Cost Efficiency of the Hong Kong Banking Sector: A Two-Stage DEA Window Analysis

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Abstract

The cost efficiency of the Hong Kong Banking sector over the period 2004 to 2014 is estimated by both traditional DEA and DEA window analysis. The two efficiency estimates are highly correlated with each other and both methods indicate an overall decrease in cost efficiency in the middle of the period, coincident with the Global Financial Crisis and, then, some recovery in efficiency. A second stage regression analysis finds that bank size and GDP growth are positively associated with efficiency, whereas revenue diversification and inflation are associated with lower efficiency. Stock exchange listing status appears to be associated with lower efficiency but no clear relationship between measures of market structure and efficiency is found.

JEL Codes: C13, G21 G23

Keywords: Cost efficiency, Banking sector, DEA Window, Hong Kong

Paper prepared for 2016 Australian Conference of Economists

1. Introduction

Hong Kong, a newly industrialized economy, is regarded as a leading centre of international finance and trade. It hosts a number of Asia-Pacific corporate headquarters. In 2014, around 70 of the 100 biggest banks in the world, 202 authorised institutions and 61 representative offices were operating in Hong Kong (KPMG, 2014). This high concentration of international banking institutions has resulted in increased competition in Hong Kong's domestic banking sector. Hong Kong's financial services industry is ranked the second most competitive in the world according to IMD (2016) and the third most competitive by GFCI (2016). Due to financial globalisation, banks everywhere are facing increased competition, requiring more efficient utilisation of financial resources as well as improvements in management quality.

DEA is a way of measuring efficiency relative to a best practice frontier (Berger et al., 2009) so managerial efforts can be best directed towards efficiency improvements. Only a few existing studies have addressed the efficiency of the Hong Kong banking sector. Kwan (2006) estimated X-efficiency using the stochastic frontier analysis (SFA) approach, while Drake et al. (2006) investigated technical efficiency using the two-stage data envelopment analysis (DEA) approach. However, both of these studies are based on datasets that cover only the pre-2001 period. The current paper uses a more recent dataset (2004-2014), which has the advantage of covering the period of the global financial crisis (GFC).

This paper addresses two questions: (i) how efficient is Hong Kong's banking sector? and (ii) what are the determinants of banking sector efficiency in Hong Kong? The rest of this paper is organised as follows. Section 2 contains a brief review of the literature on approaches to measuring bank efficiency and studying the determinants of bank efficiency. Sources of data and the methods used are discussed in Section 3. Section 4 presents the empirical results and Section 5 concludes.

2. Literature review

2.1 Approaches to measuring bank efficiency

In the literature on bank efficiency, or firm or decision-making unit (DMU) efficiency in general, there are two widely-used approaches: stochastic frontier analysis (SFA) is a

parametric approach that uses econometric techniques and data envelopment analysis (DEA) is a non-parametric linear-programming technique used to find a best practice frontier. DEA was first developed by Charnes et al. (1978). It does not require the specification of a functional form nor assumptions related to the distribution of an inefficiency term, as does SFA, since it ignores random error. For each individual bank, DEA identifies a peer bank or banks and then estimates the efficiency of each individual bank with respect to the best-practice banks from amongst its peers. Best-practice is not some theoretical ideal; rather, the best-practice bank (or banks) amongst its peers is assigned an efficiency score of 100% or 1. This approach has been used by, amongst others, Ahmad and Luo (2010), Brissimis et al. (2008), Casu and Girardone (2006), Casu and Girardone (2009), Mlambo and Ncube (2011), Nguyen et al. (2014), Rahman and Rosman (2013), Tan and Floros (2013).

One of the difficulties with DEA is that it may identify too many DMUs as 100% efficient if there are too few observations (DMUs) relative to the number of measured inputs and outputs. This can considerably reduce its usefulness as a practical guide to efficiency improvement. Window Analysis was introduced by Charnes et al. (1985); by treating a DMU considered at different points in time as a distinct DMU, the numbers of observations available for applying the DEA technique can be increased. For example, observing n DMUs, over t different time periods, would give nt observations. This approach raises the degrees of freedom in efficiency estimation (Avkiran (2004) and Asmild et al. (2004)) and should reduce the number of DMUs identified as 100% efficient.

2.2 Determinants of bank efficiency

In the literature on the determinants of bank efficiency, the majority of empirical studies focus on testing either the 'quiet life' hypothesis (QLH) or the 'information generation' hypothesis (IGH). The QLH, first tested in the banking industry by Berger and Hannan (1998), considers the relationship between market power (or concentration) and efficiency. It suggests that banks with market power can attain supernormal profits by exercising that power without the need to strive for efficiency. Thus, a higher degree of market concentration will go together with lower efficiency, while competition will foster bank efficiency. In contrast, the IGH, first proposed by Marquez (2002), suggests that increasing bank competition causes a decrease in the information-gathering capacity of banks

and a consequent increase in the probability of adverse borrower selection which can make banks less efficient.

The IGH and QLH are, in effect, two sides of the same proposition. The IGH suggests a positive relationship between market power and bank efficiency, while the QLH suggests that this relationship is negative. The empirical evidence, as shown in Table 1, is mixed, sometimes even within the one study. For example, Maudos and De Guevara's (2007) findings suggest that the relationship between concentration and cost X-efficiency, in the banking industry of fifteen EU countries over 1993–2002, differs in the deposit and loan markets. The relationship is positive in the loan market but negative in the deposit market. A study by Williams (2012) on banks in Latin America over 1985–2010 also suggests that the relationship between market power and efficiency is positive in asset markets but turns negative in deposit markets. In general, findings appear to be sensitive to the details of the sample under study.

TABLE 1 ABOUT HERE

A number of factors other than the degree of competition in the market have been found to be associated with efficiency. For the transition economies of South-Eastern Europe, Fang et al. (2011) find that, in addition to market power, institutional development is positively related to bank efficiency and, moreover, that ownership is a significant determinant of bank efficiency. Tan and Floros (2013), for the Chinese banking system between 2003 and 2009, find that risk, bank size, inflation and economic growth are positively related to efficiency. For China over the period 2003-11, Wang et al. (2014) note the positive effect of banking reform and disposal of non-performing loans on bank efficiency, with state-owned commercial banks achieving higher efficiency scores than joint-stock commercial banks in the pre-reform period with this gap narrowing in the post-reform period. Also for China, Hou et al. (2014) find not only intense market competition resulting in efficiency, but risk taking and bank size being positively related to technical efficiency.

Turning to the two studies, mentioned in the introduction, that are specific to the Honk Kong banking sector, Kwan (2006) used the SFA approach to estimate the X-efficiency of banks between 1992 and 1999. X-efficiency was found to improve with technological innovation, while bank size, deposit to asset ratio, loan to asset ratio, provision for losses and

loan growth were all positively related to efficiency. Off-balance sheet activities were found to negatively affect efficiency. Drake et al. (2006) investigated the relationships between macroeconomic conditions, regulatory factors and bank efficiency over 1995-2001 using the two-stage DEA approach. Their findings differed by size and type of institution, but efficiency was not significantly affected by Hong Kong's accession to the People's Republic of China, the South East Asian crisis or financial deregulation.

3. Methods and data

3.1 Two-stage DEA Window Analysis

The first stage: measuring cost efficiency by DEA Window Analysis

Banks can be thought of as multi-product firms (Sealey and Lindley, 1977) which produce a number of different outputs (y_i) by using a number of different inputs (x_i) at given prices (w_i) with the objective of minimizing total costs. DEA is a nonparametric linear programming (LP) technique that permits evaluation of the relative efficiency of decision-making units (DMUs) without imposing *a priori* weights on the inputs and outputs. In solving such an LP problem simultaneously for a set of DMUs, weightings are chosen that maximise the efficiency score of each DMU relative to the best-performing peer or peers.

Charnes et al. (1978) proposed the DEA-CCR model, which imposes constant returns to scale (CRS). The CRS assumption would only be appropriate if all banks in the sample were operating at their optimal scales, which is a very stringent condition. The DEA-BCC model of Banker et al. (1984) extends the DEA-CCR model by allowing variable returns to scale (VRS). Following Banker et al. (1984) and Fare et al. (1985), this study uses a VRS cost minimization DEA model for calculating cost efficiency (CE) as follows:

$$\min_{z, x_i} w_{i0} x_{i0}^*$$

Subject to

$$\sum_{k=1}^{K} z_k y_{jk} - y_{j0} \geq 0, \qquad j = 1, 2, ..., m$$

$$\sum_{k=1}^{K} z_k x_{ik} - x_{i0}^* \leq 0, \qquad i = 1, 2, ..., n \qquad (3.1)$$

$$\sum_{k=1}^{K} z_k = 1$$

$$z_k \geq 0, \qquad k = 1, 2, ..., K$$

where:

k: the number of the banks (k = 1, ..., K)

x_{ik}: i[th] input of bank k (i = 1, ..., n)

x_{i0}^*: the cost minimizing vector of input quantities for the evaluated bank

w_{i0}: a vector of the given input prices

w_{ik}: i[th] input price of kth bank

y_{j0}: the vector of output levels

z: the intensity vector

Cost efficiency is defined as the ratio of a bank's estimated minimum cost to produce a certain output to the actual cost of production (Berger and Mester, 1997, Coelli et al., 2005). Therefore, the cost efficiency (CE) of the kth bank is the ratio of the minimum cost to the actual cost or observed cost:

$$CE_k = \frac{\sum_{i=1}^{n} w_{ik} x_{ik}^*}{\sum_{i=1}^{n} w_{ik} x_{ik}} \qquad (3.2)$$

The data available allow measurement of two outputs: earning assets other than loans (y_1) (calculated as the sum of total securities and other investments) and total loans (y_2). There are three inputs: total deposits (x_1) (measured by total funding), total physical capital (x_2) (measured by fixed assets) and labour (x_3) (measured by personnel expenses). The input prices are: w_1 (calculated as the ratio of total interest expenses to total funding), w_2 (the price of physical capital, which is the ratio of other operating costs to fixed assets) and w_3 (the price of labour which is the ratio of personnel expenses to total assets.[1]

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[1] The appropriate formula for the labour price is the ratio of personnel expenses to the number of employees. Employee data, however, are not provided in sufficient detail in our dataset; following Maudos and De Guevara (2007), the ratio of personnel expenses to total assets is used as a proxy for the price of labour.

Efficiency scores of individual banks in a panel dataset could be estimated by establishing one best-practice frontier for all banks throughout the whole of the time period under analysis. This would be making the assumption that the production technology is unchanged over the whole period; which seems unlikely, particularly in an industry in which technological change has been rapid. An alternative approach is DEA Window Analysis (Charnes et al., 1985). A 'window' length (number of years) is chosen for analysis; this allows for an increase in the number of observations but without imposing unchanging technology over too long a time frame. The analysis is repeated by moving the 'window' forward one period (year) at a time. Here, we choose a window of three years so that there are nine windows over the period of 2004 to 2014. The first window includes the first three years of the research period. The remaining windows are formed by excluding the first year in the former window and including the following year. For example, the first window covers years of 2004-06, the second window is from 2005-07 and the period 2012-14 constitutes the last window.

The second stage: regression analysis of the determinants of efficiency

The truncated regression model in equation (3.3) is used to examine the determinants of cost efficiency.

$$EFF_{k,t} = \beta_0 + \beta_1 SIZE_{k,t} + \beta_2 RD_{k,t} + \beta_3 LISTED_{k,t} + \beta_4 MCON_{k,t}$$
$$+ \beta_5 INF_t + \beta_6 GDPG_t + \beta_7 CRISIS_t + \varepsilon_{k,t} \tag{3.3}$$

The dependent variable, $EFF_{k,t}$, is the cost efficiency of the kth bank in year t derived from the DEA window model.

The independent variables include the following bank-specific measures: bank size, revenue diversification and the listing status of banks. Bank size (SIZE) is measured by the natural logarithm of total assets. This variable is expected to have a positive correlation with cost efficiency due to economies of scale. Revenue diversification (RD) is calculated as the ratio of non-interest income over total revenue[2]. The impact of revenue diversification on cost efficiency could be either positive or negative. There is some evidence that diversification of

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[2] Total revenue is the sum of gross interest and dividend income and total non-interest operating income.

revenue streams can improve bank performance (Chiorazzo et al., 2008, Demirgüç-Kunt and Huizinga, 2010, Elsas et al., 2010). A well-managed bank's ability to reduce costs could allow it to improve the quality of fee-based and commission-based products and thereby to earn higher non-interest revenues (DeYoung and Rice, 2004). Other evidence indicates that revenue diversification has a negative impact on bank performance (Baele et al., 2007, Berger et al., 2000, Demsetz and Strahan, 1997, De Jonghe, 2010, DeYoung and Roland, 2001, DeYoung and Rice, 2004, Fiordelisi et al., 2011, Lepetit et al., 2008, Stiroh, 2004). An increasing non-interest income ratio can increase competition in non-interest income activities, thus leading to higher risk-taking by banks. The increased costs of monitoring risks might reduce efficiency (Tan, 2014). Additionally, bank performance does not necessarily get any direct boost from revenue diversification (Mercieca et al., 2007, Trujillo-Ponce, 2013). The listing status of banks (LIST) is a dummy variable which takes value 1 if the bank is listed on the Hong Kong Stock Exchange (HKEx) and 0 otherwise.

The model also includes a number of market-level and macroeconomic independent variables.

Market concentration (MCON) is measured either by the Herfindahl Hirschman index (HHI) or the concentration ratio (CR). The HHI is the sum of the market shares of each bank. The concentration ratio is the percentage of market share held by the largest banks in the banking industry. The three-bank concentration ratio (CR$_3$) is calculated as:

$$CR_3 = \frac{total\ assets\ of\ the\ 3\ biggest\ banks\ at\ year\ t}{total\ assets\ of\ K\ banks\ at\ year\ t}$$

See the discussion in the literature review for conflicting hypotheses (QLH and IGH) and evidence on the effect of market concentration on efficiency.

To account for the impact of the macroeconomic environment on bank efficiency, three variables are included in the model: inflation (INF), the growth rate of gross domestic (GDPG) and a variable to capture the effect of the GFC (CRISIS). GDPG is expected to have a positive influence on efficiency. In a high growth economy, the loan default rate should fall, which may help banks to reduce costs and enhance efficiency. In contrast, INF is expected to

be negatively related to efficiency since high inflation may result in an increase in bad debts. CRISIS takes the value of one for the 2008 crisis year and zero otherwise.

3.2 Data

In terms of type of financial institutions, the Hong Kong banking system is divided in two groups: commercial banks and other financial institutions including investment banks, financial companies and bank holding companies. The sample is an unbalanced panel made up of 25 commercial banks, 5 investment banks, 6 bank holding companies and 5 finance companies. The data cover the 2004–2014 period and were derived from the Bankscope Fitch-IBCA database, which consists of the annual financial statements of individual institutions. The macroeconomic data were sourced from the International Financial Statistics database (IFS) of the International Monetary Fund. All input, output and control variables were inflation-adjusted, as necessary, to 2004 as base year.

Table 2 summarizes the descriptive statistics of variables used for DEA stage of the analysis.

TABLE 2 ABOUT HERE

4. Empirical results

4.1 Results of DEA and DEA Window analysis

Table 3 shows the cost efficiency scores for the two types of banks (commercial banks and other financial institutions) and the whole banking system in Hong Kong over 2004-2014, estimated by both traditional DEA and DEA Window Analysis. To estimate these annual average efficiency scores weighted averages were used instead of simple averages. The weight for each bank and each financial institution for each year is based on total assets.

TABLE 3 ABOUT HERE

Spearman's rank order correlation coefficient between cost efficiency scores derived from the traditional DEA and DEA Window Analysis models is 0.89499 (p=0.01) so that the two approaches rank the banks reasonably consistently.

The DEA Window estimates are higher than the traditional DEA estimates for all types of banks and the whole banking system. In addition, commercial banks seem to be more efficient than other financial institutions. Efficiency scores of commercial banks over the first half of period (over 2004-2008) are higher than those in the later period.

Figures 1 and 2 show the cumulative distributions of the DEA Window efficiency scores and the traditional DEA efficiency scores, respectively, at the beginning, middle and end of the period under consideration. The middle window covers the start of the GFC.

FIGURES 1 AND 2 ABOUT HERE

Comparing the distributions of the first and middle windows in Figure 1 clearly shows that efficiency dropped markedly from 2004-06 to 2008-2010. In each of these periods, the window analysis ranks only a single bank as 100% efficient. The worst performing banks around the time of the GFC fall far below the relative performance of the worst performing banks in the earlier better times. The distribution of efficiency in the middle period is below that in the earlier period across the entire distribution. By 2012-14, efficiency has recovered but not to pre-crisis levels, with the most inefficient banks recovering about half of their losses in relative inefficiency. The window efficiency analysis scores three banks as 100% efficient by the end of the period; at the top end of the distribution, the institutions are more tightly clustered in their performance than a decade earlier.

Figure 2, which displays the efficiency scores from the traditional DEA analysis, paints a similar picture of efficiency decline in the aftermath of the GFC as the Windows DEA analysis. The traditional analysis is less able to pick out a single high-performing institution, with four banks being rated as 100% efficient in 2004, five as 100% efficient in 2009 and six in 2014. This means that more care is needed in interpreting the graph as the traditional method gives a tighter distribution of efficiency. Nevertheless, it would seem that, in general, efficiency has recovered post-GFC.

4.2 Determinants of cost efficiency in Hong Kong banking

Table 4 shows the descriptive statistics of variables used in the regression stage of the analysis.

In Table 5 the estimated results from six variants of the truncated regression model in equation (3.3) are given. Models 1 and 2 exclude the CRISIS variable while models 3 and 4 exclude macroeconomic conditions (as measured by INF and GDPG). Models 5 and 6 use all variables. Odd-numbered models use the concentration ratio (CR3) and even-numbered models use the Herfindahl Hirschman index (HHI) to account for market structure.

The coefficient on SIZE is positive and statistically significant at the 1 percent level for all models. The estimate is robust; across all variants of the model, it is 0.10 to two significant figures. This result suggests that larger banks are more cost efficient. The coefficients on both RD and LIST are negative and significant at the 1 percent level in every model and these estimates are also very robust; the coefficient on RD is -0.3 (agreeing to one significant figure across all six models) and the coefficient on LIST is -0.14 (agreeing to two significant figures across all models. Both revenue diversification and listed status negatively affect cost efficiency. Perhaps banks with higher ratios of non-interest income to total income are less efficient because of high costs associated with non-traditional activities. Growing competition to provide a wider range of banking services may also increase costs. There may be costs associated with dividends and listing fees that cause listed banks to have lower efficiency scores than non-listed banks.

Results concerning the relationship between market concentration and cost efficiency are not consistent, usually not being statistically significant. In model 1, the coefficient on HHI is positive and significant but, in model 6, the coefficient on CR3 is negative and significant. The inconsistency of these findings repeats the inconclusive pattern of results from the literature summarised in Table 1.

The coefficient on INF is negative in all models, but only attains statistical significance in model 6. A negative relationship between inflation and efficiency would suggest that banks find it more difficult to manage their costs in times of high inflation but, because of the general lack of statistical significance, not much confidence can be placed here

in such an interpretation. GDP growth shows up consistently as positively related to efficiency; the coefficient on GDGP is positive and statistically significant in all six models and is reasonably robust across the different specifications. Strong economic growth makes it easier for banks to attain higher efficiency levels.

Finally, the coefficient on CRISIS is positive for all tested models, but statistically significant only for models 5 and 6. This positive link between efficiency and the GFC may be explained by the fact that banks in Hong Kong decreased their deposit interest rates dramatically from 2.4 percent in 2007 to 0.4 percent in 2008 and even 0 percent over 2009-2014[3], thereby incurring lower costs during the crisis. Nevertheless, one might question the plausibility of a positive effect of the GFC on bank efficiency, particularly in the light of Figure 1.

5. Conclusion

This study employs two-stage DEA Window Analysis to measure the cost efficiency of Hong Kong banks in the first stage and then examine the determinants of cost efficiency over 2004-2014 in the second stage.

In the first stage, the cost efficiency scores of banks in Hong Kong are estimated by both traditional DEA and DEA Window Analysis. The results from the two approaches are highly correlated. Commercial banks are found to be more efficient than other financial institutions. Efficiency estimates by the Window method are higher than those by traditional DEA for all types of banks. There is a clear pattern in the efficiency estimates of an overall fall in efficiency in the middle years of the sample period, followed by some degree of recovery.

In the second stage, a truncated regression model is used to investigate the determinants of the estimates of cost efficiency found in the first stage. Bank size was found to be positively related to efficiency, while revenue diversification and listing status

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[3] Source: World Bank (http://data.worldbank.org/indicator)

negatively affect efficiency. High rates of economic growth were found to positive influence efficiency.

There is no doubt that government action to ensure macroeconomic stability, in the form of strong GDP growth and low inflation, should make cost efficiency easier to manage, not just for banks, but for all firms. Banks themselves can improve efficiency by growing but, in the process of expansion, need to carefully manage diversification of services to avoid any negative consequences for costs. We fail to detect much influence on efficiency from the market structure of the Hong Kong banking sector, at least as measured by the CR3 ratio or HHI, but this may be due to little variation in either of these measures over the sample period as their standard deviations are each a magnitude lower than their means, which is not the case for the other independent variables in the model.

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Table 1: Results of studies testing IGH/QLH

Source	Country/countries time period	Relationship between market power and efficiency
Koetter et al. (2008)	USA	POSITIVE
Delis and Papanikolaou (2009)	EU (10 States) 1994-2005	NEGATIVE
Maudos and De Guevara (2007)	EU (10 States) 1993-2002	POSITIVE (loan market) NEGATIVE (deposit market)
Casu and Girardone (2009)	EU 2000-2005	POSITIVE
Schaeck and Čihák (2008)	USA 1995-2005	POSITIVE
Kirkpatrick *et al.* (2008)	Sub-Saharan Africa 1992-1999	POSITIVE
Chen (2009)	Sub-Saharan Africa 2000-2007	NEGATIVE
Turk Ariss (2010)	DCs 1999-2005	NEGATIVE (cost efficiency) POSITIVE (profit efficiency)
Pruteanu-Podpiera *et al.* (2008)	Czech Republic 1994-2005	POSITIVE
Williams (2012)	Latin America 1985-2000	POSITIVE (loan market) NEGATIVE (deposit market)

Table 2: Descriptive statistics of variables used to estimate cost efficiency

Variable	Definition	Mean	Std. Dev.	Min	Max
y_1	Other earning assets	15297144	41389292	23.410	306580259
y_2	Total loans	15331239	35288150	25.567	270816322
x_1	Total deposits	29775935	75977071	11709.77	529019163
x_2	Total physical capital	524967.4	1358487	10.448	8994230
x_3	Labour	199010.8	548611.6	400	4105909
w_1	The price of deposits	0.021	0.018	0.0003	0.226
w_2	The price of physical capital	3.325	7.162	0.046	72
w_3	The price of labour	0.011	0.019	0.001	0.305

Notes: y_1, y_2, x_1, x_2 and x_3 are in thousands of USD, w_1, w_2 and w_3 are ratios.

The number of observations for each variable is 405.

Table 3: Weighted average cost efficiency scores

Year	DEA WINDOW			TRADITIONAL DEA		
	Commercial banks	Non-commercial banks	Banking system	Commercial banks	Non commercial banks	Banking system
2004	0.895	0.748	0.872	0.809	0.688	0.790
2005	0.945	0.872	0.934	0.888	0.809	0.876
2006	0.959	0.859	0.943	0.918	0.794	0.899
2007	0.963	0.831	0.943	0.934	0.742	0.905
2008	0.945	0.839	0.929	0.910	0.778	0.891
2009	0.875	0.649	0.842	0.735	0.556	0.709
2010	0.900	0.719	0.871	0.788	0.632	0.763
2011	0.915	0.898	0.913	0.804	0.804	0.804
2012	0.882	0.832	0.875	0.828	0.776	0.820
2013	0.895	0.821	0.884	0.869	0.776	0.855
2014	0.901	0.839	0.891	0.894	0.832	0.884
Average over whole period	**0.916**	**0.810**	**0.900**	**0.853**	**0.744**	**0.836**

Table 4: Descriptive statistics of variables in the truncated regression

Variables	Number of Observations	Mean	Std. Dev.	Min	Max
EFF (DEA Window)	405	0.724	0.241	0.061	1
SIZE	405	15.441	2.220	9.959	20.306
RD	405	0.266	0.222	-0.230	1.688
LIST	405	0.333	0.472	0	1
HHI	405	0.199	0.008	0.184	0.214
CR3	405	0.633	0.011	0.612	0.649
INF	405	2.675	1.770	-0.372	5.281
GDPG	405	4.376	3.192	-2.459	8.7
CRISIS	405	0.096	0.295	0	1

Table 5: Determinants of cost efficiency in Hong Kong banking: Truncated regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Dependent variable: cost efficiency (DEA Window Analysis)					
SIZE	0.1020 $(0.0104)^{***}$	0.1002 $(0.0104)^{***}$	0.1004 $(0.0109)^{***}$	0.1002 $(0.0110)^{***}$	0.1022 $(0.0102)^{***}$	0.1004 $(0.0099)^{***}$
RD	-0.3034 $(0.0647)^{***}$	-0.3010 $(0.0654)^{***}$	-0.3196 $(0.0683)^{***}$	-0.3221 $(0.0688)^{***}$	-0.2894 $(0.0644)^{***}$	-0.2596 $(0.0637)^{***}$
LIST	-0.1439 $(0.0376)^{***}$	-0.1434 $(0.0382)^{***}$	-0.1418 $(0.0398)^{***}$	-0.1428 $(0.0401)^{***}$	-0.1447 $(0.0372)^{***}$	-0.1415 $(0.0364)^{***}$
HHI	4.5538 $(2.0756)^{**}$		3.7510 (2.6971)		0.6558 (2.8804)	
CR3		-0.8419 (1.7771)		1.3641 (1.8124)		-5.0105 $(2.0186)^{**}$
INF	-0.0062 (0.0102)	-0.0126 (0.0102)			-0.0185 0.0119	-0.0303 $0.0107)^{***}$
GDPG	0.0207 $(0.0055)^{***}$	0.0195 $(0.0056)^{***}$			0.0211 $(0.0054)^{***}$	0.0268 $0.0058)^{***}$
CRISIS			0.0221 (0.0753)	0.0691 (0.0644)	0.1579 $(0.0840)^{*}$	0.2574 $(0.0697)^{***}$
CONS	-1.6333 $(0.4714)^{***}$	-0.1406 (1.1425)	-1.3626 $(0.5735)^{**}$	-1.4778 $(1.1745)^{***}$	-0.8479 (0.6107)	2.4688 $(1.2750)^{*}$

Notes: 405 observations, standard errors in parentheses,

* p< 0.1, ** p< 0.05, *** p< 0.01.

Figure 1: Cumulative distributions of Window efficiency scores

Legend: 2004-06, 2008-10, 2012-14
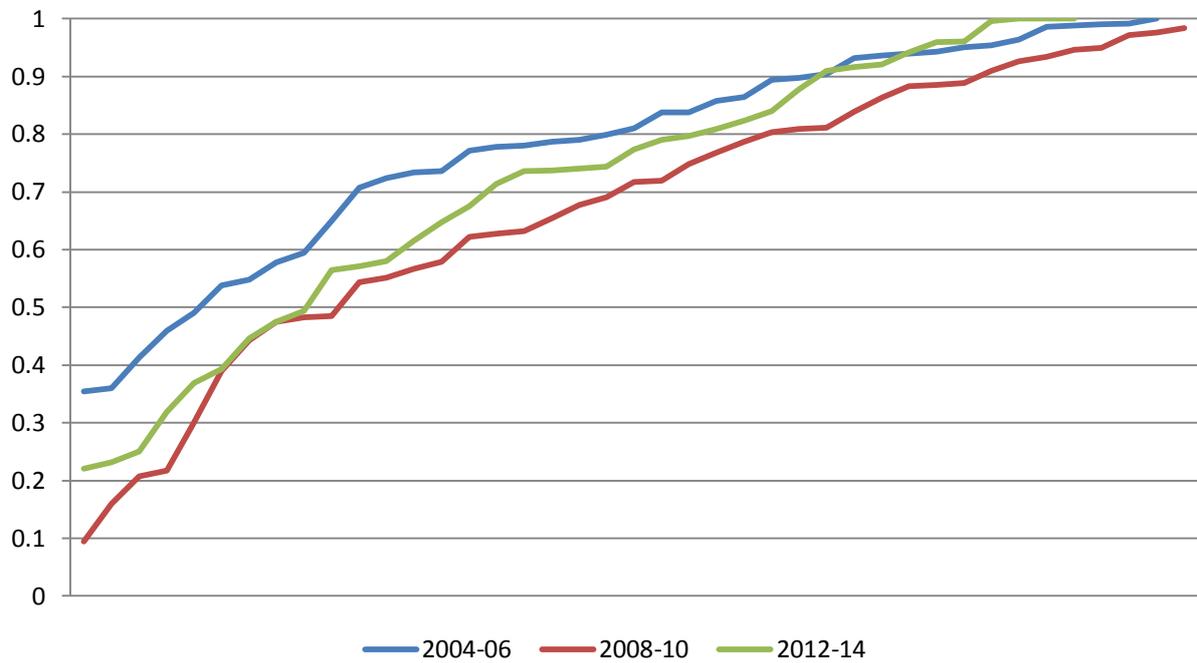
Figure 2: Cumulative distributions of DEA efficiency scores

Legend: E2004, E2009, E2014