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Fintech Contribution to Health Sector Performance in Waemu

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Abstract

The recent emergence of financial technologies (Fintech) in the countries of the West African Economic and Monetary Union (WAEMU) has sparked growing interest, particularly with regard to their impact on the health sector. This study analyses the contribution of Fintech to the performance of health systems in the eight countries of the Union over the period 2011-2021. Methodologically, it uses two approaches : the double bootstrap DEA method developed by Simar and Wilson (2007) and the quantile moments method developed by Machado and Silva (2019). The results indicate that healthcare systems in the region are marked by technical inefficiency, with an average corrected score of 55.3%. Furthermore, the positive effect of Fintech appears to be particularly pronounced in countries with the lowest levels of healthcare performance (quantiles 10, 25 and 50).

JEL classification: O33, D24, I10, C15, C21.
Keywords: Fintech, Performance, Health Systems, Double Bootstrap DEA, Quantile Moments.

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1. Introduction

According to the theory of endogenous growth, human capital, defined as the sum of knowledge, skills, experiences, and personal attributes that individuals accumulate and that enhance their ability to produce goods and services, plays a crucial role in economic growth and development. However, to fully leverage the potential of human capital, an essential prerequisite is health. Indeed, a healthy population not only constitutes a productive workforce but is also essential for the overall well-being of society (Borgonovi et al., 2018). Unfortunately, in many developing countries, particularly in West Africa, health systems are often characterized by poor performance. This is reflected in a life expectancy of 63 years on average at birth within the union and an average infant mortality rate of 60 deaths per thousand live births (WDI, 2021).

According to WHO (2012), this poor performance is due, among other factors, to several doctors per capita that is well below the recommended standard, inadequate and outdated health infrastructure, and the exorbitant cost of medical care in a context of precarious income. Consequently, this poor performance leads to reduced life expectancy and higher mortality rates compared to other regions (Kizito et al., 2012). Additionally, there is a disparity in performance levels within the union. In terms of life expectancy at birth, there are, respectively, 60 years in Burkina Faso, 59 years in Côte d'Ivoire, 60 years in Mali, and notably 62 years in Niger (WDI, 2021). Regarding infant mortality rates, there are, respectively, 60 deaths per 1,000 births in Côte d'Ivoire, 88 deaths per 1,000 births in Guinea-Bissau, 76 deaths per 1,000 births in Mali, and 80 deaths per 1,000 births in Niger (WDI, 2021).

Recently, the rise of financial technologies, widely known as Fintech, has attracted global attention. These advances have radically transformed the banking sector, fundamentally reshaping how financial transactions are executed and supervised. By introducing digital solutions, Fintech have improved efficiency, reduced costs, and expanded access to financial services for millions of people worldwide (Aker and Mbiti, 2010; Aron, 2018). This digital transformation in finance has sparked a growing interest in leveraging Fintech technologies in various fields, including health. The potential influence of Fintech on the health sector is now seen as a promising path to improve the efficiency of health systems, especially in developing countries (Wiedmaier-Pfister and Leach, 2015).

This trend can also be observed among WAEMU countries, although the trends are somewhat less pronounced. The adoption rate of digital financial services within the union increased from 2% in 2010 to 59% in 2021 (BCEAO, 2021). Nevertheless, these statistics highlight significant differences between countries in 2021, with 90% in Côte d'Ivoire, 43% in Senegal, 33% in Mali, and only 3.62% in Niger (BCEAO, 2021).

The literature indicates that financial technology (Fintech) improves financial inclusion and increases individuals' income. These technologies can significantly improve access to healthcare by minimizing payment system inefficiencies and streamlining medical transactions, notably through implementing digital payment systems and online health insurance (Asongu et al., 2023; Lucero-Prisno et al., 2022). Cambaza (2023) suggests that specific financial technologies, such as blockchain, provide a secure and transparent infrastructure for managing medical information.

Moreover, the introduction of Fintech has paved the way for alternative financing methods that are less restrictive than traditional methods. These platforms facilitate funding through crowdfunding and peer-to-peer solutions, enabling companies and institutions to raise the necessary funds to finance projects in the health sector (Meiling et al., 2021; Kenworthy, 2019). Finally, Jing et al. (2022) emphasized that using machine learning methods can significantly improve the quality of diagnosis thanks to their advanced predictive capabilities. This ability enables healthcare professionals to detect diseases earlier, refine treatment recommendations, and overall improve medical outcomes.

The integration of machine learning into medical diagnostic practices is highly promising for more personalized and effective care by leveraging data to support smarter clinical decisions tailored to each patient. Based on the literature review, most studies acknowledge the benefits of Fintech in the health sector. Recent empirical verifications in developing countries, such as the West African Economic and Monetary

Union, point in this direction. Therefore, this study focuses on Fintech's contribution to the performance of health systems in WAEMU countries.

The interest of this study is twofold. First, most studies focused on the impact of financial technology on health, notably Meiling et al. (2021) and Jing et al. (2022), use individual indicators such as mortality and life expectancy to measure performance. While these variables provide an important perspective, their selection does not reflect the overall performance of the health system. Indeed, these isolated indicators do not account for the complexity and interdependence of different aspects of the health system. This study aims to analyze the overall performance of the health system by adopting a more comprehensive and integrated approach. It examines the impact of Fintech technologies while assessing the performance of health systems, considering a range of factors and dynamics that influence the overall performance of these systems.

Secondly, given the heterogeneity of economic development within the Alliance, it is important to recognize that the effects of Fintech may vary depending on the performance level of each country's health system. This variability requires a method capable of accurately capturing these differences. To assess this impact according to different performance levels, the quantile moments method developed by Machado and Silva (2019) was used. This innovative approach allows for the analysis of the impact of Fintech on health systems at different points of performance distribution, thus providing a more nuanced understanding of its impact.

Through this approach, it is possible not only to determine the impact of Fintech on the health system as a whole but also to understand how this impact differs between countries with low and high health performance levels. This takes into account the heterogeneity of the countries and adapts policy recommendations to the specific needs of each group of countries.

The rest of this article is structured as follows. The first part concerns the literature review, the second part focuses on the methodological framework, the third part highlights the interpretation and discussion of the results, and it concludes with the conclusion.

2. Literature review

Fintech has recently attracted keen interest in professional and academic circles due to its potential impacts on the health sector. Several studies have been conducted in response to these reflections, some of which have focused on the ability of financial technologies to facilitate access to medical care. Ahmed and Cowan (2021) studied the impact of mobile money transfers on healthcare utilization in western Kenya from a microeconomic perspective. According to their findings, these services, thanks to the increased ease of informal borrowing, encourage households to increase their use of formal healthcare services, particularly clinical visits, consultations, and spending on medicines, compared to those who do not use them.

Based on the study on household living standards in Ghana, Bukari and Koomson (2020) demonstrate that rural households' access to healthcare is improved through the adoption of payments, with a particularly marked impact in large households. Baridam and Govender (2019) study the impact of information and communication technologies (ICT) on health in the Niger Delta, a major oil region in Nigeria. Their conclusion shows that the use of ICT remains relatively low in the provision of healthcare services and that more significant integration of these technologies could significantly impact improving health services in this region.

Alongside microeconomic research, other researchers have studied the impact of Fintech on health outcomes in a macroeconomic context. For example, Dutta and al. (2019) studied the impact of these technologies on health in 30 Asian countries from 2000 to 2016. Using FMOLS and DOLS techniques, they find that these technologies contribute to improving health performance in these countries. In the same context, Jing and al. (2022) studied the impact of Fintech in 18 Asian countries between 2007 and 2019. They demonstrated the positive effects of these technologies on health using two-stage least squares (2SLS) and system GMM, particularly by reducing the infant mortality rate and increasing life expectancy.

Furthermore, Asongu and al. (2023) conducted a study on a sample of 43 sub-Saharan African countries using quantile regressions. According to these authors, advances in mobile money are relevant for improving health outcomes in countries where life expectancy is below average. In contrast to this research, Meiling and al. (2021) examine the impact of Fintech on health enterprise outcomes in a sample of 11 Asia-Pacific countries. The authors observe that using the system GMM improves the performance of health enterprises through digital financial technologies. Moreover, the evolution of information and communication technologies reinforces the correlation between financial development and health enterprise outcomes.

At the end of this study, there seems to be a general trend regarding the benefits brought by the emergence of Fintech in the health sector, even though empirical studies on this subject are still recent in sub-Saharan Africa. Moreover, life expectancy and infant mortality rates are often used as health indicators in available macroeconomic studies to assess performance.

This study differs from previous ones by including the overall performance of the health system and considering differences in performance levels between states, to consider essential aspects such as accessibility, quality of care, availability and quality of health infrastructure, and equity in the distribution of medical resources. Policymakers and stakeholders could be further guided by this perspective to maximize the benefits of Fintech in the health sector.

3. Methodology

This research is conducted according to two main axes. The first is to assess the impact of Fintech on the performance of health systems, while the second examines this impact according to the performance distribution level. Two approaches were employed to achieve these objectives: the Simar and Wilson (2007) double bootstrap DEA and the Machado and Silva (2019) quantile moments method.

3.1 Double Bootstrap DEA Method

In specialized literature, frontier analysis methods are often used to assess the performance of health systems, allowing for an understanding of their efficiency. So far, three main frontier analysis approaches have been distinguished: the non-parametric approach, the parametric approach, and the semi-parametric approach. Mathematical programming is used for the first, called Data Envelopment Analysis (DEA). The second is based on an econometric approach known as Stochastic Frontier Analysis (SFA). Finally, the third option, double bootstrap DEA, is an improvement of the first, considering its various limitations and difficulties. These three approaches have in common the work of Farrell (1957).

Indeed, the parametric approach is used when there is a single output and multiple inputs. However, when multiple sources of energy and inputs exist, using the DEA method (non-parametric approach) can lead to an overestimation bias. This can happen due to overestimating efficiency scores due to the correlation between input and output variables or if the selected output parameters are inadequate. One of the main disadvantages of this method is its complete ignorance of the existence of random shocks and the statistical properties associated with the error term, which can lead to biased scores (Wijesiri et al., 2015) and unbalanced economic policies.

To address these issues, it is essential to use the two-stage double bootstrap DEA method suggested by Simar and Wilson (2007) to obtain unbiased efficiency scores.

In short, while the DEA method offers benefits such as its flexibility, it also presents limitations, such as the risk of overestimation, which is essential to consider when making estimates. In this situation, it is crucial to use bias correction methods, such as bootstrap methods. Unlike other simulation methods (Monte-Carlo, Bayesian, Jackknife, etc.), the bootstrap only deals with the information available in the original sample.

Since non-parametric methods have limitations, a semi-parametric approach has been developed to solve measurement problems. This method mainly uses non-parametric methods, such as DEA, to correct the biases that it does not consider. In this article, we opted for Algorithm 2 because of its multiple benefits.

Step 1: Measuring Efficiency Using DEA Method
Estimating the efficiency of health systems in different countries by DEA involves solving K linear programs for each health system, given an input level and an output level, as follows:

$$TE_1(x,y) = \theta\{\theta / \theta \succ 0;\}$$
$$y_i \leq \sum_{i=1}^{n} \lambda_i y_i$$
$$x_i \geq \sum_{i=1}^{n} \lambda_i y_i \tag{1}$$
$$\sum_{i=1}^{n} \lambda_i = 1$$
$$\lambda_i \geq 0; i = 1, \ldots.. n$$

With the input vector X_i, the output vector Y_i for each country i, and θ_i an optimization parameter. By hypothesis, technical efficiency θ_i cannot be negative or greater than one; in other words, $0 \leq \theta_i \leq 1$.
To determine the efficiency scores of health systems, the input-oriented DEA model with variable returns to scale was chosen. This orientation is selected due to the difficulty of controlling health outcomes without mastering production factors such as capital and labor. Indeed, health outcomes generally escape decision-makers (like the state), while the decision to allocate production factors falls under the purview of the states and the relevant ministries. Services provided by the state to citizens are assumed to be exogenous (Kounetas and Papathanassopoulos, 2013). As for the assumption of variable returns to scale adopted in our analysis, it is justified by the fact that health systems, especially in developing countries, do not generally operate at an optimal scale. While efficiency scores provide information on the performance level of the units (countries), they do not explain the causes or identify the levers that could improve or maintain this performance, which is crucial for all public policies. This underscores the importance of the second step of our analysis, which aims to identify the determinants of technical efficiency.

Step 2: Double Bootstrap DEA or Algorithm 2 of Simar and Wilson (2007)
The determinants of technical efficiency in WAEMU countries' health systems are estimated by regressing efficiency scores on explanatory variables. This two-step approach requires that the explanatory variables in the second step must not be correlated with the variables in the first step, i.e., the inputs and outputs used in the DEA method (Coelli et al., 1998). The literature distinguishes two types of estimation models that Simar and Wilson (2007) improved in Algorithm 2 by applying the double bootstrap. This process involves a truncated regression with double bootstrap using the maximum likelihood method (looping over DEA). Besides inference issues, the use of standard methods (Tobit and truncated regression) also raises the question of efficiency score bias due to the correlation between environmental variables and the error term (Tauchmann, 2015; Simar and Wilson, 2007). To circumvent this problem, the second algorithm integrates a parametric bootstrap in the first step to account for the efficiency score bias and obtain corrected scores. This involves double resampling of the original data with looping. The estimation model for the determinants of the efficiency scores of the health systems of the countries concerned strictly follows Algorithm 2 of Simar and Wilson (2007), whose main steps are as follows:
Starting from the initial sample, technical efficiency scores are estimated under input-oriented DEA: $\widehat{\theta}\left(i = 1, \ldots\ldots\ldots n\right)$.

The estimators $\widehat{\beta}$ are obtained from a truncated regression $0 \prec \widehat{\theta}_i - \beta z_i + \varepsilon_i \leq 1$, using $m \prec n$ observations with $\widehat{\theta} \prec 1$, $\widehat{\theta}_i$ is the technical efficiency score of the health system of the country i estimated under DEA, ε_i is normally distributed with a left truncation at $-z_i\widehat{\beta}$ and a right truncation at $1 - z_i\widehat{\beta}$, z_i

is the vector of environmental variables that affect the efficiency of the health systems, and β is the vector of parameters to be estimated.
Through four successive iterations, a bootstrap sample of estimators is drawn $L_1 = 1000$ times, a bootstrap sample of estimators $B_i = \left\{\widehat{\theta}_{ib}^*\right\}_{b=1}^{L_1}$; $i = 1,.....n$ is obtained. We have proceeded as follows:

For each $i = 1,.....n$, extract ε_i from the distribution $N\left(0;\widehat{\sigma}^2\right)$ truncated at the left at $-z_i\widehat{\beta}$ and truncated at the right at $1 - z_i\widehat{\beta}$.

Then calculate the estimator θ_i^* such that $\theta_i^* = z_i\widehat{\beta} + \varepsilon_i$; $i = 1,.....n$. (2)

Next, construct a pseudo-sample $\left(x_i^*, y_i^*\right)$, with $x_i^* = x_i$ and $y_i^* = y_i\widehat{\theta}_i / \theta_i^*$

The new DEA estimator or bootstrap estimator $\widehat{\theta}_i^*; i = 1,....n$ is calculated from the created pseudo-sample $\left(x_i^*, y_i^*\right)$; in other words, the variables X and Y are respectively replaced by $Y^* = \left\{y_i^*\ i = 1,......n\right\}$ et $X^* = \left\{x_i^*\ i = 1,......n\right\}$ in the initial program.

For each health system $\left(i = 1,.....n\right)$ the unbiased estimator $\widehat{\widehat{\theta}}_i\left(i = 1,.....n\right)$ is calculated using the bootstrap estimators B_i and the initial estimators $\widehat{\theta}_i$.

A truncated regression of $\widehat{\widehat{\theta}}_i\left(i = 1,.....n\right)$ on $z_i(i = 1,....n)$ is estimated to obtain the estimators $\widehat{\widehat{\beta}}$.

Through successive iterations (in three steps) $L_1 = 2000$ times, a bootstrap sample of estimators $\Delta = \left\{\widehat{\widehat{\beta}}_{ib}^*\right\}_{b=1}^{L_2}$; $i = 1,.....n$ is obtained. To do so, we proceed as follows:

For each $i = 1,....n$, extract ε_i from the distribution $N\left(0;\widehat{\widehat{\sigma}}^2\right)$ truncated at the left at $-z_i\widehat{\widehat{\beta}}$ and truncated at the right at $1 - z_i\widehat{\widehat{\beta}}$

Then calculate the estimator θ_i^{**} such that $\theta_i^{**} = z_i\widehat{\widehat{\beta}} + \varepsilon_i; i = 1,.....n$. (3)

A truncated regression by maximum likelihood of θ_i^{**} on z_i is estimated to obtain the estimators $\widehat{\widehat{\beta}}^*$.
Finally, the bootstrap estimators Δ and the initial estimators $\widehat{\widehat{\beta}}$ are used to construct the confidence intervals for each element β. The confidence interval for any β_j is constructed by finding the values $a_{\alpha/2}$ et $b_{\alpha/2}$

such that $P\left(-b_{\alpha/2} \leq \widehat{\beta}_j^* - \widehat{\beta}_j \leq -a_{\alpha/2}\right) = 1 - \alpha$, (4)

Which gives an estimated confidence interval of: $\left[\widehat{\beta}_j + a_{\alpha/2}; \widehat{\beta} + b_{\alpha/2}\right]$.

It should be noted that the bias in the Simar and Wilson (2007) double bootstrap DEA model is non-positive and is obtained as follows:

$$\widehat{\widehat{\beta}}_i = \widehat{\theta}_i - biais\left(\widehat{\theta}_i\right) \quad \text{with} \quad Biais\left(\widehat{\theta}_i\right) = \left(\frac{1}{L_1}\sum_{b=1}^{L_1}\widehat{\theta}_{ib}^*\right) - \widehat{\theta}_i \tag{5}$$

3.2 Quantile Moments Method (MMQR)

Once the efficiency scores have been calculated using the double bootstrap DEA, it is essential to determine whether Fintech has a similar influence on the health performance of countries with high scores as it does on those with low scores. Quantile regressions are estimation techniques designed to describe the impact of explanatory variables on a variable of interest across different levels of development or performance to account for heterogeneity. They are more robust and provide more precise information than classic linear regressions because they consider the conditional distribution of the variable of interest in its entirety, not just its mean. According to D'haultfœuille and Givord (2014), quantile regression can be more appropriate in the context of censored or truncated variables, as is the case in this study, where the variable of interest is truncated (Simar and Wilson, 2007).

Such an analysis implies that the impact of Fintech varies depending on the level of performance. From a methodological perspective, the Quantile Moments Method (MMQR) of Machado and Silva (2019) offers the ability to evaluate the variability of the effect according to quantiles. Based on the work of Koenker and Bassett (1978), quantile regression is an extension of ordinary least squares. Its advantage lies in its robustness to errors and outliers. Moreover, unlike the ordinary least squares method, which is subject to certain assumptions (normality, homoscedasticity, absence of outliers, etc.), quantile regression allows for complete relaxation of assumptions, making it a flexible method.

The MMQR method studies the impact of the conditional heterogeneous covariance of explanatory variables on the overall distribution of the dependent variable (performance) by allowing for the presence of an individual fixed effect. This method has the main benefit of considering potential endogenous variables among the explanatory variables. It is suitable for panels with individual effects, provides reliable estimates for nonlinear models, and accounts for possible asymmetries. Even if heterogeneity is not accounted for by fixed effects, the application of the MMQR method allows for addressing this issue due to its ability to provide heterogeneous estimates across the entire variance.

Furthermore, the heterogeneous coefficients indicate that the MMQR method addresses the issue of heterogeneity. The MMQR method is thus used because it handles heterogeneity and endogeneity by considering the asymmetric and nonlinear association between the dependent variable and the explanatory variables. Thus, the conditional quantiles $QY(\tau / X)$ are estimated as follows:

$$Y_{it} = \alpha_i + X_{it}^{'}\beta + (\delta_i + Z_{it}^{'}\gamma)U_{it} \tag{6}$$

The probability $P\{\delta_i + Z_{it}^{'}\gamma \succ 0\} = 1$. $(\alpha, \beta^{'}, \delta, \gamma)$ represents the parameters to be estimated. The individual fixed effects *i* are denoted by (α_i, δ_i), $i = 1, \ldots\ldots\ldots, n$, and the k-vector of recognized elements of X is indicated by Z which are differentiable transformations with the component l known as:

$$Z_l = Z_l(X), \quad l = 1, \ldots\ldots., k \tag{7}$$

all X_{it} are independently and identically distributed (iid) and are independent of time (t). U_{it} is independently and similarly distributed among individuals (i) and over time (t), and is orthogonal to X_{it} and normalized to meet the moment conditions of Machado and Silva (2019), which do not imply strict exogeneity. The above equation consequently implies the following:

$$Q_y(\tau / X_{it}) = (\alpha_i + \delta_i q(\tau)) + X_{it}^{'} + Z_{it}^{'}\gamma q(\tau) \tag{8}$$

with $X_{it}^{'}$ represents the vector of explanatory variables. The quantile distribution of the dependent variable (performance) is represented by $Q_y(\tau / X_{it})$ and this distribution postulates that the structural quantiles are distributed to the dependent variable Y_{it} based on the distribution (location) of the explanatory variables $X_{it}^{'}$.

The individual fixed effects (i) and the quantile fixed effects (τ) are demonstrated by the scalar coefficient:

$$-\alpha_i(\tau) = \alpha_i + \delta_i q(\tau) \tag{9}$$

The individual effect is not represented by the intercept shift, unlike the fixed effects characteristic of ordinary least squares. These parameters remain constant over time, with varied effects that can vary according to the conditional distribution quantiles of the endogenous variable. The sample quantile (τ) represented by $q(\tau)$ can be evaluated by addressing the resulting optimization problem written in the previous equation:

$$min_q \sum_i \sum_t \rho_\tau(R_{it} - (\delta_i + Z_{it}^{'}\gamma)q) \tag{10}$$

with $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A \succ 0\}$ indicating the check function.

3.3 Data and variables

The survey covers the eight member countries of WAEMU and spans a period of 11 years, from 2011 to 2021. The information used is primarily sourced from the BCEAO (2021) and WDI (2021). The performance of health systems is evaluated in this study based on technical efficiency estimated using the double bootstrap DEA method. The selection of input and output sources is based on studies (Tiehi, 2020; Diarrassouba, 2018; Coulibaly, 2018; Ataké, 2018). Three variables are selected as inputs in this document: the number of nurses and midwives, the number of doctors, and the number of beds. Regarding outcomes, life expectancy at birth and maternal mortality rate are considered.

In this study, financial technology (Fintech) is a variable of interest, assessed based on the rate of use of digital financial services. This measure reflects the acceptance of Fintech solutions by users, evaluating the use of digital financial services such as mobile payments and money transfers. According to Asongu et al., (2023), the growth in access to financial opportunities offered by Fintech allows financial institution clients to benefit from an increased ability to improve their socio-economic situation. These new opportunities can include improvements in well-being prospects, particularly positive effects on health.

The model includes control of corruption as an institutional variable. Corruption control is assessed on a scale from -2.5 to 2.5. A value close to the lower bound indicates an institutional environment characterized by high levels of corruption and fraud, while a value close to the upper bound indicates a high-quality institutional environment. According to Dukhan (2010), significant corruption can lead to the diversion of public resources intended for health towards other uses, potentially reducing the efficiency of health systems.

In analyzing the performance of health systems, population density, which measures the number of inhabitants per square kilometer, was selected as a variable to represent the importance of the high demographic growth that the sub-region has experienced for several years. Indeed, high population density can increase the use of health services and put more pressure on health systems (Ambapour, 2004). This situation can lead to more dysfunctions and thus decrease the performance of health systems.

The urbanization rate represents the growth of the population in urban areas, leading to the expansion of cities, transformation of landscapes, and concentration of economic and social activities in urban centers. Generally, it is associated with the creation of health infrastructures that benefit from superior technical facilities (Mbau et al., 2023).

Finally, education is evaluated based on the primary school enrollment rate. According to Hendi (2017), it plays a crucial role and is often linked to positive health outcomes.

Indeed, education enhances the skills of healthcare professionals, leading to more accurate diagnoses and more effective care. Furthermore, it informs the population about preventive measures and healthy lifestyle habits, contributing to a decrease in the frequency of diseases.

The summary of the variables is presented in the table below:

Table 1: Summary of Variables

	Variables	Definitions
Outputs	**Lif_exp**	Life expectancy at birth per year
	Mmr	Maternal mortality rate per 100,000 inhabitants
Inputs	**Nurse**	Number of nurses and midwives per 1,000 inhabitants
	Doct	Number of doctors per 1,000 inhabitants
	Bed	Number of beds per 1,000 inhabitants
Exogenous Variables	**Fintech**	The rate of use of digital financial services in percentage
	Corruption	Control of corruption ranging from -2.5 to 2.5
	Density	Population density in number of inhabitants/km²
	Urban	Urbanization rate in percentage
	Education	Primary school enrollment rate in percentage

Source: Authors, based on literature

4. Results and interpretations

This section is dedicated to the preliminary analysis and the discussion of the results obtained from our various estimations. The table below presents the descriptive statistics of the variables.

Table 2: Descriptive Statistics Analysis

Variables	Obs	Mean	Std. dev.	Min	Max
Fintech	88	22.61	24.343	0	93.07
Corruption	88	-0.639	0.407	-1.597	0.058
Density	88	70.321	39.390	13.145	158.94
Urban	88	4.057	0.657	2.932079	5.432
Education	88	95.82	20.693	65,40025	128.25

Source: Authors, based on data from WDI (2021) and BCEAO (2021)

Fintech services have an average usage rate of 22.61%, with values ranging from 0 to 93.07%, indicating a very uneven adoption. Overall, the quality of institutions is poor, with an average of -0.639 for the control of corruption. The population has an average density of 70.321%, with a standard deviation of 39.390, reflecting significant demographic disparity among the Union's countries. The average urbanization rate of 4.057%, with variations from 2.932% to 5.432%, suggests similar characteristics in terms of urbanization. Finally, the average primary school enrollment rate is 95.82%, with a standard deviation of 20.693 and values ranging from 65.40% to 128.25%. These data highlight a certain disparity in primary school enrollment rates. These figures help to understand the fluctuations and main trends of the variables analyzed, which is essential to grasp the underlying dynamics of health systems and socio-economic factors in WAEMU countries. It is now time to analyze the results of the double bootstrap DEA method for the next step.

4.1 DEA double bootstrap results

Algorithm 2 of Simar and Wilson (2007) provides bias-corrected estimates of efficiency scores while simultaneously examining serial correlation. Unlike Simar and Wilson, who focus on output-oriented technical efficiency, this study adopts an input-oriented approach according to Badunenko and Tauchmann (2019). The results are presented in the following table:

Table 3: Average Technical Efficiency Score of Double Bootstrap DEA

Dmu/Country	DEA standard	DEA double bootstrap (Algorithm 2)
	Average Scores	Bias-Corrected Average Scores
Benin	0.583	0.489
Burkina Faso	0.703	0.624
Côte d'Ivoire	0.511	0.425
Guinée-Bissau	0.431	0.347
Mali	1.000	0.832
Niger	0.944	0.703
Sénégal	0.686	0.566
Togo	0.556	0.438
Total	0.677	0.553

Source: Authors, based on data from WDI (2021) and BCEAO (2021)

The results show that the average DEA score decreases from 67.7% to 55.3%, suggesting a 12.4% overestimation of the technical efficiency of health systems in the WAEMU area. The random errors overlooked in the initial DEA model are responsible for this overestimation. The double bootstrap DEA method helps correct this shortcoming. Overall, the average performance of WAEMU countries is 55.3%. The result of this inefficiency is a 45% gap between the results achieved and the results that should have been achieved if resources in the Union's countries had been used more efficiently.

Moreover, the table highlights those countries such as Mali and Niger have the highest efficiency scores, with respective values of 83.2% and 70.3%, while Guinea-Bissau has the least efficient health system with a score of 34.7%. The WHO health indicators of these countries are consistent with those of other WAEMU countries. These countries, despite their low health budget, perform better than a country like Côte d'Ivoire, whose results remain insufficient despite the significant resources allocated.

In the second phase, the study focuses on the elements (advantages or challenges) that impact the technical efficiency of health systems. Simar and Wilson (2007) suggest that a positive coefficient indicates a negative impact on efficiency, while a negative coefficient suggests a positive impact. The conclusions obtained help identify the key factors affecting the health system outcomes in this region.

The estimation results are presented in the following table:

Table 4: Inefficiency Determinants Results

Efficiency Bscore	Observed Coef.	Std. Err. Bootstrap	Z	P>z	[95%	Conf.Interval
Fintech	-0.105*	0.055	-1.910	0.056	-0.209	0.007
Corruption	0.058	0.053	1.100	0.272	-0.048	0.164
Density	-0.001	0.001	-0.820	0.414	-0.002	0.001
Urban	0.131***	0.022	6.050	0.000	0.089	0.173
Education	-0.003	0.001	-1.870	0.062	-0.006	0.000
Constante	0.396***	0.120	3.300	0.001	0.154	0.617
Sigma	0.111***	0.009	12.570	0.000	0.090	0.124

Source: Authors, based on data from WDI (2021) and BCEAO (2021).

Note : *** ; ** ; * Indicate statistical significance at 1%, 5%, and 10%, respectively. Sigma represents the standard deviation of the errors obtained in the truncated regression of the DEA scores on the environmental variables. The significance of this indicator makes the estimation valid.

According to the analysis of the table, the financial technology variable shows significant importance at the 10% level and hurts technical performance. The increasing use of Fintech is associated with a reduction in technical inefficiency, leading to an increase in technical efficiency. In this way, the advancement of financial technologies results in improved performance of healthcare systems in the WAEMU countries.

This result is consistent with the findings of Meiling et al. (2021) and Jing et al. (2022), who demonstrated that the evolution of Fintech improves health performance. From a theoretical perspective, this result could be explained by several important mechanisms.
First, Fintech simplifies access to healthcare services by enabling digital payments and streamlining transactions, which promotes financial inclusion and access to care for underserved populations (Asongu et al., 2023). Second, they play a crucial role in reducing expenses by automating billing procedures, minimizing administrative errors, and improving fund management. Additionally, crowdfunding platforms and peer-to-peer (P2P) lending offer new financing methods for healthcare facilities, enabling them to raise funds for infrastructure projects or medical equipment (Meiling et al., 2021; Kenworthy, 2019).
According to Cambaza (2023), the use of technologies such as blockchain could improve diagnostics by ensuring the integrity and security of medical data and facilitating precise and reliable access to information necessary for more effective diagnostics.

4.2 Quantile moments results (MMQR)
The table below presents the results of the quantile moments method.

Table 5: Results of the quantile moments

QUANTILE MOMENT (MMQR)							
	Location	**Scale**	**10**	**25**	**50**	**75**	**90**
Fintech	0.105** (0.026)	-0.069*** (0.005)	0.211*** (0.004)	0.159*** (0.005)	0.099** (0.040)	0.043 (0.313)	0.013 (0.780)
Corruption	-0.060 (0.273)	0.092*** (0.001)	-0.202** (0.019)	-0.133** (0.046)	-0.052 (0.359)	0.021 (0.668)	0.061 (0.303)
Density	0.0006 (0.392)	-0.0001*** (0.002)	0.002 (0.033)	0.001* (0.079)	0.0005 (0.487)	-0.0004 (0.532)	-0.0009 (0.237)
Urban	-0.127*** (0.000)	-0.006 (0.557)	-0.118*** (0.000)	-0.122*** (0.000)	-0.128*** (0.000)	-0.133*** (0.000)	-0.136*** (0.000)
Education	-0.002* (0.092)	0.002*** (0.002)	-0.001 (0.629)	-0.0006 (0.727)	0.002* (0.077)	-0.005*** (0.001)	0.006*** (0.000)
Constant	0.596*** (0.000)	0.027 (0.655)	0.554*** (0.002)	0.574*** (0.000)	0.590*** (0.000)	0.620*** (0.000)	0.632*** (0.000)

Source: Authors, based on data from WDI (2021) and BCEAO (2021).
Note: The values in parentheses are the p-values, while *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

The previous table, presenting the results of the quantile moments, is divided into two parts. The first two columns (location and scale) constitute the first part, which shows the average effect of the variables and their distribution across the quantiles. The second section of the table provides an overview of the results based on distribution. The initial two columns highlight that the Fintech variable has a positive impact on location and a negative impact on scale. This suggests that the increasing rate of Fintech technology use improves, on average, the technical efficiency of healthcare systems while also reducing the dispersion of the observed efficiency.
In the second part of the table, the study's findings highlight that financial technologies (Fintech) positively impact the technical efficiency of healthcare systems across all indicators studied. However, this influence is significant only at the lower and median values (from 10 to 50). This observation suggests that Fintech contributes to significant improvements in countries where healthcare systems are less efficient. At first glance, this result may seem contradictory, but it finds its validity in the specific context of the WAEMU.
Indeed, this could be explained by the fact that the countries with the least efficient healthcare systems are those where Fintech technologies are most widely used. Côte d'Ivoire, Mali, and Niger are perfect examples

of this reality. In Côte d'Ivoire, even though the healthcare system has a performance score of 42.5%, the Fintech technology usage rate is 90.2%. In contrast, Mali and Niger, which have Fintech usage rates of 33.35% and 3.62% in 2021, respectively (BCEAO, 2021), have some of the highest healthcare performance scores, with 83.2% and 70.3%, respectively.

In this way, in countries where healthcare systems are less efficient, the influence of Fintech is particularly evident despite their poor performance because these countries often benefit from advanced technological infrastructure that facilitates the rapid adoption of Fintech innovations. Thanks to this favorable technological context, Fintech can strengthen its positive impact by filling gaps in healthcare systems. With the integration of Fintech, access to healthcare services becomes easier, payment management improves, and resources are optimized, leading to improved healthcare system efficiency.

Fintech companies are improving low-efficiency healthcare systems through mobile health financing and remote diagnosis. These technologies offer fast and innovative solutions that are particularly well suited to contexts where healthcare infrastructure is limited. Fintech, for example, offers the possibility of remote diagnosis through telemedicine, supported by secure digital payment solutions. These innovations enable patients living in rural or underserved areas to access online medical consultations, receive regular follow-up care, and obtain appropriate prescriptions more quickly via a telemedicine platform. The integration of Fintech into this process reduces barriers related to travel, costs, and waiting times, while improving health coverage and continuity of care. In addition, these digital applications allow users to save specifically for their future healthcare expenses ("health savings goals"). In emergencies, instant health loans can be granted based on an algorithmic analysis of the user's financial behavior. On the other hand, in countries with efficient healthcare systems, the low rate of Fintech use can be limiting and diminish their influence. Despite their progress in health, these countries may be less motivated to adopt Fintech technologies massively due to their satisfaction with existing infrastructure.

Well-managed and efficient healthcare systems might limit access to new technological solutions, which would limit the potential effect of Fintech. Moreover, the presence of well-established processes and practices in these systems can hinder innovation and the adoption of new features. As a result, the benefits of Fintech, such as resource optimization and improved access to healthcare services, may be less evident in these situations. Thus, the low rate of Fintech use in countries with high-performing healthcare systems restricts their ability to fully exploit technological advantages, reducing their overall impact. Concerning the literature, our results confirm those of Asongu et al. (2023), who proved in a study conducted on a sample of 43 sub-Saharan African countries that Fintech contributes to improving health performance, especially in countries with less efficient healthcare systems. The result of this convergence highlights the crucial importance of Fintech technologies as a lever for improvement in situations where healthcare systems are less efficient. Overall, Fintech is opening up and optimizing healthcare services by enabling the digitization and monetization of remote consultations.

Corruption control is of paramount importance and negatively impacts healthcare system outcomes, especially at lower levels, such as the 10th and 25th percentiles. In countries where healthcare systems are not performing well, this result can be largely attributed to the regularity of corrupt practices in the health sector. The situation is particularly concerning in the context of WAEMU. There is a low level of corruption control, with an average level of -0.64, indicating an environment where anti-corruption mechanisms are weak. Corruption persists due to this weakness in governance, which exacerbates the structural challenges faced by the region's healthcare systems. The findings obtained correspond to the research of Vian (2020), which emphasizes that corruption is a national concern that compromises the health sector's objectives in terms of equity, access, and quality. In this way, corruption diminishes healthcare system outcomes in the WAEMU region. Thus, it is essential to improve corruption control to strengthen healthcare system performance in these countries and, consequently, improve population health.

The rate of urbanization is high and has a negative impact on the performance of health systems in all regions. This suggests that increasing urbanization is associated with a decline in the efficiency of health systems, regardless of the level of performance of these systems. In theory, the concentration of populations in cities should allow for economies of scale (a hospital serves more people, transport networks are denser). In practice, in developing countries, the pace of urbanization often exceeds the capacity of health infrastructure to adapt and invest. In addition, urban health centers are chronically overcrowded with long waiting lines, consultation time per patient is shortened, and healthcare staff are overworked. This overload can lead to a decline in the quality of care, thereby reducing the effectiveness of health systems. In addition, urban environments can present new public health challenges, such as infectious diseases and lifestyle-related problems, making healthcare management more difficult. Thus, even when healthcare systems are efficient, increasing urbanization can have a negative impact on their overall effectiveness. These findings are consistent with Tiebout's (1956) "voting with your feet" theory, which argues that urbanization results from poor provision of public goods and services, including healthcare. However, these results contradict the research of Miao and Wu (2016), which suggests that urbanization improves access to health services and provides better resources, thereby improving the health of residents. In sum, the paradox is not that urbanization is inherently bad for health, but that rapid, unplanned urbanization without strategic investment in health and social infrastructure leads to inefficient systems. Efficiency is not an automatic consequence of density; it is the result of policy choices and sound management.

According to human capital theory, the observed positive effect aligns with the theory that education is closely related to health. Nwakobi's research (2020) demonstrates a positive correlation between education and better healthcare system performance. However, this negative consequence could be attributed to unevenly distributed and inefficient education systems, which may lead to lower healthcare system performance. Despite the frequent association of education with improved health, the persistence of socio-economic inequalities (unemployment, income inequality, gender inequality) can lead to disparities in health performance. Access to education in Africa, particularly in WAEMU countries, could hinder the development of productive sectors such as healthcare. Moreover, gaps in technical advancements due to limited educational capital accumulation can hinder health advances and accentuate disparities in healthcare system performance. It is important to note that despite the essential role of education in improving healthcare performance, the persistence of inequalities and socio-economic disparities can lead to disparities in healthcare system performance.

5. Conclusion

This study aimed to analyze the contribution of Fintech to the performance of healthcare systems. This was achieved using a sample of eight WAEMU countries from 2011 to 2021. The double bootstrap DEA method by Simar and Wilson (2007) and the quantile moments method by Machado and Silva (2019) were used methodologically. The studies highlight a technical efficiency rate of healthcare systems in the Union of 55.3%. Moreover, the advancement of Fintech technologies plays an important role in improving healthcare system performance. When evaluating the effect of Fintech according to the performance level of healthcare systems, it appears that these technologies particularly enhance health performance in countries with lower performance levels. Based on the results obtained, several recommendations can be made to improve the contribution of Fintech to healthcare system performance. First, it is essential to strengthen the integration of Fintech technologies into healthcare systems, especially in countries where these technologies have already had a significant positive effect. Policies should promote the use of digital financial solutions to improve access to and efficiency of healthcare services. Subsequently, policies must be adjusted according to national contexts. Targeted support could be more beneficial for countries with lower health performance to improve their infrastructure and integrate Fintech, while those with higher-performing healthcare systems should focus on optimizing the impact of Fintech already in place. It is also crucial to invest in technological infrastructure and the training of healthcare professionals to maximize the benefits of Fintech. Investing in financial management systems and the digital skills of healthcare professionals can enhance their efficiency and ability to leverage technological advancements. It is advisable to encourage the use of innovative financing mechanisms, such as crowdfunding and peer-to-peer (P2P) lending, to support health projects in countries with pressing needs. These mechanisms could provide crucial resources for improving health infrastructure and services, especially in countries where systems are less efficient. Ultimately, the integration of Fintech and digital technology in healthcare offers immense potential for improving access to and the effectiveness of care. However, its success depends on adapting to the realities on the ground.

Indeed, the lack of digital skills, unsuitable interfaces (language, culture), and the cost of equipment and connectivity exclude the most vulnerable populations (the elderly, the precarious, and rural communities), widening inequalities. In addition, infrastructure failures linked to the lack of reliable internet connections and, above all, resilient electrical systems (frequent power cuts) paralyze hospitals and render cloud solutions and telemedicine ineffective. Thus, without an inclusive strategy that invests heavily in training, accessibility, and basic infrastructure (energy, network), the digital revolution in healthcare risks exacerbating existing divides rather than bridging them. To maximize the positive impact of Fintech on the performance of healthcare systems, it will be necessary to conduct regular studies and data analyses to adjust policies and optimize Fintech integration strategies.

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