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The role of bank affiliation in bank efficiency: a fuzzy multi-objective data envelopment analysis approach

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Abstract
This paper examines differences in bank efficiency between banks affiliated with single-bank holding companies and those affiliated with multi-bank holding companies by applying a fuzzy multi-objective two-stage data envelopment analysis technique. Using a sample of U.S. commercial banks covering 1994–2018, the results show that banks affiliated with multi-bank holding companies are more efficient than those affiliated with single-bank holding companies, suggesting that the former takes advantage of their parents' resources to enhance their efficiency, consistent with the internal capital market theory. They also show that banks with a powerful CEO exhibit lower efficiency than others. Moreover, there is an inverted U shape relationship between multi-bank holding company structure and bank efficiency, suggesting the presence of an optimal number of multi-bank holding subsidiaries that maximizes efficiency.

Keywords Bank holding companies · Bank efficiency · CEO power · Multi-objective programming · Data envelopment analysis

JEL Classification G20 · G21 · G28 · C61 · C67

1 Introduction

Bank inefficiency is considered as one of the main reasons behind the financial crisis that has shaken the U.S. banking system during 2007–2009 (Assaf et al. 2019). Since the Bank Holding Companies Act of 1956, bank holding company (BHC hereafter) structures have become dominant in the US banking industry (Koutsomanoli-Filippaki et al. 2012). They controlled over 15 trillion USD in total assets, accounting for more than 95% of total US

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banking assets in 2015. Kane (1996) emphasizes that the holding company framework can re-engineer the organisations to squeeze a large product line and geographically dispersed network. The rapid increase in the number of BHC subsidiaries has raised concerns on whether BHC structures enhance the efficiency of banks at the subsidiary level (Kashian et al. 2019). On the one hand, Assaf et al. (2019) find that efficient banks are more resilient to financial crises than their inefficient peers. Specifically, banks with lower cost and revenue efficiency could suffer higher bank risk (Fiordelisi et al. 2011). On the other hand, Luo et al. (2011) and Barth et al. (2008) state that financial crises have harmed banking activities from the funding side and the lending side, significantly reducing bank efficiency. In fact, banks reduced their lending activities (De Haas and Van Horen 2013), while at the same time suffering from pressure due to the risk of withdrawal of deposits from customers (Martinez Peria and Schmukler 2001). While the difference in bank efficiency between diversified and focused bank structures is questionable[1], it is essential for the regulators to increase bank efficiency at different bank holding company structures, leading to more stable U.S. banking industry.

This paper applies Data envelopment analysis (DEA hereafter) to assess bank efficiency since this technique has been widely used as a tool to measure performance in the banking industry (Wang et al. 2014; Barth et al. 2013). The DEA approach is a commonly applied non-parametric method to compute efficiency scores. It is combined here with a second stage regression analysis to determine factors explaining the level of bank efficiency (Casu et al. 2011; Curi et al. 2013). More specifically, we use a fuzzy multi-objective two-stage DEA approach to measure bank efficiency. This technique has been used by Wang et al. (2014) for bank holding company efficiency. Different from Wang et al. (2014), we focus on the subsidiary level of BHCs and compare the efficiency between banks belonging to a single-BHC and those that belong to a multi-BHC.

This study adopts the fuzzy approach developed by Zimmermann (1978) that transforms a multi-objective programming problem into a single-objective programming problem. We choose to apply fuzzy multi-objective DEA because this technique has several advantages compared to conventional DEA. First, a conventional DEA methodology considers the production procedure as a 'black box' with insufficient details to identify sources of inefficiency. Indeed, the bank production function is complex with the interaction of different activities and divisions (Zimmermann 1978). Second, conventional DEA gives a relatively large number of efficient DMUs, implying weak discriminating power. Fuzzy multi-objective DEA combines all the efficiency functions of each DMU into one function, providing more accurate result (Wang et al. 2014).

By using commercial bank data from 1994 to 2018, this paper examines the difference in bank efficiency between a multi-BHC and a single-BHC at the subsidiary level.[2] On the one hand, multi-BHCs can strengthen their finance by diversifying their funding externally and creating internal capital funding (San-Jose et al. 2018). Multi-BHCs can also lessen financial difficulties and avoid bankruptcy for their affiliates by transmitting their source of finance to them. Moreover, one subsidiary within a multi-BHC can share resources with other subsidiaries. On the other hand, multi-bank holding's affiliates have lower efficiency due to their structure (Makinen and Jones 2015). A multi-BHC has more than two subsidiaries;

[1] A diversified bank structure is defined as a bank that owns two or more bank units while focused bank structure is a bank that has only one bank unit.

[2] We define banks at the subsidiary (or affiliate) level as banks that belong to BHCs. A single-BHC has one bank unit while a multi-BHC has two or more bank units. We interchangeably use affiliates, affiliated banks, and subsidiaries throughout our paper. More specifically, banks that belong to a single-BHC are called single-BHC affiliates whereas those belonging to a multi-BHC are considered as multi-BHC affiliates.

making it, therefore, relatively difficult for multi-BHCs to distribute their financial resources equally between their affiliates. In addition, there is a competition at the affiliation level that may lead to higher cost of raising capital and reduce bank efficiency. Using several estimation techniques, i.e., fixed effect, truncated regression, difference-in-difference regression based on propensity score matching and dynamic treatment, we show that multi-BHC affiliates exhibit higher efficiency scores than their single counterparts. This result is consistent with the internal capital market theory, suggesting that multi-BHC affiliates can receive resources both from their parents and other banks that belong to the same multi-BHC.

There is also a possibility that affiliates of a multi-BHC suffer from high risk despite their benefit from the internal capital market. Hughes et al. (1996) state that diversification causes an increase in the proportion of loan to assets, which leads to higher credit risk. Berrospide et al. (2016) explain the risk transmission channel between BHC affiliates. More specifically, BHC affiliates could endure negative spillover effect through internal capital market when their peers suffer from local economic or credit shocks.

There could also be a link between efficiency and bank concentration, bank size and bank structure (Demirgüç-Kunt and Levine 2000). For instance, in dynamic and expanding markets, banks may benefit from growing demand, increased activity in branch offices, and expanded networking that could improve efficiency and vice versa. However, dealing with more customers could generate inefficiencies because of the need to meet all of their diverse requirements. Gonzalez (2009) suggest that ignoring endogeneity leads to biased estimation given the endogeneity nature of bank structures. To solve a possible endogeneity issue, we apply a difference-in-difference method based on propensity score matching. We first match banks switching their status from single-BHC affiliates to multi-BHC affiliates with banks that hold the same status based on bank characteristics such as bank size and bank capital. We then estimate a difference-in-differences regression to consider whether and how banks affect their efficiency when they switch their status from single-BHC affiliates to multi-BHC affiliates. We find that single-BHC affiliates that switch to multi-BHC affiliates gain higher efficiency.

We also test whether corporate governance, especially CEO power could influence the effect of bank structure on bank efficiency. Prior literature does not show clear-cut findings regarding the relationship between CEO power and bank efficiency, especially within different banking structures. Stulz (1988) and Bhagat and Jefferis (2002) suggest that bank governance plays an important role in explaining bank efficiency. On the one hand, powerful CEOs are likely to dominate boards, affect their decisions, and encourage the adoption of risky activities, leading to lower efficiency. On the other hand, powerful CEOs are more inclined to reduce conflicts between board members, hence increasing bank efficiency. We find that multi-BHC with powerful CEOs are less efficient. This result is consistent with prior research (Bitar et al. 2018; Haque and Brown 2017) and provides practical implications for bank regulators, especially for bank activities within different BHC structures.

Our paper contributes to several strands of literature. First, it applies a fuzzy multi-objective two-stage DEA technique that considers the structure of US banks. This technique is an advanced performance measurement tool that combines efficiency functions of all DMUs into one function and increases discriminating power (Wang et al. 2014). Second, it relies on internal capital market theory to expand our knowledge regarding the efficiency of multi-BHC subsidiaries. Third, our paper contributes to the recently growing literature on the role of CEO power in the banking industry. Fourth, it expands the literature comparing the efficiency between multi- and single-BHC subsidiaries. Our evidence shows an inverted U-shape relationship between multi-BHC network and bank efficiency, suggesting the existence of an optimal number of subsidiaries in BHC structures to gain the highest efficiency levels.

The rest of the paper is organised as follows. Section 2 lays out the theoretical framework and develops the hypotheses. Section 3 presents the multi-objective two-stage DEA. Section 4 describes the data and regression models. Section 5 presents the analyses and explains the empirical results. Section 6 reports robustness checks. The last section concludes.

2 Theoretical framework and hypotheses development

2.1 BHC structures and bank efficiency

A multi-BHC structure is organised as a hierarchy structure in which a holding company's parent is located at the top. The parent company controls a lead bank while other bank subsidiaries can work as full-service branches. Contrariwise, Watkins and West (1982) define a single-BHC as a structure that includes a single bank and a number of nonbank subsidiaries.

Diversification at the parent level may increase the parent's capacity to create an internal capital market and acquire better financing deals. The internal capital market theory suggests that the creation of an internal capital market, where the parents allocate their resources across different projects, could reduce the need and the cost of external financing. This theory explains many benefits for subsidiaries. For instance, Houston and James (1998) find that affiliated banks have lower cash flow sensitivity of loan growth than stand-alone banks, implying that banks belonging to a banking group are more likely to reduce the cost of raising funds externally. Cremers et al. (2010) and Kashian et al. (2019) state that headquarters of banking groups can provide their affiliations with intertemporal insurance when experiencing shortfalls in funding. In addition, multi-BHC affiliates can access to internal secondary loan market of their parents, hence, the subsidiaries holding less capital can originate loans and sell them to better-capitalized affiliates. Therefore, the subsidiaries can mitigate any capital constraint on their loan production.

Internal capital markets are regarded as a "source-of-strength" (Mirzaei and Moore 2019; Chronopoulos et al. 2013). For instance, headquarters can divert resources from other affiliates to rescue troubled subsidiaries. The "too-big-to-fail" resolution demonstrates that counterparties of troubled corporations need to be protected to decrease the collateral damage that was caused by the bankruptcy of that firm (Evanoff and Ors 2008; Kaufman 2014). In addition, headquarters can reallocate resources or reduce earnings volatility, that lead to lower risk-taking at the affiliate level of more diversified bank groups (Ly et al. 2018). Overall, a multi-BHC has more subsidiaries than single-BHC and allows them to have more internal resources. From the above arguments, we draw our first hypothesis.

Hypothesis 1 Multi-BHC affiliates exhibit higher efficiency than single-BHC affiliates.

2.2 CEO power and bank efficiency

CEOs are more powerful and play a more important role in the decision-making process of their banks when they also chair the board of directors and have longer tenure at their position. In general, researchers find that CEO power has a detrimental effect on bank performance and efficiency. For instance, De Haan and Vlahu (2016) find that CEO power has a negative impact on bank performance as it leads to CEO entrenchment, hence, preventing other board members accessing information flows, influencing board decisions and undermining monitoring function of independent directors (Mollah and Zaman 2015). Lewellyn and Muller-Kahle (2012) shows that CEO power measured by CEO duality reduces banks' efficiency partly due to excessive concentration of power in one person's hands.

More specifically, CEO duality is the situation in which CEO is also the chair of the board. CEO duality may have a detrimental effect on bank performance, board monitoring and its influence on board decisions (Lasfer 2006). For example, a powerful CEO has the ability to influence the selection of board members with the appointment of non-executive directors who are unlikely to influence their decisions (Adams and Mehran 2012; Chen et al. 2018; De Jonghe et al. 2012). Nevertheless, a powerful CEO can have a positive impact on bank performance and bank efficiency. In particular, a combined role of CEO and chairman may prevent the agency problem within banks by reducing the likelihood of conflict between CEO and board members, thereby, improving banks' performance and banks' efficiency (Stoeberl and Sherony 1985). Moreover, CEO duality enhances banks' leadership, hence, directing banks' objective in a clear manner and enhancing bank stability (Anderson and Anthony 1986).

Several studies on banks have already addressed the issues regarding the impact of CEO power on bank performance and bank efficiency. Pi and Timme (1993) show that banks with non-duality CEO are more cost efficient than those with CEO duality. Grove et al. (2011) show that CEO tenure is negatively associated with bank performance and loan quality. However, Simpson and Gleason (1999) argue that US banks experience lower probability of financial distress when CEO is also a chair of board of directors because of better strategic vision and leadership. Therefore, it can be argued that

Hypothesis 2 CEO power affects bank efficiency at BHC subsidiary level.

3 Fuzzy multi-objective two-stage DEA for BHC affiliations

3.1 Fuzzy multi-objective two-stage DEA

The DEA method is a widely used technique in measuring efficiency in the banking industry. The conventional DEA ignores the production process and considers it a "black box" as it totally ignores what happens inside. This paper adopts a relational two-stage DEA model along with a fuzzy multiple objective programming design to analyse the organizational structure and production process of commercial banks. We focus on technical efficiency measured by dividing the weighted sum of outputs by the weighted sum of inputs. We consider input oriented instead of output oriented since bank managers have greater influence over bank inputs rather than bank outputs (Fethi and Pasiouras 2010).

We follow Wang et al. (2014) to construct the fuzzy multi-objective two-stage DEA. Model (1) evaluates the relative efficiency of nDMU_j(j $= 1, 2, \ldots$ n), each with m inputs x_{ij}(i $=$ $1, 2, \ldots,$ m), q intermediate product $k_{pj}(p = 1, 2, \ldots, q)$ and s output $y_{rj}(r = 1, 2, \ldots, s)$. If we consider the efficiency ratio of all DMUs, the multiple objectives program can be shown as

$$
\begin{aligned}
z_1 &= max\frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}}\\
&\ldots\\
z_n &= max\frac{\sum_{r=1}^{s} u_r y_{rn}}{\sum_{i=1}^{m} v_i x_{in}}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&\text{s.t.}\\
&\frac{\sum_{p=1}^{q}\eta_p k_{pj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1, 2, \ldots, n\\
&\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{p=1}^{q}\eta_p k_{pj}} \le 1, \quad j = 1, 2, \ldots, n\\
&\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1, 2 \ldots, n\\
&u_r, \eta_p, v_i \ge \varepsilon > 0 \;\; r = 1, \ldots, s \;\; i = 1, \ldots, m \;\; p = 1, \ldots, q
\end{aligned}
$$

In model (1), z_1 is the efficiency of DMU_1 while u_r, η_pandv_i are the factor weights. However, for computational convenience, the model can be re-expressed as

$$
\begin{aligned}
&z_1 = max\frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}}\\
&\cdots\\
&z_n = max\frac{\sum_{r=1}^{s} u_r y_{rn}}{\sum_{i=1}^{m} v_i x_{in}}\\
&\text{s.t.}\\
&\sum_{p=1}^{q}\eta_p k_{pj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, 2, \ldots, n\\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q}\eta_p k_{pj} \le 0, \quad j = 1, 2, \ldots n\\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, 2, \ldots, n\\
&u_r, \eta_p, v_i \ge \varepsilon > 0 \;\; r = 1, \ldots, s \;\; i = 1, \ldots, m \;\; p = 1, \ldots, q
\end{aligned}
\tag{2}
$$

To solve this model, Zimmermann (1978) fuzzy approach has been adopted, which transforms a multiple objective program into a single objective program. With regard to its objective function, each DMU illustrates its level of achievement through means of the membership function. The membership function is illustrated as follows

$$
h_j(z_j) = \begin{cases} 0 & if \;\; z_j \le z_j^l \\ \frac{z_j - z_j^l}{z_j^u - z_j^l} & if \;\; z_j^l \le z_j \le z_j^u \\ 1 & if \;\; z_j \ge z_j^u \end{cases} \tag{3}
$$

where z_j is the efficiency of DMU_j, z_j^l and z_j^u illustrate the lower bound and upper bound of the objective function, respectively. The membership function of z_j is denoted by $h_j(z_j)$. Within this function, the highest value of $h_j(z_j)$ equals 1 and the lowest value equals 0. We solve the model by maximizing the minimum of the membership function in Model (3), which can be written as follows

$$
\max_{u,v,\eta} \min_{j}^{\mathrm{n}} h_j(z_j) \tag{4}
$$

s.t.

$$\sum_{p=1}^{q} \eta_p k_{pj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, 2, \ldots, n$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \eta_p k_{pj} \leq 0, \quad j = 1, 2, \ldots n$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, 2, \ldots, n$$
$$u_r, \eta_p, v_i \geq \varepsilon > 0 \;\; r = 1, \ldots, s \;\; i = 1, \ldots, m \;\; p = 1, \ldots, q$$

Since efficiency of DMU_j ranges from 0 to 1, the membership function $h_j(z_j)$ can be simplified as z_j. For computational convenience, the auxiliary variable ψ is introduced as follows

$$\psi = \min_{j}^{\mathrm{n}} z_j \tag{5}$$

We can rewrite Eq. (5) as

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \geq \psi, \quad j = 1, 2 \ldots, n \tag{6}$$

Combining Eqs. (4) and (6), we can rewrite the following mathematical programming model

$$\max_{u,v,\eta} \psi \tag{7}$$

s.t.

$$\sum_{r=1}^{s} u_r y_{rj} - \psi \sum_{i=1}^{m} v_i x_{ij} \geq 0, \quad j = 1, 2, \ldots, n$$
$$\sum_{p=1}^{q} \eta_p k_{pj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, 2, \ldots, n$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \eta_p k_{pj} \leq 0, \quad j = 1, 2, \ldots n$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, 2, \ldots, n$$
$$u_r, \eta_p, v_i \geq \varepsilon > 0 \;\; r = 1, \ldots, s \;\; i = 1, \ldots, m \;\; p = 1, \ldots, q$$

Applying bisection method to solve this model, we get the value of factor weight u_r^*, η_p^*, v_i^* to measure efficiency as follows

$$z_j^h = \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{i=1}^{m} v_i^* x_{ij}} = \frac{\sum_{p=1}^{q} \eta_p^* k_{pj}}{\sum_{i=1}^{m} v_i^* x_{ij}} * \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{p=1}^{q} \eta_p^* k_{pj}} = z_j^{h1} * z_j^{h2} \tag{8}$$

In which, z_j^{h1}, z_j^{h2}andz_j^h are the efficiency of first stage, second stage and the whole process, respectively.

3.2 Production process

As banks play an intermediate role in transforming deposits into lending and investments we follow the intermediate approach to construct input, output and intermediate products (Favero and Papi 1995). The production process includes two stages. For the first stage, the inputs are interest expense and non-interest expense (Harris et al. 2013). Deposits play an intermediate role between the first and second stage. Holod and Lewis (2011) state that deposits should be considered as the intermediate product of the process as deposits play a dual role in bank production procedure. Outputs include loans, interest income and non-interest income (Harris et al. 2013). The outputs of the first stage are inputs for the second stage.

4 Data and regression model

4.1 Sample

This study uses panel data of BHC affiliates for the period 1994–2018. Each bank subsidiary that belongs to a BHC is treated as a DMU. We exclude stand-alone banks, banks with foreign ownership and keep only banks belonging to holding companies. We also discard banks with missing values for the inputs or outputs needed to run DEA and those with no data available for at least half of the study period. After cleaning the data, we use the "Jackstrap" methodology to obtain a homogenous dataset (Chortareas et al. 2013) by applying bootstrap and calculating each DMU efficiency score relative to all other DMUs when a DMU is removed from the dataset. By doing so, outlier banks with data errors can be detected and removed from the dataset. The final sample consists of 3853 banks from 1994 to 2018.

We primarily obtain the input and output data from Call report and CEO data from Boardex and SNL Financial that is part of S&P Global Market Intelligence. We match Boardex data with financial data from Call Report. CEO details are from Boardex (e.g., CEO tenure and CEO duality). When CEO information is not available in Boardex, we look at it in Bloomberg and bank annual reports.

4.2 Variables and regression model

To evaluate the effect of bank type on bank efficiency, we estimate the following model

$$Bank\ efficiency_{it} = \beta_0 + \beta_1 * MBHC\ affiliate_{it} + \sum_{i=1}^{n} \beta_i * Controls_{it} + \lambda_t + \varepsilon_{it} \quad (9)$$

where the dependent variable is *Bank efficiency* of BHC affiliates measured by fuzzy multi-objective two-stage DEA. *MBHC affiliate* is a dummy variable that takes the value of 1 when banks are multi-BHC affiliates; and 0 if they are single-BHC affiliates. *Controls* are control variables that are deemed to affect bank efficiency. λ_t is a year dummy variable that captures year-fixed effects.

We use different control variables that affect bank efficiency such as *Bank size, Bank capital, Bank non-performing loan,* and *Bank profit*. Ly et al. (2017) find that the likelihood of BHC affiliates being acquired targets in mergers and acquisitions changes across various asset size, therefore, *Bank size* is measured as the natural logarithm of total asset and is included to capture the size effects of BHC affiliates. Benston (1965) and Miller and Noulas

(1996) show that large banks can take advantage of economies of scale and are more efficient than others. *Bank capital* is measured as total bank capital divided by total assets. There are opposite views on the effect of *Bank capital* on bank performance and efficiency. On the one hand, by a study of 72 countries during the period 1999–2007, Barth et al. (2013) find that well-capitalized banks exhibit higher efficiency. On the other hand, bank capital can negatively affect bank performance and efficiency, encouraging banks to take excessive risks (Altunbas et al. 2007). *Bank non-performing loan* is measured as total bank non-performing loan divided by total assets. The importance of non-performing loans has been discussed by Berger and DeYoung (1997), who consider that non-performing loans have a detrimental effect on banks' efficiency and stability because of asset quality deterioration. Karadima and Louri (2020) also argue that financial and debt crises in the euro area highlight the serious problem of non-performing loans faced by majority of banks. *Bank profit* is measured by net income divided by total assets. We expect bank profit ratio to have a positive impact on bank efficiency as highly profitable banks are preferred by clients, attracting more deposit and better customers (Miller and Noulas 1996).

We apply ordinary least square, fixed effect and truncated regression approaches. The latter is common in estimating the factors affecting bank efficiency as efficiency lies between 0 and 1. We also apply parametric bootstrapping to enhance the reliability of the results.

5 Analysis and results

5.1 Descriptive statistics and correlation analysis

Table 1 summarizes descriptive statistics of variables used in the DEA model for single-BHC affiliates, multi-BHC affiliates and the whole sample. We winsorize all continuous variables at the 1st and 99th percentile to minimize the effect of outliers.

The descriptive statistics from Table 1 show that multi-BHC affiliates seem to operate more efficiently than single-BHC affiliates with an average efficiency score of 0.50 and 0.43, respectively. Multi-BHCs tend to be larger, have higher capital ratio, higher profit ratio but lower deposit ratio.[3]

5.2 The impact of bank structure on bank efficiency

Table 2 reports the results of our main regression. We adjust standard errors for heteroscedasticity and cluster them at the bank level. Year dummies are included in all models to control for year-fixed effects.

The coefficient of our main variable, *MBHC affiliate*, is positively and statistically significant at the 1% levels, implying that multi-BHC affiliates have higher efficiency than single-BHC affiliates. The results are consistent for OLS, fixed effect and truncated regression. According to internal capital market theory, headquarters of multi-BHC can diversify and obtain better finance, creating internal capital for banks at both parents and affiliate level. Multi-BHCs have more subsidiaries than single-BHCs and, therefore, allow affiliates to access more internal resources than their single-BHC counterparts. The subsidiaries, therefore, can take advantage of better financing with lower cost and reduce the effect of undesirable output by sharing risks between subsidiaries (Lamont 1997; Stein 1997).

[3] Correlation matrix and VIF are available from the authors upon a request. They suggest the absence of multicollinearity as correlation coefficients between control variables and VIFs are low.

Table 1 Descriptive statistics

	Observations	Standard deviation	Mean	Minimum	First quartile	Median	Third quartile	Maximum
Panel A: Single-BHC affiliates								
Bank inputs								
Bank interest expense	63,737	1.18	1.85	0.12	0.70	1.78	2.90	4.25
Bank non-interest expense	63,737	0.91	3.01	1.27	2.43	2.89	3.42	7.02
Intermediate product								
Bank deposit	63,737	6.09	84.47	58.68	81.63	85.88	88.9	92.78
Bank outputs								
Bank interest income	63,737	0.01	0.06	0.02	0.04	0.05	0.07	0.09
Bank non-interest income	63,737	0.60	0.76	0.09	0.41	0.63	0.93	4.61
Bank lending	63,737	14.34	62.5	22.72	53.48	63.99	73.15	89.68
Bank efficiency								
Bank efficiency	63,737	0.17	0.43	0.11	0.31	0.43	0.52	1
Conventional efficiency	63,737	0.08	0.75	0.63	0.69	0.73	0.79	1
Control variables								
Bank size	64,325	1.22	11.84	9.42	10.98	11.73	12.57	16.10
Bank capital	64,101	2.70	10.24	5.57	8.43	9.72	11.4	21.96
Bank Non-performing loan	48,869	1.56	1.22	0	0.24	0.69	1.54	8.82
Bank profit	64,325	0.76	0.93	− 2.64	0.66	0.99	1.31	2.81
CEO power								
CEO duality	6366	0.43	0.24	0	0	0	0	1
CEO tenure	6347	0.96	1.65	0	1.10	1.79	2.40	3.95
Organizational structure								
Ln(total subsidiaries)	64,427	0.31	0.08	0	0	0	0	10
Organizational complexity	64,325	0.02	0.01	0.001	0.001	0.01	0.02	0.15

Table 1 continued

	Observations	Standard deviation	Mean	Minimum	First quartile	Median	Third quartile	Maximum
Panel B: Multi-BHC affiliates								
Bank inputs								
Bank interest expense	17,439	1.18	2.06	0.12	1.00	2.07	3.09	4.25
Bank non-interest expense	17,439	0.95	2.88	1.27	2.29	2.74	3.27	7.02
Intermediate product								
Bank deposit	17,439	7.75	82.88	58.68	79.66	84.9	88.54	92.78
Bank outputs								
Bank interest income	17,439	0.02	0.06	0.02	0.05	0.06	0.07	0.09
Bank non-interest income	17,439	0.77	0.89	0.09	0.46	0.69	1.04	4.61
Bank lending	17,439	14.5	63.33	22.72	54.55	65.24	73.77	89.68
Bank efficiency								
Bank efficiency	17,439	0.17	0.50	0.11	0.39	0.49	0.6	1
Conventional efficiency	17,439	0.10	0.78	0.63	0.71	0.76	0.83	1
Control variables								
Bank size	17,756	1.49	12.02	9.42	10.99	11.78	12.78	16.1
Bank capital	17,158	3.26	10.27	5.57	8.11	9.39	11.46	21.96
Bank Non-performing loan	14,056	1.44	1.07	0	0.19	0.60	1.34	8.82
Bank profit	17,756	0.76	1.09	− 2.64	0.79	1.13	1.47	2.81
CEO power								
CEO duality	2030	0.46	0.31	0	0	0	1	1
CEO tenure	2020	0.91	1.52	0	0.69	1.61	2.2	3.87

Table 1 continued

	Observations	Standard deviation	Mean	Minimum	First quartile	Median	Third quartile	Maximum
Organizational structure								
Ln(total subsidiaries)	17,936	0.93	1.49	0.69	0.69	1.10	1.95	8.70
Organizational complexity	17,756	0.05	0.05	0.001	0.01	0.03	0.07	0.15
Panel C: Whole sample								
Bank inputs								
Bank interest expense	81,176	1.19	1.90	0.12	0.75	1.85	2.94	4.25
Bank non-interest expense	81,176	0.92	2.99	1.27	2.40	2.86	3.39	7.02
Intermediate product								
Bank deposit	81,176	6.51	84.13	58.68	81.23	85.68	88.82	92.78
Bank outputs								
Bank interest income	81,176	0.01	0.06	0.02	0.04	0.06	0.07	0.09
Bank non-interest income	81,176	0.65	0.79	0.09	0.42	0.64	0.95	4.61
Bank lending	81,176	14.38	62.68	22.72	53.68	64.29	73.31	89.68
Bank efficiency								
Bank efficiency	81,176	0.17	0.44	0.11	0.33	0.44	0.54	1
Conventional efficiency	81,176	0.09	0.76	0.63	0.69	0.74	0.80	1
Control variables								
Bank size	82,081	1.29	11.88	9.42	10.98	11.74	12.61	16.1
Bank capital	81,259	2.83	10.24	5.57	8.36	9.66	11.41	21.96
Bank Non-performing loan	62,925	1.54	1.18	0	0.23	0.67	1.49	8.82

Table 1 continued

	Observations	Standard deviation	Mean	Minimum	First quartile	Median	Third quartile	Maximum
Bank profit	82,081	0.76	0.96	– 2.64	0.68	1.02	1.35	2.81
CEO power								
CEO duality	8396	0.44	0.25	0	0	0	1	1
CEO tenure	8367	0.95	1.61	0	0.69	1.61	2.3	3.95
Organizational structure								
Ln(total subsidiaries)	82,363	0.78	0.39	0	0	0	0.69	10
Organizational complexity	82,081	0.03	0.02	0.001	0.001	0.01	0.02	0.15

This table presents the summary statistics of multi-bank holding company's affiliates, single-bank holding company's affiliates and whole sample. *Bank interest expense* is total interest expense divided by total asset. *Bank non-interest expense* is total non-interest expense divided by total asset. *Bank deposit* is total deposit divided by total asset. *Bank interest income* is total interest income divided by total asset. *Bank non-interest income* is total non-interest income divided by total asset. *Bank lending* is total loan divided by total asset. *Bank efficiency* is banks technical efficiency measured by fuzzy multi-objective two-stage DEA. *Conventional efficiency* is bank technical efficiency measured by conventional DEA. *Bank size* is log of total asset. *Bank capital* is total capital divided by total asset. *Bank non-performing loan* is loans with 90 days past due or more and still accrued divided by total loan. *Bank profit* is net income divided by total asset. *CEO duality* is a dummy variable equals 1 if CEO is a chairman, otherwise 0. *CEO tenure* is natural logarithm of 1 plus tenure of CEO. *Ln(total subsidiaries)* is natural logarithm of total bank and non-bank subsidiaries

Table 2 Efficiency comparisons between single-bank holding company's affiliates and multi-bank holding company's affiliates

Variable	Bank efficiency		
	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*
MBHC affiliate	0.008***	0.028***	0.007***
	(4.639)	(12.432)	(10.463)
Bank size	0.006***	0.009***	0.006***
	(8.532)	(5.551)	(23.702)
Bank capital	0.005***	0.004***	0.004***
	(17.152)	(14.195)	(41.295)
Bank non-performing loan	− 0.002***	− 0.004***	− 0.003***
	(− 5.313)	(− 9.897)	(− 13.081)
Bank profit	0.023***	0.019***	0.026***
	(21.715)	(19.362)	(60.400)
Constant	0.379***	0.355***	0.383***
	(38.663)	(19.313)	(113.267)
Bank fixed effect	No	Yes	No
Year dummy	Yes	Yes	Yes
Number of observations	62,554	62,554	62,010
R^2	0.766	0.762	

This table reports impact of bank structure on bank efficiency at the affiliated level. The dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. *MBHC affiliate* takes value of 1 if banks belong to multi-bank holding company and 0 if banks belong to single-bank holding company. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first model uses ordinary least square regression with year dummy. The second model uses fixed effect at both bank and year level. The third model uses truncated regression model with efficiency truncated at the value of 1. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

For control variables, we find that large banks perform better, which is consistent with Barth et al. (2013), suggesting that larger banks may get benefit from economies of scale. Demsetz and Strahan (1995) state that large banks can take advantage of diversification. Diversification effect mostly dominates the internalization effect in multi-BHC structure, therefore, the multi-BHC subsidiaries can gain more benefits from the diversified structure (Ly and Shimizu 2018). *Bank capital* has a positive impact on bank efficiency, which is consistent with Barth et al. (2013). *Bank non-performing loan* has a negative effect on bank efficiency, implying that non-performing loans have a detrimental effect on banks' efficiency and stability because of asset quality deterioration (Berger and DeYoung 1997). *Bank profit* exhibits a positive relationship with bank efficiency, indicating that profitable banks have higher efficiency. High profitable banks are preferred by clients, attracting more deposit and best potential borrowers (Miller and Noulas 1996).

5.3 Difference-in-difference based on propensity score matching analysis

From the previous analysis, multi-BHC affiliates are found to be more efficient than their single-BHC counterparts. It can be argued that the difference in bank efficiency may not be caused by the difference in bank types, i.e. either single-BHC or multi-BHC structure, however, due to the endogenous decision made by CEO to become such bank type or due to omitted bank characteristics.

To control for endogeneity, our test focuses on banks switching their parents from single-BHC affiliates to multi-BHC affiliates. We make an assumption that banks that change their status may not change their characteristics during such a short period, but their efficiency changes after switching their status. Difference-in-differences approach eliminates the unobserved heterogeneity and increases the evaluation quality (Blundell and Costa Dias 2000). This section, thus, tests whether banks switching from single-BHC affiliates to multi-BHC affiliates exhibit higher efficiency levels by applying a difference-in-difference regression based on propensity score matching method.

We conduct the test in two steps. First, we divide our sample into two sub-samples, namely, banks that change their status from single-BHC affiliates to multi-BHC affiliates (treated group) and those that do not change their status (control group). We use propensity score matching with nearest neighbour matching to match banks that do not change their status with those that change their status based on bank-specific characteristics such as bank size, capital ratio, non-performing loan ratio and profit ratio. We match the groups in the same year to rule out the difference between macroeconomics conditions across different years.

We then estimate differences in bank efficiency between treated banks and non-treated banks by the running a following difference-in-difference regression.

$$\begin{aligned} Bank\ efficiency_{it} &= \beta_0 + \beta_1 Treat_i + \beta_2 Post_i + \beta_3 Treat_i * Post_i \\ &\quad + \sum_{i=1}^{n} \beta_i * Controls_{it} + \lambda_t + \varepsilon_{it} \end{aligned} \tag{10}$$

$Treat_i$ is equals to 1 for banks that change the status; and 0 for banks that do not change the status. This variable is time-invariant. $Post_i$ is a dummy variable equal to 1 for the time after banks change their status and 0 for other periods. The most important variable is the interaction between $Treat_i$ and $Post_i$, indicating changes in difference between treated and non-treated bank before and after status changes. We include year fixed effect in the equation.

Table 3 reports the difference-in-difference regression results for two windows: (i) [− 1, + 1] that includes 1 year before and 1 year after the banks change their status; and (ii) [− 2, + 2] that captures the effects of 2 year before and 2 year after the banks change their status. In all regressions shown in Table 3, the interaction term between $Treat_i$ and $Post_i$ is positively and statistically significant at the 1% threshold level, implying that single-BHC affiliates tend to increase their efficiency after switching to multi-BHC affiliates compared to single-BHC affiliates that keep the same status.[4]

We follow Leung et al. (2019) to apply a dynamic treatment method with this sample to see how the difference between treated banks and non-treated banks changes over different periods based on the following equation:

$$\begin{aligned} Bank\ efficiency_{it} &= \lambda_0 + \lambda_1 * Before_{it}^{-2or-1} + \lambda_2 * Current_{it}^{0} \\ &\quad + \lambda_3 * After_{it}^{+1} + \lambda_4 * After_{it}^{+2} + \sum_{i=1}^{n} \lambda_i * Controls_{it} + \alpha_t + \varepsilon_{it} \end{aligned} \tag{11}$$

[4] In an unreported falsification test, the interaction effect (*Treat*Post*) is no more statistically significant at conventional levels when we randomly assign treated and non-treated banks, which means that our difference-in-difference results are unlikely to be driven by concurrent unobserved events other than that changing the status from Single-BHC to Multi-BHC.

Table 3 Difference in difference based on propensity score matching

Variable	Bank efficiency					
	[− 1, + 1]			[− 2, + 2]		
	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*	Model 4 *OLS*	Model 5 *Fixed effect*	Model 6 *Truncated*
Treat	0.042***		0.041***	0.030***		0.031***
	(3.484)		(3.181)	(2.973)		(3.158)
Post	0.018		0.018	0.007		0.005
	(1.372)		(1.577)	(0.591)		(0.559)
*Treat*Post*	0.070***	0.082***	0.058***	0.084***	0.094***	0.080***
	(4.356)	(4.975)	(3.711)	(6.001)	(8.758)	(6.290)
Bank size	0.012***	0.055**	0.013***	0.009***	− 0.013	0.009***
	(2.898)	(2.250)	(5.317)	(3.132)	(− 0.469)	(4.155)
Bank capital	0.009***	0.005	0.005***	0.007***	0.010**	0.004***
	(4.582)	(0.935)	(3.978)	(3.286)	(2.131)	(3.591)
Bank non-performing loan	− 0.002	− 0.018*	0.001	− 0.000	− 0.005	0.001
	(− 0.558)	(− 1.844)	(0.429)	(− 0.078)	(− 1.190)	(0.362)
Bank profit	0.015**	− 0.023	0.020***	0.024***	0.017	0.036***
	(2.294)	(− 1.315)	(3.946)	(2.797)	(1.420)	(7.194)
Constant	0.281***	− 0.115	0.295***	0.297***	0.595*	0.321***
	(4.766)	(− 0.409)	(7.176)	(6.494)	(1.716)	(9.273)
Bank fixed effect	No	Yes	No	No	Yes	No
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	502	502	491	694	694	676
R^2	0.718	0.491		0.729	0.664	

This table reports the impact of changing from single-BHC affiliates to multi-BHC affiliates using difference-in-differences based on propensity score matching. The dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. *Treat* takes the value of 1 if banks switch from single BHC affiliates to multi-BHC affiliates, otherwise 0. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first three models cover 1 year period before and after treatment. The last three models cover a two year period before and after treatment. The first and the fourth model use ordinary least square regression with year dummy. The second and the fifth model use fixed effect at both bank and year level. The third and the sixth model use a truncated regression model with efficiency truncated at the value of 1. Other control variables include bank size, capital ratio, non-performing loan, profit ratio. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level
Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

where $Before_{it}^{-2or-1}$ is a dummy variable that is equal to 1 for each of the two years before banks switch from single-BHC affiliate to multi-BHC affiliate. $Current_{it}^{0}$ is a dummy variable that is equal to 1 for the year when banks switch their status. $After_{it}^{+1}$ ($After_{it}^{+2}$) is a dummy variable that is equal to one year (two years) after changing their status, respectively. We include year fixed effect in the equation.

Table 4 Dynamic treatment

Variable	Bank efficiency		
	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*
$Before^{-2\ or\ -1}$	− 0.003	− 0.006	− 0.003
	(− 0.231)	(− 0.645)	(− 0.342)
$Current^{0}$	0.037**	0.041***	0.013
	(2.477)	(2.643)	(1.095)
$After^{+1}$	0.044***	0.025*	0.046***
	(3.689)	(1.783)	(4.100)
$After^{+2}$	0.040***	0.049***	0.042***
	(4.058)	(4.481)	(3.569)
Control	Yes	Yes	Yes
Bank fixed effect	No	Yes	No
Year fixed effect	Yes	Yes	Yes
Number of observations	768	768	751
R^2	0.665	0.655	

This table examines the dynamic treatment effect of BHC affiliates on bank efficiency. The dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. We regress bank efficiency on four indicators variables known as $Before^{-2\ or\ -1}$, $Current^{0}$, $After^{+1}$, $After^{+2}$ to examine how bank efficiency changes when banks switch from Single-BHC affiliates to multi-BHC affiliates. $Before^{-2\ or\ -1}$ is a dummy variable equal to 1 for one or two years prior to changing in bank status. $Current^{0}$ is a dummy variable equal to 1 if it is the year that banks change their status. $After^{+1}$ is a dummy variable equal to 1 if it is one year after banks change their status. $After^{+2}$ is a dummy variable equal to 1 if it is two years after banks change their status. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first model uses ordinary least square regression with year dummy. The second model uses fixed effect at both bank and year level. The third model uses truncated regression model with efficiency truncated at the value of 1. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

Table 4 reports the results of the dynamic treatment method. The coefficient of $Before^{-2or-1}$ is small and insignificant, suggesting no systematic differences in pre-trend between the treated and control banks and the parallel assumption is likely satisfied (Roberts and Whited 2013). Compared to the pre-treatment years, we observe an increase in bank efficiency when banks change their status from single-BHC affiliates to multi-BHC affiliates. The effect is especially stronger for 1 and 2 years after banks change their status. This quasi-natural experiment reaffirms our main finding that multi-BHC affiliates are more efficient than single-BHC affiliates.

5.4 Optimal structure of BHC and bank efficiency

The previous results suggest that multi-BHC affiliation has higher efficiency than single-BHC affiliation. This section tests whether and how the network size of multi-BHC can affect bank efficiency. In other words, is there an optimal network size that can maximize bank efficiency? More specifically, network size of BHC is measured by a total number of bank subsidiaries and non-bank subsidiaries. To assess the existence of this optimal point, we consider a quadratic model to test a potential U shaped form of bank network where

Table 5 The impact of bank holding company network on bank efficiency

Variable	Bank efficiency	
	Model 1 *Fixed effect*	Model 2 *Truncated*
MBHC-network^2	− 0.003***	− 0.001***
	(− 10.134)	(− 3.739)
MBHC-network	0.017***	0.006***
	(10.371)	(9.443)
Bank size	0.006***	0.005***
	(4.060)	(20.440)
Bank capital	0.004***	0.004***
	(13.944)	(41.343)
Bank non-performing loan	− 0.004***	− 0.003***
	(− 9.762)	(− 12.982)
Bank profit	0.019***	0.027***
	(19.656)	(60.692)
Constant	0.386***	0.390***
	(21.487)	(113.601)
Bank fixed effect	Yes	No
Year fixed effect	Yes	Yes
Number of observations	62,554	62,010
R^2	0.765	

This table reports the impact of MBHC network on bank efficiency. The main dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. *MBHC-network* is measured by total of bank subsidiaries and non-bank subsidiaries. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first model uses fixed effect at both bank and year level. The second model uses truncated regression model with efficiency truncated at the value of 1. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level

Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

$MBHC\_network_{it}$ is measured as the natural logarithm of total number of BHC subsidiaries including bank and non-bank subsidiaries

$$Bankefficiency_{it} = \beta_0 + \beta_1 * MBHC\_network_{it} + \beta_2 * MBHC\_network_{it}^2 + \sum_{i=1}^{n} \beta_i * Controls_{it} + \lambda_t + \varepsilon_{it} \tag{12}$$

An optimal point is obtained by taking the derivative of the efficiency score with respect to *MBHC_network* and setting it to zero. The impact of *MBHC_network* on *Bank efficiency* has been depicted in the Table 5.

The coefficient of *MBHC_network* is positive and statistically significant, while the coefficient of its square is negative and significant at the 1% level for fixed effect and truncated regressions. This finding confirms that there is an inverted U curve relationship and an optimal number of subsidiaries for multi-BHC to obtain the highest efficiency. As it can be seen from Table 5, the optimal number of subsidiaries for multi-BHC is 20.[5] This finding suggests that

[5] The number of bank subsidiaries varies in our sample from 2 to 64. The natural logarithm of 20 is almost 3.

although multi-BHC affiliate is more efficient than single-BHC affiliates, there is an optimal number of subsidiaries that multi-BHC should consider to enhance their affiliates' efficiency.

5.5 CEO power and bank efficiency

This section assesses the effect of CEO power on bank efficiency. It proxies for CEO power using *CEO tenure* and *CEO duality*. CEOs are expected to have more power to influence the decisions of the bank when they stay longer in the bank or chair the board (Pathan 2009). On the one hand, CEOs with more power better monitor the bank. On the other hand, according to Fama and Jensen (1983), the presence of powerful CEOs often signal the absence of internal control mechanisms that can adversely affect bank efficiency (Table 6).

The results regarding the effect of CEO power on bank efficiency are portrayed in Table 6 and are consistent with our expectation. They show that CEO power (proxied by *CEO duality* and *CEO tenure*) has a negative impact on bank efficiency. The results are statistically significant at the 1% level and are consistent with Grove et al. (2011), De Jonghe et al. (2012), and De Haan and Vlahu (2016). For instance, De Haan and Vlahu (2016) suggest that banks that combine CEO and chairman positions underperform their peers in terms of performance and cost efficiency as powerful CEOs tend to take higher risks and reduce bank efficiency. The interaction between *CEO tenure* and *MBHC affiliate* is negative and statistically significant, implying that when CEOs stay longer at the helm of a multi-BHC affiliate, bank efficiency is significantly reduced. This is because CEOs in multi-BHC affiliates tend to take more risk in particular when they manage the bank for a long time. The same results are found with *CEO duality* as a proxy for CEO power.

This result has important implications for regulators, policymakers and bank managers since CEO power is detrimental to bank efficiency. Therefore, regulators and bank managers should consider the risk of giving CEOs more power.

6 Robustness test

6.1 Alternative measures of bank efficiency

This section applies a conventional DEA technique as an alternative measure for bank efficiency. Although conventional DEA ignores the bank operational procedure, this technique has been applied widely in the banking literature. Conventional DEA is easy to apply and especially effective to simultaneously combine inputs and outputs of different natures. We choose deposit ratio, interest expense ratio and non-interest expense ratio as inputs while loan ratio, interest income ratio and non-interest income ratio as outputs (Harris et al. 2013). We use input oriented rather than output oriented since it is difficult for banks to enhance their outputs given certain level of inputs.

Table 7 shows that our results are robust irrespective of the efficiency measure, which confirms that multi-BHC affiliates have higher efficiency than single-BHC affiliates. In addition, *Bank size*, *Bank capital* and *Bank profit* have a positive and significant impact on bank efficiency. *Bank profit* has a large economic impact on bank efficiency, implying that the bank that generates a high level of profit often operates more efficiently than others.

Table 6 The impact of CEO power on bank efficiency

Variable	Bank efficiency					
	Model 1 *Fixed effect*	Model 2 *Truncated*	Model 3 *Fixed effect*	Model 4 *Truncated*	Model 5 *Fixed effect*	Model 6 *Truncated*
MBHC affiliate	0.052***	0.014***	0.059***	0.016***	0.067***	0.022***
	(7.999)	(5.175)	(6.963)	(3.571)	(7.335)	(4.656)
CEO duality	−0.013***	−0.005**			−0.014***	−0.005*
	(−2.687)	(−2.011)			(−2.881)	(−1.850)
*MBHC affiliate*CEO duality*	−0.033***	−0.021***			−0.031***	−0.021***
	(−3.302)	(−4.064)			(−3.193)	(−4.024)
CEO tenure			−0.004**	−0.005***	−0.004**	−0.005***
			(−2.222)	(−3.962)	(−2.316)	(−3.831)
*MBHC affiliate*CEO tenure*			−0.011***	−0.006**	−0.010**	−0.006**
			(−2.624)	(−2.461)	(−2.508)	(−2.351)
Bank size	0.014***	0.006***	0.015***	0.005***	0.015***	0.006***
	(2.863)	(7.116)	(3.036)	(6.112)	(3.121)	(6.934)
Bank capital	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(6.553)	(16.638)	(6.497)	(16.328)	(6.534)	(16.315)
Bank non-performing loan	−0.002	−0.000	−0.002	−0.000	−0.002	−0.000
	(−1.418)	(−0.453)	(−1.323)	(−0.177)	(−1.365)	(−0.313)
Bank profit	0.020***	0.026***	0.021***	0.027***	0.021***	0.027***
	(6.481)	(17.192)	(6.656)	(18.019)	(6.709)	(17.902)
Constant	0.283***	0.370***	0.272***	0.385***	0.269***	0.378***
	(4.783)	(30.991)	(4.505)	(31.677)	(4.434)	(31.092)
Bank fixed effect	Yes	No	Yes	No	Yes	No
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	6159	6077	6141	6059	6141	6059
R^2	0.712		0.709		0.711	

This table reports the effect of CEO duality and CEO tenure on bank efficiency. The main dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. *CEO duality* equals to 1 if CEO is also a chairman, otherwise 0. *CEO tenure* is log of CEO tenure plus 1. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. Model 1 and model 2 report the effect of CEO duality on bank efficiency. Model 3 and 4 considers the effect of CEO tenure on bank efficiency. Model 5 and 6 include all variables. Other control variables include bank size, capital ratio, non-performing loan, profit ratio. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

Table 7 The effect of bank structure on bank efficiency measured by conventional DEA

Variable	Conventional efficiency		
	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*
MBHC affiliate	0.018***	0.015***	0.014***
	(9.618)	(8.149)	(24.259)
Bank size	0.020***	0.015***	0.018***
	(27.735)	(9.663)	(82.676)
Bank capital	0.007***	0.007***	0.006***
	(26.235)	(25.103)	(64.084)
Bank non-performing loan	0.001***	−0.000	0.001***
	(2.982)	(−0.077)	(8.068)
Bank profit	0.018***	0.015***	0.019***
	(16.678)	(19.586)	(52.314)
Constant	0.387***	0.458***	0.420***
	(44.870)	(26.380)	(144.521)
Bank fixed effect	No	Yes	No
Year dummy	Yes	Yes	Yes
Number of observations	62,554	62,554	60,674
R^2	0.304	0.299	

This table reports the impact of bank structure on bank efficiency at the affiliated level. The dependent variable is *Conventional efficiency* measured by conventional data envelopment analysis. *MBHC affiliate* takes value of 1 if banks belong to multi-bank holding company and 0 if banks belong to single-bank holding company. Their control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first model uses ordinary least square regression with year dummy. The second model uses fixed effect at both bank and year level. The third model uses truncated regression model with efficiency truncated at the value of 1. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level

Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

6.2 Impact of organizational complexity on bank efficiency

There is a possibility that organizational complexity might affect bank efficiency. According to Stein (2002), organizations with centralized structure are more complex and have tendency to rely on hard information, while organizations with decentralized structure are less complex and tend to rely more on soft information. In addition, there is an incentive for small organizations to produce soft information due to the centralization in decision making of the authority. Meanwhile, large organizations could acquire hard information due to broader scope for resource allocation. Berger et al. (2005) find that large banks mainly lend to larger firms with good account records while small banks tend to lend to more difficult credits. Therefore, complexity of bank structure would have an effect on bank efficiency.

We follow Assaf et al. (2019) to capture organizational complexity with ratio of total active subsidiaries over bank total asset times one thousand. Bank holding companies with more affiliations per value of assets could have more complex structures.

Table 8 shows that complexity of bank organization has a positive and significant impact on bank efficiency at a threshold level of 1%. Banks with more complex structure tend to achieve better efficiency due to internal capital market regarded as "source of strength". For example, the affiliations of multi-bank holding companies could receive capital injection in

Table 8 The impact of organizational complexity on bank efficiency

Variable	Bank efficiency					
	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*	Model 1 *OLS*	Model 2 *Fixed effect*	Model 3 *Truncated*
MBHC affiliate	0.008***	0.028***	0.007***			
	(4.639)	(12.432)	(10.463)			
Organizational complexity				0.177***	0.273***	0.158***
				(6.264)	(6.812)	(15.094)
Bank size	0.006***	0.009***	0.006***	0.009***	0.011***	0.008***
	(8.532)	(5.551)	(23.702)	(9.642)	(6.408)	(28.605)
Bank capital	0.005***	0.004***	0.004***	0.005***	0.004***	0.004***
	(17.152)	(14.195)	(41.295)	(17.235)	(13.491)	(41.220)
Bank non-performing loan	− 0.002***	− 0.004***	− 0.003***	−0.002***	−0.004***	−0.003***
	(− 5.313)	(− 9.897)	(− 13.081)	(−5.166)	(−9.797)	(−12.781)
Bank profit	0.023***	0.019***	0.026***	0.024***	0.019***	0.027***
	(21.715)	(19.362)	(60.400)	(21.968)	(20.109)	(61.290)
Constant	0.379***	0.355***	0.383***	0.347***	0.331***	0.354***
	(38.663)	(19.313)	(113.267)	(28.221)	(16.935)	(91.325)
Bank fixed effect	No	Yes	No	No	Yes	No
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	62,554	62,554	62,010	62,554	62,554	62,010
R^2	0.766	0.762		0.767	0.766	

This table reports impact of bank structure on bank efficiency at the affiliated level. The dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. *MBHC affiliate* takes value of 1 if banks belong to multi-bank holding company and 0 if banks belong to single-bank holding company. *Organizational complexity* equals total subsidiaries divided by total asset times 1000. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. The first model uses ordinary least square regression with year dummy. The second model uses fixed effect at both bank and year level. The third model uses truncated regression model with efficiency truncated at the value of 1. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level

Significance at the 10%, 5%, and 1% level is indicated by *, **, *** respectively

case of funding shortfall. In addition, those banks can access federal funds and large CDs markets easier (Ashcraft 2006) and lend mainly to large firms with higher amount of loans (Berger et al. 2005). Therefore, bank efficiency could be enhanced due to lower cost of capital and higher amount of loans produced.

6.3 Additional test

We next conduct a number of cross-sectional tests. These additional tests allow us to identify factors that strengthen or weaken the effect of BHC structure on bank efficiency. By adopting this approach we can assess the relevance of alternative explanations of the relationship between BHC affiliation and bank efficiency such as bank capital, bank soundness (bank profitability), asset quality and bank size. As it can be seen from Table 9, the results are robust regardless of bank size, asset quality, bank performance, and bank age, implying that

Table 9 Additional test

Panel A: Partitioned by bank size

Variable	Bank efficiency			
	Large bank		*Small bank*	
	Fixed effect	*Truncated*	*Fixed effect*	*Truncated*
MBHC affiliate	0.033***	0.002***	0.027***	0.011***
	(8.786)	(2.902)	(8.821)	(10.063)
Control variable	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	34,525	34,369	28,029	27,641
R^2	0.780		0.746	

Panel B: Partitioned by asset quality

Variable	Bank efficiency			
	Low asset quality		*High asset quality*	
	Fixed effect	*Truncated*	*Fixed effect*	*Truncated*
MBHC affiliate	0.030***	0.006***	0.027***	0.009***
	(10.831)	(7.016)	(7.332)	(7.153)
Control variable	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	41,410	41,196	21,144	20,814
R^2	0.766		0.759	

Panel C: Partitioned by financial performance

Variable	Bank efficiency			
	Low earnings		*High earnings*	
	Fixed effect	*Truncated*	*Fixed effect*	*Truncated*
MBHC affiliate	0.039***	0.006***	0.020***	0.006***
	(11.749)	(6.344)	(7.123)	(6.363)
Control variable	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	29,914	29,607	32,640	32,403
R^2	0.753		0.785	

Table 9 continued

Panel D: Partitioned by bank age

Variable	Bank efficiency			
	Young		*Old*	
	Fixed effect	*Truncated*	*Fixed effect*	*Truncated*
MBHC affiliate	0.031***	0.004***	0.026***	0.007***
	(7.670)	(3.025)	(9.509)	(9.459)
Control variable	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	19,310	19,076	43,244	42,934
R^2	0.708		0.800	

Panel E: Partitioned by crisis

Variable	Bank efficiency			
	Before crisis		*After crisis*	
	Fixed effect	*Truncated*	*Fixed effect*	*Truncated*
MBHC affiliate	0.032***	0.006***	0.043***	0.007***
	(14.104)	(9.156)	(4.828)	(2.953)
Control variable	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	47,241	47,184	11,777	11,295
R^2	0.525		0.848	

This table reports the effect of bank structure on bank efficiency. The dependent variable is *Bank efficiency* measured by a fuzzy multi-objective two-stage data envelopment analysis. Other control variables include *Bank size, Bank capital, Bank non-performing loan, Bank profit*. Panel A reports the effect of bank structure on bank efficiency regarding bank size. Small bank is defined as bank with total assets lower than average bank asset each year while large bank has total asset larger than average total asset. In panel B, the sample is divided by average asset quality each year. In panel C, the sample is divided by average bank performance each year. In Panel D, the sample is divided by average bank age each year. In panel E, the sample is divided by crisis which happens during 2007-2009. In each panel, The first and the third columns uses fixed effect model with year fixed effect while the second and the fourth column use truncated regression model. t-statistics are reported in parentheses. Standard errors are robust and clustered at bank level

***, ** and *Significance at 1%,5% and 10% level respectively

multi-BHC affiliations have higher efficiency than SBHC affiliations irrespective of the bank characteristics. The results also do not depend on whether the analysis is conducted before or after the global financial crisis of 2007–2008.

7 Conclusion

This paper examines and compares bank efficiency between single-BHC affiliates and multi-BHC affiliates. It measures bank efficiency by applying a fuzzy multi-objective two-stage data envelopment analysis technique. Using a sample of US commercial banks data from 1994 to 2018, it shows that multi-BHC affiliates have higher efficiency than single-BHC affiliate. By applying difference-in-differences estimation technique based on propensity score matching approach, the empirical results suggest that banks enhance their efficiency when they change their status from single- to multi-BHC affiliate, which reinforces our conclusions. We use internal capital market theory to explain why multi-BHC affiliates have higher efficiency than single-BHC affiliates. When banks switch from single-BHC to multi-BHC, they can access to more funds in internal capital markets, expanding their operation, and attracting more deposits at a lower cost. As a result, multi-BHC affiliates exhibit higher efficiency levels than single-BHC affiliates.

One limitation of this study is the fact that the decision maker preferences over the potential adjustments of various inputs and outputs are not considered (Golany 1988). To the extent that the DMUs are efficient or inefficient, the assessment relies on the uncertainty over the choice of inputs and outputs (Stolp 1990). Therefore, Peykani et al. (2019) suggest customizing fuzzy DEA models according to properties of DMUs.

Appendix

See Table 10.

Table 10 List of variables

Variable	Abbreviation	Calculation	Source
I. Inputs			
Interest expense ratio	*Bank interest expense*	Total interest expense/Total asset%	Call report
Noninterest expense ratio	*Bank non-interest expense*	Total non-interest expense/Total asset%	As above
II. Intermediate product			
Deposit ratio	*Bank deposit*	Total deposit/Total asset%	As above
III. Outputs			
Loan ratio	*Bank lending*	Total loan/Total asset%	As above
Interest income ratio	*Bank interest income*	Total interest income/Total asset%	As above
Non-interest income ratio	*Bank non-interest income*	Total non-interest income/Total asset%	As above
IV. Efficiency			
Efficiency with Fuzzy multi-objective DEA	*Bank efficiency*	Fuzzy multi-objective DEA with interest expense ratio and non-interest expense ratio as inputs, deposit ratio as intermediation, loan ratio, interest income ratio and non-interest income ratio as outputs.	Authors' calculation
Conventional efficiency	*Conventional efficiency*	Conventional DEA with interest expense ratio, non-interest expense ratio and deposit ratio as inputs, loan ratio, interest income ratio and non interest income ratio as outputs.	Authors' calculation
V. Control variables			
Bank size	*Bank size*	Ln(total asset)	Call report
Non-performing loan	*Bank non-performing loan*	Total non-performing loan/Gross loan%	As above
Capital ratio	*Bank capital*	Total capital/Total asset%	As above
Profitability ratio	*Bank profit*	Net income/Total asset%	As above
VI. CEO power			
CEO duality	*CEO duality*	1:CEO is chairman, Otherwise 0	Boardex
Natural logarithm of (1 + CEO tenure)	*CEO tenure*	Ln(1 + tenure of CEO)	As above

Table 10 continued

Variable	Abbreviation	Calculation	Source
VII. Organizational structure			
Natural logarithm of total susbidiaries	*Ln(total subsidiaries)*	Ln(total number of subsidiaries)	Call report
Organizational complexity	*Organizational complexity*	Total active subsidiaries times 1000 divided by total asset	Call report

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