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Published in:
European Journal of Operational Research

DOI:
[10.1016/j.ejor.2021.01.036](https://doi.org/10.1016/j.ejor.2021.01.036)

Publication date:
2021

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Document Version
Peer reviewed version

[Link to publication in Discovery Research Portal](#)

Citation for published version (APA):
Kourtzidis, S., Matousek, R., & Tzeremes, N. (2021). Modelling a Multi-period Production Process: Evidence from the Japanese Regional Banks. *European Journal of Operational Research*, 294(1), 327-339.
<https://doi.org/10.1016/j.ejor.2021.01.036>

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Modelling a Multi-period Production Process: Evidence from the Japanese Regional Banks

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Abstract

This paper applies the additive relational network DEA model to examine the multi-period efficiency and productivity of Regional Banks I and II in Japan between 2002 and 2017. The examined timeframe covers two turbulent periods; the Global Financial Crisis and the economic recession in the aftermath of the Great East Japan Earthquake. We extend the additive relational network DEA model into a multi-period structure in order to evaluate the overall efficiency for the time period in question, as well as the annual period efficiencies. We show that the overall efficiency can be expressed as a weighted average of the period efficiencies. In addition, we examine the implications of different returns to scale assumptions. The newly proposed model is able to calculate common-weight Malmquist Productivity Indices. The results reveal a dispersion of inefficiency levels for Japanese Regional Banks in general, and a difference between Regional Banks I and II in particular. Furthermore, the Global Financial Crisis caused a significant negative effect on the productivity growth and the technical progress of Japanese Regional Banks, while the Great East Japan Earthquake had a negative effect on the technical efficiency change.

Keywords: Data envelopment analysis; Japanese banks; Network DEA; Productivity growth.

1. Introduction

Since the 1990s the Japanese economy has experienced a turbulent economic period. This included the burst of the real estate bubble, which resulted in the collapse of asset prices, the liquidation of non-bank financial institutions that were responsible for mortgage loans, an evolving problem of non-performing loans and eventually the failure of major banking institutions (Hoshi and Kashyap, 2010). The extreme economic conditions forced the Japanese government to intervene and provide a rescue plan for the banks. In the late 1990s at the peak of the financial crisis, the banking sector went through an intensive restructuring and consolidation process, which significantly affected the Japanese banking sector including Regional Banks. This unprecedented reconstruction attracted considerable research interest in the Japanese banking system, see, for example, Assaf et al. (2011), Fukuyama and Weber (2015, 2017), Mamatzakis et al. (2015), and Fukuyama and Matousek (2017, 2018) among others.

In 2007 Japan again relapsed into economic depression caused by the Global Financial Crisis (GFC). Specifically, during the second half of 2007, the GFC affected Japan with a fall in the Nikkei stock exchange, severe losses in bank equity portfolios and lower credit ratings (Fujii and Kawai, 2010). In 2008, the economic crisis then moved to the real economy after a substantial decline in the export of motor vehicles, information technology and capital goods. These adverse economic conditions were mainly caused by demand shocks in the US and Europe (Sommer, 2009). A direct consequence was a severe economic recession with a sharp decline in GDP of 5.4% in 2009. In March 2011 the Great East Japan Earthquake (GEJE) hit the Pacific coast. The subsequent effect on the economy resulted in further supply chain disruptions, decline in exports and energy production, power shortages, increased oil and gas imports and a decrease in consumer demand for domestic goods. This in turn led to a sharp increase in business bankruptcies (Besstremyannaya, 2017).

Based on the foregoing, this study explores how the particular segment of the Japanese banking sector represented by the Regional Banks has adjusted to these disruptions. Regional Banks are considered to play a pivotal role within the Japanese financial system. Regional Banks experienced a sharp increase in the volume of non-performing loans (NPLs) along with a deterioration in bank capital and a rise in financial losses (Fukuyama and Matousek, 2017). As Mamatzakis et al. (2015) point out, the Japanese government failed to address the underlying issues of the sector which resulted in a further weakening of their financial position. Regional Banks currently face weak profitability, which force them to make riskier investments (Tomisawa, 2019).

This study provides a fresh insight into the Japanese banking sector by examining the efficiency of Japanese Regional Banks from 2002 to 2017. This time period starts after the extensive consolidation

process that took place in the late 1990s and covers two periods of high economic uncertainty, including the GFC and the GEJE. The analysis of the effect of two crises with different and distinct characteristics on Japanese Regional Banks is of extreme importance. This is because the Japanese financial system relies on banks in general and SMEs, which are the backbone of the economy, rely on Regional Banks in particular. Besstremyannaya (2017) shows that the GFC (2007–2009) and the economic recession following the GEJE (2011–2013) had an adverse effect on banks' cost efficiency. This study sheds light on the endogenous and exogenous factors that might undermine the performance of Regional Banks. Rather than following the previous studies which focused on the cost and revenue efficiency of Japanese banks during periods of financial distress, this paper examines technical efficiency, productivity change and its determinants. Thus, this study differs from the previous research by considering shifts in the frontier over time rather than focusing entirely on changes in the dispersion around the frontier.

In terms of methodological contribution, our approach builds on the previous research on relational network Data Envelopment Analysis (DEA) models and banking efficiency. The evaluation of the efficiency and productivity of banking institutions is one of the most important applications of DEA (Emrouznejad and Yang, 2018). Despite the extensive range of literature evaluating banking institutions, there remain several current contested issues that take into account the unique features of banking production. At the core of the discussion about the modelling of the bank production process is the so-called *deposits dilemma*, which refers to the use of deposits either as inputs or as outputs. As Berger and Humphrey (1992) argue, deposits are understood as: (i) inputs under the intermediation approach; (ii) outputs under the production approach; or, (iii) either as inputs or as outputs based on the net contribution of deposits to the bank revenue under the cost approach. In order to preserve the dual role of deposits, an alternative approach has been proposed by Fukuyama and Weber (2010) which is based on the network DEA framework. The main idea here is that deposits serve as an intermediate measure in a two-stage network model, therefore they are considered as outputs in the first stage and inputs in the second.

Furthermore, the incorporation of the time component is an important element in the evaluation of bank efficiency. There are a number of studies, see for example Kao and Hwang (2008), Chen et al. (2009) and Wang and Chin (2010), which use the aggregated data from a number of years in order to evaluate the efficiency of the whole period. Other studies such as Portela et al. (2012) use the average data for a number of years in order to assess the efficiency. Kao and Hwang (2014) pointed out that those two approaches should yield the same results due to the unit-invariant property. Alternatively, the efficiency scores for all independent time periods should be aggregable into an overall efficiency score.

That raises questions regarding the correct form of aggregation. In order to solve this issue, Kao and Hwang (2014) suggested an approach that takes into account each individual period of time. Then it is possible to evaluate both the efficiency for the whole period as well as the efficiency for each year by applying a parallel structure. This model ensures that in order for a DMU to be efficient for the whole period, it needs to be efficient in all individual years, which is not the case with all the previous approaches.

The choice of the network structure reflects the assumption about the contribution of each stage to the overall efficiency. Relational network DEA models assume a mathematical relationship (multiplicative or additive) and yield efficiency scores for the two stages. The multiplicative model of Kao and Hwang (2008) implicitly assumes that the two stages contribute equally to the overall process while the additive model of Chen et al. (2009) determines the contribution of each stage endogenously based on the most favourable outcome for the DMU.

Our study considers the aforementioned issues and contributes to the literature by introducing a novel multi-period additive relational network DEA model that is underpinned by an investigation of the model characteristics, such as the implications of the returns-to-scale assumption. Due to its multi-period parallel structure, the model differs from previous relational network studies which are static in nature (Kao and Hwang, 2008; Chen et al., 2009; Kourtzidis et al., 2018). The proposed model also differs from Kao and Hwang (2014) by adopting an additive instead of a multiplicative efficiency decomposition. The additive nature of the model is a more attractive and reasonable choice, since it determines the contribution of each stage endogenously based on the most favourable outcome for the DMU. Essentially, it allows the asymmetrical contribution of individual stages to the overall process. Next, we demonstrate that the overall efficiency, in an additive relational network DEA model with a parallel structure, is the weighted average of the subsystems' efficiencies. For each subsystem, the attached weight is the ratio of total inputs in the subsystem over total inputs in the overall system. Moreover, the new model allows us to evaluate the overall efficiency through the years and the efficiency of each individual year. A common-weight global Malmquist Productivity Index (MPI) can be calculated in order to measure productivity change between two periods. The MPI which is calculated from the multi-period structure, calculates the efficiency scores using the same frontier facet for every year. Therefore, the results are more comparable among different DMUs compared to those calculated from a conventional MPI (Kao and Hwang, 2014).

The rest of the paper is organized as follows: Section 2 presents a background on Japanese banking and the most recent review of the literature; Section 3 demonstrates the framework and the

methodology used throughout the paper; and Section 4 discusses the empirical application to the Japanese regional banking sector. Section 5 provides our conclusions.

2. Literature Review

2.1. Japanese banks: empirical research on banking efficiency

The Japanese banking system consists of various types of banks which can be classified under three broad categories (Fukuyama and Matousek, 2017). The first category includes banks with international activities; City Banks which are large national banks with overseas branches, and Trust Banks which focus mainly, but not entirely, on trust services. The second category includes Regional Banks which usually operate in a specific prefecture and have close ties to local companies and local authorities. They can be further classified as Regional Banks I and second-tier regional banks (Regional Banks II).¹ Originally, second-tier banks were joint stock companies called *Sogo Banks*, which later were converted to Regional Banks and finally classified as ordinary commercial banks in 1989 (Second Association of Regional Banks, 2018). Regional Banks I and II conduct similar operations, but they have different origins. Regional Banks are characterized by low capitalisation and they act as the main provider of finance to SMEs. The third category consists of small financial institutions – credit banks and credit cooperatives – which have a large share of the deposit market.

Evaluating the efficiency of the Japanese banking system has attracted much academic interest over the past two decades, mainly due to the economic situation during the 1990s, the extensive consolidation and the impact on bank performance. Starting with the seminal work of Fukuyama (1993), DEA models have been used to evaluate the efficiency of Japanese banks. Fukuyama (1993) investigated the technical efficiency (TE), the pure technical efficiency (PTE) and the scale efficiency (SE) of City and Regional Banks. He found that the main source of technical inefficiency was the PTE rather than the SE, especially for the Regional Banks. In a similar framework, Drake and Hall (2003) considered an extended sample of Japanese banks and found some evidence of scale inefficiencies, however, the main source of technical inefficiency was again the PTE. Fukuyama (1995) then studied the effect of the financial crisis of the early 1990s on the change in productivity of Japanese banks and found a different effect on each bank. However, the results showed strong evidence that the main driver of productivity growth was the technical change component, while the main driver of productivity regress was the efficiency change

¹ Regional Banks I are members of the Regional Banks Association of Japan while Regional Banks II are members of the Second Association of Regional Banks. For a full list of member see the JBA (2019) and for the relevant definitions see the Bank of Japan: <https://www.boj.or.jp/en/statistics/outline/note/financial.htm/>.

component. Fukuyama and Weber (2005) evaluated the input allocative efficiency using a directional distance function (DDF) model and found an increased inefficiency over time. Barros et al. (2012) analysed the technical efficiency of Japanese banks using a non-radial DDF model. They found that a further restructuring was needed for the Regional Banks. Liu and Tone (2008) introduced a three-step approach to measure the technical efficiency of City Banks and Regional Banks during the South-East Asian Financial Crisis and the dot-com bubble. The results of the three-step approach revealed that these two crises had no effect on Japanese banks' technical efficiency. Drake et al. (2009) investigated the efficiency of Japanese banks using a slacks-based model and three different approaches in modelling the bank output; the intermediation, the production, and the profit/revenue. There was a substantial variation of the results across the three approaches.

Recently, a number of papers have studied the Japanese banking system using a network DEA framework. Fukuyama and Weber (2015) constructed a dynamic network DEA model, which allows for an intertemporal resource reallocation, in order to examine the efficiency of City Banks and Regional Banks. Along the same lines, Fukuyama and Weber (2017) constructed a dynamic Luenberger productivity indicator in order to study the commercial banks (City Banks and Regional Banks) and Shinkin banks that are cooperative financial institutions, during the period 2007–2012. The results of the dynamic model for commercial banks revealed a productivity regress during 2007–2008 and productivity growth for the rest of the period. This was attributed to technical change since the efficiency change was negative for most of the time period. However, the results of the static model revealed productivity growth during 2007–2008 and productivity regress for three out of the four remaining periods. The results for Shinkin banks were also different for the dynamic and the static models. In a recent study, Fukuyama and Matousek (2017) developed a network revenue function which applies a weakly efficient frontier to explore the performance of Regional Banks over the period 2001–2013. They showed that Regional Banks should improve their cost side.

2.2. Network DEA and banking

Conventional DEA models treat the Decision Making Unit (DMUs) as a black box which employs inputs in order to generate outputs, without considering any procedures taking place inside the DMU. Starting with the seminal work of Färe and Grosskopf (1996), network DEA models unravel the black box and take into consideration the stages inside the DMU. Kao and Hwang (2010) distinguished the three categories of network DEA models that depend on assumptions about the relationship between two stages: (i) independent models that apply a conventional DEA model separately to each stage, without taking into

account possible interactions between the stages (Wang et al., 1997; Seiford and Zhu, 1999); (ii) connected models that take into account the interactions between the stages (Färe and Grosskopf, 1996); and (iii) relational models that can calculate the stage efficiencies and assume a mathematical relationship between the stages, which can be either multiplicative or additive (Kao and Hwang, 2008; Chen et al., 2009).

A substantial part of DEA literature has been focused on banking applications. The pioneering work of Sherman and Gold (1985) represented the first application of DEA in banking and since then, there has been a plethora of papers that use a DEA model to assess the performance of banking institutions (among others Lozano-Vivas et al., 2002; Portela and Thanassoulis, 2006, 2007; Fethi and Pasiouras, 2010; Barros et al., 2012; Curi et al., 2015; Curi and Lozano-Vivas, 2015). The seminal papers of Wang et al. (1997) and Seiford and Zhu (1999) were the first applications of network DEA in the banking sector. Various types of network DEA models have been employed to study banking efficiency. Mukherjee et al. (2003) used various resources as inputs, service quality variables as intermediate variables, and performance measurement variables as outputs to study Indian public sector banks. Zha and Liang (2010) constructed a cooperative model where inputs are allocated between the two stages. Du et al. (2011) then introduced a Nash bargaining game that provides an innovative way to study the profitability and marketability of US commercial banks. Wang et al. (2014a) applied an additive relational model to study the deposit generation and the profit earning of Chinese commercial banks. Wang et al. (2014b) used financial ratios to construct a fuzzy multi-objective model and study US bank holding companies. In the Brazilian banking context, a network structure with cost efficiency in the first stage and productive efficiency in the second stage was investigated by Wanke and Barros (2014). Lozano (2016) investigated the efficiency of banking institutions and bank branches using a general slacks-based network DEA model. Degl'Innocenti et al. (2017) and Kourtzidis et al. (2018) assessed the productivity growth in the European Union and a panel of Central and Eastern European countries respectively, during the GFC. Fukuyama and Matousek (2017, 2018) introduced a revenue efficiency network model to study Japanese banks.

In line with our research focus, a number of studies use the dynamic element of time in the analysis. Akther et al. (2013) examined the case of Bangladeshi commercial and government-owned banks for the time period 2005–2008 and used outputs from a previous period as inputs in a subsequent period. Fukuyama and Weber (2013), Avrikan (2015) and Zha et al. (2016) applied a dynamic network DEA model where carry-overs from previous periods affect the efficiency of following periods. Kao and Liu (2014) constructed a multi-period model for Taiwanese commercial banks, where different time periods were considered as sub-processes in a parallel network DEA model. The advantage of this model is the

evaluation of the efficiency for the overall period and for each year using the same frontier facet. Kao and Hwang (2014) extended this approach to network DEA using a multiplicative relational DEA model. The multiplicative model implicitly assumes that the two stages contribute equally to the overall process, which is a very restrictive assumption.

2.3. Gaps in the literature and proposed solutions

In relation to our study, Fukuyama and Weber (2017) and Fukuyama and Matousek (2017) are the most direct references, however, these papers have a few distinctive characteristics. Compared to Fukuyama and Weber (2017) our study is different in several ways. To begin with, our paper covers a significantly larger time period that starts in 2002 after the extensive consolidation of the Regional Banks and ends in 2017, allowing an up-to-date evaluation of the efficiency and productivity change. Therefore, we are able to investigate five phases of the Japanese economy starting in the post restructuring period and covering two crises; the GFC and the economic recession in the aftermath of the GEJE. This is the first study to analyse technical efficiency and productivity change of Japanese Regional Banks during these five phases. Furthermore, compared to Fukuyama and Weber (2017), our paper investigates the Regional Banks rather than different types of Japanese banks, therefore it narrows down the scope and allows a more focused discussion of the policy implications. Regarding the modelling framework, our proposed network model allows the examination of the first and second stage efficiencies and as a result it provides a greater depth of information regarding the sources of inefficiency. Finally, the productivity index that we use is a Global Malmquist Productivity Index (MPI). This has a number of advantages, including circularity and a single measure of productivity without the need for the geometric mean approach; as a result it avoids any infeasibility issues due to the mixed periods. If we then compare the contribution of our study to Fukuyama and Matousek (2017), the key distinguishing characteristics are that we do not focus on the revenue efficiency of Regional Banks, but on the productivity change and its determinants. Thus, this study differs by considering shifts in the frontier over time, rather than focusing entirely on changes in the dispersion around the frontier.

In addition, based on this brief literature review we identify the following gap. So far the empirical research does not address the important question that is the modelling of the multi-period process in a way that allows the asymmetrical contribution of individual stages to the overall process. In this paper we adopt the multi-period framework and we modify it accordingly in order to accommodate the case of the additive relational network DEA model. The additive model determines the contribution of each stage

endogenously based on the most favourable outcome for the DMU. This makes the additive model a more attractive and reasonable choice.

3. Methodology

This section discusses the methodological framework that is applied in this study. We start the discussion with the additive relational network DEA model and its extension to the multi-period framework. This is then followed by a discussion about the returns to scale and the analysis of productivity change and its decomposition.

3.1 Additive relational network DEA model

Let us assume a network process with two stages and an additive relationship between them. The efficiency of the overall process will be the weighted average of the stage efficiencies, where the weights represent the contribution of each stage to the overall efficiency. For the j th DMU ($j = 1, \dots, n$) we define x_{ij} ($i = 1, \dots, m$), z_{dj} ($d = 1, \dots, D$) and y_{rj} ($r = 1, \dots, s$) as the i th input, the d th intermediate variable and the r th output respectively and v_i , w_d and y_r as their respective multipliers. Then, the overall efficiency for DMU 0 can be presented as:

$$E_0 = \xi_1 \frac{\sum_{d=1}^D w_d z_{d0}}{\sum_{i=1}^m v_i x_{i0}} + \xi_2 \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{d=1}^D w_d z_{d0}}, \quad (1)$$

where ξ_1 and ξ_2 are the weights of each stage representing its relative contribution to the whole process. Chen et al. (2009) defined the contribution of each stage relative to its size that can be proxied by the total inputs. Thus, the weight of the first stage is the ratio of total inputs of the first stage over the total inputs of the whole process, and similarly the weight of the second stage is the ratio of total inputs of the second stage over the total inputs of the whole process. The weights ξ_1 and ξ_2 can be calculated as:²

$$\xi_1 = \frac{\sum_{i=1}^m v_i x_{i0}}{\sum_{i=1}^m v_i x_{i0} + \sum_{d=1}^D w_d z_{d0}}, \quad \xi_2 = \frac{\sum_{d=1}^D w_d z_{d0}}{\sum_{i=1}^m v_i x_{i0} + \sum_{d=1}^D w_d z_{d0}}. \quad (2)$$

According to Chen et al. (2009), the linear programming model which calculates the overall efficiency E_0 under constant returns-to-scale (CRS) can be presented as:

$$E_0 = \max \sum_{d=1}^D w_d z_{d0} + \sum_{r=1}^s u_r y_{r0} \quad (3)$$

$$\text{s. t.} \quad \sum_{i=1}^m v_i x_{i0} + \sum_{d=1}^D w_d z_{d0} = 1$$

² Where ξ_1 and ξ_2 range from 0 to 1 and $\xi_1 + \xi_2 = 1$.

$$\sum_{d=1}^D w_d z_{dj} - \sum_{i=1}^m v_i x_{ij} \leq 0,$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{d=1}^D w_d z_{dj} \leq 0,$$

$$u_r, w_d, v_i \geq \varepsilon; j = 1, \dots, n; i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

where ε is a small non-Archimedean number (Charnes et al., 1979).

3.2 Multi-period model

In line with Kao and Hwang (2014), we extend our analysis to the multi-period case. For the j th DMU ($j = 1, \dots, n$) in the k th period ($k = 1, \dots, p$) we define $x_{ij}^{(k)}$ ($i = 1, \dots, m$), $z_{dj}^{(k)}$ ($d = 1, \dots, D$) and $y_{rj}^{(k)}$ ($r = 1, \dots, s$) as the i th input, the d th intermediate variable and the r th output respectively in period k . Note that $x_{ij} = \sum_{k=1}^p x_{ij}^{(k)}$, $z_{dj} = \sum_{k=1}^p z_{dj}^{(k)}$ and $y_{rj} = \sum_{k=1}^p y_{rj}^{(k)}$. Therefore, model (4) yields the overall efficiency for the entire time period since it is evaluated using the totals of the inputs, intermediate variables and outputs for all p periods. In order to take into account the efficiency for each period, we need to add the relative constraints; $\sum_{d=1}^D w_d z_{dj}^{(k)} - \sum_{i=1}^m v_i x_{ij}^{(k)} \leq 0$ and $\sum_{r=1}^s u_r y_{rj}^{(k)} - \sum_{d=1}^D w_d z_{dj}^{(k)} \leq 0$ for the first and the second stages respectively. This will allow us to study the aggregation of the individual periods' efficiencies and identify the period with the greatest impact. Then the single-period model (3) will be extended into a multi-period model as follows:

$$E_0^G = \max \sum_{d=1}^D w_d z_{d0} + \sum_{r=1}^s u_r y_{r0} \quad (4)$$

$$\text{s. t.} \quad \sum_{i=1}^m v_i x_{i0} + \sum_{d=1}^D w_d z_{d0} = 1$$

Stage 1 constraints

$$\sum_{d=1}^D w_d z_{dj} - \sum_{i=1}^m v_i x_{ij} \leq 0,$$

$$\sum_{d=1}^D w_d z_{dj}^{(k)} - \sum_{i=1}^m v_i x_{ij}^{(k)} \leq 0,$$

Stage 2 constraints

$$\sum_{r=1}^s u_r y_{rj} - \sum_{d=1}^D w_d z_{dj} \leq 0,$$

$$\sum_{r=1}^s u_r y_{rj}^{(k)} - \sum_{d=1}^D w_d z_{dj}^{(k)} \leq 0,$$

$$u_r, w_d, v_i \geq \varepsilon; j = 1, \dots, n; i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s; k = 1, \dots, p$$

Because we add more constraints, efficiency scores calculated from model (4) are lower than or equal to those that are calculated from model (3). The first set of constraints for each one of the two stages is redundant. After we obtain the optimal solution to (4), we calculate the efficiency for the two stages in the case of unique efficiency decomposition as follows:

$$E_0^{G1} = \frac{\sum_{d=1}^D w_d^* z_{d0}}{\sum_{i=1}^m v_i^* x_{i0}} \quad \text{and} \quad E_0^{G2} = \frac{\sum_{r=1}^s u_r^* y_{r0}}{\sum_{d=1}^D w_d^* z_{d0}} \quad (5)$$

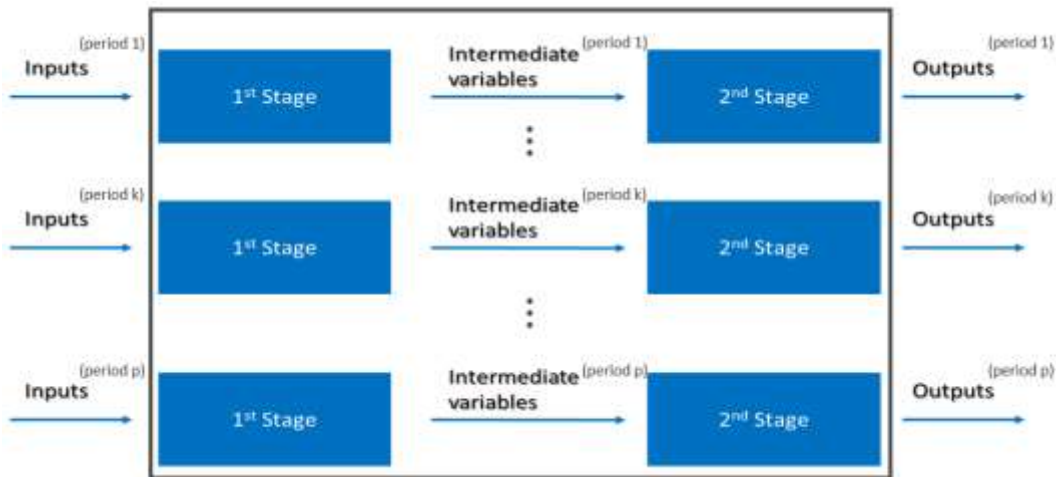
Note that if the decomposition is not unique and there are multiple solutions, there is a need for an additional linear program. This allows us to find the set of multipliers that produces the largest efficiency score for one of the two stages, while maintaining the overall efficiency constant (Kao and Hwang, 2008).³

In a similar way the period efficiencies can be calculated as:

$$E_0^{G(k)} = \frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}, \quad E_0^{G1(k)} = \frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)}} \quad \text{and} \quad E_0^{G2(k)} = \frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}^{(k)}} \quad (6)$$

Figure 1 is the visual representation of this multi-period two-stage network structure. It will be noticed that this is a parallel structure with p subsystems (periods).

Figure 1: Multi-period network structure



³ For a detailed presentation in the case of the additive network DEA model see Chen et al. (2009).

Kao (2009) proved that the overall efficiency in a parallel model is the weighted average of the subsystems' efficiency. He used as a weight, the ratio of total inputs in each subsystem over total inputs in the overall system. Kao and Hwang (2014) showed that this is also valid for a two-stage network model with multiplicative efficiency decomposition. Here, we demonstrate that the same holds in the case of an additive model, where the overall efficiency is the weighted average of the individual periods' efficiency. In specific:

$$\begin{aligned}
E_0^G &= \sum_{k=1}^p \alpha^{(k)} E_0^{G(k)}, & \alpha^{(k)} &= \frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0} + \sum_{d=1}^D w_d^* z_{d0}} & (7) \\
E_0^{G1} &= \sum_{k=1}^p \check{\alpha}^{(k)} E_0^{G1(k)}, & \check{\alpha}^{(k)} &= \frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}} \\
E_0^{G2} &= \sum_{k=1}^p \hat{\alpha}^{(k)} E_0^{G2(k)}, & \hat{\alpha}^{(k)} &= \frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}}
\end{aligned}$$

We can work backwards to verify these relationships:

$$\begin{aligned}
\sum_{k=1}^p \alpha^{(k)} E_0^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0} + \sum_{d=1}^D w_d^* z_{d0}} \right) \cdot \left(\frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0} + \sum_{d=1}^D w_d^* z_{d0}} \right) = E_0^G & (8) \\
\sum_{k=1}^p \check{\alpha}^{(k)} E_1^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}} \right) \cdot \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}} \right) = E_0^{G1} \\
\sum_{k=1}^p \hat{\alpha}^{(k)} E_2^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}} \right) \cdot \left(\frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{r=1}^s u_r^* y_{r0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}} \right) = E_0^{G2}
\end{aligned}$$

Therefore, the overall efficiency in a parallel model with p periods is the weighted average of the periods' efficiency, and each DMU obtains the most favourable weights to aggregate the period efficiencies into the overall efficiency. The overall efficiency can be decomposed into stage efficiencies for each period in two ways:

$$\begin{aligned}
E_0^G &= \xi_1^* \frac{\sum_{d=1}^D w_d^* z_{d0}}{\sum_{i=1}^m v_i^* x_{i0}} + \xi_2^* \frac{\sum_{r=1}^s u_r^* y_{r0}}{\sum_{d=1}^D w_d^* z_{d0}} = \xi_1^* \cdot E_0^{G1} + \xi_2^* \cdot E_0^{G2} = \xi_1^* \cdot \left(\sum_{k=1}^p \check{\alpha}^{(k)} E_0^{G1(k)} \right) + \xi_2^* \cdot \left(\sum_{k=1}^p \hat{\alpha}^{(k)} E_0^{G2(k)} \right) & (9) \\
E_0^G &= \sum_{k=1}^p \alpha^{(k)} E_0^{G(k)} = \sum_{k=1}^p \alpha^{(k)} \left(\xi_1^* \cdot E_0^{G1(k)} + \xi_2^* \cdot E_0^{G2(k)} \right)
\end{aligned}$$

Subsequently, the DMU is overall efficient if and only if it is efficient in both stages for every period. This allows decision makers to focus on the inefficient stage for future improvements.

Furthermore, in equation (6) we calculate the period efficiencies based on the optimal multipliers

from model (4). However, the optimal solution might not be unique and subsequently the period decomposition might not be unique either. Following Kao and Hwang (2014), we solve this issue by maximizing the efficiency of a period t while keeping the overall efficiency constant at E_0^{G*} , as calculated in model (4). The efficiency for period t can be calculated as:

$$\begin{aligned}
E_0^{G(t)} &= \max \sum_{d=1}^D w_d z_{d0}^{(t)} + \sum_{r=1}^s u_r y_{r0}^{(t)} & (10) \\
\text{s. t.} \quad & \sum_{i=1}^m v_i x_{i0}^{(t)} + \sum_{d=1}^D w_d z_{d0}^{(t)} = 1 \\
E_0^{G*} \cdot & \left(\sum_{i=1}^m v_i x_{i0} + \sum_{d=1}^D w_d z_{d0} \right) = \sum_{d=1}^D w_d z_{d0} + \sum_{r=1}^s u_r y_{r0} \\
& \sum_{d=1}^D w_d z_{dj}^{(k)} - \sum_{i=1}^m v_i x_{ij}^{(k)} \leq 0, \\
& \sum_{r=1}^s u_r y_{rj}^{(k)} - \sum_{d=1}^D w_d z_{dj}^{(k)} \leq 0, \\
& u_r, w_d, v_i \geq \varepsilon; j = 1, \dots, n; i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s; k = 1, \dots, p
\end{aligned}$$

The efficiency of another period h can be calculated by keeping the overall efficiency constant at E_0^{G*} and the efficiency of period t constant at $E_0^{G(t)*}$. The process can be continued until we find a solution for every period, by keeping the previously evaluated efficiencies constant at their optimal level. For example, if there are 16 periods to be evaluated, as is the case for the empirical application in this paper, then there are 17 models in total that need to be evaluated; 1 time the overall multi-period model (4) and 16 times the period specific model (10) adding an additional constraint for every period. Although several optimisations should be run for every DMU which adds computational burden, the model is implementable with ease. There is a technical problem that might arise when solving model (10) and that is possible infeasibilities due to rounding errors (Kao, 2017).

3.3 Returns to scale

The use of the CRS assumption has been linked with the operation at an optimal scale across all DMUs. There are various issues which can force DMUs to operate at a non-optimal scale, such as imperfect competition, regulations and financial constraints (Coelli et al., 2005). In such cases, a variable returns-to-scale (VRS) assumption is preferred. However, the assumption of VRS leads to a lower discrimination

power (Asmild et al., 2004) as well as to a systematic bias when calculating productivity change using a Malmquist productivity index (Grifell–Tatje and Lovell, 1995). As Fethi and Pasiouras (2010) showed, the majority of the DEA studies in banking use a VRS model. There are, however, studies that use either a CRS model (Asmild et al., 2004) or use both CRS and VRS models (Canhoto and Dermine, 2003).

From a modelling perspective, the VRS assumption requires the introduction of free variables u^1 and u^2 in model (3), for the first and second stages respectively.⁴ The overall efficiency under the VRS assumption can be calculated as:

$$E_0 = \xi_1 \frac{\sum_{d=1}^D w_d z_{d0} + u^1}{\sum_{i=1}^m v_i x_{i0}} + \xi_2 \frac{\sum_{r=1}^S u_r y_{r0} + u^2}{\sum_{d=1}^D w_d z_{d0}} \quad (11)$$

Similarly, introducing the free variables u^1 and u^2 in model (4) will result in the VRS version of the multi-period additive relational network DEA model, where $u^{1(k)}$ and $u^{2(k)}$ are seen as the corresponding vector of free variables for the p periods. Then, three equations (8) would become:

$$\begin{aligned} \sum_{k=1}^p \hat{\alpha}^{(k)} E_0^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) \cdot \left(\frac{\sum_{r=1}^S u_r^* y_{r0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)} + u^{1(k)} + u^{2(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{r=1}^S u_r^* y_{r0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)} + u^{1(k)} + u^{2(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)} + \sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = E_0^G \\ \sum_{k=1}^p \check{\alpha}^{(k)} E_1^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{i=1}^m v_i^* x_{i0}^{(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)}} \right) \cdot \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)} + u^{1(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)} + u^{1(k)}}{\sum_{i=1}^m v_i^* x_{i0}^{(k)}} \right) = E_0^{G1} \\ \sum_{k=1}^p \hat{\alpha}^{(k)} E_2^{G(k)} &= \sum_{k=1}^p \left(\frac{\sum_{d=1}^D w_d^* z_{d0}^{(k)}}{\sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) \cdot \left(\frac{\sum_{r=1}^S u_r^* y_{r0}^{(k)} + u^{2(k)}}{\sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = \sum_{k=1}^p \left(\frac{\sum_{r=1}^S u_r^* y_{r0}^{(k)} + u^{2(k)}}{\sum_{d=1}^D w_d^* z_{d0}^{(k)}} \right) = E_0^{G2} \end{aligned} \quad (12)$$

The three equations (12) hold if and only if $\sum_{k=1}^p u^{1(k)} = u^1$ and $\sum_{k=1}^p u^{2(k)} = u^2$. Therefore, these two summing constraints are required to be included in the VRS version of the model. A potential problem is the number of free variables included in the model. They increase by four for each year of the analysis (each free variable u^1 and u^2 is expressed as the difference of two non-negative variables). For example, if the examined time-period is 16 years, as is the case in this paper, there will be 64 new variables. Furthermore, a high number of variables in a DEA model leads to a lack of discrimination, a problem known as the *curse of dimensionality* (Charles et al., 2019; Sickles and Zelenyuk, 2019). Therefore, in a real life application this model would be considered as a suitable option only if the number of years was relatively low and the number of DMUs very high.

⁴ See model (17) in Chen et al. (2009).

3.4 Productivity change

Based on the works of Shephard (1953) and Malmquist (1953) on input distance functions and Shephard (1970) on output distance functions, Caves et al. (1982) developed the MPI to examine the productivity changes between two periods. This type of MPI is calculated based on the technology of one period. On the contrary, a global MPI considers the technology of all periods in order to calculate the index (Pastor and Lovell, 2005). There are three appealing features about global MPI: (i) it is circular, which means that the productivity change between two periods t and l can be calculated as $MPI^{t,l} = MPI^{t,k} \cdot MPI^{k,l}$ for any period k between t and l ; (ii) it provides a single productivity measure without a need for the geometric mean approach; and (iii) it is immune to infeasibilities usually arising from the mixed periods problem.

Similarly, the period efficiencies based on the overall efficiency of model (4) that are calculated from the equations (6) use the same set of multipliers. Therefore, each individual period efficiency is based on the same frontier facet and the corresponding indices are common-weight global MPIs. Following Kao and Hwang (2014), the common-weight global MPI can be calculated as:

$$MPI^{t,l} = D_c^G(x^l, y^l) / D_c^G(x^t, y^t) = E_c^{G(l)} / E_c^{G(t)} \quad (13)$$

where D stands for distance function and c for constant returns to scale. For example, $D_c^G(x^l, y^l)$ is the distance function of inputs-outputs (x,y) in period l using the global technology of all p periods as a benchmark technology. Accordingly, $E_c^{G(l)}$ is the efficiency for period l and $E_c^{G(t)}$ is the efficiency for period t , calculated from equations (6) under the CRS assumption.

The $MPI^{t,l}$ can be decomposed in order to identify the sources of productivity change. We apply a two-way decomposition which is based on the CRS technology that was introduced by Färe et al. (1994a). The productivity change is decomposed into an efficiency change term, which shows whether the distance of a DMU from the frontier has changed over time and a technical change term, which shows the shift in the frontier. Alternative decomposition approaches such as Färe et al. (1994b), Ray and Desli (1997) and Weelock and Wilson (1999) use both CRS and VRS components.⁵ To avoid the aforementioned problems of the multi-period VRS model, we apply the decomposition of Färe et al. (1994a) and we focus only on CRS technology. We can define $D_c^l(x^l, y^l)$ as the distance function of inputs-outputs (x,y) in period l using period l as a benchmark technology. The $MPI^{t,l}$ in (13) can be decomposed as:

⁵ See Kourtzidis et al. (2018) for a discussion on the alternative decomposition approaches

$$MPI^{t,l}(x^t, y^t, x^l, y^l) = Eff_ch \cdot Tech_ch = \frac{D_c^l(x^l, y^l)}{D_c^t(x^t, y^t)} \cdot \left[\frac{D_c^G(x^l, y^l)}{D_c^l(x^l, y^l)} \cdot \frac{D_c^t(x^t, y^t)}{D_c^G(x^t, y^t)} \right] \quad (14)$$

We calculate the above MPI by using the non-parametric estimators from models (3) and (4) and equations (6), where, $E_c^{G(l)}$ is the efficiency for period l and $E_c^{G(t)}$ is the efficiency for period t , calculated from the multi-period model (4) and equations (6) under the CRS assumption, $E_c^{(l)}$ is the efficiency for period l and $E_c^{(t)}$ is the efficiency for period t , calculated from model (3) under CRS assumption. Then equation (14) can be re-written as follows:

$$MPI^{t,l} = Eff_{ch} \cdot Tech_{ch} = \frac{E_c^{(l)}}{E_c^{(t)}} \cdot \left[\frac{E_c^{G(l)}}{E_c^{(l)}} \cdot \frac{E_c^{(t)}}{E_c^{G(t)}} \right] \quad (15)$$

4. Empirical Application

In this section we apply our model to study the efficiency and productivity of Regional Banks I and II in Japan during the period from 2002 to 2017. The period of study begins in the aftermath of the 1990s financial crisis, which caused the extensive restructuring of Japanese banks, and covers two turbulent periods, the GFC and the economic recession in the aftermath of the GEJE.

4.1. Data and model description

Our representative sample includes 51 Regional Banks I and 23 Regional Banks II. As discussed in Section 2.1, Regional Banks I and II have similar characteristics such as low capitalisation, they are operating in specific districts and they are involved in similar operations in which they compete with each other, such as the financing of SMEs and local governments. The specification of the inputs and outputs are in line with Fukuyama and Matousek (2011) and Holod and Lewis (2011). The first stage uses the total number of employees and fixed assets as inputs to produce deposits which are the intermediate variables in our model. The second stage uses deposits that are deployed for the production of loans and securities. This approach ensures the dual role of deposits and addresses the *deposits dilemma* as described in Section 1. Following Besstremyannaya (2017), we divide the period from 2002 to 2017 into five sub-periods that include: (i) the period after the extensive restructuring of Japanese banks and before the GFC (2002–2007); (ii) the period during the GFC (2007–2009); (iii) the period after the GFC and before the GEJE (2009–2011); (iv) the period of the economic recession in the aftermath of the GEJE (2011–2013); and (v) the period that captures the recovery after the turbulent periods (2013–2017). Table A1 in the Appendix

presents the descriptive statistics for our dataset throughout the years. The data sample is collected from the banks' balance sheets which are provided by the Japanese Banks' Association⁶ and are measured in million Yen. Data for the number of employees are collected from DataStream.

4.2. Results

The proposed multi-period additive relational network DEA model (4) is applied to assess the efficiency and productivity of the 74 Japanese Regional Banks. Based on the previous discussion, we choose a CRS over a VRS model to avoid the curse of dimensionality. In addition, as discussed in Section 2.1, Regional Banks I and II perform similar operations and operate under the same framework, therefore a CRS assumption is valid. In our case, we find that the CRS model has a unique efficiency decomposition across years and stages. This is important because we can directly use equations (6) for the period and stage efficiencies and avoid possible infeasibilities from additional linear programs (LP) like model (10) due to additional equality constraints (Kao, 2017).

Table 2 presents the detailed results for the case of the *Chiba Bank*, which is the most efficient bank, as an illustrative example. Here we present the detailed results only for one bank. The results for all banks are available upon request. Columns 3-5 present the average period efficiency, the weight for each period calculated from equations (7) and the MPI for the consecutive yearly periods calculated from (13), e.g. third row presents the MPI for the period 2002–2003. Columns 6-7 and 8-9 present the same for the first and second stages respectively. As demonstrated in equations (8), the overall efficiency and the stage efficiencies for the whole period are the weighted average of the period efficiencies. Therefore, when we use period efficiencies in column 3 and the weights in column 4, we can calculate the overall efficiency for the *Chiba Bank* as a weighted average which is 0.806. We can calculate the weighted average for the first stage and the second stage efficiencies from columns 6-7 and 8-9 as 0.760 and 0.865 respectively. It is worthwhile noting that even though *Chiba Bank* is the most efficient bank in the entire period analysed, in terms of individual years it is the most efficient only in one period (2006). However, it is consistently ranked among the top four banks during the entire time period. Furthermore, the efficiency level gradually increases throughout the entire time period, starting from 0.691 in 2002 and reaching 0.901 in 2017. The main driver for this is the increase in first stage efficiency, which was relatively low at the beginning of the time period at 0.598 but reached a very high level later at 0.939, rather than the second stage efficiency, which was stable and high, ranging from 0.80 to 0.85 across the entire time period. Indeed, the first stage

⁶ These balance sheets can be found at: <https://www.zenginkyo.or.jp/en/stats/year2-01/>

efficiency was lower than the second stage efficiency up until 2014, and after that point it became greater. The gradual increase in the first stage efficiency can be attributed to the growth of deposits throughout the entire time period, which was consistently positive after 2003 with an average of 3.48% per year. Over the same time, a similar growth pattern for loans that was consistently positive after 2003 with an average of 3.69% per year, kept the second stage efficiency at a high level. The strong position of *Chiba Bank* in terms of deposits and loans is evident by the high credit ratings, such as A1 rating for the long-term bank deposits (Moody's, 2015). Similarly, the ranking of individual variables through the years provides further insights. Specifically, *Chiba Bank* has the highest fixed assets, deposits and loans across all years. *Chiba Bank* has the second highest number of employees and the bank is among the top ten banks with the highest volume of securities. In terms of the productivity change, due to the circularity property the overall MPI for the whole period is the product of all period MPIs in column 5, which is 1.304, revealing that the performance of *Chiba Bank* has significantly improved during the whole period from 2002 to 2017.

Table 2: Period efficiencies and MPI for the case of the *Chiba Bank*

Year k	Period t,l	$E_0^{G(k)}$	$\alpha^{(k)}$	$MPI^{t,l}$	$E_0^{G1(k)}$	$\tilde{\alpha}^{(k)}$	$E_0^{G2(k)}$	$\hat{\alpha}^{(k)}$
2002	-	0.6909	0.0583	-	0.5976	0.0642	0.8470	0.0504
2003	2002-2003	0.6927	0.0572	1.0026	0.6098	0.0625	0.8286	0.0501
2004	2003-2004	0.7196	0.0560	1.0388	0.6443	0.0599	0.8365	0.0508
2005	2004-2005	0.7537	0.0561	1.0474	0.6906	0.0584	0.8450	0.0531
2006	2005-2006	0.8063	0.0571	1.0698	0.7349	0.0579	0.9033	0.0560
2007	2006-2007	0.8025	0.0590	0.9953	0.7484	0.0595	0.8747	0.0585
2008	2007-2008	0.7946	0.0598	0.9902	0.7374	0.0606	0.8722	0.0587
2009	2008-2009	0.7980	0.0608	1.0043	0.7346	0.0617	0.8844	0.0596
2010	2009-2010	0.7962	0.0628	0.9977	0.7348	0.0637	0.8798	0.0615
2011	2010-2011	0.7981	0.0645	1.0024	0.7478	0.0649	0.8653	0.0639
2012	2011-2012	0.8144	0.0652	1.0204	0.7671	0.0650	0.8762	0.0655
2013	2012-2013	0.8361	0.0657	1.0266	0.7950	0.0644	0.8879	0.0674
2014	2013-2014	0.8526	0.0667	1.0197	0.8454	0.0636	0.8610	0.0707
2015	2014-2015	0.8743	0.0687	1.0255	0.8922	0.0639	0.8541	0.0750
2016	2015-2016	0.8904	0.0701	1.0184	0.9225	0.0642	0.8556	0.0779
2017	2016-2017	0.9008	0.0721	1.0117	0.9387	0.0655	0.8604	0.0808

The overall efficiency scores for the entire period and for all banks are presented in Table 3. Columns 2-4 and 6-8 are the CRS efficiency scores calculated from the multi-period model (4). The number in brackets denotes the ranking of each bank. Note that RB I and RB II denote Regional Banks I and II respectively. *Chiba Bank* is the most efficient bank with an efficiency score of 0.806 and the Miyazaki Taiyo Bank is the

least efficient bank with an efficiency score of 0.409. Only five banks achieve overall efficiency above 0.750 and 11 banks above 0.700. Regarding the first stage, only one bank achieves an efficiency score over 0.750 (Chiba Bank) and three banks achieve an efficiency score above 0.700. Regarding the second stage, eight banks achieve an efficiency score above 0.900 and 58.1% of banks an efficiency score above 0.850. The most efficient bank in the second stage is Kansai Urban Banking Corporation with an efficiency score of 0.946.

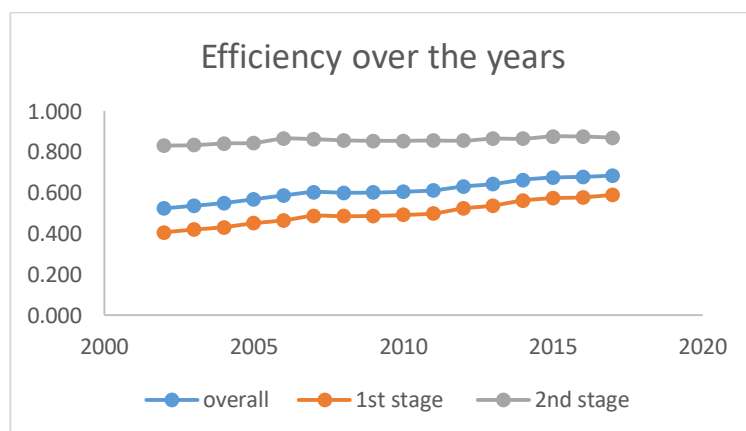
Table 3: Multi-period efficiency for 74 Japanese banks

Bank	E_0^G	E_0^{1G}	E_0^{2G}	Bank	E_0^G	E_0^{1G}	E_0^{2G}
77 Bank [RB I]	0.785 [4]	0.729	0.862	Joyo Bank [RB I]	0.757 [5]	0.671	0.885
Aichi Bank [RB II]	0.618 [37]	0.499	0.855	Juroku Bank [RB I]	0.617 [38]	0.494	0.867
Akita Bank [RB I]	0.638 [31]	0.524	0.855	Kagoshima Bank [RB I]	0.594 [44]	0.455	0.898
Aomori Bank [RB I]	0.630 [32]	0.512	0.862	Kansai Urban Banking Corporation [RB II]	0.691 [12]	0.550	0.946
Awa Bank [RB I]	0.668 [19]	0.560	0.861	Keiyo Bank [RB II]	0.679 [16]	0.586	0.836
Bank of Iwate [RB I]	0.707 [11]	0.621	0.844	Kita Nippon Bank [RB II]	0.542 [56]	0.431	0.800
Bank of Kochi [RB II]	0.457 [70]	0.324	0.869	Kiyo Bank [RB I]	0.640 [30]	0.533	0.841
Bank of Kyoto [RB I]	0.732 [7]	0.605	0.941	Michinoku Bank [RB I]	0.651 [26]	0.570	0.792
Bank of Nagoya [RB II]	0.626 [35]	0.551	0.851	Mie Bank [RB I]	0.617 [39]	0.485	0.888
Bank of Saga [RB I]	0.543 [55]	0.427	0.813	Minami Nippon Bank [RB II]	0.442 [72]	0.322	0.812
Bank of the Ryukyus [RB I]	0.552 [54]	0.432	0.829	Minato Bank [RB II]	0.579 [47]	0.450	0.867
Bank of Toyama [RB I]	0.510 [66]	0.385	0.833	Miyazaki Bank [RB I]	0.559 [53]	0.411	0.920
Chiba Bank [RB I]	0.806 [1]	0.760	0.865	Miyazaki Taiyo Bank [RB II]	0.409 [74]	0.293	0.804
Chiba Kogyo B. [RB I]	0.663 [22]	0.561	0.845	Musashino Bank [RB I]	0.659 [23]	0.547	0.865
Chikuho Bank [RB I]	0.457 [71]	0.330	0.843	Nagano Bank [RB II]	0.566 [51]	0.448	0.828
Chugoku Bank [RB I]	0.718 [10]	0.596	0.923	Nanto Bank [RB I]	0.682 [14]	0.574	0.868
Chukyo Bank [RB II]	0.573 [50]	0.442	0.870	Ogaki Kyoritsu Bank [RB I]	0.603 [41]	0.471	0.884
Daisan Bank [RB II]	0.514 [62]	0.390	0.831	Oita Bank [RB I]	0.594 [43]	0.462	0.882
Daishi Bank [RB I]	0.663 [21]	0.554	0.861	San in Godo Bank [RB I]	0.667 [20]	0.551	0.878
Daito Bank [RB II]	0.476 [68]	0.360	0.799	Shiga Bank [RB I]	0.672 [17]	0.558	0.876
Ehime Bank [RB II]	0.530 [59]	0.396	0.867	Shikoku Bank [RB I]	0.630 [33]	0.517	0.848
Eighteenth Bank [RB I]	0.583 [46]	0.449	0.882	Shimizu Bank [RB I]	0.541 [57]	0.423	0.821
Fukui Bank [RB I]	0.629 [34]	0.507	0.870	Shizuoka Bank [RB I]	0.796 [3]	0.699	0.934
Fukuoka Chuo B. [RB II]	0.412 [73]	0.286	0.853	Suruga Bank [RB I]	0.655 [25]	0.579	0.785
Fukushima Bank [RB II]	0.510 [65]	0.383	0.844	Taiko Bank [RB II]	0.564 [52]	0.443	0.839
Gunma Bank [RB I]	0.726 [8]	0.615	0.906	Tochigi Bank [RB II]	0.589 [45]	0.483	0.809
Hachijuni Bank [RB I]	0.798 [2]	0.727	0.896	Toho Bank [RB I]	0.686 [13]	0.617	0.798
Higashi Nippon [RB II]	0.609 [40]	0.479	0.882	Tohoku Bank [RB I]	0.509 [67]	0.389	0.816
Higo Bank [RB I]	0.642 [29]	0.524	0.867	Tokyo Tomin Bank [RB I]	0.720 [9]	0.646	0.835
Hiroshima Bank [RB I]	0.738 [6]	0.634	0.901	Tomato Bank [RB II]	0.512 [64]	0.374	0.881

Hokkoku Bank [RB I]	0.643 [28]	0.518	0.884	Tottori Bank [RB I]	0.528 [61]	0.404	0.836
Hokuetsu Bank [RB I]	0.603 [42]	0.491	0.830	Towa Bank [RB II]	0.528 [60]	0.403	0.837
Hokuto Bank [RB I]	0.576 [49]	0.456	0.839	Tsukuba Bank [RB I]	0.579 [48]	0.468	0.815
Howa Bank [RB II]	0.460 [69]	0.337	0.827	Yachiyo Bank [RB II]	0.534 [58]	0.422	0.799
Hyakugo Bank [RB I]	0.649 [27]	0.532	0.869	Yamagata Bank [RB I]	0.669 [18]	0.553	0.879
Hyakujushi Bank [RB I]	0.625 [36]	0.493	0.895	Yamaguchi Bank [RB I]	0.512 [63]	0.380	0.862
Iyo Bank [RB I]	0.679 [15]	0.546	0.922	Yamanashi Chuo B. [RB I]	0.659 [24]	0.540	0.880

Figure 2 reveals that the average overall efficiency and the average efficiency of the first stage have been improved through the analysed period from 0.524 to 0.685 and from 0.407 to 0.590 respectively, while the second stage efficiency remained stable at a high level. The results are consistent across the years for most of the analysed banks, with some notable exceptions. Tokyo Tomin Bank, which was ranked as the 9th most efficient bank for the overall period, is the most notable example, achieving the best efficiency score for the time period 2002–2011 (with the exception of 2006, when the bank achieved the second highest efficiency score), while for the last three years this bank was among the five least efficient banks. In 2002, this bank achieved an efficiency score of 0.756, increasing to 0.872 in 2009, and decreasing afterwards to its lowest point at 0.491 in 2017. The driver behind this significant change is the bank's inputs. During the first decade the bank had very low inputs, especially fixed assets, which started to increase from 2012 and they were doubled in 2015. However, this increase in inputs was not followed by an increase in loans, securities or deposits. The other banks which achieved the highest efficiency for at least one year (Chiba Bank, Hachijuni Bank, 77 Bank) consistently achieved very high ranking across the analysed period.

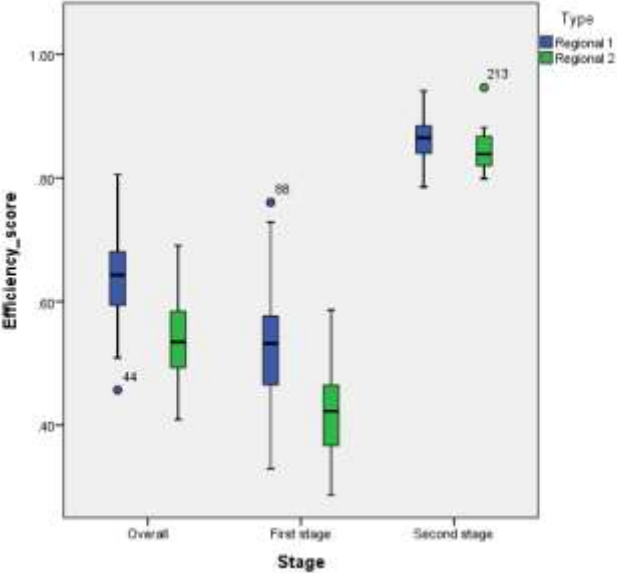
Figure 2: Average period efficiency through the years



An interesting aspect of our analysis is whether there is any difference between Regional Banks I

and II. Figure 3 is a clustered boxplot, which presents the difference between Regional Banks I and II for the overall, the first stage and the second stage efficiency scores. Evidently, there is a difference between Regional Banks I and II, with the former performing better in all stages. This difference is more distinct for the overall model and the first stage, while it is less distinct for the second stage. There are also three extreme observations, Chikuhō Bank (44) that shows the worse performance in the segment of Regional Banks I for the overall model. Chiba Bank (88) performs significantly better than the rest of the Regional Banks I for the first stage. Finally Kansai Urban Banking Corporation (213) performs better than the rest of the Regional Banks II for the second stage (and Regional Banks I). Although both Regional Banks I and II conduct similar activities within a specific district and mainly has SMEs or local government clients, there are a few differences that might explain the gap in efficiency levels. Regional Banks I are bigger in size than Regional banks II and also the restructuring process differed between the two types of regional banks (Fukuyama and Matousek, 2017). Specifically, regional banks have been assisted through capital injections and M&A with government intervention, however, the financial support between the two types of regional banks was not the same as the second tier banks had to cope with their non-performing loans by themselves.

Figure 3: Comparison of efficiency levels for Regional Banks I and II



Note: Numbers 44, 88 and 213 refer to the extreme observations. Observations 1–74 refer to the overall efficiency scores, 75–148 to the first stage efficiency scores and 149–222 to the second stage efficiency scores for the 74 banks.

The average productivity change per year, along with the decomposition is presented in Table 4. Specifically, column 2 presents the MPI for each subsequent biannual period and column 3 the MPI for the

individual sub-period. Similarly, columns 4 and 5 present the technical efficiency change and columns 6 and 7 the technical change. The productivity change, the technical efficiency change and the technical change for the entire period are presented in the last row. Note that the circularity property does not hold for average results, but only for single banks. Therefore, if we multiply the $MPI^{t,l}$ for every biannual period t and l in Table 2 starting from 2002–2003 and ending in 2016–2017, the result will be the $MPI^{t,l}$ for the time period 2002–2017. However, the same does not hold in Table 4. If we multiply the average MPI for each biannual period starting from 2002–2003 and ending in 2016–2017, the result will be different from the average MPI of 1.3185 for the time period 2002–2017 which is reported in Table 4. Overall, we notice that there is a productivity growth during the entire period, which is mainly attributed to the technical change component.

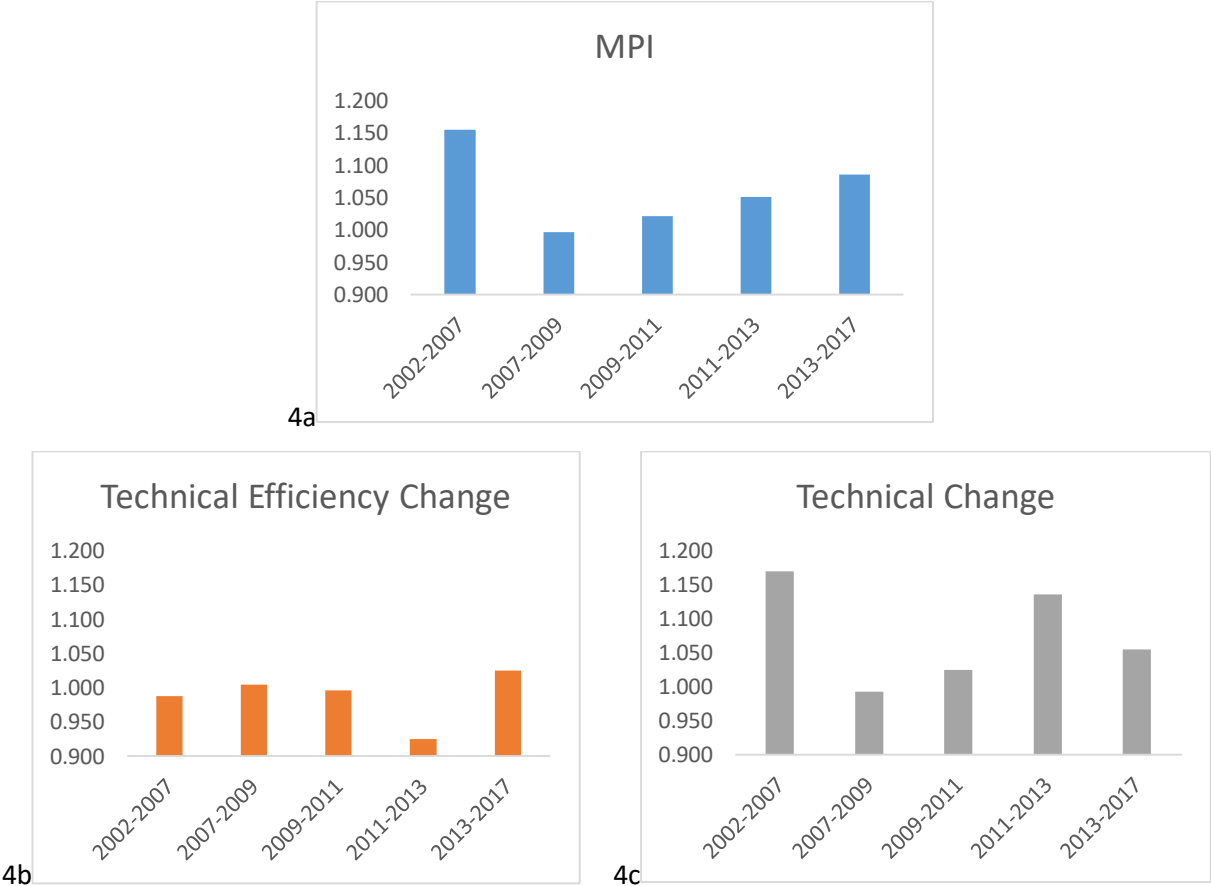
Table 4: Malmquist Productivity Index and decomposition

	MPI		Efficiency Change		Technical Change	
2002-2003	1.0259		1.0086		1.0171	
2003-2004	1.0267		0.9982		1.0285	
2004-2005	1.0339	1.1552	0.9945	0.9873	1.0396	1.1693
2005-2006	1.0322		0.9894		1.0432	
2006-2007	1.027		0.9968		1.0310	
2007-2008	0.9958	0.9968	0.9819	1.0044	1.0141	0.9926
2008-2009	1.0012		1.0231		0.9789	
2009-2010	1.0087	1.0213	1.0113	0.9963	0.9974	1.0247
2010-2011	1.0123		0.9852		1.0275	
2011-2012	1.0314	1.0511	0.9669	0.9250	1.0680	1.1351
2012-2013	1.0187		0.9569		1.0632	
2013-2014	1.0507		1.0171		1.0296	
2014-2015	1.0167	1.0859	0.9775	1.0248	1.0399	1.0547
2015-2016	1.0055		1.0299		0.9772	
2016-2017	1.0101		1.0012		1.0087	
2002-2017	1.3185		0.9290		1.4184	

Finally, we turn our attention to the individual sub-periods. Figure 4 is the visual representation of our results, where Figure 4a demonstrates the productivity change, Figure 4b the technical efficiency change and Figure 4c the technical change throughout the individual sub-periods. We observe a high productivity change of 1.1552 during the pre-crisis sub-period, which is entirely attributed to the technical change of 1.1693, since the technical efficiency change is around one. The GFC appears to affect Japanese Regional Banks unfavourably. We observe a sharp drop of 13.7% in productivity growth and 15.1% in the

growth of technical change, while the technical efficiency change remains around the same levels only with a slight increase. The sub-period after the GFC and before the GEJE is then relatively stable. We may observe the conflicting results for technical efficiency change and technical change during the GEJE. On one hand, there is a sharp increase in technical change at 1.1351, which seems unaffected by the GEJE. On the other hand, the technical efficiency change component 0.9250 is considerably low in this sub-period, presumably, owing to the GEJE. In the aftermath of the GEJE, we notice an increase in the technical efficiency change at 1.0248, while the growth rate of the technical change is slowed down. The productivity change replicates the technical change until 2011 and then gradually increases for the rest of the sub-period. That counterbalances the effects of the technical efficiency change and technical change. In particular, there is no significant difference in productivity change or its components between Regional Banks I and II, with the only exception being the technical change for Regional Banks II during the GEJE, which remained at the same level as before the earthquake, and sharply increased afterwards, surpassing the relative increase for Regional Banks I.

Figure 4: MPI and its components in the five sub-periods



5. Conclusions

The paper introduces a multi-period additive relational network DEA model to assess the efficiency and productivity of 74 Japanese Regional Banks I and II during the period from 2002 to 2017. We contribute to the literature in the following ways. Firstly, we investigate five phases of the Japanese economy, starting in the post restructuring period and covering two crises; the GFC and the economic recession in the aftermath of the GEJE. This is the first study to analyse the technical efficiency and the productivity change of Japanese Regional Banks during these five phases. Secondly, we introduce a multi-period model that allows the asymmetrical contribution of individual stages to the overall process. Furthermore, we demonstrate that the overall efficiency in the additive relational network DEA model with a parallel structure, is the weighted average of the sub-systems' efficiency. For each sub-system, the attached weight is the ratio of total inputs in the sub-system over total inputs in the overall system. This new multi-period model is used to evaluate the overall efficiency of the entire period of the analysis, as well as the period efficiencies, the productivity change and its decomposition.

The results reveal that the overall and first stage efficiencies improve through the years, while the second stage efficiency is stable at a high level through the entire time period. Furthermore, there is a difference in efficiency levels for Regional Banks I and II, with the former performing better than the latter. In addition, there is a productivity growth of 1.3185 through the entire time period, which is entirely attributed to the technical change component. The decomposition of the productivity change through the five periods under examination provides useful insights regarding the behaviour of banks during crises and policy implications for the decision makers. Overall, the results provide evidence that the GFC had a significant impact on the performance of Japanese Regional Banks. Regardless of the fact that our findings align with Fukuyama and Matousek (2017), who found that the revenue performance of Japanese Regional Banks was affected by the GFC, the research scope of our study is completely different. Instead of focusing solely on efficiency scores, this paper examines the performance of Regional Banks from a productivity perspective and investigates the sources of productivity change. In the case of the GFC, the main driver behind the sharp decrease in the productivity growth of the Japanese Regional Banks is the technical change, rather than the technical efficiency change component. This means that the GFC affected the ability of the banks to optimally combine inputs and outputs and caused distortions in the production possibility frontier, which can be explained by the financial environment in Japan during the GFC (the fall of the Nikkei stock exchange, lower credit ratings, etc) and the general economic environment in the country (huge decline in exports, deep economic recession and decline in GDP growth).

Moreover, this is in line with studies on productivity performance in other countries, where

technical change is the main driver for productivity regress during periods of financial crisis (Degl'Innocenti et al., 2017). From a bank manager's perspective, this finding means that during a financial crisis, the banks choose to focus on the technical efficiency side by utilising their existing resources, rather than on the technical change side by investing on innovation and new technologies. From a decision maker's perspective (such as the government and central bank), this finding means that the target should be to stimulate the technical change during periods of financial crisis, in order to ignite productivity growth. Indeed, for the case of Japan, in an attempt to inject money in the banking system, the Bank of Japan launched a quantitative easing round in 2011 (Matousek et al., 2019). This coincided with the start of the sharp growth in technical change and productivity growth in our study.

The GEJE had no effect on technical change, on the contrary, the Japanese Regional Banks experienced technical progress for the entire time period after the GFC. However, the GEJE affected the technical efficiency change component, thus the ability of the banks to utilise their existing resources. As a result, despite growth in productivity for the entire period after 2010, it can be suggested that technical efficiency change hampered the rate of this growth. Besstremyannaya (2017) also found a significant impact of the GEJE on the cost efficiency of Japanese banks, although this impact was heterogeneous and differed between high-cost and low-cost banks. Our results reveal that the impact of the GEJE on the technical efficiency change is similar for all the regional banks.

It is worthwhile mentioning that the methodology introduced in this paper can be generalised to more than two stages and applied to applications outside the banking field. Furthermore, an interesting direction for future research would be the incorporation of non-performing loans (NPLs) into the suggested modelling framework. This is particularly important for Japanese Regional Banks that have been facing the problem of increased NPLs for the past two decades (Fukuyama and Matousek, 2017) and currently are once more subject to sweeping reforms (Harding, 2020). Another interesting dimension for future research would be the examination of alternative decomposition approaches for the MPI, such as those suggested by Ray and Desli (1997) and Wheelock and Wilson (1999). However, this would require a VRS term, therefore a solution for the problem of dimensionality created by the free variables in each period of the analysis.

Acknowledgements

We would like to thank the members of the North American Productivity Workshop (NAPW) X, which took place on 11–15 June 2018 in Miami for the comments made on an earlier version of this paper. We would also like to thank Professor Dyson and the reviewers of the journal for the comments made in an earlier

version of our paper.

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Appendix

Table A1: Descriptive statistics

		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Fixed assets	Mean	36745.5	35836.6	35554.3	34750.6	33635.1	31998.9	32141.2	32546.9	32293.7	32108.2	31844.1	31530.8	32269.3	32805.4	33170.5	33039.0
	Std. dev	23411.0	22554.3	21642.8	21024.2	20395.2	19897.9	19958.1	20353.7	20054.3	20184.0	19960.4	20226.5	20731.0	20874.9	20902.3	20896.6
	Min	5243	5051	4946	4913	4815	4637	4564	4513	4603	4466	4808	5043	4942	4740	4897	4693
	Max	109687	103747	101097	98403	95627	89272	90270	90841	88779	91028	93301	93529	97580	97250	96934	96120
Number of employees	Mean	1995.9	1936.2	1896.2	1841.1	1809.9	1806.3	1846.3	1879.2	1931.4	1955.8	1936.9	1911.3	1896.6	1892.1	1909.3	1911.7
	Std. dev	1010.2	980.8	940.4	919.9	911.9	927.7	953.1	980.3	1000.6	1019.4	1015.5	1009.0	999.7	983.0	995.3	1011.1
	Min	468	436.0	424.0	412.0	406.0	421.0	451.0	423.0	401.0	383.0	362.0	369.0	342.0	329.0	336.0	337.0
	Max	4839	4839.0	4839.0	4839.0	4839.0	4839.0	4761.0	4732.0	4649.0	4490.0	4491.0	4454.0	4399.0	4420.0	4437.0	4543.0
Deposits	Mean	2279944	2277888	2304043	2346253	2365507	2422549	2456722	2510427	2604798	2665001	2768766	2835944	2950818	3043333	3100014	3166877
	Std. dev	1516159	1505152	1506845	1538722	1562331	1611548	1629944	1679404	1729753	1777968	1846932	1939356	1998516	2085311	2151128	2213919
	Min	325943	330657	337969	353638	356395	347587	351525	358860	362943	371505	374504	402929	415216	432026	437108	441243
	Max	7218238	7174913	7266461	7594015	8009102	8371579	8401098	8529344	8805261	9138396	9376500	9636831	10121889	10733396	11140215	11565778
Loans	Mean	1674038	1655971	1666232	1683536	1726953	1784487	1829055	1900275	1919999	1948464	1986955	2033382	2114080	2193903	2274274	2358922
	Std. dev	1113942	1087508	1091434	1114751	1155789	1213430	1258744	1338279	1352069	1385911	1410538	1484168	1519541	1584079	1650387	1736928
	Min	251354	255898	256001	255811	260182	255775	255857	266844	269742	270882	276819	282053	274062	275185	281817	284337
	Max	5749973	5606409	5678111	5881472	6167437	6407516	6656245	6991343	7158314	7371452	7581708	7912140	8083049	8461180	8797479	9305388
Securities	Mean	611746	641310	691464	738087	793347	778804	744151	710050	795991	836287	913303	976114	1002726	1061736	1021271	974529.2
	Std. dev	490441	515119	550597	588732	657263	637961	609488	548576	606490	627292	694870	782150	808801	832669	792653.9	749885.4
	Min	44444	42834	53469	64654	70844	73399	72689	60068	73581	72231	74633	91809	98872	99135	93980	91721
	Max	2039529	2070023	2255553	2430824	2634013	2607267	2732104	2293862	2712081	2761760	2866325	3402860	3716530	3683636	3478904	3242629