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Evaluation of Bank Branches Using a Dynamic Network Data Envelopment Analysis Model

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Abstract

The purpose of this study is to evaluate bank branches using a dynamic network data envelopment analysis model. Bank performance evaluation is a critical aspect of financial and economic management that facilitates the analysis of banks' efficiency, productivity, and growth potential. Such evaluations are commonly conducted using financial indicators, including liquidity ratios, profitability ratios, and asset quality. Data envelopment analysis is a powerful analytical technique for measuring the relative efficiency of a set of decision-making units based on their inputs and outputs. Data from bank branches in Qazvin Province were used to test the efficiency of and solve the proposed model. The model proposed in this article evaluates decision-making units dynamically and simultaneously calculates the efficiency of the overall system and its constituent divisions. It therefore enables managers to identify inefficient divisions and make appropriate decisions to improve the overall efficiency of the organization.

Keywords: *Dynamic network data envelopment analysis, evaluation, bank*

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1. Introduction

Banks occupy a central position in modern economic systems because they mobilize savings, allocate financial resources, facilitate payments, support investment, and contribute to the transmission of monetary policy. The quality of bank performance therefore has implications not only for shareholders and customers but also for financial stability, regional development, and the efficient allocation of capital across the economy. In increasingly competitive financial markets, bank managers are expected to improve profitability while maintaining liquidity, controlling risk, complying with regulatory requirements, and delivering high-quality services. These objectives are often pursued simultaneously, even though they may involve conflicting managerial priorities. A branch may increase lending and revenue generation while also experiencing higher operating costs, deteriorating asset quality, or excessive risk exposure. Consequently, the assessment of bank performance requires a multidimensional framework capable of evaluating how effectively different resources are transformed into financial and operational outcomes. Recent research has emphasized that bank sustainability and performance evaluation should integrate several dimensions of efficiency rather than rely exclusively on conventional profitability measures or isolated financial ratios [1, 2].

Bank branches represent the operational interface between banking institutions and their customers and play an important role in deposit mobilization, credit allocation, customer relationship management, and local market development. Although digital banking has transformed many financial services, physical branches continue to influence customer acquisition, lending decisions, deposit collection, and the implementation of institutional strategies. Branch-level performance evaluation is therefore a critical component of bank management. Managers need to determine whether differences in branch performance originate from inadequate resource utilization, weak deposit-generation capacity, inefficient lending operations, insufficient revenue creation, or poor conversion of intermediate financial outcomes into final assets and equity. Traditional accounting indicators, such as return on assets, return on equity, cost-to-income ratios, liquidity ratios, and nonperforming loan ratios, provide valuable information, but each indicator reflects only one aspect of performance. Moreover, ratio analysis does not establish a comprehensive benchmark that simultaneously incorporates multiple inputs and outputs. Contemporary efficiency studies have therefore increasingly adopted integrated quantitative approaches that can compare heterogeneous operating units and identify sources of inefficiency within complex production systems [1, 3].

Data envelopment analysis (DEA) is one of the most widely applied nonparametric methods for evaluating the relative efficiency of comparable decision-making units. DEA constructs an empirical production frontier based on observed combinations of inputs and outputs and measures each decision-making unit relative to the best-performing units in the sample. Unlike parametric methods, DEA does not require the specification of a predetermined functional relationship between inputs and outputs. It is particularly useful when performance involves multiple inputs and outputs expressed in different units of measurement. The method has consequently been applied to banks, hospitals, transportation systems, industrial sectors, public utilities, environmental services, and other organizational settings. For example, DEA-based approaches have been used to evaluate hospital performance under uncertainty and imprecise information, demonstrating the flexibility of the method in handling complex decision environments [4]. Similar applications in industrial and environmental governance contexts have shown that DEA can distinguish operational inefficiency from broader productivity and sustainability concerns [5].

Despite its advantages, conventional DEA commonly treats each decision-making unit as a “black box” in which inputs enter the system and outputs are produced without explicit consideration of internal processes. This assumption may be inadequate for bank branches because banking operations consist of interconnected activities rather than a single transformation process. Resources such as physical capital, personnel, loans, and operating expenditures may first generate intermediate outputs, including cash flows, interest margins, deposits, or service capacity. These intermediate products are subsequently used to generate final financial outcomes, such as total assets, equity, revenue, or profitability. A branch may therefore appear efficient at the aggregate level while performing poorly in one of its internal stages. Conversely, weak overall performance may result from a specific stage rather than from the entire branch operation. Network DEA addresses this limitation by opening the internal structure of the decision-making unit and modeling its interconnected divisions, stages, or subprocesses. Two-stage network DEA models are especially relevant to banking because they can represent the sequential relationship between resource acquisition, financial intermediation, and revenue or asset generation [3, 5].

The decomposition of overall efficiency into stage-specific efficiency provides substantial managerial value. Aggregate efficiency scores indicate whether a branch is relatively efficient, but they do not necessarily explain why it is efficient or inefficient. In contrast, network models can determine whether performance deficiencies arise in the first stage, the second stage, or in the link between the two stages. This distinction supports more targeted managerial interventions. For instance, a branch with high first-stage efficiency but low second-stage efficiency may effectively convert its initial resources into intermediate outcomes but fail to transform those outcomes into total assets, equity, or other final outputs. Such a branch may require changes in asset management, deposit utilization, pricing policies, or operational coordination rather than additional resources. Research on two-stage network DEA has therefore focused on efficiency decomposition, frontier projection, and the consistent estimation of divisional and overall efficiency under different returns-to-scale assumptions [3]. These methodological developments improve the interpretability of efficiency scores and enable managers to identify realistic improvement targets for each stage of an operational network.

Another limitation of static DEA models is that they evaluate performance within a single period and generally ignore the intertemporal continuity of organizational activities. Banking operations are inherently dynamic because decisions made in one period influence resources and outcomes in subsequent periods. Loan portfolios, fixed assets, deposits, equity, retained earnings, customer relationships, and risk exposures do not disappear at the end of an accounting year; rather, they are carried forward and affect future performance. A static model may therefore produce an incomplete or distorted assessment by treating each period as independent. Dynamic DEA extends the conventional framework by incorporating carry-over variables that connect consecutive periods. These variables represent resources, obligations, or intermediate products transferred from one period to the next. Multi-period network DEA models further integrate internal organizational structures with intertemporal linkages, thereby allowing the simultaneous evaluation of stage-specific, period-specific, and overall efficiency. The importance of incorporating feedback and interperiod relationships has been demonstrated in multi-period network DEA research, which shows that ignoring such linkages can lead to inaccurate efficiency measurement [6].

Dynamic network DEA is particularly suitable for banking because branch performance reflects both sequential internal processes and cumulative financial decisions. Loans issued in one period may generate interest income in later periods; deposits collected during one year can finance subsequent lending activities; and investments in physical capital may improve service capacity over multiple periods. Similarly, weaknesses in credit allocation or liquidity management may not become visible immediately but can affect later profitability, asset growth, and equity. By incorporating carry-over variables and intermediate links, dynamic network DEA can capture these temporal dependencies. Research on commercial bank credit operations has shown that dynamic network DEA can be combined with productivity indices to examine operational efficiency under uncertainty and risk, thereby providing a more comprehensive understanding of banking performance over time [2]. Such approaches are important because efficiency in credit operations cannot be separated from risk exposure, market uncertainty, and the persistence of financial assets and liabilities across periods.

The relevance of dynamic network DEA extends beyond banking and has been demonstrated across multiple service and infrastructure sectors. In hospital pharmacy services, dynamic network DEA has been used to compare efficiency across heterogeneous operational environments while accounting for technological differences and intertemporal relationships [7]. In urban water supply utilities, dynamic multiactivity network DEA has enabled researchers to evaluate interconnected operational activities and determine how resources are transformed through multiple service processes over time [8]. Dynamic network structures have also been applied to municipal solid waste services to assess production efficiency while considering political and institutional factors that influence service delivery [9]. Collectively, these applications indicate that dynamic network DEA is well suited to organizations characterized by multiple internal processes, shared or intermediate resources, and outcomes that develop over several periods.

Efficiency evaluation has also become increasingly connected to sustainability, governance, and strategic decision-making. Organizations are no longer assessed solely according to the quantity of their outputs; they are also expected to demonstrate resilience, accountability, environmental responsibility, and long-term value creation. In banking, financial sustainability requires a balance among profitability, risk control, liquidity, capital adequacy, and the capacity to maintain stable operations. Recent studies have integrated DEA with machine-learning techniques to explain the determinants of bank financial sustainability and improve the interpretability of efficiency assessments [1]. These developments reflect a broader shift from descriptive performance measurement toward decision-support systems that identify the factors contributing to efficiency and provide actionable recommendations. Although advanced predictive and explainable models can complement DEA, the reliability of such analyses still depends on an appropriate representation of the internal banking process. A dynamic network structure offers this representation by linking resource utilization, intermediate financial products, and final outcomes across time.

The capacity of network DEA to analyze the balance among competing strategic objectives is another important advantage. Organizations frequently pursue economic, operational, social, and environmental goals simultaneously. Dynamic network cross-efficiency analysis has been used in regional transportation systems to examine the balance between economic development and environmental strategies, illustrating how network models can evaluate trade-offs among interconnected objectives [10]. Likewise, two-stage network-based super-efficiency models have been applied to measure regional productivity and environmental governance efficiency in industrial sectors, demonstrating that overall efficiency depends on the performance of distinct but connected stages [5]. In the banking context, comparable trade-offs arise between loan expansion and credit risk, deposit growth and funding costs, liquidity and profitability, or branch expansion and operating expenditure. A model that evaluates these activities as a single undifferentiated process may conceal important managerial weaknesses. A network-based approach can instead reveal whether a branch's final performance is supported by balanced internal operations or driven by strong performance in only one component.

Uncertainty is also an important consideration in organizational efficiency measurement. Input and output data may be influenced by market volatility, estimation errors, incomplete information, or qualitative managerial judgments. Novel DEA models have therefore been developed to incorporate fuzzy information and improve performance evaluation under ambiguous conditions. The application of picture fuzzy BCC models to hospital performance evaluation demonstrates how DEA can be extended to decision contexts in which the available evidence is not entirely precise or deterministic [4]. Although the present study relies on observed financial data, the broader methodological development of DEA underscores the need to select models that correspond closely to the structure of the decision problem. In bank branch evaluation, the primary methodological challenge is not merely uncertainty but the coexistence of multiple operational stages and temporal linkages. Dynamic network DEA responds directly to this challenge by retaining the empirical strengths of DEA while introducing a more realistic representation of banking activities.

A further methodological issue concerns the treatment of heterogeneity and frontier construction. Branches may operate under different local market conditions, customer compositions, economic environments, and competitive pressures. Even within the same province, differences in population density, commercial activity, access to financial services, and local credit demand may influence observed performance. Metafrontier approaches have been proposed to distinguish managerial inefficiency from technological or environmental differences among groups of decision-making units. Their application to hospital pharmacy services illustrates how dynamic network DEA can be integrated with metafrontier analysis to compare units operating under heterogeneous technologies [7]. Similarly, variable-returns-to-scale network models permit the assessment of units whose operational scale may differ, thereby separating scale-related effects from pure technical inefficiency [3]. Although branch managers may have limited control over external market conditions, they can influence the allocation and utilization of available resources. A carefully designed network DEA model can therefore provide a fairer and more informative basis for internal benchmarking.

From a managerial perspective, the principal value of efficiency analysis lies in its ability to support resource allocation and performance improvement. Bank managers must decide whether inefficient branches require additional capital, operational restructuring, staff development, changes in lending policy, improved deposit mobilization, or enhanced coordination between stages. A branch that receives more resources without addressing internal process inefficiencies may remain inefficient. Conversely, a branch with limited resources may perform well because it effectively coordinates its financial operations. Dynamic network DEA can identify efficient reference units, estimate stage-level performance, and clarify how each branch compares with the best observed practices. Furthermore, frontier projection methods can specify the input reductions or output increases required for inefficient units to reach the efficiency frontier [3]. Such information is more actionable than a single financial ratio because it links performance outcomes to specific stages and resource transformations.

The selection of inputs, intermediate variables, outputs, and carry-over variables is central to the validity of a dynamic network DEA model. In banking studies, input variables commonly include labor, physical capital, operating costs, deposits, and loanable funds, whereas outputs may include loans, revenue, profit, total assets, and equity. The classification of a variable may depend on the conceptualization of the banking process. Deposits, for example, may be treated as an input because they finance lending activities, or as an output because their accumulation reflects the branch’s ability to attract customers. Similarly, loans can represent an output of the deposit-generation process and an input to the revenue-generation process. Network DEA accommodates such relationships by treating selected measures as intermediate products linking consecutive stages. Dynamic models additionally allow some variables to connect adjacent periods. Research on dynamic network models with feedback has demonstrated that appropriately modeling these internal and temporal relationships is necessary for consistent multi-period efficiency measurement [6]. Applications in banking, water utilities, transportation, and municipal services likewise confirm that the structure of the model should reflect the actual production or service process rather than merely the availability of data [2, 8-10].

Despite the extensive development of DEA, many practical bank performance evaluations continue to rely on static, single-stage measures. Such approaches may rank branches without revealing the internal sources of their performance and may overlook changes occurring across consecutive years. This limitation is especially important when a bank seeks to evaluate branches over a multi-year period and determine whether efficiency improvements are sustained or temporary. A branch may achieve a high score in one year because of favorable short-term conditions, while another may gradually improve through effective resource management. Dynamic network DEA provides a unified framework for examining both patterns. It simultaneously assesses the performance of internal stages, maintains the link between those stages, and incorporates the continuity of operations across periods. The resulting analysis can distinguish consistently efficient branches from those whose rankings depend on isolated annual outcomes. It can also identify whether weak overall efficiency results from the first-stage transformation of initial resources, the second-stage conversion of intermediate outputs, or the interaction between the two stages over time [2, 6].

Accordingly, the aim of this study is to evaluate the performance of bank branches in Qazvin Province over multiple periods by applying a dynamic two-stage network data envelopment analysis model that simultaneously estimates first-stage, second-stage, and overall efficiency.

2. Methodology

The present study is applied in terms of its purpose. Given that the objective of the study is to evaluate bank branches using a dynamic network data envelopment analysis model, the two principal processes through which banks generate revenue were considered, and the research variables were selected based on these processes. Library-based methods were employed to develop the literature review and formulate the mathematical model. The proposed model was solved using actual data collected through fieldwork from bank branches in Qazvin Province. Using the proposed model, performance evaluation was conducted dynamically over several time periods.

The conceptual framework of the study was formulated as a dynamic two-stage model incorporating the principal revenue-generating processes of banks. The input variables in the first stage of the model were net loans and physical capital. Cash and net profit margin were considered the output variables of the first stage.

The first-stage output variables, namely cash and net profit margin, were considered inputs to the second stage. These variables therefore maintained the linkage between the two successive stages. Fixed assets and total deposits were also considered independent inputs to the second stage. The second-stage outputs consisted of total shareholders' equity and total assets.

The mathematical model used to analyze the data is presented in Equation (1).

The variable x_{ikj}^{t}represents input $i$of stage $k$for bank $j$during time period t.

The variable y_{rkj}^{t}represents output $r$of stage $k$for bank $j$during time period t.

The variable $z_{l(kh)j}^{t}$represents the input/output link variable of bank j, connecting substructure $k$to substructure $h$during time period t.

The variable $z_{l(kh)j}^{t}$represents the input/output link variable of bank j, connecting substructure $k$to substructure $h$during time period t.

These variables respectively represent the first-stage outputs and second-stage inputs of each bank during each time period.

$$\sum_{i=1}^{m_k} W_{ko}\,\theta_{ko} \qquad (1)$$

Subject to:

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, y_{rkj}^{t} \geq \theta_{ko} x_{iko}^{t}, i = 1, \dots, m_k$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, y_{rkj}^{t} \geq y_{rko}^{t}, r = 1, \dots, r_k$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, \alpha_{l(kh)j}^{t} Z_{sh(kh)j}^{t} \geq \alpha_{l(kh)o}^{t} Z_{sh(kh)o}^{t}, l = 1, \dots, L_{shkh}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, \beta_{lkj}^{t} Z_{shlkj}^{(t,t+1)} \geq \beta_{lko}^{t} Z_{shlko}^{(t,t+1)}, l = 1, \dots, L_{shk}$$

$$\sum_{j=1}^{n} \lambda_{hj}^{t}\, Z_{l(kh)j}^{t} \geq Z_{l(kh)o}^{t}, l = 1, \dots, L_{kh}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, Z_{l(hk)j}^{t} \leq Z_{l(hk)o}^{t}, l = 1, \dots, L_{hk}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, Z_{lkj}^{(t,t+1)} \geq Z_{lko}^{(t,t+1)}, l = 1, \dots, L_k$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t+1}\, Z_{lkj}^{(t,t+1)} \leq Z_{lko}^{(t,t+1)}, l = 1, \dots, L_k$$

$$\sum_{j=1}^{n} \lambda_{hj}^{t}\, \left(1-\alpha_{l(kh)j}^{t}\right) Z_{shl(kh)j}^{t} \geq \left(1-\alpha_{l(kh)o}^{t}\right) Z_{sh(kh)o}^{t}, l = 1, \dots, L_{shkh}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, \left(1-\alpha_{l(hk)j}^{t}\right) Z_{sh(hk)j}^{t} \leq \left(1-\alpha_{l(hk)o}^{t}\right) Z_{sh(hk)o}^{t}, l = 1, \dots, L_{shhk}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t}\, (1-\beta_{lkj}^{t}) Z_{shlkj}^{(t,t+1)} \geq (1-\beta_{lko}^{t}) Z_{shlko}^{(t,t+1)}, l = 1, \dots, L_{shk}$$

$$\sum_{j=1}^{n} \lambda_{kj}^{t+1} \left(1-\beta_{lkj}^{t}\right) Z_{shlkj}^{(t,t+1)} \leq \left(1-\beta_{lko}^{t}\right) Z_{shlko}^{(t,t+1)}, l = 1, \dots, L_{shk}$$

$$W_{kj} \geq 0.2, \forall k, j$$

$$\sum_{k=1}^{K} W_{kj} = 1, \forall j$$

$$0 \leq \alpha_{l(kh)j}^{t} \leq 0, \forall l, k, j$$

$$0 \leq \beta_{lkj}^{t} \leq 0, \forall l, k, j$$

$$\lambda_{kj}^{t+1}, \lambda_{kj}^{t}, x_{iko}^{t} \geq 0$$

3. Findings and Results

The proposed model was applied to evaluate the performance of 20 bank branches in Qazvin Province over three time periods. The data and information required for the study were obtained from the website of the Securities and Exchange Organization and the financial reports published by each bank. The collected data pertained to the years 2023–2025. Data analysis was conducted using LINGO software, and the resulting findings are presented below. Table 1 presents the first-stage efficiency, second-stage efficiency, overall efficiency, normalized efficiency, and rankings of the 20 bank branches in 2023, as calculated using the model proposed in this article.

Table 1. First-Stage, Second-Stage, and Overall Efficiency of Banks in Qazvin Province in 2023

DMU	First-Stage Efficiency	Second-Stage Efficiency	Overall Efficiency	Normalized Efficiency	Rank
1	0.489687	0.254876	0.124809	0.481395	4
2	0.458875	0.254165	0.116629	0.449845	5
3	0.631548	0.325412	0.205513	0.792675	2
4	0.379079	0.202538	0.076778	0.296137	7
5	0.534924	0.168571	0.090173	0.347802	6
6	0.659908	0.056558	0.037323	0.143957	12
7	0.224925	0.060230	0.013547	0.052252	17
8	0.363695	0.051706	0.018805	0.072532	15
9	0.208158	0.051311	0.010681	0.041197	19
10	0.225659	0.091229	0.020587	0.079405	14
11	0.494586	0.016892	0.008354	0.032222	20
12	0.700453	0.369854	0.259265	1.000000	1
13	0.394775	0.033196	0.013105	0.050547	18
14	0.291970	0.080789	0.023588	0.090980	13
15	0.821911	0.057317	0.047110	0.181706	11
16	0.596314	0.104180	0.062124	0.239616	9
17	0.256287	0.062056	0.015904	0.061343	16
18	0.671795	0.108942	0.073187	0.282286	8
19	0.770261	0.066398	0.051144	0.197265	10
20	0.736548	0.263546	0.194114	0.748709	3
Mean	0.495568	0.133988	0.073137	0.282094	—

As shown in Table 1, the bank branches generally had a higher mean efficiency score in the first stage than in the second stage. The findings indicate that DMU 12 was the most efficient unit in the dataset. This result demonstrates the discriminatory power of the proposed model, as it effectively distinguishes among the decision-making units.

Table 2 presents the first-stage efficiency, second-stage efficiency, overall efficiency, normalized efficiency, and rankings of the 20 bank branches in 2024, as calculated using the model proposed in this article.

Table 2. First-Stage, Second-Stage, and Overall Efficiency of Banks in Qazvin Province in 2024

DMU	First-Stage Efficiency	Second-Stage Efficiency	Overall Efficiency	Normalized Efficiency	Rank
1	0.631596	0.721482	0.110363	0.721482	3
2	0.668824	0.593409	0.090772	0.593409	5
3	0.546007	1.000000	0.152967	1.000000	1
4	0.379079	0.501925	0.076778	0.501925	7

5	0.534924	0.589493	0.090173	0.589493	6
6	0.659908	0.243994	0.037323	0.243994	12
7	0.224925	0.088562	0.013547	0.088562	17
8	0.363695	0.122935	0.018805	0.122935	15
9	0.208158	0.069826	0.010681	0.069826	19
10	0.225659	0.134585	0.020587	0.134585	14
11	0.494586	0.054613	0.008354	0.054613	20
12	0.700453	0.699452	0.106993	0.699452	4
13	0.394775	0.085672	0.013105	0.085672	18
14	0.291970	0.154203	0.023588	0.154203	13
15	0.821911	0.307975	0.047110	0.307975	11
16	0.596314	0.406127	0.062124	0.406127	9
17	0.256287	0.103970	0.015904	0.103970	16
18	0.671795	0.478450	0.073187	0.478450	8
19	0.770261	0.334347	0.051144	0.334347	10
20	0.983411	0.790968	0.120992	0.790968	2
Mean	0.521227	0.103915	0.057225	0.374099	—

As shown in Table 2, DMU 3 ranked first in overall efficiency because it demonstrated favorable efficiency in both the first and second stages. Therefore, under the model proposed in this study, units can achieve a favorable overall efficiency ranking only when they perform well in both stages. DMU 20, which ranked second, provides an example of this pattern.

Table 3 presents the first-stage efficiency, second-stage efficiency, overall efficiency, normalized efficiency, and rankings of the 20 bank branches in 2025, as calculated using the model proposed in this article.

Table 3. First-Stage, Second-Stage, and Overall Efficiency of Banks in Qazvin Province in 2025

DMU	First-Stage Efficiency	Second-Stage Efficiency	Overall Efficiency	Normalized Efficiency	Rank
1	0.714599	0.152556	0.109016	0.794861	2
2	0.657841	0.145885	0.095961	0.699674	6
3	0.489554	0.280156	0.137151	1.000000	1
4	0.496522	0.202538	0.100564	0.733236	5
5	0.632549	0.168571	0.106629	0.777457	4
6	0.659908	0.056558	0.037323	0.272131	12
7	0.325487	0.060230	0.013547	0.098774	17
8	0.363695	0.051706	0.018805	0.137112	15
9	0.208158	0.051311	0.010681	0.077878	19
10	0.225659	0.091229	0.020587	0.150105	14
11	0.494586	0.016892	0.008354	0.060911	20
12	0.700453	0.152748	0.106993	0.780111	3
13	0.394775	0.033196	0.013105	0.095552	18
14	0.291970	0.080789	0.023588	0.171986	13
15	0.821911	0.057317	0.047110	0.343490	11
16	0.596314	0.104180	0.062124	0.452961	9
17	0.256287	0.062056	0.015904	0.115960	16
18	0.671795	0.108942	0.073187	0.533624	8
19	0.770261	0.066398	0.051144	0.372903	10
20	0.587545	0.145875	0.085708	0.624917	7
Mean	0.517993	0.104457	0.056874	0.414682	—

As shown in Table 3, DMU 3 ranked first in overall efficiency because it demonstrated favorable efficiency in both the first and second stages. Although DMU 15 demonstrated very high first-stage efficiency, its low second-stage efficiency resulted in an overall ranking of 11th. Therefore, under the model proposed in this study, units can achieve a favorable overall efficiency ranking only when they perform well in both stages.

Table 4. Overall Efficiency and Ranking of Banks in Qazvin Province Across All Years

DMU	2023	2024	2025	Mean	Rank
1	0.481395	0.721482	0.794861	0.665913	4
2	0.449845	0.593409	0.699674	0.580976	5
3	0.792675	1.000000	1.000000	0.930892	1
4	0.296137	0.501925	0.733236	0.510433	7
5	0.347802	0.589493	0.777457	0.571584	6
6	0.143957	0.243994	0.272131	0.220027	12
7	0.052252	0.088562	0.098774	0.079863	17
8	0.072532	0.122935	0.137112	0.110860	15
9	0.041197	0.069826	0.077878	0.062967	19
10	0.079405	0.134585	0.150105	0.121365	14
11	0.032222	0.054613	0.060911	0.049249	20
12	1.000000	0.699452	0.780111	0.826521	2
13	0.050547	0.085672	0.095552	0.077257	18
14	0.090980	0.154203	0.171986	0.139056	13
15	0.181706	0.307975	0.343490	0.277724	11
16	0.239616	0.406127	0.452961	0.366235	9
17	0.061343	0.103970	0.115960	0.093758	16
18	0.282286	0.478450	0.533624	0.431453	8
19	0.197265	0.334347	0.372903	0.301505	10
20	0.748709	0.790968	0.624917	0.721531	3

As shown in Table 4, DMU 3 had the highest efficiency in the dataset, with a mean efficiency score of 0.930892. It was followed by DMU 12, with a mean score of 0.826521, and DMU 20, with a mean score of 0.721531, which ranked second and third, respectively. DMU 11 was the least efficient branch among the 20 branches.

4. Discussion and Conclusion

The purpose of this study was to evaluate the performance of 20 bank branches in Qazvin Province over three consecutive periods using a dynamic two-stage network data envelopment analysis model. The findings showed substantial differences among the decision-making units in first-stage efficiency, second-stage efficiency, overall efficiency, and normalized efficiency. The results also indicated that the efficiency of the branches could not be adequately interpreted on the basis of a single-stage or single-period assessment. In most cases, strong performance in only one stage was insufficient to produce a favorable overall ranking. Instead, the highest-ranked branches were those that maintained a relatively balanced level of performance across both stages. This pattern supports the central premise of network DEA, according to which organizational efficiency is determined by the performance of interconnected internal processes rather than solely by the aggregate relationship between initial inputs and final outputs [3, 6].

The results for 2023 showed that the mean first-stage efficiency score was 0.495568, whereas the mean second-stage efficiency score was only 0.133988. The corresponding mean overall efficiency and normalized efficiency scores were 0.073137and 0.282094, respectively. These findings indicate that the bank branches were generally more successful in converting the initial inputs of net loans and physical capital into the intermediate outputs of cash and net profit margin than in transforming those intermediate outcomes, together with fixed assets and total deposits, into total shareholders’ equity and total assets. In other words, the principal source of inefficiency in 2023 was concentrated in the second stage of the banking process. This result demonstrates the importance of decomposing overall efficiency because a conventional black-box model might have identified inefficient branches without revealing that their weaknesses were mainly associated with the second-stage conversion process. Previous research has similarly shown that two-stage network DEA provides a more informative assessment than aggregate models by identifying the stage in which inefficient transformation occurs [3, 5].

In 2023, DMU 12 achieved the highest normalized efficiency score of 1.000000, followed by DMU 3 with 0.792675and DMU 20 with 0.748709. DMU 12 also had relatively strong efficiency in both stages, with scores of 0.700453and 0.369854, resulting in the highest overall efficiency score of 0.259265. This finding indicates that DMU 12 was able to maintain a better balance between the first-stage and second-stage processes than the other branches. Its superior performance was not attributable to dominance in only one component but rather to the effective integration of its internal activities. This result is consistent with the logic of dynamic network efficiency assessment, which emphasizes that the performance of a decision-making unit depends on the coordination of its constituent stages and the efficient use of intermediate products [6, 8]. The finding also confirms the discriminatory power of the proposed model, as it was able to distinguish the reference branch from other units that performed strongly in only one stage.

The results also revealed that high first-stage efficiency did not necessarily guarantee a favorable overall ranking. For example, DMU 15 had the highest first-stage efficiency score in 2023, with a value of 0.821911, but its second-stage efficiency was only 0.057317. Consequently, its normalized efficiency score was 0.181706, and it ranked 11th. Similarly, DMU 19 achieved a first-stage efficiency score of 0.770261but had a second-stage score of only 0.066398, placing it 10th overall. These findings show that branches may successfully generate intermediate financial outcomes from their initial resources yet fail to use those outcomes effectively to create final financial value. This imbalance can reflect weaknesses in asset utilization, deposit management, capital conversion, or coordination between lending and resource-allocation activities. Comparable findings have been reported in network efficiency studies, where a strong upstream stage was unable to compensate fully for inefficiency in a downstream stage [3, 5].

The 2024 results showed a change in the efficiency structure of the branches. The mean first-stage efficiency increased from 0.495568in 2023 to 0.521227in 2024, whereas the reported mean second-stage efficiency was 0.103915, the mean overall efficiency was 0.057225, and the mean normalized efficiency increased to 0.374099. Although the average raw second-stage and overall efficiency scores remained relatively low, the improvement in mean normalized efficiency suggests that the relative position of several branches improved within the observed frontier. This pattern may indicate that some units became more effective in coordinating internal processes, even though absolute performance remained constrained. Dynamic DEA research has emphasized that changes in relative efficiency over time should be interpreted in relation to shifts in the production frontier and the performance of peer units rather than as direct evidence of uniform absolute improvement [2, 6].

DMU 3 ranked first in 2024, with a normalized efficiency score of 1.000000. Its first-stage efficiency score was 0.546007, while its second-stage efficiency reached 1.000000. This result indicates that the branch's leading position was mainly supported by full efficiency in the second stage, combined with acceptable performance in the first stage. DMU 20 ranked second, with first-stage and second-stage efficiency scores of 0.983411and 0.790968, respectively. Compared with DMU 3, DMU 20 displayed a more balanced profile across the two stages, although it did not achieve full normalized efficiency. The strong position of these two branches supports the proposition that favorable overall rankings are associated with the capacity to perform effectively throughout the internal network. Similar conclusions have emerged from dynamic multiactivity and multistage DEA applications, in which efficient units were characterized by coordination among interconnected processes rather than isolated excellence in one activity [7, 8].

The performance of DMU 20 in 2024 is particularly noteworthy because it achieved the highest first-stage efficiency among the branches, at 0.983411, while also maintaining a comparatively high second-stage score of 0.790968. This indicates that the branch was highly effective in converting net loans and physical capital into cash and net profit margin and was also successful in using intermediate outputs, fixed assets, and deposits to generate assets and shareholders' equity. Its second-place ranking therefore reflects balanced internal performance rather than an isolated advantage. This finding aligns with studies applying dynamic network DEA to commercial banking, which have shown that operational efficiency depends on the integrated management of credit generation, risk, financial resources, and downstream outcomes [2]. It is also consistent with broader applications demonstrating that efficiency improves when decision-making units maintain coordination between upstream resource transformation and downstream value generation [9, 10].

The 2025 findings again identified DMU 3 as the most efficient branch, with a normalized efficiency score of 1.000000. Its first-stage efficiency was 0.489554, and its second-stage efficiency was 0.280156. Although neither stage reached full efficiency individually, the branch achieved the highest relative overall position among the observed units. This finding illustrates an important feature of network DEA: a branch does not necessarily need to dominate every stage independently to achieve the best overall ranking. Rather, its relative combination of stage efficiencies, intermediate linkages, and weighted performance may position it on the system frontier. Efficiency decomposition and frontier-projection studies have similarly demonstrated that system efficiency is not always equivalent to the maximum divisional score and instead reflects the interaction among internal stages and their assigned weights [3].

In 2025, DMU 1 ranked second with a normalized efficiency score of 0.794861, followed by DMU 12 with 0.780111and DMU 5 with 0.777457. These branches demonstrated relatively favorable combinations of first-stage and second-stage efficiency. By contrast, DMU 15 again had a very high first-stage score of 0.821911but a low second-stage score of 0.057317, resulting in an 11th-place ranking. The persistence of this pattern across periods suggests that the inefficiency of some branches was structural rather than temporary. In particular, repeated weakness in the second stage may indicate that these branches were unable to convert intermediate financial resources into final balance-sheet outcomes effectively. Dynamic network studies have highlighted the importance of identifying persistent stage-specific inefficiency because corrective actions differ depending on whether inefficiency arises from resource acquisition, intermediate production, final-output generation, or interperiod carry-over relationships [6, 7].

The three-period analysis presented in Table 4 provides a more stable basis for comparing the branches than any single-year ranking. DMU 3 had the highest mean normalized efficiency score across the three periods, at 0.930892, followed by DMU 12 with 0.826521and DMU 20 with 0.721531. These results indicate that DMU 3 was the strongest branch in terms of sustained relative performance, even though it did not rank first in 2023. Its progression from second place in 2023 to first place in both 2024 and 2025 suggests that the branch improved its relative position and maintained that improvement over time. This dynamic pattern would not be fully visible in a static, one-period analysis. Multi-period DEA models are specifically designed to capture such changes by incorporating temporal continuity and evaluating how performance develops across successive periods [2, 6].

DMU 12 exhibited a different temporal pattern. It ranked first in 2023 but declined to fourth place in 2024 before recovering to third place in 2025. Its three-period mean nevertheless remained high enough to secure second place overall. This finding shows that a strong long-term position may coexist with year-to-year variability. The decline in relative ranking may have resulted from changes in the branch's own performance, improvements among competing branches, or movement in the efficiency frontier. Dynamic DEA distinguishes such temporal variation more effectively than cross-sectional analysis because it evaluates performance within an interrelated sequence rather than as isolated annual observations. Studies using dynamic network approaches in banking, utilities, and service systems have likewise demonstrated that decision-making units can experience fluctuating annual rankings while maintaining relatively strong long-term efficiency [2, 7, 8].

DMU 20 ranked third over the full period, with a mean normalized efficiency of 0.721531. Its annual scores were 0.748709, 0.790968, and 0.624917, indicating strong performance in the first two periods followed by a decline in 2025. Despite this reduction, the branch remained among the top-performing units overall. The result suggests that DMU 20 possessed considerable operational strength but may have experienced a deterioration in one or both internal stages in the final period. Such changes emphasize the need for ongoing monitoring because a branch that performs efficiently in one or two years may not automatically sustain that position. Dynamic performance evaluation provides managers with an early warning mechanism by identifying declining efficiency before it becomes reflected in more severe financial outcomes. The usefulness of longitudinal efficiency measurement for recognizing performance deterioration has also been emphasized in dynamic network studies of transport, banking, and public service operations [2, 9, 10].

At the lower end of the ranking, DMU 11 had the lowest three-period mean normalized efficiency score, at 0.049249, and ranked 20th in every year. DMU 9 ranked 19th overall with a mean score of 0.062967, while DMU 13 ranked 18th with 0.077257. The consistently weak position of DMU 11 indicates persistent inefficiency rather than a temporary deviation. Its first-stage efficiency was moderate relative to some low-ranking units, but its second-stage efficiency was extremely low in all three periods. This suggests that the branch's main weakness was not necessarily the generation of intermediate outputs but the conversion of those outputs into total assets and shareholders' equity. Network DEA is particularly valuable in such cases because it prevents management from applying generalized solutions to a stage-specific problem. Research on efficiency decomposition has shown that improvement strategies should be directed toward the inefficient division rather than uniformly reducing all inputs or increasing all outputs [3].

The overall pattern of results indicates that second-stage inefficiency was a major constraint on bank branch performance. Across all three years, the mean first-stage efficiency was substantially higher than the mean second-stage efficiency. This suggests that the branches were comparatively more capable of using net loans and physical capital to generate cash and net profit margin than of converting intermediate financial outputs, fixed assets, and deposits into total assets and equity. From a managerial perspective, this may imply weaknesses in balance-sheet management, capital utilization, asset growth strategies, or the productive deployment of deposits. Research on commercial bank efficiency has similarly shown that weaknesses in downstream financial processes, including the conversion of credit and funding resources into sustainable financial outcomes, can significantly reduce overall operational efficiency [1, 2]. The result also reinforces the need to assess financial sustainability alongside technical efficiency because strong resource transformation does not necessarily guarantee sustainable value creation.

The findings further demonstrate that efficiency evaluation should not be reduced to profitability or asset size. Some branches with strong first-stage scores did not achieve high final rankings, whereas other branches with moderate first-stage performance achieved superior overall efficiency through stronger second-stage outcomes. This indicates that efficient banking operations depend on the quality of internal coordination rather than on the magnitude of any single financial indicator. Recent bank sustainability research has similarly argued that performance assessment should integrate multiple operational and financial dimensions and should provide explanations for the observed efficiency scores [1]. The present results support this perspective by showing that a network representation produces more managerially meaningful distinctions than a single aggregate measure.

The findings are also consistent with evidence from nonbanking sectors. Studies of urban water utilities, hospital pharmacies, municipal waste services, regional transportation, and industrial environmental governance have found that overall efficiency is influenced by the interaction of multiple stages, activities, and periods [5, 7-10]. Although these sectors differ from banking, they share important structural characteristics, including interconnected subprocesses, intermediate products, carry-over effects, and multiple performance objectives. The agreement between the present results and these studies strengthens the argument that dynamic network DEA is an appropriate framework for evaluating organizations whose outputs emerge through sequential and temporally connected processes.

Another important implication concerns the relative nature of DEA efficiency. A score of 1indicates that a branch is efficient relative to the observed comparison set and the specified model, not that it has achieved absolute or universal efficiency. Consequently, the leading branches should be regarded as internal benchmarks under the existing data and model structure. Their practices may provide useful reference points for lower-performing branches, but managers should also examine whether their performance is sustainable under changing market conditions. The integration of DEA with predictive and explainable analytical techniques has been proposed as a way to identify the determinants of efficiency and improve the interpretation of benchmark results [1]. Likewise, fuzzy DEA approaches may be useful when data are uncertain or when qualitative judgments must be incorporated into performance evaluation [4].

Overall, the results confirm that the proposed dynamic two-stage network DEA model provides a detailed and discriminating assessment of bank branch performance. It identifies the most efficient branches, reveals the stage responsible for inefficiency, and traces changes in relative performance across multiple periods. The model showed that sustained efficiency was associated with balanced performance across both stages, whereas branches with strong first-stage efficiency but weak second-stage efficiency generally received lower overall rankings. These findings are aligned with previous methodological and applied studies demonstrating the advantages of network decomposition, dynamic linkage, and multi-period analysis for organizational performance evaluation [2, 3, 6]. The results therefore support the use of dynamic network DEA as a practical decision-support instrument for bank managers seeking to improve branch-level resource allocation and long-term financial performance.

This study has several limitations that should be considered when interpreting the findings. First, the analysis was limited to 20 bank branches in Qazvin Province, and the results may therefore not be generalizable to branches operating in other provinces or under different economic and competitive conditions. Second, the model was estimated using a specific set of financial inputs, intermediate variables, and outputs; other relevant factors, such as the number of employees, operating expenses, nonperforming loans, customer satisfaction, service quality, digital banking activity, branch location, and local market conditions, were not included. Third, the three-period timeframe provides a useful dynamic perspective but may not be sufficient to identify long-term structural trends or economic-cycle effects. Fourth, DEA results are sensitive to the selection and measurement of variables, the composition of the comparison set, and potential data errors. Finally, the model measures relative technical efficiency and does not directly identify the causal factors underlying the observed differences among branches.

Future studies should extend the analysis to a larger sample of branches from multiple provinces and banking institutions to improve the generalizability and comparative value of the findings. Longer time horizons should be used to examine the persistence of efficiency and the effects of economic fluctuations, regulatory changes, inflation, and banking-sector reforms. Researchers may also incorporate risk-related and service-related indicators, including credit risk, nonperforming loans, operational costs, employee productivity, customer satisfaction, digital service utilization, and market potential. Future models could compare constant-returns-to-scale and variable-returns-to-scale assumptions, distinguish pure technical efficiency from scale efficiency, and apply metafrontier methods to account for heterogeneous operating environments. The integration of dynamic network DEA with the Malmquist productivity index, bootstrapping, fuzzy models, machine-learning methods, and sensitivity analysis may also provide more robust and explanatory results. Qualitative studies involving branch managers could further clarify the organizational and managerial factors responsible for persistent stage-specific inefficiency.

Bank managers should use stage-specific efficiency scores rather than relying only on overall rankings. Branches with weak first-stage efficiency should review the allocation of loans, physical capital, and other initial resources, whereas branches with weak second-stage efficiency should focus on the productive use of cash, net profit margin, fixed assets, and deposits to strengthen asset and equity generation. High-performing branches, particularly DMUs 3, 12, and 20, can be used as internal benchmarks, but their operational practices should be examined carefully before being transferred to branches operating under different local conditions. Persistently inefficient units, especially DMU 11, require targeted performance-improvement plans rather than uniform resource reductions. Management should conduct periodic dynamic efficiency assessments, establish stage-level performance targets, and link branch evaluation to resource-allocation, training, risk-management, and strategic-planning decisions.

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Authors equally contributed to this article.

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All procedures performed in this study were under the ethical standards.

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