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Too big to succeed? Banking sector consolidation and efficiency

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ABSTRACT

This study examines the effect of banking sector consolidation on bank profit and cost efficiency using data from Japan. Our analysis shows that bank merger events have little impact on profit efficiency, but significantly lower cost efficiency. This suggests that government-coordinated consolidation of banks, especially in a post-crisis environment, results in less cost efficient entities, although the bottom line of profit efficiency is maintained. Our analysis of changes in banking sector competitiveness over the same period suggests that these merged banks are able to maintain their "bottom line" due to increased market power.

1. Introduction

With the global banking sector more consolidated than ever in the wake of the 2008 global financial crisis, the question of how banking sector consolidation affects efficiency is more important than ever. Research suggests that there are strong incentives for banks to consolidate. For example, U.S. banks

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that are "too big to fail" enjoy higher credit ratings (Morgan and Stiroh, 2005) and banks are willing to pay a premium for mergers that place them in that category (Brewer and Jagtiani, 2011). But there is some evidence that large banks tend to be less efficient than small banks (Berger and Mester, 1997; Bonin et al., 2005; Matousek, 2008; Papadopoulos, 2010; Sufian, 2010). Size considerations aside, the role of regulators in arranging mergers may be a significant factor. In the United States in the 1980s, for example, Peristiani (1997) found that FDIC-assisted mergers tended to reduce cost efficiency. In response to the wave of bank consolidation following the global financial crisis of 2008, regulators worldwide are openly discussing whether and how to limit banks from becoming "too big to save" (The Economist, 2011). This study aims to inform the policy debate by providing empirical evidence on how commercial bank mergers affect banking sector profit and cost efficiency.

This study addresses this question using the case of Japan in the wake of its own financial crisis in the late 1990s. The efficiency of Japan's banking sector has been explored in work by Altunbas et al. (2000), Assaf et al. (2011), Drake and Hall (2003), Drake et al. (2009), Harimaya (2008) and Uchida and Satake (2009), but investigations on the effects of bank mergers on efficiency have focused on small credit associations (Yamori and Harimaya, 2010) or mutual banks (Yamori and Harimaya, 2009). This is the first comprehensive study to investigate the question of how commercial bank mergers affect bank profit and cost efficiency in Japan.

Japan's experience with banking sector consolidation may be relevant to other economies affected by the 2008 crisis because Japan is one of the few developed economies with a large presence in the global banking sector to have experienced a banking crisis in recent history and many of the policy responses taken in Japan bear similarities to those of U.S. policy makers in the aftermath of 2008 (Hoshi and Kashyap, 2010). Like the mergers of the U.S. banks in 2008, the rapid consolidation of the Japanese banking sector after Japan's banking crisis in the late 1990s was helped along, implicitly or explicitly, by regulators.

The rest of this paper is organized as follows. Section 2 describes some of the institutional detail of Japan's banking sector before and after its concerted consolidation around 2000. Section 3 presents the methodology and data used to measure the profit and cost efficiency of each bank. Section 4 reports our main empirical results and Section 5 presents additional analysis of banking sector competitiveness to help interpret those results. Section 6 concludes.

2. The Japanese banking sector, 1996–2009

Table 1 overviews Japan's banking sector during the period 1996–2009. One thing evident from Table 1 is that the Japanese banking sector has experienced considerable change since 1996.

In 1996, the original ten city banks,[1] combined with Japan's seven trust banks and three long-term credit banks made up the famous "top 20 large banks" which dominated the banking sector, accounting for nearly 70% of total bank assets. But while the city, trust and long-term credit banks dominated in size, by far most of the banks fell into the smaller regional or regional II bank categories. In 1996 the regional and regional II banks accounted for more than 80% of the total number of banks in Japan, but only 30% of the market as measured by total assets.

Since that time, the total number of banks has shrunk by 21% (31 banks out of a total 148 in 1996). Nearly a half of that total has been bank failures. The changes seen in Table 1 are not all failures, and also reflect considerable merger activity and turnover. Old banks, including the specific cases mentioned above, often failed or were nationalized, but were then absorbed into existing banks or merged into completely new banks. Many of the failed regional II banks were absorbed by the other regional banks.

While the total number of banks has been steadily falling, the total assets of the banking sector has been relatively stable, leaving Japan's banking sector even more concentrated than it was at the start of the sample. Reflecting some of the structural changes discussed above, the market share of small banks, those with total assets of less than 1 trillion yen, has gradually shrunk over the sample period.

[1] Changes in the banking sector are eroding the meaning of such divisions, but with rare exception banks in Japan still fall into five distinct categories: trust banks, long-term credit banks, and three kinds of commercial banks – city banks, regional banks and regional II banks.

Table 1
Overview of banking sector, 1996–2009.

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Number of observations														
By bank type														
City	10	9	9	9	9	7	6	7	7	6	6	6	6	6
Trust	7	7	7	7	6	5	5	5	5	4	4	4	4	4
Long-term credit	3	3	1	1	2	3	2	2	2	2	2	2	2	2
Regional	64	64	64	64	64	64	64	63	63	63	63	63	63	63
Regional II	64	62	60	55	54	53	53	50	48	47	46	45	44	42
By bank size														
Mega	2	2	1	1	2	3	5	5	5	4	4	4	4	4
Large	14	14	12	12	13	9	5	5	5	5	5	5	6	7
Medium	87	86	86	82	79	82	83	83	82	81	81	82	81	79
Small	45	43	42	41	41	38	37	34	33	32	31	29	28	27
Total	148	145	141	136	135	132	130	127	125	122	121	120	119	117
Market share (measured by total assets deflated with GDP deflator, trillion yen at 2000 price)														
By bank type														
City	50.5%	50.4%	50.9%	51.3%	52.5%	50.2%	54.1%	55.1%	54.6%	54.4%	53.2%	53.6%	54.5%	54.2%
Trust	7.8%	8.0%	8.2%	8.5%	8.1%	8.3%	8.2%	7.9%	7.6%	7.6%	7.8%	7.9%	7.9%	7.7%
Long-term credit	10.2%	9.9%	5.5%	5.2%	6.6%	6.9%	1.7%	1.6%	1.5%	1.7%	2.0%	2.2%	2.1%	1.9%
Regional	23.4%	23.6%	26.2%	26.7%	25.3%	26.8%	27.8%	27.3%	28.3%	28.3%	29.0%	28.4%	27.9%	28.5%
Regional II	8.1%	8.1%	9.2%	8.4%	7.4%	7.8%	8.3%	8.1%	7.9%	7.9%	8.0%	7.9%	7.6%	7.6%
By bank size														
Mega	15.7%	16.5%	9.1%	9.0%	17.6%	31.8%	49.8%	50.0%	49.5%	49.4%	48.3%	48.9%	50.0%	49.7%
Large	50.5%	50.5%	52.9%	53.1%	48.9%	31.4%	12.3%	11.7%	11.4%	11.9%	12.1%	12.0%	13.1%	14.2%
Medium	30.6%	29.9%	34.6%	34.5%	30.4%	33.9%	35.0%	35.6%	36.5%	36.1%	37.1%	36.7%	34.7%	34.0%
Small	3.1%	3.1%	3.4%	3.4%	3.1%	2.9%	3.0%	2.7%	2.7%	2.6%	2.6%	2.4%	2.2%	2.1%
Banking sector size, concentration and merger event														
Size (measured by total assets at 2000 price)	831.4	822.2	756.5	737.7	813.2	763.3	740.1	750.9	743.4	752.2	729.1	750.7	753.8	784.3
Concentration (Herfindahl–Hirschman Index)	374.4	389.2	383.7	384.2	410.6	510.8	566.2	563.4	554.3	741.3	702.9	707.7	740.2	736.8
Number of merger events	1	0	0	1	2	3	3	3	2	3	1	1	1	3

Notes: Bank type definitions follow Japanese Bankers Association.
Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price).

A much more dramatic drop in market share can be seen in the large banks, those with total assets of more than 10 trillion yen: by the end of Japan's "Big Bang" financial deregulation in 2001, the market share of those large banks shrunk and a year later it was less than a quarter of what it had been 6 years earlier. But new banks classified as what we term "mega-banks" had emerged in the meantime. These are the flagship banks of Japan's three huge financial groups, each with total assets of over 55 trillion yen: Sumitomo Mitsui Banking Corporation (SMBC), formed in 2001, Mizuho Bank and Mizuho Corporate Bank, formed in 2002, and Bank of Tokyo-Mitsubishi UFJ, formed in 2005.

The consolidation of Japan's banking sector over the period is also evident in the increase in the Herfindahl–Hirschman Index (HHI), a market concentration index calculated as the sum of square of each bank's total assets as a percent of the banking sector's aggregate assets: $\mathrm{HHI}_t = \sum \left(\left((\text{total assets})_{i,t}/(\text{banking sector total asstes})_t\right) \times 100\right)^2$, where subscript i stands for bank i and t for time t.[2] The index started from 374 in 1996 and nearly doubled, to 737, by 2009.

Japan's massive banking sector consolidation from the late 1990s portended the structural changes that were to hit the other major developed economies in the wake of the global financial crisis of 2008. Like the other economies hit by the 2008 crisis, Japan is a developed economy and has a large presence in the global banking sector. As other authors have pointed out (see, for example, Hoshi and Kashyap, 2010) many of the policy responses taken in Japan bear similarities to those of U.S. policy makers in the aftermath of 2008. In the analysis to follow, we examine Japan's experience with banking sector consolidation and investigate the effect it had on bank efficiency.

3. Methodology and data

3.1. Estimating efficiency

The first step in our analysis is to use stochastic frontier analysis (SFA) to estimate the *in*efficiency of each bank. The stochastic frontier general formulation is expressed as follows:

$$Y_{i,t} = BX_{i,t} + \Gamma Z_{i,t} + \varepsilon_{i,t} \tag{1}$$

In Eq. (1), $Y_{i,t}$ represents the log of the outcome variable, profit or cost, of the ith firm at time t. Vector $X_{i,t}$ contains the logarithm of inputs and outputs. Vector $Z_{i,t}$ contains control variables such as bank type and, following the approach suggested by Altunbas et al. (2000), variables to control for asset quality and risk. SFA is a parametric technique that separates the stochastic error term into an error term v and an inefficiency term u. Thus, the stochastic error term $\varepsilon_{i,t}$ is actually $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$ for the profit function and $\varepsilon_{i,t} = v_{i,t} + u_{i,t}$ for the cost function. $v_{i,t}$ and $u_{i,t}$ are independently distributed; $v_{i,t}$ is a normally distributed random error to account for statistical noise, and $u_{i,t}$ is a non-negative random variable distributed half-normally that is associated with *in*efficiency of bank i at time t.

A Fourier functional form is used to estimate both profit and cost functions of Eq. (1). McAllister and McManus (1993) and Mitchell and Onvural (1996), among others, argue that the Fourier flexible functional form, which adds trigonometric terms to a standard translog function, offers a better global approximation to the underlying profit or cost function across a broad range of outputs.

First, we estimate the profit function:

$$\begin{aligned}
\ln\left(\frac{\pi+\theta}{w_3 q}\right)_{i,t} &= \alpha_0 + \sum_{j=1}^{3} \alpha_j \ln\left(\frac{y_j}{q}\right)_{i,t} + \sum_{h=1}^{2} \beta_h \ln\left(\frac{w_h}{w_3}\right)_{i,t} + \eta_1 \ln(z)_{i,t} \\
&+ \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \alpha_{jk} \ln\left(\frac{y_j}{q}\right)_{i,t} \ln\left(\frac{y_k}{q}\right)_{i,t} + \frac{1}{2}\sum_{h=1}^{2}\sum_{l=1}^{2} \beta_{hl} \ln\left(\frac{w_h}{w_3}\right)_{i,t} \ln\left(\frac{w_l}{w_3}\right)_{i,t} \\
&+ \frac{1}{2}\eta_{11} \ln(z)_{i,t} \ln(z)_{i,t} + \sum_{j=1}^{3}\sum_{h=1}^{2} \gamma_{jh} \ln\left(\frac{y_j}{q}\right)_{i,t} \ln\left(\frac{w_h}{w_3}\right)_{i,t} + \sum_{j=1}^{3} \zeta_{j1} \ln\left(\frac{y_j}{q}\right)_{i,t} \ln(z)_{i,t}
\end{aligned}$$

[2] The higher the index, the more concentrated the market, with 10,000 being monopoly and 10,000/N being perfect competition (where N is the number of banks). We use total assets to calculate the index.

$$+\sum_{h=1}^{2}\xi_{j1}\ln\left(\frac{w_h}{w_3}\right)_{i,t}\ln(z)_{i,t}+\sum_{j=1}^{3}[\psi_j\cos x_j+\omega_j\sin x_j]_{i,t}$$

$$+\sum_{j=1}^{3}\sum_{k=1}^{3}[\psi_{jk}\cos(x_j+x_k)+\omega_{jk}\sin(x_j+x_k)]_{i,t}+\tau_1\left(\frac{NPL}{L}\right)_{i,t}+\tau_2\left(\frac{LA}{TA}\right)_{i,t}+\tau_3 ZScore_i$$

$$+\tau_4\left(\frac{NPL}{L}\right)_{i,t}\ln(z)_{i,t}+\tau_5\left(\frac{LA}{TA}\right)_{i,t}\ln(z)_{i,t}+\tau_6 ZScore_i\ln(z)_{i,t}+\delta_t\Delta r_t^{JGB}+\rho_i I_i+v_{i,t}-u_{i,t} \qquad (2)$$

In Eq. (2), subscripts i and t represent bank i and time t, respectively. π represents profit and θ represents the absolute value of the minimum profit (π) over all banks in the sample – we add this constant because several observations report profit less than 0 but the log of a negative number is undefined. q represents total assets, which we use as a normalizer. y_j, and y_k represent the jth and kth output (total loans, total securities or trading income), respectively. w_h represents the hth input price (the price of deposits, price of physical capital or price of labor).[3]

Equity capital, z, is included as a standalone quasi-fixed input or netput instead of as a control, since in much of the recent literature equity is incorporated as an input which, along with deposits or other borrowed funds, can be used to finance bank assets (see Akhigbe and Stevenson, 2010 and Altunbas et al., 2000 among others). Since equity capital also affects a bank's ability to absorb losses, it is included in level form as opposed to a ratio (Berger and Bonaccorsi di Patti, 2006). As with other variables in the efficiency calculation, equity capital is interacted with inputs, outputs, control variables and itself.

In research on efficiency in Japanese banking, Altunbas et al. (2000) and Hughes et al. (2001) find that if equity capital, risk-taking and asset quality are not taken into account, optimal bank size is misspecified. Building on their research, we expand the control variables to include controls for credit risk, liquidity risk, insolvency risk and interest rate risk. Credit risk, or asset quality, is addressed by including the ratio of non-performing loans to total loans, NPL/L. Liquidity risk is controlled for by including the ratio of liquid assets to total assets, LA/TA. Insolvency risk, or bank stability, is measured by a Z-score, a risk measure commonly used in the empirical banking literature to reflect a bank's probability of insolvency (Lepetit and Strobel, 2013, p.73).

In addition, many studies, such as Flannery and James (1984), suggest that maturity mismatch of assets and liabilities, or interest rate risk, affects bank profitability. Interest rate risk cannot be measured directly, but we include the change in short-term (1 year) Japanese government bond (JGB) yields, Δr_t^{JGB}, as a proxy. In the Appendix, we also report results that include time fixed effects (year dummies), T_t, to account for fluctuations in JGB yields and other macroeconomic fluctuations that affect banks. In all specifications, we include dummies for bank type, I_i.

The trigonometric term, x_j is the adjusted value of output $\ln(y_j/z)$ such that their interval is between 0 and 2π.[4] $v_{i,t}$ represents random error term of bank i in time t. $u_{i,t}$ represents the *in*efficiency of bank i at time t, which is assumed to follow a half-normal distribution.[5]

α, β, η, γ, ζ, ξ, ψ, ω, τ, δ, ρ are the parameters to be estimated. Symmetry conditions ($\alpha_{jk}=\alpha_{kj}$ and $\beta_{hl}=\beta_{lh}$ for all couples j,k and h,l) that the order of differentiation does not change the results are imposed *a priori* during estimation.

[3] A standard profit function would specify output prices as well, but as noted by Berger and Mester (1997), output prices are not accurately measured for the banking sector. In the banking efficiency literature it has become standard practice to use an alternative profit function such as Eq. (2), employing the same exogenous variables.

[4] Following previous studies using the Fourier flexible functional form, we limit the span of x_j to the interval $[0.2\times 2\pi, 0.8\times 2\pi]$ to avoid estimation problems at the end points around those two limits. x_j is calculated as $x_j=0.2\pi-\varphi_j b_j+\varphi_j\ln(y_j/z)$, where $\varphi_j=0.8\times 2\pi/(a_j-b_j)$, a_j and b_j are the maximum and minimum values of $\ln(y_j/z)$.

[5] In addition to one-sided distributions of the inefficiency error term, the half-normal, truncated-normal, exponential and gamma distributions are also commonly used. However, Altunbas and Molyneux (1996) find that efficiency estimates are relatively insensitive to these different distributional assumptions.

We then estimate the cost function:

$$
\begin{aligned}
\ln\left(\frac{C}{w_3 q}\right)_{i,t} &= \alpha_0 + \sum_{j=1}^{3}\alpha_j \ln\left(\frac{y_j}{q}\right)_{i,t} + \sum_{h=1}^{2}\beta_h \ln\left(\frac{w_h}{w_3}\right)_{i,t} + \eta_1 \ln(z)_{i,t} \\
&+ \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\alpha_{jk}\ln\left(\frac{y_j}{q}\right)_{i,t}\ln\left(\frac{y_k}{q}\right)_{i,t} + \frac{1}{2}\sum_{h=1}^{2}\sum_{l=1}^{2}\beta_{hl}\ln\left(\frac{w_h}{w_3}\right)_{i,t}\ln\left(\frac{w_l}{w_3}\right)_{i,t} \\
&+ \frac{1}{2}\eta_{11}\ln(z)_{i,t}\ln(z)_{i,t} + \sum_{j=1}^{3}\sum_{h=1}^{2}\gamma_{jh}\ln\left(\frac{y_j}{q}\right)_{i,t}\ln\left(\frac{w_h}{w_3}\right)_{i,t} + \sum_{j=1}^{3}\zeta_{j1}\ln\left(\frac{y_j}{q}\right)_{i,t}\ln(z)_{i,t} \\
&+ \sum_{h=1}^{2}\xi_{j1}\ln\left(\frac{w_h}{w_3}\right)_{i,t}\ln(z)_{i,t} + \sum_{j=1}^{3}[\psi_j\cos x_j + \omega_j \sin x_j]_{i,t} \\
&+ \sum_{j=1}^{3}\sum_{k=1}^{3}[\psi_{jk}\cos(x_j+x_k) + \omega_{jk}\sin(x_j+x_k)]_{i,t} + \tau_1\left(\frac{NPL}{L}\right)_{i,t} \\
&+ \tau_2\left(\frac{LA}{TA}\right)_{i,t} + \tau_3 ZScore_i + \tau_4\left(\frac{NPL}{L}\right)_{i,t}\ln(z)_{i,t} + \tau_5\left(\frac{LA}{TA}\right)_{i,t}\ln(z)_{i,t} \\
&+ \tau_6 ZScore_i \ln(z)_{i,t} + \delta_t \Delta r_t^{JGB} + \rho_i I_i + v_{i,t} + u_{i,t}
\end{aligned} \tag{3}
$$

Eq. (3) is basically the same as Eq. (2) except that the composite error term is now defined as $v_{i,t} + u_{i,t}$ and profit is replaced with total cost, C.

Eqs. (2) and (3) are estimated using maximum likelihood estimation. Profit, cost and outputs are divided by total assets q to reduce potential heteroskedasticity associated with bank size and divided by input w_3 to satisfy the price homogeneity condition that a proportionate increase in the inputs increases profit or costs by the same degree.[6] In addition, input prices, outputs, netputs and total assets are normalized by their sample means, since theoretically the translog specification of the dual cost function is justified as a local second-order Taylor-series approximation, and the Fourier functional form we use is based on a translog specification.

After estimating Eqs. (2) and (3), the efficiency of each bank can be isolated employing Battese and Coelli's (1988) point estimator:

$$
\text{efficiency}_{i,t} = E[\exp\{-u_{i,t}\}|\varepsilon_{i,t}] = \left[\frac{1-\Phi\left(\sigma_* - (\mu_{*i,t}/\sigma_*)\right)}{1-\Phi(-\mu_{*i,t}/\sigma_*)}\right]\exp\left(-\mu_{*i,t} + \frac{1}{2}\sigma_*^2\right) \tag{4}
$$

where $\mu_{*i,t} = -\varepsilon_{i,t}\sigma_u^2/\sigma_u^2 + \sigma_v^2$, $\sigma_* = \sigma_u\sigma_v/\sqrt{\sigma_u^2+\sigma_v^2}$ and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

3.2. Rank efficiency

The profit and cost efficiency obtained from Eqs. (2) and (3) are cardinal numbers, which have the benefit that the difference between any two values has an exact meaning. For example, a bank with profit efficiency of 1 is fully maximizing its profit but a bank with profit efficiency of 0.5 is realizing only 50% of its potential profit, or is wasting half of its potentially attainable profit. Similarly, a bank with cost efficiency of 1 is fully minimizing its cost but a bank with a cost efficiency of 0.7 is minimizing only 70% of its cost, or wasting 30% of its expenses.

However, the trade-off for this advantage is that because efficiency is an estimate, there is no "true" population from which it is drawn and there is no reason to impose any particular distributional

[6] This does not mean that we are assuming constant returns to scale frontier, where no scale economy exists.

Table 2
Descriptive statistics, 1996–2009.

	Observations	Mean	Standard deviation	Min	Max
Outcome					
Profit (π)	1818	37,639	99,278	−160,269	1,295,860
Cost (C)	1818	108,265	254,078	3,761	2,626,037
Outputs					
Total loans (y_1)	1818	3,557,621	7,830,012	102,055	69,413,456
Total securities (y_2)	1818	1,830,764	5,307,649	3	61,696,968
Trading income (y_3)	1817	3,001	19,088	1	426,900
Input prices					
Price of deposits (w_1)	1818	0.003	0.003	0.0002	0.03
Price of physical capital (w_2)	1818	0.46	0.25	0.01	3.06
Price of labor (w_3)	1818	8.37	1.56	4.76	17.78
Quasi-fixed input					
Total equity (E)	1818	245,485	565,608	−214,505	7,318,250
Normalizer					
Total assets (z)	1818	5,901,594	14,625,437	155,043	149,007,568
Risk variables					
Credit risk (NPL/L) (%)	1818	5.66	4.13	0	73.32
Liquidity risk (LA/TA) (%)	1818	6.55	3.24	0	33.41
Insolvency risk (Z-score) (%)	1814	2,688	1,730	−157	11,057
Interest rate risk (change in 1 year JGB yield) (%)	1818	−3.41	20.10	−36.79	46.65

Notes: Units are million yen (at 2000 price). The sample is 151 banks over 14 years. Changes in the banking sector as discussed in section 2 yield a total of 1818 observations.

assumption on our efficiency estimates. This makes parametric inferences theoretically invalid. To overcome this problem, it is possible to calculate rank efficiency as follows:

$$\text{Rank efficiency}_{i,t} = \frac{\text{order}_{i,t} - 1}{n_t - 1} \tag{5}$$

Eq. (5) applies a 0 to 1 uniform distribution to the efficiency each year, resulting in a rank efficiency measure that has an imposed uniform distribution. In Eq. (5), $\text{order}_{i,t}$ refers to the ascending order of the profit (cost) efficiency of bank i in time t and n_t is the number of banks in time t. That is, the order of the most efficient bank in time t equals n_t and its rank efficiency in time t would be $(n_t - 1)/(n_t - 1) = 1$. In the same way, the order of the least efficient bank at time t is 1 and its rank efficiency at time t would be $(1 - 1)/(n_t - 1) = 0$. Thus, every bank falls within the interval [0,1] with most efficient bank being 1 and least efficient bank being 0.

Unlike the original efficiency, the difference between any two values of rank efficiency does not have any exact meaning: it only means that one bank is less efficient than the other or vice versa. However, rank efficiency is reported and analyzed in the regression analysis to follow because it's uniform distribution lends it to standard parametric regression analysis.

3.3. Data

Table 2 reports the summary statistics of the data used in efficiency estimation: 151 city, trust, long-term credit, regional and regional II banks' unconsolidated balance sheets and income statements for fiscal years 1996–2009.[7] Balance sheet and income statement data are obtained from the *Analysis of Financial Statements of All Banks* published by the Japanese Bankers Association. Since trust and long-term credit banks are included, items specific to those banks are included to accurately capture their activities.

[7] Our sample does not include Japan Post, since it is not a private bank, and a few Japanese Bankers Association member banks that are substantially different from other members: the Norinchukin Bank, Orix Trust & Banking, Nomura Trust and Banking, Seven Bank and Citibank Japan.

In Table 2, profits are net operating profits and costs are the sum of interest expenses, personnel expenses, non-personnel expenses and the amount of loan-loss provisions and write-offs. Interest expenses include trust accounts and equivalent series, such as interest on debentures, from long-term credit banks' accounts, to better capture these banks' activities.

In defining inputs and outputs we employ the intermediation approach by which inputs – labor, physical capital and deposits[8] – are used to produce earning assets. As shown in Table 2, total loans (y_1) and total securities (y_2) are earning assets. Both include trust account items. The off-balance sheet portion of non-interest income, trading income (y_3) is also included as a proxy for off-balance sheet activities, following Clark and Siems (2002) and Orea and Kumbhakar (2004).

For both the profit and cost functions, three input prices are used. Consistent with most previous studies these are: the price of deposits (w_1), calculated as the ratio of interest expenses (including interest on debentures for long-term credit banks and fund-raising expenses for trust banks) to deposits (including debentures for long-term credit banks and fund-raising for trust banks); the price of physical capital (w_2), calculated by dividing overhead expenses other than personnel expenses by the book value of fixed assets; and the price of labor (w_3), calculated by dividing the personnel expenses by the number of employees.

Equity capital (z) is included as a standalone quasi-fixed input or netput, as other authors have called it. Focusing on simple accounting profit or cost rather than true economic profit or cost – which include the cost of equity – may bias profit and cost efficiency estimates.[9] Including equity capital as a quasi-fixed input or netput captures the relationship of the standard accounting or cash-flow profit and cost to the level of equity capital (Hughes and Mester, 2008, p. 17). In addition, including equity capital as quasi-fixed input or netput enables us to capture bank's ability to absorb losses (Berger and Bonaccorsi di Patti, 2006).

Total assets (q) are a normalizer. Since profits, costs and outputs are proportional to bank size, without normalization the size of composite error term would also be proportional to bank size. Normalizing profits, costs and outputs by bank size as measured by total assets allows us to have a composite error term that is comparable even across banks of different size (Berger et al., 2009).

Of the four risk variables, the first, asset quality or credit risk is represented by the ratio of non-performing loans to total loans (NPL/L). Non-performing loans include loans to borrowers in process of legal bankruptcy, past due loans in arrears by 3 months or more and restructured loans (loans whose interest was lowered, term was extended, etc., to help borrowers to avoid bankruptcy). Liquidity risk (LA/TA), is represented by the ratio of liquid asset to total assets. Liquid assets are assets that can be converted into cash quickly and include cash and due from banks and call loans. Insolvency risk, represented by the Z-score, is calculated as each individual bank's mean ROA plus mean equity to total assets divided by the standard deviation of total assets for each individual bank. Conceptually, the Z-score is the ratio of each bank's capital buffer (capital plus profit) to the volatility of its return, so is inversely related to the probability of default. Taken literally, it measures the number of standard deviations that a bank's return has to fall below its expected value to deplete equity and make the bank insolvent (Fu et al. (2014)). Interest rate risk is proxied by the average annual change in the 1 year Japanese government bond yield, Δr^{JGB}, as reported by the Ministry of Finance.[10]

4. Results

4.1. Bank efficiency by M&A status

The stochastic frontier parameter estimation results for Eqs. (2) and (3) are reported in detail in Appendix Table A1. There are two important points to note from Table A1. First, the likelihood ratio

[8] Some studies of bank efficiency classify deposits as an output, but Hughes et al. (2001) find that "the *data strongly imply that deposits function as inputs in production*" (p. 2177). We are unable to replicate their test here since we divide our variables by total assets in order to control for heterogeneity according to bank size, but we assume their results, which were also based on a study of the Japanese banking system, are valid here.

[9] We thank an anonymous referee for pointing this out.

[10] http://www.mof.go.jp/english/jgbs/reference/interest_rate/index.htm.

Table 3
Median efficiency by M&A status.

	Profit efficiency	Rank profit efficiency	Cost efficiency	Rank cost efficiency	Number of banks	Total observations
Before M&A	$0.69^{(---)}$	$0.43^{(---)}$	$0.82^{(---)}$	0.47	40	305
	(0.110)	(0.251)	(0.087)	(0.313)		
After M&A	0.72	0.40	$0.80^{(---)}$	$0.29^{(---)}$	17	108
	(0.121)	(0.272)	(0.100)	(0.232)		
Never M&A	$0.74^{(+++)}$	$0.52^{(+++)}$	$0.85^{(+++)}$	$0.52^{(+++)}$	106	1413
	(0.095)	(0.241)	(0.060)	(0.239)		
Full Sample	0.73	0.5	0.84	0.5	147	1808
	(0.100)	(0.252)	(0.065)	(0.252)		

Notes: Superscript (+), (++), (+++) indicate the efficiency estimate is statistically significantly positive compared to the other banks in the sample at the 10%, 5% and 1% level, respectively. Similarly, (−), (−−), (−−−) indicate the estimate is statistically significantly negative compared to the other banks in the sample at the 10%, 5% and 1% level, respectively. Significance levels are based on the non-parametric Mann–Whitney *U* test. Median absolute deviation is in parentheses below each median estimate.

test statistic are very large for both the profit and cost efficiency estimates. This indicates that the variation of the profit and cost inefficiency estimates across banks are very large and highly statistically significantly different from zero, prompting an interest in what drives these large difference in efficiency among banks in the sample. Secondly, the ratio of the standard deviation of the inefficiency estimates to the standard deviation of the estimated random error term are quite large. This suggests that differences in the ability of banks in the sample to convert inputs and outputs into profits and costs are mostly due to differences in efficiency rather than random error.

The next step is to explore the relationship between the efficiency and rank efficiency estimates and bank M&A activity. We start by looking for differences in bank efficiency by M&A status. In Table 3, we report the efficiency and rank efficiency estimates for banks of various M&A status. As discussed above, we cannot impose any distributional assumptions on profit and cost efficiency estimates. To avoid making unnecessary distributional assumptions, we report the median (rather than mean) efficiency for each group and examine the statistical significance of differences in the median efficiency using a non-parametric Mann–Whitney *U*-test. The simple mean and standard parametric *t*-test might be preferred for the rank efficiency estimates since they have an imposed uniform distribution. The differences in efficiency among banks with different M&A status using parametric techniques are reported in Appendix Table A2. The results are qualitatively similar.

M&A status is defined as banks that (i) never experienced a merger event or (ii) were involved in a merger as either an acquirer bank or a target bank during the sample period. Thus the banks are categorized into three groups. "Before M&A" denotes acquirer and target banks before the acquisition. "After M&A" denotes the acquirer banks after their formation or acquisition. "Never M&A" is a group of banks that never experienced a merger event during the sample period.

Both median profit and cost efficiency are reported in Table 3, along with the respective median rank efficiency. Although these results are only aggregate median values, they suggest that banks that engage in mergers and acquisitions tend to be *less* profit and cost efficient. Banks that never experienced an M&A event report the highest median efficiency. Banks that experience an M&A event thus start out with lower profit and cost efficiency, but cost efficiency, at least, seems to fall even further after an M&A event. This is indicated by the median cost efficiency for the "After M&A" group of 0.80 in column 3 of Table 3, which a Mann–Whitney *U*-test indicates is statistically significantly less than the cost efficiency of the other banks in the sample at a 1% confidence level. This finding is consistent with the mean rank profit efficiency results reported in column 4 of Table A2.

4.2. Regression analysis

The median efficiency levels presented in Table 3 are suggestive. But while we can conclude from those estimates that the "After M&A" group is less profit efficient than the "Before M&A" or "Never M&A" groups, there are two important questions that cannot be answered by a simple table of median efficiency. Firstly, we cannot tell whether the differences in efficiency are the result of the merger activity or simply reflect other factors such as the size of the banks involved in the mergers. Secondly, we are unable to tell whether the merger activity statistically significantly changes efficiency *within* the acquirer bank: Table 3 might simply reflect the differences in efficiency between merger acquirers and targets as “After M&A” only contains acquirers. To investigate these two points, regression analysis is required.

In the regression analysis, cost and profit efficiency and rank profit and cost efficiency are regressed on variables indicating merger and acquisition status and bank size following a reduced-form equation:

$$\text{Efficiency}_{i,t} = \alpha + \sum_{j=2}^{3} \beta_j \,\text{M\&A status}^j_{i,t} + \gamma\,\text{target}_{i,t} + \sum_{k=2}^{4} \delta_k\,\text{size}^k_{i,t} + \varepsilon_{i,t} \tag{6}$$

In Eq. (6), $M\&A\,\text{status}^j_{i,t}$ represents the M&A status as defined above, and $\text{size}^k_{i,t}$ indicates bank size as defined by total assets (deflated by 2000 prices) of bank *i* at time *t*. A “Target” bank dummy is included so that the “After M&A” dummy shows the efficiency change *within* the acquirer banks. Bank-type dummies and controls for asset quality and risk variables are not included in the regression stage because these factors are already accounted for in the SFA efficiency estimation. Observations for merged banks are limited to 3 years around the merger event (excluding the year of merger) to avoid inclusion of other events. All observations are included for banks that never experience a merger event.

Coefficient estimates are obtained using a semi-parametric technique[11] which does not impose an assumed distribution on the dependent variables: quantile (median) regression. Although quantile regression is less efficient than OLS when the distributional assumptions of OLS are satisfied, quantile regression has the advantage that it provides valid coefficient estimates without distributional assumptions.[12] The results of analysis using quantile regression are reported in Table 4. As a robustness check we also report pooled cross-section ordinary least squares (OLS) estimates[13] and OLS estimates using bootstrapping techniques in the Appendix. Readers will note that the results reported below are robust to these alternate estimation techniques.

The results reported in Table 4 suggest that small banks tend to be highly statistically significantly more profit efficient than other banks in the sample,[14] although there is no statistically significant difference in the cost efficiency by bank size. Interestingly, there is also no statistically significant difference in the profit or cost efficiency of the target banks in the mergers.

Turning to the main variable of interest, M&A status, we see the same basic patterns observed in Table 3. Even after controlling for bank size, the “Never M&A” group reports highly statistically significantly higher profit efficiency. Of the banks that merge, the target banks do not exhibit statistically significantly different characteristics than their acquirer banks, and in the three year period post-merger the “After M&A” acquirer banks do not exhibit any statistically significant change in their profit efficiency (columns 1–4).

The “After M&A” acquirer banks do, however, report highly statistically significantly *lower* cost efficiency (columns 5–8) in the three years post-merger. This last finding is robust even after controlling for bank size and to the use of both cost efficiency and rank cost efficiency estimates.

Readers are reminded that since we have controlled for the “target” dummy, the “After M&A” coefficient estimate reflects the *change* in efficiency of banks that acquired other banks during the

[11] Greene (2011) categorizes quantile regression as “semi-parametric”, because as in parametric estimation, a functional form is specified, but as with non-parametric estimation, there is no need to impose distributional assumptions.

[12] For an overview of the differences between OLS and quantile regression, readers are referred to Koenker and Hallock (2001).

[13] Panel estimation with individual random or fixed effects might seem preferable, but a model with individual fixed effects *and* size or M&A status dummies is over-identified. We are uncomfortable with a random effects model either since we cannot test to confirm that the unobserved heterogeneity for each bank is uncorrelated with the independent variables. However, as a robustness check we estimated Eq. (6) using a random effects model and found the results were quantitatively and qualitatively similar.

[14] As a robustness check, we split our sample of banks into small/medium banks and large/mega banks and confirmed that the results reported in Table 4 are qualitatively the same for both sub-samples. Results are available upon request from the authors. In brief, those results show that although smaller banks tend to be more profit efficient, there is no strong evidence that the effects of M&A events on efficiency are different for small/medium banks than for large/mega banks.

Table 4
The effect of M&A on bank efficiency – median regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
Specification	Median regression							
Dependent Variable	Profit efficiency		Rank profit efficiency		Cost efficiency		Rank cost efficiency	
After M&A	**0.06***	**0.05**	**0.09**	**0.09**	**−0.05****	**−0.06****	**−0.23*****	**−0.22****
	[0.035]	**[0.034]**	**[0.093]**	**[0.091]**	**[0.023]**	**[0.023]**	**[0.087]**	**[0.089]**
Never M&A	0.08***	0.08***	0.22***	0.19***	−0.01	−0.01	−0.08	−0.07
	[0.026]	[0.025]	[0.069]	[0.066]	[0.017]	[0.017]	[0.065]	[0.065]
Target	0.05*	0.05	0.13	0.08	−0.02	−0.02	−0.06	−0.09
	[0.033]	[0.031]	[0.088]	[0.084]	[0.022]	[0.021]	[0.083]	[0.082]
Mega		0.03		0.14		0.02		0.08
		[0.037]		[0.100]		[0.025]		[0.098]
Large		0.01		0.01		−0.03*		−0.01
		[0.022]		[0.058]		[0.015]		[0.057]
Small		0.04***		0.11***		0.01		0.06**
		[0.010]		[0.027]		[0.007]		[0.027]
Constant	0.66***	0.65***	0.30***	0.30***	0.85***	0.86***	0.60***	0.57***
	[0.025]	[0.024]	[0.068]	[0.066]	[0.017]	[0.016]	[0.064]	[0.064]
Observations	1590	1590	1590	1590	1590	1590	1590	1590
Pseudo *R*-squared	0.006	0.015	0.008	0.018	0.002	0.005	0.006	0.009
Number of banks	146	146	146	146	146	146	146	146
Number of years	14	14	14	14	14	14	14	14

Note: Standard errors in brackets below each coefficient estimate.
Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price).
* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

sample period. The results reported in Table 4 indicate that a merger even in itself significantly reduce the cost efficiency of the merged entity in the 3 years after the merger event.

5. Banking sector competitiveness

The key finding of the regression analysis presented above – that merger events do not affect profit efficiency but seem to lead to a deterioration in cost efficiency in the merged bank – naturally leads to the question of *why*. There may be many different ways in which merger events affect efficiency, but one channel may be that banking sector consolidation affects the competitiveness of the banking sector, thus affecting efficiency. To help interpret our key finding, in this section we investigate recent trends in the competitiveness of Japan's banking sector.[15]

5.1. Trends in banking sector competitiveness in Japan

Uchida and Tsutsui (2005) provide the most rigorous estimates of banking sector competitiveness in Japan. Examining the period 1974–2000, they conclude that city banks were competitive over the period 1984–1997, but that competition among those largest banks began to decline in the late 1990s, perhaps due to Japan's banking crisis and pressure on banks to deal with their non-performing loans. Unfortunately, the period covered in Uchida and Tsutsui's (2005) study ends in 2000, the year in which many of the mega-mergers of interest for our study occurred. To explore what happened to banking sector competitiveness in Japan after 2000, we construct our own measure of Japanese banking sector competitiveness, the Lerner Index.

[15] We thank an anonymous referee for this suggestion.

The Lerner Index is a measure of market power for each bank-year observation: the higher the index, the more market power the bank has.[16] The Lerner Index is a proxy for the monopoly mark-up, and calculated as the difference between average revenue and marginal cost, expressed as a ratio of average revenue, or:

$$\text{Lerner Index}_{i,t} = \frac{AR_{i,t} - MC_{i,t}}{AR_{i,t}} \tag{7}$$

where $AR_{i,t}$ is average revenue (ordinary income divided by total assets) of bank i at time t, serving as a proxy of the output price set by the bank. $MC_{i,t}$ is marginal cost of bank i at time t. Since we cannot directly observe each banks' marginal cost, we estimate it using the methodology of Fu et al. (2014). We first estimate the following translog cost function with ordinary least squares:

$$\begin{aligned}\ln\left(\frac{C}{w_2}\right)_{i,t} = {} & \alpha_0+\alpha_1 \ln(TA)_{i,t} + \beta_1 \ln\left(\frac{w_1}{w_2}\right)_{i,t} + \frac{1}{2}\alpha_{11}(\ln(TA)_{i,t})^2 + \frac{1}{2}\beta_{11}\left(\ln\left(\frac{w_1}{w_2}\right)_{i,t}\right)^2 \\ & + \gamma_{11}\ln(TA)_{i,t}\ln\left(\frac{w_1}{w_2}\right)_{i,t} + \delta_1 Trend_t + \delta_2 Trend_t^2 + \delta_3 \ln\left(\frac{w_1}{w_2}\right)_{i,t} Trend_t \\ & + \delta_4 \ln(TA)_{i,t} Trend_t + \varepsilon_{i,t}\end{aligned} \tag{8}$$

In Eq. (8), subscripts i and t represent bank i and time t, respectively. C is total cost. TA is total assets. w_1 is the price of deposits and w_2 is the price of labor and physical capital. $Trend_t$ is a linear time trend and ε is the error term.

We then take the derivative of total cost with respect to total assets, which gives us marginal cost:

$$MC_{i,t} = \frac{\partial C_{i,t}}{\partial TA_{i,t}} = \frac{C_{i,t}}{TA_{i,t}}\left(\alpha_1 + \alpha_{11}\ln(TA)_{i,t} + \gamma_{11}\ln\left(\frac{w_1}{w_2}\right)_{i,t} + \delta_4 Trend_t\right) \tag{9}$$

Finally, we plug in the coefficient estimates in Eq. (9), resulting in an empirical estimate of marginal cost as follows:

$$\widehat{MC}_{i,t} = \frac{C_{i,t}}{TA_{i,t}}\left(\hat{\alpha}_1 + \hat{\alpha}_{11}\ln(TA)_{i,t} + \hat{\gamma}_{11}\ln\left(\frac{w_1}{w_2}\right)_{i,t} + \hat{\delta}_4 Trend_t\right) \tag{10}$$

Using $\widehat{MC}_{i,t}$ in place of $MC_{i,t}$ in Eq. (7), we calculate the Lerner Index estimates.

Figs. 1 and 2 present some aggregate characteristics of our Lerner Index estimates.

In Fig. 1, we note that among our sample of Japanese banks over the period 1996–2009, the long-term credit banks enjoy the most market power, followed by the trust banks and city banks. As might be expected, the smaller regional I and regional II banks have less market power. Indeed, Fig. 2 suggests that the differences in market power by bank type may be due to differences in bank size: large and mega banks have higher indices than small and medium banks, suggesting that larger banks tend to have more market power.

Finally, in Fig. 3, we turn to aggregate trends in the Lerner Index over time. As illustrated in Fig. 3, the trend in the Lerner Index supports the earlier findings of Uchida and Tsutsui (2005): on aggregate, the competitiveness of the Japanese banking sector was rising in the 1990s, but competitiveness then began to decline in the late 1990s, soon after the outbreak of Japan's banking crisis in 1997. Using our Lerner Index estimate, this is illustrated by a falling aggregate index from 1996–1998, then an upward trend in the index – indicating *more* market power by Japanese banks – after 1998. This upward trend continues over the sample period and by 2009 the aggregate Lerner Index had risen by about 75%, indicated a highly statistically significant increase in market power over most of the sample period.

[16] Elzinga and Mills (2011) give a detailed discussion of this index.

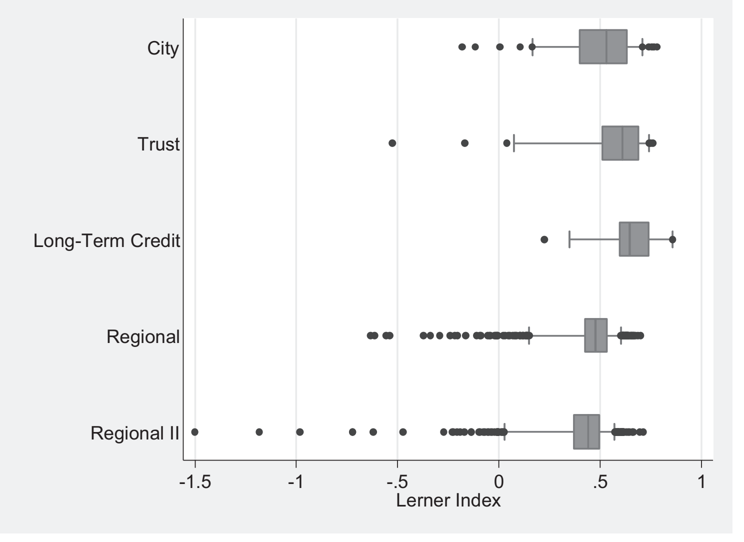

Fig. 1. Market power by type. *Note*: The line in the middle of each box indicates the median and the left and right edges of the boxes indicate the 25th and 75th percentiles, respectively. The left and right whiskers indicate the 5th percentile and 95th percentiles, respectively. Observations outside the 5th and 95th percentiles are plotted on the left and right of the whiskers.

5.2. *Banking sector consolidation and competitiveness*

The analysis of trends in banking sector competitiveness helps in interpreting our efficiency results. Since the late 1990s, there has been an increase in M&A activity in Japan. This increase in M&A activity has resulted in a more consolidated banking sector: fewer banks of larger size (see Table 1). Our Lerner Index estimates suggest that this trend has resulted in banks enjoying increased market power. Fig. 4,

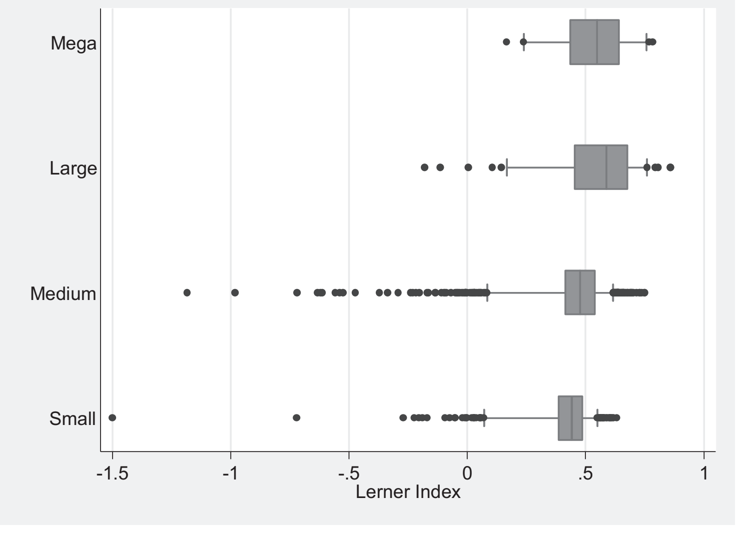

Fig. 2. Market power by size. *Note*: The line in the middle of each box indicates the median and the left and right edges of the boxes indicate the 25th and 75th percentiles, respectively. The left and right whiskers indicate the 5th percentile and 95th percentiles, respectively. Observations outside the 5th and 95th percentiles are plotted on the left and right of the whiskers.

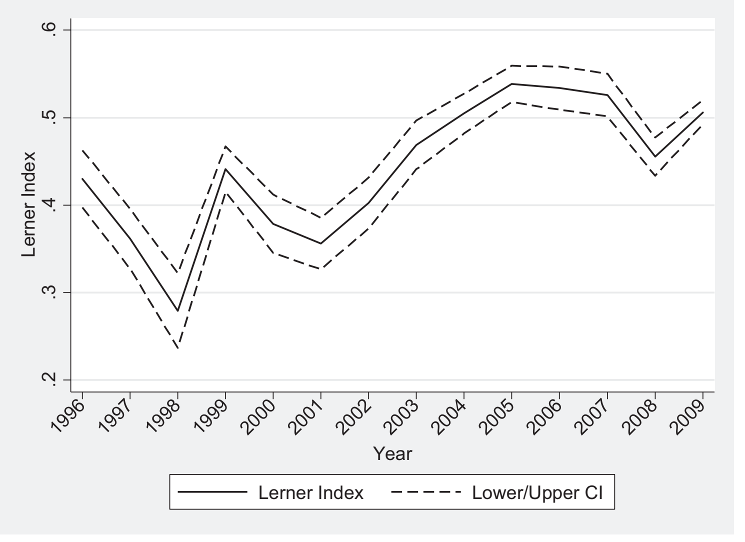

Fig. 3. Change in banking sector competitiveness.

below, confirms that on average, banks that merge enjoy an increase in market power in the post-merger period. In other words, as many might suspect, banking sector consolidation tends to result in a less competitive banking sector.

In Table 5, we report the results of the following specification that includes a control for market power as measured by the Lerner Index in our basic specification (Eq. (6)).

$$\text{Efficiency}_{i,t} = \alpha + \eta \text{Lerner}_{i,t} + \sum_{j=2}^{3} \beta_j M\&A\,\text{status}_{i,t}^{j} + \gamma\,\text{target}_{i,t} + \sum_{k=2}^{4} \delta_k \text{size}_{i,t}^{k} + \varepsilon_{i,t} \tag{11}$$

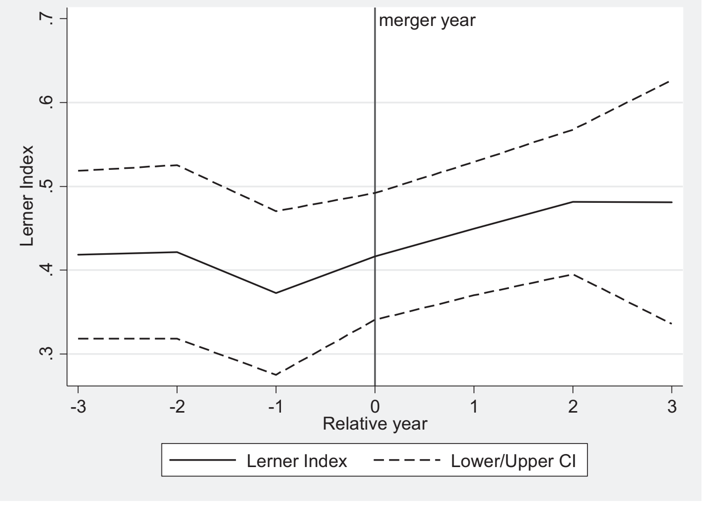

Fig. 4. Change in market power around merger events – merger acquirer.

Table 5
The Effect of M&A on Bank Efficiency – Median Regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
	Small and Medium Banks				Large and Mega Banks			
Specification	Median Regression							
Dependent variable	Profit efficiency	Rank profit efficiency	Cost efficiency	Rank cost efficiency	Profit efficiency	Rank profit efficiency	Cost efficiency	Rank cost efficiency
After M&A	**0.01**	**−0.03**	**−0.06***	**−0.24***	**0.06**	**0.17**	**−0.08***	**−0.23**
	[0.039]	**[0.103]**	**[0.023]**	**[0.088]**	**[0.042]**	**[0.113]**	**[0.024]**	**[0.098]**
Never M&A	0.10***	0.27***	−0.02*	−0.14***	−0.10***	−0.24***	−0.00	−0.02
	[0.024]	[0.062]	[0.014]	[0.053]	[0.034]	[0.091]	[0.020]	[0.078]
Target	0.11***	0.23***	−0.01	−0.06	−0.09***	−0.24***	0.00	0.05
	[0.029]	[0.076]	[0.017]	[0.065]	[0.034]	[0.093]	[0.020]	[0.080]
Lerner Index	**0.22***	**0.39***	**0.41***	**0.98***	**0.24***	**0.43***	**0.41***	**1.01***
	[0.025]	**[0.065]**	**[0.015]**	**[0.056]**	**[0.025]**	**[0.069]**	**[0.015]**	**[0.059]**
Mega	−0.37***	−0.58***	−0.00	0.13	−0.14***	−0.33***	−0.01	−0.05
	[0.059]	[0.154]	[0.035]	[0.132]	[0.037]	[0.101]	[0.022]	[0.087]
Large	−0.09***	−0.12*	−0.05***	−0.17***	−0.10***	−0.23***	−0.04***	−0.14***
	[0.023]	[0.060]	[0.014]	[0.051]	[0.021]	[0.057]	[0.012]	[0.049]
Small	0.03***	0.07***	0.02***	0.06***	0.03***	0.07***	0.02***	0.06**
	[0.009]	[0.025]	[0.006]	[0.021]	[0.009]	[0.026]	[0.006]	[0.022]
Constant	0.54***	0.06	0.68***	0.20***	0.73***	0.55***	0.66***	0.06
	[0.025]	[0.065]	[0.015]	[0.056]	[0.034]	[0.093]	[0.020]	[0.080]
Observations	1595	1595	1595	1595	1580	1580	1580	1580
Pseudo *R*-squared	0.060	0.054	0.186	0.137	0.045	0.039	0.186	0.137
Number of banks	139	139	139	139	136	136	136	136
Number of years	14	14	14	14	14	14	14	14

Note: Standard errors in brackets below each coefficient estimate.
Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price).
Time fixed effects included in efficiency estimation.

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

This is of interest since it may provide information on the relationship between market power and efficiency, and because it provides a purer estimate of the effect of merger activity on efficiency after having controlled for market power. Since we noted above some differences in efficiency and market power by bank size (Table 4 and Fig. 2), we divide our sample of merged banks into two subsamples: those that remain small and medium in size, even after the merger event, and those that are categorized as large or mega banks after the merger event.

However, the results reported in Table 5 do not provide strong evidence that the impact of market power on efficiency is different for small-medium banks than for large-mega banks. Although small banks still tend on average to be more efficient, regardless of bank size, banks with higher market power (a higher Lerner Index) tend to be more profit and cost efficient. Furthermore, for both subsamples of small-medium banks and large-mega banks, even after controlling for market power, our main finding reported above – that merger events do not have a statistically significant impact on profit efficiency but tend to lower cost efficiency – remains robust. Taken together, these findings suggest that although mergers reduce banks' cost efficiency, thanks to increased market power, they are also able to generate higher revenues and therefore maintain profit efficiency.

6. Conclusion

This study examines the impact of merger activity on bank profit and cost efficiency, looking in particular at the experience of Japan after its own banking crisis in the late 1990s. Our analysis shows that profit efficiency is unaffected, but cost efficiency decreases after merger events. By controlling for potential differences in banks that are targeted for acquisition, we are able to isolate the actual *change* in profit and cost efficiency resulting from takeover. It is the least profit efficient banks in the sample that engage in M&A activity in the first place, and they experience no significant increase in profit efficiency in the three years following a merger event. On the other hand, there appears to be no statistically significant difference in the cost efficiency of banks that engage in M&A activity in our sample, but banks that merge exhibit statistically significant *declines* in cost efficiency in the three years following a merger. This finding holds even after controlling for time variant macroeconomic events, bank size, bank type, and bank asset quality and risk factors. The empirical results are robust to various empirical specifications including ordinary least squares, semi-parametric quantile regression and bootstrapping techniques.

An analysis of banking sector competitiveness helps in interpreting these results. Since the late 1990s, there has been a significant consolidation in Japan's banking sector and at the same time an increase in aggregate bank market power as measured by the Lerner Index. This suggests that as the banking sector consolidated, banks increased in size and gained market power. Indeed, when we examine our sample of merger events we note that banks that merge tend to enjoy an increase in market power. However, even after controlling for the effect of market power, our main result – that banking sector consolidation tends to reduce cost efficiency but has no significant impact on profit efficiency – remains robust. Taken in combination with our findings on banking sector efficiency, we suspect that although mergers reduce banks' cost efficiency, thanks to their increased market power, they are also able to generate higher revenues and therefore maintain profit efficiency. We hope to explore the question of *how* banking sector consolidation may affect efficiency, including the channel of market power, in more detail in future research.

One major policy reaction to the recent global financial crisis has been government-coordinated bank consolidations and our findings may be relevant in interpreting the effects of that wave of merger activity in other countries as well. For example, banking sector consolidation in Japan was quite similar to the recent banking sector consolidation in the United States: both were conducted in the wake of a banking sector crisis with government coordination or intervention. Our findings suggest that, while banking sector consolidation in the wake of financial crisis may help banks survive by becoming too big to fail, it has resulted in a significant reduction in cost efficiency and no change in the bottom line of profit efficiency, perhaps making them "too big to succeed".

Appendix.

Table A1
Efficiency estimation results.

	(1)		(2)	
Sample	All banks			
Specification	Maximum likelihood (stochastic frontier estimation)			
Dependent variable	$\ln\left(\frac{\pi+\theta}{w_3 z}\right)$		$\ln\left(\frac{C}{w_3 z}\right)$	
Explanatory variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
$\ln\left(\frac{y1}{q}\right)$	-0.71	[1.001]	1.54^{**}	[0.636]
$\ln\left(\frac{y2}{q}\right)$	7.67	[9.442]	-13.24^{**}	[5.473]
$\ln\left(\frac{y3}{q}\right)$	-1.07^{***}	[0.248]	-0.00	[0.160]
$\ln\left(\frac{w1}{w3}\right)$	-0.01	[0.027]	0.29^{***}	[0.016]
$\ln\left(\frac{w2}{w3}\right)$	0.28^{***}	[0.055]	0.01	[0.031]
$\ln(z)$	-0.69^{***}	[0.036]	-0.15^{***}	[0.022]
$0.5\cdot\left(\ln\left(\frac{y1}{q}\right)\right)^2$	2.09	[4.837]	2.19	[2.893]
$\ln\left(\frac{y1}{q}\right)\cdot\ln\left(\frac{y2}{q}\right)$	-0.58	[0.534]	-1.17^{***}	[0.335]
$\ln\left(\frac{y1}{q}\right)\cdot\ln\left(\frac{y3}{q}\right)$	-0.18^{**}	[0.085]	0.09^{*}	[0.044]
$0.5\cdot\left(\ln\left(\frac{y2}{q}\right)\right)^2$	2.51	[3.350]	-4.70^{**}	[1.952]
$\ln\left(\frac{y2}{q}\right)\cdot\ln\left(\frac{y3}{q}\right)$	-0.10^{***}	[0.029]	-0.03	[0.019]
$0.5\cdot\left(\ln\left(\frac{y3}{q}\right)\right)^2$	-0.26^{***}	[0.070]	-0.01	[0.044]
$0.5\cdot\left(\ln\left(\frac{w1}{w3}\right)\right)^2$	-0.03^{*}	[0.017]	0.13^{***}	[0.010]
$\ln\left(\frac{w1}{w3}\right)\cdot\ln\left(\frac{w2}{w3}\right)$	-0.02	[0.024]	-0.02^{*}	[0.014]
$0.5\cdot\left(\ln\left(\frac{w2}{w3}\right)\right)^2$	0.07	[0.040]	-0.05^{**}	[0.024]
$0.5\cdot(\ln(z))^2$	0.12^{***}	[0.015]	0.01	[0.009]
$\ln\left(\frac{y1}{q}\right)\cdot\ln\left(\frac{w1}{w3}\right)$	0.21^{**}	[0.083]	0.19^{***}	[0.049]
$\ln\left(\frac{y1}{q}\right)\cdot\ln\left(\frac{w2}{w3}\right)$	0.28^{*}	[0.156]	0.42^{***}	[0.092]
$\ln\left(\frac{y2}{q}\right)\cdot\ln\left(\frac{w1}{w3}\right)$	-0.00	[0.021]	0.05^{***}	[0.013]
$\ln\left(\frac{y2}{q}\right)\cdot\ln\left(\frac{w2}{w3}\right)$	0.02	[0.052]	0.14^{***}	[0.031]
$\ln\left(\frac{y3}{q}\right)\cdot\ln\left(\frac{w1}{w3}\right)$	0.01^{*}	[0.005]	-0.00	[0.003]
$\ln\left(\frac{y3}{q}\right)\cdot\ln\left(\frac{w2}{w3}\right)$	0.04^{***}	[0.011]	0.01^{**}	[0.006]
$\ln\left(\frac{y1}{q}\right)\cdot\ln(z)$	0.21^{**}	[0.095]	0.30^{***}	[0.057]
$\ln\left(\frac{y2}{q}\right)\cdot\ln(z)$	-0.07^{**}	[0.029]	0.04^{**}	[0.017]
$\ln\left(\frac{y3}{q}\right)\cdot\ln(z)$	-0.03^{***}	[0.007]	0.00	[0.004]
$\ln\left(\frac{w1}{w3}\right)\cdot\ln(z)$	0.01	[0.009]	0.02^{***}	[0.005]
$\ln\left(\frac{w2}{w3}\right)\cdot\ln(z)$	0.05^{**}	[0.022]	-0.01	[0.013]
$\cos(x_1)$	-2.58	[6.529]	-2.47	[3.937]
$\sin(x_1)$	0.74	[1.653]	1.97^{**}	[1.005]
$\cos(x_2)$	-29.62	[34.986]	48.88^{**}	[20.230]
$\sin(x_2)$	-11.90	[29.461]	36.38^{**}	[17.531]
$\cos(x_3)$	1.23	[0.811]	0.27	[0.501]
$\sin(x_3)$	-0.73^{**}	[0.306]	-0.11	[0.179]
$\cos(2x_1)$	0.18	[0.639]	0.59	[0.377]
$\sin(2x_1)$	0.19	[0.300]	-0.32^{**}	[0.144]
$2\cdot\cos(x_1+x_2)$	-0.02	[0.414]	-0.78^{***}	[0.264]
$2\cdot\sin(x_1+x_2)$	-0.66	[0.606]	-1.58^{***}	[0.378]

Table A1 (*Continued*)

	(1)		(2)	
Sample	All banks			
Specification	Maximum likelihood (stochastic frontier estimation)			
Dependent variable	$\ln\left(\frac{\pi+\theta}{w_3 z}\right)$		$\ln\left(\frac{C}{w_3 z}\right)$	
Explanatory variables	Coefficient estimates	Standard errors	Coefficient estimates	Standard errors
$2\cdot\cos(x_1+x_3)$	−0.03	[0.113]	0.17***	[0.060]
$2\cdot\sin(x_1+x_3)$	0.27**	[0.121]	−0.11*	[0.065]
$\cos(2x_2)$	−1.98	[2.360]	−1.92	[1.482]
$\sin(2x_2)$	−4.37	[4.933]	7.00**	[2.840]
$2\cdot\cos(x_2+x_3)$	0.21***	[0.067]	0.04	[0.037]
$2\cdot\sin(x_2+x_3)$	−0.50***	[0.136]	−0.15	[0.090]
$\cos(2x_3)$	0.52***	[0.097]	0.06	[0.060]
$\sin(2x_3)$	−0.38***	[0.048]	−0.02	[0.029]
Change in JGB yield	0.00***	[0.000]	−0.00***	[0.000]
City	−0.52***	[0.081]	−0.07*	[0.041]
Trust	−0.21**	[0.092]	−0.22***	[0.051]
Long-term credit	−0.47***	[0.089]	−0.58***	[0.056]
$\left(\frac{NPL}{L}\right)$	−0.00	[0.003]	0.03***	[0.002]
$\left(\frac{LA}{TA}\right)$	0.01***	[0.004]	0.01***	[0.002]
ZScore	0.00	[0.000]	−0.00	[0.000]
$\left(\frac{NPL}{L}\right)\cdot\ln(z)$	0.00	[0.002]	−0.00***	[0.001]
$\left(\frac{LA}{TA}\right)\cdot\ln(z)$	0.00*	[0.002]	0.00***	[0.001]
$ZScore\cdot\ln(z)$	−0.00***	[0.000]	−0.00*	[0.000]
Constant	−5.96	[26.453]	45.49***	[15.122]
Observations	1808		1808	
Number of banks	147		147	
Log likelihood	−491.70		501.00	
σ_u^2	0.29		0.07	
LR test for σ_u^2	835.40		150.10	
$\frac{\sigma_u}{\sigma_v}$	4.54		2.78	

Note: σ_u^2 is variance of inefficiency term and shows how much variation the estimated inefficiency has among banks. The LR test for σ_u^2 tests the null hypothesis that $\sigma_u^2 = 0$. σ_v is variance of random error term, and the ratio $\frac{\sigma_u}{\sigma_v}$ shows how much inefficiency is important relative to random error.

* Statistical significance at 10 percent level.

** Statistical significance at 5 percent level.

*** Statistical significance at 1 percent level.

Table A2
Mean efficiency by M&A status.

	Profit efficiency	Rank profit efficiency	Cost efficiency	Rank cost efficiency	Number of banks	Total observations
Before M&A	$0.70^{(---)}$	$0.45^{(---)}$	$0.80^{(---)}$	$0.46^{(--)}$	40	305
	(0.149)	(0.295)	(0.124)	(0.318)		
After M&A	0.73	0.48	$0.77^{(---)}$	$0.37^{(---)}$	17	108
	(0.152)	(0.340)	(0.146)	(0.309)		
Never M&A	$0.74^{(+++)}$	$0.51^{(+++)}$	$0.84^{(+++)}$	$0.52^{(+++)}$	106	1413
	(0.133)	(0.285)	(0.091)	(0.281)		
Full Sample	0.73	0.5	0.83	0.5	147	1808
	(0.139)	(0.291)	(0.103)	(0.291)		

Notes: Superscript (+), (++), (+++) indicate the efficiency estimate is statistically significantly positive compared to the other banks in the sample at 10%, 5% and 1% level, respectively. Similarly, (−), (−−), (−−−) indicate the estimate is statistically significantly negative compared to the other banks in the sample at the 10%, 5% or 1% level. Significance is based on a parametric *t*-test. Standard deviation is in parenthesis below each mean estimate. Time fixed effects are included in the efficiency estimation.

Table A3a
The effect of M&A on bank efficiency – ordinary least squares.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
Specification	Ordinary least squares							
Dependent variable	Profit efficiency		Rank profit efficiency		Cost efficiency		Rank cost efficiency	
After M&A	**0.04**	**0.05****	**0.07**	**0.08**	**−0.06*****	**−0.06*****	**−0.12****	**−0.13****
	[0.025]	**[0.026]**	**[0.053]**	**[0.055]**	**[0.018]**	**[0.019]**	**[0.053]**	**[0.055]**
Never M&A	0.06***	0.05***	0.12***	0.11***	0.02	0.02	0.01	0.00
	[0.019]	[0.019]	[0.040]	[0.040]	[0.014]	[0.014]	[0.039]	[0.040]
Target	0.02	0.01	0.04	0.02	−0.01	−0.01	−0.02	−0.02
	[0.024]	[0.024]	[0.051]	[0.051]	[0.017]	[0.017]	[0.050]	[0.050]
Mega		−0.06**		−0.03		0.02		0.06
		[0.028]		[0.061]		[0.021]		[0.061]
Large		−0.02		0.01		−0.01		−0.03
		[0.017]		[0.035]		[0.012]		[0.035]
Small		0.03***		0.06***		0.00		0.00
		[0.008]		[0.017]		[0.006]		[0.016]
Constant	0.68***	0.68***	0.39***	0.38***	0.81***	0.82***	0.51***	0.51***
	[0.018]	[0.019]	[0.039]	[0.040]	[0.013]	[0.014]	[0.039]	[0.040]
Observations	1590	1590	1590	1590	1590	1590	1590	1590
R-squared	0.01	0.02	0.01	0.02	0.03	0.03	0.01	0.01
F statistic	5.71	6.44	4.89	4.56	13.63	7.07	3.69	2.19
F statistic (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04
Number of banks	146	146	146	146	146	146	146	146
Number of years	14	14	14	14	14	14	14	14

Note: Standard errors in brackets below each coefficient estimate. Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price). Time fixed effects included in efficiency estimation.

** Statistical significance at 5 percent level.

*** Statistical significance at 1 percent level.

Table A3b
The effect of M&A on bank efficiency – OLS with bootstrapping.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
Specification	OLS with bootstrapped standard errors							
Dependent variable	Profit efficiency		Rank profit efficiency		Cost efficiency		Rank cost efficiency	
After M&A	**0.04**	**0.05***	**0.07**	**0.08**	**−0.06****	**−0.06****	**−0.12****	**−0.13****
	[0.030]	**[0.032]**	**[0.063]**	**[0.064]**	**[0.028]**	**[0.029]**	**[0.059]**	**[0.061]**
Never M&A	0.06***	0.05**	0.12***	0.11**	0.02	0.02	0.01	0.00
	[0.022]	[0.024]	[0.043]	[0.044]	[0.019]	[0.019]	[0.045]	[0.046]
Target	0.02	0.01	0.04	0.02	−0.01	−0.01	−0.02	−0.02
	[0.028]	[0.028]	[0.054]	[0.054]	[0.024]	[0.025]	[0.056]	[0.057]
Mega		−0.06		−0.03		0.02		0.06
		[0.046]		[0.078]		[0.026]		[0.070]
Large		−0.02		0.01		−0.01		−0.03
		[0.022]		[0.040]		[0.015]		[0.038]
Small		0.03***		0.06***		0.00		0.00
		[0.007]		[0.016]		[0.005]		[0.016]
Constant	0.68***	0.68***	0.39***	0.38***	0.81***	0.82***	0.51***	0.51***

Table A3b (*Continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
Specification	OLS with bootstrapped standard errors							
Dependent variable	Profit efficiency		Rank profit efficiency		Cost efficiency		Rank cost efficiency	
	[0.022]	[0.024]	[0.042]	[0.044]	[0.019]	[0.019]	[0.044]	[0.045]
Observations	1590	1590	1590	1590	1590	1590	1590	1590
R-squared	0.01	0.02	0.01	0.02	0.03	0.03	0.01	0.01
Wald test	13.42	34.62	13.42	27.42	17.05	17.49	8.44	9.71
Wald test (p-value)	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.14
Number of banks	146	146	146	146	146	146	146	146
Number of years	14	14	14	14	14	14	14	14

Note: Bootstrapped standard errors (with 2000 replications) in brackets below each coefficient estimate.
Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price). Time fixed effects included in efficiency estimation.

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table A3c
The Effect of M&A on Bank Efficiency – Median Regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	3 years before and after M&A for M&A banks and all years for never M&A banks							
Specification	Median regression							
Dependent variable	Profit efficiency		Rank profit efficiency		Cost efficiency		Rank cost efficiency	
After M&A	**0.07****	**0.05**	**0.11**	**0.06**	−**0.07*****	−**0.06*****	−**0.24*****	−**0.25*****
	[0.031]	**[0.032]**	**[0.093]**	**[0.095]**	**[0.020]**	**[0.020]**	**[0.090]**	**[0.091]**
Never M&A	0.08***	0.07***	0.19***	0.16**	−0.01	−0.02	−0.09	−0.12*
	[0.023]	[0.023]	[0.069]	[0.070]	[0.015]	[0.015]	[0.067]	[0.066]
Target	0.04	0.04	0.09	0.04	−0.03	−0.02	−0.12	−0.17**
	[0.030]	[0.029]	[0.088]	[0.088]	[0.019]	[0.019]	[0.085]	[0.083]
Mega		0.02		0.09		−0.01		−0.04
		[0.035]		[0.105]		[0.022]		[0.100]
Large		0.01		0.05		−0.01		−0.07
		[0.021]		[0.061]		[0.013]		[0.058]
Small		0.02**		0.08***		0.00		0.03
		[0.010]		[0.029]		[0.006]		[0.027]
Constant	0.68***	0.68***	0.33***	0.33***	0.87***	0.87***	0.61***	0.64***
	[0.023]	[0.023]	[0.068]	[0.069]	[0.014]	[0.015]	[0.065]	[0.066]
Observations	1590	1590	1590	1590	1590	1590	1590	1590
Pseudo R-squared	0.005	0.008	0.007	0.012	0.002	0.003	0.005	0.007
Number of banks	146	146	146	146	146	146	146	146
Number of years	14	14	14	14	14	14	14	14

Note: Standard errors in brackets below each coefficient estimate. Small: bank size less than 1 trillion yen; medium: 1–10 trillion yen; large: 10–55 trillion yen; mega: more than 55 trillion yen (measured by total assets at 2000 price). Time fixed effects included in efficiency estimation.

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

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