration. Mispricing, absolute mispricing, underpricing and overpricing are each sorted into 5 groups by time to expiration in descending order, with each group covering roughly 20 trading days. The group means (medians) are then checked for monotonic orderings. Shaded columns indicate the location of the significant monotonic relationships observed. The null hypothesis of equal means across the groups is tested by *F*-statistics of an OLS regression on dummy variables representing the groups. The null hypothesis of equal medians across the groups is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952); Kendall's (1938) tau-b coefficients are also calculated to help identify the direction of median orderings. A: *F*-statistics. B: Standardised Jonckheere-Terpstra statistics. C: Kendall's tau-b coefficients (one-tailed). ** denotes significance at the 5% level.

Table 11 Nikkei 225 Futures Mispricing and Stock Volatility

	Mispricing (%)		Absolute mispricing (%)		Underpricing (%)		Overpricing (%)		
Stock volatility (%) †	Mean	Median	Mean	Median	Mean	Median	Mean	Median	No. of obs
Panel A: OSE									
(0.0289, 0.1926]	-0.0812	-0.0489	0.3342	0.2431	-0.3741	-0.2822	0.2843	0.2057	908
(0.0205, 0.0289]	-0.0680	-0.0356	0.2728	0.2076	-0.3028	-0.2425	0.2342	0.1884	901
(0.0158, 0.0205]	-0.0665	-0.0439	0.2527	0.1892	-0.2758	-0.2003	0.2210	0.1692	921
(0.0120, 0.0158]	-0.0208	-0.0025	0.2259	0.1665	-0.2443	-0.1819	0.2072	0.1553	895
(0.0019, 0.0120]	-0.0149	0.0015	0.1861	0.1272	-0.2024	-0.1300	0.1701	0.1251	900
Test statistics	A: 6.6462**		A: 46.0638**	B: 12.7057** C: 0.1380**	A: 27.9851**	B: -10.0536** C: -0.1487**	A: 16.6563**	B: 7.3849** C: 0.1183**	
Panel B: SGX									
(0.0283, 0.1908]	-0.0636	-0.0436	0.3391	0.2591	-0.3726	-0.2841	0.2997	0.2290	918
(0.0202, 0.0283]	-0.0631	-0.0477	0.2807	0.2146	-0.3016	-0.2333	0.2530	0.1952	921
(0.0156, 0.0202]	-0.0635	-0.0516	0.2666	0.1986	-0.2959	-0.2159	0.2296	0.1866	909
(0.0119, 0.0156]	-0.0071	-0.0008	0.2483	0.1740	-0.2546	-0.1845	0.2420	0.1601	919
(0.0019, 0.0119]	-0.0247	-0.0037	0.2087	0.1402	-0.2291	-0.1539	0.1875	0.1248	907
Test statistics			A: 27.9282**	B: 11.8805** C: 0.1283**	A: 17.8626**	B: -8.6795** C: -0.1281**		B: 7.8965** C: 0.1252**	
Panel C: CME									
(0.0286, 0.1988]	0.2086	0.1321	1.1504	0.8740	-1.0344	-0.7510	1.2474	0.9607	905
(0.0205, 0.0286]	0.1416	0.1411	0.8161	0.6337	-0.7667	-0.5800	0.8549	0.6907	898
(0.0158, 0.0205]	0.0490	0.0529	0.7139	0.5523	-0.6991	-0.5136	0.7273	0.5679	900
(0.0122, 0.0158]	0.0140	0.0724	0.6823	0.5482	-0.7218	-0.5557	0.6482	0.5429	903
(0.0057, 0.0122]	0.0556	0.0981	0.5157	0.4104	-0.5333	-0.4391	0.5024	0.4011	904
Test statistics			A: 95.7191**	B: 15.5154** C: 0.1688**			A: 73.7710**	B: 14.0211** C: 0.2063**	

Notes: This table provides tests of the relationship between Nikkei futures mispricing and stock volatility. Stock volatility is estimated by the fitted value of the conditional variance of a GARCH (1, 1) model of Bollerslev (1986) with a constant mean equation. Mispricing, absolute mispricing, underpricing and overpricing are each sorted into 5 groups of roughly equal size by the volatility estimate in descending order. The group means (medians) of the mispricing data are then checked for monotonic orderings. Shaded columns indicate the location of the significant monotonic relationships observed. The null hypothesis of equal means across the groups is tested by *F*-statistics of an OLS regression on dummy variables representing the groups. The null hypothesis of equal medians across the groups is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952); Kendall's (1938) tau-b coefficients are also calculated to help identify the direction of median orderings. A: *F*-statistics. B: Standardised Jonckheere-Terpstra statistics. C: Kendall's tau-b coefficients (one-tailed). † 28 trading days during 14/10/2008-21/11/2008 (OSE, SGX), 15/10/2008-21/11/2008 (CME) are excluded from the data because of extreme volatility. ** denotes significance at the 5% level.

Table 12 Path Dependence in Nikkei 225 Futures Mispricing

Scenario	Conditional probability	No. of obs
Panel A: OSE		
0.5% Transaction costs		
Lower-lower	0.88	56
Lower-upper	0.13	8
Upper-upper	0.74	20
Upper-lower	0.26	7
χ^2 statistic	42.2593**	
Panel B: SGX		
0.5% Transaction costs		
Lower-lower	0.83	44
Lower-upper	0.17	9
Upper-upper	0.63	12
Upper-lower	0.37	7
χ^2 statistic	24.4290**	
Panel C: CME		
1.5% Transaction costs		
Lower-lower	0.55	18
Lower-upper	0.45	15
Upper-upper	0.75	38
Upper-lower	0.25	13
χ^2 statistic	12.5276**	

Notes: This table provides evidence of path dependence in Nikkei futures mispricing. The conditional probabilities are calculated for each of four scenarios: *lower-lower*, *lower-upper*, *upper-upper* and *upper-lower*. A *lower-upper* scenario describes the case that mispricing hits an upper bound on day $t+1$, given that it hits a lower bound on day $t-1$ and returns to zero on day t ; the other scenarios are defined analogously. The transaction costs are 0.5% for the OSE and SGX, 1.5% for the CME. The χ^2 tests are based on the null hypothesis that there is no association between hitting a lower (upper) bound on day $t+1$ and hitting a lower (upper) bound on day $t-1$, given that mispricing returns to zero on day t . ** denotes significance at the 5% level.

Table 13 Linearity Tests

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: The linearity test H_{01} for different d						
d						
1	2.25E-09	1.04E-14	6.01E-04	6.26E-07	9.10E-02	9.71E-06
2	3.61E-07	4.05E-01	1.99E-07	1.95E-02	1.66E-03	8.56E-04
3	6.04E-04	1.40E-01	1.34E-02	2.68E-03	2.04E-01	2.43E-06
4	1.51E-02	7.95E-04	1.93E-01	1.05E-02	1.47E-02	6.14E-06
5	2.35E-01	5.05E-02	1.01E-02	1.04E-03	1.97E-01	2.43E-05
Panel B: The linearity tests H_{01} - H_{03}						
d	1	1	2	1	2	3
H_{01}	2.25E-09	1.04E-14	1.99E-07	6.26E-07	1.66E-03	2.43E-06
H_{02}	2.33E-06	1.05E-12	1.34E-03	3.50E-06	3.25E-01	1.58E-06
H_{03}					4.56E-04	

Notes: This table reports the results of linearity tests for each Nikkei market in each sample. An auxiliary regression by OLS as equation (13) is run:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^p (\beta_{0j}y_{t-j} + \beta_{1j}y_{t-j}y_{t-d} + \beta_{2j}y_{t-j}y_{t-d}^2) + v_t$$

The three hypotheses, $H_{01}:\beta_{1j}=\beta_{2j}=0$, $H_{02}:\beta_{1j}=0$, $H_{03}:\beta_{2j}=0 \mid \beta_{1j}=0$ are tested by F -statistics. The p -values of the F -statistics are reported. Panel A shows the results of testing H_{01} for different d selected from $\{1, 2, 3, 4, 5\}$. d is determined as the candidate that generates the smallest p -value of the test. Panel B shows the p -values from testing the three hypotheses for the determined d .

Table 14 The ESTAR-GARCH Model

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
ESTAR coefficients						
p	6	4	5	4	4	4
d	1	1	2	1	2	3
γ	0.0009 (0.0073)	1.9950 (3.7140)	0.0100 (0.1426)	1.9395 (4.0019)	1.87E-05 (0.0002)	0.1790 (0.5151)
GARCH coefficients †						
ω	1.09E-07 (3.1334)	9.15E-07 (4.3185)	4.76E-09 (1.3183)	6.22E-06 (5.9142)	2.31E-06 (3.9524)	4.43E-06 (3.3150)
a_1	0.0539 (6.3732)	0.2275 (4.9765)	0.0963 (4.1796)	0.4857 (4.3766)	0.0967 (7.2329)	0.1359 (6.0890)
a_2			-0.0909 (-4.1561)			
b_1	0.9371 (100.3153)	0.6813 (14.5597)	1.6254 (13.1883)	0.1353 (1.6621)	0.8789 (53.6774)	0.8323 (32.7779)
b_2			-0.6311 (-5.2261)			
Evaluation						
LM(12)	[0.7523]	[0.6074]	[0.7065]	[0.7221]	[0.5550]	[0.2492]
ARCH(12)	[0.9254]	[0.1436]	[0.4823]	[0.8853]	[0.9035]	[0.5948]
BDS	[0.5540]	[0.1140]	[0.5860]	[0.3780]	[0.7780]	[0.4160]

Notes: This table shows the estimation and evaluation results of the ESTAR-GARCH model, equations (9)-(12):

$$y_t = k + \sum_{j=1}^p \pi_j y_{t-j} + (k^* + \sum_{j=1}^p \pi_j^* y_{t-j}) \times T(y_{t-d}) + u_t, \quad T(y_{t-d}) = 1 - \exp[-\gamma(y_{t-d} - c^*)^2];$$

$$u_t = \sigma_t \eta_t, \quad \sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2.$$

The model restriction is $k=k^*=c^*=0$. Diagnostic checks include the LM serial correlation test (LM) of Eitrheim and Teräsvirta (1996), the ARCH-LM test (ARCH) of Engle (1982), and the BDS independence test (BDS) of Brock *et al.* (1996). LM(12) and ARCH(12) are respective test statistics up to order 12. Numbers in parentheses are z-statistics. Numbers in square brackets are p -values. † For SGX (sample A), a GARCH (2, 2) model, $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b_1 \sigma_{t-1}^2 + b_2 \sigma_{t-2}^2$ is used as equation (12).

Table 15 ESTAR-GARCH Adjustment Coefficients

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Testing for mean reversion and heterogeneity (H_{04})						
j						
Middle regime adjustment coefficients (π_j)						
1	0.2364	-0.0330	0.2165	0.0122	0.1465	0.1838
2	0.1526	0.0072	0.2015	-0.0169	0.0008	0.1435
3	0.0566	0.0578	0.0581	0.0364	0.0289	0.0972
4	0.0873	0.0658	0.0684	0.0522	0.0452	0.0542
5	0.0466		0.0453			
6	0.0417					
Outer regime adjustment coefficients ($\pi_j + \pi_j^*$)						
1	-3.3217	0.4086	2.0409	0.3195	271.6848	0.0020
2	-8.6056	0.2500	-2.0802	0.2822	-105.0828	0.0497
3	4.7032	0.1415	-0.1437	0.1525	861.8622	0.0383
4	-5.7465	0.0709	1.4438	0.0966	-223.4954	0.1097
5	9.6187		1.6468			
6	-4.3070					
$Wald_1$	536.7086	1040.5250	602.6965	986.1742	72.5323	81.8551
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Panel B: Testing for symmetric adjustments (H_{05})						
j						
1	0.0001	16.0093	0.0218	8.0261	0.0000	0.5650
	[0.9941]	[0.0001]	[0.8826]	[0.0046]	[0.9998]	[0.4523]
2	0.0001	10.6217	0.0237	22.0329	0.0000	0.2517
	[0.9941]	[0.0011]	[0.8776]	[0.0000]	[0.9998]	[0.6158]
3	0.0001	1.3075	0.0125	3.5653	0.0000	0.2910
	[0.9941]	[0.2528]	[0.9111]	[0.0590]	[0.9998]	[0.5896]
4	0.0001	0.0057	0.0216	0.7220	0.0000	0.1620
	[0.9941]	[0.9397]	[0.8831]	[0.3955]	[0.9998]	[0.6873]
5	0.0001		0.0223			
	[0.9941]		[0.8813]			
6	0.0001					
	[0.9941]					
Joint $Wald_2$	0.0001	49.4841	0.0364	67.5145	0.0000	1.1603
	[1.0000]	[0.0000]	[1.0000]	[0.0000]	[1.0000]	[0.8846]

Notes: This table reports the adjustment coefficients estimated from the ESTAR-GARCH model, equations (9)-(12), and the associated Wald statistics. Panel A shows the adjustment coefficients in the middle regime (π_j) and the outer regime ($\pi_j + \pi_j^*$), $j=1, 2, \dots, p$. $Wald_1$ is a χ^2 statistic to test H_{04} : $\pi_j = \pi_j + \pi_j^* = 0$. Rejection of H_{04} indicates the mean-reverting behaviour of mispricing and the heterogeneity in arbitrage activities. $Wald_2$ is a χ^2 statistic to test H_{05} : $\pi_j = \pi_j + \pi_j^*$. Rejection of H_{05} indicates asymmetric adjustments in different regimes. Panel B shows the results of $Wald_2$ separately for each j and jointly for all j . Numbers in square brackets are p -values.

Footnotes

- ¹ In June 2014, the market capitalisation of the constituent stocks in the Nikkei was \$4.49 trillion, or 64% of all stocks in the First Section of the TSE (data from Nikkei Inc.).
- ² When SGX changed from open outcry to the electronic trading system (ETS), investors were given time to adapt to the ETS in overnight sessions and there was a period when both systems were available for trading. The ETS started to rival open outcry in volume from about 01/11/2004, and shortly after, ETS became the only trading mechanism. SGX futures prices are compiled using settlement prices on the floor before 01/11/2004, and those on the ETS afterwards. A Quandt-Andrews unknown breakpoint test suggests that there were no discernible breaks in the compiled price series around the changeover date.
- ³ Interest rates and exchange rate are from *Datastream*; the dividend yield is from Thomson Reuters' *Eikon*.
- ⁴ Individual investors are not considered as they account for a small proportion of the trading volume of Nikkei futures, and typically face higher transaction costs than institutional investors and brokers. The width of the no-arbitrage band set by transactions costs is determined by investors with the lowest costs (MacKinlay and Ramaswamy, 1988; Gay and Jung, 1999).
- ⁵ These estimates are based on: Brenner *et al.* (1989a; 1989b; 1990) who estimate transaction costs in the OSE and SGX to be 0.5%, 1.0% and 2.0%; and Board and Sutcliffe (1996) who estimate the transaction costs of spread arbitrage in the CME to be 1.0%.
- ⁶ A long arbitrage requires buying stock and selling futures at time t ; then selling the stock and repurchasing the futures at expiration. A short arbitrage requires selling stock and buying futures at time t ; then repurchasing the stock and selling the futures at expiration.
- ⁷ Adding dummies to represent trading days before and after the June and December payment dates, we find that their significance declines as the distance from the payment dates increases. A minor puzzle is that β_{10} (the last trading day of June) is never significant, although end-June usually sees

the most dividend payouts in a year. Further regressions suggest that this may be due to time-related anomalies such as a turn-of-the-month effect. Results are available on request.

- ⁸ Exchange rate futures cannot eliminate the risk as the cost of the index futures at expiration (S_T) is unknown at time t (Board and Sutcliffe, 1996).
- ⁹ We thank an anonymous referee for suggesting this model.
- ¹⁰ Equation (6) is initially constructed twice: first, using a constant covariance with ρ estimated by the Pearson correlation coefficient; and second, using a time-varying covariance estimated using a Dynamic Conditional Correlation (DCC)-GARCH model (Engle, 2002). Comparing the results from these two methods, the mean differences in mispricing turn out to be insignificant, but the constant covariance model generates significantly lower median mispricing estimates. For accuracy, and for consistency with the model of Baxter and Rennie (1996), we therefore estimate equation (6) using a constant covariance. This may perhaps also reduce the dual hypothesis problem as it does not require a GARCH process to estimate the time-varying covariance.
- ¹¹ For the OSE and SGX Nikkei futures, $\rho\sigma_S\sigma_E=0$.
- ¹² The TSE uptick rule stipulates that the price of a short sale must be above the last traded price of a stock if the last traded price is lower than the previous traded price or at the last traded price if the last traded price is higher than the previous traded price. During the 2008 global financial crisis, short-selling was banned on Japanese stock exchanges. From November 2013, the uptick rule has applied only when the stock price falls by 10% of a trigger price which is published daily by the TSE, and once active the uptick rule lasts until the end of the next trading day (data from TSE).
- ¹³ To obtain sufficient mispricing observations, transaction costs are not included in the analysis in Section 4.2 and 4.3.
- ¹⁴ The ESTAR specification is better than other smooth transition models in being able to capture the mean-reverting behaviour in mispricing that we have identified.
- ¹⁵ Exceptionally, a GARCH (2, 2) process is found necessary to model the SGX (sample A).
- ¹⁶ The ESTAR-GARCH model is sensitive to outliers (Chan and McAleer, 2002). 7 trading days are

found to produce excessive ARCH effects in the SGX residuals. These are removed from the data at the same time by regressing SGX mispricing on a constant, time to expiration and dummy variables representing the outliers.

- ¹⁷ Augmented Dickey-Fuller (1979, 1981), Phillips-Perron (1988), Zivot-Andrews (1992) and Kwiatkowski-Phillips-Schmidt-Shin (1992) tests are carried out. Results of these tests are available on request.
- ¹⁸ The stationarity and ergodicity of the ESTAR-GARCH model and the existence of moments are proved in Chan and McAleer (2002).

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