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VaR and Stress Tests: The Impact of Fat-Tail Risk and Systemic Risk on Commercial Banks in Hong Kong and China

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Abstract

This study shows that the statistical property of the commercial banks' rate of returns can be used to explain the resistance to using Value-at-risk (VaR) and stress tests to determine banks' capital adequacy. We showed that "fat-tail" risk requires more capital than the "normal tail" risk estimated by VaR, which assumes normal distribution. The puzzle that most banks in Europe and Asia maintained higher capital levels than required by regulators before the 2008 financial crisis can be reinterpreted as rational action to protect financial companies against abnormal fat-tail risk, which may reflect inside information, such as off-balance sheet activities, rather than regulations. Micro- and macro-prudential policies are needed not only to discourage fat-tail risk seeking, but also to cover the higher social costs caused by higher systemic risk and bank diversification, which are affected by the heaviness of the tail and limited liability of bank charter.

Keywords: Value-at-Risk, Stable Paretian distribution, Systemic risk, Fat-tail risk, Off-balance sheet activities

JEL classification: G22, G28, G33

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1. Introduction and Objectives

Basel II and III require commercial banks to increase risk-based capital to about 8% to 12%. In addition to the Value-at-Risk (VaR) exercise, commercial banks must conduct stress tests (ST) to assess tail risk under different stressful micro- and macro-economic scenarios. Many financial companies in Europe refused to increase their capital level because of the statistical problem associated with stress tests. Some of them believed that ST were “black boxes” and they overestimated capital requirement¹. The argument is not consistent with the fact that the US government had to inject US\$235 billion into the banking system as part of the Troubled Asset Relief Program (TARP) in 2008 and 2009 [see Berlin (2011)]. However, the statistical problems of VaR and ST have been recognised by many researchers, such as Kupiec (2000) and Berkowitz (1999, 2000) and Berkowitz et al. (2011). This study attempts to provide a better alternative to assess extreme risk and optimal bank capital. Our analyses are based on the following questions: Why did the capital requirement estimated by financial companies tend to be different from regulators? Can stress tests be replaced by other tests that will capture extreme risk, but will not have the same statistical weaknesses? Will the statistical property of risk affect the optimal capital estimates for the individual banks and the banking system? If so, does it mean optimal capital for the individual banks can be different from the optimal “social capital”?

This study recommends using the stable Paretian distribution to replace stress tests in estimating VaR and extreme risk. The distribution is consistent with the “fat-tail” stylised fact documented by numerous studies [see for example Cont (2001)]. It can also explain the different impact of bank diversification on individual banks and society: optimal capital for individual banks can be suboptimal for the society. The advantages of using the stable Paretian distribution are briefly reviewed below.

First, the characteristic exponent estimate of the stable Paretian distribution is less than 2. Its tails are “fatter” than the Gaussian distribution, which is a special member of the stable family. The tail risk of

¹ German bank Helaba failed the test but withdrew from the test, contesting the methodology used and releasing its own results on its website (See BBC

News, Business, 15 July 2011). Nordbank and Norddeutsche Landesbank both challenged the stress test results saying they did not reflect their strength. Nordbank said “this result in no way reflects the economic reality of our banks”. (“8 Banks Flunk European Stress Test; 16 More Barely Pass,” USA Today, July 15, 2011).]

the VaR method, based on normal distribution, may be underestimated if the underlying process is stable [see more discussion in section III]. Adding the stress test to VaR to correct for the deficiency implicitly assumes mixed distribution that may not be as parsimonious and could suffer from statistical problems, such as non-coherence (see more discussion below).

Second, stable Paretian distribution is “self-similar” and the Generalised Central Limit Theorem (GCLT) can be applied. In other words, the sum of stable variables can converge to stable. Statistical properties and inferences can be made accordingly. Other fat-tail distributions, such as Student-t with more than three degrees of freedom, are not self-similar and therefore the distribution of the sum of random variables will not have the same shape. McCulloch (1997) has discussed the importance of using large sample size to estimate the tail index of the stable Paretian distribution.

Third, because the stable Paretian distribution can capture *abnormal* risk and *normal* risk at the same time, it can resolve the “excessive capital” puzzle documented by many studies: Before the 2008 financial crisis, many banks in Europe, US, and Hong Kong maintained higher capital levels than required by regulators [see Dietrich and Vollmer (2004) Angora et al. (2009), Berger et al. (2008) and Wong et al. (2006)]. Assuming Gaussian distribution, some studies believe the behaviour is not rational because it increased banks’ cost of capital. Fat-tail distribution provides another explanation: financial companies have inside information about the “fat-tail” risk of their investments, such as off-balance sheet activities, and therefore were willing to reserve more capital as a buffer for extreme risk.

Similarly, it is argued that higher capital requirements can discourage risk seeking because of the “skin in the game” proposition. The stable Paretian distribution implies that extra capital maintained by financial companies may be due to fat-tail risk, thus it is *voluntary* and rational behavior, not *involuntary* or irrational. Moreover, although some bankers may have taken “excessive risk” to benefit from the “too big to fail (TBTF) policy”, underpriced insurance, such as the Federal Deposit insurance Corporation (FDIC) in the US or forbearance [See So and Wei (2004)], excessive risk must be redefined as “excessive” above and beyond “fat-tail” risk, not “normal risk”.

Finally, as mentioned above, the stable distribution can be used to show the different impact of bank diversification on optimal *private capital level for individual banks and optimal social capital level for the banking industry*. That in turn can reconcile the dispute between bankers and regulators regarding capital adequacy discussed above. Ibragimov, Jaffee and Walden (2011, hereafter IJW) proved that

moderate heavy tailed distribution had a significant impact on diversification and capital requirement: “...the negative externality arises because intermediaries’ actions to diversify that are optimal for individual intermediaries may prove to be suboptimal for society...” (p.333). Miles, et al. (2013) also demonstrates that the “social benefits” for banks to fund their assets with loss-absorbing capital, equity, are much larger than the “private costs”. Using Student-t distribution, Beale et al. (2011) reach similar conclusions. Using a different rationale, Bimpikis and Tahbaz-Salehi (2014), Wagner (2010, 2011), Acharya (2009) and Schaffer (1994) also find that bank diversification may not be optimal for society. Unlike IJW and this study, the importance of fat-tail distribution is not emphasised by the studies.

Using an approach similar to So and U (2016), this study shows the statistical distribution of the rate of return of the commercial banks in Hong Kong and China have tails fatter than normal. The goodness of fit tests reveal that the Paretian stable is preferable to Student-t, or mixed distributions with time-varying volatility. The probability associated with financial crises and market crashes, and thus systemic risk of the banking system in Hong Kong and China, is higher. We develop a model with stable uncertainty to re-estimate VaR and systemic risk for banks in Hong Kong and China and find that the capital levels are higher than regulatory capital.

Unlike other studies, we use a relatively new statistical technique developed by Coronel-Brizio and Hernandex-Montoya (2005) to determine the optimal cutoff at the tail so efficient and reliable tail estimates can be obtained. Because the density of the stable distribution is undefined, but the characteristic function is well known, we employ the Fourier Cosine expansion developed by Fang and Oosterlle (2008, 2011) to approximate the cumulative distribution function (see more in the Model section). We also strengthened the VaR by using Extreme Market Loss (EML) and Tail Risk Tolerance (TRT) to capture the magnitude and duration of crises (see section IIIC for details). We studied the off-balance sheet activities to assess the impact of micro and macro-prudential policy on the risk-seeking behaviour of banks by using a regime-shifting regression method [Kane and Unal (1990)] to convert book value into market value and to study the changes of bank behaviour and structural changes.

The findings of this paper will have significant implications for policy making and risk management. The micro-prudential policy that attempts to discipline shareholders against excessive risk seeking

should be modified to address fat-tail risk which can influence the “social” optimal level of diversification of individual banks. Macro-prudential policy that controls counterparty risk and contagion must also consider the statistical properties of risk. If the fat-tail statistical properties cannot be changed, regulators may have to set up policies to restrict the investments and/or assets of financial companies. Unfortunately, some of the restrictions set up after the 2008 financial crisis have been repealed by the new administration of the US government in June of 2017, another Great Recession cannot be ruled out after five to ten years.

Finally, thin-tail and fat-tail distribution will require opposite risk management policies and strategies for banks and investors. CoVar will need to be used to measure systemic risk, as Adrian and Brunnermeier (2011) will not be as perfect, as pointed out by Ibragimov et al (2011). New statistics taking into account fat-tail risk may be necessary.

The next section will review related studies. Our model will be provided in Section III. Hypotheses and data will be provided in Section IV. Methods will be discussed in Section V and empirical results and analyses will be available in Section VI. The final section contains suggestions and conclusion.

2. Related Studies

The Weaknesses of Value-at-Risk and Stress Tests

Hull (2009) pointed out that, using Value-at-Risk (VaR), “we are $1-\theta$ percent certain we will not lose more than VaR (θ) dollars in time T ”. $1-\theta$ is therefore the confident level. It is a measure to reveal the potential losses of bank holding companies under the probability framework,

$$\Pr (\text{Returns} < -\text{VaR}(\theta)) = \theta \quad (1)$$

Adding the time dimension to equation (1), VaR attempts to provide a single number to summarise the potential losses of portfolios or assets at time t .

$$\text{Returns at time } t < -\text{VaR}(\theta) \quad (2)$$

Under the Gaussian distributional assumption, the above measure can be rewritten as $\text{VaR}(\theta) = \mu + N^{-1}(1 - \theta)\sigma$, where $N^{-1}(\theta)$ is the inverse of the cumulative distribution function with zero mean and unit variance, μ and σ are the expected return and the standard deviation respectively.

Artzner et al. (1999) and McNeil et al. (2005) pointed out that although VaR has become a standard for measuring and assessing risk in financial institutions, it does not meet the “coherent” standard: homogeneity (larger positions bring greater risk); monotonicity (greater returns come with greater risk); sub-additivity (risk of sum cannot be greater than sum of the risk) and the risk-free condition (more investment in risk-free assets generates lower portfolio risk) [see Rosenberg and Schuermann (2004) and Bradley and Taqqu (2002) for similar discussion].

Kwiatkowski and Rebonato (2010) discussed another coherent problem due to “aggregation” of individual stress events. They recommend an approach to bypass the specification of unconditional probabilities of the individual stress events by using a linear programming approach that assures the subjective conditional probabilities chosen by the risk manager are internally consistent. Similar to Kwiatkowski and Rebonato (2010), Rosenberg and Schuermann (2004, hereafter RS) emphasised the importance to integrate market, credit and operational risks that may have different distributional shapes, such as fat tails.

Stress Tests and Stable Paretian Distribution

Berkowitz (1999, 2000) recommends partitioning the states of nature into normal and stress stages. The distribution of the portfolio returns of commercial banks, given a pricing model H with factors f and a simulated distribution f_s , will be

$$R_t = P(H(f)) \quad (3)$$

under normal economic conditions. The stress test forecast distribution will be

$$R_{s,t} = P(H(f_s)) \quad (4)$$

where the subscript represents stressful economic conditions. If the bank's objective is to maximise its firm value subject to the condition that the probability of its value will not drop below the average value [see Basak (1998)]:

$$\begin{aligned} &\text{Maximise: } E_g [U (R_{t+1})] \\ &\text{Subject to: } \Pr (R_{t+1} \geq \bar{R}) \geq 1 - p \end{aligned} \quad (5)$$

where p is between 0 and 1. Note that banks use VaR to maximise next period wealth will have portfolio value satisfying a $(1-p)$ level of VaR.

Berkowitz (2000) recommends applying the above idea to a stress test with two separate forecasts. The optimal combination of these forecasts will be unique in the sense that it combines the basic model VaR with the results from a stress test to become a single "best" forecast:

$$\begin{aligned} &\text{Maximise: } E_h [U (R_{t+1})] \\ &\text{Subject to: } \Pr (R_{t+1} \geq \bar{R}) \geq 1 - p. \end{aligned} \quad (6)$$

Berkowitz (1999) has proved that a linear combination is not possible if the probability of stress is non-zero. Moreover, if the scenarios of a stress test cannot occur, the optimal rule is no stress test. Thus coherent risk management based on VaR and stress test is not feasible. He recommends using a "meta-distribution" of factors to assign a positive probability to all scenarios, normal and crashes:

$$x \sim \begin{cases} f(\cdot) & \text{with probability } 1 - \alpha \\ f_s(\cdot) & \text{with probability } \alpha \end{cases} \quad (7)$$

So and U (2016) recommended using stable Paretian distribution to reconcile the incoherent and aggregate problems. As the tail of the stable distribution is fatter than normal, the "extra-ordinary" risk, targeted by the stress tests, can be captured. The Generalised Central Limit Theorem (GCLT) can also be applied to the stable family, to which Gaussian is a special member. Its characteristic exponent estimate equals 2 and skewness equals 0 (symmetric). VaR can thus be implemented directly. In other words, the stable distribution provides a feasible and statistically sound method to combine and aggregate the stand-alone stress losses in a coherent manner. The new Extreme

Market Loss (EML) measure recommended in this study is similar to the expected loss of VaR (see more discussion in section III.)

Optimal Bank Capital and Social Capital: Implications of Bank Diversification and Fat-tail Distribution

Diversification will be effective in reducing portfolio risk in a Gaussian environment [see Samuelson (1967a)]. However, the optimality of diversification may not hold under extremely heavy-tailed distribution [Samuelson (1967b), Fama (1965)]. Using majorisation theory [see Marshall et al. (2011)], Ibragimov (2015) has shown that diversification is related to the tail of the distribution. The stable Paretian distribution is moderately heavy-tailed and diversification is still effective at the bank level. However, it may not be desirable for regulators and society because fat-tailed distribution has more mass at the tail that reflects “lower probability for massive collapse of intermediaries” [Ibragimov et al. (2011)]. In other words, systemic risk increases and limited liability may allow banks not to internalise the rebuilding costs of the banking industry after massive defaults.

Ibragimov et al. (2011) has shown that the value of an intermediary is a function of cash inflow from investments divided by the risk premium determined by market risk and default risk. Because of incentive effect, the intermediary will take on an infinitely large portfolio and therefore the “numerator effect dominates the denominator effect” (p. 338). As the society and the individual intermediaries’ objectives may not be aligned, the “social value” of the intermediary can be affected by the changes of bank values plus the probability of all intermediaries, default or not. The latter is affected by risk sharing among the banks. If the tail index is moderately heavy but not extremely heavy (less than 1), then it can be optimal for an intermediary to share risk, regardless of the number of risk classes and diversification. For society, risk sharing is optimal when the tail index is greater than 1 and the risk classes are greater than the optimal diversification threshold [see equations (23) and (24) of Ibragimov et al. (2011) for details.]

Optimal Capital of Banks in Hong Kong and China and Prudential Policies

Wong et al. (2005) found that many banks in Hong Kong “maintain capital adequacy ratios (28.3%) well above the regulatory requirement (10.3%)” (p.14). The researchers believed the high capital buffer could be due to an agency problem, information asymmetries, or a “mismatch between the expectation of the regulator and banks over the approach to maintaining a capital buffer to prevent a breach of capital requirements” (p.14). In this study, we propose another possibility: that excessive capital may be used to protect banks against fat-tail risk.

Miles, et al. (2013) demonstrated that the “social benefits” for banks to fund their assets with loss-absorbing capital, equity, are much larger than “private costs”. They found that “...the amount of equity capital that is likely to be desirable for banks to use is very much larger than banks have used in recent years and also much higher than target agreed under the Basel III framework”. (p.1). While the term “fat-tail” is not used, the reference to the rare disaster of Barro (2006), the 2009 global banking crisis, and the use of mean, variance, skewness and kurtosis to choose the parameters for their model, we believe that Miles et al. are referring to fat-tail risk. Miles et al.’s specification of the macro- economic variables is consistent with the analysis of sovereign tail risk of Fong, Li and Fu (2015). They found global and domestic risk factors are important in explaining sovereign tail risk and explanatory power increases with the severity of tail risk.

Banks in China on the other hand tend to be under-capitalised. In 2011, Bloomberg reported that “China has increased capital requirements for its five biggest banks above the minimum 11.5 percent mark to guard against risks in the banking sector....China’s banking regulator could raise the capital adequacy ratio for banks to as high as 14%....” (Bloomberg, Business, Monday, April 25, 2011). In 2015, China’s bank regulators conducted a series of stress tests on the nation’s lenders to assess their exposure to risks related to the slumping property market and mounting local government debt (Wall Street Journal, April 26, “China Bank Regulators Conduct More Stress Tests”, William Kazer.) Anderson, of the International Financing Review (April 26, 2016), reported that China’s four largest banks were under pressure to begin boosting their total loss-absorbing capacity (TLAC) within months. That was because faster credit growth and increasing bad loans had added to the amount of capital needed to comply with international standards for systemically important banks. Chinese banks have

until 2025 to raise their TLAC buffer to 16% of risk-weighted assets. So why are the capital level of banks in Hong Kong and China so different from each other?

Following Alfon et al. (2004), Wong et al. (2005) study the impact of bank's internal considerations, market discipline, and regulatory framework on capital adequacy ratio (CAR). Their regression results showed regulatory capital requirements, size, growth, real return on equity, peer group and interbank borrowing were all significant statistically, except risk (the ratio of bank's assets with 100% risk weight to total assets). The insignificant finding of risk and capital is a puzzle, given that the risk-return relationship is well known in finance. Wong et al. pointed out that it is possible risky asset ratio is a poor proxy, or the assessments of the banks and regulators regarding relative riskiness are similar. This study proposed another possibility, that is, the higher capital level may be an insurance against tail risk.

The relationship between "excess" capital buffers (above the minimum ratios) and tail risk, however, is controversial. Perotti et al. (2011) showed that higher capital could reduce banks' excessive risk-taking. However, higher capital may enable banks to take more tail risk, without the fear of breaching the minimal capital ratio. "...Therefore, higher capital may create incentives for risk-taking instead of mitigating them." (Perotti et al. 2011, p.3). Many studies have found that banks have engaged in off-balance sheet transactions, such as credit default swaps, options and carry trades to increase profits. This study examined their impact on the risk of financial companies, using them to shed light on the effectiveness of micro- and macro-prudential policies.

3. The Model

A. Value-at-Risk (VaR) and Stable Uncertainty of Bank

To estimate the VaR with stable uncertainty, So and U (2015) and U (2016) recommended restating the VaR as²

² See McCulloch (1985) for using stable uncertainty to price FDIC insurance and So and Wei (1997) for pricing FDIC with forbearance.

$$\Pr [P(w,t) < -V(t, 1-\theta)P(w,t)] = \theta \quad (1')$$

where $V(t, 1-\theta)P(w,t)$ is the VaR of the portfolio return $P(w,t)$ with confident level $1 - \theta$ at time t .

The returns ($r_{i,t}$) of the stock or portfolio can be determined by either the simple Capital Asset Pricing Model (CAPM) or other factor models such as

$$r_{i,t} = \psi_i X_t + \varepsilon_{i,t} \quad (8)$$

where $r_{i,t}$ is the random bank returns, X_t is the random “market” returns, ψ_i is the coefficient and $\varepsilon_{i,t}$ is the error term. Since they are not normal, correlation concepts cannot be used. Stable maximum likelihood methods must be employed.

The log characteristic function of the stable distribution can be expressed as

$$\ln \phi(x) = \begin{cases} i\delta x - |cx|^\alpha \left[1 - i\beta \operatorname{sign}(x) \tan\left(\frac{\pi\alpha}{2}\right) \right], & \alpha \in (1, 2] \\ i\delta x - |cx| \left[1 + \frac{2i}{\pi} \beta \operatorname{sign}(t) \ln(x) \right], & \alpha = 1 \end{cases}, \quad (9)$$

There are four parameters in this function: α , β , c , δ . The parameter α is the most important for comparing Gaussian and stable Paretian hypotheses. α determines the extreme tails of the distribution, which takes any value in the interval $0 < \alpha \leq 2$. When $\alpha = 2$, the relevant stable Paretian distribution is the normal distribution. When $0 < \alpha < 2$, the tail areas of the stable distribution become “fatter” than normal. β is an index of skewness that can take any value in the interval $-1 \leq \beta \leq 1$. When $\beta = 0$ the distribution is symmetric. When $\beta > 0$ the distribution is skewed right and when $\beta < 0$ the distribution is skewed left. c is the scale parameter that measures dispersion and δ is the location parameter. As the tail of the stable family is moderately heavy, based on Ibragimov et al. (2011), bank diversification will still reduce risk and the “coherent” problem can be avoided.

Moreover, the Dynamic Conditional Correlation (DCC) multivariate GARCH model, recommended by Engle and Sheppard (2001) and Engle (2002), is necessary because the error term and correlation matrices are time-varying.

Using this framework, U (2016, p. 57) has shown that $P(w,t)$ is a weighted sum of three components: the time-varying intercept of equation (8), the time varying “market risk”, reflected by ψ_i , and the disturbances.

B. Time Varying Systemic Risk and Bank Capital

To incorporate the stable uncertainty, time varying systemic risk, and heteroskedasticity of the disturbances of bank returns, we modified equation (8) to a GARCH model of Glosten et al. (1993). The model can capture the asymmetric effects of news on market fluctuations. The stable Paretian distributions are recommended by Fama (1965), Mandelbrot (1963) and references therein. The stable-GJR(1,1) is given as follows:

$$R_{i,t} = \delta_i + \varepsilon_{i,t} \quad (10)$$

$$c_{i,t}^\eta = \mu_i + \left(\gamma_i + \psi_i I^-(\varepsilon_{i,t-1}) \right) |\varepsilon_{i,t-1}|^\eta + \phi_i c_{i,t-1}^\eta, \quad (11)$$

where $\varepsilon_{i,t} \sim S_{\alpha,\beta}(\delta, c)$ is stably distributed with characteristic exponents α , skewnesses β , scales c , and locations δ . For other distributional assumptions, $\eta = 2$ (c^2 is variances), otherwise $\eta = \alpha$. Moreover, we can simply extend to stable-GJR(p,q) from equation (11). $I^-(x)$ is an indicator function, where it is equal to 1, if $x < 0$, otherwise it is 0. To avoid unconditional c^η becoming infinity, we restrict $\gamma_i + \zeta\psi_i + \phi_i < 1$, where $\zeta = E[I^-]$.

Heteroskedasticity can be corrected by using standardised returns [see Bollerslev (1987)],

$$\tilde{R}_{i,t} = a_i \tilde{R}_{m,t} + b_i I^-(\tilde{R}_{m,t}) \tilde{R}_{m,t} + \tilde{\xi}_{i,t}, \quad (12)$$

where $\tilde{R}_{i,t} = (R_{i,t} - \delta_i)/c_{i,t}$, $\tilde{R}_{m,t} = (R_{m,t} - \delta_m)/c_{m,t} = \varepsilon_{m,t}$, R_m is market returns that follow the model in (10) and (11). The mean of $\tilde{\xi}_{i,t}$ equals zero. Since we focus on the downside risk of the firm, equation (12) can be rewritten as

$$R_{i,t} = \delta_i + \frac{(a_i + b_i I^-(\tilde{R}_{m,t})) (R_{m,t} - \delta_m) c_{i,t}}{c_{m,t}} + c_{i,t} \tilde{\xi}_{i,t}, \quad (13)$$

It is a dynamic CAPM model whose systematic risk (beta) is time-varying according to fluctuations of market returns and stock returns. Schwert and Seguin (1990) applied heteroskedasticity to the CAPM and developed a dynamic model with the time-invariant correlation. Our model is similar to Schwert and Seguin (1990) when the distributional assumption of $\tilde{\xi}_{i,t}$ is Gaussian. Another dynamic model used in Acharya et al. (2012) is the dynamic conditional correlation (DCC) model. However, the DCC model is not suitable for the stable distributional assumption because it requires a finite second moment. Rather than using DCC frameworks, we considered the algorithm in Nolan and Ojeda (2013) and the moving window to estimate the parameters. This algorithm allows the non-normally distributed random variables to regression analysis.³ The moving window method and OLS are applied to other distributional assumptions.

C. Value-at-Risk: Extreme Market Losses and Tail Risk Tolerant

To compare the stable VaR with regulatory capital, we used the concepts and definitions in Table 1:

Daily market returns less than $-\text{VaR}(1\%, R_{m,t})$ are denoted as EMLs. We assume there are 252 trading days in 1 year. The empirical probability of EMLs (ρ_t) is as follows,

$$\rho_t = \frac{\# \text{ of market returns between } t \text{ and } t_N < -\text{VaR}(1\%, R_{m,t})}{\# \text{ of trading days between } t \text{ and } t_N} \quad (14)$$

ρ_t depends on the VaR estimates, and VaR estimates depend on distributional assumptions, such as stable, sstable, nstable, normal, GED, and student-t. It is an unobservable measure at time t .⁴

Tail Risk Tolerance (TRT) is proposed to address the weaknesses of VaR and the probability of EMLs. TRT does not only reveal the *magnitude of the crisis* that the bank can combat but also the

³ Other methods such as OLS, Generalised Method of Moment (GMM) require a finite second moment of the random variables. Nolan and Ojeda (2013) solved this problem by using the Maximum Likelihood method.

⁴ This measure is consistent with the argument on stress testing from Supreme Court Justice Potter Stewart, who pointed out professionals believe that "we can't define it, but we know it when we see it" [see Berkowitz (1999)]

duration of the crisis. This measure exposes the actual likelihood of EMLs that the bank can face to be able to remain solvent in the future. To illustrate the TRT, we first recalled the systemic risk (SRISK) and one-day marginal expected shortfall (MES) from Acharya et al. (2012),

$$SRISK = kd_{i,t} - (1 - k)(1 - LRMES_{\theta,i,t})e_{i,t} \quad (15)$$

where k is capital adequacy ratio (8% in Hong Kong and China), $d_{i,t}$ and $e_{i,t}$ are debts and equity of the bank i at time t .

$$\begin{aligned} LRMES_{\theta,i,t} &= 1 - \exp\left(-\sum_{j=1}^n MES_{\theta,i,t_j}\right) \\ &\approx 1 - \exp(-\rho_t(t_N - t)MES_{\theta,i,t}) \end{aligned} \quad (16)$$

where $t \leq t_1 < t_2 < \dots \leq t_N$, t_i are the days of extreme events. By using equation (13), MES can be rewritten as

$$\begin{aligned} MES_{\theta,i,t} &= E_{t-1}[-R_{i,t} | R_{m,t} \leq -\text{VaR}(\theta, R_{m,t})] \\ &= -\delta_i - (a_i + b_i)c_{i,t}E_{t-1}\left[\varepsilon_{m,t} \mid \varepsilon_{m,t} < -\frac{\text{VaR}(\theta, R_{m,t}) + \delta_m}{c_{m,t}}\right] \end{aligned} \quad (17)$$

Therefore, to obtain SRISK, we should calculate the conditional expected returns in equation (17). TRT is the ρ_t (the probability of EML) such that the systemic risk in equation (15) equals zero, then TRT of the bank i at time t is denoted as $\rho_{i,t}$. Notably, when ρ_t is zero, systemic risk in equation (15) equals the amount of debt on the right hand side of the equation. Since SRISK is the amount of insufficient capital (less than 8% regulatory capital) that banks must raise when suffering from extreme market losses, it is related to the debt on the right hand side. However, it may not be qualified as Tier 1 or Tier 2 capital, unless it is contingent convertible bonds (CoCo Bond) that can become equity after conversion.

$$\rho_{i,t} = \ln \frac{\left(\frac{1 - k}{k \cdot LVG_{i,t}}\right)}{(t_N - t)MES_{\theta,i,t}} \quad (18)$$

$$\frac{\partial \rho_{i,t}}{\partial e_{i,t}} = \frac{1}{e_{i,t}(t_N - t)MES_{\theta,i,t}} \quad (19)$$

$$\frac{\partial \rho_{i,t}}{\partial d_{i,t}} = -\frac{1}{d_{i,t}(t_N - t)MES_{\theta,i,t}} \quad (20)$$

where $LVG_{i,t} = d_{i,t}/e_{i,t}$ is the debt/equity ratio.

D. Aggregate Tail Risk Tolerance

After introducing the TRT for individual banks, we need to extend it to address the stability of the banking system, or the aggregate TRT. The banking system will be considered fragile if the aggregate TRT is lower than the probability of EMLs, otherwise it is relatively healthy. The idea of the aggregate TRT comes from Hovakimian et al. (2012). We substituted the value-weighted MES ($\sum_{i=1}^n MES_{\theta,i,t}$) and the aggregate leverage ($\sum_{i=1}^n d_{i,t} / \sum_{i=1}^n e_{i,t}$) into equation (18). Unlike SRISK, the aggregated TRT indirectly captured the interconnectedness of individual banks. Stiglitz (2009) and others have pointed out that the “great recession” may be caused by the interconnectedness of financial companies around the world.

E. Prudential Policies and Risk-Seeking Behavior

Perotti et al. (2011) showed higher capital could reduce banks’ excessive (normal) risk-taking because of the “skin in the game” effect. That is the cornerstone of the traditional approach to capital regulation, which is less effective because regulations lag behind financial innovations (see Buser, Chen and Kane (1981) and Kane (1984). Higher capital levels may encourage banks to take more tail risk (extra-ordinary risk), without the fear of breaching the minimal capital ratio. Acharya et al. (2009) showed how the 2007-2009 tail risk was manufactured by new financial innovations, such as derivatives and securitisation. Banks no longer performed their financial intermediation function, but profited from trading and non-interest income.

Regime Switching Models and Off-balance Sheet Activities

Kane and Unal (1990) introduced the regime switching model to study unbookable equity, market returns and interest rates. Following their study, we first denote the unbookable equity of the bank as the difference between the market equity and book equity:⁵

$$U_t = MV_t - BV_t. \quad (21)$$

The switching regression with n -regime specification is given below:

$$\frac{\Delta U_t}{U_{t-1}} = \beta_j + \beta_{mj} R_{mt} + \beta_{rj} R_t + v_{jt}, \quad (22)$$

where $j = 1, \dots, n$, $t = 1, \dots, T$, R_t is the risk-free rate at time t , $R_{mt} = (P_{mt} - P_{mt-1})/P_{mt-1}$, P_{mt} is the market index at time t , v_{jt} is a disturbance term assumed to be distributed $N(0, \sigma_{vt}^2)$. The likelihood function for an n -regime specification is given below:

$$\log L = -\frac{T}{2} \log 2\pi - \frac{1}{2} \sum_{t=1}^T \log \sigma_{vt}^2 - \frac{1}{2} \sum_{t=1}^T \frac{[\sum_{s=1}^n v_{ts} \gamma_{ts}]^2}{\sigma_{vt}^2}, \quad (23)$$

where $\sigma_{vt}^2 = \sum_{s=1}^n \sigma_{st}^2 \gamma_{ts}^2$ is the weighted average of variance of v_{jt} on different regimes, $\gamma_{ts} =$

$\prod_{j=0}^{s-1} D_{tj} \prod_{w=s}^n (1 - D_{tw})$, D_{tj} is a normal cumulative distribution function from $-\infty$ to t with mean Z_j^* and variance σ_j^{*2} . The restriction of the mean and variance is $1 < Z_1^* < \dots < Z_n^* < T$, $0.01 \leq \sigma_j^{*2} \leq 2$.

We used Conn et.al. (1997)'s genetic algorithm to maximise the likelihood function to obtain the parameters.

Off-balance Sheet Activities and Risk

Ye (2015) used the ratio of off-balance sheet income to operating income (soinor) to investigate the off-balance sheet activities of the banks. He used ROR_{ROA} and ROR_{ROE} to measure the overall risk of the banks

⁵ In Kane and Unal (1990), $MV_t = U_t + kBV_t + e$. Since we do not have enough sample banks, we set $k = 1$ and $e = 0$.

$$ROR_{ROAit} = \frac{ROA_{it}}{\sigma_{it}(ROA)};$$

$$ROR_{ROEit} = \frac{ROE_{it}}{\sigma_{it}(ROE)}$$

$\sigma_{it}(ROA)$ and $\sigma_{it}(ROE)$ are the three-year rolling standard deviations of ROA and ROE respectively.

The higher this index, the higher the stability of the bank.

To measure the bankruptcy risk, he used the indicator $ADZP$,

$$ADZP_{it} = \frac{ROA_{it} + EQ_{it}}{\sigma_{it}(ROA)},$$

where EQ_{it} is the equity of the bank. The higher this index, the lower the banks' bankruptcy risk.

Credit risk can be measured by the non-performing loan ratio (NPL),

$$NPL = \frac{\text{Substandard loans} + \text{doubtful loans} + \text{loss loans}}{\text{total loans}}.$$

The higher this index, the higher the credit risk.

To measure the tail risk, we included the Value-at-Risk (VaR) at the 1% confident level under stable Paretian distributions.

$$\Pr(X < -VaR) = 1\%,$$

where $X \sim S(\alpha, \beta, c, \delta)$ is stably distributed with parameters α, β, c , and δ . The higher this index, the higher the tail risk of the bank.

The independent variables are soinoir, Requirement Reserve Ratio in China (RRR), and Loan-to-Value Ratio (LTV) in Hong Kong, with other control variables: Total assets (TA) to control the bank size, asset growth rate (AG) to control the development speed of the bank, ownership equity ratio (EQ) to control for financial leverage and loan to deposit ratio (LD) to control the efficiency of assets utilization.

$$TA = \ln(\text{total asset}),$$

$$AG = \frac{TA_{t+1} - TA_t}{TA_t},$$

$$EQ = \frac{\text{Shareholder's equity}}{\text{total assets}},$$

$$LD = \frac{\text{Total loans}}{\text{total deposit}}.$$

The regression is given below:

$$DV_{it} = \text{Const}_t + b_{i1}Soinor_{it} + b_{i2}RRR_t + b_{i3}LTV_t + TA_{it} + AG_{it} + EQ_{it} + LD_{it} + e_{it}, \quad (24)$$

where DV_{it} are the dependent variables including ROR_{ROA} , ROR_{ROE} , $ADPZ$, NPL , $VaR(\text{stable})$ and $VaR(\text{normal})$.

4. HYPOTHESES AND DATA

Hypotheses

Based on the above discussion, this study will have the following hypotheses:

H1: *The distribution of bank returns follow the stable Paretian distribution with characteristic exponent less than 2 and therefore is moderately heavy-tailed;*

H2: *The capital level based on the non-normal stable is higher than the estimates from the VaR and stress-tests;*

H3: *The non-normal systemic risk will also generate higher cost of capital for banks because of the higher extreme risk;*

H4: *"Excessive capital" is no longer excessive after using stable Paretian distribution to determine capital requirement;*

H5: *Off-balance sheet activities are affected by prudential policies.*

Data and Time Periods

The daily returns of the Hang Seng Index from 1996 to 2006 in DataStream were used to estimate the parameters of the stable distribution and systemic risk of the factor model discussed in the methodology section below. The daily stock prices of the following banks were obtained from DataStream: Chong Hing Bank, BOC Hong Kong (HDG), Dah Sing Banking GP, HSBC Holdings, Hang Seng Bank and Bank of East Asia.

The number of shares outstanding and quarterly liabilities were obtained from the Bankscope. The market capital of individual banks is the product of the number of shares outstanding and the stock price. The return on equity (ROE), return on asset (ROA), total assets, substandard loans, doubtful loans, loss loans, total loans, off-balance sheet incomes, net operating income, and total deposit are obtained quarterly in Datastream. The quarterly risk-free rate is the base rate from the Hong Kong Monetary Authority.

Similar data was collected for the following banks in Mainland China: Bank of China, China Construction Bank, China Merchants Bank, China Minsheng Banking, Hua Xia Bank, Industrial and Com. Bank of China, Ping An Bank, Shai, and Shanghai Pudong Development Bank. We tried to include both policy banks and non-state owned commercial banks.

Because of data availability and the need to compare the in-sample and out-of-sample performance, different time periods were used for our analyses. For example, we collected data from 1992 to 2016. We then used 1996 to 2006 daily market returns to estimate the parameters of the stable-GARCH model. Therefore, the time period of Table 1 and Table 8 is from 1996 to 2006. After the parameters were fixed, we calculated the TRT between 2007 and 2016 (See Figure 1 to Figure 8). For the switching model and off-balance sheet regression, we used the quarterly data from 1992 to 2015 because data was only available up to 2015.

5. METHODOLOGY

Engle (2002, 2011) and Engle and Sheppard (2001) recommended the dynamic conditional correlation multivariate (DCC) model to allow for time varying correlations of the disturbances. We used the following steps recommended by U (2016) to compute stable Paretian VaR:

1. The Liu and Brorsen (1995) method is used to estimate the parameters of the random returns that follow stable GARCH process.
2. The Nolan and Ojeda (2013) method is used to estimate the slope coefficients of the one-factor model of the return-generating process for each bank. If the disturbances are symmetrically stable, then McCulloch (1998)'s maximum likelihood method can also be used.
3. After obtaining the weights for the stocks of the market portfolio, the Fourier-cosine method with characteristic functions is used to compute cumulative density function (CDF), followed by the Newton-Raphson method to compute VaR (see more details below for the estimation of heteroskedastic models that may have fat tail).

Fourier-cosine Method

To calculate the conditional expectation in MES, A Fourier-series based method was introduced. Fang and Oosterlee (2008) proposed a Fourier-cosine expansion method to price European options. The density function is expressed by the cosine series, by which the indefinite integral can be theoretically solved. Recall Equation (18), the conditional expectation can be cut off by an optimal value, say as κ .

$$MES_{\theta,i,t} = -\delta_i - \frac{(a_i + b_i)c_{i,t}}{F(\tau)} \left[\int_{-\infty}^{\kappa} x dF(x) + \int_{\kappa}^{\tau} xf(x) dx \right] \quad (25)$$

where $\tau = -(VaR(\theta, R_{m,t}) + \delta_m)/c_{m,t}$, κ is a significant large value such that the pdf can be approximated by the power law.⁶ For stable Paretian distribution,

$$f(-x) \sim \alpha c^\alpha D_\alpha (1 - \beta) x^{-(1+\alpha)}, x > \kappa \text{ and } \beta < 1 \quad (26)$$

where $D_\alpha = \sin(\pi\alpha/2)\Gamma(\alpha)/\pi$, $\Gamma(x)$ is gamma distribution. By using Fourier-series expansion, the first term and second term in the bracket in Equation (25) can be calculated as

$$\int_{-\infty}^{\kappa} x dF(x) = \frac{\alpha}{1-\alpha} c_{m,t}^\alpha D_\alpha (1-\beta) \kappa^{1-\alpha} \quad (27)$$

the second term can be estimated by

$$\begin{aligned} \int_{\kappa}^{\tau} x f(x) dx &\approx \frac{\tau^2 - \kappa^2}{2(v-u)} \\ &+ \sum_{n=1}^N \frac{A_n(v-u)}{n\pi} \left\{ \tau \sin\left(\frac{n\pi(\tau-u)}{v-u}\right) - \kappa \sin\left(\frac{n\pi(\kappa-u)}{v-u}\right) \right. \\ &\left. + \frac{v-u}{n\pi} \left[\cos\left(\frac{n\pi(\tau-u)}{v-u}\right) - \cos\left(\frac{n\pi(\kappa-u)}{v-u}\right) \right] \right\} \end{aligned} \quad (28)$$

where

$$A_n = \frac{2}{v-u} \operatorname{Re} \left\{ \Phi\left(\frac{n\pi}{v-u}\right) \cdot \exp\left(-\frac{in\pi u}{v-u}\right) \right\}$$

$\operatorname{Re}(x)$ is the real part of x , $\Phi(x)$ is the characteristic function of the random variables, i is the imaginary unit, $[u, v]$ is the truncated interval in Fourier-series expansion. We choose $\delta_m \pm 2c_{m,t} \cdot 10^3$ and $N = 2^{15}$. The details of the Fourier-series expansion method on the calculation of TRT can be obtained in So and U (2013, 2016).

⁶ Coronel-Brizio and Hernandez-Montoya (2005) proposed a method based on the Anderson-Darling statistic method to determine the optimal cutoff from historical data. We obtained the largest κ among different banks as the optimal cutoff in (25).

6. RESULTS AND ANALYSES

HONG KONG

Parameter estimates

Table 2 gives the parameter estimates of the GJR(1,1) model with different distributional assumptions. The column “stable” means the residuals of market returns are stably distributed, so “normal”, “GED”, and “student-t” are normal distribution, generalised error distribution, and student-t distribution respectively. The row “ α or ν ” shows the thicknesses of the tails. For the stable and GED models the tail is fatter than normal if the value is less than 2. For the student-t model the tail is fatter than normal if the value is greater than 3. The results show the tail of the distribution is significantly fatter than normal. By comparing the stable model with other non-normal models, we found the GED and student-t performed better. However, we should emphasise that the weights of each sample are the same in likelihood function values. The outliers do not occur frequently but they may cause damage to the banking system. Berkowitz (2001) proposed a modified likelihood ratio test that enlarges the effect on the outliers. However, non-nested types of this test are still void. The KS test of different models shows the stable model is the only model in which standardised returns are consistent with the standard stable distribution in out-of-sample data. In other words, the forecasting power of the stable model is better than other models. It supports the determination of capital requirements with the stable model, especially for crises.

Tail Risk Tolerance (TRT) of Banks in Hong Kong

Figure 1 shows the difference between the aggregate TRT and the probability of EMLs with stable and normal distributions. Obviously, the banking system is healthy if the difference is greater than 0. The results show that the banking system is far below 0 from 2007 to 2009. Presumably, the subprime mortgage crisis is the main trigger that affects the banking system in Hong Kong and other countries. Another period that the difference is far below 0 is from 2011 to 2013. This is when the subprime mortgage crisis spills over to European countries and the concern of the debt default in Greece has a

big effect on the bond market in Europe. The interest rate of 10-year Greece government bonds rises to a peak of 30%. The uncertainty of European markets also affects the banking system in Hong Kong. The concern about the slowdown of China economy growth in late 2014 is the main factor that led to the difference of TRT and probability of EMLs far below 0. Moreover the changes of the trading mechanism of the stock market in China make a huge impact on the financial market. The Hong Kong stock market obviously cannot stay alone in this slump. Figures 3 to 8 show the TRT of individual banks in Hong Kong. They are Chong Hing Bank, BOC Hong Kong (HDG.), Dah Sing Banking Group, HSBC Holdings, Hang Seng Bank, and Bank of East Asia. We found that only Hang Seng Bank had sufficient capital to overcome all crises between 2007 and 2016. HSBC had relatively low TRT. Meanwhile, the stock price of HSBC plunges from around \$150 a share to \$40 a share with more than 70% losses.

Regime Switching Model

Table 3 shows there are three regimes for the market and interest sensitivity of unbookable equity for the banks in Hong Kong. The first switch occurred in the first quarter of 1993 and the second switch occurred in the second quarter of 2009. Interestingly, the second switch date was almost the same as the first announcement of loan-to-value caps from the Hong Kong SAR. Hong Kong SAR changed the loan-to-value caps to at most 60% for all real estate greater than or equal to HK\$20 million to inhibit the overheated housing price. In addition, the unbookable equity was positively related to the market and interest sensitivity in the second regime (1993/Q2 to 2009/Q2). The relationship becomes insignificant in the third regime (2009/Q3 to 2015/Q4). It shows that the banks seem to increase the unbookable equity in the bull market, but do not significantly change the portion of the unbookable equity after the subprime mortgage crisis. In other words the Hang Seng Index drops rapidly after 2009. The insignificant change of the unbookable equity meant the banks did not properly reduce the unbookable equity by comparing with the raising unbookable equity in the bull market.⁷ Later on, we show the relationship between the unbookable equity and the risk of the bank.

⁷ Table 3 shows β_{m2} and β_{r2} are significantly different from 0 but β_{m3} and β_{r3} are not. While, Table 4 shows β_{m2} and β_{m3} , β_{r2} and β_{r3} are not significantly different.

Off-Balance Sheet Activities and Bank Risks

Table 5 shows that the ratio of off-balance sheet income to operating income (soinor) had a positive impact on the credit risk (NPL) of HSBC, Bank of China (Hong Kong) and Dah Sing (This is half of our sample banks and two of them are large banks in Hong Kong). If higher off-balance sheet income is generated by higher unbookable equity, higher unbookable equity will imply higher credit risks. According to the activities of changing of unbookable equity of the banks before and after the subprime mortgage crisis (Table 3), the transparency of off-balance sheet data should be improved. In contrast to the banking data in US, the banks should release the off-balance sheet data in the call report every financial year. Thus investors have more comprehensive data to analyse the banks' risks. Table 6 shows that the reserve requirement ratio in China had the most impact on Bank of China (Hong Kong).

Table 7 shows that the loan-to-value caps in Hong Kong had positive impacts on Value-at-Risk (VaR) under stable Paretian distributions in all sample banks in Hong Kong. In contrast to VaR under normal distributions, only Hang Seng and Bank of China (Hong Kong) were significant. It implies that the lower loan-to-value ratio can reduce the Value-at-Risk of the banks, especially for tail risk. Therefore, the macro-prudential policies seem to be effective.

China

Parameter Estimates

Table 8 shows the parameter estimates of the GJR(1,1) model with different distributional assumptions. The results show that the shape parameter is significantly less than 2 in stable Paretian and generalised error distributions. However, the shape parameter is not significantly greater than 3 in the student-t distribution. According to the Likelihood ratio test, AICC and BIC values, the stable model performs better than normal but worse than GED and student-t. However the KS test shows the standardised out-of-sample returns follow the standard stable distribution. For other distributional assumptions, their standardised returns failed the KS test. The results support that the stable model may predict the behaviour of the returns of the Shanghai Stock Exchange Composite Index better than others.

Tail Risk Tolerance (TRT) of different banks on the Shanghai Stock Exchange

Figure 10 shows the aggregate TRT dropped below the probability of EMLs after 2012. Meanwhile, the Chinese GDP growth was less than 8%. Investors were seriously concerned with the slowdown of the Chinese market. Moreover, the local debt issue and shadow banking may have affected the stability of the banking system. The spillover of the subprime mortgage crisis from the US also influenced China. In contrast to Figure 10, we found that the banking system in Hong Kong was relatively healthier than that of Mainland China. The leverage of Hong Kong banks was about 10, much lower than Mainland China banks. Figures 12 to 19 give the TRT of different banks in Mainland China. We found China Construction Bank was relatively healthy compared to other banks in China, since only its TRT was greater than the probability of EMLs before 2014. Unlike Hong Kong, the small banks in Mainland China seem to have higher leverage than larger banks. It may be another important factor that affects the stability of the banking system in Mainland China.

7. SUGGESTIONS AND CONCLUSION

The empirical results in this study confirm that the stock returns of the banks in Hong Kong and Mainland China are fat tailed, which has significant implications for policy makers and risk management. Diversification under fat tail distribution is *optimal at the individual bank level but sub-optimal at the social level*. Although financial companies are able to benefit from diversification, it can create higher “systemic risk”, reflected by the higher “probability for massive collapse of intermediaries” [Ibragimov, Jaffee and Walden (2011)]. Regulation, rather than deregulation, may be more desirable in Hong Kong even if it is the “freest market”, according to Milton Friedman.

Theoretically, the associated externality caused by limited liability should be more serious in Hong Kong, not Mainland China, because of its tight government intervention policies. Moreover, the policy banks in Mainland China have an implicit guarantee from the government. As the guarantee is a put option and is underpriced, the stock prices and the market value of the policy banks should have

smaller tail risk than Hong Kong. However, our results showed the opposite: the stable estimates for the banks in Mainland China are slightly smaller than those from Hong Kong and therefore have higher fat-tail risk. In other words, the banks in Mainland China have “larger” probability of extreme price changes. This is consistent with the “banking crises” cycle in Mainland China: many policy banks need government support or indirect bailouts every five to ten years. We speculate that the subsidy from the guarantee or bailout may be offset by the higher regulatory/policy risk that tends to change more frequently than in Hong Kong. Agency problem may also create externality to the banking sector in Mainland China.

Our stable Value-at-Risk estimates revealed that most banks in Hong Kong and Mainland China underestimated the probability of financial crisis, and their capital levels were not sufficient to cover fat-tailed risk, except Hang Seng Bank in Hong Kong and Construction Bank in China. As one of the largest international financial centres, the systemic risk of the banks in Hong Kong may be influenced more by inter-connectedness of banks around the world [Stiglitz (2009)] than the banks in Mainland China. Market forces can be used to explain the “high” capital level maintained by banks in Hong Kong. Banks in Mainland China, on the other hand, were under-capitalised. It is possible that in addition to market disciplines, active government interventions in terms of reserve requirement, interest rates and housing prices had significant impacts on the profitability and risk of the banks. Banks in Mainland China had no incentive to keep more capital for extreme risk because they were protected by the safety net provided by the government. As a Special Administrative Region (SAR) of China, the Hong Kong economic and political conditions are influenced heavily by Mainland China. However, the same safety net is not provided to financial companies in Hong Kong. Therefore micro- and macro prudential policy could be important considerations. This recommendation is supported by our results, which revealed loan-to-value ratio, among several other variables, was one of the most effective instruments to control default risk in Hong Kong.

References

- Acharya, Viral, Thomas Cooley, Matthew Richardson and Ingo Walter. 2009. "Manufacturing Tail Risk A Perspective on the Finance Crisis of 2007-2009" in Foundations and Trends in Finance, Vol. 4, No. 4, 247-325.
- Acharya, V., L. H. Pedersen, T. Philippon, and M. P. Richardson. 2010. *Regulating Wall Street: The Dodd-Frank Act and the new architecture of global finance*. John Wiley & Sons, Inc., Hoboken, New Jersey.
- Adrian, T. and M. Brunnermeier, M. 2009. *CoVar*. Unpublished working paper. Princeton University.
- Alfon, I., Argimon, I. and Bascunana-Ambros, P. 2004. What Determines How Much Capital is held by UK Banks and Building Societies? *FSA Occasional Paper*, Financial Services Authority
- Agur, Itai and Maria Demertzis. 2012. "Excessive Bank Risk Taking and Monetary Policy." European Central Bank. Working paper series, no. 1457.
- Ang, A., J. Chen, and Y. Xing . 2006. Downside risk. *Review of Financial Studies* 19(4), 1191–1239.
- Angora, A., Isabelle Distinguin and C. Rugmintwari. 2009. Excess Capital of European banks: does bank heterogeneity matter? Working paper. University of Limoges.
- Artzner, P., Delbaen, F., Eber, J.M., Heath, D.. 1999. "Coherent Measure of Risk," *Mathematical Finance* 9, 203-228.
- Bawa, V. S. and E. B. Lindenberg. 1977. Capital market equilibrium in a mean-lower partial moment framework. *Journal of Financial Economics* 5(2), 189–200.
- Beale, N., David Rand, Heather Battey, Karen Croxson, Robert May, and Martin Nowak. 2011. Individual versus Systemic Risk and the Regulator's Dilemma. *PNAS Early Edition.*, pp.1 to 6.
- Berger, A., R. DeYoung, M. Flannery, D. Lee, and O. Oztekin. 2008. How do large banking organizations manage their capital ratios? *Journal of Financial Services Research*, Dec. Vo. 34, Issue 2, 123-49.
- Berkowitz, J.. 1999. A coherent framework of stress testing. *FEDS Working Paper No. 99–29*.
- Berkowitz, J.. 2001. Testing Accuracy of Density Forecasts, Applications to Risk Management" *Journal of Business and Economic Statistics* 19, 465-474.
- Berkowitz, J., P. Christoffersen and D. Pelletier. 2011. Evaluating Value-at-Risk Models with Desk-level Data. *Management Science*, 57, 2213-2227.
- Berlin, Mitchell. 2011. Can we explain Banks' Capital Structure? *Business Review*, Q2, pp.1-11.
- Bimpikis, K. and Alireza Tahbaz-Salehi. 2014. "Inefficient Diversification", Working Paper. Stanford University.
- Bollerslev, T..1987. A conditional heteroskedasticity time series model for speculative prices and rates of return. *Review of Economics and Statistics* 69(3), 542–557.
- Bradley and Taqqu. 2001. Financial Risk and Heavy Tails in Heavy-tailed distributions in Finance" Svetlozar T. Rachev, editor, North Holland. 2002.

- Buser, S., Edward Kane, Andrew Chen. 1981. "Federal Deposit Insurance, Regulatory Policy, and Optimal Bank Capital" *Journal of Finance*, 36, 51 to 60.
- Conn, A. R., N. I. M. Gould, and Ph. L. Toint. 1997. A Globally Convergent Augmented Lagrangian Barrier Algorithm for Optimization with General Inequality Constraints and Simple Bounds. *Mathematics of Computation*, 66(217), 261–288.
- Cont, Rama. 2001. Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues. *Quantitative Finance*. Vol. 1, 223-236.
- Coronel-Brizio, H.F. and A.R. Hernandex-Montoya. 2005. On Fitting the Pareto Levy Distribution to Stock Market Index Data: Selecting a Suitable Cutoff Value." *Physica A*, 354, 437-449.
- Dietrich, D. and Uwe Vollmer. 2004. Why do banks hold capital in excess of regulatory requirements? A Functional Approach. Working paper no. 192, Halle Institute for Economic Research.
- Engle, R. F. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics* 20(3), 339–350.
- Engle, R. F.. 2011. Dynamic conditional beta. Volatility Institute Manuscript, NYU.
- Engle, R. F. and K. Sheppard. 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate Garch. Working Paper 8554, National Bureau of Economic Research.
- Fama, E. 1965. The behavior of stock market prices. *Journal of Business* 38(1), 34–105.
- Fang, F. and C. W. Oosterlee. 2008. A novel pricing method for European options based on Fourier-cosine series expansions. *SIAM J. Scientific Computing* 31(2), 826–848.
- Fang, F. and C. W. Oosterlee. 2011. A Fourier-based Valuation Method for Bermudan and Barrier Options under Heston's Model. *SIAM Journal on Financial Mathematics*, 2, 439-63.
- Fong, Tom, Ka-Fai Li, and John Fu. 2015. "Accounting for Sovereign Tail Risk in Emerging Economies: The Role of Global and Domestic Risk Factors." HKIMR Working Paper No. 24/2015.
- Glosten, L. R., R. Jagannathan, and D. E. Runkle. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48(5), 1779–1801.
- Hovakimian, A., E. J. Kane, and L. Laeven. 2012. Tracking variation in systemic risk at us banks during 1974–2013. Working Paper 18043, National Bureau of Economic Research.
- Hull, J. 2009. *Risk Management and Financial Institutions*, Wiley Finance. Wiley.
- Ibragimov, Rustam, Dwight Jaffee and Johan Walden. 2011. Diversification Disasters. *Journal of Financial Economics* 99, 333-348.
- Kane, Edward. 1984. "Technological and Regulatory Forces in the Developing Fusion of Financial-Services Competition," *Journal of Finance*, 39, 759-772.
- Kane, E. J. and H. Unal. 1990. Modeling Structural and Temporal Variation in the Market's Valuation of Banking Firms. *Journal of Finance* 45(1), 113—136.
- Kupiec, P.H. 2000. Stress Tests and Risk Capital. *Operational Risk and Regulation*, 2, 27-39.
- Kwiatkowski, Jan and Riccardo Rebonato, 2010. "A Coherent Aggregation Framework for Stress Testing and Scenario Analysis." Working Paper, Oxford University.

- Mandelbrot, B.. 1963. The variation of certain speculative prices. *Journal of Business* 36(4), 394–419.
- McCulloch, J. Huston. 1998. "Linear Regression with Symmetric Stable Disturbances," In Robert Adler, Raya Feldman, and Murad Taqqu, eds., *A Practical Guide to Heavy Tails: Statistical Techniques for Analysing Heavy Tailed Distributions*, Birkhäuser, 359-76.
- McCulloch, J. Huston. 1997. "Measuring Tail Thickness in Order to Estimate the Stable Index : A Critique," *Journal of Business and Economic Statistics* 15, 74-81.
- McCulloch, J. Huston. 1985. "Interest-Risk Sensitive Deposit Insurance Premia: Stable ACH Estimates," *Journal of Banking and Finance*, 9, 137-56.
- Miles, David, Jing Yang and Gilberto Marcheggiano, 2013. "Optimal Bank Capital." *The Economic Journal*, 123, 1-37.
- Nolan, J. P. and D. Ojeda. 2013. Linear and nonlinear regression with stable errors. *Journal of Econometrics* 172(2), 186–194.
- Perotti, Enrico, Lev Ratnovski and Razvan Vlahu. 2011. "Capital Regulation and Tail Risk". IMF working paper. WP/11/188.
- Samuelson, Paul. 1967a. General Proof that Diversification Paid. *Journal of Financial and Quantitative Analyses*. 2, 1-13.
- Samuelson, Paul, 1967b. Efficient Portfolio Selection for Pareto-Levy Investments. *Journal of Financial and Quantitative Analyses*. 2, 107-122.
- Schwert, G. W. and P. J. Seguin. 1990. Heteroskedasticity in stock returns. *Journal of Finance* 45(4), 1129–1155.
- Shaffer, S. 1994. Pooling Intensifies Joint Failure Risk. *Research in Financial Services* 6, 249-280.
- So, Jacky C. and U Sio Chong. 2013. Financial Crisis, Capital Requirement and Stress Tests: Evidence from the Extreme Value and Stable Paretian Estimates, paper presented at the Annual Conference of the Western Economic Association International 10th Biennial Pacific Rim Conference, Tokyo, Japan.
- So, Jacky C. and U. Sio Chong. 2016. VaR and Stress Tests: The Impact of Fat-Tail Risk and Systemic Risk on Capital Requirements of Financial Institutions, Working Paper.
- So, Jacky C. and Jason Z. Wei. 2004. Deposit Insurance and Forbearances Under Moral Hazard." *The Journal of Risk and Insurance*, vol. 71, 707-735.
- Stiglitz, J. E.. 2009. The current economic crisis and lessons for economic theory. *Eastern Economic Journal* 35(3), 281–296.
- U., Sio Chong. 2016. Value-at-Risk, Stress Tests and Stable Paretian Distribution- The Implementation for Bank Capital. Ph.D. Dissertation, Faculty of Business Administration, University of Macau.373-386.
- Wagner, W. 2010. Diversification at Financial Institutions and Systemic Crises. *Journal of Financial Intermediation* 19,
- Wong, Jim, Ka-Fai Choi and Tom Fong. 2005. "Determinants of the Capital Level of Banks in Hong Kong." *Hong Kong Monetary Authority Quarterly Bulletin*, pp. 14 to 37.

Wong, Jim, Ka-Fai Choi and Tom Fong. 2006. "A Framework for Macro Stress Testing the Credit Risk of Banks in Hong Kong." Hong Kong Monetary Authority Quarterly Bulletin, pp. 25-38.

Ye, K. W. 2015. Off-Balance Sheet Activities and Bank Risks: An Investigation of the Listed Commercial Banks in China (1999—2013). *Annals of Financial Economics* 10(1), 1550004.

Figure 1: The difference between the aggregate tail risk tolerance and the probability of extreme market losses with stable and normal distributions (Hong Kong)

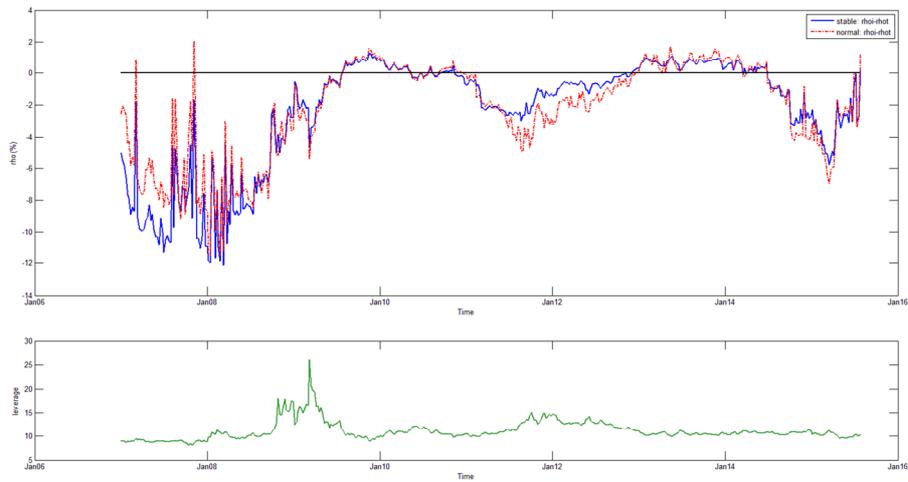


Figure 2: The aggregate tail risk tolerance of the Hang Seng Index under stable-GJR(1,1)

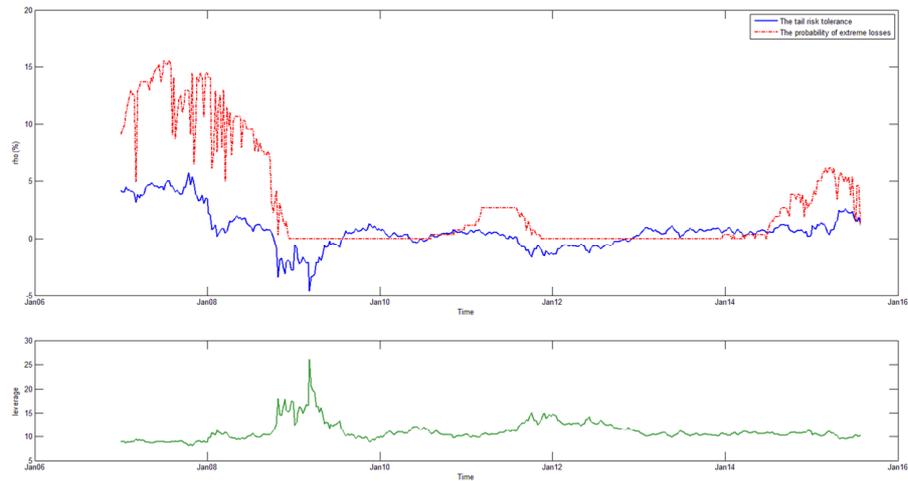


Figure 3: The tail risk tolerance of Bank of East Asia under stable-GJR(1,1)

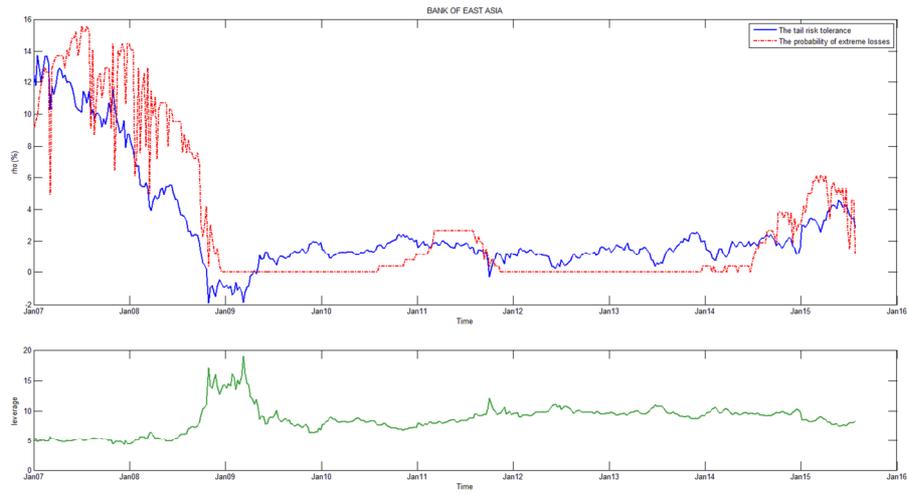


Figure 4: The tail risk tolerance of Chong Hing Bank under stable-GJR(1,1)

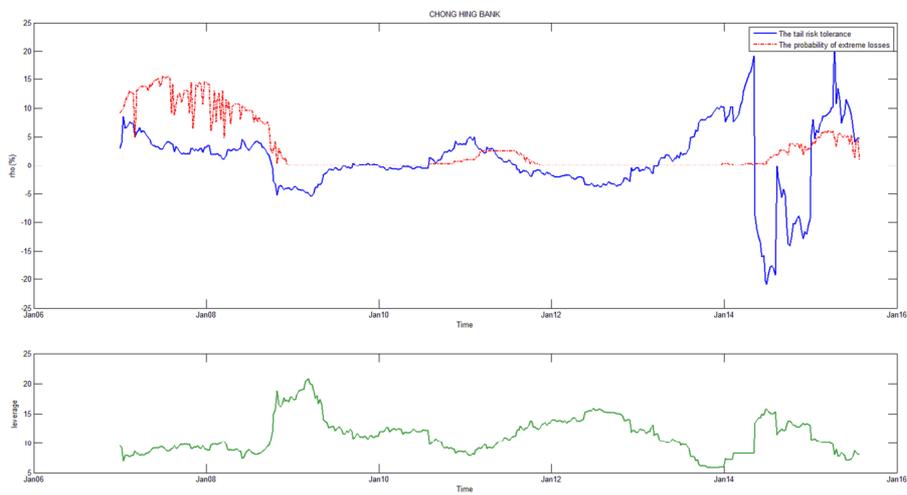


Figure 5: The tail risk tolerance of Hang Seng Bank under stable-GJR(1,1)

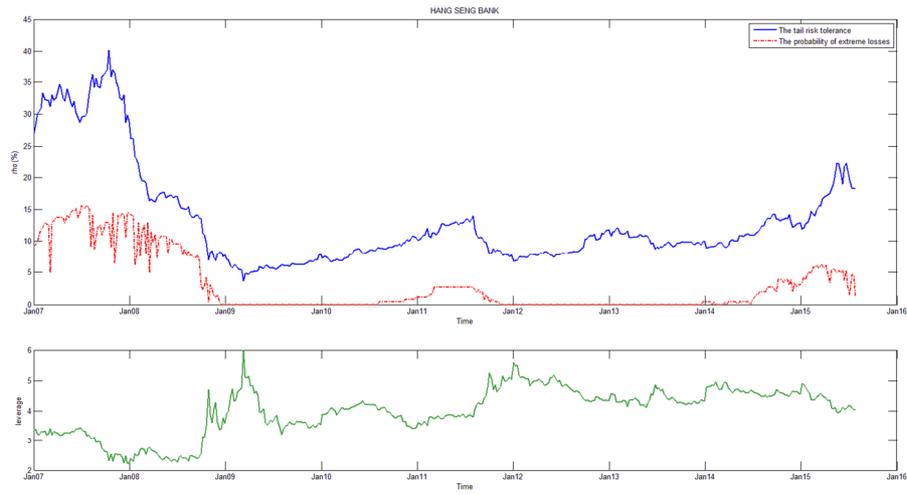


Figure 6: The tail risk tolerance of HSBC Holdings under stable-GJR(1,1)

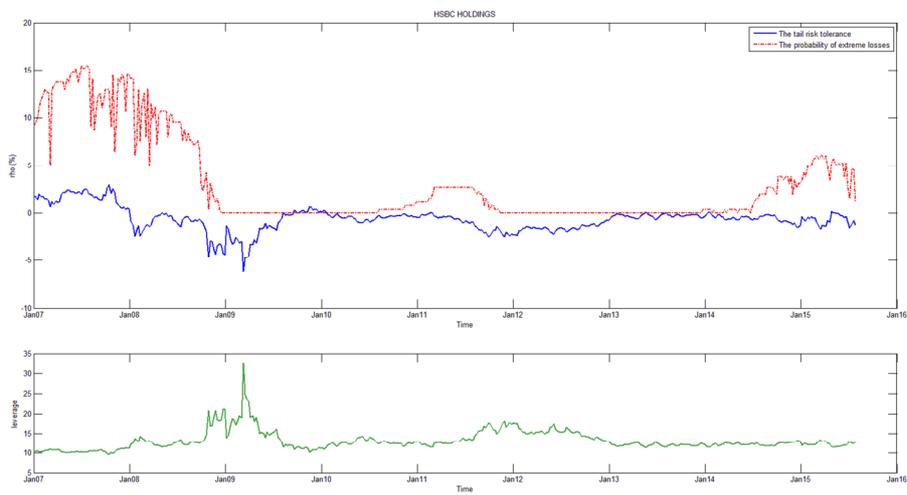


Figure 7: The tail risk tolerance of BOC HONG KONG (HDG.) under stable-GJR(1,1)

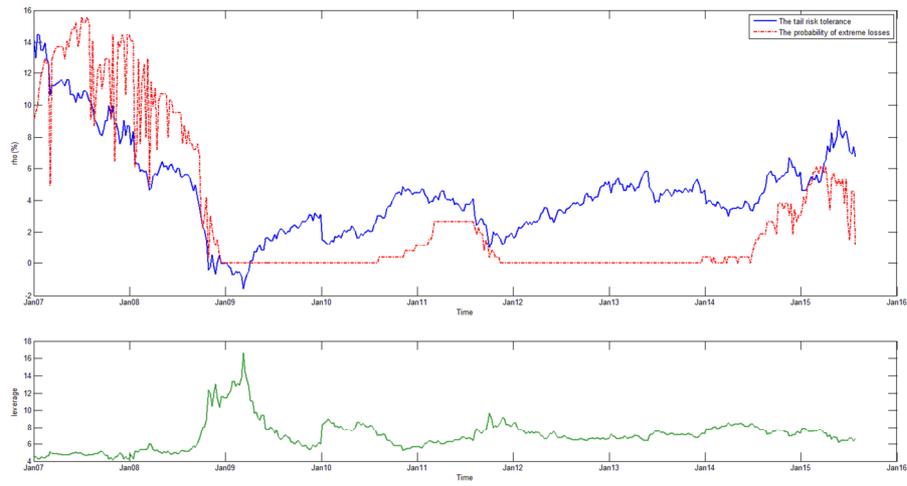


Figure 8: The tail risk tolerance of DAH SING BANKING GP. under stable-GJR(1,1)

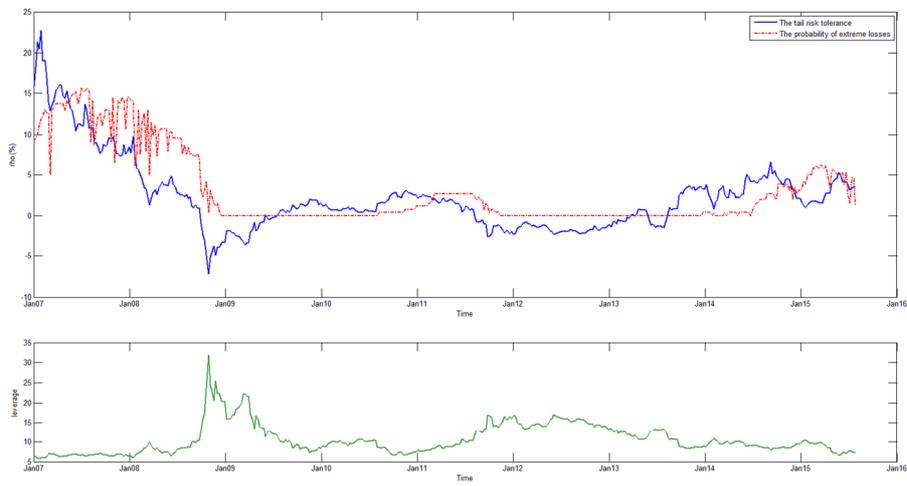


Figure 9: The soignor (Off-balance sheet income/net operation income) of different banks

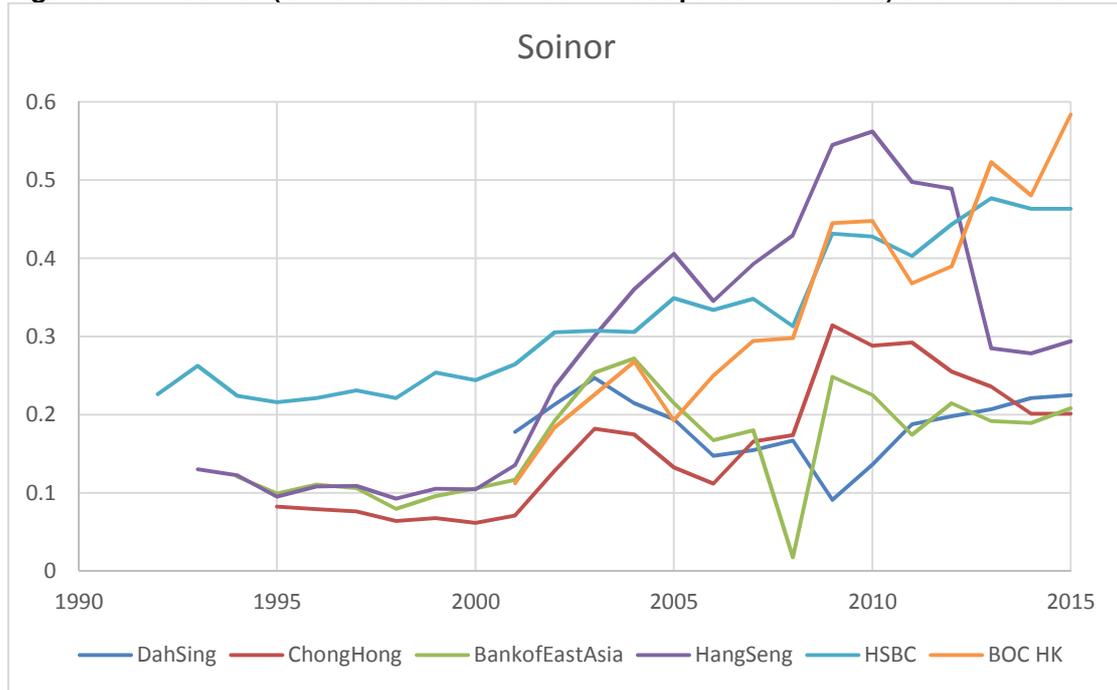


Figure 10: The difference between the aggregate tail risk tolerance and the probability of extreme market losses with stable and normal distributions (Shanghai)

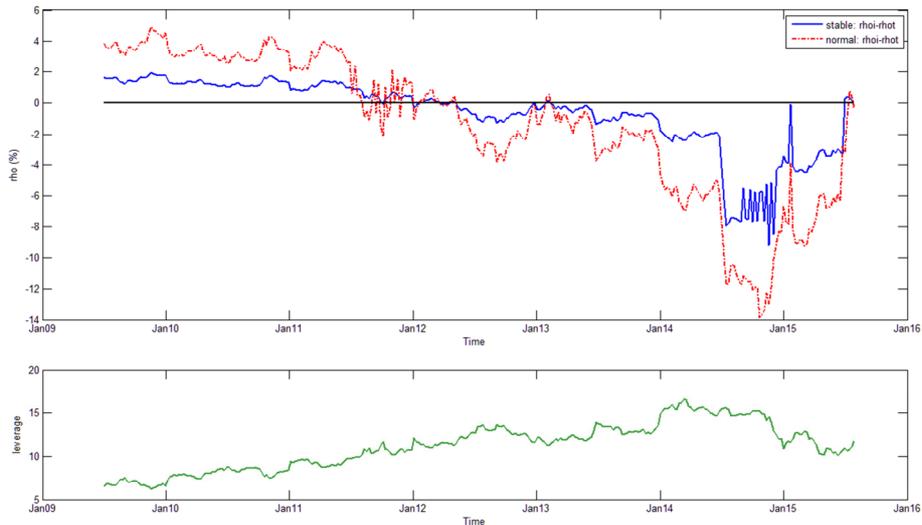


Figure 11: The aggregate tail risk tolerance of the Shanghai Stock Exchange Composite Index under stable-GJR(1,1)

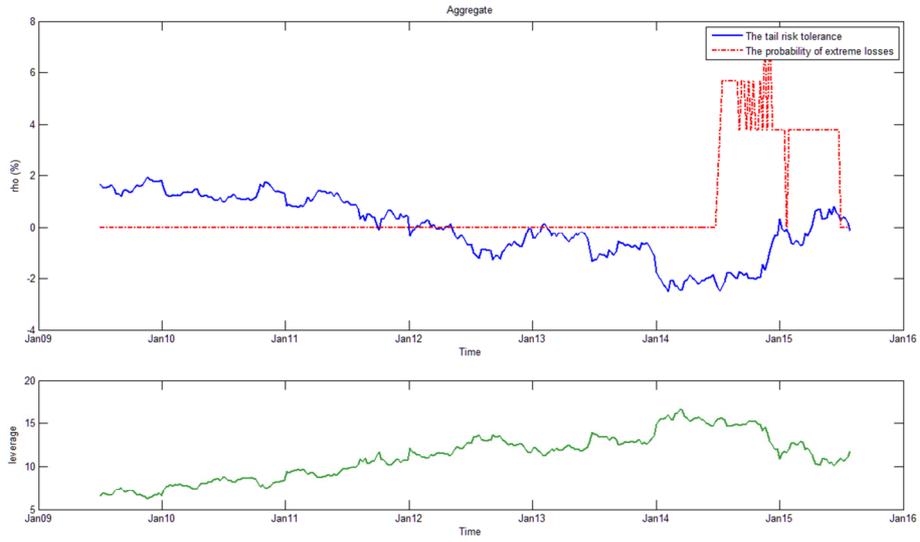


Figure 12: The tail risk tolerance of Bank of China under stable-GJR(1,1)

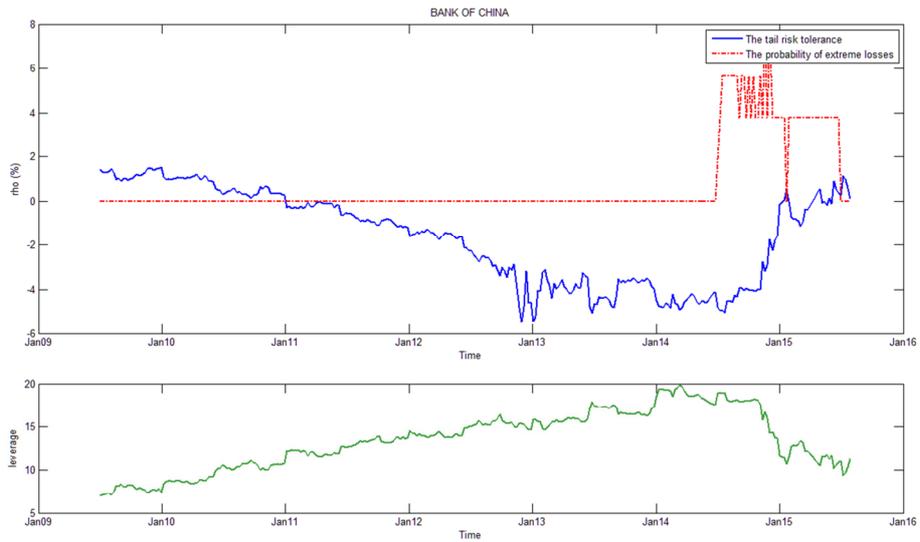


Figure 13: The tail risk tolerance of China Construction Bank under stable-GJR(1,1)

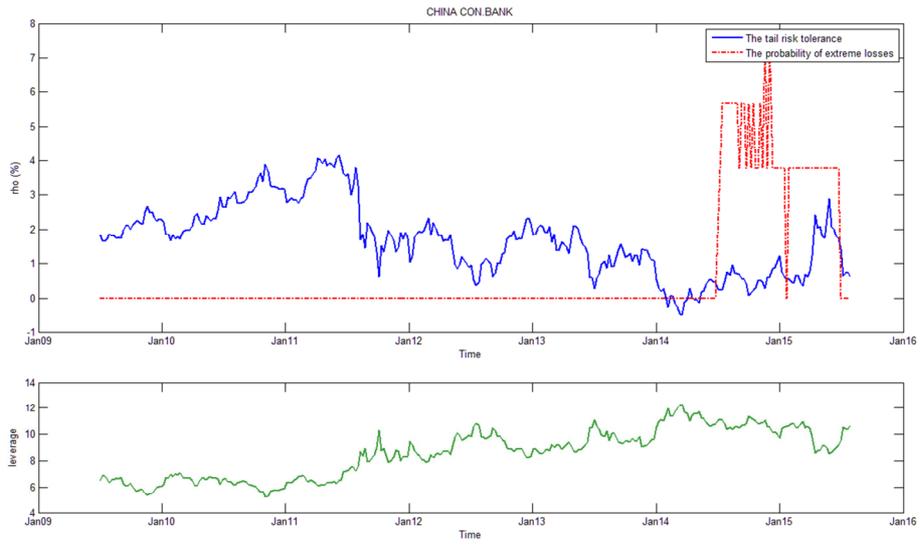


Figure 14: The tail risk tolerance of China Merchants Bank under stable-GJR(1,1)

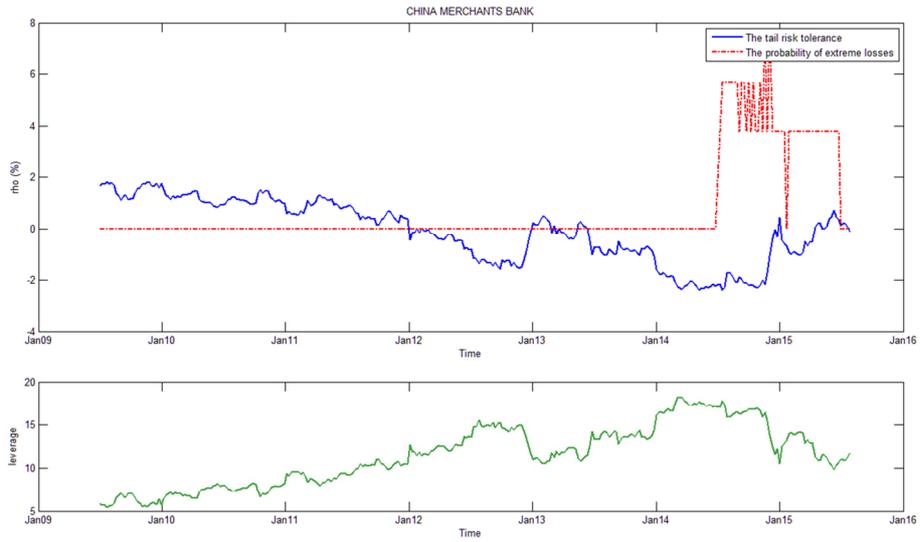


Figure 15: The tail risk tolerance of China Minsheng Bank under stable-GJR(1,1)

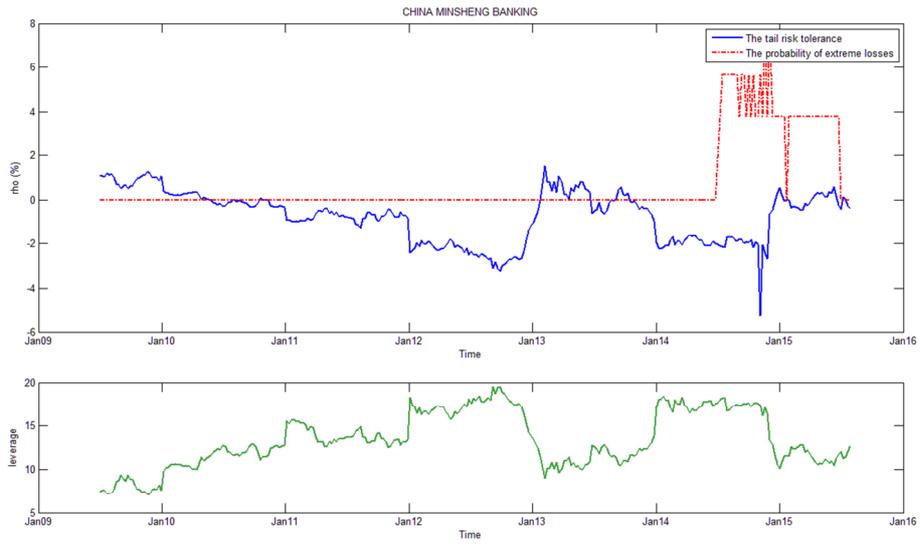


Figure 16: The tail risk tolerance of Hua Xia Bank under stable-GJR(1,1)

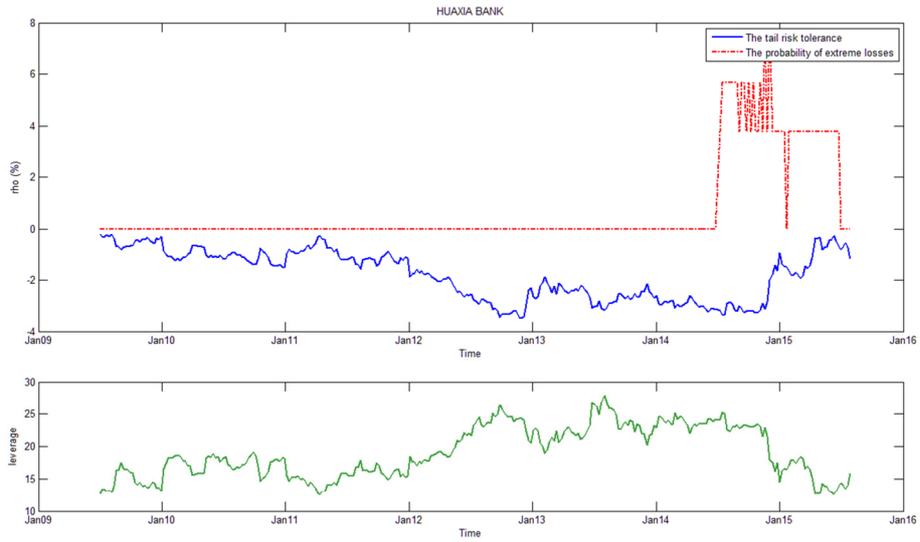


Figure 17: The tail risk tolerance of Industrial & Commercial Bank Of China under stable-GJR(1,1)

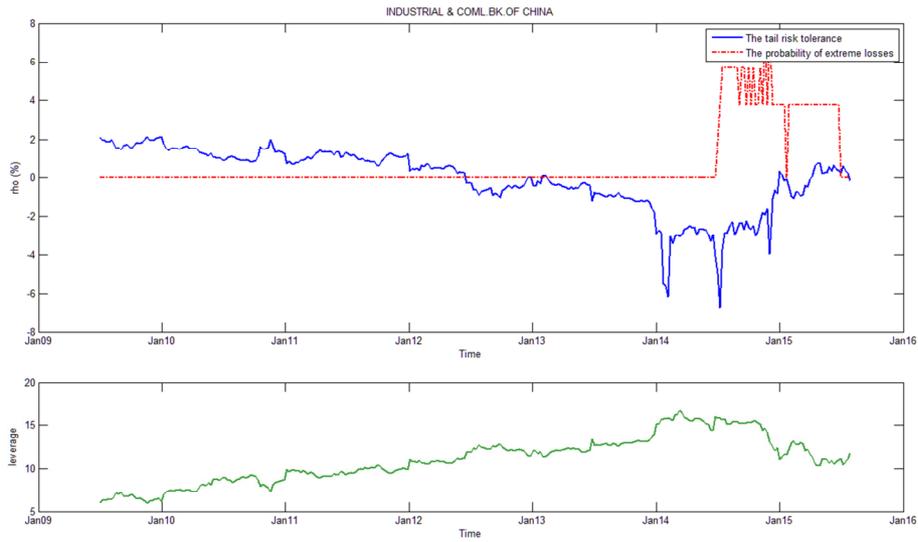


Figure 18: The tail risk tolerance of Ping An Bank under stable-GJR(1,1)

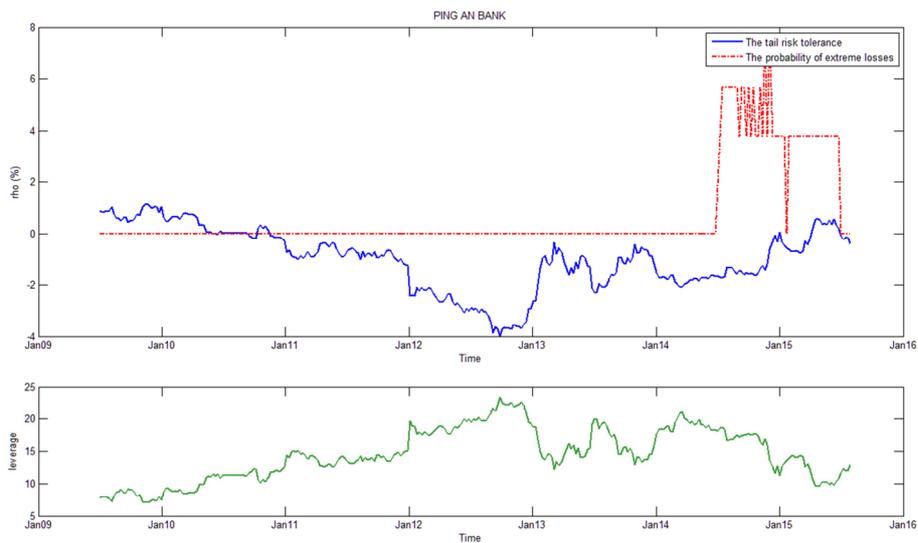


Figure 19: The tail risk tolerance of Shanghai Pudong Development Bank under stable-GJR(1,1)

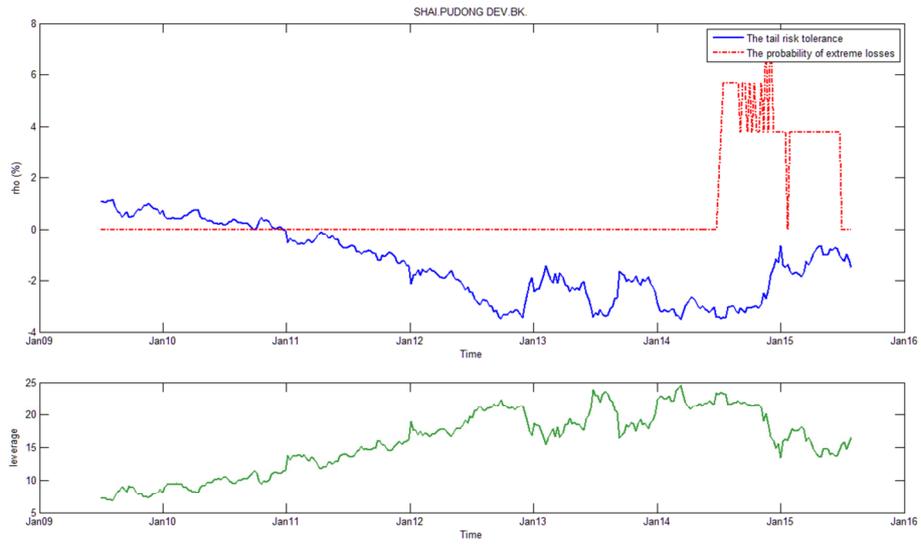


Table 1: The relationship among SRISK, EMLs, MES, ρ_t , TRT ($\rho_{i,t}$)

Measure	Definition	Formulae
EMLs	Extreme market losses	$-VaR(1\%, R_{m,t})$
ρ_t	Probability of EMLs in the future	(14)
MES	One-day marginal expected shortfall	(17)
SRISK	The expected capital shortfall of a financial institution conditional on a crisis	(15)
TRT ($\rho_{i,t}$)	The level of ρ_t that the bank is able to bear without getting into bankruptcy	(18)

Table 2: Maximum Likelihood estimates of the GJR(1,1) model with different distributional assumptions. The data is the Hang Seng Index from 1 January 1996 to 31 December 2006

	stable	std	normal	std	GED	std	student-t	std
δ_m	0.049	0.013**	0.036	0.023	0.000	0.000	0.050	0.020*
μ	0.006	0.002**	0.019	0.005**	0.016	0.005**	0.014	0.005**
γ	0.006	0.003*	0.023	0.007**	0.018	0.008*	0.015	0.007
ψ	0.028	0.005**	0.071	0.012**	0.069	0.015**	0.066	0.014**
ϕ	0.951	0.007**	0.933	0.008**	0.943	0.010**	0.947	0.009**
α or ν	1.821	0.031 [†]	2		1.1	0.046 [†]	5.048	0.542 [‡]
β	-0.065	0.165	0					
ML	-4793		-4855		-4738		-4772	
AICC	9600		9720		9488		9556	
BIC	9642		9750		9523		9591	
KS pvalue	0.156		0.017		0.019		0.007	
LR(nonnest)			2.844**		-4.864**		-4.833**	

For the stable Paretian distribution, the parameter α is the characteristic exponent, for the normal distribution, $\alpha = 2$. For the GED and student-t distributions, ν is the shape parameter. The AICC is the Akaike information criterion with the correction on finite sample sizes, the BIC is the Bayesian information criterion that gives a higher penalty on the number of variables. The p-value of the KS test is calculated by using standardized returns from 1st January 2007 to 31st December 2010. LR(nonnested) is the Vuong (1989)'s non-nested likelihood ratio test. We test the significant difference between the stable Paretian distribution and other distributions. * Since the stable Paretian distribution nests the normal distribution, we can directly calculate $2LR=2(\log(\text{stable})-\log(\text{normal}))$. Obviously, the results are greater than 100, the stable model is significantly different from the normal model. * and ** denoted as 95% and 99% are significantly different from 0 respectively. † and ‡ denote as 99% are significantly less than 2 and greater than 3 respectively.

Table 3: The parameters of the regime switching model of unbookable equity of the banks in Hong Kong

Starting Year/Qtr	1992/Q2	std
β_1	1.670	1.72
β_{m1}	-3.067	6.54
β_{r1}	4.313	26.48
Ending Year/Qtr	1993/Q1	
Starting Year/Qtr	1993/Q2	
β_2	-0.882	0.38*
β_{m2}	2.581	0.99**
β_{r2}	11.671	5.29*
Ending Year/Qtr	2009/Q2	
Starting Year/Qtr	2009/Q3	
β_3	0.2528	0.39
β_{m3}	1.2273	1.6
β_{r3}	6.5388	8.41
Ending Year/Qtr	2015/Q4	
LogLik	-304.609	

The sum of the total unbookable equity of banks in Hong Kong is used in the regression. The data is in quarter from 1992 to 2015. * and ** denoted as 95% and 99% are significantly different from 0 respectively.

Table 4: Likelihood-Ratio Test Results to Determine Parameter Equality across Regimes

$\beta_1 = \beta_2$	110.86**
$\beta_2 = \beta_3$	8.63**
$\beta_{m1} = \beta_{m2}$	32.59**
$\beta_{m2} = \beta_{m3}$	0.72
$\beta_{r1} = \beta_{r2}$	4.3*
$\beta_{r2} = \beta_{r3}$	0.38

The critical values of χ^2 at 5% significant and 1% significant for one d.f. are 3.84 and 6.63. * and ** denoted as 95% and 99% are significantly different respectively.

Table 5: The summary of the significant impact of “soinor” on dependent variables (ROA, ROE, ADZP, NPL, VaR(stable), and VaR(norm)) respectively

IV=soinor	ROA	ROE	ADZP	NPL	VaR(stable)	VaR(norm)
Bank of East Asia					-	
Hang Seng	++		++			
HSBC		--		++	++	++
BOC				++	+	++
Dah Sing	+			++		
Chong Hing		+		--		

- and -- are 95% and 99% significantly less than 0.

+ and ++ are 95% and 99% significantly greater than 0.

Table 6: The summary of the significant impact of “Reserve Requirement Ratio in China (RRR) with 1 quarter lag” on dependent variables (ROA, ROE, ADZP, NPL, VaR(stable), and VaR(norm)) respectively

IV=RRR (1Q lag)	ROA	ROE	ADZP	NPL	VaR(stable)	VaR(norm)
Bank of East Asia				--		
Hang Seng				--		+
HSBC		++				--
BOC	--	--	--		++	++
Dah Sing				++	++	++
Chong Hing	--	-	--		+	

- and -- are 95% and 99% significantly less than 0.

+ and ++ are 95% and 99% significantly greater than 0.

Table 7: The summary of the significant impact of “Loan-to-value ratio with 1 quarter lag (LTV)” on dependent variables (ROA, ROE, ADZP, NPL, VaR(stable), and VaR(norm)) respectively

IV=LTV (1Q lag)	ROA	ROE	ADZP	NPL	VaR(stable)	VaR(norm)
Bank of East Asia				++	+	
Hang Seng	-			-	++	++
HSBC				++	+	
BOC	+	+	++	--	++	+
Dah Sing	+				+	
Chong Hing					++	

- and -- are 95% and 99% significantly less than 0.

+ and ++ are 95% and 99% significantly greater than 0.

Table 8: Maximum likelihood estimates of the GJR(1,1) model with different distributional assumptions. The data we used is the Shanghai Stock Exchange Composite Index from 1 January 1996 to 31 December 2006

	stable	std	normal	Std	GED	std	student-t	std
δ_m	0.003	0.028	0.000	0.000	0.000	0.000	0.027	0.018
μ	0.057	0.012**	0.029	0.007**	0.161	0.038**	0.199	0.049**
γ	0.062	0.011**	0.054	0.007**	0.136	0.026**	0.179	0.038**
ψ	0.062	0.019**	0.025	0.010*	0.088	0.038*	0.174	0.060**
ϕ	0.736	0.034**	0.926	0.007**	0.755	0.039**	0.734	0.038**
α or ν	1.613	0.036 [†]	2		1.1 [†]	0.048	3.215	0.238
β	-0.074	0.126	0					
ML	-4865		-5096		-4819		-4841	
AICC	9743		10202		9649		9694	
BIC	9785		10232		9685		9730	
KS pvalue	0.126		0.000		0.011		0.000	
LR(nonnest) *			5.108**		-2.912**		-5.628**	

For the stable Paretian distribution, the parameter α is the characteristic exponent, for the normal distribution, $\alpha = 2$. For the GED and student-t distributions, ν is the shape parameter. The AICC is the Akaike information criterion with the correction on finite sample sizes, the BIC is the Bayesian information criterion that gives a higher penalty on the number of variables. The p-value of the KS test is calculated by using standardised returns from 1st January 2007 to 31st December 2010. LR(nonnested) is the Vuong (1989)'s non-nested likelihood ratio test. We test the significant difference between the stable Paretian distribution and other distributions. * Since the stable Paretian distribution nests the normal distribution, we can directly calculate $2LR=2(\log(\text{stable})-\log(\text{normal}))$. Obviously, the results are greater than 100, the stable model is significantly different from the normal model. * and ** denoted as 95% and 99% are significantly different from 0 respectively. † and ‡ denoted as 99% are significantly less than 2 and greater than 3 respectively.