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# Pan-African banks, banking interconnectivity: A new systemic risk measure in the WAEMU

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ABSTRACT

This paper examines the existence of potential systemic risk in the banking sector of the West African Economic and Monetary Union (WAEMU) by using hand-collected bank-level data from all WAEMU countries for 2000–2017. One original aspect of our paper is the estimation of probabilities of default, in conjunction with the CIMDO method (Consistent Information Multivariate Density Optimizing) and the use of clustering techniques. We find that most of the banks have a very low probability of default, but there is a high joint probability of default for most pairs of banks. Therefore, there are seeds of systemic risk in the WAEMU: if the financial strength of large banking groups deteriorates, there could be contagion effects that could weaken the union. The use of quantile estimation has helped to determine banks' characteristics that may explain the systemic risk.

## 1. Introduction

The subprime crisis that started manifesting in summer 2007 shook the foundations of the international financial system. The fragility of the international financial system was exposed partly due to the bankruptcy of Lehman Brothers in September 2008. The bankruptcy of this large bank questioned the concept of *too big to fail*. Bankruptcies of large banks leading to a financial crisis through interconnectivity, the impact of a debt crisis, sudden changes in interest rates, and deregulation are some of the known vulnerabilities of the banking system (Oort, 1990) which were highlighted by the crisis.

This paper contributes to this emerging literature on systemic risk by measuring the systemic risk in the banking sector of the West African Economic and Monetary Union (WAEMU[1]) which is currently dominated by pan-African banks. Pan-African banks are banking institutions whose main investor is based (headquartered) in Africa. To the best of our knowledge, this paper is the first to address this question using bank-level data as well as the cluster method and focusing on the WAEMU. There is a 2015 study by the International Monetary Fund (IMF) attempted to address the question of the systemic risk of African banks but lacked a real measure by limiting itself to a simple descriptive analysis (Enoch et al., 2015).

Few papers have studied African financial systems risk. Khiari and Nachnouchi (2018) proposed a map of the risks for Tunisian banks to shed light on the factors that influence these risk levels, which are key to the involvement of such banks in systemic risk. Fall

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[1] The WAEMU is a monetary union composed of eight countries (Benin, Burkina Faso, Cote d'Ivoire, Bissau- Guinea, Mali, Niger, Senegal, Togo). This union has a unique monetary policy and one regulator for the banking sector.

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(2017) used the CIMDO approach developed by Segoviano (2006) and Segoviano and Goodhart (2009) to study systemic risk within the WAEMU banking systems. This study showed a deterioration trend in the stability of the WAEMU banking sector since 2004 as a result of external factors (oil shock, international economic, and financial crises). However, this analysis does not identify the banking system-level interconnections of this union as the study is based on aggregate data.

This paper starts from a simple observation: the rapid expansion of pan-African banks poses supervisory challenges that, if left unaddressed, may increase systemic risks. The systemic nature of pan-African banks needs appropriate regulatory measures to prevent potential contagion. A new trend is emerging, and it is leading to an increase in banking relations between developing countries and to a South-South regionalization of international banking operations. As a result, African banking models are rising to a new critical size. For example, between 2009 and 2010 the net profits, the total assets, and the number of accounts of Coris Bank – a pan-African bank operating in 7 African countries – increased by 112%, 64%, and 122%, respectively (Annual Reports and Orbis Bank Database). Between 2016 and 2017 the same indicators grew by 20%, 28%, and 14%, respectively.

According to McKinsey & Company (2018), the African banking market is the second market in the world in terms of growth and profitability[2]. Data from McKinsey Global Banking Pools in 2018 projects annual growth in banking activity on the continent to be around 8.5% for 2017 to 2022, which will generate sales of nearly US $129 billion of which US $53 billion would come from retail banking (Chironga et al., 2018).

As the African banking sector is marked by exceptional growth, it would be interesting to look into the level of risk to which African financial centers could be exposed as well as the reforms to be envisaged to promote a stable banking market than can contribute to economic growth and development of the region. Indeed, Langfield and Pagano (2016) found that an increase in the size of the banking system relative to equity and private bond markets is associated with more systemic risk.

Our contribution to the literature on African banking systemic risk analysis is threefold. Firstly, we propose a relevant indicator of systemic risk using the approach developed by Guerra et al. (2016), who made improvements by introducing cluster analysis based on correlations to bank default. Secondly, we explicitly analyze the behavior of foreign banks[3], especially pan-African banks, in the WAEMU. The case of the WAEMU is interesting since it is a monetary union composed of eight countries in which banks are subject to the supervision of a single community regulator: The Banking Commission. Thirdly, the banking sector in this region has been dominated by French banks since independence in the 1960 s. However, the trend in the number and the share of pan-African banks in the region has increased significantly. For instance, the share of Pan-African banks – i.e., their total assets as a percentage of total banking sector assets – increased from 20% in 2000 to 52% in 2017. The question, therefore, arises as to whether pan-African banks can be considered to present very low systemic risks. Indeed, as the networks develop new channels for the transmission of macro-financial risks, ripple effects in the home and host countries may appear. Nevertheless, these systemic risk ripple effects could be more substantial in developed economies than in developing countries because the financial and interbank markets are less integrated in developing countries.

The paper uses a two-step approach to analyze systemic risk. First, it estimates the probabilities of default of banks, and computes an indicator of systemic risk of the banking sector of the WAEMU starting from the principle that a bank default can lead to cascading bankruptcies in case of strong interconnections. Next, potential contagion mechanisms are identified between banks through networks based on clustering techniques. The systemic risk, stemming from the interconnection among banks, appears if a shock on a bank belonging to a network has an impact on another bank not belonging to this network.

The remainder of the paper is organized as follows. Section 2 presents the potential systemic risks in pan-African banking. Section 3 is devoted to a review of the current literature on systemic risk. The methodology is presented in Section 4. Section 5 presents the data and variables while the empirical results are presented in Section 6 and we conclude in Section 7.

## 2. Pan-African banking and systemic risk

From the end of the 1990 s, regional or pan-African banks came mainly from Nigeria, Morocco, and Libya. The proportion of banks that were defined as pan-African was<30% in 2000 but was estimated at above 60% by 2017 in the WAEMU. This expansion of regional banks can be explained, on the one hand, by the search for profit which is closely linked to the region's strong economic growth (more than 5% since 2012). On the other hand, banks operating in this union are entitled to a single authorization which gives a banking institution the right to have an active presence in another member state of the union without having to immediately build up capital. Also, the prudential rules of minimum capital of the regional regulator motivate banks to optimize their capital. Therefore, banks in this monetary union are more motivated to deploy activities beyond a single country.

For the past thirty years, the banking literature has focused on the foreign bank and domestic bank dichotomy. The regionalization of African banks creates a new paradigm that is not yet well described in the literature.

So-called "foreign", "international" or "cross-border" banks are banking institutions whose origins are in a foreign country. Pan-African banking groups, according to Caruana (2014), are establishments that are domiciled in Africa and have subsidiaries in several countries of the continent. This type of bank practically dominates the African banking market today. The geographic footprint of pan-African banks can be measured by the number of countries where the bank is present (Fig. 1). They represent more than 60% of total assets of banks located in Africa. If we take the example of the WAEMU zone, the French Treasury Department stated in a note

[2] https://www.consultancy.africa/news/366/africas-banking-sector-the-second-most-profitable-in-the-world-says-mckinsey (accessed on March 2021).

[3] Pan-African banks are foreign banks with headquarter in Africa compared to other conglomerates.

from May 2017 that “the combined market share of groups with African capital increased from 49% in 2004 to 70% in 2015. The French subsidiaries shares were halved (29% to 14%) over the same period”. The pan-African group Ecobank is the clearest expression of this new strategy. This group is now active in 36 African countries (Fig. 1). It also has offices in Paris, Beijing, Dubai, Johannesburg, and London, allowing it to raise capital in wealthy countries to encourage investment across the African continent. However, this increasingly Pan-African banking market presents risks that are important to note.

Apart from Standard Bank, via its subsidiary Stanbic, or even Nedbank, via Ecobank, South African banks remain cautious in terms of geographic expansion. On the contrary, Moroccan banks promote regional diversification. As for Nigerian banks, they encountered difficulties in French-speaking Africa, notably through Diamond Bank, sold to the NSIA group in 2017. Faced with the three large African countries with dominant banking systems (South Africa, Morocco, Nigeria), we note the continuous breakthrough of the banks of the WAEMU-CEMAC (Central African Economic and Monetary Community). Thus, the resilience of BGFI Bank, the leader in Central Africa, and the rapid rise of Coris Bank as a big actor in West Africa and listed on the Abidjan Regional Stock Exchange (BRVM), is a clear testimony for an external growth strategy. Oragroup, Nsia Bank, and Afriland First Bank have each set up a significant regional dynamic as well.

Our study concentrates on the WAEMU region for three main reasons:

- The dynamism of the region contrasts considerably with other African areas[4]. Boosted by the continent’s economic growth and high profitability levels, the banking sector has shown strong momentum over the past decade, making it the second-fastest in terms of growth and profitability in the world[5].
- Additionally, we have observed spectacular development of the banking industry and successful integration compared to other regions. One aspect of this growth has been the radical change in the competitive landscape with the emergence of Pan-African banks developing cross-border banking and challenging the traditional players and supervisors.
- Finally, the concept of pan-African banking that is characteristic of the WEAMU region is new and differs from the concept of foreign and domestic banking and consequently, there are no academic analyses of the interconnection issues involving pan-African banks.

The emergence of pan-African banks is associated with an extension of credit to the economy (Kanga et al., 2018; Léon and Zins, 2020). Table 1 shows that the credit-to-asset ratio ranged from 30% (FBN) to 73% (First Rand) in 2017 (Annual reports and Orbis Bank Database). Pan-African banks are relatively solid for the most part. Indeed, leverage – defined by the ratio between capital and the total asset – varied between 3% (Kenya Commercial Bank) and 17.5% (GT Bank) when we examined the continent’s top seventeen pan-African banks in 2017. Six of these banks (BCP, BMCE BoA, FBN, Kenya Commercial Bank, Oragroup, Coris Bank) have a leverage of<8%.

These numbers indicate that some banks have relatively low capitalization levels. Some studies dealing with the WAEMU area show that pan-African banks developed mainly through subsidiaries, i.e. the acquisition of existing banks. The penetration of pan-African banks has increased the level of competition in the banking sector (Léon, 2016; Kanga et al., 2018). This competition has reduced the profit of domestic and foreign banks, especially French banks. Via this mechanism, competition is likely to generate fragility in the banking sector of the WAEMU area (Kanga et al., 2021).

As stated above, the question, therefore, arises as to whether, behind their capacity to integrate the continent, African banks can be considered to present very low systemic risks. This paper aims to help answer this question.

## 3. Literature review

Research on systemic risk began well before the 2007 financial crisis. Silva et al. (2017) carried out a literature review by classifying 266 articles published before September 2016. A similar study was undertaken by Benoît et al. (2017). One output of these extensive reviews of the literature has been the identification of the most influential articles related to the analysis of systemic risk. The literature can then be divided into two generations of research.

### 3.1. Two generations of research

The first generation focused on issues related to bank panics and crashes. Many authors have contributed to such analyses (Kindleberger and Aliber, 1978; Bryant, 1980; Stiglitz and Weiss, 1981; Bernanke, 1983; Diamond and Dybvig, 1983; Gorton, 1988; Calomiris and Gorton, 1991; Kaminsky and Reinhart, 1999; Allen and Gale, 2000; Summer, 2003; Lehar, 2005; Das and Uppal, 2004;

[4] Average annual GDP growth since 2000 is over 5%, placing Africa as the second-fastest growing economy behind Latin America. Real GDP growth, estimated at 3.4% for 2019, is projected to accelerate to 4.1% in 2021. Growth fundamentals are also improving, with a gradual shift from private consumption toward investment and exports. And for the first time in a decade, investment accounted for more than half the continent’s growth, with private consumption accounting for less than one-third. See Zied Loukil « Can Africa’s banking sector maintain its growth momentum? » March 2021, Partner - Mazars. https://www.consultancy.africa/news/366/africas-banking-sector-the-second-most-profitable-in-the-world-says-mckinsey (accessed on March 2021).

[5] McKinsey Global Banking (2018) Pools://www.mckinsey.com/~/media/mckinsey/industries/financial%20services/our%20insights/african%20retail%20bankings%20next%20growth%20frontier/roaring-to-life-growth-and-innovation-in-african-retail-banking-web-final.ashx

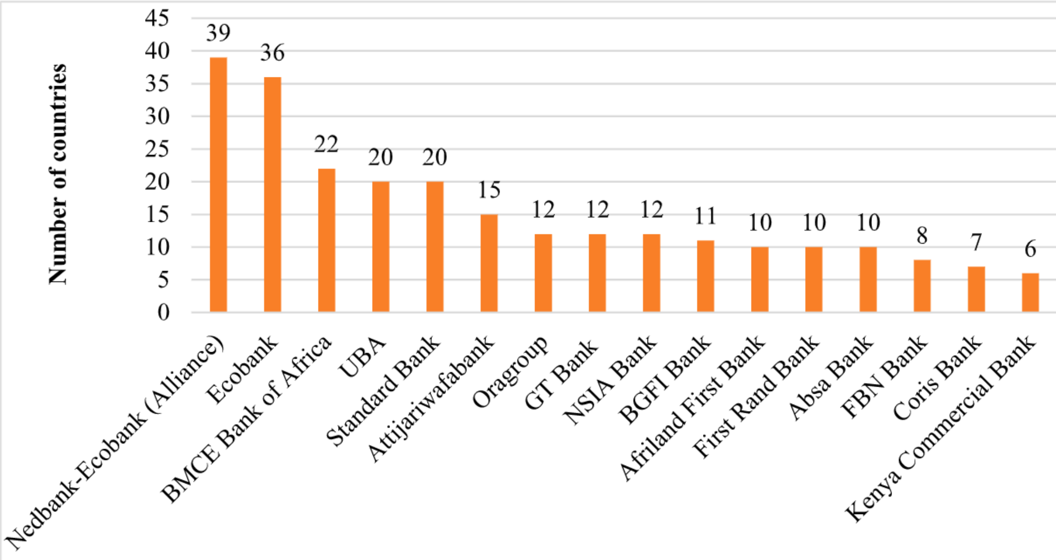


**Fig. 1.** The geographic footprint of pan-African banks in 2019: number of countries where the bank is present – Data collected from bank activity reports.

**Table 1**
Characteristics of the top-17 pan-African banks collected from bank activity report in 2017.

| Rank | Name | Total asset* | Revenue-to-asset ratio (%) | Net Profit-to-revenue ratio (%) | Loan-to-asset ratio (%) | Capital-to-asset ratio (%) |
|---|---|---|---|---|---|---|
| 1 | Standard Bank | 129,747 | 5.7 | 27.0 | 52.7 | 9.4 |
| 2 | First Rand | 93,337 | 5.7 | 32.1 | 73.2 | 8.5 |
| 3 | Absa | 78,615 | 1.7 | 70.8 | 65.3 | 9.4 |
| 4 | Nedbank | 63,680 | 4.9 | 27.7 | 70.5 | 8.7 |
| 5 | Attijari Wafa | 47,213 | 4.4 | 25.5 | 59.8 | 9.9 |
| 6 | BCP | 40,000 | 4.3 | 20.6 | 37.5 | 7.4 |
| 7 | BMCE BoA | 29,000 | 4.5 | 21.5 | 61.8 | 6.6 |
| 8 | Ecobank | 20,169 | 3.1 | 46.7 | 40.6 | 8.0 |
| 9 | FBN | 13,815 | 10.5 | 10.2 | 30.2 | 5.8 |
| 10 | UBA | 12,082 | 4.1 | 39.1 | 35.2 | 10.3 |
| 11 | GT Bank | 8143 | 13.2 | 42.3 | 38.3 | 17.5 |
| 12 | Kenya Com. Bank | 5847 | 2.5 | 72.6 | 63.1 | 3.0 |
| 13 | BGFI Group | 4561 | 6.8 | 9.9 | 67.9 | 15.5 |
| 14 | Oragroup | 3318 | 5.8 | 23.3 | 57.8 | 4.3 |
| 15 | Coris Bank | 3049 | 7.0 | 28.2 | 70.0 | 6.6 |
| 16 | NSIA Banque | 1658 | 6.2 | 17.5 | 67.9 | 8.1 |
| 17 | Afriland First Bank | 1581 | 5.2 | 8.5 | 60.0 | 12.0 |

Source: Annual reports and Orbis Bank Database, own calculation.
* numbers in million € unless otherwise indicated.

Elsinger et al., 2006). Some authors have shown that bank panics, contagion effects, and information asymmetry are important factors that can lead to systemic crises. Others have focused on liquidity issues, bank interconnectedness, and the definitions and measures of systemic risk.

The second generation emerged in the aftermath of the 2007 financial crisis. Numerous theoretical and empirical studies have been conducted. These studies have enriched the development of the first generation by determining causes, new definitions, and measurement tools for predicting systemic risk. In its 2009 annual report, the IMF drew attention to the need for regulators to develop tools for detecting systemic risks at an early stage. The volume of research on measuring the spread of credit risk between financial institutions and sovereign risk between economies has grown rapidly after the global financial crisis. In general, second-generation research has been based on a wide range of approaches. In a report published in 2009, the IMF, the Bank for International Settlements (BIS), and the Financial Stability Board (FSB) proposed a methodology for assessing the systemic importance of a financial institution based on indicators of size, interconnectedness, and substitutability. Acemoglu et al. (2015), studied the phenomenon of financial contagion through a model of balance based on an economy that produces a single good with the presence of a network of interconnected banks. When the magnitudes of negative shocks affecting financial institutions are sufficiently reduced, a more connected financial network (corresponding to a more diversified network structure of interbank liabilities) can improve financial stability. However, from a certain point, significant interconnections are a potential source of financial instability. The important result that emerges from their research is that the same factors that contribute to resilience under certain conditions can become important sources of systemic risk.

### 3.2. Other new measures proposed by the second generation of research

Other approaches have been used in the second-generation literature. Numerous authors developed approaches based on structural models, such as those proposed by Black and Scholes (1973) and Merton (1974), to estimate systemic risk. These models are based on banks' balance sheet information or the liability structure of economies. These approaches involve estimating probabilities of default (PDs) and loss given default (LGD). This information is used to construct systemic risk indicators based on dependency events such as consistent information multivariate density optimization (CIMDO), banking system multivariate density (BSMD), networks, clusters, and classification trees. These proposed indicators capture not only the information available from an individual bank but also their dependence on default in a portfolio approach (Segoviano, 2006; Tabak and Staub, 2007; Segoviano and Goodhart, 2009; Kuzubaş *et al.*, 2014; Guerra et al., 2016).

Other examples include reduced-form approaches that use time-series methods to analyze the credit risk structure of banks or economies by studying extreme events based on historical returns or the implied probabilities of derivatives, such as CDS spreads (Huang et al., 2009; Segoviano and Goodhart, 2009; Acharya et al., 2010; Gray and Jobst, 2010; Giglio, 2016). Value at Risk (VaR) and its extensions have also been used to measure systemic risk. A CoVaR methodology is a reduced-form approach (Adrian and Brunnermeier, 2008) aiming to examine the contribution of individual financial institutions to systemic risk using accounting and financial ratios and other balance sheet data of the institutions concerned, such as equity values. Fong et al. (2009) found that CoVaRs can indicate the interdependence of financial institutions in Hong Kong but they used stock market data rather than CDS market data. Roengpitya and Rungcharoenkitkul (2010) applied the same methodology to analyse the Thai banking system. Chan-Lau (2008, 2010) adopted a similar approach but used CDS spreads of financial institutions in the United States, Europe, and Japan.

The concepts of VaR and CoVaR are not limited to the study of systemic risk. Wong and Fong (2011) used CoVaR as a starting point to examine how loan provisions contribute to the procyclicality of banking systems. Schechtman and Gaglianone (2012) used a similar approach in their stress-testing exercises to estimate banks' credit risk. Acharya et al. (2012) showed that expected capital shortfall captures, in a single measure, many of the characteristics considered important for systemic risk such as size, leverage, and interconnectedness. These characteristics tend to increase a firm's capital shortfall when there are widespread losses in the financial sector.

Hurlin et al. (2017) proposed a bootstrap simulation methodology for a sample of US financial institutions. They compared CoVaR, marginal expected shortfall (MES), and systemic risk measure (SRISK) and concluded that only SRISK can be estimated with sufficient precision to allow for a meaningful ranking. Dungey et al. (2018) used a panel of over 500 U.S. firms over 2003–2011 and found evidence that intervention programs (such as TARP) act as circuit breakers in crisis propagation. Kolari et al. (2020) suggested a new measure of systemic risk using mapping and regression methods. Default probabilities for U.S. banks were aggregated into a single macro measure, which had predictive power to detect systemic volatility prior to the 2008–09 crisis. According to their measure, systemic risk returned to normal levels by 2012.

### 3.3. Systemic risk in the African financial system and contributions of the paper

Despite the advanced development of our current understanding, few studies have studied African financial systems. A study conducted in 2015 by the IMF showed that there has been a rapid expansion of pan-African banks in recent years as highlighted in section 2. This study limits the approach to balance sheet statistical analyses focusing on the size of banks and found that it is important to minimize contagion, especially given the high risks in banking activity on the continent. Generally, the expansion of pan-African banks reflects the increase in economic integration in Africa and contributes to enhancing competition, supporting financial inclusion, and fostering greater economies of scale. However, the rapid expansion of pan-African banks poses supervisory challenges that, if left unaddressed, may increase systemic risks. More than a demonstration of the systemic nature of pan-African banks, this IMF study makes recommendations for regulators to prevent potential contagion.

A recent study by Fall (2017) on systemic risk in the WAEMU banking system used the CIMDO approach. The analysis is comprehensive, and the conclusions focus on issues of information asymmetry. However, this analysis does not identify the banking system-level interconnections of this union as the study is based on aggregate data.

Khiari and Nachnouchi (2018) mapped risks for Tunisian banks to shed light on the factors that influence their risk levels, which are key to the involvement of such banks in systemic risk. Using a unified approach combining CoES and multidimensional scaling (MDS) techniques, the map revealed that public banks are the most involved in systemic risk, followed closely by the two largest private banks.

Many methods have been proposed by the second generation of research. Methods based on CDS, SRISK, VaR, CoVaR, and the expected shortfall will be difficult to apply. Data on CDSs do not exist for WAEMU banks, while methods based on VaR and its variants seem difficult to apply to detect interconnectivity phenomena. For these reasons, we use the Merton model based on the distance-to-default to estimate the probability of bank default and the CIMDO approach to assess system risk.

We contribute to the literature on systemic risk analysis in two ways. First, we propose a relevant indicator of systemic risk using the approach developed by Guerra et al. (2016), who made improvements by introducing a cluster analysis based on correlations to bank default. Next, we explicitly analyze the behavior of foreign banks, especially pan-African banks, in the WAEMU.

## 4. Methodology

Our methodology is based on the work of Segoviano (2006), Segoviano and Goodhart (2009), and Guerra et al. (2016) and consists of assessing systemic risk in three steps. The first step is to assess banks' PD using Merton's (1974) distance-to-default (DD) model. The volatility of assets and the implied value of assets in the Merton (1974) model are estimated using the Duan method (Duan, 1994; 2000). The PDs calculated from this "raw"[6] approach is a relative measure of risk, i.e. it is helpful to discern between "good" banks (i.e. banks with low probability of default) and "bad" banks (i.e. banks with high probability of default) in a relative ranking sense. We use the individual PDs to construct clusters of banks in the second step. Unlike Guerra et al. (2016), we use a classification algorithm that combines the tree covering the minimum weight or minimum spanning tree (MST) and the $k$ nearest neighbors (kNN). This is an unsupervised classification approach in which the numbers of nearest neighbors and clusters are selected automatically. This approach has been extensively used in the recent literature to study contagion (see for example, Miccichè et al., 2003; Zhang et al., 2020). In the third step, we evaluate the joint PD by using the CIMDO, and construct stability indicators for the banking system.

**Step 1: Estimation of individual PDs**

The Merton (1974) model is based on the financial structure of the firm and options theory. A bank is financed essentially through equity (shares) and zero-coupon bonds with a face value of D. This model assesses a firm's short-term default risk. The zero-coupon bond debt is assumed to last one year ($T = 1$). The total value of the assets is then equal to the sum of the value of the shares and the debt. The change in the market value of the assets follows a geometric Brownian motion (GBM):

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \tag{1}$$

where $dW_t = \varepsilon\sqrt{dt}$ and $\varepsilon \to N(0,1)$. $V$ represents the value of the company's assets, $\mu$ the instantaneous drift, and $\sigma$ the instantaneous volatility of the assets; $W$ is a standard Wiener process.

The asset value follows a stochastic process because its changes over time are at least partly random. Starting from the representation as a stochastic GBM-type process and using Ito's lemma, one can derive the trajectory of the value of the company's assets:

$$dlog(V_t) = \left(\mu - \frac{\sigma^2}{2}\right)dt + \sigma dW_t \tag{2}$$

In the Merton (1974) model based on the DD, the share value represents the price of the call option. The strike price is controlled by the firm's debt. The share value is derived from the call pricing according to the Black–Scholes formula:

$$E_T = V_T\Phi(d_1) - D_T e^{-rT}\Phi(d_2) \tag{3}$$

and

$$\begin{aligned} d_1 &= \frac{\ln\left(\frac{V_T}{D_T}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \\ d_2 &= \frac{\ln\left(\frac{V_T}{D_T}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \end{aligned} \tag{4}$$

where $r$ is the risk-free rate, and $\Phi$ is the standard normal cumulative distribution function. The introduction of the risk-free rate by Black and Scholes makes it possible to analyze the risk-neutral behavior or the possibility of no-arbitrage opportunity (AOA). In both cases, $\mu$ is replaced by $r$.

The PD is defined as follows:

$$PD_T = \Phi\left(-\mathrm{d}_2^*\right) = \Phi\left(-\frac{\ln\left(\frac{V_T}{T}\right) + \left(\mu - \frac{\sigma^2}{2}\right)\mathrm{T}}{\sigma\sqrt{\mathrm{T}}}\right) \tag{5}$$

where $d_2^*$ is the DD.

There is a controversy regarding the determination of the average value and volatility of assets because they are unobservable. Duan (1994, 2000) suggested the use of a maximum likelihood method for determining both value and volatility of assets. His approach is particularly applicable to financial institutions and large firms.

Let $X$ be a vector of unobservable $n$-dimensional random variables and $Y$ a vector of observable $n$-dimensional random variables. According to Duan's theorem, if the transformation from $X$ to $Y$ is element by element, i.e., for all $i$, then

[6] The Merton (1974) approach provides a distance to default (DD), but this requires considerable calibration exercises to convert the DD to a useable PD. This article did not rely on calibration, that is what the used the word "raw" approach.

$$L(Y,\theta) = L_X(\widehat{x}_1, \cdots, \widehat{x}_n, \theta) - \sum_{i=1}^{n} ln\left|\frac{dT_i(\widehat{x}_i, \theta)}{dx_i}\right| \tag{6}$$

$$\widehat{x}_i(\theta) = T_I^{-1}(y_i; \theta)$$

Starting from the equation (2) with an unobservable $V$, the log of the likelihood can be written as follows:

$$L_V(V_1, \cdots, V_n, \mu, \sigma) = -\frac{n-1}{n}\left(\ln(2\pi) + \sigma^2\right) - \sum_{t=2}^{n}\ln(V_t) - \frac{1}{2\sigma^2}\sum_{t=2}^{n}\left[\ln\left(\frac{V_t}{V_{t-1}}\right) - \mu - 0,5\sigma^2\right]^2 \tag{7}$$

Therefore, one needs to maximize this likelihood (ML) to get the values of $V$ and $\sigma$.

Step 2: Clustering

The clustering is based on correlation analysis. It uses a modified Pearson correlation defined by:

$$d(i,j) = \sqrt{2(1-\rho(\mathrm{i},\mathrm{j}))} \tag{8}$$

where $\rho(i,j)$ is the Pearson correlation coefficient between the probability of default of banks $i$ and $j$.

This distance has been widely used in the financial literature (e.g., Miccichè et al., 2003; Guerra et al., 2016). This distance lies between 0 and 2 and decreases with the correlation $\rho(i,j)$. It is zero when the PDs of the two banks in the pair are perfectly and positively correlated ($\rho(i,j) = 1$), i.e. the two banks will default simultaneously. It equals 2 when $\rho(i,j) = -1$ for all $i$ and $j$.

This distance enables the construction of a bank grouping tree using the K-means method or the moving center method. According to this method, it is necessary to identify banks that have the same characteristics, i.e., whose distance is small. Banks in the same group should be more similar, while those in other groups should be distant.

Step 3: Estimation of PDs determined by CIMDO and banking system stability indicators

CIMDO generates a non-parametric multivariate density function. Its advantage is that it describes the dependency structure of the default to be determined. The algorithm starts with a prior distribution of the joint PD and computes the posterior multivariate distribution. The default dependencies are estimated from an optimization process in which the prior joint PD density is updated by integrating the available information from the probability of default of each bank and a default threshold[7]. At the end of the process, the multivariate density of the banking system (MDBS) constructed from the pair of banks is computed[8].

In the bivariate case, the objective function is written as

$$Z(p,q) = \iint p(x,y) ln\frac{p(x,y)}{q(x,y)} dxdy \tag{9}$$

In equation (9), $x$ and $y$ are two banks, $p(x,y)$ and $q(x,y)$ represent posterior and prior densities, respectively. The prior distribution $q(x,y)$ is defined as a bivariate normal density function with zero mean and a known variance–covariance matrix $\Omega$. The posterior distribution is unknown. To get the posterior density, the following program is solved

$$Min\left\{Z(p,q) = \iint p(x,y) ln\frac{p(x,y)}{q(x,y)} dxdy\right\} \tag{10}$$

under the following constraints:

$$\iint p(x,y)\varphi_{(DSx,\infty)} dxdy = PD_t^x \tag{11}$$

$$\iint p(x,y)\varphi_{(DSy,\infty)} dxdy = PD_t^y \tag{12}$$

$$\iint p(x,y) dxdy = 1 \tag{13}$$

where $PD_t^x$ and $PD_t^y$ are probabilities of default of each bank in the pair, and $\varphi_{(DSx,\infty)}$ and $\varphi_{(DSy,\infty)}$ measure the distance between the prior and the posterior distributions for banks $x$ and $y$, respectively.

The solution of this optimization program is as follows:

$$\widehat{\mathrm{p}(\mathrm{x},\mathrm{y})} = q(\mathrm{x},\mathrm{y}) \times exp\left[\sum_{i=0}^{2}\gamma_i\varphi(DS_i,\infty) - 1\right] \tag{14}$$

where $\varphi(DS_0,\infty) = 1$ and $\gamma_i$ are Lagrange multipliers.

In the paper, we use on the joint probability of default of the banks in the pair denoted $\mathrm{JPoD}_{xy}$ as the measure of the banking sector stability indicator. It is defined by:

[7] The default threshold is provided at the beginning of the algorithm, but the final result does not depend on the initial threshold.

[8] This approach can also be estimated from the copulas, in which case a CIMDO copula is obtained. This is useful because it controls the nonlinear dependence between the two processes. It has not been considered in this paper.

$$\mathrm{JPoD}_{xy} = P(\mathrm{X} \cap \mathrm{Y}) = P(\mathrm{X} \geq \mathrm{DSx}, \mathrm{Y} \geq \mathrm{DSy}) = \iint_{DSx,DSy}^{+\infty} \widehat{p(x,y)}dxdy \tag{15}$$

## 5. Data and variables

As Guerra et al. (2016), this paper uses accounting data to estimate the probabilities of bank default following Merton's (1974) model as described in the previous section. We rely on accounting data instead of financial market data because the financial market is underdeveloped in the WAEMU. Only 13 banks are listed on the stock market out of more than 100 banks in the region. The turnover rate – i.e., the ratio of the value of total shares traded to market capitalization – is very low (3.4% compared to 6.8% in Morocco in 2017 according to the Global Financial Development Database 2019). The accounting data come from the WAEMU Banking Commission.

Merton's (1974) model requires six input variables, namely equity, assets, asset volatility, equity volatility, liabilities, and the risk-free interest rate. Equity is calculated as the sum of share capital, capital premiums, reserves, revaluation differences, and retained earnings. We follow the regulatory framework of the WAEMU which is strongly based on the Basel I Accord[9]. Equity volatility is calculated as the standard deviation of the annual equity capital growth rate. Banks' liabilities are the sum of financial debts – debts to customers, interbank debts, and debts represented by the security. The information on the type of customers (corporate or household) or the maturity of debt is not available. Therefore, it is not possible to distinguish between short and long-term debt. The repo rate of the Central Bank of West African States (BCEAO) is used as the risk-free rate in the absence of AAA sovereign securities. The value of the total asset and asset volatility are estimated using the methodology proposed by Duan (2000).

To construct the final database, we start with the whole universe of banks in the WAEMU and consider the following criteria: (i) we removed banks with missing information on liabilities (debt) or negative equity capital, (ii) we removed banks with less than five successive observations (five years) to allow the equity volatility to be calculated as required in the Merton model. The final database contains 102 banks covering the period 2000–2017 and contains the unbalanced panel, with 1431 observations (bank years). This constitutes 87% of the initial number of observations.

## 6. Empirical results

### 6.1. Analysis of probability of default

This study computes the risk-neutral PDs. This estimate showed that some banks have a constant probability of default over the entire study period, that is the variance is zero. For these banks, we cannot estimate the distance defined by equation (8) used to construct clusters because it requires standard deviation on denominator. Therefore, these banks have been removed from the analysis. In what follows, 82 banks are considered, with a total of 1138 observations. Fig. 2 gives the composition of the sample. Almost three-quarters (72%) of the sample of banks (number of observations) are owned by foreign investors. Also, 58% of for all banks in the sample are owned by African investors.

Table 2 presents the distribution of default probabilities overtime after excluding banks with zero-variance PDs. The table shows the average PD, the standard deviation, the main quartiles, and the minimum and maximum values. The values of probabilities of default are generally low. The maximum value of the third quartile of PDs is 13.8% (in 2000). However, a small number (5) of banks have very high probabilities of default, that is PDs greater than 50%. These five banks are in Benin (1), Burkina Faso (1), Senegal (1), and Togo (2), and most of them have been recently recapitalized, which has significantly increased the volatility of equity capital and thus increased their PDs[10]. After a recapitalization, one would normally expect a lower PD. However, since the volatility of equity capital is calculated over the entire period of existence of the bank in the data sample, a large increase in equity capital (for instance recapitalization) from one year to the next increases its volatility, that is why the PD increases.

To understand the role played by the origin of the banks, we compare the PDs by the country of origin of the main shareholder of the bank.

The results of the comparison (see Table 3) show that the average probability of default of domestic banks is higher than that of foreign banks. The difference between the average probabilities of default is significant at the 5% level. This invalidates the *market risk theory* which stipulates that foreign banks bear more risk than domestic banks due to their poor knowledge of the market (*managing from distance*). Conversely, we find that foreign ownership is associated with lower risk, certainly, because banks with foreign capital have better access to capital markets, greater risk diversification capacity, and access to advanced technologies for collecting and evaluating information.

An in-depth analysis shows that French banks have a lower risk of default than other banks, including pan-African banks. This preliminary analysis indicates that the risk of default of French banks is less than that of pan-African banks, and pan-African banks have a lower risk of default compared to domestic banks. French banks are well-grounded and have a better knowledge of the region compared to pan-African banks because they have been settled there since independence.

[9] The prudential framework of the BCEAO was strongly influenced by Basel I until January 2018, when it moved to Basel II and III.

[10] The PD in the Merton model is sensitive to the volatility of equity.

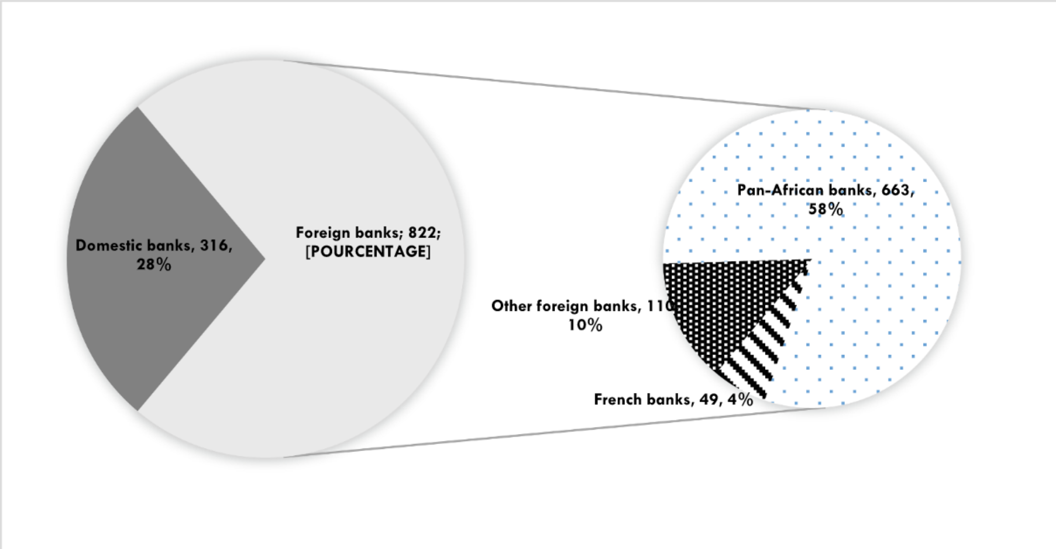


**Fig. 2.** Composition of the sample (domestic, foreign banks). For each pie, the figure displays the category of banks, the number of observations (bank-year), and the percentage in the total number of observations.

**Table 2**
Distribution of bank default probabilities, 2000–2017.

| | Observation | Mean | Std. Dev | Minimum | 1st quantile | Median | 3rd quantile | Maximum |
|---|---|---|---|---|---|---|---|---|
| 2000 | 40 | 0.097 | 0.179 | 0.000 | 0.000 | 0.001 | 0.138 | 0.739 |
| 2001 | 42 | 0.09 | 0.161 | 0.000 | 0.000 | 0.001 | 0.123 | 0.749 |
| 2002 | 44 | 0.086 | 0.163 | 0.000 | 0.000 | 0.001 | 0.114 | 0.736 |
| 2003 | 46 | 0.083 | 0.164 | 0.000 | 0.000 | 0.001 | 0.103 | 0.741 |
| 2004 | 51 | 0.077 | 0.156 | 0.000 | 0.000 | 0.001 | 0.058 | 0.739 |
| 2005 | 54 | 0.104 | 0.205 | 0.000 | 0.000 | 0.002 | 0.128 | 0.907 |
| 2006 | 68 | 0.092 | 0.193 | 0.000 | 0.000 | 0.002 | 0.074 | 0.943 |
| 2007 | 69 | 0.092 | 0.191 | 0.000 | 0.000 | 0.003 | 0.075 | 0.954 |
| 2008 | 68 | 0.095 | 0.191 | 0.000 | 0.000 | 0.005 | 0.097 | 0.958 |
| 2009 | 68 | 0.088 | 0.186 | 0.000 | 0.000 | 0.005 | 0.068 | 0.979 |
| 2010 | 67 | 0.08 | 0.156 | 0.000 | 0.000 | 0.003 | 0.074 | 0.753 |
| 2011 | 72 | 0.076 | 0.152 | 0.000 | 0.000 | 0.003 | 0.074 | 0.773 |
| 2012 | 74 | 0.076 | 0.153 | 0.000 | 0.000 | 0.003 | 0.073 | 0.774 |
| 2013 | 77 | 0.078 | 0.168 | 0.000 | 0.000 | 0.003 | 0.058 | 0.95 |
| 2014 | 73 | 0.079 | 0.173 | 0.000 | 0.000 | 0.003 | 0.065 | 0.999 |
| 2015 | 77 | 0.088 | 0.183 | 0.000 | 0.000 | 0.005 | 0.08 | 0.966 |
| 2016 | 76 | 0.08 | 0.171 | 0.000 | 0.000 | 0.004 | 0.059 | 0.965 |
| 2017 | 72 | 0.076 | 0.171 | 0.000 | 0.000 | 0.002 | 0.063 | 0.964 |
| Total | 1138 | 0.085 | 0.173 | 0.000 | 0.000 | 0.002 | 0.08 | 0.999 |

Notes: This table describes the evolution of the probabilities of default from 2000 to 2017 estimated by Merton's model. The raw data come from the banking commission of the WAEMU.

**Table 3**
Mean comparison test results of average probability of default between categories of bank.

| | Group 1 | | Group 2 | | Comparison | |
|---|---|---|---|---|---|---|
| | Observations | Means | Observations | Means | Difference | P-value |
| Domestic (Group 1) *versus* foreign (Group 2) | 316 | **0.104** | 822 | 0.077 | 0.027 | 0.013 |
| Non pan-African (Group 1) *versus* pan-African (Group 2) | 475 | 0.093 | 663 | 0.079 | 0.014 | 0.160 |
| Non-French (Group 1) *versus* French (Group 2) | 1089 | **0.087** | 49 | 0.029 | 0.058 | 0.000 |
| Pan-African (Group 1) *versus* French (Group 2) | 663 | **0.079** | 49 | 0.029 | 0.049 | 0.000 |
| Domestic (Group 1) *versus* pan-African (Group 2) | 316 | **0.104** | 663 | 0.079 | 0.025 | 0.029 |

Notes: This table compares the average probability of default of banks between different categories. Group 1 refers to the category before "*versus*" in each row and Group 2 refers to the second category after "*versus*" in each row. For example, domestic *versus* foreign compares the average default probabilities of domestic banks *versus* that of foreign banks. Comparison tests are performed using the *t*-test (with unequal variance and Welch correction).

### 6.2. Clustering

After estimating the probabilities of default, we calculate the distance defined by equation (8). This calculation requires pairs of banks. Since the panel is unbalanced, some banks could not be paired. Pairs could only be formed for 56 banks when we consider the entire 2000–2017 period. Therefore, the analysis in this section is based on the 56 banks included in the pairs.

Following the estimation of this distance, we used the minimum spanning tree graphs algorithm by Inostroza-Ponta (2008) to categorize banks over the 2000–2017 period. The result is displayed as a graph in which a node represents a bank and an edge is a link between pairs of banks. The length between two nodes corresponds to the distance described by equation (8). The algorithm combines the minimum spanning tree (MST) and the $k$-nearest neighbors (kNN) to highlight the most important relationships between banks in the sample. This is an unsupervised approach with an automatic selection of $k$: the number of groups and number of banks per group is *a priori* unknown. Fig. 3 shows the results of the clustering.

The algorithm identified 12 clusters, i.e. 12 groups of banks. We find that banks in a cluster are interconnected, meaning that the risk of contagion is high in each cluster, and this risk decreases with the distance between two nodes. Recall that the closer two banks (nodes) are on the graph, the more their probabilities of default are positively correlated.

Table 4 describes the different clusters. The average probabilities of default are higher in clusters C9, C10, C12, C2, and C1 compared to the other clusters. Clusters C1, C2 and C12 are close and are located in the lower part of Fig. 3, while the other two clusters (C9 and C10) are located in the upper part of the graph. The location indicates that clusters C9 and C10 are not close to the other clusters with a similar range of probability of default. Furthermore, except for cluster C12, the other clusters with more than two banks have a core bank around which the other banks gravitate.

These results imply that if a core bank goes bankrupt, it can have a negative impact on all other banks in the cluster. Also, given the proximity of certain clusters, there are potential contagion mechanisms between clusters. This is consistent with the findings by the IMF (2017), which sounded the alarm about the increase in credit risk and the concentration of loans: the ratio of the non-performing loans to total loans remained relatively high for several banks in this region.

Table 5 shows the differences in the average probabilities of default of banks in a cluster in columns with those in rows. For example, the difference between the average PDs of cluster C3 (in a row) and cluster C1 (in a column) is 0.089 and significantly different from zero at the 1% level (***). This implies that the average probability of default of banks in cluster C1 is significantly higher than that of banks in cluster C3 by 8.9 percentage points at the 1% level. Overall, this table shows that the average probabilities of default of the C1 and C2 clusters are not statistically different at the 10% level, so are the clusters C5 and C7. We find that the average probabilities of default of clusters C1 and C2 are higher than those of other clusters apart from clusters C9, C10, and C12. These latter clusters have higher average probabilities of default than those of clusters C1 and C2.

Given the number of banks in clusters C1, C2, and C10, there may be cascading bankruptcy in the case of bank failure of these clusters. Consequently, it is necessary for the supervisor to monitor the co-movements of banks, even though the probability of default of each bank is very low. Table 5 highlights the possible systemic risk if financial strength deteriorates in the banking sector. The banking commission has implemented important reforms to improve the supervision of cross-border banking groups with systemic weight. Also, it creates the financial stability fund and the deposit guarantee fund to limit the effect of bankruptcy.

### 6.3. Analysis of the joint probabilities of default (JPoD)

The third step of the analysis is the computation of the joint probabilities of default (JPoD) using the CIMDO method. The following sub-sections describe the JPoDs and analyze their determinants.

#### 6.3.1. Description of the joint probabilities of default (JPoD)

Table 6 shows the evolution of JPoD over the 2000–2017 period. The average JPoD varied between 50.6% and 56.1% over this timeframe. It is worth noting that JPoDs are heterogeneous between pairs of banks, and the annual growth rate reaches up to 29% for some pairs of banks. The high average value of JPoDs means banks have a high probability of joint default in the WAEMU. This does not necessarily mean that individual banks have high probabilities of default. As we have shown in the previous section, the probability of default for a single bank is on average 8.5%. The results on the joint probabilities of default indicate that if a bank goes bankrupt, the risk of contagion or the risk that other banks go bankrupt is high.

Several factors can explain this result including the interconnection between the banks. The banking sector in the WAEMU region is dominated by pan-African banking groups and subsidiaries of European banks (mostly French). Depending on the bank's position in the network, bankruptcy can have a significant effect on the stability of other banks. Another interconnection channel is the interbank market. Even if few banks participate in the interbank market, pronounced participation of some banks in the market can favor the propagation of shocks. In the next section, we will examine the determinants of the JPoDs.

*6.3.1.1. Determinants of JPoDs.* After computing the JPoDs and highlighting the existence of a potential systemic risk, this section will assess the determinants of the joint probabilities of default by using a simple econometric framework. The econometric analysis is based on the Capital Asset Management Earning Liquidity and Sensitivity to market risk methodology popularized by the Federal Reserve and the Federal Deposit Insurance Corporation. The regression model is specified as follows:

$$JPoD_{ijt} = \alpha_{ij} + \lambda_t + X_{ijt}\beta + \varepsilon_{ijt} \quad (16)$$

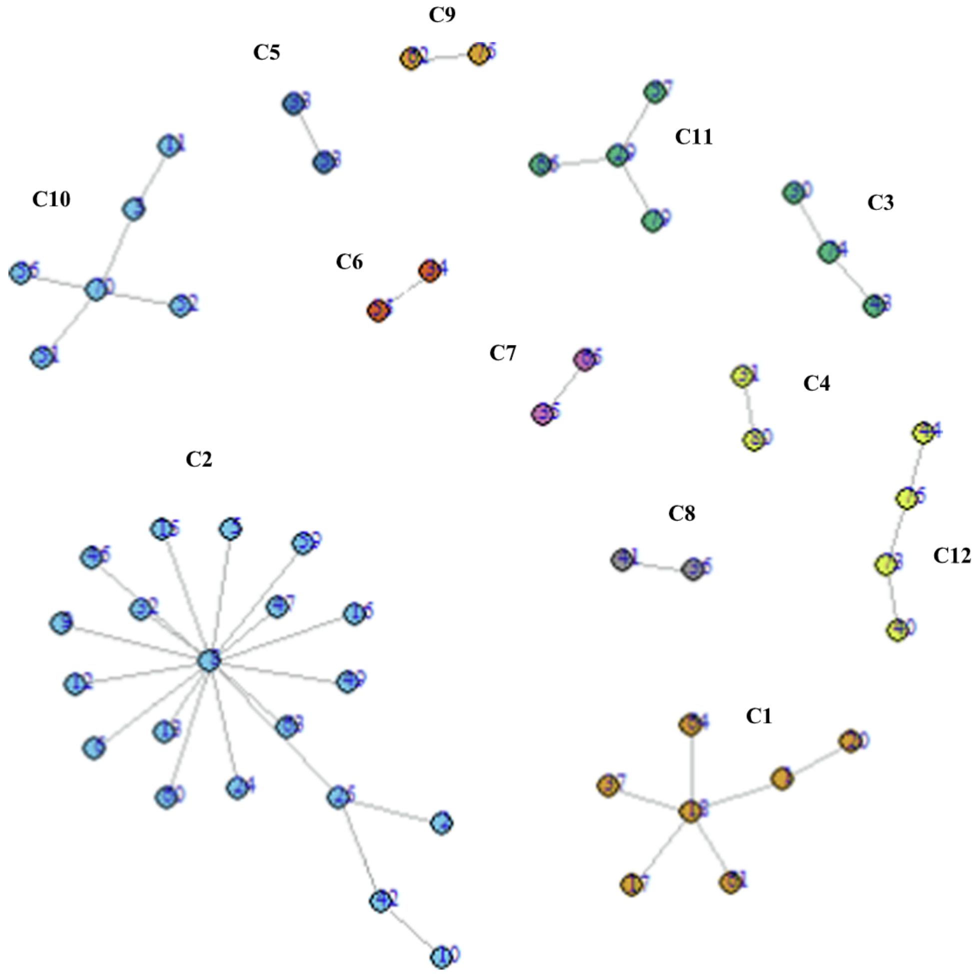


**Fig. 3.** Clustering based on MST-kNN algorithm applied to the default probabilities of the banks.

**Table 4**
Descriptive statistics by cluster identified in Fig. 3.

| Clusters | Observations | Mean | Std. Dev | Minimum | 1st quantile | Median | 3rd quantile | Maximum |
|---|---|---|---|---|---|---|---|---|
| C1 | 95 | 0.096 | 0.080 | 0.000 | 0.040 | 0.051 | 0.187 | 0.267 |
| C2 | 299 | 0.102 | 0.195 | 0.000 | 0.000 | 0.002 | 0.085 | 0.782 |
| C3 | 36 | 0.007 | 0.009 | 0.000 | 0.000 | 0.002 | 0.018 | 0.020 |
| C4 | 24 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| C5 | 16 | 0.004 | 0.004 | 0.000 | 0.000 | 0.004 | 0.007 | 0.008 |
| C6 | 17 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| C7 | 30 | 0.003 | 0.004 | 0.000 | 0.000 | 0.000 | 0.007 | 0.010 |
| C8 | 24 | 0.064 | 0.054 | 0.003 | 0.005 | 0.073 | 0.124 | 0.135 |
| C9 | 36 | 0.311 | 0.185 | 0.119 | 0.130 | 0.303 | 0.486 | 0.516 |
| C10 | 90 | 0.261 | 0.309 | 0.001 | 0.002 | 0.131 | 0.531 | 0.999 |
| C11 | 55 | 0.002 | 0.004 | 0.000 | 0.000 | 0.000 | 0.001 | 0.020 |
| C12 | 47 | 0.145 | 0.282 | 0.000 | 0.000 | 0.000 | 0.006 | 0.708 |

**Table 5**
Mean comparison test of PDs between clusters.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| C2 | −0.006 | | | | | | | | | | |
| C3 | 0.089*** | 0.095*** | | | | | | | | | |
| C4 | 0.096*** | 0.102*** | 0.007*** | | | | | | | | |
| C5 | 0.093*** | 0.098*** | 0.003* | −0.004*** | | | | | | | |
| C6 | 0.096*** | 0.102*** | 0.007*** | 0.000** | 0.004*** | | | | | | |
| C7 | 0.093*** | 0.099*** | 0.004** | −0.003*** | 0.001 | −0.003*** | | | | | |
| C8 | 0.033** | 0.039** | −0.057*** | −0.064*** | −0.060*** | −0.064*** | −0.060*** | | | | |
| C9 | −0.215*** | −0.209*** | −0.304*** | −0.311*** | −0.307*** | −0.311*** | −0.308*** | −0.247*** | | | |
| C10 | −0.164*** | −0.159*** | −0.254*** | −0.261*** | −0.257*** | −0.261*** | −0.258*** | −0.197*** | 0.050 | | |
| C11 | 0.095*** | 0.101*** | 0.005*** | −0.002** | 0.002** | −0.002** | 0.002* | 0.062*** | 0.309*** | 0.259*** | |
| C12 | −0.049 | −0.043 | −0.138*** | −0.145*** | −0.142*** | −0.145*** | −0.142*** | −0.082* | 0.166*** | 0.115** | −0.144*** |

Notes: This table presents the difference of the average probabilities of default between the clusters in columns and those in rows. We performed a mean comparison test with unequal variance and Welch correction. ***, **, and * indicate the significance of the differences at the 1%, 5%, and 10% levels, respectively. For example, 0.089 *** in row C3 and column C1 indicates that the average probability of default for banks in cluster C1 is greater than that for banks in cluster C3 by 8.9 percentage points at the 1% level.

**Table 6**
Distribution of the joint default probabilities of banks, 2000–2017.

| Year | Number of couples | Average | Std. Dev. | Minimum | 1st quantile | Median | 3rd quantile | Maximum |
|---|---|---|---|---|---|---|---|---|
| 2001 | 1465 | 0.506 | 0.291 | 0.000 | 0.214 | 0.674 | 0.682 | 0.948 |
| 2002 | 1594 | 0.526 | 0.279 | 0.000 | 0.526 | 0.676 | 0.683 | 0.948 |
| 2003 | 1710 | 0.552 | 0.261 | 0.000 | 0.610 | 0.678 | 0.684 | 0.948 |
| 2004 | 1829 | 0.555 | 0.258 | 0.000 | 0.617 | 0.678 | 0.683 | 0.948 |
| 2005 | 2036 | 0.561 | 0.253 | 0.000 | 0.628 | 0.678 | 0.683 | 0.948 |
| 2006 | 2414 | 0.513 | 0.284 | 0.000 | 0.469 | 0.674 | 0.683 | 0.948 |
| 2007 | 3437 | 0.536 | 0.269 | 0.000 | 0.573 | 0.674 | 0.683 | 0.948 |
| 2008 | 3346 | 0.535 | 0.270 | 0.000 | 0.577 | 0.675 | 0.684 | 0.945 |
| 2009 | 3330 | 0.538 | 0.271 | 0.000 | 0.588 | 0.676 | 0.684 | 0.946 |
| 2010 | 3426 | 0.546 | 0.264 | 0.000 | 0.607 | 0.676 | 0.684 | 0.953 |
| 2011 | 3402 | 0.548 | 0.264 | 0.000 | 0.613 | 0.676 | 0.684 | 0.897 |
| 2012 | 3908 | 0.551 | 0.258 | 0.000 | 0.608 | 0.675 | 0.684 | 0.903 |
| 2013 | 4164 | 0.555 | 0.253 | 0.000 | 0.610 | 0.675 | 0.684 | 0.904 |
| 2014 | 4321 | 0.554 | 0.252 | 0.000 | 0.604 | 0.674 | 0.683 | 0.944 |
| 2015 | 4092 | 0.552 | 0.254 | 0.000 | 0.602 | 0.674 | 0.684 | 0.959 |
| 2016 | 4409 | 0.541 | 0.262 | 0.000 | 0.584 | 0.673 | 0.683 | 0.949 |
| 2017 | 4099 | 0.553 | 0.253 | 0.000 | 0.601 | 0.674 | 0.684 | 0.949 |
| Total | 52,982 | 0.545 | 0.263 | 0.000 | 0.597 | 0.675 | 0.684 | 0.959 |

Notes: This table describes the evolution of the joint default probabilities of banks from 2000 to 2017 estimated by CIMDO's approach. The raw data come from the banking commission of the WAEMU.

where $JPoD_{itj}$ is the joint probability of default of a couple of banks $i$ and $j$ on year $t$. $X_{ijt}$ is a vector of variables calculated from the balance sheet of bank $i$ and $j$ of the pair on year $t$. More precisely, we take the average[11] of the variables for each bank in the pair, weighted by their respective total assets. We also control for macroeconomic factors specific to the countries in which banks operate. For this category (i.e., country variables) real GDP is used as the weight. $\alpha$ and $\lambda$ are pairs of banks (or countries) fixed effects and time fixed effects, respectively. The control variables are summarized in Table 7.

Table 8 presents the correlation matrix between the different variables. The low correlation values show that the risk of multicollinearity is low.

We used quantile regression to estimate the equation (16). This choice is motivated by the non-normality of the distribution of the joint probabilities. The joint probabilities of default have an asymmetric distribution (Fig. 4). Therefore, linear regression would not provide a comprehensive view of the effects of the explanatory variables on the probability of default. However, we present the results of linear regression before presenting those based on quantile regression for comparison purposes.

Table 9 presents the results from the two estimation techniques. The results show that interbank debt moderates the joint probability of default. The level of interbank debt is negatively associated with the probability of default. This result is consistent with the literature which states that the markets discipline the banks (King, 2008). The interbank market plays a supervisory role through peer monitoring. However, the interbank debt seems to increase the joint probabilities of default for pair of banks with a low joint probability of default (up to the median).

We also find that a high level of liquidity – measured by the deposit-to-total assets ratio – increases the joint probability of default banks. But, it is worth noting that the level of liquidity contributes to reducing the joint probability of default, especially for pairs of banks with a very low and very high joint probability of default (lower than to the 25th percentile and greater than the 75th percentile). For these categories of banks, a low level of liquidity exposes them to a bank run which can increase the risk of bankruptcy.

Moreover, the level of bank capitalization reduces the joint probability of bank default, which is consistent with the fact that the level of capitalization is a signal of the solvency of banks, especially when the pair of banks has a high joint probability of default. On the other hand, the level of capitalization tends to increase the joint risk of default for pair of banks with a low (up to the median) joint probability of default. Although capitalization is a signal of the solvency of the banks, this result can be explained by the fact that the better-capitalized banks are, the more they can engage in risky activities, which could contribute to reducing the stability of the system.

The level of risk provisions is positively associated with the joint probability of default for pair of banks with a high joint probability of default. Provisioning is a proxy for the level of risk exposure of banks, and the higher the pair of banks is exposed to risk, the more likely they are to default.

An increase in political stability – high values of political stability and absence of violence indicator – increases the joint probability of default across quantiles. Political stability and absence of violence/terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. This variable is used to control for the institutional quality

[11] The joint probabilities of default changes with a correlation between default events for any two entities. Therefore, taking variables related to each bank in the pair would be more suitable. However, in doing so, the estimates show opposite signs for some controls (results are available upon request from the authors). For example, return on asset (ROA) of one bank in the pair is positively associated with the JPoD while the ROA of the second bank is negatively associated with the JPoD. These findings make policy implications difficult to convey. Hence, we follow Gorea and Radev (2014) to get the average of control variables. We believe taking the average can help convey the key message easily.

**Table 7**
Description of the variables.

| Variables | Description |
|---|---|
| JPoD | Joint probabilities of default |
| ROA | Return on assets |
| Equity | Capital-to-asset ratio |
| Deposits | Customer deposit to total asset |
| LLRL | Loan loss provisions to total assets |
| Det_Interbanc | Interbank debt (log) |
| Inflation | CPI inflation rate |
| OUTGAP | Output gap constructed by using the HP filter applied to the log of the real GDP |
| PS | Political stability and absence of violence |

**Table 8**
Correlations matrix.

| | JPoD | Interbank_Debt | Deposit | Equity | LLRL | ROA | Inflation | OUTGAP | PS |
|---|---|---|---|---|---|---|---|---|---|
| JPoD | 1 | | | | | | | | |
| Interbank_Debt | 0.112*** | 1 | | | | | | | |
| | 0.000 | | | | | | | | |
| Deposit | −0.067*** | −0.433*** | 1 | | | | | | |
| | 0.000 | 0.000 | | | | | | | |
| Equity | 0.018*** | −0.351*** | −0.230*** | 1 | | | | | |
| | 0.000 | 0.000 | 0.000 | | | | | | |
| LLRL | −0.045*** | −0.059*** | 0.193*** | 0.111*** | 1 | | | | |
| | 0.000 | 0.000 | 0.000 | 0.000 | | | | | |
| ROA | 0.102*** | 0.252*** | −0.038*** | −0.223*** | −0.121*** | 1 | | | |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | | | |
| Inflation | 0.023*** | 0.204*** | −0.146*** | −0.049*** | −0.027*** | 0.057*** | 1 | | |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | | |
| OUTGAP | 0.001 | 0.257*** | −0.196*** | −0.125*** | −0.061*** | 0.063*** | 0.189*** | 1 | |
| | 0.781 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | |
| PS | −0.001 | −0.075*** | 0.022*** | 0.001 | −0.125*** | −0.036*** | −0.039*** | 0.230*** | 1 |
| | 0.783 | 0.000 | 0.000 | 0.876 | 0.000 | 0.000 | 0.000 | 0.000 | |

Notes: This table presents the pairwise correlation matrix of the variables used in this paper. The raw data are obtained from the WAEMU Banking Commission. The values in parentheses are *p* values that reflect the significance of each correlation value. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

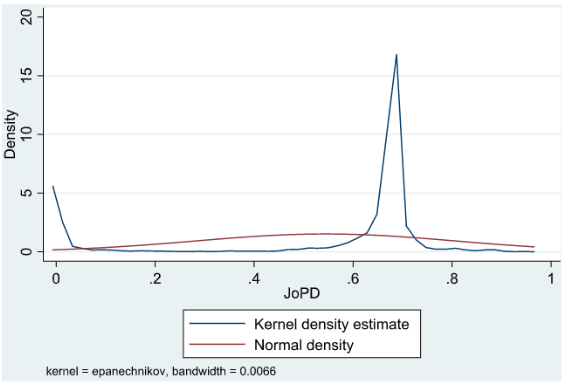


**Fig. 4.** Kernel density of joint probability of default.

within the country. A higher value of PS means lower political risk or higher quality of institutions. A better quality of institutions is associated with low transaction costs (Mishra and Montiel, 2013) which allows firms to adjust faster to their target capital structure (Öztekin and Flannery, 2012) and, in the case of banks, to increase their lending (Haselmann et al., 2010). Therefore, we expect a positive relationship between PS and bank profitability. Through profitability, we expect a negative relationship between PS and risk. Our results do not confirm this assumption when we use quantile regression. One explanation is that an improvement in the business environment is associated with an increase in credit activity and can lead to an increase in the level of default risk.

The level of inflation (a proxy for macroeconomic instability) is positively associated with the joint probability of default, while the business cycle (measured by the output gap) is negatively associated with this probability. These results indicate that the characteristics of the country in which banks operate play a role in their risk of bankruptcy. The output gap is used to control for the demand-

**Table 9**
Determinants of JPoDs estimated based on the full sample.

| | Robust regression (robust to outliers) | | | Quantile regression | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | q10 | q25 | q50 | q75 | q90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Interbank debt | −0.009*** | −0.012*** | −0.012*** | 0.000 | 0.572*** | 0.024*** | −0.006*** | −0.034*** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.018) | (0.002) | (0.001) | (0.002) |
| Customer deposit | 0.073*** | 0.082*** | 0.077*** | −0.027*** | 2.615*** | 0.307*** | −0.079*** | −0.279*** |
| | (0.013) | (0.014) | (0.014) | (0.004) | (0.198) | (0.023) | (0.009) | (0.030) |
| Capital | −0.026*** | −0.028*** | −0.029*** | 0.003*** | 1.246*** | 0.064*** | −0.004 | −0.067*** |
| | (0.003) | (0.003) | (0.003) | (0.001) | (0.042) | (0.006) | (0.003) | (0.009) |
| Provision | 0.255*** | 0.264*** | 0.259*** | −0.001 | −3.694*** | −0.035 | 0.163*** | 0.844*** |
| | (0.020) | (0.020) | (0.020) | (0.002) | (0.455) | (0.033) | (0.017) | (0.057) |
| Return on asset | −0.038*** | −0.038*** | −0.036*** | −0.005*** | 4.978*** | 0.276*** | −0.060*** | −0.327*** |
| | (0.007) | (0.007) | (0.007) | (0.001) | (0.198) | (0.018) | (0.007) | (0.023) |
| Pan-African dummy | −0.003*** | −0.003*** | −0.003*** | 0.000*** | 0.079*** | 0.000 | −0.001*** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.018) | (0.000) | (0.000) | (0.001) |
| Inflation | 0.011** | 0.037*** | 0.030*** | 0.001*** | −0.041 | 0.005 | 0.011*** | 0.028** |
| | (0.005) | (0.010) | (0.010) | (0.001) | (0.067) | (0.007) | (0.004) | (0.012) |
| Output gap | −0.006** | −0.011*** | −0.015*** | −0.001*** | −0.351*** | −0.031*** | −0.006*** | −0.001 |
| | (0.003) | (0.003) | (0.004) | (0.000) | (0.029) | (0.004) | (0.001) | (0.004) |
| Political stability | −0.006*** | −0.005** | 0.003 | 0.001*** | 0.061** | 0.008*** | 0.007*** | 0.037*** |
| | (0.002) | (0.002) | (0.004) | (0.000) | (0.027) | (0.003) | (0.001) | (0.005) |
| Constant | 0.684*** | 0.688*** | 0.690*** | 0.002*** | −0.433*** | 0.620*** | 0.697*** | 0.758*** |
| | (0.002) | (0.002) | (0.002) | (0.000) | (0.037) | (0.004) | (0.002) | (0.004) |
| Countries' pair fixed effects | No | Yes | Yes | No | No | No | No | No |
| Time fixed effects | No | No | Yes | No | No | No | No | No |
| Observations | 52,120 | 52,120 | 52,120 | 52,120 | 52,120 | 52,120 | 52,120 | 52,120 |
| R-squared | 0.017 | 0.020 | 0.029 | | | | | |

Notes: This table presents the determinants of the JPoDs. The explanatory variables are reported in Table 7. Columns (1) to (3) report the estimation using robust regression techniques and columns (4) to (8) report the results by using quantile regressions. qx refers to the qx$^{th}$ percentile. Robust standard deviation in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

side effect. The demand factor may affect bank stability through its effect on capital accumulation and bank profit. Banks should be more profitable during economic booms and less during a bust. Therefore, our result confirms the negative relationship between the output gap and risk.

Finally, we control for the pan-African status of banks. The pan-African dummy takes one if a bank in the pair is a pan-African bank and zero otherwise. The results indicate that a presence of a pan-African bank in the pair of banks is associated with an increase in the joint probability of default for pair of banks with a low probability of default. But the opposite result is obtained for pair of banks with a high probability of default. Therefore, the effect of pan-African bank status is non-linear.

*6.3.1.2. Robustness check.* This section presents further analyses performed to ascertain the robustness of the previous results. We first analyze the determinants of the probability of default. Second, we check if the regressions on the determinants of JPoDs are sensitive to the size of banks. Third, we check the sensitivity of the estimations of PDs. Fourth, we complement our analysis by using with the expected loss given default (LGD).

Finally, we perform additional regressions by considering other control variables. We control for external factors (external balance, real exchange rate, oil price volatility, external demand) as well as domestic factors (concentration of the banking sector and concentration of loans). The results of this last additional robustness check are provided in the section A of the online Appendix.

**a) Determinants of the probability of default**

Although the paper focuses on systemic risk, we examine the determinants of bank default probabilities. The results are reported in Table 10. We find that that the interbank market plays a disciplinary role as an increase in interbank debt is associated with a lower probability of default. We also find that big banks have a lower probability of default, and that loan loss provisions – which reflect reflects the level of credit risk – are associated with higher default. These results do not contradict those obtained above on systemic risk.

**b) Robustness regarding the determinants of JPoDs**

To ascertain the results of the estimates, we split the sample according to the size of the pair of banks. We use the total size of the pair of banks and apply *k*-median clustering algorithm to get three categories: small, medium, and large banks. Panels A, B, and C of Table 11 present the results of the estimates. The results do not significantly change depending on the bank size. Therefore, the size of the pair of banks does not drive the main results of this paper.

**c) Robustness regarding the estimations of PDs**

**Table 10**
Determinants of PDs.

| | Robust regression (robust to outliers) | | | | | | Quantile regression | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | q10 | q25 | q50 | q75 | q90 | q10 | q25 | q50 | q75 | q90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Interbank debt | −0.003* | 0.000 | −0.007*** | 0.000 | −0.011*** | −0.001 | −0.000 | −0.001 | −0.042*** | −0.162*** | −0.327*** | −0.000 | −0.000 | −0.036 | −0.203 | −0.291** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.000) | (0.001) | (0.015) | (0.052) | (0.071) | (0.000) | (0.001) | (0.027) | (0.129) | (0.137) |
| Customer deposit | −0.012 | 0.010 | −0.017 | 0.048 | −0.045 | 0.037 | −0.000 | −0.004 | −0.191* | 0.097 | 2.300** | −0.000 | −0.001 | −0.161 | −0.068 | 2.684* |
| | (0.028) | (0.029) | (0.028) | (0.031) | (0.031) | (0.034) | (0.000) | (0.005) | (0.107) | (0.354) | (1.067) | (0.000) | (0.008) | (0.156) | (0.732) | (1.467) |
| Capital | 0.008 | 0.005 | 0.003 | −0.007 | −0.008 | −0.021*** | −0.000 | −0.001 | −0.068** | −0.287*** | −0.606*** | −0.000 | −0.001 | −0.067** | −0.304*** | −0.646*** |
| | (0.006) | (0.007) | (0.006) | (0.007) | (0.007) | (0.007) | (0.000) | (0.001) | (0.033) | (0.093) | (0.147) | (0.000) | (0.001) | (0.033) | (0.088) | (0.152) |
| Provision | 0.176*** | 0.193*** | 0.143*** | 0.171*** | 0.243*** | 0.281*** | 0.000 | 0.030 | 1.118** | 4.574*** | 3.801** | 0.001 | 0.035 | 1.124** | 4.473*** | 3.498** |
| | (0.046) | (0.047) | (0.046) | (0.048) | (0.052) | (0.053) | (0.002) | (0.051) | (0.542) | (0.854) | (1.628) | (0.002) | (0.047) | (0.570) | (0.893) | (1.513) |
| Return on asset | −0.017 | −0.011 | −0.013 | 0.003 | −0.028* | −0.005 | −0.000 | −0.005 | −0.082 | −0.410* | −1.124* | −0.000 | −0.005 | −0.074 | −0.441** | −1.119** |
| | (0.013) | (0.014) | (0.013) | (0.014) | (0.015) | (0.016) | (0.000) | (0.005) | (0.067) | (0.221) | (0.629) | (0.000) | (0.004) | (0.063) | (0.207) | (0.560) |
| Size | | −0.001** | | −0.003*** | | −0.004*** | | | | | | −0.000 | −0.000 | −0.001 | 0.005 | −0.012 |
| | | (0.000) | | (0.001) | | (0.001) | | | | | | (0.000) | (0.000) | (0.003) | (0.015) | (0.025) |
| Pan-African dummy | −0.004*** | −0.004*** | −0.004*** | −0.006*** | −0.004*** | −0.005*** | −0.000 | −0.000 | −0.015*** | −0.042*** | −0.005 | −0.000 | −0.000 | −0.015*** | −0.041*** | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.004) | (0.011) | (0.031) | (0.000) | (0.000) | (0.004) | (0.013) | (0.028) |
| Inflation | 0.004 | 0.008 | 0.009 | 0.018 | 0.011 | 0.015 | −0.000 | 0.000 | 0.032 | 0.066 | −0.098 | −0.000 | 0.000 | 0.036 | 0.084 | −0.107 |
| | (0.013) | (0.013) | (0.022) | (0.023) | (0.024) | (0.024) | (0.000) | (0.001) | (0.029) | (0.183) | (0.653) | (0.000) | (0.001) | (0.028) | (0.192) | (0.626) |
| Output gap | −0.006 | −0.002 | −0.015 | −0.014 | −0.002 | 0.000 | −0.000 | −0.000 | −0.007 | −0.027 | −0.141 | −0.000 | −0.000 | −0.007 | −0.014 | −0.072 |
| | (0.008) | (0.008) | (0.009) | (0.009) | (0.010) | (0.011) | (0.000) | (0.001) | (0.028) | (0.090) | (0.244) | (0.000) | (0.001) | (0.026) | (0.081) | (0.202) |
| Political stability | 0.011** | 0.007 | 0.016*** | 0.010* | −0.013 | −0.021** | 0.000 | 0.001 | 0.023 | 0.117 | 0.598** | 0.000 | 0.001 | 0.022 | 0.095 | 0.619** |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.010) | (0.010) | (0.000) | (0.001) | (0.016) | (0.081) | (0.297) | (0.000) | (0.001) | (0.016) | (0.074) | (0.254) |
| Constant | 0.011*** | 0.020*** | 0.011*** | 0.034*** | 0.021*** | 0.053*** | 0.000 | 0.001 | 0.080*** | 0.264*** | 0.464*** | 0.000 | 0.001 | 0.083*** | 0.256*** | 0.552*** |
| | (0.003) | (0.005) | (0.004) | (0.006) | (0.004) | (0.007) | (0.000) | (0.001) | (0.023) | (0.068) | (0.108) | (0.000) | (0.001) | (0.026) | (0.054) | (0.155) |
| Countries fixed effects | No | No | No | No | Yes | Yes | No | No | No | No | No | No | No | No | No | No |
| Time fixed effects | No | No | Yes | Yes | Yes | Yes | No | No | No | No | No | No | No | No | No | No |
| Observations | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 |
| R-squared | 0.087 | 0.092 | 0.106 | 0.133 | 0.165 | 0.207 | | | | | | | | | | |

Notes: This table presents the determinants of the PDs. Columns (1) to (6) report the estimation using robust regression techniques and columns (7) to (16) report the results by using quantile regressions. qx refers to the $qx^{th}$ percentile. Robust standard deviation in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

**Table 11**
Panel A: Determinants of JPoDs estimated based on the sample of small banks.

| | Robust regression (robust to outliers) | | | Quantile regression | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | q10 | q25 | q50 | q75 | q90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Interbank debt | −0.020*** | −0.021*** | −0.020*** | −0.000 | 0.449*** | 0.029*** | −0.008*** | −0.049*** |
| | (0.002) | (0.002) | (0.002) | (0.000) | (0.055) | (0.006) | (0.002) | (0.005) |
| Customer deposit | 0.086*** | 0.095*** | 0.114*** | −0.018*** | 0.213 | 0.345*** | −0.067*** | −0.168*** |
| | (0.026) | (0.027) | (0.027) | (0.004) | (0.528) | (0.059) | (0.021) | (0.047) |
| Capital | −0.026*** | −0.028*** | −0.029*** | 0.003*** | 0.990*** | 0.083*** | 0.002 | −0.049*** |
| | (0.005) | (0.006) | (0.006) | (0.001) | (0.088) | (0.012) | (0.005) | (0.011) |
| Provision | 0.237*** | 0.243*** | 0.275*** | −0.007* | −12.651*** | −0.177** | 0.098*** | 0.684*** |
| | (0.041) | (0.041) | (0.042) | (0.004) | (1.166) | (0.082) | (0.027) | (0.096) |
| Return on asset | 0.040*** | 0.033** | 0.041*** | −0.006*** | 3.608*** | 0.429*** | −0.038*** | −0.250*** |
| | (0.013) | (0.013) | (0.013) | (0.002) | (0.287) | (0.033) | (0.012) | (0.033) |
| Pan-African dummy | −0.006*** | −0.006*** | −0.006*** | 0.000*** | 0.315*** | 0.003** | −0.002*** | −0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.022) | (0.001) | (0.001) | (0.001) |
| Inflation | 0.008 | 0.051*** | 0.036** | 0.000 | −0.136 | 0.001 | 0.011** | 0.047*** |
| | (0.008) | (0.018) | (0.018) | (0.000) | (0.150) | (0.011) | (0.005) | (0.017) |
| Output gap | −0.017*** | −0.024*** | −0.027*** | −0.002*** | −0.513*** | −0.058*** | −0.010** | −0.029** |
| | (0.007) | (0.009) | (0.009) | (0.001) | (0.105) | (0.012) | (0.004) | (0.012) |
| Political stability | −0.002 | −0.000 | 0.012 | 0.002*** | −0.039 | 0.017** | 0.008*** | 0.027*** |
| | (0.004) | (0.004) | (0.008) | (0.000) | (0.067) | (0.007) | (0.002) | (0.008) |
| Constant | 0.694*** | 0.698*** | 0.696*** | 0.001*** | −0.327*** | 0.607*** | 0.698*** | 0.768*** |
| | (0.003) | (0.004) | (0.004) | (0.000) | (0.078) | (0.010) | (0.003) | (0.008) |
| Countries' pair fixed effects | No | Yes | Yes | No | No | No | No | No |
| Time fixed effects | No | No | Yes | No | No | No | No | No |
| Observations | 25,380 | 25,380 | 25,380 | 25,380 | 25,380 | 25,380 | 25,380 | 25,380 |
| R-squared | 0.024 | 0.026 | 0.038 | | | | | |

Panel B: Determinants of JPoDs estimated based on the sample of medium-sized banks

| | Robust regression (robust to outliers) | | | Quantile regression | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | q10 | q25 | q50 | q75 | q90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Interbank debt | −0.001 | −0.004* | −0.003 | −0.017** | −0.030 | −0.004* | −0.011*** | −0.030*** |
| | (0.002) | (0.002) | (0.002) | (0.007) | (0.019) | (0.002) | (0.001) | (0.005) |
| Customer deposit | 0.132*** | 0.182*** | 0.197*** | −0.296** | −0.222 | 0.099*** | −0.117*** | −0.279*** |
| | (0.021) | (0.023) | (0.023) | (0.139) | (0.239) | (0.036) | (0.014) | (0.043) |
| Capital | 0.013* | 0.012* | 0.011 | 0.012 | 0.541*** | 0.073*** | −0.005 | −0.060*** |
| | (0.007) | (0.007) | (0.007) | (0.010) | (0.050) | (0.010) | (0.006) | (0.012) |
| Provision | 0.226*** | 0.253*** | 0.243*** | −0.009 | −0.997*** | 0.040 | 0.182*** | 0.481*** |
| | (0.028) | (0.029) | (0.030) | (0.025) | (0.382) | (0.043) | (0.028) | (0.062) |
| Return on asset | −0.168*** | −0.160*** | −0.168*** | −0.030* | 2.000*** | 0.036 | −0.124*** | −0.451*** |
| | (0.012) | (0.012) | (0.013) | (0.016) | (0.266) | (0.022) | (0.016) | (0.035) |
| Pan-African dummy | −0.001 | −0.001** | −0.001** | 0.001* | 0.005 | 0.001 | 0.001* | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.005) | (0.000) | (0.000) | (0.001) |
| Inflation | 0.011 | 0.039** | 0.031** | −0.003 | −0.213*** | −0.010 | 0.009* | −0.010 |
| | (0.007) | (0.016) | (0.016) | (0.005) | (0.065) | (0.009) | (0.006) | (0.019) |
| Output gap | −0.019*** | −0.028*** | −0.027*** | −0.007* | −0.209*** | −0.033*** | −0.018*** | −0.025*** |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.046) | (0.006) | (0.002) | (0.006) |
| Political stability | 0.010*** | 0.013*** | 0.007 | 0.008* | 0.044 | 0.020*** | 0.014*** | 0.072*** |
| | (0.003) | (0.003) | (0.006) | (0.004) | (0.032) | (0.004) | (0.002) | (0.007) |
| Constant | 0.671*** | 0.670*** | 0.671*** | 0.040** | 0.611*** | 0.668*** | 0.705*** | 0.757*** |
| | (0.003) | (0.004) | (0.004) | (0.018) | (0.034) | (0.004) | (0.002) | (0.008) |
| Countries' pair fixed effects | No | Yes | Yes | No | No | No | No | No |
| Time fixed effects | No | No | Yes | No | No | No | No | No |
| Observations | 17,327 | 17,327 | 17,327 | 17,327 | 17,327 | 17,327 | 17,327 | 17,327 |
| R-squared | 0.034 | 0.041 | 0.052 | | | | | |

Panel C: Determinants of JPoDs estimated based on the sample of large banks

| | Robust regression (robust to outliers) | | | Quantile regression | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | q10 | q25 | q50 | q75 | q90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Interbank debt | 0.004 | 0.007* | 0.007* | 0.381 | 0.060* | 0.000 | −0.013*** | −0.075*** |
| | (0.004) | (0.004) | (0.004) | (0.238) | (0.032) | (0.006) | (0.003) | (0.013) |
| Customer deposit | 0.012 | −0.031 | −0.052 | 2.724 | 1.686*** | 0.106* | −0.185*** | −1.074*** |
| | (0.035) | (0.036) | (0.036) | (1.968) | (0.371) | (0.064) | (0.029) | (0.139) |
| Capital | −0.084*** | −0.098*** | −0.064*** | 5.952*** | 0.730*** | 0.036*** | −0.026** | −0.184*** |

(continued on next page)

**Table 11** (*continued*)

Panel C: Determinants of JPoDs estimated based on the sample of large banks

| | Robust regression (robust to outliers) | | | Quantile regression | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | q10 | q25 | q50 | q75 | q90 |
| | (0.009) | (0.010) | (0.011) | (1.872) | (0.062) | (0.014) | (0.010) | (0.027) |
| Provision | 0.443*** | 0.511*** | 0.584*** | 4.340*** | −2.858*** | −0.046 | 0.307*** | 1.652*** |
| | (0.031) | (0.031) | (0.032) | (1.591) | (0.544) | (0.074) | (0.058) | (0.087) |
| Return on asset | 0.025 | 0.020 | 0.021 | 4.064** | 1.768*** | 0.097*** | −0.031 | −0.513*** |
| | (0.019) | (0.020) | (0.020) | (1.786) | (0.236) | (0.031) | (0.025) | (0.090) |
| Pan-African dummy | −0.001*** | −0.001*** | −0.001* | 0.091*** | 0.005 | −0.000 | −0.000 | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.031) | (0.003) | (0.000) | (0.000) | (0.001) |
| Inflation | −0.027** | −0.032 | −0.013 | −2.286** | −0.100* | −0.008 | −0.008 | 0.005 |
| | (0.012) | (0.025) | (0.025) | (1.094) | (0.055) | (0.008) | (0.009) | (0.025) |
| Output gap | −0.002 | 0.013*** | −0.003 | −0.234 | −0.064** | −0.009 | 0.005* | 0.026*** |
| | (0.003) | (0.004) | (0.007) | (0.186) | (0.032) | (0.006) | (0.003) | (0.008) |
| Political stability | −0.009** | −0.011*** | 0.018 | 0.976*** | −0.064** | 0.007 | 0.002 | 0.015 |
| | (0.004) | (0.004) | (0.016) | (0.375) | (0.026) | (0.005) | (0.003) | (0.012) |
| Constant | 0.675*** | 0.677*** | 0.679*** | −0.987** | 0.387*** | 0.667*** | 0.712*** | 0.865*** |
| | (0.006) | (0.008) | (0.008) | (0.463) | (0.063) | (0.010) | (0.006) | (0.028) |
| Countries' pair fixed effects | No | Yes | Yes | No | No | No | No | No |
| Time fixed effects | No | No | Yes | No | No | No | No | No |
| Observations | 9,413 | 9,413 | 9,413 | 9,413 | 9,413 | 9,413 | 9,413 | 9,413 |
| R-squared | 0.036 | 0.048 | 0.897 | | | | | |

Notes: This table presents the determinants of the JPoDs. The explanatory variables are reported in Table 7. Columns (1) to (3) report the estimation using robust regression techniques and columns (4) to (8) report the results by using quantile regressions. qx refers to the qx$^{th}$ percentile. Robust standard deviation in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Finally, we apply the comparable approach (Blochwitz et al., 2000) fully described in the section B of the online appendix. The aim of the comparable approach is to infer the value of equity of unlisted firms by using the EBITDA-to-equity ratio of listed companies. We use the market value of equity to calculate the EBITDA-to-equity ratio of listed companies. For each year, we assume that the average[12] EBITDA-to-equity ratio of listed banks is similar to that of unlisted banks. Knowing this ratio, we estimate an implied equity value for unlisted banks. Next, we apply Merton's model to re-estimate the probability of bank default by using the new calculated equity (the equity of listed banks comes from the market). We compare the PDs obtained from the "original" method (described above in section 4) and the comparable approach ("comparable").

Fig. 5 provides evidence that PDs estimated by both methods have similar densities, even though the method described in section 4 (*original*) seems to overestimate low probabilities of default (lower tail of the distribution). Whether the method we use, some banks have almost zero probability of default. This is due to their high level of capital combined with low volatility of equity. For instance, the average equity-to-asset ratio of banks with zero probability of default is double that of banks with a positive probability of default (20.5% *versus* 9.6%).

Furthermore, we calculate the correlation to the default (asset correlations) by using the "original" and "comparable" approaches. We follow Basel II definition of the asset correlations which is (Hull, 2018):

$$\rho_i \approx 0.12^*(1 - \exp(-50^* PD_i)) \tag{17}$$

Fig. 5 also gives the distribution of the correlations of the default and Table 12 provides descriptive statistics. The correlation to the default is very similar when we look at the categories of banks, especially among big banks.

**d) Loss Given Default (LGD)**

The previous analysis is based on PDs. We complement the analysis with the expected loss given default (LGD) which is another risk indicator. It is defined as the incurred loss percentage over owed credit in case of default[13]. The average LGD is about 17.8% and varies from 15.8% (big banks) to 19.0% (small banks).

Since the LGD is expected to be higher in the event of financial distress, we report the evolution of the 90th percentile of LGD by subcategory of banks (small, medium, and large) in Fig. 6. In the full sample and in the subcategory of small banks, the 90th percentile LGD has a decreasing trend with an increase between 2007 and 2011. In the medium-sized banks' subcategory, this indicator has a trend on the rise with a peak in 2008. Big banks have low LGDs perhaps due to their access to financial markets and better screening technology.

### 6.4. Discussion

This paper contributes to the regulatory debate involving pan-African banks in the WAEMU. It suggests a new measure of systemic

[12] Using the median instead of the average of EBITDA-to-equity ratio will not significantly change the results as the correlation between the mean and the median is 0.92. Moreover, we cannot take into account bank size since only large banks are listed.

[13] The section C of the online appendix describes the methodology used to compute the LGD and Table C1 presents the distribution of the LGD.

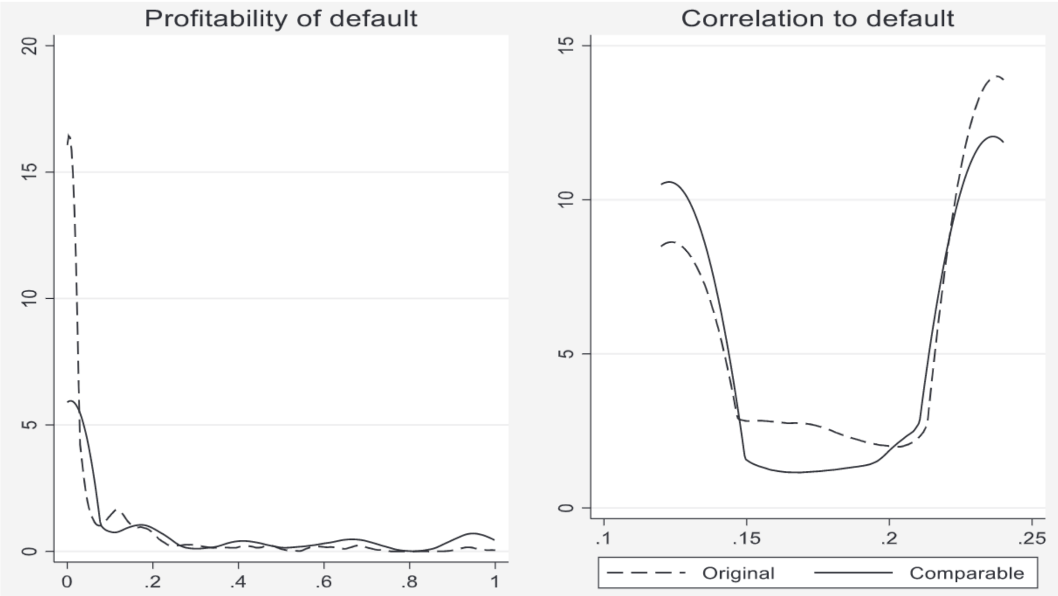


**Fig. 5.** Density of probability default and correlation to the default using two approaches: Original (i.e., the method described in section 4) and Comparable (i.e., the comparable approach).

**Table 12**
Distribution of the correlation to the default estimated by the two methods.

| | Observations | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|
| Small banks | | | | | |
| $\rho$(original) | 570 | 0.181 | 0.053 | 0.120 | 0.240 |
| $\rho$(Comparable) | 415 | 0.170 | 0.055 | 0.120 | 0.240 |
| Medium banks | | | | | |
| $\rho$(original) | 188 | 0.202 | 0.050 | 0.120 | 0.240 |
| $\rho$(Comparable) | 174 | 0.188 | 0.056 | 0.120 | 0.240 |
| Big banks | | | | | |
| $\rho$(original) | 206 | 0.206 | 0.047 | 0.120 | 0.240 |
| $\rho$(Comparable) | 196 | 0.207 | 0.047 | 0.120 | 0.240 |

Notes: () is the method used to compute the PD. Small are banks with total assets less than XOF 100 bn and big banks have total assets more than XOF 200 bn. Other banks are medium-sized. This is the classification used by the regulator.

risk by estimating the probability of default and contagion risk in the WAEMU zone. In sub-Saharan Africa, in general, and especially in the WAEMU, we have witnessed a rapid growth of banking models with a strong geographic footprint. Faced with this rapid change, the aim of this paper is to develop the first systemic risk indicators for the banking sector in this area on the principle that the default of a bank can lead to cascading bankruptcies.

We find that most of banks have a very low probability of default. However, due to the high level of joint probabilities of default, if the financial strength of some banks deteriorates, there could be contagion effects leading to a weakened union through interconnection. Therefore, there is a seed of systemic risk in the WAEMU. The use of quantile regression helps to determine factors influencing systemic risk.

This issue has been pointed out by the IMF (2017), which has already warned about the increase in credit risk and the concentration of loans. Knowing the default probabilities allows the analysis of clusters of banks to identify those with a similar risk of default. Therefore, banks belonging to the same cluster have similar default characteristics. Potential contagion mechanisms are identified across the different groups. In these networks, some banks are interconnected with each other and, consequently, the systemic risk appears if a shock on a bank belonging to a network has an impact on another bank not belonging to this network. The seeds of a possible systemic risk arise when the financial strength deteriorates.

The evolution of default probabilities over the period from 2001 to 2017 is cyclical and has gone through four phases. Between 2001 and 2006, the downward trend marked a period of strong stability in the banking system. From 2006 to 2010, there was a sharp increase in the joint probabilities of default. This period coincided with that of the 2007 financial crisis. From 2010, the trend was reversed, and the banking system was maintained by a very accommodating monetary policy applied by the BCEAO following the international financial crisis. Beyond 2014, a trend reversal was observed; the probabilities of default returned to their upward profile.

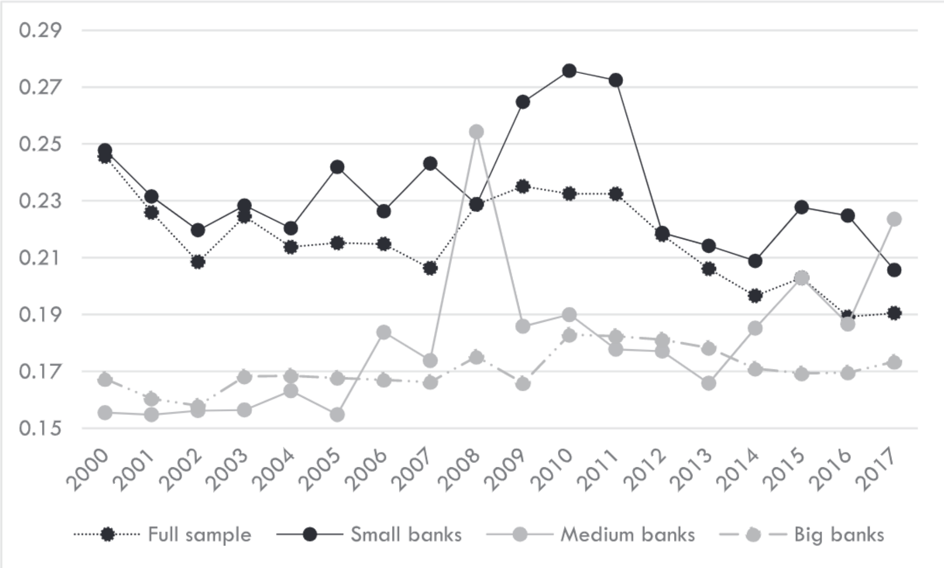


**Fig. 6.** Evolution of the 90th percentile of LGD by bank size. Note: Small are banks with total assets less than XOF 100 bn and big banks have total assets more than XOF 200 bn. Other banks are medium-sized. This is the classification used by the regulator.)

From January 2017, significant liquidity problems were observed in the WAEMU capital market. Data on weekly liquidity injections shows that between January 2017 and December 2018, all banks auctioned at the counter for the minimum bid rate of 4.5%. An increase in interbank debt seems to have increased the joint probability of default when banks had a low to medium risk of default.

The Banking Commission of the WAEMU, which represents the banking supervisory body, has already initiated major reforms related to (i) supervising cross-border banking groups with systemic weight, (ii) supervising on a consolidated basis, and (iii) participating in colleges of supervisors.

In addition to these measures, the Central Bank and the Banking Commission have created the Financial Stability Fund and the Deposit Guarantee Fund.

In the WAEMU, the assessment of systemic risks is carried out by the Committee for Financial Stability, which is composed of the BCEAO, the Banking Commission, and the Financial Market Regulatory Authority. The Regulatory Authorities initiated a framework of financial protection against systemic risk (IMF, 218 – IMF Report No. 2018/106 May). This framework includes:

(i) a financial guarantee fund to ensure the payments from the interbank clearing system,
(ii) a bank deposit guarantee scheme financed by deposit-taking institutions,
(iii) a bank resolution fund, which should be supported by an internal bailout mechanism for creditors.

Also, banks have been encouraged to diversify their portfolio to limit the concentration of risks: diversifying risks reduces systemic risk, improves the estimation of sovereign credit risk, and boosts market liquidity.

Overall, the results show that there are seeds of systemic risk in the WAEMU banking sector. A deterioration in the financial solidity of large pan-African groups with a large geographic footprint could generate contagion effects that are detrimental to the financial stability of the area.

## 7. Conclusion

In this paper, we have introduced a new measure of systemic risk based on a three-step approach. The first step estimates banks' probabilities of default by using the Merton model. The value and volatility of assets are estimated using the maximum likelihood method proposed by Duan (1994, 2000). The second step builds banks' clusters by combining a minimum spanning tree algorithm and the *K*-means technique. In the third step, we use the CIMDO method to estimate the joint probabilities of default. The systemic risk analysis is based on the clustering and the joint probabilities of default.

We investigate the potential systemic risks that can emanate from Pan-African bank in the WAEMU region. The rise and domination of the Pan-African banks has changed the banking landscape in the region. The results of the estimates show that PDs are higher for pan-African banks compared to French banks. Greater integration has advantages, but interconnection means that more countries are more exposed to the fallout from cross-border shocks.

The paper shows that there are seeds of systemic risk in the WAEMU banking sector. A weakening in the financial solidity of large pan-African groups could generate contagion effects that would be detrimental to the financial stability. In this paper, we have also identified variables such as asset profitability, interbank debts, provisions, deposits, and the level of equity that significantly influence banks' joint PDs.

We confirm that cooperation in cross-border surveillance is therefore necessary. It has already started, but enhanced and ongoing collaboration is essential. The rapid expansion of pan-African banks poses challenges, including the following five:

- Improving monitoring by enhancing the limited capacity in this region and by addressing the lack of resources.
- Transparency and disclosure, good governance, solid prudential supervision, a legal and regulatory framework that supports global supervision and crisis management, especially in host countries. The ability and convenience of owners and shareholders, particularly bank holding companies, is not always fully assessed and in some cases, ownership structures are opaque.
- The absence of a single accounting standard across the continent makes it difficult to assess the overall situation of banks. And in many countries, monitoring of the conduct of business is only starting now.
- Lack of regulatory oversight of bank holding companies and their supervision on a consolidated basis in certain jurisdictions of origin must be addressed.
- Memoranda of understanding guaranteeing a complete exchange of information are necessary between all the houses and the hosts.

The BCEAO has undertaken important measures in recent years to control the situation and we suggest that these measures should be deepened. The key reforms include (i) supervision of cross-border banking groups with systemic importance, (ii) supervision on a consolidated basis, and (iii) participation in the colleges of supervisors. In addition to these measures, the financial stability fund and the deposit guarantee fund have both been created. The methodology used in this paper can be enriched by using detailed data from the interbank market, which will constitute a future focus for our research.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2021.101405.

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