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Spatial Effect of Fintech on the Living Conditions of Households in the WAEMU Zone

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Abstract

The objective of this research is to analyze the effect of fintech on the living conditions of households in the WAEMU zone based on the principles of spatial econometrics. Our study covers the period from 2011 to 2021. After detecting spatial autocorrelation, the information criteria of Akaike and Schwarz indicate that a Spatial Error Model (SEM) should be used. The results show that fintech has a positive effect on the living conditions of households in the WAEMU zone. In other words, fintech improves the living conditions of households in the WAEMU zone. In terms of economic policy implications, the study suggests that the authorities strengthen digital infrastructure and improve the quality of institutions while promoting a better regulatory framework.

Keywords

Fintech, Living Conditions, Spatial Econometrics, WAEMU, SEM

1. Introduction

Since the 90 s, information and communication technologies (ICTs) have spread exponentially almost everywhere in the world. Their rapid expansion has given rise to the hypothesis of the emergence of a new "digital" industrial revolution in the economic literature (David, 2000). The financial sector has also undergone something of a technological revolution in recent decades, as ICT platforms have facilitated the diffusion of a range of financial technologies (Kanga et al., 2022).

The term \"Fintech\" is a contraction of \"Financial Technology\". This concept refers to technologies associated with the financial sector (Vives, 2022). Fintechs can also be defined as companies or company representatives that combine financial services with modern and innovative technologies (Dorfleitner et al., 2017).

They aim to simplify and make finance more accessible, offering better and cheaper services in a context where two billion people, or more than half of the world's working-age population, are not yet banked and do not have access to safe, reliable, and affordable financial services, according to the Global System for Mobile Communications (GSMA, 2016). The digitalization of the economy is transforming economic exchanges and promoting growth, employment, poverty reduction and social and financial inclusion (Andrianaivo & Kpodar, 2011). But while the spread of fintech has transformed the financial landscape, there remains controversy in the literature regarding the effect of fintech on living conditions.

Regarding the optimistic trend, Fintech improves financial inclusion (Noreen et al., 2022; Mustafa et al., 2023), reduces transaction costs (Wang et al., 2021), provides access to faster and cheaper financing for the poor, increases literacy rates through information sharing (Morgan, 2021), creates employment opportunities for citizens (Hussain et al., 2021), and reduces poverty and inequality (Ofosu-Mensah Ababio et al., 2021), which has a positive effect on living conditions.

For the defenders of the pessimistic current, the more FinTech develops, the more people who are excluded from financial services will be harmed more (Malady, 2016), because digital financial service providers are for-profit companies that use digital finance to maximize their profit, namely banks and financial and non-financial institutions. This could increase poverty and inequality as Fintechs give the advantage to middle- and high-income customers.

The effect of Fintech on household living conditions remains enigmatic since few studies have examined the effect of technological change in the financial services sector on variables measuring the standard of living of populations. Indeed, between 2011 and 2021, in the WAEMU zone, the HDI increased slightly from 0.44 to 0.48 (UNDP, 2021). Access to electricity and drinking water in the said area have improved from 32.54% and 61.51% respectively to about 45.45% and 66.98% over the same period (WDI, 2021). These positive increases in these living standards indicators between 2011 and 2021 may suggest that there are close links between the living conditions of the WAEMU populations and the rise of Fintech.

In addition, from 2011 to 2021, the score of the Gini index[1] of the WAEMU zone increased from 0.57 to 0.59, thus proving an increase in income inequality (World Inequality Report 2022).

In view of these controversies and the statistics presented in the paragraphs above, what is the effect of fintech on the living conditions of households in the WAEMU zone?

The objective of this research is to analyze the spatial effect of Fintech on the living conditions of households in the WAEMU zone.

Studying the effect of Fintech on the living conditions of households in WAEMU zones has several socioeconomic, academic, and scientific interests. Socio-economically, Fintech has the potential to transform access to financial ser-

[1]The Gini coefficient is a number varying from 0 to 1, where 0 means perfect equality, where all the incomes of all people are equal in a given period of time, and 1 means perfect inequality.

vices, which can improve the quality of life of households, foster financial inclusion, and boost the local economy. Analysing this effect provides a better understanding of how these innovations can contribute to poverty reduction and improved living conditions. Scientifically, their impact on households can generate new data and knowledge on people's financial behaviours, the challenges of technology adoption, and the effects of public policies. It can also contribute to the development of theoretical models on innovation and economic development.

The rest of the paper presents the literature, then the methodology, followed by the discussion of the results, and finally the conclusion.

2. Overview of the Literature

2.1. Theoretical Review on the Adoption and Use of ICT and Fintech

Many theoretical models have been put in place regarding technology in the banking sector to understand the elements that influence its adoption and use. The theory of reasoned action (ART) was developed by Fishbein (1967) and then popularized in the 1980s. The theory aims to explain an individual's decision to engage in a particular behavior based on pre-existing behavioral attitudes and intentions. The TAM theory proposed by Davis (1989) considers the perception of utility and the perception of ease of use that promote the intention to accept and use technology. According to the theory of diffusion of innovation, founded by Rogers (1983), the more the innovation has an advantage for the user, the more compatible it is with the user's existing values, the more the user will be tempted to adopt it. In addition, an innovation with less complexity and ease of use is easily adopted by the user if the consumer has the opportunity to try it safely (Darpy & Volle, 2007). According to the theory of transaction costs, there are costs that are automatically associated that must be minimized in order for the firm to produce the good optimally (Williamson, 1979). Cost reduction is one of the main benefits of digitalization (Lambin & De Moerloose, 2021).

2.2. Theoretical Review between Fintech and Health

Healthcare costs are high, and healthcare organizations are constantly looking for ways to streamline their operations and reduce overhead costs (Tourkakis & Chatzipetrou, 2024). Fintech solutions such as automated billing and payment systems, blockchain technology[2] for secure transactions, and predictive analytics for financial forecasting can help healthcare organizations achieve these goals. Fintech innovation in the healthcare sector can lead to cost savings, increased revenue, and better resource allocation, which ultimately benefits both healthcare organizations and patients (Odeyemi, 2024). These platforms provide patients with more convenient payment options and can help healthcare organizations reduce the

[2]Blockchain is a vast, shared, and secure chain of information made up of "blocks". Each block provides the history of all transactions throughout the data processing cycle, to ensure a reliable traceability system.

time and resources spent on billing and collections. Moreover, during COVID-19, financial services around the world called for \"going digital\" for financial transactions. \"There are also a few areas that have seen an increase in digital payments thanks to increased adoption during the lockdown. These include online marketplaces, online pharmacies,… (Rahmati et al., 2021).

2.3. Theoretical Review between Fintech and the Human Development Index

The literature on the relationship between fintech and human development has produced mixed results. Several authors argue that the adoption of fintech in developing countries contributes to the improvement of the human development index through social well-being.

2.4. Empirical Review

The empirical literature on the relationship between Fintech and living conditions is recent, but has produced mixed results. Appiah-Otoo and Song (2021) examined the direct and indirect effects of financial technology (fintech) and its third-party payment and credit sub-measures on poverty as measured by per capita household consumption using the Generalized Moments Method (GMM). The results further showed that fintech complements economic growth and financial development to reduce poverty in China. Jing et al. (2022) confirm that the association between the internet and the infant mortality rate is negative; whereas this association is positive in the context of the Internet and life expectancy, with both 2SLS and GMM.

Also, Demir et al. (2020) argue that FinTech affects inequality directly and indirectly through financial inclusion. They used quantile regression analysis to determine whether these effects differ across countries with different levels of income inequality. In addition, Etudaiye-Muhtar et al. (2024) studied the impact of Fintech on human development in 43 countries in sub-Saharan Africa between 2002 and 2021, particularly with regard to the fight against energy poverty. Based on the random effect (RE), the generalized linear model (GLM) and the generalized moment method (GMM), the results confirm that fintech has a significant positive impact on socio-economic conditions, represented by the HDI, and the impact becomes increasingly important in the face of a constant energy supply.

3. Methodological Approach

3.1. Data Collection and Variables

These data were extracted from several reliable and recognized sources: the World Bank's World Development Indicators (WDI) and Worldwide Governance Indicators (WGI), the United Nations Development Programme (UNDP) and World Inequality. The study period is from 2011 to 2021, allowing us to explore trends over a decade.

The variables used are presented in the following Table 1.

Table 1. Overview of variables.

Variables	Descriptions
"Living Conditions Index" (LCI)	To measure the living conditions of populations in the WAEMU zone, we created a composite index using the Principal Component Analysis (PCA) method in SPSS Statistics, which we will refer to as the \"Living Conditions Index\" (LCI) in the context of our study. This variable ranges from 0 to 1, with a value closer to 1 indicating higher living conditions. The LCI is constructed using the following variables: Human Development Index (HDI): It measures the level of human development. Gini Coefficient (GINI): It measures the inequality of income distribution within a population. Access to Electricity (AEL): This variable refers to the proportion of the population with access to electricity sources. Access to Drinking Water (AEP): This variable measures the proportion of the population with access to an improved source of drinking water, such as taps, boreholes, or protected wells.
Electronic money services (TUME):	The rate of use of electronic money services is a direct indicator of FinTech adoption by end users
Access to credit (CRED)	This is the ratio of domestic credit to the private sector as a percentage of GDP.
Population growth rate (TCPOP)	A general definition is that population growth refers to the difference between the size of a population at the end and at the beginning of a given period (usually one year).
Trade openness (OUV)	The level of trade in the economy is measured by the simple arithmetic average of exports and imports of goods and services (as a percentage of GDP).
Institutions (INST):	Based on six indicators, namely \"citizen voice and accountability (VCR)\", \"political stability and absence of violence/terrorism (SP)\", \"effectiveness of public authorities (EPP)\", \"quality of regulation (QR)\", \"rule of law (ELR)\", \"control of corruption (CC)\". Each indicator is based on a scale ranging from −2.5 to 2.5 (from lowest quality of institutions to very good quality).
Foreign direct investment (FDI):	Foreign direct investment is defined as the net inflow of investment to acquire a sustainable stake in the management (10% or more of voting shares) of an enterprise operating in an economy other than that of the investor.

Source: Authors, based on literature review.

The dependent variable

Human Development Index (IDH): It measures the level of human development in a country by considering criteria such as life expectancy, education level, and per capita income. The HDI ranges from 0 to 1, with a value closer to 1 indicating a higher level of human development.

Gini Coefficient (GINI): It measures the inequality of income distribution within a population. The Gini coefficient ranges from 0 to 1, where 0 represents perfect equality in income distribution, and 1 represents perfect inequality. This measure is widely used and recommended by the European Union and Eurostat for its interpretability.

Access to Electricity (AEL): This variable refers to the proportion of the population with access to electricity sources. Access to electricity is crucial for economic and social development, as it directly impacts education, health, industry, and the overall well-being of households.

Access to Drinking Water (AEP): This variable measures the proportion of the population with access to an improved source of drinking water, such as taps, boreholes, or protected wells. Better access to drinking water is critical for public health and improves the quality of life for individuals.

Using these variables, we constructed the LCI, which synthesizes various dimensions of well-being and living conditions of households in the WAEMU zone. This composite index provides an overview of living conditions in the region and serves as the basis for analyzing the effects of financial technologies on these conditions.

The rate of use of electronic money services (TUME): The rate of use of electronic money services is a direct indicator of FinTech adoption by end users. Unlike the density of mobile money agents or the volume of digital payments, which respectively measure the geographic availability of services and transactional activity, this rate reflects the actual engagement of users with these technologies in their daily lives. Studies, such as that of Aker and Mbiti (2010), have shown that the adoption of electronic money plays a key role in financial inclusion, especially in rural areas where access to traditional banking services remains limited. The rate of use thus allows for measuring the effective integration of FinTech services into households, which is essential for evaluating their impact on the living conditions of populations.

Furthermore, according to He et al. (2024), this rate of use is particularly relevant for assessing the social and economic effects of FinTech on households, as it captures the extent of adoption of digital services in daily practices, unlike other measures that focus solely on the availability of services.

Access to credit (CRED): This is the ratio of domestic credit to the private sector as a percentage of GDP. Domestic credit provided by the financial sector includes all credit extended to the various sectors on a gross basis, with the exception of credit to the central government, which is net. This variable does not take into account loans granted by the public treasury, the central bank, and development banks. The expected sign can then be positive.

Population growth rate (TCPOP): A general definition is that population growth refers to the difference between the size of a population at the end and the beginning of a given period (usually one year). More specifically, it is the difference between the size of a population on 1 January of two consecutive years. The expected sign is negative.

Trade openness (OUV): The level of trade in the economy measured by the simple arithmetic average of exports and imports of goods and services (as a percentage of GDP). Its expected effects are positive.

Institutions (INST): based on six indicators, namely \"citizen voice and accountability (VCR)\", \"political stability and absence of violence/terrorism (SP)\", \"effectiveness of public authorities (EPP)\", \"quality of regulation (QR)\", \"rule of law (ELR)\", \"control of corruption (CC)\". Each indicator is based on a scale ranging from −2.5 to 2.5 (from lowest quality of institutions to very good quality). Thus, depending on the value of the latter, a state could therefore assess the level of functioning of these institutions of governance. The expected sign is positive.

Foreign direct investment (FDI): Foreign direct investment is defined as the net inflow of investment to acquire a sustainable stake in the management (10% or more of voting shares) of an enterprise operating in an economy other than that of the investor. This is the sum of equity, reinvestment of profits, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows (new investment minus divestments) into the reporting economy from foreign investors and is divided by GDP. The expected sign is positive.

3.2. Presentation of the Model

Spatial Analysis

Spatial analysis is a branch of geography that studies the link between the phenomena observed in an area and those of neighboring areas within a territory. It allows for the analysis of interactions and influences between different geographic regions. Brunet (1992) defined it as a \"set of mathematical and statistical methods aimed at specifying the nature, quality, and quantity attached to places and the relationships they maintain \u2013 the whole constituting space by simultaneously studying attributes and locations\".

Spatial analysis is based, in particular, on the definition of a spatial weight matrix and the concept of spatial autocorrelation.

A spatial weight matrix

It is essential to construct a spatial weight matrix. The weight matrix or neighborhood matrix \"W\" makes it possible to quantify the proximity relationships between the countries studied. This square matrix of dimension (n x n), where n is the number of spatial units, has elements that represent how the unit i and the unit j are spatially connected. However, the elements of the diagonal of this matrix are zero because no spatial unit can be its own neighbor. Le Gallo (2002) classifies weight matrices into two main categories: w_{ij} generalized weight matrices and contiguity matrices.

The contiguity between two regions is defined by the fact that they share a common border. This matrix takes the values 1 and 0. The value 1 indicates a neighbor relationship, and 0 otherwise. Each term is defined as follows: w_{ij}

$$w_{ij} = \begin{cases} amp;1 \text{ If regions } i \text{ and } j \text{ are contiguous} \\ amp;0 \text{ otherwise} \end{cases} \tag{1}$$

Due to the existing geographical proximity between WAEMU countries, it is necessary in the case of our spatial analysis to quantify this proximity by the 1st order contiguity matrix in the sense of Queen, as used by Safae and Radouane (2023).

Next, it is crucial to understand spatial autocorrelation. Spatial autocorrelation refers to the relationship between observed values of a variable at different locations in space. It is of paramount importance in spatial analysis. According to Le Gallo (2002), spatial autocorrelation is defined as the correlation, positive or negative, between a variable and itself, depending on the geographical distribution of the data. As for Anselin (2001), spatial autocorrelation is the concordance of similar values in terms of location. Several specific tests are implemented to evaluate this autocorrelation.

Spatial autocorrelation

Spatial autocorrelation indices are tools that determine the presence and intensity of spatial dependence in data. In the literature, we find among these indices those of Moran, Geary, and Getis-Ord. However, the most commonly used index is Moran's index (Moran's I). This index is defined by the following formula:

$$I_{Moran} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \quad (2)$$

where:

- i, j represent spatial units
- n is the number of spatial units
- x_i represents the value of the variable in unit i
- $\bar{x}$ is the mean of X
- w_{ij} represents the spatial proximity between i and j

The values of the Moran index range from −1 to 1. If the Moran index shows a negative value, then the nearby areas have very different values. On the other hand, a positive value of the Moran index means that neighbouring areas have similar values. Finally, on the basis of these results, an appropriate econometric model is chosen to analyze the phenomena studied.

Spatial Models

Among the spatial models we can mention: the spatial autoregressive model (SAR), the spatial error model (SEM), the combined autoregressive spatial model (SAC), and the Durbin spatial model (SDM). The spatial autoregressive (SAR) model or spatially shifted endogenous variable model mainly examines whether the dependent variable has diffusion phenomena in a region. The specification for this model is as follows:

$$\text{Y}=\rho \text{WY}+\text{X}\beta+\varepsilon \quad (3)$$

ρ is the spatial autocorrelation coefficient, which shows the effects of fallout from neighboring regions on the region as such. W is the spatial weight matrix.

The spatial error model (SEM) is used to correct for errors that can be correlated between different geographic units. Its general form can be represented as follows:

$$Y = X\beta + u \quad \text{With:} \quad u = \lambda Wu + \varepsilon \quad (4)$$

λ is the coefficient that measures the spatial correlation of errors. u is an independent random error.

The combined spatial autoregressive model (SAC) combines the characteristics of both the SAR model (influence of neighbors on the dependent variable) and the SEM model (correlation of errors between neighbors). It can be noted as follows:

$$Y = \rho WY + X\beta + u \quad \text{With:} \quad u = \lambda Wu + \varepsilon \tag{5}$$

The Durbin spatial model (SDM) is used to capture both the interaction effect of the endogenous variable and the spatial effects of the spatially shifted explanatory variables. This model is used to capture the marginal effects (direct, indirect, and total) of all spatially lagged variables. The model is written:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \tag{6}$$

In all equations:

W represents the weight matrix.

X represents the explanatory variables.

β represents the parameters for the explanatory variables.

4. Results and Interpretations

This section is dedicated to the analysis of the data and the results obtained from our various estimates.

4.1. Descriptive Statistics

The interest of descriptive statistics is that they make it possible to describe the data in a synthetic way. This descriptive analysis focuses on means, standard deviations, and maximums and minimums. Table 2 below provides a general overview of the data for our different study variables.

Table 2. Descriptive statistics of the variables.

Variables	Averages	Standard deviations	Minimum	Maximum
ICV	0.445	0.255	0.010	0.880
TUME	22.618	24.343	0	93.070
CRED	20.002	6.677	7.398	30.417
OUV	28.108	4.822	17.756	41.073
TCPOP TC	2.845	0.444	2.055	3.867
INST	−0.652	0.325	−1.323	−0.042
IDE	2.623	2.566	−2.574	13.438

Source: Authors, from the World Inequality Database, WDI, MFI, UNDP, BCEAO (2021).

We notice that, on a scale from 0 to 1, the average LCI of our sample is 0.445. Its minimum observed value is 0.01 and its maximum value reaches 0.88. In addition, the average rate of use of electronic money in the WAEMU zone is 22.618 and has a dispersion of 24.343. Its highest value is 93.07 and the minimum value is 0. In terms of access to credit, it has an average score of 20.002, a minimum of −7.398 and a maximum of 30.417 with a standard deviation of 6.677. Trade openness records an average of 28.108, with a low dispersion of 4.822 in the WAEMU countries. The maximum value of trade openness is 41.073 and the minimum value is 17.756. Also, the population growth rate has an average level of 2.845 and a dispersion (0.444) around its average. Its highest level is 3.86 and its lowest level is 2.055. In addition, the average institutions and the average corruption control in WAEMU countries are −0.652 and 2.623, with standard deviations of 0.325 and 2.566. The highest institution score is −0.042 and the lowest is −1.323. For foreign direct investment, its highest value is 13.438 and its lowest value is −2.574.

4.2. Results of the Spatial Analysis

4.2.1. Spatial Autocorrelation

Based on the results presented in Table 3 below, we observe a significant negative spatial autocorrelation (Moran's I) with a value of −0.023 at the 5% threshold. This suggests that neighboring countries have divergent living conditions, which can be attributed to several economic and political factors. Firstly, differences in financial infrastructure between countries can explain these disparities: some countries in the WAEMU zone benefit from better digital infrastructure, thus promoting the adoption of FinTech and improving living conditions, while others, with less developed infrastructure, are less able to take advantage of these technologies. Furthermore, uneven economic growth between countries plays a key role, as rapidly growing countries have resources to invest in technology, which boosts financial inclusion, while countries experiencing economic slowdown face financial barriers. Moreover, political stability and regulatory frameworks are crucial: countries with policies favorable to FinTech see broader adoption of digital financial services, leading to improvements in living conditions, while countries with political instability or restrictive regulations risk falling behind in FinTech adoption. In summary, these economic and political factors contribute to the spatial heterogeneity observed in the effects of FinTech on household living conditions in the WAEMU zone.

Table 3. Detection of global autocorrelation.

	TESTS	
	Moran's I	Geary's C
ICV	−0.023** (0.012)	1.248*** (0.012)

Source: Authors, from World Inequality Database, WDI, MFI, UNDP, BCEAO (2021).

4.2.2. Estimation of SAC, SAR, SDM, and SEM Models

The results obtained from the estimation of the different models are summarized in Table 4.

Table 4. Estimation of spatial models (SAC, SAR, SDM, and SEM).

Variables	SAC	SAR	SDM	SEM
Constant	0.9463201*** (0.000)	1.079334*** (0.000)	1.242076*** (0.000)	0.9698034*** (0.000)
TUME	0.0016786*** (0.001)	0.002009*** (0.000)	−0.0000724 ns (0.914)	0.0012533** (0.002)
CRED	0.0130949*** (0.000)	0.0145066*** (0.000)	0.0145061*** (0.000)	0.120475*** (0.000)
OUV	0.0012902 ns (0.662)	−0.0016631 ns (0.570)	−0.0011922 ns (0.674)	0.0020283 ns (0.471)
TC POP	−0.1699349*** (0.000)	−0.2038728*** (0.000)	−0.2506366*** (0.000)	−0.183882*** (0.000)
INST	0.1742186*** (0.000)	0.0986544** (0.005)	0.01703489** (0.008)	0.2206481*** (0.000)
IDE	−0.002188 ns (0.594)	−0.0006546 ns (0.882)	0.0027896 ns (0.486)	−0.0021324 ns (0.600)
R^2	0.9073	0.8794	0.8968	0.9146
Rho (ρ)	−0.0803004 ns (0.169)	−0.02505726*** (0.000)	−0.2918764*** (0.000)	
Lambda (λ)	−0.1182201** (0.005)			−0.1571961*** (0.000)
Log Likelihood	89.6641	84.1550	99.7145	88.6903
AIC	0.0060	0.0078	0.0070	0.0055
PEN	0.0073	0.0095	0.0101	0.0067

Source: Authors, from World Inequality Database, WDI, MFI, UNDP, BCEAO (2021). *Level of significance*: —*Significant at* 1%, —*Significant at* 5%, —*Significant at* 10%, *and ns—Not Significant.*

The values in parentheses represent the p-values associated with the values.

In general, we observe that the coefficients of determination (R^2) are high, exceeding 50% in all regressions. This indicates that our independent variables explain more than 50% of the variation in the dependent variable. At first glance, it should be noted that the sign of the coefficient for each of the independent variables remains constant in the four models (SAC, SAR, SDM and SEM). This suggests that the effect of each variable on LCI is robust, regardless of the model used.

The e-money utilization rate has a generally positive and significant effect on the LCI, although the significance thresholds vary, except in the case of SDM where the effect is negative and not significant. Access to credit has a positive and significant effect on the LCI at the 1% level. In contrast, trade openness has a positive effect in the SAC and SEM models, and a negative effect in the SAR and SDM models, but these effects are not significant in all models. The population growth rate has a significant negative effect on the LCI at the 1% level in all models. In contrast, institutions have a positive and significant effect on the LCI at the 1% level in all models, with varying significance thresholds. As far as foreign direct investment is concerned, it has a negative and not significant effect in most models except in the SDM where the effect is positive and not significant.

As far as the information criteria are concerned, the AIC and BIC values are minimized in the spatial error model, with an AIC of 0.005 and a BIC of 0.007. Therefore, the most suitable model for our data is the SEM model, which corresponds to Equation (2):

$$\begin{aligned} ICV_{it} &= \beta_0 + \beta_1 TUME_{it} + \beta_2 CRED_{it} + \beta_3 OUV_{it} + \beta_4 TCPOP \\ &+ \beta_5 INST_{it} + \beta_6 IDE_{it} + \lambda \mathrm{Wu}_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

The majority of the coefficients in this model are significant, with the exception of trade openness and foreign direct investment. In addition, the "Lambda" autocorrelation coefficient is non-zero and significant at the 1% level. This clearly indicates interdependence between the WAEMU countries. Therefore, the hypothesis of spatial dependence between the levels of human development of these countries cannot be rejected. The "Lambda" coefficient is negative, with a value of −0.157, which highlights an inverse correlation in spatial errors. In other words, a one-unit increase in unobserved shocks in neighbouring countries tends to reduce unobserved errors in the country under study by 0.157 units. With this in mind, we will proceed with the estimation by the SEM model.

4.3. Interpretations and Discussions of Results

4.3.1. Interpretations of the Results

From Table 4, it appears that the coefficient of the rate of use of electronic money services is positive and statistically significant at the 5% threshold on the index measuring the living conditions of the populations in the WAEMU zone. A 1% increase in the rate of use of electronic money services improves the living conditions of households in the WAEMU zone by 0.001. Similarly, access to credit and to institutions has positive and statistically significant coefficients on the index of household living conditions in the WAEMU area at the 1% threshold. In contrast, the coefficient of the population growth rate is negative and significant at the 1% threshold on the financial inclusion index. Only trade openness and foreign direct investment have positive and negative coefficients, respectively, which are especially not significant on the financial inclusion index. Furthermore, the results indicate that trade openness (OUV) and foreign direct investment (FDI) do not have a statistically significant effect on living conditions. This lack of a significant relationship can be explained by several factors. On the one hand, the potential benefits of trade openness and FDI do not necessarily translate into immediate improvements in living conditions, especially if the gains from trade and foreign investment are not widely redistributed or are concentrated in certain sectors. On the other hand, these effects may be indirect or delayed over time, depending on the capacity of local institutions to channel economic benefits toward the well-being of the population. Thus, these results suggest that policies aimed at improving living conditions in the study area should go beyond simply promoting trade liberalization and FDI, placing greater emphasis on the quality of governance, market regulation, and financial inclusion through instruments such as FinTech.

4.3.2. Discussion of the Results

Table 4 shows that the coefficient of the rate of use of electronic money services is positive and statistically significant at the 5% threshold on the index measuring the living conditions of the populations in the WAEMU zone. A 1% increase in the rate of use of electronic money services improves the living conditions of households in the WAEMU zone by 0.001. These results are close to those of Appiah-Otoo and Song (2021), Jing et al. (2022). There are a number of reasons for this.

First, e-money makes it easier for more people to access financial services, including those who did not have access to traditional banks. Indeed, over our study period, the use of electronic money has increased considerably in the WAEMU zone (BCEAO, 2021). Households have used it to make transactions easier, to receive payments, to save… This has helped to improve their financial situation, and therefore their living conditions. Indeed, money transfers, payments for goods and services are made faster and without high fees (Moov, Orange Money, Wave, online banking services, etc.), which alleviates the economic burden on households in the WAEMU zone.

Also, in the field of education, it facilitates the payment of school fees and supplies, making access to education more affordable for families. For example, in the case of C\u00f4te d'Ivoire, some registration fees are paid directly through electronic payment platforms (Moov, Orange Money, Wave, online banking services, etc.). In addition, electronic payment platforms are also used to distribute scholarships or grants directly to students or schools, which ensures better management of funds and an improvement in their living conditions.

When it comes to healthcare, e-money enables fast and secure payments for healthcare services, reducing financial barriers to accessing care. This allows for better financial management of health services and for immediate patient care on the other.

Finally, electronic money promotes local and regional trade, which is essential for the economic development of the WAEMU zone. It contributes to the transparency and traceability of transactions, which helps to fight corruption and build trust in the economic system. Controlled corruption, as recommended by Acemoglu and Robinson (2006) and North (1990), is essential for growth and economic development, which will inevitably have positive repercussions on the daily lives of households in the WAEMU zone.

In addition, this table shows that the coefficient of access to credit (CRED) is positive and significant on living conditions. This shows that access to credit has a positive effect on living conditions. This implies that when households have better access to credit, it can allow them to invest in income-generating activities, and to access essential services, which improves the incomes and therefore the living conditions of households in the WAEMU zone.

For the population growth rate (TCPOP), the coefficient is negative, indicating that population growth is deteriorating living conditions. Indeed, when the population increases, its evolution increases the pressure on already insufficient resources, on jobs that are becoming scarce, which harms the quality of life of households.

As for the quality of institutions (INST), the coefficient is positive and significant on the living conditions of households. This shows that the quality of institutions has a significant effect on living conditions. Strong institutions can foster a stable economic environment, encourage investment, and improve access to services, resulting in better living conditions.

5. Conclusion

The purpose of this paper was to empirically analyze the spatial effect of Fintech on the living conditions of households in the 8 WAEMU countries of Benin, Burkina Faso, C\u00f4te d’Ivoire, Guinea-Bissau, Mali, Niger, Senegal and Togo, over the period 2011-2021. At the end of the estimates of the spatial models (SAR, SEM, SDM and SAC) and an optimal choice (smallest CSA), the results of the SEM estimator revealed that the coefficient of the rate of use of electronic money services is positive and statistically significant at the 5% threshold on the index measuring the living conditions of the populations in the WAEMU zone. A 1% increase in the rate of use of electronic money services improves the living conditions of households in the WAEMU zone by 0.0012533. If we consider these results, the major lesson that can be drawn is that the use of electronic money in WAEMU countries improves the living conditions of households. Therefore, as an implication, the government should promote access to e-money services, especially for marginalized populations. This can include awareness campaigns and incentives for Fintech companies to operate in rural or disadvantaged areas. Invest in technology infrastructure to ensure reliable and secure access to Fintech services. This includes improving internet connectivity and setting up digital payment systems. Promote a better regulatory framework and improve the control of corruption to allow better transparency and traceability of transactions, which will support innovation while protecting consumers in the WAEMU zone. Promote training programs to raise awareness among households about the benefits and use of Fintech services. This can help maximize their utilization, which will improve their living conditions in the long run.

However, it should be noted that the relationship between the adoption of financial technologies (FinTech) and improved living conditions could be bidirectional. While FinTech solutions can promote financial inclusion and contribute to better living conditions, it is also possible that higher living standards stimulate demand for and adoption of these technologies. This possible endogeneity suggests a potential reverse causality, which is a limitation of the current analysis and calls for further investigation, particularly through econometric approaches that can correct for this bias.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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