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Political Risk and Stock Returns: The Case of Hong Kong

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We focus on the 1989-1993 period, during which political issues such as the question of Hong Kong's democracy after 1997, China's most-favored-nation trade status, and China's human rights development and political reform movement have all contributed to Hong Kong's stock price movements. Modeling market volatility using a jump-diffusion process finds that the volatility of the benchmark Hang Seng Index is driven by a highly persistent component, punctuated by large jumps which are highly related to political events. These results suggest that the Hong Kong market is affected by both economic and political factors which impact future profitability and investor confidence.

Keywords: jump-diffusion process, volatility, democracy, most-favored-nation trade status.

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Little work has been done to characterize the empirical effects of political events on financial markets. In this paper we attempt to measure the impact of political risk on asset prices, focusing on the Hong Kong equity market. Hong Kong serves as the ideal case study, for two reasons: the political situation is fluid, unpredictable, and characterized by the occurrence of definitive events, and the market movements are volatile, partially reflecting the political event risk.

We focus on the 1989-1993 period, during which political issues such as the question of Hong Kong's democracy after 1997, China's most-favored-nation trade status, and China's human rights development and political reform movement have all contributed to Hong Kong's stock price movements. Modeling market volatility using a jump-diffusion process finds that the volatility of the benchmark Hang Seng Index is driven by a highly persistent component, punctuated by large jumps which are highly related to political events. These results suggest that the Hong Kong market is affected by both economic and political factors which impact future profitability and investor confidence.

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Studies suggest a close association between political risks and financial markets.[2] Dramatic political changes such as the transformation from a market economy to a socialist economy cause huge financial losses to shareholders, shifting corporate ownership from shareholders to the state and resulting in the suspension of stock trading.[3] Disputes of trade policy between two nations often result in large exchange rate movements, upsetting capital flows in the world market, while changes in government fiscal and monetary policies affect inflation and interest rates, thereby moving financial markets.

Despite the huge potential impact of political forces on financial markets, there has been little empirical study on the effects of political factors on security prices and volatilities.[4] Instead, most studies focus exclusively on the impact of economic events on security prices -- it is perhaps no wonder, then, that many researchers find that a large fraction of significant market movements are difficult to explain. Roll

[2]See Alesina and Sachs (1988), Aliber (1975), and Buchanan (1970).

[3]After the 1949 Communist revolution, the Chinese government suspended trading indefinitely on the Shanghai Stock Exchange. The government also nationalized almost all companies in 1958. For details, see Chow (1994).

[4]Previous studies, such as Cutler (1988) and Cutler, Poterba, and Summers (1989), did examine the relationship between stock returns and political news. But they found little evidence of significant impact of political on stock prices. Moreover, they did not study the impact of political news on the time-variation of volatility.

(1988) concludes that over 60% of monthly stock price movements are left unexplained by asset pricing models using systematic economic influences, industry influences and firm-specific events, whereas Fama (1990) discovers that a combination of real and financial variables explains only 58% of the variation in annual returns, leaving a substantial residual amount unexplained.

In this paper, we study the relationship between political factors and stock returns, focusing on the experience of Hong Kong from 1989 to 1993. Hong Kong offers an ideal case study, because of the large number of political shocks that have occurred and the volatility of price movements during the sample period. We construct indices that capture political event risk related to three issues that have affected contemporary Hong Kong, and attempt to gauge the effects of these political issues on market return and volatility movements. The issues we choose include: (i) the question of Hong Kong's democracy after 1997, (ii) China's most-favored-nation trade status, and (iii) China's human rights developments and political reforms. Is there any relationship between the large price movements and political shocks? How large an affect do political events have on market volatility? These are the types of questions which we will address in this paper.

The format of the paper is as follows. Section I contains a brief history of Hong Kong and the development of its stock market. We chronicle Hong Kong's unstable political environment over the last 50 years -- there have been times when the future of Hong Kong was quite uncertain, and these uncertainties have greatly contributed to market volatility. Section II describes the data, including some unique features of the Hong Kong stock market. We find that the quarterly equity return in Hong Kong has been approximately 8% over the period 1984-1993, roughly 5% higher than the corresponding 3% for the U.S. equity market,[5] while quarterly return volatility has been 16%, about double the corresponding 8% for the U.S. We also describe the construction and composition of our political risk indices.

Section III employs an event study methodology to examine the direct impact of political changes on security returns. We show that political events during the sample period have significantly affected movements in the Hang Seng Index. Section IV details a regression analysis that attempts to provide a robust test of the importance of political factors by incorporating economic factors, such as inflation and economic growth, in accounting for return movements. We find significant evidence of political influences.

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[5]The exchange rate has been pegged (HK$7.8 to US$1) since October 1983.

Section V describes a volatility model to describe the huge movements in the Hong Kong stock index. The model is a derivative of the ARCH class of models first introduced by Engle (1982), combined with a jump process. We link the volatility changes to political events using two methodologies, and find the volatility effects of the political risk variables to be significant -- the results are presented in Section VI. Finally, Section VII concludes.

I. A Brief History of Hong Kong and Its Stock Market

Hong Kong is situated on the south east coast of China. It covers an area of 411 square miles and has a population of 6 million people. Hong Kong's economy is based primarily on trade and financial services, which together account for 44% of its GDP in 1991. As a major trading center in the Pacific Rim region, re-exports (goods that are shipped through Hong Kong) accounts for 78% of its total exports. China is by far the largest trading partner, providing about 60% of re-exports and 38% of imports in 1991. Since 1976, Hong Kong has enjoyed one of the most robust economic growth rates in the world, with an average real growth rate of 11% per year -- the per capita GDP of $16,444 in 1992 is one of the highest in the region.

Hong Kong became a British colony in 1842, when China lost the Opium War to the United Kingdom. Several further defeats led China to cede part of Kowloon in 1860, and in 1898, the British leased a section of the Chinese mainland and several islands (the New Territories) for 99 years.

The Hong Kong Stock Exchange was founded in 1891, but it only became an important source of capital funds in the late 1960's, as a result of Hong Kong's industrialization. Due to its close proximity to China, Hong Kong's market has always been under strong influence of China's political events.

As a result of the massive influx of foreign capital in the late 1950s, rapid industrial development led to a major boom in the stock market during early 60's. The boom was cut short in 1966 when the Cultural Revolution launched by Chairman Mao Zedong in China appeared to spin out of control. China plunged into a state of total chaos and civil war, and the turmoil spilled over to Hong Kong as it was flooded by a large number of refugees from China. In 1967, the reckless Red Guards made several unauthorized attempts to cross the border to "liberate" Hong Kong, causing panic among local residents. The political disturbances led the Hong Kong Stock Exchange to suspend its operations for 10 days in order to prevent a possible selling panic. In 1967, share prices and turnover fell to their lowest points since 1961.

During the period of 1969-1973, there was another major boom in the Hong Kong equity market. The Hang Seng Index quintupled from December 1971 to March 1973.[6] After a major set back during the oil crisis of 1974-1975, the market started recouping its losses as its economy experienced impressive growth -- an average increase of 8.7 percent from 1976-1989. Meanwhile, China made dramatic changes in its economic policies after the death of Chairman Mao Zedong. The free market-oriented economic reform policy adopted by the Chinese government altered foreign investor's perceptions of Hong Kong's political risk and encouraged foreign investment in Hong Kong. The Hang Seng Index reached record highs during the years 1979 and 1981, closing at 1405.82 at the end of 1981.

In September 1982, Mrs. Margaret Thatcher, the British Prime Minister, visited Beijing to discuss the future of Hong Kong after the expiry of the lease of the New Territories in 1997. China demanded that Hong Kong be returned to China in 1997 -- the Hang Seng Index crashed to a low of 676.3 points towards the end

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[6]This is attributed by most analysts to the restoration of business confidence after the political disturbances of 1967, the impressive growth of the Hong Kong economy, the remarkably consistent performance of most listed companies, and the resolution of the international currency crisis. See Figure 1.

of 1982, down more than 50% from the peak of 1981. Negotiations between the British and Chinese governments resumed in the second half of 1983, but there was slow progress on the settlement of the lease. In response, the Hang Seng Index plummeted again towards the end of 1983.

In 1984, China and the United Kingdom worked out a "one country, two system" formula in which China guaranteed Hong Kong's current capitalist way of life for 50 years after the United Kingdom returned Hong Kong to China in 1997. A joint declaration of agreement was signed by the governments in December 1984. The Hang Seng Index started recovering from the losses of the previous two years and continued to rise to an all time high of 3,950 on October 1, 1987; the world-wide market crash later that month brought the Index down by over 40%.

Following the crash of October 1987 through June 1989, the Hang Seng Index soared almost 50%. The advance was most notable in the months of April and May 1989, when student demonstrations in China raised the possibility of real political reform. However, the killing of pro-democracy students in Beijing's Tiananmen Square in early June 1989, caused many investors to dump their shares, pushing the stock market down to 2093.61 on June 5, a decline of more than 36 percent from the peak of May 15 (see Figure 1).

Since the Tiananmen Square crackdown, the Hang Seng Index has soared again to record highs. It grew over 40% in 1991. In 1992 the Hong Kong market had the highest growth of all the world's markets, appreciating 28%. In 1993 it did even better than in previous years, rising a breath-taking 115%, closing at another high of 11888.30 on December 31, 1993.[7]

It is worth noting that the Hong Kong stock market has suffered one political shock after another from 1989 to 1993. Three political issues in particular were pervasive during the period: China's progress on human rights and political reform, China's trading status with the U.S., and Hong Kong's political future. The most dramatic example of a human rights-related event was, of course, the Tiananmen Square incident, but several other events occurred during the sample period -- each potentially affecting the economic outlook for Hong Kong. In addition, the U.S. came close several times to canceling China's

[7]The major reason for the market's stellar performance in the 1990s is Hong Kong's tantalizing connection to mainland China -- a country with a free-market-oriented economic policy, a potentially large market of 1.2 billion people, and a strong track record of high economic growth. Many financial analysts believe that the only relatively safe way to invest in China is through Hong Kong's equity market. The Hong Kong Stock Exchange not only lists many local companies that do business in China, it even lists two dozen "red chip" companies wholly owned by the Peoples' Republic of China. Moreover, the Hong Kong dollar is pegged to the U.S. dollar, which eliminates any currency risk that might scare away foreign investors.

most-favored-nation (MFN) trading status based on China's human rights record, seriously threatening Hong Kong's position as China's trading window to the West. Another major political storm broke in October 1992, when Hong Kong's new governor, Chris Patten, introduced new democratic reform measures in Hong Kong's legislature. China, furious about these measures, threatened to abandon its 1984 agreement with Britain, which guaranteed Hong Kong's current socio-economic system for 50 years after 1997. China and the United Kingdom held seventeen rounds of unsuccessful talks -- the uncertainty surrounding these talks sent waves of political shocks that buffeted the stock market.

The objective of this paper is to focus on this politically stormy time period of 1989-1993, analyzing the political shocks and evaluating their impact on Hong Kong stock price and volatility movements.

II. The Data

The primary sample period we examine extends from 1989-1993. We employ the following variables in studying the linkage between political risk and stock returns in Hong Kong:

1. Daily, weekly and quarterly stock returns data, derived from changes in the levels of the Hang Seng Index. The daily

data cover the sample period from 1989-1993. The weekly and quarterly data cover the sample period from 1969-1993. The data are obtained from Datastream and Bloomberg, respectively.

2. Quarterly industrial production growth and inflation, computed from the Hong Kong industrial production index and consumer price index, respectively, covering the sample period from 1971-1993. The data are obtained from Datastream.

3. Political news indices, derived from the abstracts of the *Wall Street Journal* and the *New York Times*. We construct three indices, each dealing with a separate political issue: (i) democracy and human rights in China (DEMO), (ii) Hong Kong's political future (HKFU), and (iii) China's Most-Favored-Nation (MFN) trading status with the U.S.

   The construction procedure is as follows. We begin by searching for all relevant news items during the sample period and classifying each item found into one of three categories: positive (good news), negative and neutral. We then assign each positive development a value of one, negative developments a value of minus one and the rest zero to construct the news indices.[8] The result is six dummy variable time series (two series, one for the *Wall Street Journal* and one for the *New York Times*, for each of the three political issues). These variables enable us to pinpoint political risk event dates.

Table 1 presents summary statistics for the Hang Seng Index returns, industrial production growth, and inflation. We also present similar results for the U.S. for comparison. Table 1 shows that Hong Kong has enjoyed explosive economic growth, growing 8 times as fast as the U.S. during the 1979-1983 time period. Real growth rates slowed down somewhat during later periods, but growth of about 4.6% per annum during the 1989-1993 period was still much higher than the 1.6% experienced by the U.S. On the other hand, Hong Kong also had much higher inflation during the whole sample period, with inflation running as high as 9.2% per annum during the 1989-1993 period, compared to 2.7% per annum for the U.S. during the same period.

[8]A political development is considered good if it: 1) improves democracy and human rights in China, 2) strengthens Hong Kong's current political and legal structure, or 3) improves the odds of letting China keep its Most-Favored-Nation trading Status with the U.S. The judgement is made by an economics graduate student who does not follow the Hong Kong market. For dates when there are several news items, we aggregate the events by summing up the assigned values for each news item.

From Table 1, we can also see that the Hang Seng Index enjoyed tremendous appreciation during the 1969-1973, 1984-1988, and 1989-1993 sample periods, much higher than that of the Dow Jones Industrial Average. In fact, the Hang Seng Index consistently beat the Dow Jones in every five-year sample period, even in terms of real rates of return. The 7.1% and 8.9% *quarterly* returns achieved during the 1984-1988 and 1989-1993 sample periods (compared to 3.3% and 2.9% for the U.S., respectively) were even more impressive, considering the fact that the exchange rate has been pegged (HK$7.8 to US$1) since October 1983. While the Hang Seng Index enjoyed remarkable returns during the sample period, the market was also much more volatile when compared to that of the U.S. Quarterly volatility was 16% for the Hang Seng Index, but only 8% for the Dow, during 1984-1993.[9]

In terms of our focus on political event risk, there are two volatility characteristics of the Hong Kong return process that are of particular interest: time-varying volatility and jump returns. We explore each of these characteristics in turn.

[9] As pointed out by Harvey (1993), other emerging markets have also experienced high rates of returns and volatilities during the last ten years. However, Hong Kong's economy has been much more robust and stable comparing to these markets. Hong Kong's market is also much larger in size. It ranks as the sixth largest stock market in the world based on total market capitalization at the end of 1993.

Time-Varying Volatility

It is widely accepted among academics and practitioners that volatility of asset returns is not constant over time, but is in fact time-varying. In particular, volatility has long been known to exhibit "clustering" - large return shocks tend to be followed by large shocks, and small shocks by additional small shocks. Indeed, the presence of clustering led Engle (1982) to introduce the popular ARCH class of volatility models, which have subsequently been used to successfully describe volatility in a wide variety of asset markets.

Closely related to the idea of volatility clustering is that of time-varying long-term volatility. Clustering could be regarded as a short-run phenomenon -- realized volatility may cluster into brief high and low periods while underlying long-run volatility remains little changed. If the duration of these high or low volatility periods extended to several months, though, we might consider the long-run volatility to be itself time-varying. Explicit modeling of this time variation would provide us with a more accurate representation of market volatility movements.

Hong Kong volatility contains such a time-varying long-term component. Figure 2 shows the absolute value of weekly returns for the Hong Kong market over the full sample period which we consider (January 1, 1969, through December 31, 1993). The volatility clustering is evident, as is the prevalence of extreme movements in the index. In addition, casual empiricism suggests the existence of well-defined high and low volatility periods _ the early and late 1970's seem relatively calm, whereas the mid-1970's are a period of extreme volatility, as are, to a lesser extent, the early 1980's and, more recently, the end of 1993. These low frequency movements in volatility are visible in Figure 3, which plots rolling one-year standard deviation of weekly returns. Figure 4 depicts the autocorrelation function for the squared returns series, which implies the presence of predictability in volatility.

Jump Returns

A more distinctive characteristic of the Hong Kong market is the prevalence of large, outlier return movements. The HSI contains many large returns -- for example, over the 500 (weekly) observation period from February 1984 to September 1993, there are 51 weeks experiencing returns of 5% or more in magnitude. [Additional graphs or tables. More detail on the return distribution.] Clearly, any model must incorporate these outlier movements to adequately represent the behavior of the Hong Kong market.

However, our interest is not in large returns in general; rather, we are particularly interested in what we term "jump" return movements, where we define a jump return as a shock that is large relative to conditional estimated volatility. In other words, we consider jumps to be surprise return moves. A particular large return may or may not constitute a jump return, depending on the estimated conditional volatility of the return. A large return occurring during a highly volatile period could be consistent with the underlying diffusion process; if so, the return would not be considered a jump. On the other hand, a return spike during a low conditional volatility period would be unusual -- the spike would be identified as a jump.

By identifying jump return dates with political events, we can assess directly the importance of political event risk and its effect on volatility. But first, we turn to investigate the effects of political risk on return.

III. Stock Returns and Political Risk: An Event Study Approach

In this section, we employ an event-study methodology to examine the impact of political news on stock prices. We compute stock returns for event dates *t* and for the ten trading day window [*t-5*,*t+5*] surrounding these dates, where we use the political risk dummy variables to mark the event dates. The results are provided in Tables 2, 3, and 4.

Table 2 measures the market response (return in excess of mean daily returns for the period of 1989-1993) to news about democracy and human rights developments in China. As expected, we can see that the market responds negatively to bad news and positively to good news at event date *t*. The responses to good news at *t* and *t+1* are statistically significant, but these gains are largely offset by losses following the good news. We also compute the cumulative returns from time *t-5* to *t+5* for both the good and bad news. The cumulative loss for bad news is 0.15% while the cumulative loss for good news is 0.32%.

Table 3 gauges the market response to news about Hong Kong's political future in China. We can see that the market responds negatively to bad news, while positively to good news at event date *t*, as expected. The response to good news at *t-1* is also statistically significant, but the gains are somewhat offset by losses following the good news. We can see the market suffers from fairly large losses (1.05 % at *t-3* and 1.03 % at *t*) due to bad news, but the loss is partly recovered after *t+2*. We can also see the same happened to good news as well. The gains at *t* and *t+1* are partly offset by losses at *t+1* and *t+2*.[10] We also compute the cumulative returns from time *t-5* to *t+5* for both the good and bad news. The cumulative loss for bad news is 1.53%, while the cumulative gains for good news is 1.43%.

Table 4 quantifies the market response to news about China's MFN trading status with the U.S. We can see that the market responds positively to both bad and good news at event date *t*, but the responses are stronger and statistically more significant before time *t*. However, the gains for good news from *t-5* to *t+1* are partly offset by losses from *t+2* to *t+4*. We also compute the cumulative returns from time *t-5* to *t+5* for both the good and bad news. The cumulative loss for bad news is 1.39%, while the cumulative gains for good news is 0.34%.

Overall, we conclude that political developments in China and Hong Kong do have significant impacts on Hong Kong's stock price movements.

IV. Stock Prices, Real Activity, and Political Risk

[10]This apparent return reversal is consistent with the result of high daily negative serial correlation found in the Hang Seng index returns. (The first-order autocorrelation is -0.28 for the daily returns.)

Using methodology developed by Fama (1990) and Schwert (1990), we turn to examine the net effect of political developments after taking into consideration real economic factors. In their work, Fama and Schwert regress stock returns on current and future changes in output to assess the effects of real shocks on stock values. Bittlingmayer (1992) extends their work by including antitrust case filings to assess the impact of antitrust enforcement on stock prices. Following Bittlingmayer (1992), we perform a similar regression analysis by including political news into the regression to evaluate the effects of political developments.

The results presented in Table 5 are based on regressions of nominal Hang Seng Index returns on current real industrial production (IP) growth, inflation, and political news. For the 1989-1993 period, the regression based on IP-growth and inflation explains 7.8% of the variation in Hang Seng returns. The negative signs on IP-growth and inflation should not be surprising, given the results of Campbell and Mei (1993), who show that the positive impacts of IP-growth and inflation on future cash flows are offset by increases in future discount rates as a result of the higher growth and inflation.

For the same period, the regression based on the three political index variables only explains 19%, 1.2% and 0.0% of the variation in Hang Seng returns. The regression using the aggregated index (SUM) explains 13.2% of the variation, while the regression on all three indices explains 20.5% of the variation. Although only the DEMO index is statistically significant, all variables have the expected positive signs, meaning a positive development (good news) with regard to political events has a positive impact on Hang Seng stock returns.[11]

The same results also hold if we include both real and political factors in the regression. From the last regression in Table 2, we can see that a positive development regarding China's democracy is associated with an average 3.05% increase in Hang Seng returns, while a negative event is associated with an average 3.05% decrease in Hang Seng returns. We present similar results for developments associated with Hong Kong's political future and China's MFN trading status with the U.S.[12]

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[11]The low t-statistics reflect the fact that we only have 20 observations in the time-series regressions. We could possibly improve the t-statistics by employing monthly data. However, monthly data on IP-growth and inflation are not available.

The discrepancy between the cumulative results in Table 2 and results in Table 5 on Democracy (DEMO) could be explained by the fact that Table 2 measures the impact of political news on daily stock price movements while Table 5 measures the impact of political news on quarterly stock price movements, which cover a longer-time period.

[12]Following Fama and Schwert, we have also included current and future IP-growth and inflation variables in the regression. Using a longer quarterly time series from 1975-1993, we find that IP growth from t to t+4 and inflation from t to t+1 only explains less than 5% of the variation in the Hang Seng index. These results are available upon request.

V. The Components-Jump Volatility Model

We now turn to introduce a volatility model constructed explicitly to capture the market characteristics of the Hong Kong market. As noted in Section II, the return process in Hong Kong appears to differ qualitatively from that of more mature equity markets, rendering standard volatility modeling approaches suspect. In particular, the very features of the equity market that make Hong Kong an ideal candidate to study the market effects of political risk -- the large shifts in underlying volatility and the prevalence of return spikes -- hamper the ability of simple implementations of ARCH-style models to accurately describe market volatility.

We construct a volatility model that explicitly accounts for these features of the return process in Hong Kong, thereby enabling us to obtain a clearer picture of the dynamic behavior of volatility and allowing us to relate directly the effects of political events to volatility movements. The model consists of two parts, which are considered jointly in the statistical estimation process: a). a fundamental ARCH-derivative model of volatility, based on the components model of Engle and Lee (1993), which captures the time-varying nature of long-term volatility, and b). a jump (*Poisson*) process, which accounts for the return spikes. We call the model a "components-jump" model. Explicitly relating estimated volatility to the political risk variables described in the section above enables us to quantify the market volatility impact of political events. After detailing the specification of the volatility model, we present the relevant parameter estimates.

The Components-Jump Model

The model is comprised of two parts: a fundamental model that is a derivative of the ARCH-class of models and based on the components model of Engle and Lee (1993), on top of which we overlay a *Poisson* jump process _ we refer to the model as a components-jump model. By augmenting the standard ARCH set-up with these extensions, we are better able to model the volatility process in Hong Kong. After providing some discussion of the model, we outline the specification of the components-jump structure.

The mechanics of the model are as follows. The core of the model is the components model, which we utilize for its ability to capture movements in long-term volatility. Over this core model we graft a jump process. The jump process essentially serves as a filter, accounting for non-persistent return shocks before core, or fundamental, volatility -- that is, volatility excluding any jump effects -- is estimated using the components model. The model pinpoints movements that are large relative to estimated conditional volatility as jumps: These jumps are assumed to be distributed normally with a given mean and variance. The mean effect of the jump is then removed before fundamental volatility is estimated. Note that not all outliers are identified as jumps. A shock occurring during a period of low volatility would be identified by the model as a jump, and no volatility effect would be imputed; however, a large move during a high volatility period would not be considered to be a jump and therefore have persistent volatility effects. Incorporation of a jump process allows to more accurately model the actual characteristics of the Hong Kong return process.

Afterwards, we add back a jump premium to the fundamental volatility estimate to arrive at the overall volatility estimate, where the jump premium is a function of the parameters of the estimated jump process. As a by-product of the estimation, the model estimates jump return dates, which we match with political event dates to assess the effects of political risk on volatility.

The particular components-jump specification we estimate is as follows:

$$r_t = a + b * r_{t-1} + \varepsilon_t + \eta_t$$

$$\varepsilon_t \mid I_{t-1} \sim F(0, h_t)$$

$$h_t = q_t + \alpha * (\varepsilon_{t-1}^2 - q_{t-1}) + \beta * (h_{t-1} - q_{t-1})$$

$$q_t = \omega + \rho * q_{t-1} + \phi * (\varepsilon_{t-1}^2 - h_{t-1})$$

$$\eta_t = \Sigma \gamma_i \quad (\text{for } i = 0 \text{ to } m_t)$$

$$\gamma_i \sim N(\psi, \sigma^2)$$

$$m_t = P(\lambda)$$

The return r_t is modeled as a function of lagged return and two error terms, ε_t and η_t. The ε_t is distributed normally given the information set I_{t-1}, with mean zero and conditional variance h_t. We refer to this conditional variance estimate as the fundamental variance (or volatility) estimate -- fundamental in the sense that it excludes any jump process-related effects. The laws of motion describing the evolution of the conditional variance h_t are the processes from the components model of Engle and Lee (1993). Conditional variance h_t is mean-reverting around the permanent, or long-term underlying, variance q_t, with the speed of mean-reversion determined by the parameters α and β. The permanent component of variance, q_t, is also time-varying, with the speed of mean reversion determined by ρ; for $\rho = 1$ the long-term volatility process is integrated. The forecasting error term $\varepsilon_{t-1}^2 - h_{t-1}$ drives the evolution of the permanent component. Engle and Lee provide additional commentary regarding the components model, and derive multi-step forecasting equations for the specification.

The jump process error η_t for period t is comprised of the sum of m_t jumps of γ_i, which is distributed normally with mean ψ and variance σ^2. In practice, m_t, which is Poisson distributed with intensity parameter λ, is generally either zero or one per period for small λ -- that is, generally there is at most one jump in each period. This specification is an extension of the model described by Jorion (1988), who proposes an ARCH-Jump model to explain foreign exchange and U.S. equity volatility.

Each period, the model examines the return forecasting error innovation $r_t - a - b * r_{t-1}$, comparing the size of the shock to the estimated fundamental conditional volatility. If this normalized error is large, the model assumes a jump has occurred; the mean effects of the jump are removed before next period's conditional volatility estimate is calculated. In this way, we exclude the (non-persistent) effects of jump return moves from affecting the estimate of fundamental volatility.

We feel the assumptions underlying the jump process are well-suited to describing the spike movements in the Hang Seng Index. We assume that the jumps are unforecastable, occurring with constant probability λ per period, regardless of whether a jump has recently occurred. Too, fitting of the model provides us with parameter estimates for the probability of occurrence, the direction, average magnitude and dispersion of each jump, which is valuable information for calculating, for example, options prices. Identification of the jump dates also allows us to account for the impact of political risk on volatility movements -- we continue this discussion in the following section.

After fundamental variance is estimated for period t, we add back a premium to account for the occurrence of the jumps, where the premium is a function of the estimated parameters of the jump process.

Parameter Estimates

In this section we present empirical estimates for the components-jump model, along with comparative estimates for Bollerslev's (1986) generalized ARCH (or GARCH) and the components model of Engle and Lee (1993) to highlight the effects of incorporation of the jump and component processes. For all specifications, we utilize the return equation outlined in the previous section.

The simple GARCH system we estimate is relatively standard, and is defined as follows:

$$\varepsilon_t \mid I_{t-1} \sim F(0, h_t)$$
$$h_t = \omega + \alpha * \varepsilon_{t-1}^2 + \beta * h_{t-1}.$$

The variance h_t evolves as a function of lagged variance and lagged squared error, and is mean-reverting around an unconditional variance $\omega / (1 - \alpha - \beta)$ -- there is no time-varying permanent component.

For the straight components model, the equation system is as presented in the section above, without the jump process-related terms.

We estimate the model using maximum likelihood estimation techniques (see Jorion, 1988, for a discussion of the likelihood function). Due to severe non-convexity of the components-jump model, we use a non-gradient based technique called simulated annealing to estimate the parameters of the model; hence, we do not report standard errors for the coefficient estimates.

We consider two sample periods for the estimation: the entire 1969-1993 period (weekly), and the 1989-1993 period (daily) that coincides with the dates of our political risk variables. The parameter estimates are presented in Table 6.

We begin with the results for the 1969-1993 period. For the GARCH(1,1) model, the average likelihood is estimated to be 1.849, while the volatility persistence rate is estimated to be $\alpha + \beta = 0.95$. Interestingly enough, the components model provides no better fit -- the likelihood is estimated to be the same as that of the GARCH(1,1). The decay rate of the permanent component, ρ, is estimated as 0.96, marginally higher than for the simple GARCH model, implying approximately 58% ($= .96^{13}$) of a shock remains after a quarter.

The addition of the jump component leads to an increase in the likelihood function -- the average likelihood increases by 0.033 to 1.882 for the GARCH(1,1) plus jump, with a larger jump of 0.04 to 1.889 for the components plus jump model. To test the GARCH (1,1) model against the GARCH-jump model, we perform a likelihood ratio test. The likelihood ratio is defined as

$$LR = -2\ln(L(\theta_0;x)/L(\theta_1;x)),$$

where $L(\theta_0;x)$ is maximum likelihood under the null hypothesis, and $L(\theta_1;x)$ is maximum likelihood over the unrestricted parameter space. Under the null, LR follows a χ^2 distribution with degrees of freedom equal to the difference in the number of parameters between the two models. As we can see from Table 6, the GARCH(1,1) model is strongly rejected in favor of the GARCH-jump model (P=0.001) and the GARCH-jump model is rejected in favor of the components-jump model (P=0.001). The jumps are estimated as having a probability of approximately 8% (8.5%), and a mean magnitude of 0.17% (1.0%) with a standard deviation of approximately 7%, for the GARCH-jump (components-jump) model.

The persistence of the component-jump model is estimated to be 0.99, implying a high level of persistence in the permanent component of the variance. The increase in ρ to 0.99 for the components-jump model, relative to the 0.96 estimate from the simple components model, is not surprising -- excluding the effects of quick-decaying return spikes results in a higher estimated overall persistence level for the components-jump model. (The simple component model is rejected in favor of component-jump model with P=0.000) Indeed, imposing a unit root on the permanent component, that is, imposing the condition that $\rho = 1$, results in only a 0.004 decline in the average likelihood. (However, the unit root-jump model is rejected in favor of components-jump with P=0.001) Whether the persistence parameter of the permanent component is actually one, or simply very close to one, is an important question, but we do not address the issue here.

More important for our purposes are the parameter estimates for the sample period coinciding with our political risk variables, 1989-1993. For the GARCH(1,1) model, the likelihood is estimated to be 2.957, with a total persistence measure of 0.94. The components model provides an incrementally better fit, with a likelihood of 2.959; the persistence of the permanent component is estimated to be 0.94 as well.

The addition of the jump process results in a substantive gain in likelihood value for both models. The GARCH-jump likelihood increases by 0.08, while the components plus jump model likelihood rises by 0.085. The jump probabilities are estimated at approximately 3% for both models, with the mean magnitude varying between -0.4% and -0.7%, and a standard deviation of about 5%. The LR test rejects all other specifications in favor of the components-jump model.[13]

The persistence of the permanent component is estimated to be 93%, which seems low given the 0.99 estimate from the 1969-1993 sample period. We attribute the low persistence estimate to

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[13] To adjust for the difference in the number of parameters in the different likelihood functions, we also compute the Schwarz statistics for various model specifications. Using the "Schwarz Criterion" of picking the model with the lowest value, our results suggest a component-jump model for the quarterly data and the GARCH-jump model for the daily data.

the occurrence of two very large return spikes during the sample period, notably the Tiananmen Square shock of June 1989, during which the Hang Seng Index fell by over 36%. The presence of these huge temporary spikes lowers the overall estimated persistence, since a large fraction of the spike disappears immediately. To check this assertion, we reestimated the model over the same sample with the spikes truncated at various levels, and over the 1000 day sample ending December 31, 1993, a sample period that excludes the large shocks, obtaining an estimate for ρ of greater than 0.99. (Results are available upon request.) Apparently, the model can successfully account for shocks of magnitude up to 7%; however, shocks larger than this in size cause a downward bias in the estimate of the persistence of the permanent component. Although we feel that an estimate of ρ closer to 0.99 is probably more descriptive of the general return process, we continue to use the parameters as reported in generating our estimated volatilities -- for short horizon (daily) volatility forecasts, the differences between the two model estimates are negligible.

Figure 5 shows the daily forecasted volatility using the components plus jump model, with an overlay of the estimated jump dates. We see that jump dates occur when the market are excessively volatile relative to recent conditions, i.e., they indicate market jumps which are difficult to justify given the conditional volatility.

In the following section, we compare the volatility estimates to the political risk variables to assess the effects of political events on the Hong Kong return process.

VI. Political Risk and Volatility Movements

In this section we describe the results of our tests of political risk effects on volatility movements in the Hong Kong equity market. We conduct two simple tests. The first involves matching the jump dates with the political risk dummy variables described above. Since the jump returns are essentially surprise market shocks, by comparing the jump dates with the dummy risk variables, we can directly assess the effects of the announcement of political events on return moves. The second test involves regressing volatility levels and changes on the political dummy variables, to ascertain the volatility magnitude of the announcement effects.

Table 7 lists the jump dates estimated by the components-jump model over the 1989-1993 period -- there are 71 days identified as having jump return movements, out of a total of

1304 observations, for a realized jump frequency of 5%. For all identified jump dates, the model estimates one jump as having occurred, that is, $m_t = 1$, except for June 5, 1989, the date of Tiananmen Square, for which the model estimates $m_t = 3$. Of these, 32 dates, or 45%, match with a non-zero political risk dummy variable, where we define a match if the news event announcement dummy falls on the same day as, or on the day following, a return jump. (Since we exclude weekends, for our purposes we consider Friday to be followed by Monday.) Sixteen of the 32 dates, or 50%, are related to the China/human rights dummy; another 10 dates, or 31%, can be attributed to Hong Kong-related political announcements. Finally, 13 dates, or 41%, are associated with MFN-related news items. (The totals add up to more than 100%, since certain dates are coded under multiple dummy variables.)

To gauge the statistical significance of having 32 dates out of 71 jump dates matched by six political series, we use a Monte Carlo simulation. We treat the jump dates as given and we randomly generate six news dummy variables with the number of news dates the same as those in the political series. We also impose the restriction that the two random series simulating the WSJ and NYT for one political development (such as Hong Kong's political future) must have the same value for certain number of dates just like WSJ and NYT reported the same news sometimes during the sample. From the 1000 simulations, we find that the probability of having 32 dates out of 71 jump dates matched by six random series is 0.6% and the probability of having 32 or more dates matched by six random series is 10%. Thus, we conclude that the 32 matches we observed from the sample is statistically significant.

The jump dates reported in Table 7 reflects the effect of exogenous events on the Hong Kong Market. They include the student demonstration in Beijing (890504), Martial Law in Beijing (890522), the Tiananmen Square incident (890605), the Sino-British dispute over Hong Kong's political reform (921201) and the improvement of Sino-British relationship (930414). They also include other major world political events such as the Gulf crisis (900806), the Allied air strike against Iraq (910177), and the Russian coup (910819).

We need to point out here that the significance of our results could be understated because we select New York based news papers rather than Hong Kong based newspapers for constructing the news series. As a result, some political news interesting to Hong Kong investors may not be reported due to lack of readership in the US. Moreover, our practice of averaging of positive and negative news may also understate the impact of news on volatility, since conflicting news could impact volatility but they are treated as neutral (dummy=0) in our studies.

Clearly, the announcements of political events have stock market implications. We now turn to directly measure the magnitudes of the announcement effects on volatility.

Tables 8 through 11 detail results of regressions of daily volatility estimates on various combinations of the political risk dummy variables. We use both daily volatility estimates *vol* and changes in volatility *dvol* as the dependent variables, and, due to the autocorrelated nature of the volatility processes, include lagged dependent variables as well. (Only regression results including the lagged dependent variable are shown -- other results available from the authors.) In addition, due to the reactive nature of the components model, we examine lagged as well as lead values of the risk variables.

Table 8 shows the results of volatility regressed on the aggregate of the absolute values of the six political indices -- the intent is to check the news effects of volatility, irrespective of the expected positive or negative effects of the news. Not surprisingly, we find lagged dependent variables to be highly significant in all cases. Focusing on the *vol* specification including leading and lagging index values, we estimate the *abs(agg(-1))* and *abs(agg(+1))* variables to be significant at standard significance levels, with a combined incremental volatility effect of 1.8%. (The R-squared for the regression is 66%.) That is, the news announcement seems to have a significant impact on corresponding volatility.

To differentiate the effects of positive and negative announcements, we regress *vol* and *dvol* on both the aggregate index and the absolute value of the aggregate index -- the results are depicted in Table 9. Again looking at the full specification for *vol*, we find most variables to be significant; in addition, we see a differential effect between positive and negative news announcements. For a single negative news event, the dummy variable is *-1*, implying an incremental volatility effect of 1.7% (= *-1* * (*-0.3%* + *0.6%* - *0.5%*) + *1* * (*1.0%* + *0.0%* + *0.5%*)), whereas for a positive news event, the volatility effect is 1.3%, a difference of 0.4%. Clearly, we find an asymmetric response to positive versus negative political news, with negative announcements resulting in larger volatility responses.

This asymmetric response to positive vs negative news is consistent with the "no news is good news" or the volatility feedback effect studied by Campbell and Hentschel (1993). When there exist volatility feedback, bad news not only affects the prospects for future dividends, but also raises future volatility thus future expected returns. As a result, stock prices have to decline more today to reflect this increase in future expected returns. The impact of good news, on the other hand, is smaller because the impacts on future dividends and future expected returns tend to offset each other.

To further investigate the effects of the different types of political risk -- China/human rights, Hong Kong political environment, or MFN -- we regress the volatility estimates on the individual dummy series. As with the aggregate index above, we include two different specifications: the absolute index values, to assess the raw effects of the news announcements, and the actual and absolute index values, to differentiate between positive and negative events. Table 10 shows the results of the regression estimations using the absolute values of the six indices. Examining the full *vol* specification, we note that only the China- and Hong Kong-related dummy variables are significant -- the MFN series is insignificant in relation to volatility movements. The China-related news announcements are most significant statistically, resulting in aggregate volatility effects of 3.5% (= *2.6% - 0.8% + 1.7%*) for the *New York Times* and -0.5% (= *-0.7% + 1.5% - 1.3%*) for the *Wall Street Journal* versions of the indices; the net effect is a volatility increase of 3.0% in reaction to a China/human rights-related announcement. The series characterizing political events in Hong Kong are also significant, with aggregate volatility effects of 0.8% and 3.4% for the *New York Times* and the *Wall Street Journal*, respectively, for a net effect of 4.2%.

Continuing the exercise, we regress *vol* and *dvol* on both the absolute value and actual disaggregated index values to ascertain any differential effects between positive and negative news -- Table 11 presents the results. Again, as above, all coefficient estimates relating to the MFN dummy variables are insignificant, implying that the MFN announcements did not affect volatility movements. Slightly over half of the China-related coefficient estimates are significant. The *New York Times* parameters indicate a 3.6% volatility increase in response to a negative news shock, versus a 3.2% positive effect -- the volatility asymmetry seems to exist. However, for the *Wall Street Journal* series, the cumulative index response is positive, implying a larger volatility effect for positive news (0.7%) relative to negative news (-1.7%). This result runs counter to our other findings. (Excluding insignificant coefficients results in a positive news/volatility effect of 1.4%, versus a negative news response of -0.8%). For the Hong Kong dummy series, the *New York Times* coefficients indicate a volatility response of 1.4% to a negative news shock, versus -0.2% for a positive announcement, while the *Wall Street Journal* estimates a large 5.5% volatility rise due to a negative shock, versus only 0.3% for a positive shock. (Excluding insignificant coefficients, the *New York Times* series indicates a 1.6% response to both positive and negative news, while the *Wall Street Journal* coefficients imply a 4.1% negative news effect, versus a 0.5% positive news effect.) The asymmetric response of volatility to news announcements holds for the disaggregated dummy variables as well as the aggregated index -- negative news announcements appear to increase volatility to a greater degree than positive news.

VII. Conclusion

In his 1988 presidential address to the American Finance Association, Roll (1998) suggests that financial science is still quite immature because of its "conspicuous lack of predictive content" about changes in asset prices. He shows that over 60% of large stock price movements are left unexplained by asset pricing models using systematic economic influences, industry influences and firm-specific events. He challenges the profession to either find some measurable influences that will explain the remaining 60% or find a coherent reason why it should remain unexplained.

This paper takes up the challenge posed by Roll by providing a systematic approach to evaluate the impact of political risk on stock price movements. We discover that political events do have a significant and measurable impact on stock returns and volatilities, in addition to economic influences. However, we still fall short of explaining all the changes in stock returns and volatilities.

Our main findings can be summarized as follows. At the return level, using an event study methodology, we find that political developments have a significant impact on daily stock returns. We also demonstrate that the addition of a political risk dummy significantly increases the explanatory power of return regressions -- industrial production growth and inflation only explain 7.8% of quarterly Hang Seng Index returns, whereas the inclusion of a single political index raises explanatory power to as much as 26.3%. In addition, we develop a model of volatility for Hong Kong that explicitly captures the exaggerated characteristics of the market. Using this components-jump model, we find that unexpected return jumps in the market are closely associated with political news, and that the impact of this news is asymmetric, with bad news having a greater volatility effect relative to good news.

The fact that China's political policy affects the Hong Kong stock market has some interesting implications for China's future decision makers. As China's continuing economic development demands more and more capital, China finds herself increasingly dependent on Hong Kong's stock market to raise funds. At the end of September 1993, China had 29 "red chip" companies listed on the Hong Kong Stock Exchange, with a total capitalization of US$11 billion; in addition, Chinese companies also invest heavily in the Hong Kong real estate market, which closely tracks the stock market. By affecting the Hong Kong stock market, Chinese government policies also impact Chinese companies directly. The various Chinese government agencies (including the military and security apparatus) which own these companies could suffer huge financial losses if certain political developments are not well received by the market. This potential for loss might offer some checks and balances to the Chinese government decision making process that might discourage the government from making political policies which would otherwise prove costly to Hong Kong and China itself as well.

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Table 1.
Summary Statistics for Quarterly Hang Seng Index Return, Real Industrial Production Growth, and Inflation

		69-73	74-78	79-83	84-88	1989-1993
	Hang Seng	10.83	3.222	4.771	7.088	8.877
		26.83	23.16	19.98	15.50	16.41
H.K.	IP-Growth	---	2.040	2.021	1.925	1.150
		---	1.799	1.096	1.343	0.476
	Inflation	---	1.496	3.080	1.228	2.382
		---	1.501	1.342	0.638	0.688
	Dow-Jones	-0.265	0.280	2.495	3.250	2.926
		6.982	10.82	7.071	9.991	5.409
U.S.	IP-Growth	0.821	0.760	0.244	0.937	0.399
		1.594	2.887	2.351	0.987	0.895
	Inflation	0.570	0.833	0.880	0.377	0.666
		0.235	0.308	0.543	0.210	0.193

Note: The first row of each panel gives the mean, the second row gives the standard deviation. The unit for the variables used here are in percentages per quarter.

Table 2.
Response to News about Democracy and
Human Rights Developments in China

	Bad News		Good News	
	Price Chg	T-statistic	Price Chg	T-statisti
t-5	-0.612	-0.969	-0.416	-2.183
t-4	0.116	0.316	0.223	0.469
t-3	0.119	0.516	-0.534	-1.177
t-2	0.113	0.443	0.095	0.518
t-1	0.087	0.284	-0.664	-0.986
t	-0.096	-0.369	0.513	2.426
t+1	0.013	0.070	0.535	2.707
t+2	-0.422	-0.736	-0.025	-0.164
t+3	0.179	0.851	0.207	0.768
t+4	0.399	2.050	-0.147	-0.841
t+5	-0.041	-0.240	-0.110	-0.449
Cum Return	-0.145		-0.323	

Note: The sample period covers 1989-1993. News about democracy and human rights in China (DEMO) is obtained from reports by the *Wall Street Journal*and the *New York Times*. We classify the news items into three categories: 1) good, 2) bad, and 3) neutral. We only evaluate the market response to good news and bad news.

Table 3.
Response to News about the
Political Future of Hong Kong

	Bad News		Good News	
	Price Chg	T-statistic	Price Chg	T-statisti
t-5	-0.130	-0.461	-0.001	-0.002
t-4	-0.036	-0.109	-0.187	-0.557
t-3	-0.705	-0.874	0.568	2.559
t-2	-0.519	-1.443	0.025	0.100
t-1	0.003	0.007	0.580	2.363
t	-1.025	-1.243	0.523	1.770
t+1	0.037	0.081	-0.340	-1.914
t+2	-0.107	-0.220	-0.121	-0.509
t+3	0.536	1.687	0.245	0.734
t+4	0.337	0.793	-0.135	-0.426
t+5	0.076	0.197	0.275	0.721
Cum Return	-1.533		1.432	

Note: The sample period covers 1989-1993. News about Hong Kong's political future (HKFU) is obtained from reports by the *Wall Street Journal*and the *New York Times*. We classify the news items into three categories: 1) good, 2) bad, and 3) neutral. We only evaluate the market response to good news and bad news.

Table 4.
Response to News about China's
Most Favor Nation Trading Status with US

	Bad News		Good News	
	Price Chg	T-statistic	Price Chg	T-statisti
t-5	-0.553	-1.894	0.325	1.349
t-4	-1.103	-1.116	0.522	2.700
t-3	-0.063	-0.240	0.005	0.025
t-2	-0.186	-0.644	0.044	0.314
t-1	0.137	0.627	0.277	1.097
t	0.223	0.557	0.038	0.140
t+1	-0.282	-1.084	0.107	0.379
t+2	0.321	1.364	-0.234	-1.222
t+3	0.086	0.400	-0.525	-1.409
t+4	-0.073	-0.357	-0.234	-0.708
t+5	0.107	0.720	0.013	0.050
Cum Return	-1.386		0.338	

Note: The sample period covers 1989-1993. News about China's Most-Favored-Nation (MFN) trading status is obtained from reports by the *Wall Street Journal*and the *New York Times*. We classify the news items into three categories: 1) good, 2) bad, and 3) neutral. We only evaluate the market response to good news and bad news.

Table 5.
Regression of Quarterly Hang Seng Index Returns on Industrial Production Growth, Inflation, and News (89Q1-93Q4)

	Cons.	IPG	INFN	DEMO	HKFU	MFN	SUM	R-square
Rt	18.13	-0.796	-3.439					0.078
	(1.04)	(-1.18)	(-0.49)					
Rt	10.32			**3.606**				0.190
	(2.97)			(2.06)				
Rt	9.213				0.844			0.012
	(2.41)				(0.46)			
Rt	8.845					0.197		0.000
	(2.35)					(0.08)		
Rt	10.13						**1.936**	0.132
	(2.82)						(1.66)	
Rt	10.28			**3.787**	0.225	1.324		0.205
	(2.79)			(1.95)	(0.12)	(0.55)		
Rt	15.96	-0.537	-2.130	**3.249**				0.224
	(0.96)	(-0.81)	(-0.32)	(1.74)				
Rt	20.92	-0.993	-4.213		1.715			0.121
	(1.17)	(-1.38)	(-0.62)		(0.88)			
Rt	20.59	-0.883	-4.484			1.020		0.087
	(1.08)	(-1.21)	(-0.59)			(0.40)		
Rt	26.06	-1.076	-5.964				**2.356**	0.263
	(1.57)	(-1.68)	(-0.92)				(2.01)	
Rt	24.86	-0.947	-5.572	3.048	1.528	2.610		0.276
	(1.29)	(-1.16)	(-0.73)	(1.46)	(0.68)	(0.94)		

Note: The sample period covers 1989-1993. We construct three daily indices, dealing with the following issues: (i) democracy and human rights in China (DEMO), (ii) Hong Kong's political future (HKFU), and (iii) China's Most-Favored-Nation (MFN) trading status with the U.S. News items are obtained from reports by the *Wall Street Journal*and the *New York Times*. We classify the news items into three categories: 1) good, 2) bad, and 3) neutral, with good news receiving a value of one and bad news a value of minus one.

We then aggregate the daily indices into quarterly indices by summing up the daily values within the quarter. The numbers highlighted are statistically significant at least at the 10% level.

Table 6.
Volatility Model Parameter Estimates

	average likelihood	α	β	ρ	ϕ	ψ	σ_{ψ}^2	λ	LR[a)]	P(LR)	SC [b)]
1969-1993 Weekly											
GARCH(1,1)	1.849	0.221	0.729						86.06	0.000	-4801
Components	1.849	0.192	0.757	0.958	0.029				104.2	0.000	-4786
GARCH(1,1)-Jump	1.882	0.138	0.805			0.002	0.005	0.081	18.25	0.001	-4865
Components-Jump	1.889	0.131	0.747	0.991	0.027	0.010	0.004	0.085			-4869*
Unit Root-Jump	1.885	0.152	0.832		0.058	0.041	0.006	0.037	10.43	0.001	-4866
1989-1993 Daily											
GARCH(1,1)	2.957	0.179	0.758						219.0	0.000	-7690
Components	2.959	0.079	0.000	0.938	0.156				221.6	0.000	-7681
GARCH-Jump	3.041	0.145	0.619			-0.004	0.002	0.030	7.824	0.020	-7888*
Components-Jump	3.044	0.145	0.479	0.928	0.017	-0.007	0.002	0.033			-7881
Unit Root-Jump	3.029	0.240	0.531		0.120	-0.117	0.007	0.006	39.12	0.000	-7849

a) LR is the likelihood ratio test. We test GARCH (1,1) against GARCH-Jump, Components against Components-Jump, GARCH-Jump against Components-Jump, and Unit Root-Jump against Components Jump respectively. P(LR) gives the statistical significance by which the model can be rejected against the alternative. Under the null, LR follow a χ^2 distribution with degrees of freedom equal to the difference in the number of parameters between the two models.

b) SC stands for the "Schwarz Criterion". $SC = -2\ln(L(\theta;x)) + K\ln(T)$, where L(*) is the likelihood function, K is the number of parameters in the model, and T is the number of observations.

Table 7.
Hong Kong Component-Jump Model Jump Dates

Mon 890130
Thu 890209
Wed 890315
Mon 890320
Thu 890330*

Thu 890504*
Fri 890519*
Mon 890522*
Mon 890605*
Fri 890804

Mon 891016*
Wed 900221*
Mon 900402*
Tue 900724
Mon 900806

Wed 900815
Wed 900822
Tue 900828
Tue 901002
Mon 901217*

Thu 910117
Tue 910205*
Fri 910315
Thu 910411
Mon 910422

Thu 910502
Tue 910521
Mon 910527*
Mon 910819
Tue 911210

Thu 920227
Wed 920408
Fri 920410
Tue 920707
Mon 920720*

Fri 920724
Mon 920817
Thu 920820*
Mon 920824*
Wed 920826*

Mon 921012*
Mon 921026*
Wed 921111*
Tue 921117*
Wed 921118*

Mon 921130*
Tue 921201*
Thu 921203
Mon 930111*
Thu 930128

Mon 930215
Fri 930226*
Thu 930311
Fri 930312
Mon 930315*

Tue 930413*
Wed 930414*
Thu 930603
Mon 930621
Tue 930803

Mon 930823
Thu 930826*
Mon 931011
Fri 931015*
Fri 931029

Wed 931103*
Mon 931129*
Mon 931206
Tue 931214
Thu 931216

Tue 931228*

*Jump date associated with political event dummy variable.

Table 8.
Regression of Daily Volatility Estimates on Political Risk Variables
Absolute Value of Aggregate Index
(T-Statistics)

<table>
<tr><th></th><th>R-squared</th><th>constant</th><th>|agg(-1)|</th><th>|agg|</th><th>|agg(+1)|</th><th>y(-1)</th></tr>
<tr><td>vol</td><td>0.663</td><td>0.043
11.338</td><td>0.012
6.341</td><td></td><td></td><td>0.791
48.396</td></tr>
<tr><td>vol</td><td>0.663</td><td>0.043
11.337</td><td>0.012
6.281</td><td>0.000
0.141</td><td></td><td>0.790
47.610</td></tr>
<tr><td>vol</td><td>0.663</td><td>0.043
11.368</td><td>0.011
5.630</td><td>0.000
-0.159</td><td>0.006
3.183</td><td>0.784
47.064</td></tr>
<tr><td>dvol</td><td>0.038</td><td>-0.002
-1.496</td><td>0.007
3.743</td><td></td><td></td><td>-0.161
-5.927</td></tr>
<tr><td>dvol</td><td>0.040</td><td>-0.001
-0.821</td><td>0.008
3.952</td><td>-0.003
-1.655</td><td></td><td>-0.158
-5.814</td></tr>
<tr><td>dvol</td><td>0.041</td><td>-0.002
-1.146</td><td>0.007
3.644</td><td>-0.004
-1.800</td><td>0.003
1.274</td><td>-0.156
-5.719</td></tr>
</table>

Table 9.
Regression of Daily Volatility Estimates on Political Risk Variables
Aggregate Index (Actual and Absolute Values)
(T-Statistics)

	R-squared	constant	agg(-1)	agg	agg(+1)	|agg(-1)|	|agg|	|agg(+1)|	y(-1)
vol	0.664	0.044	-0.003			0.011			0.789
		11.437	-1.543			6.009			48.164
vol	0.666	0.042	-0.003	0.005		0.011	0.001		0.794
		11.007	-1.872	2.599		5.919	0.460		47.448
vol	0.668	0.043	-0.003	0.006	-0.005	0.010	0.000	0.005	0.783
		11.296	-1.470	3.007	-2.931	5.375	0.236	2.758	46.546
ddvol	0.038	-0.002	0.000			0.007			-0.162
		-1.499	0.138			3.709			-5.908
ddvol	0.051	-0.001	-0.001	0.007		0.008	-0.002		-0.154
		-0.914	-0.520	3.892		3.918	-0.991		-5.638
ddvol	0.053	-0.002	-0.001	0.008	-0.002	0.007	-0.002	0.003	-0.149
		-1.268	-0.382	4.062	-1.069	3.605	-1.150	1.276	-5.442

Table 10.
Regression of Daily Volatility Estimates on Political Risk Variables
Absolute Value of Individual Indexes
(T-Statistics)

			Index (Lead/Lag)							
	R-squared	constant	NYT-China -1	WSJ-China -1	NYT-HK -1	WSJ-HK -1	NYT-MFN -1	WSJ-MFN -1	NYT-China 0	WSJ-China 0
vol	0.674	0.045	0.029	-0.005	-0.003	0.027	0.000	0.006		
		11.982	8.182	-0.888	-0.492	4.025	0.027	0.877		
vol	0.678	0.044	0.029	-0.004	-0.004	0.027	0.001	0.006	-0.007	0.017
		11.649	8.242	-0.783	-0.606	4.074	0.095	0.852	-1.832	3.129
vol	0.684	0.045	0.026	-0.007	-0.001	0.026	0.002	0.005	-0.008	0.015
		11.924	7.293	-1.217	-0.191	4.049	0.342	0.783	-2.369	2.790
dvol	0.054	-0.002	0.019	-0.008	-0.008	0.023	0.001	0.005		
		-1.589	5.148	-1.291	-1.191	3.251	0.163	0.708		
dvol	0.068	-0.002	0.021	-0.006	-0.009	0.023	0.001	0.005	-0.013	0.014
		-0.986	5.679	-1.064	-1.232	3.339	0.154	0.713	-3.508	2.507
dvol	0.087	-0.002	0.019	-0.008	-0.005	0.023	0.002	0.006	-0.015	0.013
		-1.056	5.047	-1.341	-0.727	3.365	0.320	0.817	-3.882	2.258

Table 10 (cont'd).
Regression of Daily Volatility Estimates on Political Risk Variables
Absolute Value of Individual Indexes
(T-Statistics)

	NYT-HK 0	WSJ-HK 0	NYT-MFN 0	WSJ-MFN 0	NYT-China 1	WSJ-China 1	NYT-HK 1	WSJ-HK 1	NYT-MFN 1	WSJ-MFN 1	y(-1)
vol											0.781
											48.122
vol	-0.010	0.009	-0.003	-0.001							0.785
	-1.525	1.324	-0.650	-0.089							47.504
vol	-0.009	0.007	-0.003	0.000	0.017	-0.013	0.018	0.001	0.002	-0.007	0.778
	-1.420	1.105	-0.594	-0.064	4.741	-2.366	2.782	0.137	0.317	-0.996	47.386
dvol											-0.155
											-5.694
dvol	-0.012	0.004	-0.003	-0.003							-0.137
	-1.770	0.627	-0.502	-0.358							-5.010
dvol	-0.012	0.003	-0.003	-0.002	0.012	-0.017	0.018	-0.006	0.002	-0.009	-0.138
	-1.666	0.431	-0.527	-0.314	3.282	-2.998	2.584	-0.814	0.408	-1.246	-5.075

Table 11.
Regression of Daily Volatility Estimates on Political Risk Variables
Individual Indexes (Actual and Absolute Values)
(T-Statistics)

			Index/Absolute Value of Index (Lead/Lag)							
	R-squared	constant	NYT-China -1	WSJ-China -1	NYT-HK -1	WSJ-HK -1	NYT-MFN -1	WSJ-MFN -1	NYT-China 0	WSJ-China 0
vol	0.677	0.046	0.002	-0.003	-0.007	-0.019	-0.001	-0.001		
		12.133	0.557	-0.529	-0.854	-2.813	-0.119	-0.142		
			0.028	-0.005	-0.004	0.024	0.000	0.007		
			7.971	-0.953	-0.495	3.505	0.002	1.011		
vol	0.683	0.043	0.001	-0.002	-0.006	-0.019	0.000	-0.002	0.004	0.012
		11.426	0.183	-0.449	-0.705	-2.892	-0.057	-0.316	1.057	2.307
			0.029	-0.004	-0.005	0.023	0.000	0.007	-0.006	0.018
			7.994	-0.772	-0.619	3.414	0.086	0.996	-1.546	3.348
vol	0.691	0.045	0.000	0.000	-0.005	-0.018	-0.001	-0.001	0.005	0.011
		11.870	0.103	0.045	-0.627	-2.719	-0.172	-0.077	1.603	2.114
			0.026	-0.008	-0.002	0.023	0.001	0.007	-0.007	0.016
			7.164	-1.442	-0.265	3.429	0.199	1.081	-1.910	2.900
dvol	0.059	-0.002	0.005	0.000	-0.003	-0.015	0.000	0.002		
		-1.626	1.396	0.007	-0.410	-2.137	0.079	0.312		
			0.019	-0.007	-0.007	0.020	0.001	0.006		
			5.183	-1.276	-0.829	2.799	0.149	0.798		
dvol	0.086	-0.002	0.002	0.000	-0.003	-0.016	0.001	0.000	0.006	0.016
		-1.065	0.670	-0.024	-0.308	-2.343	0.166	0.041	1.750	2.944
			0.021	-0.006	-0.008	0.020	0.001	0.006	-0.011	0.016
			5.656	-0.961	-0.935	2.739	0.135	0.813	-2.933	2.864
dvol	0.107	-0.002	0.002	0.002	-0.002	-0.017	0.000	0.002	0.007	0.015
		-1.137	0.489	0.276	-0.199	-2.378	-0.052	0.249	1.997	2.675
			0.019	-0.008	-0.004	0.020	0.001	0.007	-0.012	0.015
			5.012	-1.422	-0.406	2.763	0.184	1.041	-3.264	2.533

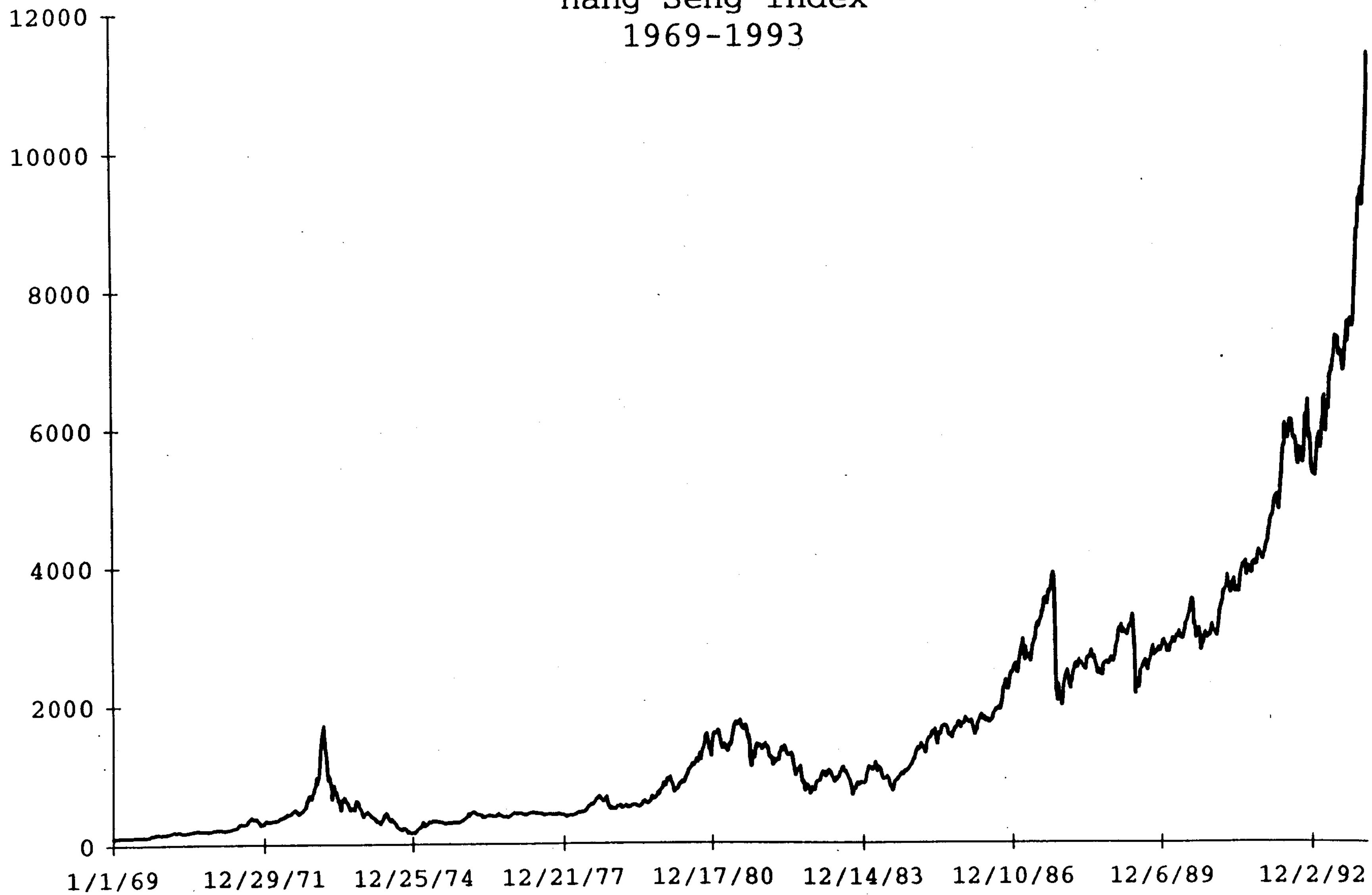
Table 11 (cont'd).
Regression of Daily Volatility Estimates on Political Risk Variables
Individual Indexes (Actual and Absolute Values)
(T-Statistics)

Index/Absolute Value of Index (Lead/Lag)

	NYT-HK 0	WSJ-HK 0	NYT-MFN 0	WSJ-MFN 0	NYT-China 1	WSJ-China 1	NYT-HK 1	WSJ-HK 1	NYT-MFN 1	WSJ-MFN 1	y(-1)
vol											0.778
											48.044
vol	0.003	0.000	-0.003	0.006							0.788
	0.350	-0.012	-0.517	0.966							47.561
	-0.009	0.008	-0.003	-0.002							
	-1.106	1.169	-0.596	-0.229							
vol	0.002	0.002	-0.003	0.007	-0.007	0.001	-0.005	-0.010	0.002	-0.005	0.778
	0.202	0.280	-0.605	1.130	-2.198	0.094	-0.701	-1.577	0.420	-0.770	47.158
	-0.008	0.007	-0.002	-0.001	0.015	-0.013	0.016	-0.001	0.001	-0.006	
	-0.994	0.969	-0.464	-0.109	4.136	-2.329	2.036	-0.195	0.168	-0.908	
dvol											-0.157
											-5.744
dvol	0.005	0.003	-0.002	0.010							-0.137
	0.607	0.378	-0.336	1.486							-5.007
	-0.009	0.004	-0.003	-0.004							
	-1.084	0.535	-0.454	-0.524							
dvol	0.004	0.004	-0.002	0.011	-0.004	0.006	-0.004	-0.007	0.004	-0.001	-0.135
	0.480	0.619	-0.364	1.590	-1.050	1.104	-0.473	-1.010	0.692	-0.186	-4.961
	-0.009	0.002	-0.002	-0.003	0.012	-0.016	0.018	-0.007	0.001	-0.008	
	-1.013	0.293	-0.420	-0.403	3.027	-2.764	2.092	-1.040	0.248	-1.196	

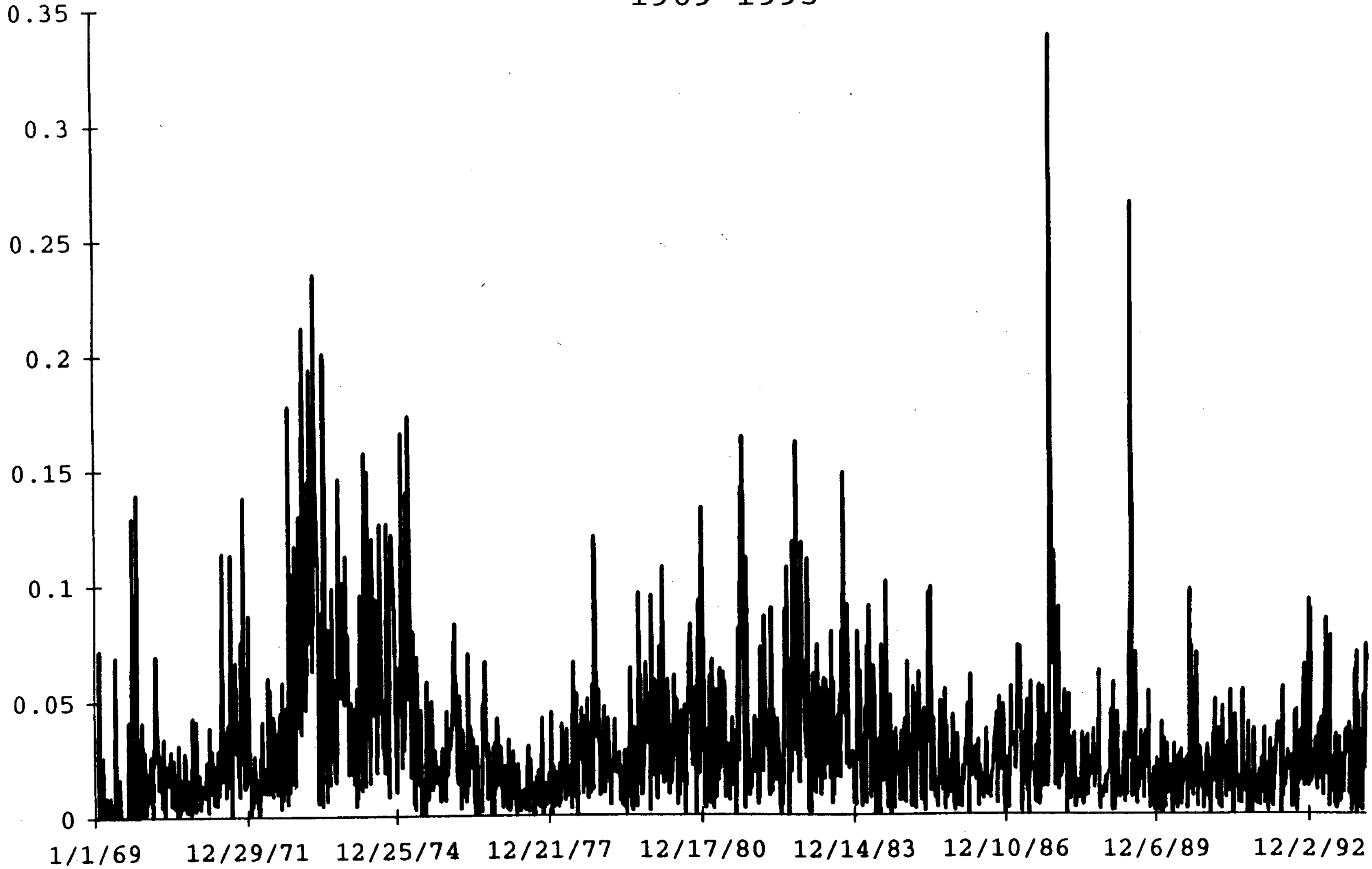
Note: First line of each specification provides coefficient estimates for actual index values; second line provides coefficent estimates for absolute value of indexes.

Figure 1.
Hang Seng Index
1969-1993



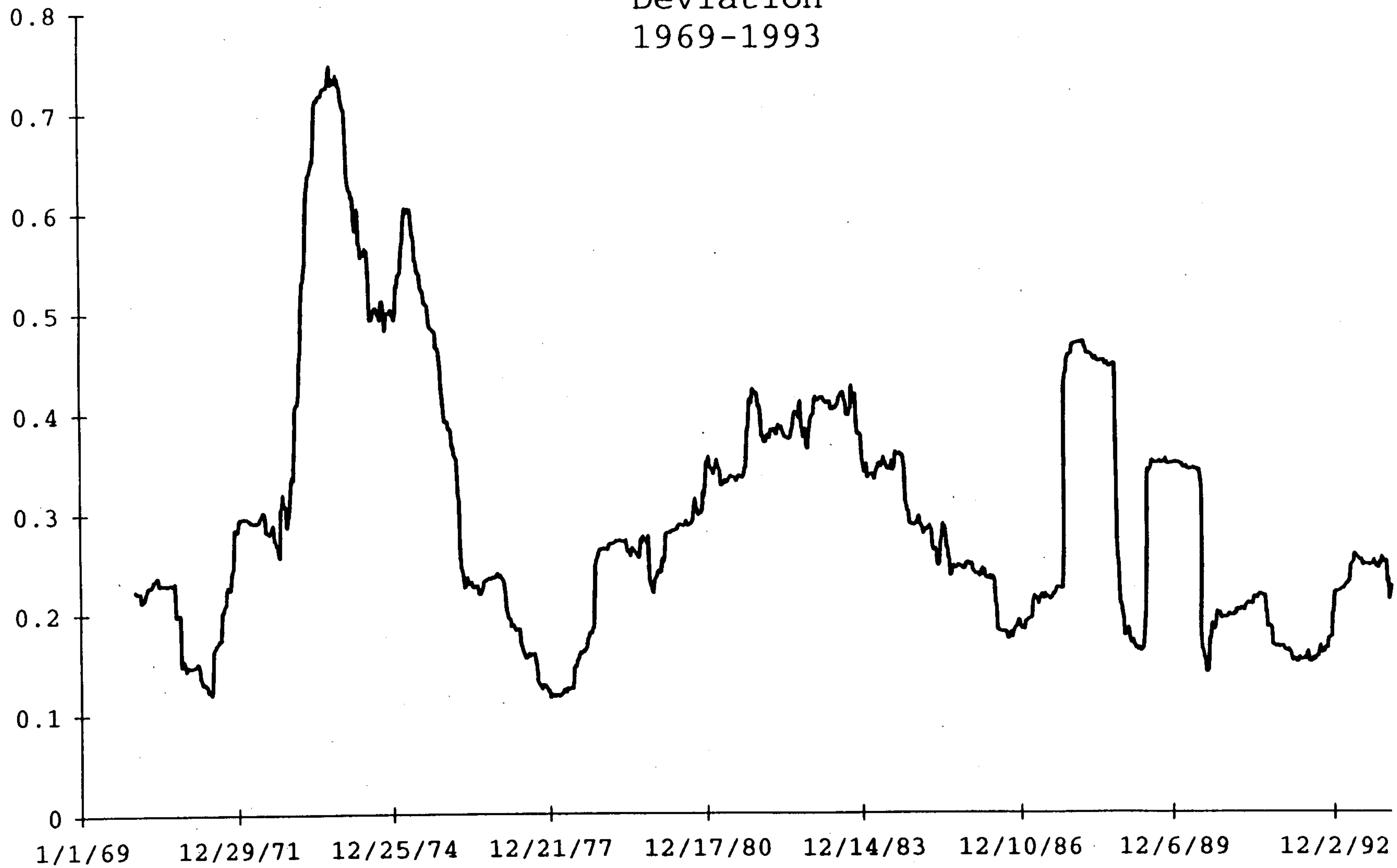
Source: Datastream.

Figure 2.
Hang Seng Index, Absolute Value of Weekly Returns
1969-1993



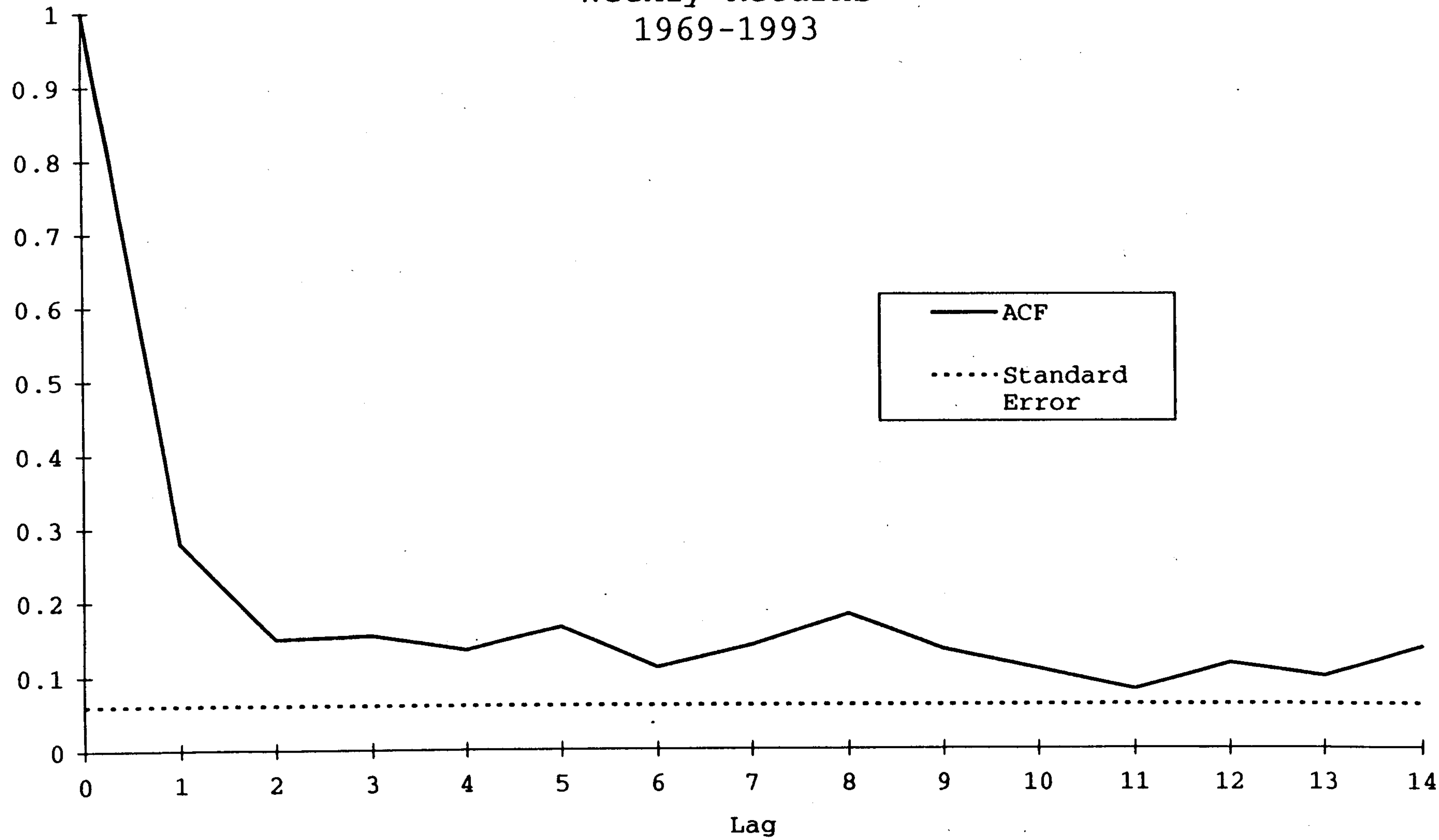
Source: Datastream

Figure 3.
Hang Seng Index Annualized Rolling One-Year Standard Deviation
1969-1993



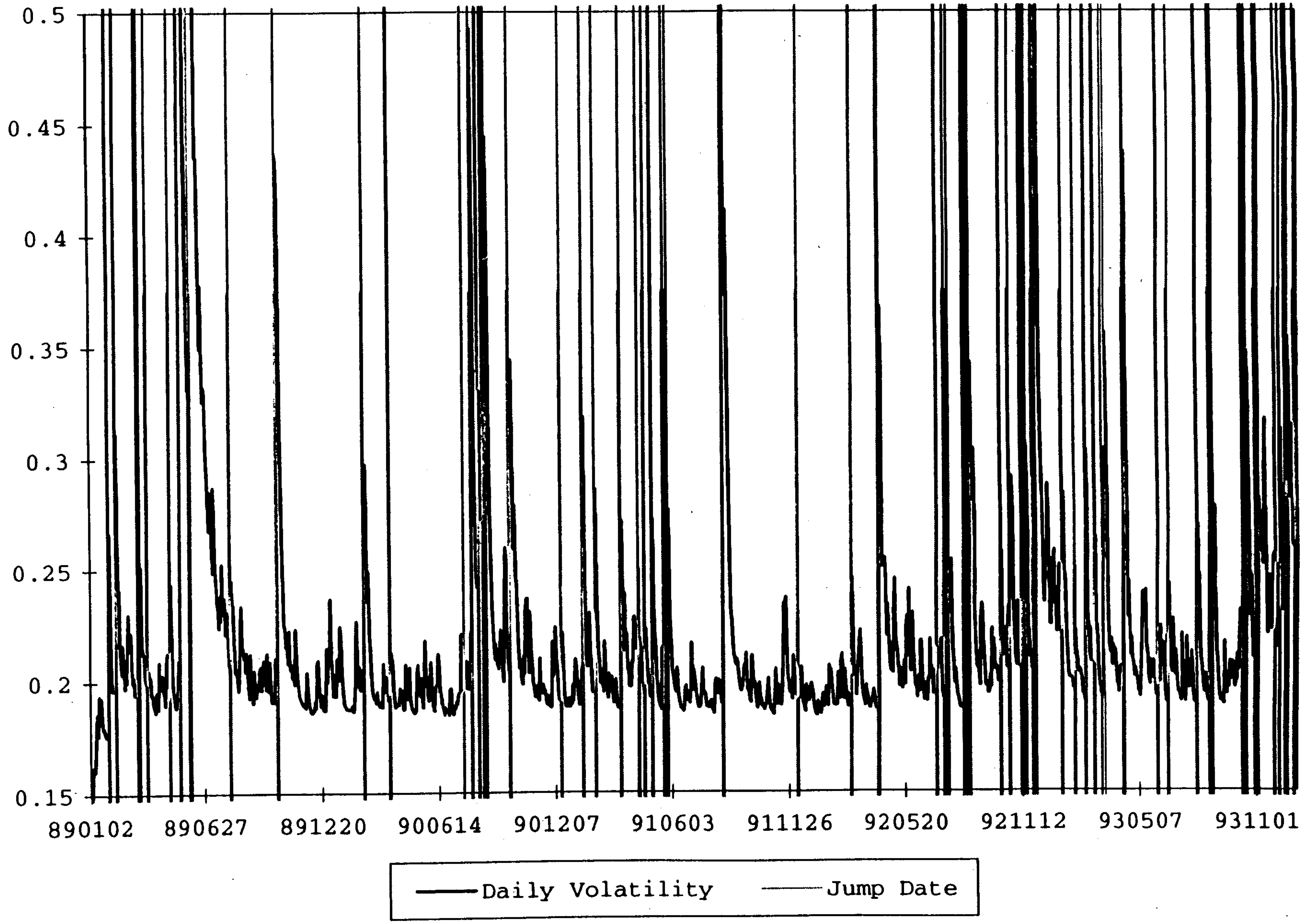
Sources: Datastream and Salomon Brothers.

Figure 4.
Autocorrelation Function for Squared Hang Seng Index
Weekly Returns
1969-1993



Source: Salomon Brothers.

Figure 5.
Hang Seng Index Daily Volatility Forecasts and
Estimated Jump Dates, 1989-1993



Source: Salomon Brothers.