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What makes the stock market jump? An analysis of political risk on Hong Kong stock returns

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Abstract

This paper employs a components-jump volatility filter to investigate the possible market impact of political risk. The filter operates by identifying jump return dates, which are then associated with political events, allowing us to measure the market return and volatility effects of political announcements. Our empirical results show that political developments in Hong Kong have a significant impact on its market volatility and return. The results have some interesting implications for option pricing and political risk management. © 2001 Published by Elsevier Science Ltd.

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Previous studies suggest a close association between political risks and stock markets.[1] Dramatic political changes such as transformation from a market economy to a socialist economy may shift corporate ownership from shareholders to the state,

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[1] See La Porta et al. (1997) for a detailed study on the impact of legal system on corporate finance.

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causing huge financial losses to shareholders.[2] Changes in government administration also tend to affect fiscal and monetary policies, thereby affecting stock markets. Despite the huge potential impact, there has been relatively little empirical study on the effects of political factors on stock prices and volatilities. Instead, most studies focus exclusively on the impact of economic events on stock prices—it is perhaps no wonder, then, that many researchers find that a large fraction of significant market movements and volatility are difficult to explain (see Roll, 1988; Fama, 1990; Schwert, 1989). Cutler et al. (1989) did study the impact of political news on stock market, but they found no evidence of significant impact on the US stock market. The only exceptions are recent studies by Chan and Wei (1996), Willard et al. (1996) and Bittlingmayer (1998), which did find some significant evidence that political news affect currency or equity markets.

In this paper, we use a components-jump volatility filter to investigate the potential impact of political events on stock markets. The filter is an extension of the ARCH-jump model presented in Jorion (1988). It identifies dates with jump, or surprise, return movements, which are then associated with political news announcements, allowing us to quantify the return and volatility effects of political events. In conducting our empirical study, we chose to focus on the Hong Kong market, which we consider an ideal case study for two reasons. (i) The Hong Kong market is characterized by a high degree of volatility, with frequent and large jumps—providing us a high degree of confidence in associating market movements with political events. (ii) Hong Kong's political shocks are frequent, unpredictable and well defined during our sample period, allowing us to construct meaningful indices of political risk.

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 an association between market jumps and political news? How large an effect do political events have on market volatility? These are the questions which we will address in this paper.

The organization of the paper is as follows. Section 1 provides a brief history of Hong Kong and major political events during the sample period. Section 2 describes a components-jump volatility filter to capture the movements in the Hong Kong stock index. Next, we link Hong Kong volatility changes to its political events using two methodologies, and find the volatility effects of the political risk variables to be significant—these results are presented in Section 3. Section 4 concludes.

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[2] 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).

1. A brief history of Hong Kong and major political events during 1989–93

Hong Kong became a British colony in 1842, when China lost the Opium War to the United Kingdom. In 1898, the British further leased the New Territories near Hong Kong for 99 years. 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 (and the New Territories) be returned to China in 1997. In 1984, China and the United Kingdom worked out a "one country, two system" formula in which China guaranteed Hong Kong's current way of life for 50 years after the return of Hong Kong to China in 1997.

During the 1989 to 1993 period covered by this study, there were many notable political events. The first was the 1989 Tienanmen Democracy Movement, when student demonstrations in China raised the possibility of real political reform. However, the crackdown in early June 1989 dashed the hopes of short-term political reform. Sino–US relations were another major source of political risk. After the June 4 Tiananmen Square Crackdown, the US came close several times to canceling China's most-favored-nation (MFN) trading status based on China's human rights record, seriously threatening Hong Kong's foreign trade and its position as China's trading window to the West. Another major source of political uncertainty came out 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 on the issue of democratic reforms.

2. The components-jump volatility filter

We now introduce a volatility filter constructed to suit the return characteristics of the Hong Kong market. The volatility filter explicitly accounts for two unique features of the return process in Hong Kong—the large shifts in underlying volatility and the prevalence of return spikes, 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 filter consists of two parts, which are considered jointly in the statistical estimation process: (a) a fundamental ARCH-derivative filter of volatility, based on the components model of Engle and Lee (1993), which captures the time-varying long-term volatility, and (b) a jump (*Poisson*) process, which accounts for the return spikes.

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

$$r_t = a + br_{t-1} + \varepsilon_t + \eta_t,$$

$$\varepsilon_t \sim N(0, h_t),$$

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

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

$$\eta_t = \sum \gamma_i \text{ (for } i = 0 \text{ to } m_t),$$

$$\gamma_i \sim N(\psi, \sigma^2) \text{ and } m_t = p(\lambda).$$

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 ρ=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. It is worth noting that the components filter reduces to a GARCH filter if the long-term variance, q_t, is constant.

The reason we introduce the component filter is because there is some evidence that Hong Kong volatility may contain a time-varying low frequency component. Fig. 1 shows the absolute value of daily returns for the Hong Kong market (the Hang Seng Index) over the sample period from 1989–1993. The data are obtained from Datastream. We can observe the presence of well-defined high and low volatility periods—the second half of 1989 and first half 1990 seem relatively calm,

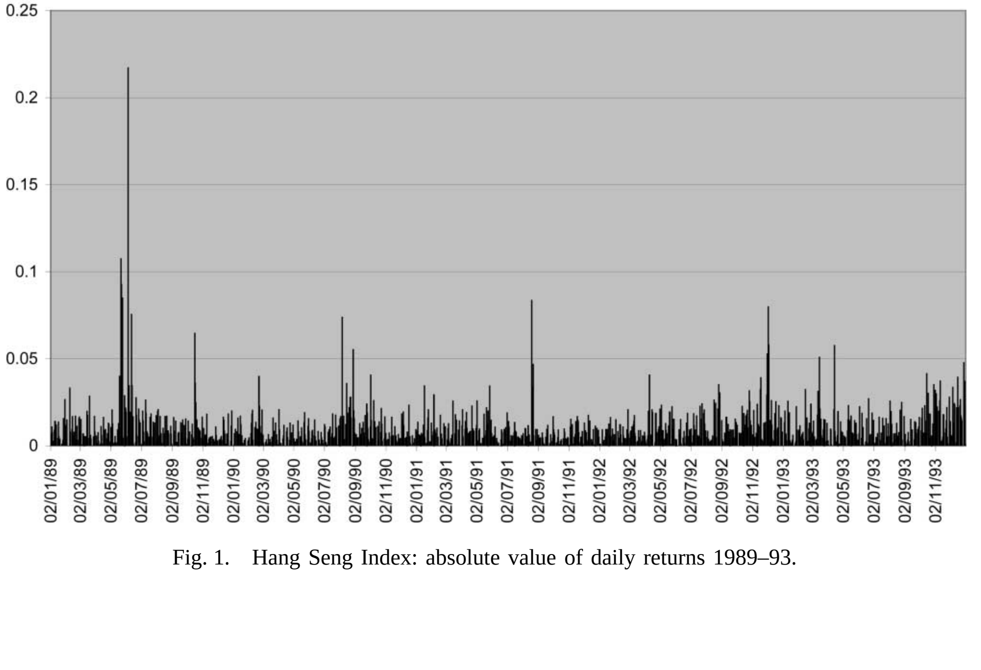

Fig. 1. Hang Seng Index: absolute value of daily returns 1989–93.

whereas the second quarter of 1989 and fourth quarter of 1992 are a period of extreme volatility, as are, to a lesser extent, the third quarter of 1993. These low frequency movements in volatility are visible in Fig. 2, which plots rolling three-month standard deviation of daily returns.

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. This jump process is used to capture a distinctive characteristic of the Hong Kong market, which is the prevalence of large, outlier return movements as evident from Fig. 1. Clearly, any filter must incorporate these outlier movements to adequately represent the behavior of the Hong Kong market. In practice, m_t, which is Poisson distributed with intensity parameter λ, is generally either zero or one per period for small λ—i.e., 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 US equity volatility.

The intuition behind the estimation procedure is as follows. Each period, the filter examines the return forecasting error innovation $r_t - a - br_{t-1}$, comparing the size of the shock to the estimated fundamental conditional volatility. If this normalized error is large, the filter 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. Note that not all outliers are identified as jumps. A shock occurring during a period of low volatility would be identified by the filter as a jump, and no volatility effect would be imputed; however, a large move during a high volatility period would not be considered as a jump and therefore have persistent volatility effects.

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 unfore-

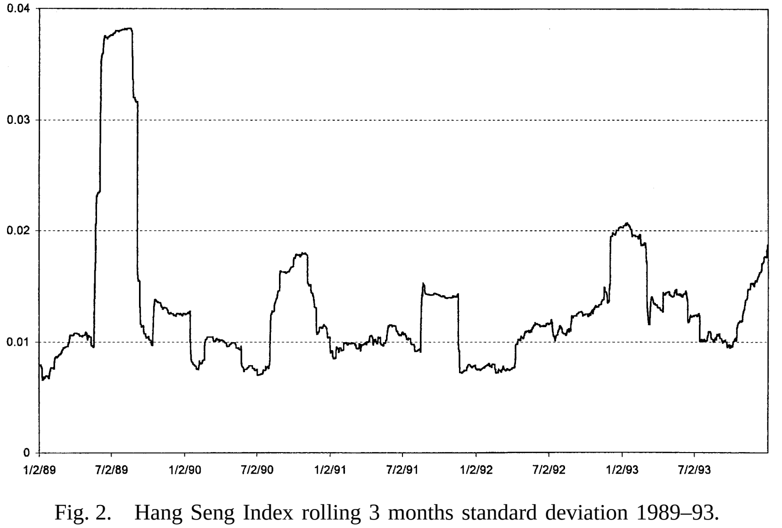

Fig. 2. Hang Seng Index rolling 3 months standard deviation 1989–93.

castable, occurring with constant probability λ per period, regardless of whether a jump has recently occurred. Fitting of the filter also 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. As a by-product of the estimation, the filter estimates jump return dates, which we match with political event dates to assess the effects of political risk on volatility.

In the next section, we will present empirical estimates for the components-jump filter, along with comparative estimates for the pure GARCH and components filters. We estimate the filter using maximum likelihood estimation techniques (see Jorion (1988) for a discussion of the likelihood function). Due to severe non-convexity of the components-jump filter, we use a non-gradient based technique called simulated annealing to estimate the parameters of the filter; hence, we do not report standard errors for the coefficient estimates.[3]

3. Empirical results

3.1. Estimating the components-jump filter

Our sample period covers the 1989–1993 period (daily) that coincides with the dates of our political risk variables. The parameter estimates are presented in Table 1. For the GARCH(1,1) filter, the average likelihood, which is defined as the maximum likelihood value divided by the sample size, is estimated to be 2.957, while the volatility persistence rate is estimated to be $\alpha+\beta=0.937$. The components filter provides only a slightly better fit—the likelihood is estimated to be almost the same as that of the GARCH(1,1). The decay rate of the permanent component, ρ, is estimated as 0.938, implying approx. 52.7% ($=0.938^{10}$) of a shock remains after ten trading days.

The addition of the jump component leads to an increase in the likelihood function—the average likelihood increases by 0.084 to 3.041 for the GARCH(1,1) plus jump, with an increase of 0.085 to 3.044 for the components plus jump filter. To test the GARCH (1,1) filter against the GARCH-jump filter, we perform a likelihood ratio test. If the nested filter is true, the likelihood ratio follows a χ^2 distribution with degrees of freedom equal to the difference in the number of parameters between the two filters. As we can see from Table 1, the GARCH(1,1) filter is strongly rejected in favor of the GARCH-jump filter ($P=0.000$) and the GARCH-jump filter is rejected in favor of the components-jump filter ($P=0.002$). The jumps are estimated

[3] Non-gradient optimization techniques are particularly useful here since the first derivatives of the objective function could be discontinous. The main drawback of the techniques is that one may not be able to obtain reliable estimates of standard errors on the parameters estimates. This is because standard errors are typically computed from the Hessian matrix at the optimum. If this matrix does not exist, or is not a good approximation to the local behavior of the likelihood function, then the standard errors have to be interpreted with care.

Table 1
Return filter parameter estimates

	α	β	ρ	ϕ	ψ	$\sigma\psi^2$	λ	Average likelihood
1989-1993 Daily								
GARCH(1,1)	0.179	0.758						2.957
Components	0.079	0.000	0.938	0.156				2.959
GARCH-jump	0.145	0.619			−0.004	0.002	0.030	3.041
Unit root-jump	0.240	0.531		0.120	−0.117	0.007	0.006	3.044
Components-jump	0.145	0.479	0.928	0.017	−0.007	0.002	0.033	3.029

	LR[a]	$P(LR)$	SC[b]
1989–1993 Daily			
GARCH(1,1) vs. GARCH-jump	219.0	0.000	−7690
Components vs. components-jump	221.6	0.000	−7681
GARCH-jump vs. components-jump	7.824	0.020	−7888[c]
Unit root-jump vs. components-jump	39.12	0.000	−7849
Components-jump			−7881

[a] Average likelihood is the maximum likelihood value divided by the sample size. LR is the likelihood ratio test. $P(LR)$ gives the statistical significance by which the model can be rejected against the alternative. Under the null, LR follow a ξ^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". $SC = -2\ln(L(*;x)) + K\ln(T)$, where $L(*)$ is the likelihood function, K is the number of parameters in the model, and T is the number of observations.

[c] The GARCH-jump filter is selected based on the "Schwarz Criterion".

as having a probability of approx. 3% (3.3%), and a mean magnitude of -0.4% (-0.7%) with a standard deviation of approx. 0.5%, for the GARCH-jump (components-jump) filter.

The persistence of the component-jump filter is estimated to be 0.62, implying a moderate level of persistence in the permanent component of the variance. The significant increase in ρ to 0.62 for the components-jump filter, relative to the 0.08 estimate from the simple components filter, is not surprising—excluding the effects of quick-decaying return spikes results in a higher estimated overall persistence level for the components-jump filter. (The simple component filter is rejected in favor of component-jump filter with P=0.000.)[4]

The *LR* tests reject all other specifications in favor of the components-jump filter. However, to adjust for the difference in the number of parameters in the different likelihood functions, we also compute the Schwarz statistics for various filter specifications. Using the "Schwarz Criterion" of picking the filter with the lowest value, our results suggest the GARCH-jump filter for the daily data.[5]

3.2. Political risk and volatility movements

Given the presence of market jumps, this section will try to associate market jumps with political news announcements and examine the effects of political risk on volatility movements in the Hong Kong equity market. We conduct two simple tests. The first test involves regressing volatility levels and changes on the political dummy variables, to ascertain the volatility impact of the announcement effects. The second 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 political news indices are derived from the abstracts of the *Wall Street Journal* and the *New York Times*. We construct three indices, each dealing with a separate

[4] Indeed, imposing a unit root on the permanent component, that is, imposing the condition that ρ=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.)

[5] The existence of large jumps in the Hang Seng Index raises an interesting question whether similar jumps are also present in other major market indices. We also examine the price process of several major market indices, such as the S&P 500, the FT 100, and the Nikkei index. We find a jump component is significantly present in all three indices. However, the jumps are more important for markets in Japan and Hong Kong than for United States and Britain. These results are available upon request. The presence of price jumps in the Hang Seng index as well as other major market indices has important implications for option pricing. The validity of classic option pricing models depends on the assumption that the price of the underlying asset follow a continuous-time diffusion process whose sample path is continuous with probability one. The existence of price jumps implies that investors will not be able to replicate the payoff structure to the option. As a result, one can not use the continuous arbitrage-free condition directly to price options. Given the fact that billions of dollars of option contracts are bought and sold everyday on these four indices in the world, our results call for the development and test of option pricing models that allow for discontinuous sample path, such as that of Merton (1976).

political issue: (i) democracy and human rights in China (DEMO),[6] (ii) Hong Kong's political future (HKFU), and (iii) China's most-favored-nation (MFN) trading status with the US 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.[7] The result is six political dummy variables 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 indices enable us to pinpoint political risk event dates.

Table 2 details results of regressions of daily volatility estimates on the aggregate of the political risk dummy variables (which is the sum of six individual series). Due to the autocorrelated nature of the volatility processes, we include lagged dependent variables as well. In addition, we also examine lagged as well as lead values of the risk variables due to the fact that news may arrive during weekends when markets were closed and the time difference between New York and Hong Kong. To differentiate the effects of positive and negative announcements, we regress *vol* on both the aggregate index and the absolute value of the aggregate index—the results are shown in Table 2. Looking at the 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% $(=-1*(-0.3\%+0.6\%-$

Table 2
Regression of daily volatility estimates[a] on political risk variables aggregate index (actual and absolute value)$\text{vol}_t = C_0 + C_1Y_{t-1} + C_2\text{agg}_{t-1} + C_3\text{agg}_t + C_4\text{agg}_{t+1} + C_5|\text{agg}_{t-1}| + C_6|\text{agg}_t| + C_7|\text{agg}_{t+1}| + \varepsilon$

	Constant	vol_{t-1}	agg_{t-1}	agg_t	agg_{t+1}	$\lvert\text{agg}_{t-1}\rvert$	$\lvert\text{agg}_t\rvert$	$\lvert\text{agg}_{t+1}\rvert$	R^2
vol	0.044	0.789	−0.003			0.011			0.664
	(11.43)	(48.16)	(−1.543)			(6.009)			
vol	0.042	0.794	−0.003	0.005		0.011	0.001		0.666
	(11.00)	(47.44)	(−1.872)	(2.599		(5.919)	(0.460)		
vol	0.043	0.783	−0.003	0.006	−0.005	0.010	0.000	0.005	0.668
	(11.29)	(46.54)	(−1.470)	(3.007)	(−2.931)	(5.375)	(0.236)	(2.758)	

[a] Note: Volatility estimates are derived from the components-jump model for the sample period of 1989-1993. *t*-Statistics are provided in parentheses.

[6] Chan and Wei (1996) also constructed an political index for DEMO and studied its impact on Hong Kong Market volatility. However, they did not study the other two indices. They also did not employ the components-jump model used in this paper.

[7] 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 MFN trading status with the US. 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.

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" effect studied by Campbell and Hentschel (1992).[8]

Fig. 3 lists the jump dates estimated by the GARCH-jump filter over the 1989–1993 period—together with the estimated daily volatility. Over all, there are 71 days identified as having jump return movements, out of a total of 1304 observations, for a realized jump frequency of 5.4%. For all identified jump dates, the filter estimates one jump as having occurred, i.e., m_t=1, except for June 5, 1989, the date of Tiananmen Square Crackdown, for which the filter estimates m_t=3. Of the 71 jumps, 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

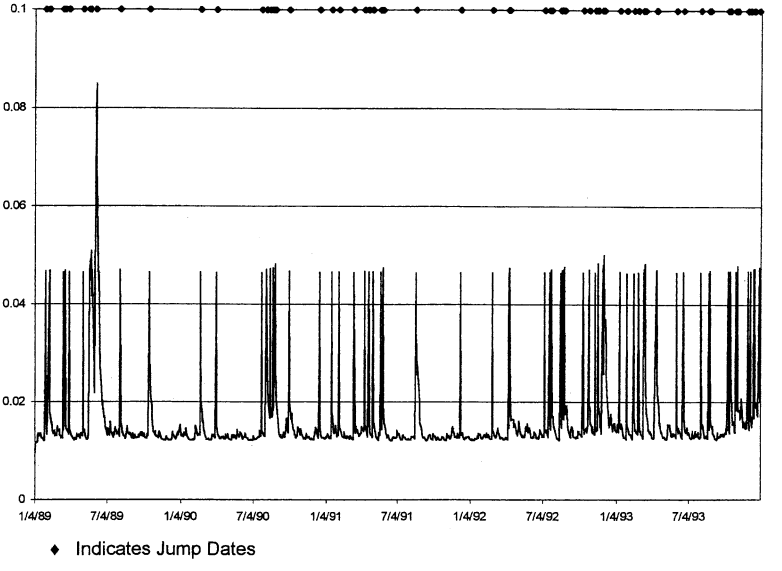

Fig. 3. Hang Seng Index daily volatility estimates based on GARCH(1,1)-jump filter and estimated jump dates. ◆ Indicates jump dates.

[8] To further investigate the effects of the different types of political risk—human rights, Hong Kong's political future, or MFN—we regress the volatility estimates on the individual dummy series. We find the individual dummies all have significant explanatory power over daily volatilities. 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. These results were presented in an earlier version of the paper and they are available from the authors upon request.

the day following, a return jump.[9] (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 less than 10%. Thus, we conclude that the 32 matches we observed from the sample is statistically significant.[10]

Critics may argue that the above results may be sensitive to the particular filters used. As a robustness check, we also perform the Cutler et al. (1989) analysis by matching news events to stock returns. Since it is hard to define what is "major" news comparing to ordinary news, our approach is to select largest market movements and then match them with headline political news. Largest market movement is defined by movements exceeding three times the Hang Seng Index daily market volatility (1.4%) during the 1989–1993 sample period. The result is reported in Table 3. As we can see from the most major market movements can be accounted for by surprising major news development, either related to major world events, such as the Gulf War and the Russian Coup, or major political developments in China, such as the June 4 army crackdown in Beijing and Sino–British standoff on democratic reform in Hong Kong.

4. Conclusion

This paper provides a systematic approach to evaluate the impact of political risk on stock price and volatility movements. Our main findings can be summarized as

[9] The time in New York is generally 12 hours behind Hong Kong time. Thus, news can be reported one day later in New York.

[10] 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.

Table 3
Largest market[a] movements and corresponding major political news

Date	% Change	Main event
06/05/89	−21.7%	June 4 army crackdown on student demonstrations in Tiananmen Square
05/22/89	−10.8%	Martial Law declared in Beijing
05/23/89	9.3%	Over a million workers and citizens were able to halt a military crackdown on pro-democracy movement in Beijing the day before.
05/25/89	−8.5%	Many conflicting developments in Beijing on the student democracy movement.
08/19/91	−8.4%	Russian coup against reformist president Gorbachev.
12/03/92	−8.0%	War of words intensifies between China and Britain following the break down of negotiations on Hong Kong's future
06/12/89	7.6%	
08/06/90	−7.4%	Gulf crisis erupted with Iraqi invasion of Kuwait.
10/16/89	−6.5%	The Communist Party in Beijing has called for a purge of its members and suggested prolonged hard line policy after June 4.
12/04/92	5.8%	
04/14/93	5.8%	China and Britain announced on April 13 to reopen talks after a long standstill.
08/28/90	5.5%	
12/01/92	−5.3%	Negotiation between China and Britain broke down. Both sides threatened to breach previous agreements on the future of Hong Kong.
03/15/93	−5.1%	Hong Kong Governor Chris Patten announced that he would unilaterally press ahead with democratic reform due to negotiation deadlock with China.
12/28/93	4.8%	
08/22/91	4.7%	Russian coup against president Gorbachev failed.

[a] Note: Largest market movement is defined by movements exceeding three times the Hang Seng Index daily market volatility (1.4%) during the 1989–1993 sample period.

follows. First of all, we extend the ARCH-jump filter of Jorion (1988) to examine the benchmark Hang Seng index. We discover that there is a significant jump component in the Hong Kong market index. Using political indices constructed for Hong Kong, 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. At the return level, we find that the largest market movements in Hong Kong were often associated with major political news.

Our work contributes to the volatility literature in a number of respects. First of all, we show that volatility movements are associated with political developments. This may help resolve the excess volatility puzzle found by previous studies that volatility moves too much to be justified by economic factors.[11] Second, our results supports the argument of Robert Merton that high stock volatility could be related to the "Peso problem", meaning there was legitimate uncertainty about the survival

[11] See Schwert (1989).

of the economic system. To the extent that political news provide information about the likelihood of survival, our study offers an indirect test of the Merton hypothesis. Our results of significant impact of political risk on volatility are consistent with the hypothesis.

Our results have several interesting implications. First of all, the presence of price jumps suggests that the conventional option pricing models which assume no price jumps may misprice derivative products associated with the benchmark market indices. This calls for the development of option pricing models which explicitly incorporate the jump process. It also suggests that a dynamic stop-loss/hedging strategy which based on the continuous market price movements may not be effective and could lead to unexpected loss when large jumps occur. Second, multi-national corporations which invest heavily in emerging markets with less stable political systems could partially hedge their political risk by taking a short position in the countries' stock markets, if these markets are sensitive to political developments. The fact that price jumps are associated with political risks may also help financial institutions constructing derivative products based on price jumps, which may help multinational corporations hedge their political risk.

Hedging political risk is an important part of the overall risk management of multinational corporations. In 1992, the developed nations made over $150 billion investment in politically unstable emerging markets. Over the last 10 years, the cumulative investment to emerging markets totaled more than $1.2 trillion. Most of these investments are exposed to various degrees of political risks. However, despite the fact that many corporations have earthquake and fire insurance, few of them have political risk insurance. Given the fact that political risk could cause huge damage to foreign investments, political risk exposure would significantly increase the likelihood of bankruptcy for multi-national firms, thereby affecting their equity and debt pricing. Moreover, because of the integration of the world economy, political risks could be systematic and be priced by the market, as we have seen from the Russian political instability and bond default in 1998. However, despite the importance, there are little work in finance literature on the pricing and management of political risks. We hope further research in this area may lead to the creation of financial markets for trading and hedging political risks.

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