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PRICE VOLATILITY OF THE NIKKEI INDEX COMPONENT STOCKS

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ABSTRACT

The Nikkei Stock Index 300, which was introduced in February 1994, consists of 145 newly selected stocks plus 155 stocks retained from the Nikkei Stock Average (NSA), while excluding 70 NSA stocks. Using cross-sectional regressions, price volatilities of three groups, consisting of 145, 155, and 70 stocks, are compared after the impact of the major determinants have been controlled. Significant one-day return volatility differentials are observed among the three groups of component stocks, with the 70 and 155 stock groups having greater volatility than the 145 stock group. A difference in multiday return volatility is noted between the 145 and 70 stock groups, but not between the 145 and 155 stock groups. While statistically significant, the economic significance is questionable given that the magnitude of the differences is small. Significant differences are detected among the three groups of component stocks in their sensitivity to futures market volatility even after cross-sectional variations in firm attributes have been controlled. Differences are noted in the speed of price adjustment to new information between the 145 stock group and the NSA 225 component stocks. This is not a surprise since the 145 stocks were not

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underlying securities for the NSA futures contracts during the study period. From the empirical evidence presented, it appears that the Nikkei Stock Index 300 is an improvement over the existing NSA, even though the economic benefits of replacing the NSA with the Nikkei 300 have yet to be fully investigated.

In September 1986 trading of the first Japanese stock index futures contract began offshore at the Singapore International Monetary Exchange (SIMEX). This contract was written on the Nikkei Stock Average (NSA), a price-weighted basket of 225 stocks traded on the first section of the Tokyo Stock Exchange (TSE). The Osaka Securities Exchange (OSE) initiated the first domestic instrument in June 1987 with the Kabusaki 50 index futures contract. It was based on a price-weighted index of 50 stocks listed on the OSE.[1] An unusual feature of this contract was the requirement that the underlying shares be physically delivered upon contract expiration. This was necessary since Japanese Securities and Exchange Law did not allow cash settlement of index futures contracts.[2]

In September 1988 an amendment to the relevant laws and regulations allowed the TSE and the OSE to trade cash-settled index futures contracts written on the NSA and the Tokyo Stock Price Index (TOPIX), a value-weighted composite index of common stocks listed on the TSE's first section, respectively. This subsequently caused the rapid expansion of the Japanese stock index futures market. Within the first year their combined trading value began to exceed that of the TSE cash market. By the end of 1991 the trading value of stock index futures, in Osaka alone, was about five times greater than Tokyo's cash market volume. The initial success of the stock index futures market, however, has been overshadowed by criticism: it is alleged that the futures market has an adverse impact on the cash market and may have caused a significant downturn since January 1990.[3]

The overall attitude of Japanese regulators regarding the relationship between the cash and futures markets is best illustrated by Sato (1993) and a TSE position paper (1993). Specifically, the TSE believes that extreme volatility in the Tokyo market has been caused by futures trading in Osaka. This in turn has driven away the investing public from the cash market. These arguments are identical to the views aired by small individual investors and the opponents of equity derivative markets after the 1987 market crash in the United States. Their contention was that individual investors were victimized by the more volatile equity derivative markets.

Since the impact of equity derivative instruments on the underlying stock market is of considerable interest to regulators, practitioners, and academic researchers, a significant amount of research has been done on this issue. Edwards (1988a, 1988b), Grossman (1988), and Becketti and Roberts (1990) conclude that index futures have an insignificant impact on cash market volatility. Harris (1989) and Damodaran (1990) report a marginal increase in the variances of S&P 500 stocks after the launching of S&P 500 index futures. Conrad (1989), Skinner (1989), and Damodaran and Lim (1991) find that both total variance and residual variance decline on option listing. Freund, McCann, and Webb (1994) observe that the variances of optioned stocks are only affected initially by option introduction. After investigating the price behavior of Japanese component stocks around expirations of stock index options and futures, Karolyi (1995) reports that the intraday return volatility in the last trading hours on expiration days and the first hours following expirations is only marginally greater than that on non-expiration days.

As part of an ongoing discussion concerned with the relationship between the cash and the derivative markets, the inadequacy of the NSA as an underlying stock index for futures and options contracts has been extensively debated in Japan. Many believe that the NSA is vulnerable to price manipulation because: (i) it is a price-weighted index; and (ii) it contains numerous small-capitalized, high-priced, illiquid stocks. As a result, the price movements of only a few stocks can easily affect the index (Toshino 1992; Adachi and Kurasawa 1993; Arai, Akamatsu, and Yoshioka 1993).

In response to this criticism, the Nihon Keizai Shimbun, Inc. (NIKKEI) began replacing inactive NSA component stocks with active issues in October 1991.[4] To maintain index continuity the maximum number of replacements was limited to six per year. In addition, the creation of a value-weighted stock index was proposed. While there is no definitive conclusion among academicians as to which type of index is superior, Arai, Akamatsu, and Yoshioka (1993) correctly point out that a value-weighted index will not necessarily correct for the effect that a few stocks continue to have on the NSA.[5] They refer to the case of bank stocks which are not very liquid despite their large market capitalization, a result of the widespread practice of cross-shareholding. Indeed, some NSA component stocks are well-known for their thin trading, while some S&P 500 component stocks similarly suffer from this problem. For S&P 500 component stocks, Harris (1989) finds that the frequency of no trading days as a percentage of trading days was 0.03 percent in 1987. During our study period, from September 1988 to December 1991, the same calculation for the NSA component stocks is 0.17 percent. Chung, Kang, and Rhee (1993) report that at least one NSA component stock was not traded on 102 out of 751 trading days examined over a three-year period, 1988-1991.

As of February 1994 the NIKKEI introduced a new value-weighted stock market index, the Nikkei Stock Index 300 (or the Nikkei 300). To create this new index, the NIKKEI identified 145 new stocks while retaining 155 of the original NSA securities. As a result, a total of 70 NSA stocks was excluded from the new index. New index futures contracts written on the Nikkei 300 were launched on February 14, 1994 by the OSE.[6] The introduction of this new index and its futures contracts has prompted an important question: Do three stock groups differ in terms of: (i) price volatility; (ii) sensitivity to futures market volatility; and (iii) the speed of price adjustment to new information? Our primary focus is to address this question.

We proceed in two phases. We first study whether the major determinants of price volatility identified by Harris (1989) for U.S. stocks are also applicable to Japanese stocks. Although it has been suggested frequently that price volatility is greater for small-capitalized, low-priced, illiquid stocks than large-capitalized, high-priced, liquid stocks, very little is known about the role of determinants such as: (i) market capitalization; (ii) share price level; (iii) liquidity; and (iv) frequency of no trading for Japanese stocks. The first phase analysis bridges this gap

In the second phase we compare price volatilities and the degree of sensitivity to futures market activities among the three stock groups containing 145, 155, and 70 securities, respectively. This is accomplished after controlling for the impact of the various determinants of price volatility.[7] We also compare the speed of price adjustment among the three stock groups. This comparison will highlight the impact trading equity derivatives on the underlying component stocks. By comparing two categories of component stocks, 225 NSA stocks and 145 non-NSA stocks, our analysis will demonstrate whether index futures trading enhances the speed of price adjustment to new information.

The remainder of this paper is organized as follows. In the next section an overview of the two indexes is presented. The second section examines the cash market volatility behavior in reaction to futures market activities. Various subsets of the NIKKEI index component stocks are contrasted to demonstrate the impacts of firm size, share price level, liquidity, and frequency of no trading on cash market volatility given high and low volatility days in the futures market. The third section compares the price volatilities, the degrees of sensitivity to future market activities, and the speed of price adjustment to new information among the three subsets of component stocks. The last section summarizes major findings.

AN OVERVIEW OF TWO MAJOR STOCK MARKET INDEXES IN JAPAN

Nikkei Stock Average and Nikkei Stock Index 300

The NSA is an arithmetic average computed by adding the prices of 225 component stocks and dividing by a denominator (divisor) which is adjusted for stock splits, right offerings, and component stock deletion or addition.[8] A total of 32 industries is represented by the 225 component stocks.[9] At the end of 1991 the chemical industry had the largest representation with 26 stocks, followed by transportation equipment containing 17, foods and electric equipment each with 16, while certain industries such as finance (excluding banks, securities, and insurance), air transportation, and communications consist of only one stock a piece. The price-weight per industry ranges from communications' 0.33 to 12.49 percent for chemicals. In addition to chemicals, at least six industries have price-weights exceeding 5 percent. They include: electric machinery (8.72%), foods (7.31%), banking (7.12%), construction (6.20%), transportation equipment (6.19%), and glass and ceramics (5.37%).

The component stocks of the Nikkei 300 represented approximately two-thirds of the TSE's total market capitalization and trading value at the end of 1991. Again, a total of 32 industries is represented by the 300 component stocks. The chemical industry has the largest representation with 37 stocks, followed by construction (27), machinery (25), foods (19), while agriculture and forestry, fishery, air transportation, and communications are represented by one stock each, and mining and shipping with two. Based on 1991 year-end prices, the largest weight is assigned to the banking industry with 22.75 percent, followed by electric equipment (8.75%), chemicals (6.95%), transportation equipment (6.35%), and electric power and gas (5.93%). The agriculture and forestry industry has the smallest weight with 0.08 percent, followed by fishery (0.09%), mining (0.21%), and warehouse and wharfing (0.25%).

Descriptive Statistics of the NSA and Nikkei 300 Index

We have obtained daily price and trading data for the NSA 225 and Nikkei 300 component stocks from the PACAP Databases-Japan for the study period, September 3, 1988 through the last trading day of 1991. September 3, 1988 is chosen since it is the first day that the OSE traded NSA futures contracts. The reason our study period begins with the trading of index futures contracts is to study the reaction of cash market volatility to activities in the futures market. The choice of 1991 as the end of our study period coincides with the data available from the 1992 version of the PACAP tapes.

Table 1 presents summary statistics of the NSA and Nikkei 300 Index component stocks, and three groups consisting of 145, 155, and 70 stocks each.[10] Cross-sectional averages of market capitalization, price level, liquidity, frequency of no trading, and systematic risk are reported along with cross-sectional standard deviations shown in parentheses. Market capitalization is computed by multiplying closing price by the number of shares outstanding. Market liquidity is measured by the ratio of daily trading value to intraday open-to-close return variance. The frequency of no trading is computed as the percentage of trading days in the study period for which no trading took place. Systematic risk is measured by the Scholes and Williams (1977) beta estimated using daily close-to-close returns for each component stock and the PACAP equally weighted market portfolio's returns adjusted for dividend reinvestment. For each component stock, the average daily observations of each variable are computed for the 829 trading days in the study period with the exception of beta estimates. The reported figures are cross-sectional averages of the relevant variables estimated for all component stocks.

Average market capitalization of the NSA component stocks is ¥1.09 trillion compared with ¥1.04 trillion for the Nikkei 300 component stocks. Although the difference in size between the component stocks of each index is insignificant, the

Table 1. Summary Statistics of the Nikkei Index Component Stocks

This table presents summary statistics of the NSA component stocks, the Nikkei 300 component stocks, and three groups consisting of 145, 155, and 70 stocks each. Averages of market capitalization, share price level, liquidity, frequency of no trading, and systematic risk are reported along with cross-sectional standard deviations shown in parentheses. Market capitalization is computed by closing price multiplied by the number of shares outstanding. Average price is based on closing prices observed. Market liquidity is measured by the ratio of trading value to open-to-close return variance. The frequency of no trading is defined by the number of no trading days as the percentage of total trading days. Systematic risk is measured by the Scholes and Williams (1977) beta estimated using daily close-to-=close returns for each component stocks and the PACAP equally weighted market portfolio's returns adjusted for dividend reinvestment For each component stocks, the average of daily observations for each variable is computed for the 829 trading days in the study period with the exception of beta estimates The reported figures are cross-sectional averages of the relevant variable across the component stocks.

		Nikkei 300	*NSA 225*	*145 Stocks*	*155 Stocks*	*70 Stocks*
a.	Market Capitalization (¥ billion)	1,043.00	1,087.00	588.20	1,464.00	255.80
		(1,755.00)	(1,883.00)	(929.90)	(2,162.00)	(278.10)
	Median (¥ Billion)	472.20)	486.20	357.50)	785.60	175.30
b.	Average Price (¥)	6,229.40	6,890 15	2,662.51	9,541 68	1,056.78
		(72,516.58)	(83,513 47)	(2,922.06)	(100,711.20)	(353.71)
	Median (¥)	1,432.50	1,095 60	1,850.85	1,212.76	941.78
c.	Market Liquidity	6.1261	6.2391	5 5128	6 6957	(5.2345
		(1.1232)	(1.1291)	(0.9453)	(0.9661)	(0.7496)
d.	Frequency of No Trading	0 0058	0 0017	0.0105	0.0014	0.0025
		(0 0194)	(0.0014)	(0.0272)	(0.0006)	(0 0022)
e.	Systematic Risk (β)	0.5470	0 554	0.5828	0 5139	0.6531
		(0.1633)	(0.1878)	(0.1615)	(0.1584)	(0.2117)

three groups of 145, 155, and 70 component stocks show relatively large differences. The 145 stocks newly added to the Nikkei 300 have an average market value of ¥588 billion, while the average size of the 155 stocks that were retained from the NSA amounts to ¥1.46 trillion. In contrast, the average size of the 70 stocks which are not included in the Nikkei 300 is ¥256 billion.

The average prices for the NSA and the Nikkei 300 component stocks are ¥6,890 and ¥6,229, respectively. A much greater difference is found in the average prices among the three groups of component stocks. The 155 stock group has an average price of ¥9,542 which is more than nine times greater than that containing 70 stocks (¥1,057). The 145 newly selected stocks for the Nikkei 300 have an average price of ¥2,663. This comparison, based on mean values, is, however, somewhat misleading because the averages estimated for the Nikkei 300, NSA 225, and the 155 group are inflated by a few high-priced stocks with par value exceeding the Japanese standard of ¥50. An extreme example is the Nippon Telegraph and Telephone Corporation (NTT). Its stock traded between ¥734,000 and ¥1.6 million in 1991. Therefore, we reported median values for share price level as well as market capitalization. The median values provide a slightly different picture. For instance, mean differences observed in share price level among the three stock groups are much smaller when the median values are compared. The 145 stock group now has a higher share price than the 155 stock group.

Market liquidity, as defined by the ratio of daily trading value to intraday open-to-close return volatility, measures the market impact of volume shocks caused by large orders. A low ratio indicates that a single large order may adversely affect price, while a high ratio indicates that volume shocks can be accommodated with a small price movement (Naidu and Rozeff 1994). Thus, the market liquidity ratio measures market depth for each of the component stocks. Average measures of market liquidity are 6.24 and 6.13 for the NSA and the Nikkei 300 component stocks, respectively. The new index component stocks show a smaller degree of market depth than the NSA component stocks, even though the difference is not significant. The 70 component stocks have the lowest value with 5.23 while the 145 and 155 stock groups come out to 5.51 and 6.70, respectively.

An interesting result is obtained regarding the frequency of no trading which is defined as the number of no trading days as the percentage of total trading days. When this frequency is estimated for the Nikkei 300 component stocks, its frequency is more than three times greater than that of the NSA 225 stocks (0.58% versus 0.17%). The Nikkei 300's higher frequency is caused by the 145 stock group which has the highest ratio (1.05%). This high ratio estimated for the 145 stocks is in contrast to 0.14 percent by the 155 stock group and 0.25 percent for the 70 stock group. This result may in part be explained by the fact that the 145 stocks were not NSA component stocks during the study period. In the U.S. market, Harris (1989) similarly finds that non-S&P 500 stocks tend to have a higher frequency of no trading.

The average beta for the Nikkei 300 is 0.5470 which is slightly lower than the 0.5574 estimated for the NSA component stocks. Of the three stock groups, the 155 stock group has the lowest beta, 0.5139, which is substantially less than the 0.6531 estimated for the group of 70 stocks. The 145 newly selected stocks for the Nikkei 300 Index have an average beta of 0.5828.

Price Volatilities

Two cash market volatility measures are introduced. Intraday volatility is calculated using Parkinson's (1980) extreme value method, while interday volatility is measured by close-to-close return variance. Parkinson's variance (V_p) is defined as $V_p = \sum_{t=1}^{n} V_{p,t}/n$, where $V_{p,t} = [\ln(P_{H,t}/P_{L,t})]^2/(4\mathrm{x}\ln 2)$; and P_H and P_L are daily high and low prices, respectively, for each component stock.

The close-to-close return variance (V_c) for each component stock is defined as $V_c = \sum_{t=1}^{n} V_{c,t}/\mathrm{n}$, where $V_{c,t} = (\ln P_{c,t} - \ln P_{c,t-1})^2$; P_c is the closing price adjusted for stock dividend and rights offerings of each component stock, the subscript t denotes trading day, and n is the number of observations.[11] In the Japanese market, one trading unit is 1,000 shares for the issues with the standard par value of ¥50. For those issues with par values greater than ¥50, the trading unit is different. For example, the trading unit of NTT stocks with par value of ¥50,000 is one share, while the unit is 100 shares for those stocks with par value of ¥500. Of the 370 Nikkei component stocks in our sample, seven issues were identified as having par values greater than ¥50.[12] In computing variances, stock prices of the seven firms are adjusted downward for the uniform par value of ¥50.[13,14]

Table 2 presents Parkinson's variance and the close-to-close return variance of the NSA and Nikkei 300 component stocks as well as the three groups consisting of 145, 155, and 70 stocks each. The reported figures are volatility measures averaged across the component stocks for each of the groups. For comparison, the two volatility measures are also reported for NSA futures contracts. Since the nearby contract is the most actively traded up to the beginning of the expiration month, the futures data of a nearby contract are used to compute the volatility measures. For the expiration month, however, data from the subsequent contract is used. Daily price and trading data for the NSA futures contracts are supplied by the OSE. Intraday volatility estimated for the NSA futures contracts is consistently smaller than that of the component stocks comprising the cash index or the three groups. For example, Parkinson's variance for the NSA futures contract is 0.7385, while the comparable variance for the NSA component stocks is 4.0329. This is not surprising since the futures data are being compared to index component stocks rather than the well-diversified cash index. For the NSA component stocks, the average Parkinson's variance is about 1.2 times greater than that of the Nikkei 300. The intraday volatility of the 70 stock group is about 1.5 times greater than the group with 145 securities and 1.4 times greater than that containing 155.

Table 2. Intraday and Interday Volatility

Table 2 presents Parkinson's variance and close-to-close return variance of the NSA futures contracts, the NSA and the Nikkei 300 component stocks, and three groups consisting of 145, 155, and 70 stocks each. Parkinson's variance is calculated by $V_{p,t} = [\ln(P_{H,t}/P_{L,t})]^2/(4\times\ln 2)$, where P_H and P_L are daily high and low prices, and subscript t denotes trading day. The close-to-close return variance is calculated by $V_{c,t} = (\ln P_{c,t} - \ln P_{c,t-1})^2$, where P_c is the closing price. Figures in parentheses are cross-sectional standard deviations

	Parkinson's Variance ($\times 10^4$)	*Close-to-Close Return Variance* ($\times 10^4$)
NSA Futures	0.7385	1.6283
	(1.2297)	(3.2644)
NSA 225 Stocks	4.0329	6.1867
	(2.8813)	(2.3121)
Nikkei 300 Stocks	3.4487	5 4258
	(2.3949)	(1.6864)
145 Stocks	3.2649	5.5756
	(2.1896)	(1.6059)
155 Stocks	3 6207	5.2868
	(2.5605)	(1.7519)
70 Stocks	4.9395	8.1664
	(3 3094)	(2.1656)

Apparently, volatility must have been a major consideration when the NIKKEI excluded the 70 component stocks from the Nikkei 300.

Several interesting observations can be made on interday volatility measures based on close-to-close returns. First, the NSA futures volatility is again much smaller than that of the cash market. For example, the close-to-close return variance of the NSA component stocks is 6.1867, which is 3.8 times greater than that of the NSA futures contract. A second interesting observation is found in the three groups. The 70 component stocks have the largest close-to-close return variance with 8.1664, while the 155 stocks have the smallest, 5.2868. The 145 stock group variance of 5.5756 falls between the previous two values. Third, the NSA component stocks show greater interday volatility when compared with the Nikkei 300 stocks. This is consistent with the results obtained with Parkinson's intraday variance.

THE CASH MARKET VOLATILITY BEHAVIOR IN REACTION TO FUTURES MARKET ACTIVITIES

The primary purpose of this section is to examine whether the major determinants of price volatility identified by Harris (1989) for U.S. stocks are also applicable to Japanese stocks. While so doing, the impact of such determinants on price volatility is highlighted. For this purpose, Nikkei index component stocks are classified into two subgroups based on four variables: (i) market capitalization; (ii) share price level; (iii) market liquidity; and (iv) frequency of no trading. The median of each variable is used as the cut-off point between the two subgroups. In addition, the 829 trading days in the study period are equally divided based on the level of futures market volatility: high or low volatility days. This two-by-two classification allows us to examine the volatility behavior of four subsets of index component stocks. For example, the Nikkei index component stocks are first classified into small- and large-capitalized stocks based on their market capitalization. Given the low and high volatility days in the futures market, we compare four sample means of price volatilities estimated for the four subgroups: (i) small-capitalized stocks on low futures volatility days; (ii) small-capitalized stocks on high volatility days; (iii) large-capitalized stocks on low volatility days; and (iv) large-capitalized stocks on high volatility days. By doing so, this empirical design will answer the question: are small-capitalized, high-priced, or illiquid stocks affected more adversely by futures market activities? This question reflects the public's perception in Japan as well as the TSE's contention about the impact of the futures market on Japanese stocks.

Table 3 summarizes price volatility of the NSA component stocks. Panel A reports the results for two subgroups consisting of 155 and 70 stocks each. The 155 stocks were retained for the Nikkei 300, whereas the set of 70 was not. The 70 component stocks have consistently greater volatility than the 155 stock group. On low volatility days in the futures market, Parkinson's variance is 43 percent greater for the 70 stocks than the 155 stocks (3.5862 versus 2.5106), while on high volatility days it is 35 percent greater (6.2456 versus 4.6434). Based on close-to-close return variance, the 70 component stocks are 67 percent riskier than the 155 stock group on low futures volatility days (5.2133 versus 3.1216), while they are 53 percent riskier on high futures volatility days (10.6801 versus 6.9793). Both sets of component stocks show strong sensitivity to the level of futures market volatility. The ratios of high volatility day variance to low volatility day variance are 2.24 and 2.05 for the 155 and 70 stocks, implying that the 155 component stocks are more sensitive to futures market activities. The variance ratios based on Parkinson's variance show a similar pattern. The variance ratio estimated for the stock group of 155 is 1.85, while the same ratio is 1.74 for the stock group of 70. This unexpected surprise will be examined in the next section of this study using a model that controls for cross-sectional variations in firm attributes.

The results reported in Panels B through E are for two subgroups of 225 component stocks classified by market capitalization, inverse share price level, market liquidity, and frequency of no trading. The following findings are notable: first, market capitalization, market liquidity, frequency of no trading and, to a lesser degree, inverse share price level are all important determinants of cash market volatility; second, cash market volatility is affected by the level of futures market volatility regardless of firm size, inverse share price level, market liquidity, and

Table 3. The Volatility Behavior of the NSA Component Stocks

Table 3 summarizes the NSA cash market volatilities The NSA stocks are classified into two subgroups based on five criteria: (i) the 70 vs. 155 stock groups, (ii) market capitalization; (iii) inverse share price level; (iv) market liquidity, and (v) frequency of no trading. In addition, 829 trading days in the study period are divided equally based on the level of futures market volatility: high or low volatility days. Market capitalization is computed by closing price multiplied by the number of shares outstanding Inverse share price level is based on closing prices observed. Market liquidity is measured by the ratio of trading value to open-to-close return variance The frequency of no trading is defined by the number of no trading days as the percentage of total trading days. The two-by-two classification is implemented to examine the volatility behavior of each of four subsets of index component stocks in reaction to futures market volatilities Given the low and high volatility days in the futures market, we compare four sample means of price volatility for the four subsets. Figures in parentheses are cross-sectional standard deviations. Statistical significance is indicated by: **at the 0.01 level, *at the 0.05 level, and + at the 0.10 level

		Parkinson's Variance (x 10^4)			Parkinson's Variance (x 10^4)		
		Futures Market Volatility Level			Futures Market Volatility Level		
		Low	High	Difference	Low	High	Difference
	155 Stocks	2.5106	4 6434	−2.1328**	3.1216	6.9793	−3 8577**
		(0.8044)	(1.3655)		(1.2137)	(2.3512)	
A. Component Stocks	70 Stocks	3.5862	6 2456	−2 6594**	5.2133	10 6801	−5.4668**
		(0.9629)	(1.4971)		(1 7274)	(2.9086)	
	Difference	−1.0756**	−1.6022**		−2.0917**	−3.7008**	
	Small	3.4009	6.0746	−2.6737	4.7962	10.0497	−5 2525**
		(0.9564)	(1.5506)		(1.7109)	(2.9416)	
B Market Capitalization	Large	2.2925	4.2135	−1.9210**	2.7533	6.2219	−3 4686**
		(0.6598)	(0.9618)		(0 8646)	(1.6648)	
	Difference	1.1084**	1.8611		2.0439**	3.8278**	
	Low	2.8287	5.0328	−2 2041**	3.5410	7.3292	−3.7882**
		(1 0975)	(1.7618)		(1.6857)	(3.0278)	
C. Inverse Share Price Level	High	2.8647	5.2553	−2.3906**	4.0096	8.9423	−4.9327**
		(0.8745)	(1.3956)		(1.6823)	(2.8872)	
	Difference	−0.0360	−0 2225+		−0.4686**	−1 6131**	

(continued)

Table 3. (Continued)

		Parkinson's Variance (x 10^4)			Parkinson's Variance (x 10^4)		
		Futures Market Volatility Level			Futures Market Volatility Level		
		Low	*High*	*Difference*	*Low*	*High*	*Difference*
D. Market Liquidity	Low	3.2770	5.8622	−2.5852**	4.5817	9 5901	−5.0084**
		(0.9377)	(1.3956)		(1.6414)	(2.8495)	
	High	2 4164	4.4259	−2.0095**	2.9688	6.6814	−3.7126**
		(0.8468)	(1.4449)		(1.3325)	(2.5354)	
	Difference	0.8606**	1.4363**		1.6129**	2 9087**	
E. Frequency of No Trading	Low	2.6899	4.9776	−2 2877**	3.4763	7.7925	−4.2532**
		(0.9311)	(1.6122)		(1.5418)	(2.9736)	
	High	3.5069	5.8448	−2.3379**	5 0336	9.8459	−3.9291**
		(0 9689)	(1.2865)		(1 7573)	(2.8511)	
	Difference	−0.8170**	−0.8672**		−1.5573**	−2.1164**	

frequency of no trading; third, the smaller the market capitalization, the greater the price volatility; fourth, the lower the market liquidity, the greater the price volatility; and fifth, stocks with high frequency of no trading tend to have greater volatility. This result is anticipated since infrequently traded stocks tend to have larger bid/ask spreads. Finally, low-priced stocks have greater volatility than high-priced stocks as anticipated.

Table 4 presents Parkinson's variance and close-to-close return variance of the Nikkei 300 component stocks. The results summarized in Panel A contrast the 145 and the 155 stock groups. The 145 group contains new stocks selected for this index while the remaining 155 stocks were retained from the NSA. Parkinson's variance is smaller for the 145 component stocks than the 155 component stocks on highly volatile days in the futures market, while no significant difference is noted between the two groups on low volatility days. Contradictory results, however, are obtained for interday volatility. Based on the close-to-close return variance, the stock group of 145 is more volatile than the 155 stocks on high as well as low volatility days. The fact that Parkinson's variance is smaller on high volatility days in the futures market for the 145 stock group indicates that large intraday price swings are of greater concern to Japanese regulators than interday variability. Parkinson's variance based on intraday high and low prices is very similar to the so-called "jump" volatility which measures extremely large price swings within a fixed time interval (Becketti and Roberts 1990).

The level of futures market volatility has a significant impact on cash market volatility. Cash market volatilities are consistently greater on high volatility days in the futures market than on low volatility days. Parkinson's variance for the 145 component stocks is 1.55 times greater on high volatility days than on low volatility days in the futures market, while the close-to-close return variance is 1.82 times greater. In contrast, the 155 component stocks have 1.85 times as much Parkinson's variance on high volatility days than on low volatility days, while the close-to-close return volatility is more than twice as great. Apparently, the 155 component stocks are more sensitive to futures market volatility than the 145 group. This is of no surprise since the group of 155 stocks were underlying securities in the NSA futures contracts during the study period, while the group of 145 was not.

The overall results summarized in Panels B through E are similar to those found for the NSA component stocks with one exception. Inverse share price level is now an important determinant of the cash market volatility. The evidence presented confirms that the major determinants of price volatility identified by Harris (1989) for U.S. stocks also apply to Japanese stocks. The most notable finding in contrasting the summary statistics found in Tables 3 and 4 is that both intraday and interday volatility measures estimated for the Nikkei 300 component stocks are in general smaller than those estimated for the NSA component stocks.

Table 4. The Volatility Behavior of the Nikkei Stock Index 300 Component Stocks

Table 4 summarizes the Nikkei 300 cash market volatilities The Nikkei 300 stocks are classified into two subgroups based on five criteria: (i) 145 vs. 155 component stocks; (ii) market capitalization; (iii) inverse share price level; (iv) market liquidity; and (v) frequency of no trading. In addition, 829 trading days in the study period are divided equally based on the level of futures market volatility: high or low volatility days. Market capitalization is computed by closing price multiplied by the number of shares outstanding. Inverse share price level is based on closing prices observed. Market liquidity is measured by the ratio of trading value to open-to-close return variance. The frequency of no trading is defined by the number of no trading days as the percentage of total trading days. The two-by-two classification is implemented to examine the volatility behavior of each of four subsets of index component stocks in reaction to futures market volatilities. Given the low and high volatility days in the future market, we compare four sample means of price volatility for the four subgroups Figures in parentheses are cross-sectional standard deviations. Statistical significance is indicated by: **at the 0.01 level, *at the 0.05 level, and + at the 0.10 level.

		Parkinson's Variance (x 10^4)			*Close-to-Close Return Variance (x 10^4)*		
		Futures Market Volatility Level			*Futures Market Volatility Level*		
		Low	*High*	*Difference*	*Low*	*High*	*Difference*
A Component Stocks	145 Stocks	2.5479	3.9561	−1 4082**	3.8567	7.0152	−3 1585**
		(0.7709)	(1.2113)		(1.2992)	(2 1534)	
	155 Stocks	2.5106	4 6434	−2.1328**	3.1216	6.9793	−3.8577**
		(0 8044)	(1.3655)		(1.2137)	(2.3511)	
	Difference	−0.0373	−0.6873**		0.7351**	0 0359	
B. Market Capitalization	Small	2.8131	4.6490	−1 8369**	4.0755	7.8660	−3.7905**
		(0.8147)	(1 5712)		(1.2649)	(2.4015)	
	Large	2.2468	3.9782	−1 7314**	2.8796	6.1329	−3.2533*
		(0.6483)	(0.9457)		(1.0520)	(1 7115)	
	Difference	0.5653**	0.6708**		1 1959**	1.7331**	
C. Inverse Share Price Level	Low	2.2890	3.9375	−1 6485**	3.3946	6.3656	−2.9710**
		(0 7713)	(1.2821)		(1.4165)	(2 0934)	
	High	2.7665	4.6849	−1 9184**	3.5559	7 6233	−4.0674**
		(0 7312)	(1.2881)		(1.1862)	(2 2401)	
	Difference	−0 4775**	−0.7474**		−0 1613	−1 2577**	

	Low	2.6708	4.4252	−1.7544**	4 0216	7 5652	−3.5436**
		(0.7724)	(1.3749)		(1.2587)	(2.0424)	
D. Market Liquidity	High	2 3872	4.2004	−1.8132**	2.9331	6.4318	−3.4987**
		(0.7791)	(1 2920)		(1.1158)	(2.3188)	
	Difference	0.2836**	0.2248*		1.0885**	1.1334**	
	Low	2.5011	4 4315	−1.9304**	3.1670	6 8722	−3.7052**
		(0.7874)	(1 3190)		(1.1692)	(2.2956)	
E. Frequency of No Trading	High	2.6016	3.9949	−1.3933**	4.2982	7.3282	−3.0300**
		(0.7876)	(1.3390)		(1.3032	(2.1186)	
	Difference	−0 1005	0.4366**		−1.1312**	−0.4560+	

PRICE VOLATILITY OF THE NIKKEI INDEX COMPONENT STOCKS

Price Volatilities of the 145, 155, and 70 Stock Groups

The determinants of market volatility in Japan emerge from the previous section's results. Market capitalization, inverse share price level, market liquidity, and frequency of no trading are all important. This finding is useful for cross-sectional regressions which control for differences in firm attributes before price volatilities are compared among the three groups of component stocks. The analysis in this section parallels the work of Harris (1989). A mean difference test is conducted to examine differences in the volatilities among the three component stock subgroups using the following model:

$$\text{STD}_i = a_0 + a_1\text{D70}_i + a_2\text{D155}_i + a_3(\text{AbsBeta}_i \times \text{MkSTD}) + a_4\text{LogMkVal}_i + a_5\text{MkLiq}_i + a_6\text{NoTradeFreq}_i + u_i, \quad (1)$$

where STD_i and MkSTD are the return standard deviations measured over one-day, five-day, 10-day, and 20-day intervals during the study period for stock i and the market portfolio, respectively.[15] The PACAP daily close-to-close returns for each component stock and the equally weighted market portfolio's returns are used. Both return series are adjusted for dividend reinvestment; $D70_i$ is a dummy variable which takes the value 1 if stock i belongs to the group of 70 stocks and zero otherwise; $D155_i$ is a dummy variable which takes the value 1 if stock i belongs to the group of 155 stocks and zero otherwise; AbsBeta_i is the absolute value of beta times the market standard deviation ($|\beta|\sigma_m$); LogMkVal_i denotes the log of market value; MkLiq_i is market liquidity; NoTradeFreq_i denotes the percentage of no trading days; and u_i is a random disturbance term. The same definitions apply to all variables in equation (1) that were introduced in the previous section. For the one-day return series, the Scholes and Williams (1977) method is used to estimate βs, while for the multiday return series the market model is used without lead and lag variables. The estimated coefficients of a_1 and a_2 indicate the mean difference in price volatilities between the groups of 70 and 145 stocks and between the groups of 155 and 145 stocks, respectively.

The above regression model differs from the Harris (1989) model in one important aspect. Inverse price level in the Harris model was replaced by the market liquidity variable because of a typical symptom of problematic multicollinearity observed.[16] The market liquidity variable is expected to serve as a proxy for market depth or liquidity which are supposed to be captured by inverse price level.

Table 5 presents a matrix of Pearson rank correlation coefficients among the variables introduced. A high correlation of 0.78 is noted between LogMkVal_i and MkLiq_i. To avoid this problem, the residuals, denoted $\varepsilon(\text{LogMkVal}_i)$, are measured from a simple regression, $\text{LogMkVal}_i = c_0 + c_1(\text{MkLiq}_i) + \gamma_i$ and substituted

Table 5. Correlation Matrix

Pearson rank correlation coefficients among dependent and independent variables are presented. STD_i and MkSTD are return standard deviations stock i and the market portfolio; AbsBeta$_i$ is the absolute beta times the market standard deviation, $(|\beta_i|\sigma_m)$, LogMkVal$_i$ denotes log market value; MkLiq$_i$ is market liquidity; NoTradeFreq$_i$ denotes no trading days as the percentage of total trading days; and ε(LogMkVal$_i$) is the residuals measured from a regression, $\text{LogMkVal}_i = c_0 + c_1(\text{MkLiq}_i) + \gamma_i$ This regression is introduced to control for the multicollinearity problem between LogMkVal$_i$ and MkLiq$_i$. β is the Scholes and Williams beta estimated using the PACAP equally weighted market portfolio's returns adjusted for dividend reinvestment. Correlation matrixes for STD_i estimated for multiday returns and the same set of independent variables are similar to the reported results below. Hence, they are not reported in this table. Statistical significance is indicated by. **at the 0.01 level, *at the 0.05 level, and + at the 0.10 level.

	AbsBeta$_i$ x MkSTD	*LogMkVal$_i$*	*MkLiq$_i$*	*NoTradeFreq$_i$*	*ε(LogMkVal$_i$)*
STD$_i$	0.6677**	−0.6164**	−0.4776**	0.0458	−0.3896**
AbsBeta$_i$ x MkSTD		−0 4827**	−0.2336**	−0.1073*	−0 4813**
LogMkVal$_i$			0.7817**	−0.0765	0.6236**
MkLiq$_i$				−0.3498**	0.0000**
NoTradeFreq$_i$					0.3158**

for LogMkVal$_i$ in equation (1). This procedure orthogonalizes the variable Log-MkVal$_i$ and the variable MkLiq$_i$.[17]

Regressions results are summarized in Table 6. The estimated coefficients of a_1 and a_2 are 0.37 percent for the 70 component stocks and 0.18 percent for the 155 stock group in the regression using one-day return standard deviations as the dependent variable. This implies that the 70 and 155 component stocks have greater volatilities than the 145 stock group. Nevertheless, the magnitude of the estimated differences is fairly small when compared to daily return standard deviations of 2.84 percent and 2.28 percent for the 70 and 155 stock groups, respectively. While the estimated coefficients are statistically significant, their economic importance may be questioned given that the differences are so small.

The 70 and 155 stock groups exhibit an interesting contrast in terms of the stabilizing effect of NSA futures trading. For the 155 stock group, the estimates of a_2 are not different from zero for multiday return volatilities but significantly positive for the one-day return interval. This implies that index futures trading is stabilizing for the group of 155 stocks (Harris 1989). In contrast, the estimates of a_1 are consistently positive and significant not only for the short-interval data but also the long-interval data. This may indicate that index futures trading is destabilizing for the 70 NSA component stocks, which justifies their exclusion from the Nikkei 300.

The estimated coefficient for (AbsBeta$_i$ x MkSTD) is significantly positive and large, without exception, while the estimated market capitalization coefficient is not a significant factor in determining the volatility differences between the three

Table 6. Mean Difference among Price Volatilities of the 145, 155, and 70 Component Stocks

A mean difference test is conducted to examine differences in the volatilities among the three component stock groups using the following model:

$$STD_i = a_0 + a_1 D70_i + a_2 D155_i + a_3(\text{AbsBeta}_i \times \text{MkSTD}) + a_4\varepsilon(\text{LogMkVal}_i) + a_5\text{MkLiq}_i + a_6\text{NoTradeFreq}_i + u_{i}, \quad (1)$$

where STD_i and MkSTD are return standard deviations stock i and the market portfolio, $D70_i$ a dummy variable which takes 1 if stock i belongs to the group of 70 stocks and zero otherwise; $D155_i$ is a dummy variable which takes 1 if stock i belongs to the group of 155 stocks and zero otherwise; and AbsBeta_i is the absolute beta times the market standard deviation, $(|\beta_i|\sigma_m)$, $\varepsilon(\text{LogMkVal}_i)$ is the residuals measured from a regression, $\text{LogMkVal}_i = c_0 + c_1(\text{MkLiq}_i) + \gamma_i$, where LogMkVal_i denotes log market value and MkLiq_i is market liquidity; and NoTradeFreq_i denotes no trading days as the percentage of total trading days; and u_i is random disturbance terms. β is estimated using the PACAP equally weighted market portfolio's returns adjusted for dividend reinvestment. The regression model is estimated for return standard deviations measured over one-day, five-day, 10-day, 20-day intervals. Figures in parentheses are t-values. Statistical significance is indicated by: **at the 0 01 level, *at the 0.05 level, and + at the 0.10 level.

	One-Day Return STD	*Five-Day Return STD*	*10-Day Return STD*	*20-Day Return STD*
Intercept	0 0228	0.0305	0.0383	0 0399
	(21.65)**	(9 46)**	(7.83)**	(4.83)**
D70	0.0037	0.0049	0.0063	0.0067
	(10.00)**	(4.33)**	(3 66)**	(2.31)*
D155	0.0018	0 0007	0.0003	−0.0003
	(5.51)**	(0.67)	(0.18)	(−0.13)
AbsBeta x MkSTD	1.0297	3 1806	5.1666	8.8672
	(14.95)**	(15.09)**	(16.13)**	(16.43)**
ε(LogMkVal)	−0.0004	−0.0007	0 0002	0.0002
	(−1.51)	(−0 98)	(0.21)	(0 10)
MkLiq	−0 0012	−0.0007	−0.0008	0.0005
	(−8.47)**	(−1.55)	(−1.13)	(0.45)
NoTradeFreq	0.0163	0.1248	0.1745	0.1538
	(2.02)**	(5.07)**	(4.66)**	(2.44)*
R^2	0.6696	0.5519	0.5542	0.5292
F-value	121.61**	73.90**	74.60**	67.43**

groups of stocks. Market liquidity has a significant, negative effect on return volatility as shown in the first column which reports one-day return volatility results. This is consistent with the prediction that volatility decreases with the degree of liquidity. The estimated coefficients become insignificant, however, in the regressions for multiday return standard deviations. The coefficient for no-trading frequency is positive and significant in all regressions, which contradict the results reported by Harris (1989) for U.S. stocks. Harris suggests that the impact of no-trading frequency on price volatility is insignificant since most U.S. stocks traded everyday. Apparently, this non-trading frequency effect is more pronounced in the Japanese market.

Sensitivity to Futures Market Activities

The 70 component stocks were excluded from the Nikkei 300 since there was a belief that these securities tended to overreact to volatility in the futures market. This can be inferred from one of the Nikkei 300 futures brochures, which states that "...the Nikkei 300 has been properly tailored to reduce the influence of futures on the cash market."[18] In this section we compare the degree of sensitivity to futures market activity among the three groups of component stocks. A cross-sectional regression model, similar to that used for comparing volatilities, is introduced to conduct a mean difference test for the degree of sensitivity to futures market volatility:

$$\text{VarRatio}_i = a_0 + a_1 D70_i + a_2 D155_i + a_3(\text{AbsBeta}_i \text{ x MkSTD}) + a_4\text{LogMkVal}_i + a_5\text{MkLiq}_i + a_6\text{NoTradeFreq}_i + u_i, \quad (2)$$

where VarRatio_i denotes the ratio of σ_H^2 to σ_L^2. σ_H^2 and σ_L^2 are the average variances of stock i on high and low volatility days respectively in the futures market while all other variable definitions are the same as those discussed previously. A high ratio of σ_H^2 to σ_L^2 indicates that a component stock is sensitive to futures market volatility, whereas a low ratio indicates the opposite.[19] The variance ratio is measured using both Parkinson's variance and the close-to-close return variance.

The intercept measures the sensitivity of the 145 component stocks, while the average differences in the sensitivity measures among the three groups of component stocks are indicated by the coefficients of *D*70 and *D*155 after the cross-sectional differences in firm characteristics have been taken into account. The estimated coefficient for (AbsBeta_i x MkSTD) is expected to be positive since the systematic risk captures market-wide price co-movement and, as a result, the high-beta stocks tend to show a higher degree of sensitivity to futures market volatility (Chan 1992). Since both LogMkVal_i and MkLiq_i capture market depth of individual component stock, they are expected to show a positive impact on the degree of sensitivity, reflecting the amount of information flow (Ross 1989). In contrast, the NoTradeFreq variable is expected to have an opposite effect on the sensitivity especially for thin issues.

Overall results are summarized in Table 7. The first column reports estimates of the coefficients when the variance ratios are computed with Parkinson's intraday variance, while the second column presents the results when the close-to-close return variance ratios are used. The estimated coefficients for a_1 and a_2 are significant in both regressions, implying that significant differences exist between the three groups of component stocks in their sensitivity to futures market volatility. This is an important result that justifies the selection of 145 new stocks for the

Table 7. Sensitivity to the Futures Market Volatility of the Index Component Stocks

A cross-sectional regression model similar to that used for comparing volatilities is introduced to conduct a mean difference test in the degree of sensitivity to the futures market volatilities among the three stock groups:

$$\text{VarRatio}_i = a_0 + a_1 D70_i + a_2 D155_i + a_3(\text{AbsBeta}_i \times \text{MkSTD}) + a_4 \varepsilon(\text{LogMkVal}_i) + a_5 \text{MkLiq}_i + a_6 \text{NoTradeFreq}_i + u_i, \quad (2)$$

where VarRatio$_i$ denotes the ratio of σ_H^2 to σ_L^2. σ_H^2 and σ_L^2 denote the average variances of stock i on high and low volatility days in the futures market; $D70_i$ a dummy variable which takes 1 if stock i belongs to the group of 70 stocks and zero otherwise; $D155_i$ is a dummy variable which takes 1 if stock i belongs to the group of 155 stocks and zero otherwise; and AbsBeta$_i$ is the absolute beta times the market standard deviation, $(|\beta_i|\sigma_m)$; ε(LogMkVal$_i$) is the residuals measured from a regression, LogMkVal$_i$ = $c_0 + c_1$(MkLiq$_i$) + γ_i, where LogMkVal$_i$ denotes log market value and MkLiq$_i$ is market liquidity; and NoTradeFreq$_i$ denotes no trading days as the percentage of total trading days; and u_i is random disturbance terms The variance ratio is measured using both Parkinson's variance and close-to-close return variance. Figures in parentheses are t-values. Statistical significance is indicated by: **at the 0.01 level, *at the 0.05 level, and + at the 0.10 level.

	VarRatio Based on Parkinson's Variance	*VarRatio Based on Close-to-Close Return Variance*
Intercept	0.8256	0.8358
	(11.23)**	(4.26)**
D70	0.0857	0.2637
	(3.33)**	(3.85)**
D155	0 0714	0.3467
	(3.20)**	(5 83)**
AbsBeta x MkSTD	23.92	77.1355
	(4.97)**	(6.02)**
ε(LogMkVal)	0.3738	0.1955
	(2.24)*	(4.40)**
MkLiq	0.0864	0.0985
	(8.57)**	(3 66)**
NoTradeFreq	−0.7079	−4.9931
	(−1.26)	(−3.33)**
R^2	0.3258	0 2770
F-value	28 99**	22.99**

Nikkei 300 since the 155 and 70 stock groups have higher degree of sensitivity than the 145 stock group even after cross-sectional firm differences have been controlled. A further test of mean differences indicates that the 70 and 155 component stocks show no significant difference in their sensitivity to futures market volatility.

The remaining coefficients suggest that: (i) systematic risk, market liquidity, and market capitalization all positively affect the degree of sensitivity to futures market volatility; (ii) frequency of no trading, however, shows a negative impact on the sensitivity.

Speed of Price Adjustment to New Information

Damodaran (1993) derives a formula that can be used to measure the speed of price adjustment to new information. His formula represents an extension of a price adjustment model developed by Roll (1984) and Amihud and Mendelson (1987). Although the Damodaran formula is simple to use, it is subject to empirical irregularities such as positive serial covariance estimates Harris (1990) and extremely large negative or positive price adjustment coefficients. Theoretically, the price adjustment coefficient, g_j, of j-interval returns should be between 0 and 2. For returns over short intervals, a large number of estimated coefficients may fall outside this range. Roll (1995) suggests an alternative method of estimating the coefficient of the speed of price adjustment by applying the model in Amihud and Mendelson (1987):

$$R_t = \ln P_t - \ln P_{t-1} = g(\ln U_t - \ln P_{t-1}) + u_t, \tag{3}$$

where U_t is an unobservable equilibrium price of a stock on date t, g is a speed of price adjustment coefficient, and u_t is white noise. By substracting the lagged value of equation (3), Roll derives

$$\begin{aligned} R_t &= g(\ln U_t - \ln U_{t-1}) + (1 - g)R_{t-1} + u_t - u_{t-1}. \\ &= a + bR_{t-1} + \xi_t, \end{aligned} \tag{4}$$

where a is the intercept, $g = 1\text{-}b$ is the coefficient of the spreed of daily price adjustment, and $\xi_t = u_t\text{-}u_{t-1}$.

Roll (1995) notes that (4) is not a well-specified regression model because it contains an unobservable explanatory variable U and the error terms are both serially dependent and correlated to the explanatory variable R_{t-1}. However, by using the even number of observations of R_t and, correspondingly, every other observation for the explanatiory variable R_{t-1}, an OLS estimator of the slope should have standard distributional properties.

Table 8 summarizes the results from this regression. We use both open-to-open and close-to-close returns for each component stock to estimate the speed of price adjustment coefficient. Cross-sectional averages and standard deviations are reported. Interestingly, on average, each of three stock groups exhibit the coefficient greater than one, which implies overreaction of traders to new information. As expected, the coefficients estimated using close-to-close returns are greater for the 70 and 155 stock groups than the 145 stock group. This can be explained by the fact that both groups of 70 and 155 stocks are underlying securities of the NSA futures contracts. When open-to-open returns (which are subject to more negative autocorrelations than close-to-close returns[20]) are used to estimate the coefficients, no significant difference is observed between the 155 stock group and the

Table 8. Speed of Price Adjustment of the Index Component Stocks

The following regression model is used to estimate the speed of price adjustment:

$$R_{j,t} = a + bR_{j,t-1} + \xi_{j,t}, \tag{4}$$

where $b_j \equiv 1 - g_j$ and g_j is the price adjustment coefficient. Observations of $R_{j,t}$ are only for t = 2,4,6,...., and every other observations for independent variable, $R_{j,t-1}$. Both open-to-open and close-to-close returns for each component stock are used to estimate the coefficient. Cross-sectional averages and starda deviations are reported with standard deviations shown in parentheses. Statistical signficance is indicated by: **at the 0 01 level and * at the 0.05 level.

	Open-to-Open Returns	*Close-to-Close Returns*
70 Component Stocks (A)	1.0473	1.1062
	(0 0978)	(0.1277)
155 Component Stocks (B)	1.0800	1.1046
	(0 0913)	(0 1224)
145 Component Stocks (C)	1.0451	1.0473
	(0.0889)	(0.1245)
A-B	−0.0327*	0.0016
A-C	0.0022	0.589**
B-C	0.0349**	0 0573**

145 stock group. However, a significant difference is found between the 70 and 155 stock groups.

CONCLUSION

Identified in this study are the major determinants of price volatility in the Nikkei index component stocks: (i) market capitalization; (ii) share price level; (iii) market liquidity; and (iv) the frequency of no trading. Consistent with evidence documented for the U.S. market, we find that: (i) the smaller the market capitalization, the greater the price volatility; (ii) the smaller the market liquidity, the greater the price volatility; (iii) low-priced stocks have greater volatilities than high-priced stocks as anticipated; and (iv) the higher the frequency of no trading, the greater the price volatility.

Using cross-sectional regressions, price volatilities of the 145, 155, and 70 stock groups are compared after the impact of the major determinants of volatility have been controlled. When one-day return standard deviations are used, significant volatility differentials are observed among the three sets of component stocks, with the 70 and 155 stock groups having greater volatility than the 145 stock group. Examining multiday return standard deviations reveals that a difference in price volatility between the 145 and the 70 stock groups is detected, while the same is not true for the 145 and the 155 stock groups. While statistically significant, the economic importance is questioned since the magnitude of the deviations is relatively small when compared to the daily return volatilities.

Significant differences are detected among the three groups of component stocks in their sensitivity to futures market volatility after cross-sectional differences in firm attributes have been isolated. The speed of price adjustment is also compared for the three stock groups. Price adjustment coefficients differ between the 145 stock group and the NSA component stocks. This is not a surprise since the NSA component stocks are expected to show more overreactions to new information than the 145 stock group during the study period.

Given the empirical evidence documented in this study, the Nikkei Stock Index 300 does appear to be an improvement over the existing NSA index, even though the economic benefits of replacing the NSA with the Nikkei 300 have yet to be fully investigated. It is too early to evaluate the full impact of the new index futures contract on price volatility in the cash market since the new contract was introduced less than a month before we completed our study.

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NOTES

1. With the exception of four securities, the Osaka 50 stocks are included in the NSA constituent stocks (Bailey 1989)

2. Although the cash settlement feature was later introduced, the Kabusaki 50 index futures never gained popularity and trading was eventually suspended in March 1992.

3. See Rhee (1993) for an examination of the financial derivatives introduced in Japan.

4. See *The Nikkei Stock Average Data Book* (1991).

5. Atchison, Butler, and Simonds (1987) demonstrate that return autocorrelations at the portfolio level are reduced more with value-weighted than equally weighted composition.

6. To promote the new futures contracts, the cash portion of margin requirements is set at a lower level for the Nikkei 300 than the NSA futures contracts as summarized below. Nikkei 300 futures contracts are, therefore, expected to gradually replace the existing NSA futures contracts. During the 15 trading days between February 14 and March 4, 1994, the cumulated trading value of Nikkei 300 futures, NSA futures, and TOPIX futures amounted to ¥13 trillion. Nikkei 300 futures accounted for 19 3 percent, while the respective trading value of NSA futures and TOPIX futures represented 53 4 percent and 27.3 percent. The 19 percent market share achieved by the Nikkei 300 futures in 15 days is remarkable for a new contract.

	First Six Months	*Next Six Months*	*After One Year*
A. Customer Margin			
Nikkei 300 futures	25% (3% in cash)	20% (3% in cash)	15% (3% in cash)
NSA futures	25% (8% in cash)	20% (5% in cash)	15% (3% in cash)

B. Member Margin

Nikkei 300 futures	20% (0% in cash)	15% (0% in cash)	10% (0% in cash)
NSA futures	20% (5% in cash)	15% (2% in cash)	10% (0% in cash)

7. It is premature to compare the price volatilities of the three stock groups before and after the inauguration of the Nikkei 300 futures contracts since the new index futures trading began less than a month ago at the time of this writing.

8. At the end of 1991, the last day of our study period, the NSA divisor was 9.992.

9. The industry classification is based on the PACAP Databases-Japan compiled by the PACAP Research Center at The University of Rhode Island in cooperation with the Daiwa Institute of Research and the Toyo Keizai, Inc. The PACAP tape lists a total of 34 industries for Japan.

10. Three firms have incomplete data on the PACAP Databases-Japan during the study period. As a result, the following number of stocks is studied for each group

NSA:	224
Nikkei 300 Index:	297
Subgroup of 145 stocks:	143
Subgroup of 155 stocks:	154
Subgroup of 70 stocks:	70

11. Recent studies that employ the identical interday volatility measure include Grossman (1988) and Skinner (1989).

12. The seven issues include Nippon Telephone and Telegraph Corp. (¥50,000), Tokyo Electric Power (¥500), Chubu Electric Power (¥500), Kansai Electric Power (¥500), Tohoku Electric Power (¥500), Toho (¥500), and Arabian Oil (¥500). The figures in parentheses are par values

13. This process of price adjustment for par value is common in Japan In computing the NSA daily index values, the same adjustment is made for those stocks to eliminate the influence of high-priced stocks on the index values.

14. No price adjustment was made for two stocks, Seven-Eleven Japan (with zero par value) and Tokyo Tokeiba (with a par value of ¥20), since their respective trading unit is 1,000 shares. Another interesting example is Sony Inc. which has a par value of ¥50, but its trading unit is 100 shares. Again, no price adjustment was made to Sony's stock prices because of its uniform par value.

15. We have not used overlapping data for the estimation of the multiday return standard deviations to avoid problems with positive autocorrelations.

16. When inverse price level was introduced in the regression model, the sign of its coefficient was negative, which is the opposite of what is expected. Using the traditional cut-off point of 30, estimated condition indexes as defined by $(\lambda_{max}/\lambda_j)^{1/2}$ suggest that the data matrix contains at least two near-linear dependencies, involving intercept, inverse price level and market capitalization, where λ_j denotes eigenvalue j and λ_{max} is the maximum eigenvalue associated with the cross-products matrix, $X'X$. With market liquidity substituting for inverse price level, the number of near-dependencies is reduced to one. This near-dependency problem was rectified by orthogonalizing LogMkVal_i and MkLiq_i.

17. With $\varepsilon(\text{LogMkVal}_i)$ replacing LogMkVal_i in the regression, collinearity diagnostics indicate that none of the condition index values is greater than 30.

18. See *Nikkei 300: 3 Advantages of Futures Trading* (1994) published by the OSE.

19. A higher degree of sensitivity does not imply the destabilizing effect of futures trading in the context of regression results in Table 6. As Harris (1989, p. 1156) points out, autocorrelations in return series play an important role in the destabilizing or stabilizing effect. The degree of sensitivity simply measures the price reaction to futures market volatility within a trading day.

20. See Amihud and Mendelson (1987) and George and Hwang (1995).

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