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PROCYCLICALITY OF LOAN-LOSS PROVISIONING AND SYSTEMIC RISK IN THE HONG KONG BANKING SYSTEM

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Abstract

This study finds that loan-loss provisioning is a main determinant of systemic risk in both the time and cross-sectional dimensions for the Hong Kong banking sector. For the time dimension, empirical evidence supports that loan-loss provisioning of banks in Hong Kong is procyclical, which could result in reductions in loan supply during economic downturns and amplify business cycle fluctuations. For the cross-sectional dimension, banks' systemic risk contributions are found to be time-varying and increase generally across banks in weak macroeconomic conditions, which is consistent with the observation that when significant rises in provisioning against loan losses are common among banks during economic downturns, the risk of systemic distress due to joint deterioration in the financial health of banks is higher. These findings suggest that countercyclical tools for loan loss reserves may be effective in reducing systemic risk in the banking system.

JEL classifications: G21; G28

Key words: Banks, countercyclical, Hong Kong, loan-loss provisioning, procyclicality, systemic risk

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Executive Summary:

- *Reducing systemic risk for the global banking system is a priority for policymakers following the global financial crisis, with growing consensus that a coherent macroprudential framework addressing risk in both the time and cross-sectional dimensions is needed to safeguard financial stability. While considerable research has shed light on risk in a particular dimension, the implications for the other are usually not adequately examined. To obtain a more comprehensive assessment, this study examines systemic risk in both dimensions and their interrelationship, using the Hong Kong banking sector as an example.*

- *For the time dimension, our empirical findings strongly support the hypothesis that loan-loss provisioning of banks in Hong Kong is procyclical, and that rises in provisioning during economic downturns could lead to significant reductions in loan supply. These findings together imply that loan supply of banks in Hong Kong is also procyclical, which could amplify business cycle fluctuations.*

- *For the cross-sectional dimension, individual banks' systemic risk contributions (or their interconnectedness) are found to be time-varying and show a clear pattern of co-movement, with much higher systemic risk being observed in weak economic environments. This finding is consistent with the observation that during economic contractions when significant increases in provisioning against loan losses are common among banks, the risk of systemic distress due to joint deterioration in the financial health of banks is higher.*

- *The empirical results have two policy implications. First, the fact that loan-loss provisioning plays a pivotal role in determining systemic risk for the Hong Kong banking sector, both in the time and cross-sectional dimensions, may suggest that countercyclical tools for loan loss reserves may be effective in reducing systemic risk in the banking sector. These findings may also reflect that current provisioning practices are prone to delayed recognition of credit losses and insufficient through-the-cycle considerations due to constraints imposed by accounting standards.*

- *Second, this study highlights that while a clear separation between the time and cross-sectional dimensions of systemic risk is conceptually desirable, as it facilitates development of analytical tools, fundamentally these two dimensions of systemic risk may be interrelated. The implications of such potential interrelationship should be assessed when formulating macroprudential policies.*

I. Introduction

In the wake of the 2008-09 global financial crisis, reducing systemic risk[2] for the global banking system is set to top the agenda for policymakers. Indeed, there is a growing consensus that a coherent macroprudential framework addressing systemic risk in both the time and cross-sectional dimensions is needed to safeguard financial stability (e.g. Bank of England, 2009; Caruana, 2010; Papademos, 2010; Strauss-Kahn, 2010). The former calls for policies to build up capital and liquidity buffers during economic upswings that can be drawn on in downturns to mitigate risks and imbalances in the financial system over time, while the latter needs policies to reduce risks stemming from high interconnectedness and common exposures of financial institutions at any particular point in time (see Caruana, 2010).

Considerable research has been undertaken by central banks and academia to contribute to the ongoing development of the policy framework. For systemic risk in the time dimension, research on the relationship between banks' provisioning practices and financial system procyclicality[3] has long been a core interest of researchers (e.g. Rajan, 1994; Cortavarria et al., 2000; Fernandez de Lis et al., 2000; Borio et al., 2001; Cavallo and Majnoni, 2002; Laeven and Majnoni, 2003; Berger and Udell, 2004; Bikker and Metzemakers, 2005; Jimenez and Saurina, 2005; Craig et al., 2006; Angklomkliew et al., 2009). There is also a large body of research on systemic risk in the cross-sectional dimension, particularly on the identification of systemically important financial institutions and the estimation of individual financial institutions' systemic risk contributions (e.g. Gropp and Moerman, 2004; Gropp and Vesala, 2004; Hartmann et al., 2005; Lehar, 2005; Adrian and Brunnermeier, 2008; Allenspach and Monnin, 2008; Fong et al., 2011; Segoviano and Goodhart, 2009; Tarashev et al., 2010).

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[2] According to the Financial Stability Board (2009), systemic risk is defined as the risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy.

[3] According to the Financial Stability Forum (2009), the term procyclicality refers to "the dynamic interactions (positive feedback mechanisms) between the financial and the real sectors of the economy. These mutually reinforcing interactions tend to amplify business cycle fluctuations and cause or exacerbate financial instability."

While these studies provide important policy insights on systemic risk in a particular dimension, their implications for the other dimension are usually not adequately examined. However, for policymakers, it is important to understand the aggregate effect of a macroprudential policy on systemic risk in these two dimensions. This is particularly so if policies addressing systemic risk in the time/cross-sectional dimensions can either exacerbate or alleviate systemic risk in the other dimension. Therefore, whether these two risk dimensions are interrelated becomes crucial to policymakers.

To obtain a more comprehensive assessment, this paper examines systemic risk in these two dimensions and also their interrelationship, using the Hong Kong banking sector as an example. For the time dimension[4], following largely the work by Laeven and Majnoni (2003), we estimate the degree of procyclicality of loan-loss provisioning[5] (*LLP*) and its potential impact on loan supply for a sample of 12 listed banks in Hong Kong. The estimation result is further compared with those of other Asia-Pacific economies. By doing so, the prevalence of a procyclical pattern in *LLP* and that in loan supply among banks in Hong Kong can be assessed relative to their counterparts in the region.

For the cross-sectional dimension, using the Merton default probability as a proxy for default risk (see Merton, 1974), we examine the interdependence of default risk of the 12 banks for the same period by applying the *CoVaR* method proposed by Adrian and Brunnermeier (2008). A regression analysis is then applied to identify the determinants of individual banks' systemic risk contributions.

Our estimation results find that LLP of banks plays a vital role in determining systemic risk in the Hong Kong banking sector both in the time and cross-sectional dimensions. The empirical evidence has important policy implications for the Hong Kong banking sector and contributes to the international discussions about approaches to reducing systemic risk. For the former, the fact that *LLP* is identified to be a key determinant of the banking sector's systemic risk suggests that forward-looking tools for loan-loss reserves (e.g. Basel Committee on Banking

4 In this study, the term "time dimension" is also known as "procyclicality dimension".
5 Loan-loss provisioning refers to expenses for bad debts in the income statement.

Supervision, 2009; Financial Stability Forum, 2009; Saurina, 2009) might be useful in reducing systemic risk in the banking system. For the latter, this study highlights that, while a clear separation between the time and cross-sectional dimensions of systemic risk is conceptually desirable, as it facilitates developments of analytical tools, essentially these two dimensions may be interrelated. Therefore, the implications for such potential interrelationship should be assessed when formulating macroprudential policies.

The rest of this paper is organised as follows. Sections II and III present the empirical specification, and data and estimation methods respectively. Section IV summarises the estimation results. Section V concludes.

II. The Empirical Specification

This section specifies econometric models for examining systemic risk in the time and cross-sectional dimensions for the Hong Kong banking sector.

Models for estimating systemic risk in the time dimension

The econometric models to examine systemic risk in the time dimension are mainly to estimate the procyclicality of *LLP* in the Hong Kong banking system, as past empirical work generally suggests it is a major contributor (e.g. Cavallo and Majnoni, 2002; Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Craig et al., 2006; Bouvatier and Lepetit, 2008). Banks' procyclical provisioning behaviour that raises (reduces) their *LLP* during economic downturns (expansions) could amplify business cycle fluctuations, because a high burden of *LLP* on banks' profitability and capital in worsening economic conditions could result in sharp reductions in lending capacity and, therefore, undermine investment and consumption.

Empirically, the degree of procyclicality can be revealed by answering two specific research questions. First, does the *LLP* of banks actually show a significant procyclical pattern (e.g. Fernandez de Lis et al., 2000; Bikker and

Metzemakers, 2005; Angklomkliew et al., 2009)? Secondly, conditional on a procyclical pattern of the *LLP*, do rises in *LLP* constrain the loan supply of banks (e.g. Bouvatier and Lepetit, 2008; Craig et al., 2006)? Two econometric equations are specified to study the two empirical questions.

To examine the cyclical pattern of the *LLP* (the first empirical question), the following model is specified:

$$\frac{LLP_{i,t}}{Loan_{i,t-1}} = \alpha_0 + \alpha_{1i}\Delta GDP_{k,t} + \alpha_{2k}\Delta Loan_{i,t} + \alpha_{3k}\frac{PBIT_{i,t}}{Assets_{i,t-1}} + \alpha_{4k}\frac{Equity_{i,t}}{Assets_{i,t-1}} + \omega_i + \varepsilon_{i,t} \tag{1}$$

where *i*, *k* and *t* index bank, economy and time respectively. The specification assumes that the ratio of *LLP* to total loans for bank *i* at time *t* responds to the real GDP growth ($\Delta GDP_{k,t}$), loan growth in real terms ($\Delta Loan_{i,t}$), profits before tax and loan-loss provisioning over total assets ($\frac{PBIT_{i,t}}{Assets_{i,t-1}}$), and shareholders' equity over total assets ($\frac{Equity_{i,t}}{Assets_{i,t-1}}$). Following the practice by Laeven and Majnoni (2003), lagged values of assets and loans are adopted to define the financial ratios to avoid potential endogeneity problems. Unobservable bank-specific effects and the remainder disturbance are captured by ω_i (with mean zero and constant variance σ_ω^2) and $\varepsilon_{i,t}$ (with mean zero and constant variance σ_ε^2) respectively. The empirical specification is largely in line with those models adopted in the literature to study the cyclical pattern of *LLP*.

The cyclical pattern of *LLP* is measured by the coefficient of $\Delta GDP_{k,t}$ (i.e. α_{1i}). A negative and significant estimate for α_{1i} indicates that banks' *LLP* tends to increase during economic downturns and decrease during upturns, supporting the hypothesis of procyclical *LLP*. Unlike past studies that usually assume an identical degree of *LLP* cyclicality for all banks (i.e. same α_{1i} for all banks)[6], the current econometric specification assumes banks have different degrees of *LLP* cyclicality. This specification allows us to assess the cyclical pattern for each bank, thus facilitating the estimation of the proportion of banks having a procyclical pattern of *LLP* in an economy; data which should be of interest to policymakers.

Other coefficients are mainly to reveal the extent to which discretionary components will affect banks' provisioning practices. Specifically, α_{2k} relates to the hypothesis that banks' tend to set aside higher provisions against latent credit risk during credit booms where credit risk is more likely to build up (see Borio et al., 2001), while α_{3k} and α_{4k} relate to the income-smoothing and capital-management hypotheses respectively (see Greenawalt and Sinkey, 1998; and Moyer, 1990). A more prudent bank tends to set aside higher *LLP* deliberately when loan growth and earnings are high and capitalisation is low, implying a positive value for α_{2k}, α_{3k} and a negative value for α_{4k}. In order to construct a parsimonious model, α_{2k}, α_{3k} and α_{4k} are assumed to be constant across banks in an economy. This specification is reasonable as the number of estimation samples is rather small.

To assess the effect of *LLP* on the loan supply of banks (the second empirical question), the following model is considered:

$$\Delta Loan_{i,t} = \beta_0 + \beta_{1i} \frac{LLP_{i,t-1}}{Loan_{i,t-2}} + \beta_{2k} \Delta GDP_{k,t} + \beta_{3k} IR_{k,t} + \nu_i + \xi_{i,t} . \qquad (2)$$

The specification assumes that real loan growth for bank *i* at time *t* is correlated with the lagged ratio of *LLP* to total loans of the bank, the real GDP growth and real interest rate ($IR_{k,t}$). Unobservable bank-specific effects and the remainder disturbance are captured by ν_i (with mean zero and constant variance σ_ν^2) and $\xi_{i,t}$ (with mean zero and constant variance σ_ξ^2) respectively.

[6] For example, Craig et al. (2006) assumed that all banks in 11 selected Asia-Pacific economies share a same degree of procyclicality.

The effect of *LLP* on loan supply is estimated by the coefficient β_{1i}, which is assumed to vary across banks. The econometric specification is consistent with empirical evidence that a bank's own financial characteristics play a vital role in determining its loan supply (see Peek and Roosengren, 1995; Altunbas et al., 2007). A negative and significant estimate for β_{1i} indicates that banks tend to reduce loan supply when *LLP* increases.

The inclusions of $\Delta GDP_{k,t}$ and $IR_{k,t}$ in the model are mainly to control for differences in loan demand and monetary conditions respectively. To reduce the number of estimated parameters, the coefficients on $\Delta GDP_{k,t}$ and $IR_{k,t}$ are assumed to be identical across banks in an economy.

The product of the bank-level estimates of α_{1i} and β_{1i} (i.e. $\alpha_{1i} \times \beta_{1i}$) allows us to assess the effect of the business cycle on loan supply transmitted from the impact of the business cycle on *LLP*. By definition, a positive value of $\alpha_{1i} \times \beta_{1i}$ indicates a procyclical pattern of loan supply, i.e. loan supply of bank *i* tends to decrease (increase) in economic downturns (expansions). A simple way to assess systemic risk in the time dimension is to calculate the proportion of banks that are estimated with a positive $\alpha_{1i} \times \beta_{1i}$. A higher proportion may indicate that the aggregate credit supply tends to reduce amid economic downturns.

Models for estimating systemic risk in the cross-sectional dimension

To examine systemic risk in the cross-sectional dimension, systemic importance for the 12 listed banks in Hong Kong is estimated for the period 1996 – 2009 using the *CoVaR* method proposed by Adrian and Brunnermeier (2008). Similar to the Value-at-Risk (*VaR*), the *CoVaR* quantifies risks under extreme conditions. In this study, we focus on the default risk of banks and, therefore, the *CoVaR* is defined as the expected maximum default risk of a bank, conditional on another bank facing extremely high default risk. If substantial risk interdependence exists, an excess of

CoVaR over *VaR*[7], denoted by $\Delta CoVaR$, should be observed. In practical terms, $\Delta CoVaR$ is a useful indicator for identifying systemically important banks and for assessing individual banks' systemic risk contributions in the cross-sectional dimension. Technical details of the estimation of $\Delta CoVaR$ are in the Appendix.

To examine factors affecting the systemic importance of banks in Hong Kong, we first derive annual estimates of $\Delta CoVaR_j$, i.e. the average increase in the default probabilities for other banks when bank *j* is suffering from extremely high default risk, for every sample bank for the period of 1996 – 2009. This results in a yearly panel data set of $\Delta CoVaR_j$. The following econometric model is then estimated using the panel data set to examine the relationship between the systemic importance of banks in Hong Kong and four potential determinants of systemic risk:

$$\begin{aligned}\Delta CoVaR_{j,t} = \phi_0 + \phi_1 \ln(Assets_{j,t}) + \phi_2 \frac{Equity_{j,t}}{Assets_{j,t}} + \phi_3 \frac{CurAss_{j,t}}{Assets_{j,t}} + \\ \phi_4 \frac{LLP_{j,t}}{Loans_{j,t}} + \pi_j + \zeta_{j,t}\end{aligned} \quad (3)$$

where $\Delta CoVaR_{j,t}$ is $\Delta CoVaR_j$ in year *t*. $\ln(Assets_{j,t})$ is the total assets in logarithmic form. $(\frac{Equity_{j,t}}{Assets_{j,t}})$ measures banks' leverage, which is defined as the ratio of shareholders' equity to total assets (the lower the ratio, the higher the banks' leverage). Liquidity is proxied by the ratio of current assets to total assets $(\frac{CurAss_{j,t}}{Assets_{j,t}})$ (the lower the ratio, the lower the liquidity). $\frac{LLP_{j,t}}{Loans_{j,t}}$, which is defined as the ratio of *LLP* to total loans, is adopted to measure the credit risk of banks' loan portfolios. π_i and $\zeta_{i,t}$ are bank-specific effects and the remainder disturbance (with mean zero and constant variance σ_ζ^2) respectively. In essence, this specification assumes that larger banks with higher leverage, lower liquidity and higher credit risk of loan portfolios

[7] The VaR is defined as the expected maximum default risk of a bank over a specific time horizon within a given confidence interval.

tend to be associated with higher systemic risk contributions. As such, a positive sign is expected for the estimated ϕ_1 and ϕ_4, while a negative sign is expected for the estimated ϕ_2 and ϕ_3.

III. Data and Estimation Method

For the analysis of the time dimension of systemic risk (i.e. equations (1) and (2)), in addition to banks in Hong Kong, the estimation sample also includes banks in the other 10 member economies of the Executives' Meeting of East Asia-Pacific Central Banks (EMEAP): Australia, China, Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, and Thailand. All banking data are obtained from Thomson Financial. Only those companies that are classified as "Banks" by Thomson Financial are included in this study. The initial data set contains 317 listed banks. To produce reliable statistical results, banks having observations for less than five years are excluded from the analysis. In addition, since Japanese banks dominate the whole estimation sample, only the 25 largest Japanese banks (in terms of total assets) are included in the study[8], so that the estimation results will not be unduly influenced by the Japanese sample. Observations with a negative ratio of equity to total assets are also excluded. This results in a yearly panel data set of 192 listed banks in EMEAP economies for the period of 1996-2009.[9] The estimation sample includes 12 banks, which have substantial operations in Hong Kong, listed in the Hong Kong Stock Exchange.

For the analysis of the cross-sectional dimension of systemic risk, daily equity price data of the 12 listed Hong Kong banks covering 1996 – 2009 are used for estimations. Equity price data and financial market data (R^{SPF}, R^{HSI} and TED) are obtained from Bloomberg. Data on banks' financial statements for equation (3) are obtained from Thomson Financial. Table 1 shows descriptive statistics for the estimation sample.

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[8] The selected Japanese banks cover around 87% of the total assets of all Japanese banks in 2008.

[9] The sample banks for Hong Kong are the same as those for estimating ΔCoVaR and equation (3).

For equations (1) to (3), the generalised least squares (GLS) method instead of the ordinary least squares (OLS) method is applied because GLS estimates, in theory, are more efficient than OLS estimates given the panel structure of the data sets.[10]

IV. Estimation Results

The main empirical findings for the time dimension of systemic risk are as follows:

(1) *LLP* of the sample banks for Hong Kong is found to be procyclical, i.e. *LLP* tends to increase (decrease) during economic downturns (expansions), as revealed from the estimation results for equation (1) (see Table 2). The average of the coefficient measuring the effect of the real GDP growth on LLP of banks (i.e. α_{1i} in equation (1)) for the sample banks in Hong Kong is estimated to be negative (-0.08). We further examine the significance of this empirical finding by studying the estimated sign and the statistical significance of α_{1i} for individual banks. To this end, the sample banks are separated into two groups based on the sign of the estimated α_{1i}. For each group, we further separate the banks by the statistical significance of α_{1i}.[11] Chart 1 presents the proportions of the two bank groups for each economy of EMEAP[12]. The result shows that around 80% of the sample banks in Hong Kong are estimated to have a significant negative correlation between *LLP* and the real GDP growth. For other EMEAP economies, the corresponding estimated proportion ranges from 69% to 100%. This may suggest that procyclical *LLP* is rather common among banks in Hong Kong, as well as in the other Asia-Pacific economies.

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[10] For panel data sets, variances of cross-sectional units may differ significantly. The OLS estimation can be statistically inefficient and can give misleading inferences when the variances of the data are unequal.

[11] In this study, an estimated coefficient is regarded as statistically significant if the p-value is smaller than 0.1.

[12] Banks in Australia and New Zealand are grouped together in this analysis because the number of banks in New Zealand in the sample is small.

(2) *LLP* is found to be negatively correlated with the loan growth of banks in Hong Kong (Table 3), suggesting that increases in *LLP* during economic downturns may constrain the loan supply. Chart 2 presents the estimation result for β_{1i} in equation (2) in a similar fashion as Chart 1. Compared with other EMEAP economies, all sample banks in Hong Kong are estimated with negative β_{1i} (i.e. lower loan supply as a result of rises in *LLP*), with 75% of them being statistically significant. Other developed EMEAP economies, including Australia and New Zealand, Japan and Singapore also show a high proportion of negative estimates (at least 69%). However, the pattern is less clear for emerging market economies (EMEs) in the region.

(3) Estimation results detailed in points 1 and 2 above suggest that the loan supply of banks in Hong Kong is likely to be procyclical (loan supply increases during economic expansions and decreases during downturns). Chart 3 reveals the prevalence of procyclical loan supply among banks in different economies.[13] It is found that, compared with banks in other EMEAP economies, the procyclical patterns of loan supply are rather common among banks in Hong Kong, as a relatively high proportion of sample banks in Hong Kong are estimated with positive $\alpha_{1i} \times \beta_{1i}$.

The main empirical findings for the cross-sectional dimension of systemic risk are summarised as follows:

(1) Individual banks' contributions to systemic risk are found to be time-varying and show a clear pattern of co-movement. Chart 4 presents the distribution of the expected maximum default risk of a bank, conditional on another bank facing extremely high default risk (i.e. $\Delta CoVaR_{j,t}$ in equation (3)) for the period of 1996-2009, which indicates that the average increase in $\Delta CoVaR_{j,t}$ for banks in different tiers (i.e. the 25th, 50th and 75th percentiles) generally moves in the same direction, particularly after 1999. Consistent

[13] The estimated $\alpha_{1i} \times \beta_{1i}$ is considered significant when both α_{1i} and β_{1i} are statistically significant at the 10% level.

with this empirical finding, a majority of pairs of banks are estimated with positive correlations between their $\Delta CoVaR_{j,t}$ (Table 4).[14]

(2) More importantly, macroeconomic conditions in Hong Kong appear to be a main contributor to the co-movement of banks' average increase in $\Delta CoVaR_{j,t}$, with much higher systemic risk being observed in weak economic environments. For instance, $\Delta CoVaR_{j,t}$ of banks increased generally during the Asian financial crisis in 1998 and the global financial crisis in 2008.

(3) For the determinants of systemic risk in the cross-sectional dimension, *LLP* is found to be positively correlated with banks' systemic risk contributions (Table 5). The empirical relationship may simply reflect that during economic downturns, (i) the risk of systemic distress due to joint deterioration in the financial health of banks is higher, as widespread increases in credit losses in the banking sector are more likely; and (ii) any significant credit losses surfacing from one bank become easier to trigger a reappraisal of risks for the whole banking sector by market participants because of a similar risk profile among banks.

(4) In addition, bank size is found to be a significant determinant of banks' $\Delta CoVaR_{j,t}$ (Table 5). Larger banks tend to have higher systemic risk contributions. This empirical result is consistent with the empirical findings for the US banking sector by Adrian and Brunnermeier (2008). However, liquidity and leverage are not significant determinants of banks' systemic risk, partly reflecting the strong capital and abundant liquidity in the Hong Kong banking system in the sample period.

[14] The pair-wise correlations are calculated using the annual estimates of $\Delta CoVaR_{j,t}$ for the period 1996-2009.

V. Conclusion

Empirical evidence in this study provides a better understanding of systemic risk in the time and cross-sectional dimensions for the Hong Kong banking sector. For the time dimension, this study provides strong empirical support for the hypothesis that loan-loss provisioning in Hong Kong is procyclical, and that rises in loan-loss provisioning could have a significant adverse impact on loan supply for the banks. More importantly, a comparative analysis shows that procyclical loan supply is rather prevalent among Hong Kong's banks.

For the cross-sectional dimension, individual banks' systemic risk contributions are found to be time-varying and show a clear pattern of co-movement, with much higher systemic risk being observed in weak economic environments. The movement of banks' systemic risk contributions is found to be driven partly by loan-loss provisioning. Loan-loss provisioning may in turn reflect that during economic downturns, (i) the risk of systemic distress due to joint deterioration in the financial health of banks is higher, as general increases in credit losses among banks are more likely; and (ii) any significant credit losses surfacing from one bank become easier to trigger a reappraisal of risks for the whole banking sector by market participants, because of a similar risk profile among banks.

These results highlight the importance of policies to reduce systemic risk in the Hong Kong banking sector. The fact that loan-loss provisioning plays an important role in determining systemic risk for the Hong Kong banking sector, both in the time and cross-sectional dimensions, may suggest that forward-looking tools for loan-loss reserves may be effective in reducing systemic risk. Our empirical findings may also reflect that current provisioning practices are prone to delayed recognition of credit losses and insufficient through-the-cycle considerations due to constraints imposed by accounting standards.

Secondly, the study highlights that while a clear separation between the time and cross-sectional dimensions of systemic risk is conceptually desirable, as it facilitates development of analytical tools, fundamentally these two dimensions of systemic risk may be interrelated. The implications of such potential interrelationship should be assessed when formulating macroprudential policies.

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Table 1. Descriptive statistics for the panel data set of banks in EMEAP economies

Economy	Loan Loss Provisioning over total loans (%)		Loan Growth in real terms (%)		Profits before tax and provisions over total assets (%)		Shareholders equity over total assets (%)		Real GDP growth (%)		Real interest rates (%)		Number of banks	Period
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median		
Australia & New Zealand	0.42	0.22	12.06	13.76	4.95	4.88	7.47	6.79	3.07	3.27	6.56	6.26	16	1996-2009
China	0.85	0.79	23.02	18.74	3.59	3.47	5.60	5.25	9.73	9.65	3.68	3.48	10	1996-2009
Hong Kong	**0.80**	**0.50**	**11.97**	**9.71**	**4.57**	**4.29**	**10.49**	**10.18**	**3.39**	**3.60**	**7.57**	**7.94**	**12**	**1996-2009**
Indonesia	2.14	1.27	0.78	2.28	12.02	10.04	13.77	10.45	3.65	4.85	2.92	4.43	43	1996-2009
Japan	0.57	0.41	3.49	3.87	1.06	0.98	5.21	5.08	0.67	1.50	2.95	3.03	23	1996-2009
Korea	2.70	1.70	8.90	9.07	5.06	4.83	4.87	4.77	4.15	4.64	4.75	4.01	25	1996-2009
Malaysia	2.25	1.78	2.30	5.17	6.97	4.97	13.25	9.55	4.55	5.82	3.59	2.66	17	1996-2009
Philippines	1.54	1.29	-0.42	-4.01	5.66	5.31	14.74	13.63	4.47	4.88	4.67	4.93	20	1996-2009
Singapore	0.78	0.51	10.53	5.97	3.53	3.51	12.13	11.46	5.07	7.25	5.07	4.59	6	1996-2009
Thailand	3.44	1.34	1.70	4.36	4.47	3.57	10.84	8.49	2.79	4.60	5.32	4.49	20	1996-2009
All economies	1.65	0.88	5.36	6.20	5.65	4.67	10.04	7.96	4.06	4.72	4.88	4.81	192	1996-2009

Note: Banks in Australia and New Zealand are grouped together in this analysis because the number of banks in New Zealand in the sample is small.

Table 2: Summary statistics for the estimated effect of the real GDP growth on loan-loss provisioning of the sample banks*

	Summary statistics for the estimated value of α_{1i}				
Economy	Mean	Median	Lower Quartile	Upper Quartile	Number of Banks
Australia & New Zealand	-0.54	-0.56	-0.58	-0.53	16
China	-0.21	-0.21	-0.21	-0.20	10
Hong Kong	**-0.08**	**-0.08**	**-0.10**	**-0.07**	**12**
Indonesia	-0.22	-0.24	-0.33	-0.07	43
Japan	-0.22	-0.21	-0.32	-0.08	23
Korea	-0.14	-0.17	-0.29	-0.06	25
Malaysia	-0.11	-0.09	-0.16	-0.04	17
Philippines	-0.21	-0.25	-0.33	-0.20	20
Singapore	-0.10	-0.14	-0.17	-0.08	6
Thailand	-0.42	-0.40	-0.64	-0.27	20
All economies	-0.23	-0.21	-0.34	-0.08	192

Note:

* Measured α_{1i} by in equation (1).

Table 3: Summary statistics for the estimated effect of loan-loss provisioning on real loan growth of the sample banks*

	Summary statistics for the estimated value of β_{1i}				
Economy	Mean	Median	Lower Quartile	Upper Quartile	Number of banks
Australia & New Zealand	-64.40	-4.03	-19.07	3.98	16
China	-30.30	-4.43	-17.31	-0.56	10
Hong Kong	**-3.90**	**-1.86**	**-5.57**	**-1.23**	**12**
Indonesia	-8.20	-0.98	-14.33	2.80	43
Japan	3.09	-1.87	-4.30	2.40	23
Korea	0.63	2.41	0.23	5.62	25
Malaysia	0.05	-1.24	-3.89	0.80	17
Philippines	-4.19	-3.60	-6.38	-1.55	20
Singapore	-2.17	-5.06	-5.76	-3.91	6
Thailand	2.95	0.46	-0.66	2.90	20
All economies	-8.77	-1.25	-5.40	2.03	192

Note:
* Measured by β_{1i} in equation (2)

Table 4. Pair-wise correlations between the systemic risk contributions of banks in Hong Kong*

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12
Bank 1	1.00											
Bank 2	0.96	1.00										
Bank 3	0.74	0.83	1.00									
Bank 4	0.47	0.86	0.43	1.00								
Bank 5	0.55	0.97	0.56	0.93	1.00							
Bank 6	0.71	0.98	0.57	0.76	0.79	1.00						
Bank 7	0.39	0.70	0.60	0.65	0.74	0.60	1.00					
Bank 8	0.98	0.90	0.75	0.97	0.91	0.92	0.95	1.00				
Bank 9	-0.73	-0.99	-0.42	0.04	-0.08	-0.36	0.22	-0.93	1.00			
Bank 10	-0.71	-0.99	-0.47	0.20	0.17	-0.23	0.17	-0.94	0.82	1.00		
Bank 11	0.12	0.99	0.27	0.65	0.47	0.58	0.40	0.91	0.24	0.17	1.00	
Bank 12	0.94	0.95	0.91	0.91	0.99	0.90	0.83	0.94	-0.96	-0.97	0.97	1.00

Note:

* Measured by $\Delta CoVaR_j$ in equation (3)

Table 5. Estimation results for the determinants of the systemic risk contributions of banks in Hong Kong*

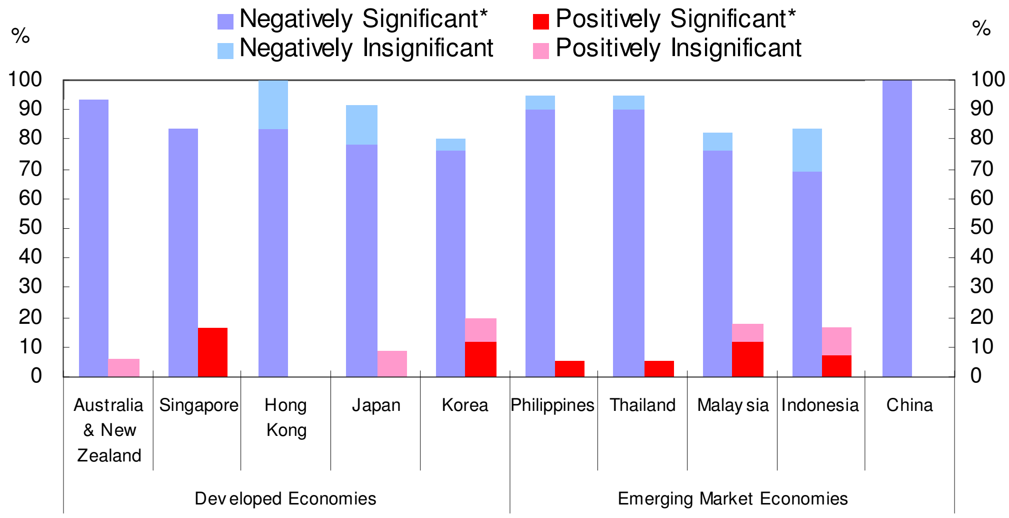
Dependent variable: $\Delta CoVaR_j$	
Explanatory variables	Estimated Coefficient
$Assets_{j,t}$	0.3388#
$Equity_{j,t}/Assets_{j,t}$	-0.0797
$CurAss_{j,t}/Assets_{j,t}$	0.0144
$LLP_{j,t}/Loans_{j,t}$	1.4829#
Constant	-4.8611
R-squared	0.1500
No. of observations	119

Notes:

*Measured by $\Delta CoVaR_j$ in equation (3).

# indicates statistical significant at the 5% level.

Chart 1: The estimated effect of the real GDP growth rate on loan-loss provisioning of the sample banks

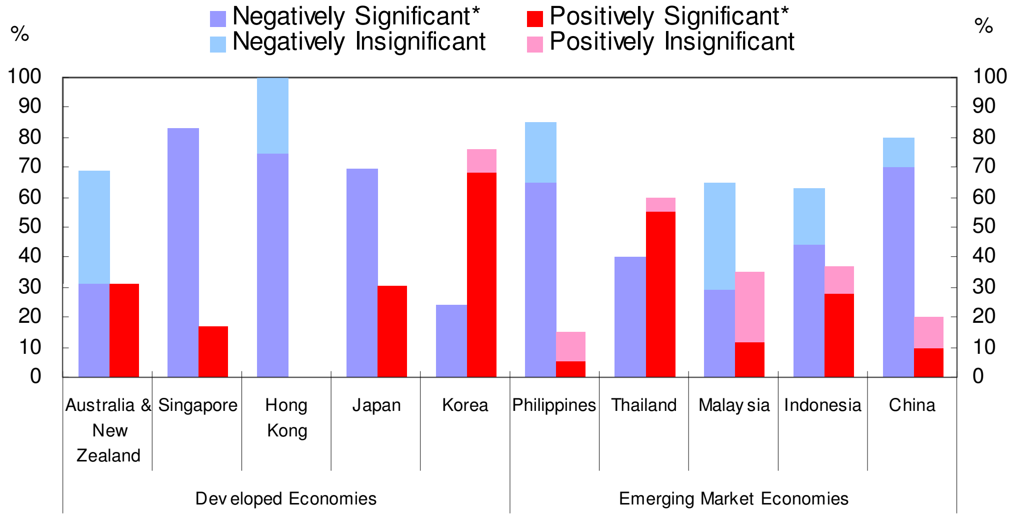


Notes:

*: Significant at the 10% level.

1. The estimated effect of the real GDP growth rate on loan-loss provisioning of the sample banks is denoted by the estimated positive or negative sign of α_{1i} in equation (1).
2. The blue/light blue bar represents the proportion of sample banks with a negative estimate for α_{1i}, whereas the red/pink bar represents the proportion of sample banks with a positive estimate for α_{1i}.

Chart 2: The estimated effect of loan-loss provisioning on real loan growth of the sample banks

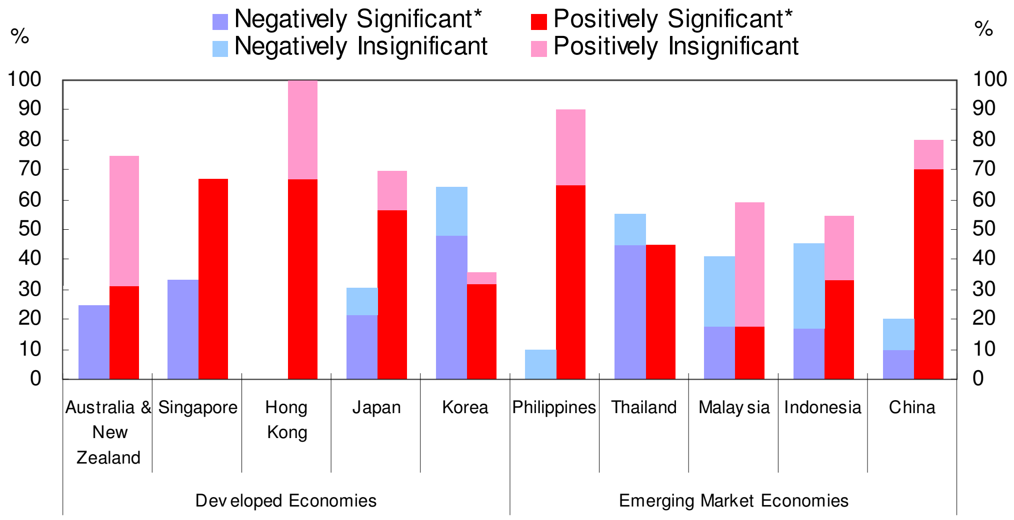


Notes:

*: Significant at the 10% level.

1. The estimated effect of loan-loss provisioning on real loan growth of the sample banks is denoted by the estimated positive or negative sign of β_{1i} in equation (2).
2. The blue/light blue bar represents the proportion of sample banks with a negative estimate for β_{1i}, whereas the red/pink bar represents the proportion of sample banks with a positive estimate for β_{1i}.

Chart 3: The estimated cyclical pattern of loan supply of the sample banks

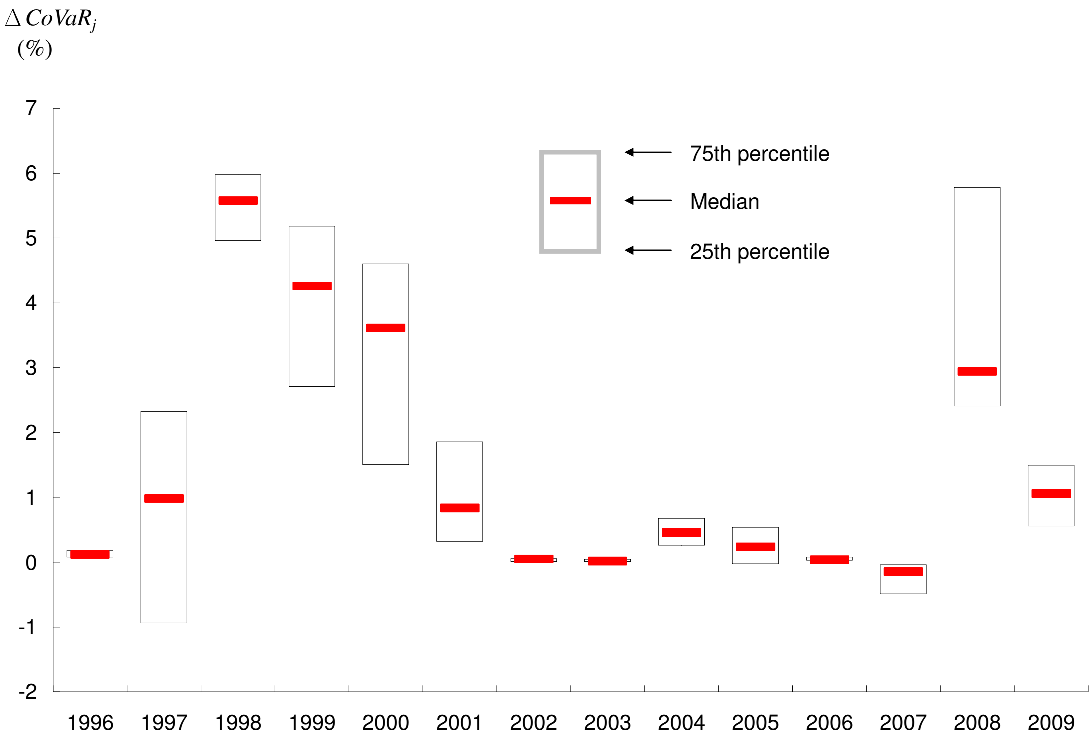


Notes:

*: Significant at the 10% level.

1. The estimated cyclical pattern of loan supply of the sample banks refers to the effect of the real GDP growth rate on real loan growth via impacts of the real GDP growth rate on loan-loss provisioning, which is measured by the positive or negative sign of $\alpha_{1i} \times \beta_{1i}$. The estimated $\alpha_{1i} \times \beta_{1i}$ is considered significant when both α_{1i} and β_{1i} are significant at the 10% level.
2. The red/pink bar represents the proportion of sample banks estimated with a procyclical pattern of loan growth (i.e. amplifying the business cycle), whereas the blue/light blue bar represents the proportion of sample banks with a countercyclical pattern of loan growth (i.e. dampening the business cycle).

Chart 4: Distribution statistics of the systemic risk contributions of banks in Hong Kong* for the period of 1996-2009



Note:

* Measured by $\Delta CoVaR_j$ in equation (3).

Appendix: Technical details of the estimation of ΔCoVaR$_j$

The *CoVaR* measure in this study, denoted by $CoVaR_q^{i|j}$, is defined as the *VaR* of bank *i* conditional on bank *j* at its level of VaR_q^j, where (1- *q*) is a given confidence level. Statistically, it can be specified as:

$$\Pr(R_{i,t} \le CoVaR_q^{i|j} \mid R_{j,t} = VaR_q^j) = q \tag{A.1}$$

where $R_{i,t}$ and $R_{j,t}$ can be any default risk measure for bank *i* and *j* at time *t* respectively. We proxy banks' default risk by the distance-to-default (*DTD*)[15], a common market-based indicator. The default risk measure for bank *i*, denoted by $R_{i,t}$, is defined as

$$R_{i,t} = DTD_{i,t} = \frac{\ln(V_{i,t} / F_{i,t}) + (\mu_i - \sigma_i^2 / 2)T}{\sigma_i \sqrt{T}} \tag{A.2}$$

where $V_{i,t}$ is the bank's asset value, $F_{i,t}$ is the face value of debt[16], μ_i is the annualised average asset returns, and σ_i is the volatility. *T* is the time horizon under assessment, which is assumed to be one year (i.e. *T*=1). In essence, $DTD_{i,t}$ measures the difference between the bank's asset value, $V_{i,t}$, and a default threshold, $F_{i,t}$, in terms of the bank's asset volatility in a given time horizon. The higher the $DTD_{i,t}$, the lower the default risk. Alternatively, one can estimate the corresponding default probability (*PD*) using the following equation,

$$PD(DTD_{i,t}) = N(-DTD_{i,t}) \tag{A.3}$$

where *N* is the cumulative normal distribution.

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[15] Ideally, credit default swap (CDS) data for banks in Hong Kong should be used as they should reflect default risk more directly. However, CDS data are only available for a small number of banks in Hong Kong. By contrast, the distance-to-default estimates, which are derived from equity prices and financial information of banks, are more readily available and, therefore, are employed in this study. Inferring default risk using the distance-to-default is common in the financial literature. See, for example, Merton (1974), Aharony et al. (1983), Gropp and Moerman (2004), Gropp and Vesala (2004), Hartmann et al. (2005), and Hui et al. (2010).

[16] Defined as total deposits.

In practice, the model parameters μ_i and σ_i, and the time series $V_{i,t}$ are not observable. However, with the assumption that $V_{i,t}$ are log-normally distributed, μ_i, σ_i, and $V_{i,t}$ can be estimated using the maximum likelihood method proposed by Duan (1994).[17] We apply the same method in this study to derive the estimates.

To obtain $CoVaR_q^{i|j}$, we first estimate the following model using the quantile regression method[18], which is a common statistical technique to model the relationship between the conditional quantile (e.g. the 99th percentile) of the dependent variable and explanatory variables:

$$R_{i,t} = \beta_{0,q}^{i|j} + \beta_{1,q}^{i|j} R_{j,t} + \beta_{2,q}^{i|j} R_t^{SPF} + \beta_{3,q}^{i|j} R_t^{HSI} + \beta_{4,q}^{i|j} TED_t + \varepsilon_q^{i|j} \quad \text{(A.4)}$$

Three control variables are included in the estimations to control for differences in financial market conditions. They are (i) the daily return of the S&P 500 Financials Index (R^{SPF}); (ii) the daily return of the Hang Seng Index (R^{HSI}); and (iii) the change in the spread between the 1-month HIBOR and the 1-month Exchange Fund Bill yield (*TED*). Control variables (i) and (ii) reflect the US and Hong Kong stock market conditions respectively, and (iii) is a proxy for the short-term liquidity condition in Hong Kong.

The estimated coefficients in equation (3) are then substituted into the following equation to obtain the $CoVaR_q^{i|j}$ estimate:

$$CoVaR_q^{i|j} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} VaR_q^j + \hat{\beta}_{2,q}^{i|j} R_j^{SPF} + \hat{\beta}_{3,q}^{i|j} R_j^{HSI} + \hat{\beta}_{4,q}^{i|j} TED_j \quad \text{(A.5)}$$

where $CoVaR_q^{i|j}$ is an estimate for bank i's default risk conditional on bank j suffering

[17] See also Li and Wong (2008).
[18] See Koenker and Bassett (1978). The coefficient estimates in equation (A.4) are obtained by minimising the sum of residuals $\sum_t (q - I_{\varepsilon \le 0}) \cdot \varepsilon_q^{i|j}$, where $I_{\varepsilon \le 0}$ is an indicator function which equals one if $\varepsilon_q^{i|j} \le 0$ and zero otherwise. The quantile, q, is set to be 1%.

from extremely high default risk equivalent to bank *j*'s *VaR* (i.e. VaR_q^j). Notice that the values of the control variables (i.e. R_j^{SPF}, R_j^{HSI} and TED_j) are those on the date when VaR_q^j is observed.

The systemic importance of bank *j* or its systemic risk contribution is measured by the following variable:

$$\Delta CoVaR_j = \sum_{i=1}^{n} \left[PD(CoVaR_q^{i|j}) - PD(VaR_q^i) \right] / n \qquad \text{(A.6)}$$

where *PD*(*CoVaR*) and *PD*(*VaR*) are the estimated default probabilities implied by the *CoVaR* and *VaR* respectively, and *n* is the number of banks in the system. This definition gives a straightforward interpretation for $\Delta CoVaR_j$, i.e. the average increase in the default probabilities for other banks when bank *j* is suffering from extremely high default risk equivalent to its *VaR*. By definition, a higher $\Delta CoVaR_j$ indicates higher systemic importance of bank *j* in the system.