Macro Stress Tests and History-Based Stressed PD: The Case of Hong Kong

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Abstract

This paper discusses the issues about the stress testing of banks' credit portfolios. Currently there is no standard methodology to perform stress tests on banks' credit portfolios and no standard to evaluate self-reported stress testing results from banks. Some banks and bank supervisors have attempted to build econometrics models for macro stress tests. These models may provide inconsistent conclusions because of insufficient data available, unstable patterns of association, nonlinear behavior of credit loss in stress conditions, and the relevance of the historical data in calibrating the model parameters. These issues on econometrics models are illustrated with data of Hong Kong in 1997-2007. This period is an unusual stress period for Hong Kong economy, having Asian financial crisis in 1997, burst of internet bubble in 2001 and SARS outbreak in 2003. With the given data, we find that it is challenging to identify suitable models for forecasting. This paper proposes a methodology to estimate history-based stressed probability of default (PD) to complement the use of macro stress tests. By analyzing the default rates of the banking sector, bank supervisors can easily identify the stressed PD of individual banks' credit portfolios. These estimates are also very helpful for bank supervisors to verify those self-reported stressed PD and to compute the capital adequacy ratios of the banks under stress.

NB: The views and analysis in the paper are those of the authors and do not represent the views of the Hong Kong Monetary Authority. Comments and enquiries can be sent to Michael C S Wong, Department of Economics and Finance, City University of Hong Kong, Tat Chee Avenue, Hong Kong (email: efmcw103@cityu.edu.hk; Tel: [852] 27887248)

1. Introduction

Stress testing on the risk of credit portfolios is an important task for banks to comply with the Basel II requirements. There is a wide range of practices among financial institutions (see for instance, Bank for International Settlements 2000; Financial Services Authority 2005; Hoggarth, Logan and Zicchino 2005). Some bank supervisors have relevant guidelines issued on stress tests, while others are still exploring suitable ways for their supervised banks. Data is always a problem in stress testing the risk of credit portfolios. Traditionally banks reported the ratio of nonperforming loans but banks are now required to report PD or default rate measured by “3-month past due”. These two sources of information are not the same. As many banks do not have sufficient history of PD for building stress-testing models, this makes stress testing a challenging task.

Some banks claim that they have successfully developed effective methodologies to conduct stress tests and report their stressed loss estimates to bank supervisors. How do bank supervisors verify these estimates? Some bank supervisors may consider the financial soundness of individual banks. Bank supervisors may sum all banks’ estimates and evaluate the impact of an economic stress on the banking sector. This comes to a critical question: How do bank supervisors know whether these stressed loss estimates are consistent and appropriate? So far there is no standard on quantitative validation for stress testing results. Given a wide range of methodologies used for stress testing, banks may intentionally consider some stress testing frameworks that provide them favorable results. If it happens, bank supervisors will underestimate the stress risk of individual banks and the whole banking sector. Obviously, there should be some yardsticks that help bank supervisors to verify the appropriateness of self-reported stress estimates.

Stress testing results of market risk and credit risk should be treated separately. Global banks have relatively large exposure to market risk because they are active and dominant in global financial trading. Other medium-sized or local commercial banks usually have the stressed loss amount coming from credit exposures. When their credit portfolios are under stress, their loss can be severe. Consider a commercial bank that specializes in providing loans to unrated corporations. Its original PD is 1%. When the market is under severe stress, according to the capital charge equation of the internal-ratings-based (IRB) approach of Basel II, the default rate of its portfolio may go up to 14%. Such a sharp increase in default rate likely imposes serious threats to the financial soundness of the bank because most banks keep their capital adequacy ratio (CAR) at the range from 11% to 15%. Therefore, if bank supervisors were unable to verify the appropriateness of stress test results, the banking system may be very vulnerable in economic downturns.

This paper aims at discussing major issues of performing macro stress tests on banks' credit portfolios and the banking system. Section 2 identifies the limitations of building econometrics models for stress testing credit portfolios. Section 3 illustrates the limitations of macro stress test models with the economic and aggregate data of Hong Kong in 1997-2007. Many banks are now required to report their stress test results. How bank supervisors evaluate the appropriateness of these self-reported figures remains to be an unsolved question. Section 4 proposes a simple methodology to estimate history-based stressed PD for individual banks. The methodology provides an effective tool for bank supervisors to verify self-reported stressed PD provided by individual banks and enables them to evaluate their capital adequacy ratios under stress. Section 5 concludes the paper.

2. Models on Macro Stress Testing

Previous studies mostly support that macroeconomic conditions affect default rates and credit risk forecasts. Default rate tends to increase in economic downturns (Fama 1986; and Wilson 1997a & b). Rating agencies tend to behave differently in different economic scenarios (Ferri, Liu and Majnoni 2001; Monfort and Mulder 2000; and Reisen 2000). Rating downgrades happen more frequently in economic downturns (Bangia, Diebold, Kronimus, Schagen, and Schuermann 2002; and Nickell, Perraudin and Varotto 2000). Also, a number of theoretical models link macroeconomic factors with credit risk (see the summary of Allen and Saunder 2003).

To effectively evaluate the impacts of economic stress on financial systems, many central banks and bank supervisors have spent effort on establishing framework for macro stress tests (Boss 2002; Hoggarth and Whitley 2003; Bundesbank 2003; Virolainen 2004; Drehmann 2005; Wong, Choi and Fong 2006). These works echoes the initiative of the Financial Sector Assessment Program (FSAP), a joint IMF and World Bank effort introduced in May 1999. The program aims to both better assess the vulnerabilities of financial systems in major economies and develop some surveillance systems on the stability of financial sector. Under this initiative, IMF develops Financial System Stability Assessments (FSSAs) that evaluate risks to macroeconomic stability stemming from the financial sector and the capacity of the sector to absorb macroeconomic shocks. A survey of relevant methodologies can be found in Sorge (2004).

In order to assess the impact of macroeconomic shocks to the financial sectors, simple models are developed to link write-offs or credit provisions (denoted by Y_t) with macroeconomic factors (denoted by X_t) and their lags (denoted by $X_{k,t}$). $X_{k,t}$ may include, among others, GDP growth, real interest rate, stock market return, property index return, and change in unemployment rate. The following are some prevalent models:

$$\text{Model 1: } \ln(Y_t) = a_0 + \sum_{k=1}^{n}\sum_{t=0}^{h} a_k X_{k,t} + u_t$$

$$\text{Model 2: } \ln\left(\frac{1-Y_t}{Y_t}\right) = a_0 + \sum_{k=1}^{n}\sum_{t=0}^{h} a_k X_{k,t} + u_t$$

In the above models, k (from 1 to n) represents the selected macroeconomic factors and t (from 0 to h) represents the selected time lags. Estimation can be based on simple regression with lags, vector autoregressive regression, seemingly unrelated regression, co-integration analysis and others. Generally, these models have the following limitations:

(1) The models study mainly the impact of macroeconomic factors on the aggregate credit quality in the banking sector as a whole. They do not evaluate their impact on individual banks. Usually, under an economic stress, banks with high risk credit portfolios and/or poor risk management systems will have strong hit. This may trigger off settlement and liquidity issues in the banking system. What bank supervisors need to do is to find out the particular banks that are more sensitive to economic stress and exercise tighter controls on them, such as higher capital requirements.

(2) The parameters in the models tend to be biased towards good or normal economic conditions. This is because a severe economic stress may happen once every 10 years. Only 10% of data used for estimation represents data under economic stress. This means, the models may underestimate the sensitivity of credit risk to economic stress.

(3) The models are assumed to follow some linear patterns. However, the impact of macroeconomic variables in a stress scenario may be totally explosive. Default rate can rise sharply in stress conditions.

(4) To build a stable econometrics model, the degree of freedom is normally expected to be 30 or more. If 5 X- variables and 2 lags are included in an econometric model, there should be at least 40 quarterly observations, 10-year data. A model with less statistical bias usually requires more data, say, 60 to 100 quarterly observations. Obviously, many commercial banks and central banks do not have sufficient data to fulfill this statistical requirement.

(5) Econometrics models generally assume a stable relationship between credit quality and macroeconomic variables in the financial sector. However, this relationship may not be stable in many economies. Also, continuous changes in banking regulation in the past 20 years affect the strategies of many banks. For instance, to reduce capital charge, some banks rebalance their credit risk via securitization, investments in foreign credit-related assets, utilizing credit derivatives, etc. The changes in the regulatory environment can

contribute substantially to the unstable association between credit risk and macroeconomic variables.

3. Can Econometrics Models Work? Some Issues in Hong Kong

Let's illustrate the above limitations of macro stress tests with the data in Hong Kong. The recent major economic downturn in Hong Kong was the Asian financial crisis in 1997. Chart 1 displays the economic times series of various macroeconomic variables in Hong Kong from Mar 1997 to Mar 2007. Default rates in the chart is the 3-month past due rate (in %) of the major banks in Hong Kong. GDP, number of unemployed persons, stock market index (Hang Seng Index) and property price index are all expressed in relative terms with their bases equal to 1 in March 1997. This helps simplify our comparison.

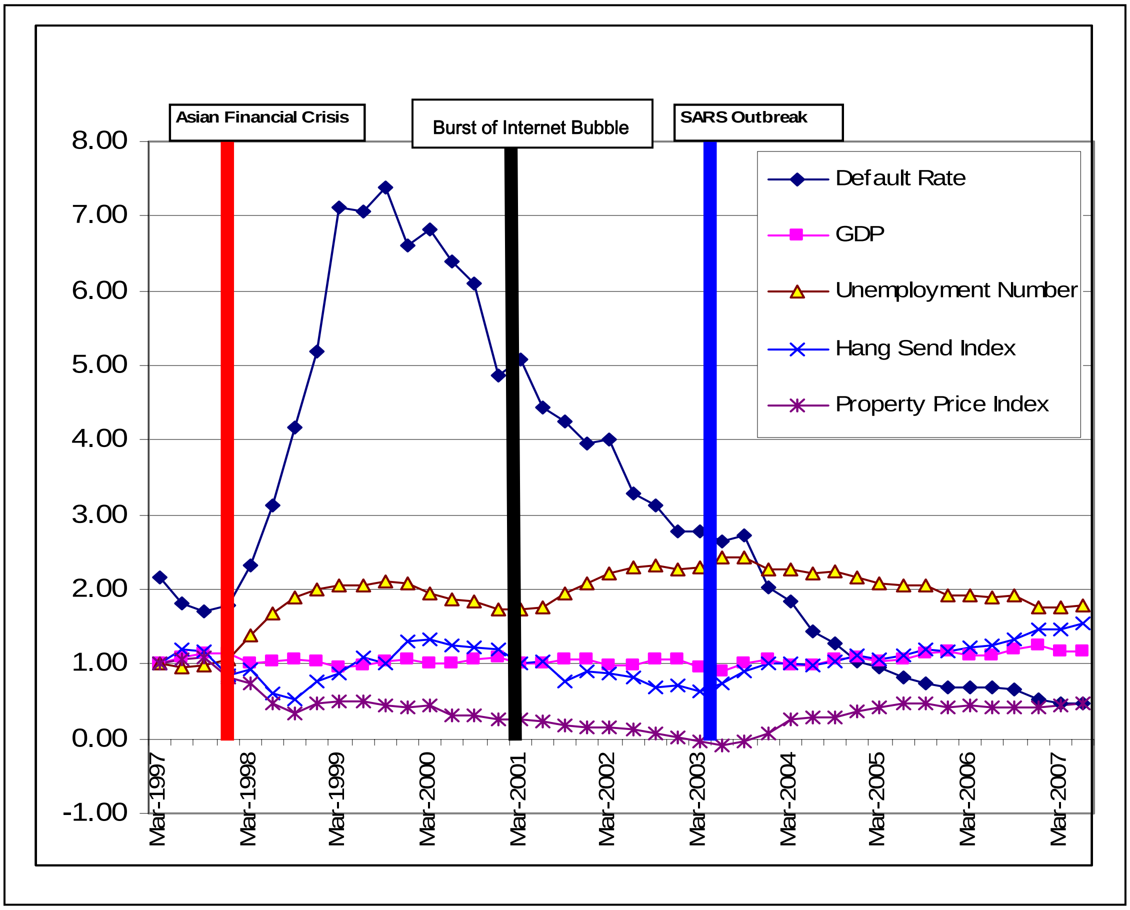
In Oct 1997, the Hong Kong dollar was strongly hit by a few global hedge funds. Then the stock market immediately declined by more than 50% and rebounded in December 1998. The property price index declined by more than 30% within 3 months after the incidence and kept on falling until September 2003. The number of unemployed persons rose sharply to its first peak in September 1999. Then it drops for several quarters and rose again to its second peak in September 2003. The nominal GDP had relatively stable behavior in the post-crisis period. The default rate started at 2.17% in March 1997 and hit its peak at 7.39% in September 1999. Then it fell gradually and consistently in the subsequent quarters.

The movements of the above time series provide some interesting implications on building econometrics models. Economic shocks on credit quality may have long-lasting lagged impact. The economic crisis in the last quarter of 1997 resulted in the highest default rate in September 1999. This lagged effect on credit quality lasted for around 2 years. This may be explained by the progressively cumulative impact of economic shocks on firms' business decisions and the labor market. When there were economic downturns, firms had their profitability decreased. Some firms then announced bankruptcy and some surviving firms cut costs by lying off employees and scaling down their investments. This process may take 1 to 2 years, gradually driving up the default rates of corporate credits, residential mortgages and other retail credits. On the other hand, the impact of economic downturns could be associated with their durations. Short duration may not trigger big jump in bankruptcy numbers and default rates because default and bankruptcy are very costly to both lenders and borrowers. Economic downturns of long duration can have tremendous effect on default rates. From a statistical perspective, a model with 4 to 8 lags (quarterly data) may be better to address the above issue of lagged impact of economic shocks. However, this model would not be feasible because of limited data available in Hong Kong.

In addition to the Asian financial crisis, Hong Kong experiences another two stressed situations after 1997. One crisis was the burst of internet bubble in March 2001. Before the burst, many internet/concept firms were established with private equities heavily involved. After the burst, many of these firms went bankrupt and their employees became jobless. In Chart 1, it is observed that the number of unemployed persons increased after the burst of the internet bubble. The stock market declined until March 2003. The property price index kept falling until June 2003. However, the default rates kept on falling after the burst of the internet bubble.

Another stressed situation was the SARS outbreak in Hong Kong in March 2003 that made the world seriously nervous. Although it was not an economic stress, it did impose threats on the Hong Kong economy. After the SARS outbreak, economic data had their trends slightly reversed. However, the magnitudes of reversal were very small. When the SARS crisis ended in Jun 2003, the economic variables continued their original trends.

Chart 1
Default Rates and Macroeconomic Variables of Hong Kong (1997-2007)



The continuous fall in default rate after March 1999 was partly due to banks tightening their lending policies. In response to the high default rate after the Asian financial crisis, many banks in Hong Kong deliberately reduced lending to risky clients, scaled down their credit lines offered to individual borrowers, and re-allocated the investments to low-risk securities. These chain reactions from banks would make an econometric model unstable.

Comparing the movements of the macroeconomic variables and the default rates in the above three stressed situations, we can easily identify no consistent pattern of association between default rate and the macrofactors. Although Wong, Choi and Fong (2006) have built two econometrics models on default rates of the credit portfolios of the banking sector in Hong

Kong, it is difficult to conduct any cross-validation on these models and to perform any out-of-sample test on their predictive accuracy.

All these modeling problems not only apply to Hong Kong but also to other Asian economies suffering from the crisis in 1997. For economies with higher degree of economic instability and/or frequent changes in government policies, econometric modeling usually suffers from similar problems. Given these constraints, how can analysts predict stressed PDs and stressed loss of the credit portfolios for individual banks and the banking system?

4. History-based Stressed PD

The above section highlights the issues of econometric methods in stress testing. This hints that bank supervisors will find it hard to verify statistically whether banks provide appropriate stressed loss estimates. An alternative that bank supervisors can consider is history-based default rates under stress. Using these figures as stressed PD is less arguable. Banks would accept that they should consider the worst scenario in their own history.

From the data given in Section 3, the highest default rate of the Hong Kong banking sector in 1997-2007 is 7.39%, which occurred in September 1999. This can be taken as a history-based stressed PD of the Hong Kong banking sector. Individual banks may report their history-based stressed PD to bank supervisors but an issue arises. Some banks may not have a long time-series of default rates. Some banks may have their risk strategies changed and their history-based stressed PD might not reflect their future stressed loss. In addition to history-based stressed PD of individual banks and the banking sector, is there any better benchmark that bank supervisors can apply to evaluate the appropriateness of self-reported stressed PD?

This section proposes a simple methodology that infers the history-based stressed PD of individual banks from the history-based stressed PD of the banking sector. In this methodology, bank supervisors can adjust the PD level of individual banks or individual credit portfolios so as to identify their stressed PD with respective to the history-based stressed PD of the banking sector.

According to the KMV default model, PD is the probability for the normalized asset level (A) going below default threshold (Q). A is assumed to stay at 0 with SD = 1, affected by macrofactors. The distance between A and Q is known as distance-to-default (DD). PD can be easily computed by N(-DD), where N( ) converts a critical value to a probability under the standard normal graph[1]. If the economy is under stress, A will depreciate and move closer to Q. This results in a smaller DD, a higher PD and finally a higher default rate. This is the meaning of stressed PD under the KMV concept. Following this logic, we make the following assumptions:

(a) Q* is an aggregate default threshold of the banking sector, which can be estimated by G(PD*). The function G( ) converts PD* (i.e. the long-run PD of the banking sector) into a critical value under the standard normal graph[2].

(b) Some banks have their default thresholds different from Q*. The threshold of a bank j, Q_j, can be estimated by $Q_j = G(PD_j)$, where PD_j is the PD of the bank. As the bank changes its PD, its new Q_j can be easily estimated. Meanwhile, different portfolios in a bank differ in their PD. This method easily predicts the default thresholds of different credit portfolios.

(c) A* should stay at zero. Under severe stress, it moves to the left from zero. As a result, the $DD^*_{Stress} = A^*_{Stress} – Q^*$ is shorter, where DD_{Stress} is the distance-to-default of the banking sector under stress and A^*_{Stress} is the aggregate asset value under stress. A^*_{Stress} is a market-wide phenomenon assumed to affect the whole banking sector. DD^*_{Stress} can be estimated by -G(Stressed PD*), which coverts the stressed PD of the banking sector into a critical value.

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[1] In EXCEL, N(-DD) can be typed as "=normsdist(-DD)"
[2] In EXCEL, G(PD) can be typed as "=normsinv(PD)".

(d) The difference between normal DD* and DD^*_{Stress} indicates the size of depreciation of the asset value under stress. This means, asset value under stress can be estimated $A^*_{Stress} = DD^*_{Stress} - DD^* = [-G(\text{Stressed PD}^*)] - [-G(PD^*)]$.

(e) If we know both A^*_{Stress} and Q_j, the DD of the bank j under stress will be known. That is equal to $A^*_{Stress} - Q_j$. The stressed PD of the bank j will thus become $N(A^*_{Stress} - Q_j)$.

$N(A^*_{Stress} - Q_j)$ can be a simple benchmark for bank supervisors to evaluate the stressed PD reported by individual banks. This considers both the history-based stressed PD of the banking sector and the PD level of individual banks.

This paper applies the data of Hong Kong to illustrate how this methodology works. The first column of Table 1 shows the actual default rate in Hong Kong in 1997-2007. The first value is the median default rate of the Hong Kong banking sector. This can be treated as the PD*, the long-run PD of the banking sector. Its corresponding default threshold will be $Q^* = G(PD^*) = -1.93$.

The maximum default rate in the period 7.39%, which can be treaded as the history-based stressed PD. Some may define stressed PD in other ways, such as highest PD at the confidence level of 95%, 99%, and 99.9%. These stressed PDs are 7.04%, 7.27% and 7.38% respectively (shown in the first column). Obviously stressed PD* at 99%, 99.9% and the maximum are very close. The second column of the table shows G(Stressed PD*). For Stressed PD* = 7.39%, we have G(Stressed PD*) = -1.45. On the basis of Assumption (d), we can get $A^*_{Stress} = [-G(\text{Stressed PD}^*)] - [-G(PD^*)] = -1.93 + 1.45 = -0.48$.

Table 1 Estimated Asset Value in Stress Conditions

	Actual Default Rate	G(Actual Default Rate)	Implied Asset Value
Median	2.68%	-1.93	0.00
95.00%	7.04%	-1.47	-0.46
99.00%	7.27%	-1.46	-0.48
99.90%	7.38%	-1.45	-0.48
Maximum	7.39%	-1.45	-0.48

History-based Stressed PD vs IRB Stressed PD

Our model discussed above assumes that A^*_{Stress} is applied to all banks. Banks simply differ in their PD levels that result in different default thresholds, i.e. Q_j. All the banks have their assets sharing the same sensitivity to macrofactors. This assumption is slightly different from the IRB (internal-ratings-based) equation of Basel II. The IRB equation aims to include the unexpected loss as the capital charge. The unexpected loss is a function of the difference between stressed PD and normal PD. The stressed PD is inferred on the assumptions that the market factor has reached the stressed condition at 99.9% confidence level. The equation assumes the presence of a parameter R (correlation), which is negatively related to PD. In other words, low-PD credit assets are more sensitive to the market factor than high-PD credit assets.

Table 2 compares our history-based stressed PD with the stressed PD of the IRB equation. There are six hypothetical banks, B01 to B06. Each has its PD_j and default threshold (Q_j). Some are low-risk (i.e. low PD) and some are high-risk (i.e. high PD). Assume that the stressed PD* of the banking sector t is 7.29% in the recent history and the long-run PD is 2.68%. The asset value under stress (i.e. A^*_{Stress}) is -0.48. The column "History-based Stressed PD" shows the stressed PD computed by $N(A^*_{Stress} – Q_j)$. The column "IRB Stressed PD" displays the stressed PD estimated by IRB capital charge equation of Basel II. That equation is shown below:

$$\text{IRB Stressed PD} = N[(1-R)^{-0.5} \times G(PD) + (R/(1-R))^{0.5} \times G(0.999)]$$

where

- $N(\ )$ = cumulative probability of a critical value in the bracket
- $G(\ )$ = inverse of a cumulative probability
- $R = 0.12 \times (1 - e^{-50 \times PD}) / (1 - e^{-50}) + 0.24 \times [1 - (1 - e^{-50 \times PD}) / (1 - e^{-50})]$

The last column R is the correlation estimated with the equation provided by Basel II document.

As bank supervisors roughly know the PD of a bank is known, they can compared its self-reported stressed PD with both the history-based stressed PD and IRB stressed PD. Bank supervisors may expect self-reported stressed PD higher than the history-based stressed PD. It is because history might repeat itself.

Table 2 clearly indicates that the history-based stressed PD is much lower than the IRB stressed PD. This implies that capital charge in IRB equation will sufficiently cover the stressed loss if history repeats itself. Let's focus on the bank B04 in the table. This bank has PD = 2.68% which is the median of the aggregate banking sector in Hong Kong. Its history-based stressed PD is 7.35%, which is the peak PD of the Hong Kong history in 1997-2007. Its IRB stressed PD is 21.48%. Both the history-based stressed PD and IRB stressed PD provide very useful references for bank supervisors to verify self-reported stressed PD of individual banks. The former one is a realistic and empirical estimate of credit risk under a stress condition in the history, while the latter one is inferred from a theoretical model.

Table 2 Stressed PD of Several Hypothetical Banks

Bank	PD_j	Default Threshold (Q_j)	Asset Value Under Stress (A^*_{Stress})	History-based Stressed PD	IRB Stressed PD	R in IRB Equation
B01	0.50%	-2.58	-0.48	1.80%	9.77%	0.21
B02	1.00%	-2.33	-0.48	3.24%	14.03%	0.19
B03	2.00%	-2.05	-0.48	5.78%	19.03%	0.16
B04	2.68%	-1.93	-0.48	7.35%	21.48%	0.15
B05	3.50%	-1.81	-0.48	9.14%	24.09%	0.14
B06	5.00%	-1.64	-0.48	12.20%	28.45%	0.13

Commercial banks may rely on their internal models to determine their stressed PD. This aims to encourage their enhancement on their risk management analysis. Bank supervisors may build econometrics models to forecast future credit quality of the banking sector. However, both the history-based stressed PD and IRB stressed PD should not be ignored because of the following reasons:

(a) With these two estimates on stressed PD, bank supervisors can easily verify self-reported stressed PD of individual banks. If a bank produces a self-reported stressed PD lower than what is expected, bank supervisors would take further actions to investigate the stress test models of the bank.

(b) With the history-based stressed PD, bank supervisors can compute credit loss of individual banks and evaluate their capital adequacy ratios under stress. This helps evaluate their possibility of capital shortfalls.

(c) For a new bank or a bank having substantially changes in their risk appetite, bank supervisors can assign an appropriate PD level and compute its history-based stressed PD. The PD assignment can be based on benchmarking with banks of similar risk profile. This enables bank supervisors to assess the risk of a bank with very limited information.

5. Conclusions

This paper has discussed the issues about stress testing risk of credit portfolios. Currently there is no standard methodology to perform macro stress tests and no standard to evaluate self-reported stressed estimates. Some banks and bank supervisors have attempted to build econometrics models for macro stress tests. These models may provide inconsistent conclusions because of insufficient data available, unstable patterns of association, nonlinear behavior of credit loss in stress conditions, and the relevance of the historical data in calibrating the model parameters. These issues on econometrics modeling have been illustrated with data of Hong Kong in 1997-2007. This period is an unusual stressed period for Hong Kong economy, having Asian financial crisis in 1997, the burst of internet bubble in 2001 and the SARS outbreak in 2003. With the given data, we find it is challenging to identify suitable models for forecasting stressed PDs.

The paper has proposed a methodology to estimate history-based stressed PD to complement the use of macro stress tests. History-based stressed PD is based on the peak default rate observed in recent history of the banking sector. This estimate can be easily converted to the stressed PD for individual banks as long as bank supervisors know the default rate of the banks' credit portfolios. With the estimates on history-based stressed PDs, bank supervisors easily verify those self-reported stressed PDs and compute the capital adequacy ratios of all banks under stress.

The discussion in this paper has not covered LGD. Some bank supervisors have set LGD = 45% for corporate credits if banks following foundation IRB. The LGD in Advanced IRB approach is a downturn LGD. Bank supervisors can rely on the LGD or average write-offs given default to calculate stressed loss.

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