Price Discovery in the Hang Seng Index Markets: Index, Futures, and the Tracker Fund

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In this paper, price discovery among the Hang Seng Index markets is investigated using the Hasbrouck and Gonzalo and Granger common-factor models and the multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model. Minute-by-minute data from the Hang Seng Index, Hang Seng Index futures, and the tracker fund show that the movements of the three markets are interrelated. The futures markets contain the most information, followed by the spot market. The tracker fund does not contribute to the price discovery process. The three markets exhibit spillover effects, indicating that their second moments are linked, even though the flow of information from the tracker fund to the other markets is minimal. Overall results suggest that the three markets have different degrees of information processing abilities, although they are

We are grateful to an anonymous reviewer, Robert Webb (the editor), and participants at the 13th Annual Asia-Pacific Futures Research Symposium in Shanghai, China, 2002, for valuable comments and suggestions.
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Received April 2003; Accepted September 2003

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The Journal of Futures Markets, Vol. 24, No. 9, 887–907 (2004)
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/fut.20112

governed by the same set of macroeconomic fundamentals. Jrl Fut Mark 24:887–907, 2004

INTRODUCTION

Recent developments in trading and telecommunication technologies have increased the information efficiency of financial markets. Consequently, market participants can access and assimilate information at low cost and asset prices can rapidly reflect this information. In an efficient market, information processing should be expeditious and the most information efficient market (asset) should lead the others. Hence, information transmission or price discovery is an indication of the relative market efficiencies of related assets.

Three major approaches to the study of the price discovery of assets have been identified in the literature. The first approach focuses on the lead-lag relationship between the prices of national markets, or between different securities. For example, Eun and Shim (1989) studied the transmission of stock prices between different countries; Stoll and Whaley (1990) and Chan (1992) examined information transmission between the stock index and index futures markets. Harris, McInish, Shoesmith, and Wood (1995) investigated the transmission of price information about IBM in different stock exchanges.

The second approach involves examination of the role of volatility in the price discovery process. Volatility spillovers are important in the study of information transmission because volatility is also a source of information. Two seminal papers (French & Roll, 1986; Ross, 1989) show that variance is an important source of information. French and Roll found that asset prices are much more volatile during exchange trading hours than at other times and that this divergence is caused by differences in the flow of information. Ross proved that asset price volatility is related to the rate of information flow in competitive asset markets. Previous studies on volatility spillovers in different national stock markets include Hamao, Masulis, and Ng (1990), Susmel and Engle (1994), Lin, Engle, and Ito (1994), Karolyi (1995), Koutmos and Booth (1995), and Booth, Chowdhury, Martikainen, and Tse (1997). The general conclusion is that volatility in one market will spill over to another market. In a study of volatility spillovers among similar assets, Chan, Chan, and Karolyi (1991), Kawaller, Koch, and Koch (1990), and Koutmos and Tucker (1996) considered information transmission between stock index and index futures markets. As with volatility spillovers among different national markets, empirical evidence indicates that the volatilities of similar assets affect one another.

The third approach attracts great attention from academia in the study of how information is transmitted among different markets. Using the common factor (or implicit efficient price) among cointegrated prices, information sharing techniques, notably the Hasbrouck (1995) and the Gonzalo and Granger (1995) models, have been used to study the contribution of price discovery from closely related markets. For example, Booth, So, and Tse (1999) studied information sharing among index derivatives and found that futures prices lead spot prices and spot prices lead options prices. A study by Chu, Hsieh, and Tse (1999) investigated price discovery among the Standard and Poor 500's (S&P 500) index, S&P 500 futures, and the S&P 500 Depository Receipt markets. They found that the futures market is the dominant source of information, followed by the Depository Receipt markets, with the spot market contributing least. Hasbrouck (2003) found that for the S&P 500 and Nasdaq-100 indexes, most of the price discovery occurs in the small-denomination futures contracts (E-minis). These examinations of information sharing are important as they deepen our understanding of the reactions of different assets to the same set of macroeconomic information.

Motivated by previous work on information sharing and volatility spillovers, the objective of this paper is to extend our understanding of information processing by investigating how information is transmitted among the Hong Kong Hang Seng Index markets. Intuitively, different index markets having the same underlying asset are affected by the same information set. Hence, differences in their information transmission abilities reflect relative efficiencies in information processing. An examination of their information transmission processes will also increase our understanding of the information processing abilities of different index markets that are linked by the same set of economic fundamentals.

The Hang Seng Index, the Hang Seng Index futures, and the tracker fund in Hong Kong are featured prominently in our investigation. Similar to the S&P 500 Depository Receipts, the tracker fund is an exchange-traded fund, the performance of which aims to track that of the Hang Seng Index. We are interested in the Hong Kong markets because Hong Kong is one of the largest developed markets in the world (International Finance Corporation, 1997). The openness of the market, the absence of controls on foreign exchange, and the market's high liquidity also make the Hong Kong market a suitable candidate for study.

In addition, Hong Kong is an important international financial center, as well as being the "gateway" to China. Economic developments in China during the past 20 years have been spectacular. With a population of over 1.2 billion people, China has come to be regarded as a market with huge potential. In recent years, foreign direct investment in China has increased greatly.[1] Paralleling China's development, the Hong Kong stock market has played a crucial role in channeling this investment capital. Therefore, an understanding of the Hong Kong stock markets is also essential to the international investor's understanding of China's business.

Specifically, we compare the percentages of information contribution among index, index futures and the index-tracker fund using the Gonzalo and Granger (1995) and Hasbrouck (1995) common-factor models. We also examine the volatility spillover effects of the three markets via a multivariate GARCH model.

We make three contributions to the research literature. First, we contribute to the extensive literature that investigates information flow and volatility clustering of financial return series. Second, we demonstrate and compare the different roles of the index markets. Third, in analyzing the institutional differences between the Hong Kong market and the S&P 500, we provide additional answers to the trading cost hypothesis. According to the trading cost hypothesis, index futures contain more information than the spot index due to their lower costs. Unlike other popular market indexes, the Hang Seng Index is skewed towards a few big firms with large weights in the index. This feature makes replicating the index in a portfolio of trades easy and a handful of spot market trades can come close to tracking the index. Hence, investigation of the Hong Kong market can provide robust tests of the trading cost hypothesis.

Our results show that the Hang Seng Index Futures market contributes the major share of the information, followed by the spot market, with the tracker fund not having a material share of the information discovery process. In addition, volatility in one market spills over to volatilities in other markets. Findings here suggest that the three index markets are linked, and information will be transmitted from one market to another. However, the markets have different abilities for information processing.

[1]Foreign direct investment in China was US$4,366 million in 1991 and has steadily increased to US$52,470 million in 2002. This represents an annual compound growth rate of 25.4% during the 12-year period.

The remainder of this paper is organized as follows. The following section gives an overview of the Hong Kong stock markets. The third section explains the data environment and presents the methodology. The fourth section discusses our empirical findings, and the final section draws conclusions.

INSTITUTIONAL DETAILS

The Hong Kong Market

The Hong Kong Exchange (HKEx) is the only organized stock exchange in Hong Kong. At the end of 2002, there were 978 firms listed on the HKEx and, according to the International Finance Corporation (IFC), the Hong Kong stock market is classified in the upper income group.

The importance of the Hong Kong market is shown by its success as a major international financial center for channeling investment funds to China. Many Chinese firms, the so-called "red chips" and the "H-shares," are listed on the HKEx (Neoh, 1998). Red chips are companies incorporated and listed in Hong Kong, but whose controlling shareholders are Chinese. Examples include CITIC, China Travel, and China Mobile. Large red chips are diversified conglomerates that have grown rapidly by the injection of assets from their parent companies and by raising funds from the public. CITIC Pacific and Guangdong Investment were added to the Hang Seng Index, Hong Kong's benchmark stock market index, in 1992 and 1994, respectively. Currently there are more than fifty red chips listed on the HKEx.

In 1993, Chinese state-owned enterprises (SOEs) started to issue shares in Hong Kong. These are called "H-shares," the "H" denoting Hong Kong, where the companies raise funds. Similarly, shares issued in London are called "L-shares," and shares issued in Tokyo are called "T-shares." Examples of H-shares include the Tsingtao Brewery Company and Shanghai Petrochemical. Unlike red chips, H-share companies tend to specialize in a single activity, usually heavy industry, or in a major infrastructure project. SOEs are selected by the Chinese government for their economic importance, management quality, technology, profitability, and international significance. In 2002, there were around forty H-shares listed on the HKEx.

The listing of red chips and H-shares on the HKEx has been one of the most important events in the recent development of the Hong Kong stock market. By signaling to the international financial community that the HKEx is a gateway to China, Hong Kong has established itself as

China's primary source of external capital. Red chips and H-shares have become a small but stable component of the portfolios of many large institutional funds.

The Hang Seng Index

The Hang Seng Index (HSI) is a value-weighted index based on 33 stocks of the largest companies in Hong Kong. The Hang Seng Index is the benchmark of the Hong Kong stock market and is widely used by fund managers as their performance reference. The Hang Seng Index is constructed by the Hang Seng Index Service Limited (HSISL), a subsidiary of the Hang Seng Bank. The Index is updated every minute during trading hours. Constituent firms of the HSI change from time to time, but the index accounts for around 70% of the total market capitalization (Young & Chiang, 1997).[2]

Unlike the Standard and Poor's 500, the Hang Seng Index is concentrated in a few big firms. The trading cost hypothesis predicts that the security incurring the lowest trading cost attracts informed trading. For the S&P 500, it is not practicable to establish 500 positions; hence, an informed trader tends to trade on the futures market or the S&P 500 Depository Market. Empirical evidence in Chu et al. (1999) gives support to the trading cost hypothesis.

However, this situation is very different in the Hong Kong environment. One particular observation of the Hang Seng Index is that there are only 33 stocks in the construction of the index. Compared to the S&P 500, establishing 33 positions is a more feasible strategy. In addition, movements of the Hang Seng Index are heavily influenced by some big firms, because of their larger weights. For example, at the end of June 2002, the weight of the HSBC in the index is 28.7%. Therefore, the price change of that single stock can have a material impact on the value of index. Two other giants, China Mobile and Hutchison Whampoa, both have significant weights, 14.7 and 8.4%, respectively, in the Hang Seng Index composition. Thus, the big three alone occupy 51.8% of the index value, and traders can easily trade in the spot market to cause changes in the futures markets. Hence, previous price discovery experience in the United States among the spot, futures, and index funds may not apply to the Hong Kong market.

[2]The market capitalizations of the Hong Kong market were US$103.3 billion in 1991 and US$456.3 billion in 2002. This represents an annual compound growth rate of 16% during the 12-year period.

Hang Seng Index Futures and the Tracker Fund

The Hang Seng Index Futures (HSIF) contract was introduced in 1986 and is cash settled. Contracts of this kind provide investors with a set of effective instruments to manage portfolio risk. The Hang Seng Index Futures contract has developed gradually into one of the most active futures contracts in the world. Because of its importance, the HSIF contract has been widely studied. Cheng, Fung, and Chan (2000) examined the impact of the 1997 Asian financial crisis on index futures markets, Fung and Draper (1999) studied the mispricing of the Hang Seng Index Futures under short sales constraints, Fung, Cheng, and Chan (1997) examined the intra-day patterns of the Hang Seng Index Futures, and Ho, Fang, and Woo (1992) investigated the intra-day arbitrage opportunities and price behavior of the Hang Seng Index Futures. Details of the contract specifications of the HSIF can be found in Table I.

The 1997 Asian financial crisis saw a wave of market collapses in Asia. The sharp depreciation of the Thai Baht marked the beginning of depreciation of many Asian currencies. Following the Baht, the South Korean Won, the Malaysian Ringgit, the Philippine Peso, the Singapore Dollar, and the Taiwan Dollar came under attack by hedge funds. During this wave of currency crises, the Hong Kong dollar maintained its peg to the U.S. dollar and did not depreciate. Nevertheless, attacks from international hedge funds caused Hong Kong interest rates to skyrocket and buffeted the stock and index futures markets.

To combat the international hedge fund attacks, the Hong Kong government acquired a substantial amount of Hong Kong shares in August 1998. To manage this stock holding, the government established the Exchange Fund Investment Limited in October 1998 to give advice on the disposal of this stock in an orderly manner.

After much debate, the government decided to sell the stocks in the form of an exchange-traded fund, the tracker fund (TF). The tracker fund aims to "track" the performance of the Hang Seng Index. Its operation is very similar to that of the S&P 500 Depository Receipts. Unlike ordinary index funds that can only be redeemed once a day, exchange-traded funds can be bought or sold on an exchange just like other listed securities. This feature greatly increases the liquidity of mutual funds and traces performance of the market index. The tracker fund was first listed on November 12, 1999. The initial public offer of the tracker fund was valued at HK$33.3 billion (around US$4.3 billion) and, at the time of launch, was the largest IPO ever in Asia, except Japan. Apart from its size, the tracker fund is particularly important because it was

TABLE I
Specifications of the Hang Seng Index Futures

Underlying Index	Hang Seng Index
Contract multiplier	HK$50 per index point
Contract months	Spot month, the next calendar month, and the next two calendar quarterly months (March, June, September, and December)
Contracted price	The price in whole index points at which a Hang Seng Index futures contract is registered by the Clearing House
Contracted value	Contracted price multiplied by contract multiplier
Minimum fluctuation	One index point
Maximum fluctuation	Nil
Position limits	Position delta for Mini-Hang Seng Index Futures, Hang Seng Index Futures, and Hang Seng Index Options combined of 10,000 long or short in all Contract Months provided the position delta for Mini-Hang Seng Index Futures shall not at any time exceed 2,000 long or short in all Contract Months combined. For this purpose, the position delta of one Mini-Hang Seng Index Futures Contract will have a value of 0.2
Large open positions	500 contracts, in any one contract month, per Exchange Participant for the Exchange Participant's own behalf; and 500 contracts, in any one contract month, per client.
Pre-market opening period	9:15 a.m.–9:45 a.m. (first trading session, Hong Kong time); 2:00 p.m.–2:30 p.m. (second trading session, Hong Kong time)
Trading hour	9:45 a.m.–12:30 p.m. (first trading session, Hong Kong time); 2:30 p.m.–4:15 p.m. (second trading session, Hong Kong time)
Trading method	Electronic order matching through the automated trading system
Last trading day	The business day immediately preceding the last business day of the contract month
Final settlement day	The first business day after the last trading day
Settlement method	Cash settlement
Final settlement price	The final settlement price for Hang Seng Index futures contracts shall be a number, rounded down to the nearest whole number, determined by the Clearing House and shall be the average of quotations of the Hang Seng Index taken at 5-minute intervals during the last trading day.
Trading fees and levies (per contract per side)	Exchange Fee: HK$10.00, Securities and Futures Commission levy: HK$1.00, Compensation fund levy: HK$0.50; Total: HK$11.50
Minimum commission (per contract per side)	Minimum Commission Rate HK$100 (overnight) (per contract per side) HK$60 (day-trade) (per contract per side)

Note. Hong Kong Exchange and Clearing Limited.

the most successful launch of exchange-traded fund outside the United States (Fleites, 2003). The success of the tracker fund also opens new ways for overseas investors to invest in Asia through exchange-traded funds.

DATA AND METHODOLOGY

Data Environment

Minute-by-minute data of the Hang Seng Index (HSI) are obtained from the HSISL. Tick-by-tick transaction data of the Hang Seng Index Futures (HSIF) and the tracker fund (TF) are supplied by the HKEx. The nearby contract is used in calculating futures returns, as it is the most actively traded. Futures contracts are rolled over to the next nearby contract upon expiration. The sample period is from November 12, 1999 to June 28, 2002, with a sample size of 156,143 observations. Given the large sample employed in the study, we adjust the significance level downward to 0.1%, instead of the commonly used 5 or 1%, to avoid the Lindley Paradox.[3]

The return of market i at time t is calculated as:

$$R_{it} = \ln(P_{it}/P_{i,t-1}) \tag{1}$$

where P_t is the index level at time t.

To study the price discovery process, data are taken at 1-minute intervals. Analysis of the intra-day price discovery process requires that the data series be synchronous. To determine if the 1-minute data interval will introduce bias into the analysis, a careful check of the trading activities of the three markets is necessary. For the three Hang Seng index derivatives markets, trading is active and the problem of nonsynchronicity is not serious. The Hang Seng Index is updated minute-by-minute and HSIF trading is very active. On average, there are more than six trades per minute. For the tracker fund, with lighter trading than the futures, there is still an average of 2.1 trades every minute. Thus the problem of infrequent trading is not serious for the three index markets.[4] Because the Hang Seng index is updated only every minute, we cannot use higher frequency data.

Common Factor Models

Arbitrage activities should keep prices in the index, futures, and tracker fund markets from diverging. Therefore, the prices of the three index

[3]As Connolly (1989) contends, the significance level should be adjusted downward with sample size; otherwise, spurious significant results (or market anomalies) would be induced by large sample-size distortion.

[4]A referee also points out that synchronicity at one-minutes intervals is not an issue. "Almost all price discovery research across markets employs spans of multimarket or multichannel trades 3 to 15 minutes long."

markets should be cointegrated and be driven by one common factor, also known as the "implicit efficient price."[5] The Vector Error Correction Models (VECMs), advocated in Engle and Granger (1987), are widely used to examine the relationships between closely linked securities.

Because one implicit assumption in studies of price discovery is that the markets share at least one common driving force, common factor models are employed in these studies. Two popular approaches have been developed in the study of common factor models to investigate the mechanics of price discovery. One is the permanent-transitory model discussed by Gonzalo and Granger (1995) and the second is the information shares model developed in Hasbrouck (1995). These two models attract great attention in academia. For example, Baillie, Booth, Tse, and Zabotina (2002), De Jong (2002), and Lehmann (2002) established the relationship between the two models. Harris, McInish, and Wood (2002a,b) and Hasbrouck (2002) enumerated the differences between the two models. Booth, Lin, Martikainen, and Tse (2002) used both models to examine the Finnish upstairs and downstairs stock markets. A number of other studies have also used the information-sharing and/or permanent-transitory models (see Tse & Erenburg, 2003, and the references therein).

Although the information-sharing and the permanent-transitory models study the same economic phenomenon, the two techniques provide different views on the price discovery process. The Hasbrouck (1995) model extracts the price discovery process using the variance of innovations to the common factor. The Gonzalo and Granger (1995) approach, however, focuses on the components of the common factor and an error correction process.

Both the information-sharing and permanent-transitory models are derived from the VECM in the following form:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta X_{t-i} + e_t \tag{2}$$

where $X_t = \{x_{it}\}$ is a 3×1 vector of cointegrated prices in the current study, Π and Γ's are 3×3 matrices of parameters, and e_t is a 3×1 vector of serially uncorrelated residuals with a variance-covariance matrix $\Omega = \{\sigma_{ij}\}$. If the prices of the three markets are cointegrated, the long-run relationship matrix Π has a reduced rank of $r < 3$, and can be decomposed as $\Pi = \alpha\beta'$, where α and β are $n \times r$ matrices. The β matrix consists of

[5]Cointegration is the presence of a stationary relationship among a nonstationary series. See Engle and Granger (1987).

the cointegrating vectors and α is the error correction (or equilibrium adjustment) matrix. If $r = 2$ and β is spanned by the differentials of each pair of price series, then all x_{it} are driven by one common factor. This is the case for the closely linked index, futures and tracker fund prices.

Hasbrouck (1995) transformed the VECM in Equation (2) into an integrated form of a vector moving average (VMA):

$$X_t = J\varphi\left(\sum_{\tau=1}^{t} e_\tau\right) + \Phi^*(L)e_t \tag{3}$$

where J is a column vector of ones, $\varphi = (\varphi_1, \varphi_2, \varphi_n)$ is a row vector, and Φ^* is a matrix of polynomials in the lag operator, L. Equation (3) is related to the common-factor representation of Stock and Watson (1988), in which

$$X_t = \omega_t + G_t \tag{4}$$

where ω_t is the common factor, and G_t is the transitory component that does not have a permanent impact on X_t. ω_t is also the efficient price in Hasbrouck's (1993) market quality model.[6]

Hasbrouck (1995) showed that the increment φe_t in Equation (3) is the common factor innovation and the component of the price change that is permanently impounded into the price. This permanent component is assumed to be driven by information and is instrumental to price discovery. He further decomposed the variance of innovations in the common factor, $var(\varphi e_t) = \varphi\Omega\varphi'$, and defined the information share of a trading center as the proportion of $var(\varphi e_t)$ that is attributable to innovations in that center.

If the variance-covariance matrix Ω is diagonal, the information share of market j is given by

$$I_j = \frac{\varphi_j^2\sigma_j^2}{\varphi\Omega\varphi'} \tag{5}$$

where φ_j is the jth element of φ. If Ω is not diagonal (i.e., the cross-equation residuals are contemporaneously correlated), the information share is not exactly identified and the results depend on the ordering of variables in the Cholesky factorization of Ω. Different orderings of the variables will create lower and upper bounds of a market's information share. The difference between the upper and lower bounds can be great if the residuals are highly correlated. Eun and Sabherwal (2003, p. 560)

[6]Note that the loading matrix of the common factor is omitted in Equation (4) because, as in Hasbrouck (1995), the cointegrating vector is spanned by the price differentials and all price series are driven by one common factor.

point out that "the information shares are not unique as they depend on the ordering of the prices. Nonuniqueness of the information shares would pose a major problem if [they] use this approach." In the Hasbrouck (1995) study of the Dow 30 stocks, the upper and lower bounds were almost the same because he used one-second prevailing quotes, which introduce very small cross-equation correlations into the model structure.

By contrast, Gonzalo and Granger (1995) decomposed the common factor ω_t into a linear combination of the prices, in which $\omega_t = \eta X_t$, where $\eta = (\eta_1, \eta_2, \eta_3)$ is the common factor coefficient vector. η is normalized so that $\sum \eta_i = 1$ and the η_i coefficients can be interpreted as portfolio weights (Harris, McInish, & Wood, 1996, 2002a,b; Ding, Harris, Lau, & McInish, 1999). Baillie et al. (2002) and De Jong (2002) proved that the information sharing and permanent-transitory models provide similar results if the contemporaneous cross-equation residuals are uncorrelated with comparable variances. If there is a strong correlation among the contemporaneous cross-equation residuals, differences in results from the two models can be substantial. An advantage of the Gonzalo and Granger model is that the common factor estimates are exactly identified, as they do not depend on the ordering of the variables.

Volatility Spillovers

First introduced by Engle (1982) and Bollerslev (1986), the ARCH and GARCH models are often used to describe time-variation in the volatility of financial returns. Like Kavajecz and Odders-White (2001), among many others, we employ the extensively used GARCH(1,1) model. They noted that this specification has the desirable features of interpretability and good fit for high-frequency data.

Several studies, e.g., Chan, Chan, and Karolyi (1991), Koutmos and Tucker (1996), and Tse (1999), have examined volatility spillovers between the index and futures markets. As argued by Ross (1989), volatility is directly related to information flow. Examination of volatility spillovers among the index, futures, and tracker fund markets will provide insights into the information-transmission mechanism.

We estimate the multivariate GARCH(1,1) model to investigate the volatility spillover process:

$$e_t = (e_{1t}e_{2t}e_{3t})' \mid \Lambda_{t-1} \sim N(0, \Omega_t), \quad \Omega_t = \{\rho_{ij}\sigma_{it}\sigma_{jt}\} \tag{6}$$

$$\sigma_{1t}^2 = \omega_1 + \alpha_1 e_{1,t-1}^2 + \gamma_1 e_{2,t-1}^2 + \lambda_1 e_{3,t-1}^2 + \beta_1 \sigma_{1,t-1}^2 \tag{7}$$

$$\sigma_{2t}^2 = \omega_2 + \alpha_2 e_{2,t-1}^2 + \gamma_2 e_{1,t-1}^2 + \lambda_2 e_{3,t-1}^2 + \beta_2 \sigma_{2,t-1}^2 \tag{8}$$

$$\sigma_{3t}^2 = \omega_3 + \alpha_3 e_{3,t-1}^2 + \gamma_3 e_{1,t-1}^2 + \lambda_3 e_{2,t-1}^2 + \beta_3 \sigma_{3,t-1}^2 \tag{9}$$

The unautocorrelated residuals, e_i's in Equations (6) to (9), are obtained from the VECM in Equation (2), Ω_t is the 3×3 time varying conditional covariance matrix with constant conditional correlations, ρ_{ij}, and Λ_{t-1} is the information set at $t - 1$.[7] In the above equations, we specify market 1 to be the spot index, market 2 to be the futures, and market 3 to be the tracker fund.

The coefficients in the above equations, α_i and β_i, represent market i's specific volatility clustering. The coefficients γ_i and λ_i describe the volatility spillovers from the other two markets to market i. For example, γ_1 and λ_1 indicate the spillovers from the futures market to the index market and from the tracker fund market to the index market, respectively.

We estimate Equations (6)–(9) simultaneously by maximizing the log-likelihood function:

$$L(\Theta) = -\sum_{t=1}^{T} (\ln|\Omega_t| + e_t'\Omega_t^{-1}e_t) \tag{10}$$

where Θ is the 18×1 parameter vector.

Estimating the VECM and multivariate GARCH model simultaneously in one step is not practical because of the large number of parameters involved. Using a two-stage approach (estimation of the VECM followed by use of the residuals in the VECM to formulate the M-GARCH model) is a more tractable method (Tse, 1999).

EMPIRICAL RESULTS

Summary Statistics

Descriptive statistics of the returns of the three index markets are given in Table II. Returns of the three index markets are not normally distributed, as shown by their excessive kurtosis. In addition, the returns of the markets are significantly positively correlated, with the index and index futures exhibiting the highest correlation, while the tracker fund seems to be more correlated with the spot than with the futures market. Results from these simple statistics suggest that the tracker fund aims to track

[7]The multivariate EGARCH model of Nelson (1991) is also estimated to allow for asymmetric volatility. However, the asymmetric volatility effect is insignificant in the three markets. Therefore, a multivariate GARCH model is used in the analysis.

TABLE II
Descriptive Statistics of Five-Minute Returns of Hang Seng Index, Hang Seng Index Futures, and the Tracker Fund

	Index markets		
Summary statistic	*Hang Seng Index*	*Hang Seng Index Futures*	*Tracker fund*
Panel A: Summary Statistics of Returns of the Three Index Markets			
Mean (10^{-5})	−1.31	−1.33	−0.95
Standard deviation (10^{-3})	2.21	1.70	5.27
Skewness	−1.41	−0.10	0.13
Kurtosis	74.48*	6.80*	10.96*
Maximum	0.04	0.02	0.05
Minimum	−0.07	−0.02	−0.04

	Hang Seng Index Futures	*Tracker fund*
Panel B: Correlation of Returns of the Three Index Markets		
Hang Seng Index	0.43*	0.30*
Hang Seng Index Futures		0.15*

* Significant at the 0.1% level.

the performance of the index, hence the stronger correlation with the spot market. The high correlation between the index and the futures market suggests that both markets are related.

Common Factor Results

As shown by the Johansen (1991) tests in Table III (Panel A), the prices in each market are cointegrated with one common stochastic factor.[8] Like Dwyer, Locke, and Yu (1994), who employ minute-by-minute data on the S&P 500 futures and cash markets, we use 10 lags of price changes in the VECM. The Johansen tests are robust to GARCH effects (see, e.g., Lee & Tse, 1996; Sin & Ling, 2002). We have also tried 5, 10, and 20 lags with all the common factor results being almost the same.

In Table III (Panel B), we present the price discovery results in the order of index, futures and tracker fund. The common factor coefficients, η_i, are 0.205 (index), 0.793 (futures), and 0.002 (tracker fund), suggesting that the futures market contributes the most to the price discovery process, followed by the index. The contribution of the tracker fund is negligible. The common factor coefficients are also tested against

[8]Because the 0.1% critical values of the Johansen tests are not available, we only report the 1% values. However, the test statistics are more than 40 times those of the 1% critical values; therefore the results should be significant at the 0.1% level.

TABLE III
Cointegration and Price Discovery

	Trace	*Critical values at the 1% level*[a]	λ_{max}	*Critical values at the 1% level*[a]
Panel A: Johansen Cointegration Tests				
$r = 2$	0.743	11.65	0.743	11.65
$r = 1$	828.5	23.52	827.7	19.19
$r = 0$	1978.9	37.22	1150.4	25.75

	Index	*Futures*	*Tracker fund*
Panel B: Estimation of Common Factor Coefficients and Information Shares			
Common factor coefficients:			
η_i[b]	0.205	0.793	0.002
Test statistic for H_o: $\eta_i = 0$	25.60	956.2	4.882
p value	$<$0.0001	$<$0.0001	0.028
Information shares[c]			
Upper bound	0.451	0.951	0.014
Lower bound	0.036	0.533	0.000
Average	0.247	0.747	0.006

[a] The critical values are obtained from Osterwald-Lenum (1992).
[b] The common factor coefficients are estimated by the Gonzalo and Granger (1995) model. The coefficients are tested by the Gonzalo-Granger Q statistic, which is distributed as $\chi^2(1)$.
[c] The information shares are calculated by the Hasbrouck (1995) model.

the null hypothesis of zero using the Gonzalo-Granger Q statistic. The coefficient of the tracker fund is not significantly different from zero ($p = 0.028$), while those of the futures and the index are significant ($p < 0.0001$).

To obtain the information shares, we estimate the VECM and follow the Baillie et al. (2002) approach closely. We report the lower bound, upper bound, and average of all permutations (of the Cholesky factorization) of information shares. The lower and upper bounds differ considerably because the cross-equation residuals are strongly correlated, with an average correlation coefficient of 0.27. Martens (1998), Baillie et al. (2002), Booth, Lin, Martikainen, and Tse (2002), and Huang (2002) also reported a substantial difference in their Hasbrouck upper and lower bounds of information shares. For a bivariate case, Baillie et al. (2002) provide various analytical examples to show that the average of the information shares given by the two permutations is a reasonable estimate of a market's role in price discovery. We also use average information shares to interpret the results. As with Gonzalo and Granger's (1995) common factor results, the futures market dominates with an information share of 0.747. The index market yields an information share of 0.247, and the share of the tracker fund is close to zero, 0.006.

Therefore, both the Hasbrouck (1995) and Gonzalo and Granger (1995) models show that the futures market leads the other two markets in compounding information into prices, while the tracker fund is a free-rider in the price discovery process.

This finding is also a manifestation of the trading cost hypothesis. Fleming, Ostdiek, and Whaley (1996) document that futures lead options, and options lead the spot market for the S&P 500 because of higher trading cost in the S&P 500 spot market. Similarly, Chu et al. (1999) found that the S&P 500 futures lead the S&P Depository Receipt markets, and the Depository Receipt markets lead the spot index. They offer this result as evidence to support the trading cost argument because of high costs and the difficulty of creating 500 individual portfolios. However, the Hang Seng Index has only 33 constituent stocks and the index is dominated by three heavily traded companies. Thus, informed traders can trade in the futures market to take advantage of the leverage effects and trade the "big three" in the spot market as "stealth trades." Hence, the lower costs in trading individual stocks in the Hong Kong market affect the information processing abilities of the tracker fund. This finding is consistent with Fleming et al. (1996) and Chu et al. (1999).

In this paper, we focus on the permanent or equilibrium dynamics among the price series. Therefore, as in many other papers, e.g., Hasbrouck (1995), Booth et al. (2002), and Eun and Sabherwal (2003), we do not examine the results of lagged price changes in the VECM (i.e., the second term in Equation 2). As mentioned in these papers, these lagged terms only describe the transitory or short-run dynamics. However, Frino, Harris, McInish, and Tomas (2004) provide a comprehensive analysis of these price-lag dynamics.[9]

Volatility Spillover Results

Results with the robust statistics of Bollerslev and Wooldridge (1992) are reported in Table IV. According to the conditional variance equation of the index market (7), we find significant volatility spillover from the futures market to the index market ($\gamma_1 = 0.033$ with t-stat. = 28.62), but almost zero spillover from the tracker fund ($\lambda_1 = 0.000$ with t-stat. = 1.43). Equation (8) shows that the index market has significant

[9]In their study of the local and nonlocal trades on futures markets, Frino et al. (2004) find that most of the coefficients of high-order lagged price changes are statistically significant. They argue that "these extended price lag dynamics likely reflect the one- to two-minute time periods required for rational expectation formation in futures markets exhibiting very high frequency trading observable with second-to-second data" (p. 12).

TABLE IV
Volatility Spillovers: Bivariate GARCH(1,1) Model

	Index	*Futures*	*Tracker fund*
ω_i (10^{-3})	0.358 (48.47)	0.013 (38.48)	0.0247 (12.78)
α_i	0.192 (153.2)	0.075 (162.6)	0.017 (221.8)
γ_i	0.033 (28.62)	0.013 (76.17)	0.016 (44.44)
λ_i	0.000 (1.43)	0.001 (3.45)	0.030 (84.84)
β_i	0.812 (635.1)	0.924 (3369.5)	0.983 (1714.1)
ρ_{12}	0.191 (70.13)		
ρ_{13}	0.119 (42.48)		
ρ_{23}	0.047 (15.92)		

Note.

$$e_t \mid \Lambda_{t-1} \sim N(0, \Omega_t), \quad \Omega_t = \{\rho_{ij}\sigma_{it}\sigma_{jt}\}$$
$$\sigma_{it}^2 = \omega_i + \alpha_i e_{i,t-1}^2 + \gamma_i e_{j,t-1}^2 + \lambda_i e_{k,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

The coefficients γ_i and λ_i describe the volatility spillovers from the other two markets to market *i*. For example, γ_1 and λ_1 indicate the spillovers from the futures market to the index market and from the tracker fund market to the index market, respectively. *t*-statistics with the Bollerslev and Wooldridge (1992) robust estimation are in parentheses.

volatility spillover to the futures market ($\gamma_2 = 0.013$ with *t*-stat. = 79.17) and the spillover from the tracker fund to the futures market is economically insignificant ($\lambda_2 = 0.001$ with *t*-stat. = 3.45). In Equation (9), we find that both the futures and index markets have significant volatility spillover to the tracker fund market with a greater influence from the futures market ($\gamma_3 = 0.016$ with *t*-stat. = 44.44, and $\lambda_3 = 0.030$ with *t*-stat. = 84.84). The results are similar if we include dummy variables for the first and last 15 minutes in the conditional variance Equations (7)–(9).

Therefore, the overall results suggest a bi-directional volatility spillover between the index and futures markets with a stronger effect from the futures to the index markets. Both markets' volatilities also spill over to the tracker fund, but this does not happen in the reverse direction. These results are consistent with the results of the common factor coefficients and information shares: the futures market contributes most in the price discovery process, while the contribution of the tracker fund is almost zero.

CONCLUSIONS

This paper examines the price discovery process among the Hong Kong Hang Seng Index markets. The price series of the index, futures, and tracker fund are cointegrated with one common factor. According to the

Gonzalo and Granger (1995) model, the common factor coefficients are 0.205 (index), 0.793 (futures), and 0.002 (tracker fund). These results show that the futures market is the main driving force in the price discovery process, followed by the index, while the contribution of the tracker fund is trivial. The test statistics of the Gonzalo and Granger model also show that the coefficient of the tracker fund is not significantly different from zero. These results are similar to Hasbrouck's (1995) average information shares: 0.247 (index), 0.747 (futures), and 0.006 (tracker fund).

The results from the multivariate GARCH models indicate that the volatilities of the index and futures markets spill over to each other with a stronger effect from the futures to the index markets. Both markets also significantly spill over to the tracker fund. In contrast, the spillovers from the tracker fund to the other two markets are insignificant. These results are consistent with the results of the two common factor models.

The overall findings are consistent with the well-documented observation that the futures market dominates the spot market in the price discovery process. However, the small contribution of the tracker fund, which aims to track the performance of the index, indicates that whether exchange-traded funds are efficient information processors will depend on the particular market setting. The trading cost hypothesis posits that the least cost instrument will lead others in the price discovery process. The particular setting of Hong Kong, given that three major stocks constitute more than 50% of the index value, makes it easier to track the index through trading of individual stocks in the spot market. Hence, in the Hong Kong market, futures lead the spot market, and the index fund does not have an impact on the processing of information.

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