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Can Corporate Financing through the Stock Market Create Systemic Risk? Evidence from the BRVM Securities Market

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Abstract

This paper investigates the systemic risk in the West African Economic and Monetary Union (WAEMU) stock exchange (Bourse Régionale des Valeurs Mobilières - BRVM). It examines the extent to which growing activities in this stock market generate systemic risk. We find strong linkages across all economic sectors of listed firms, with the financial and industrial sectors being the center of the system around which the other sectors revolve. Financial institutions are not the only source of systemic risk in the WAEMU region, even though they play an important role in the system. Finally, using panel regressions, we find that big, high-growth and profitable firms contribute more to systemic risk than others. Overall, we find that the determinants of systemic risk depend on the indicator used to assess it and the sectors in which companies operate.

Keywords**:** Systemic risk, Financial stability, BRVM, WAEMU

JEL Classification: G01; G15; G20

1. Introduction

The 2007–2008 global financial crisis has renewed the interest in systemic risk analysis. Systemic risk is a multiform concept and hard to define, but you know it when you see it (International Monetary Fund, 2009). It can be defined as "*the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy*" (Group of Ten, 2001). This definition focuses on the loss of confidence, increases in uncertainty, the fact that a substantial portion of the financial system is concerned, and ultimately the significant adverse effects on the real economy (Eijffinger, 2011).

Although a large body of the financial literature has investigated systemic risk, there is still a need to monitor this risk because, it could, in the event it materializes, affect the real economy as mentioned above. Moreover, the literature survey on systemic risk by Silva et al. (2017) highlights among other gaps, the need to: (i) study systemic risk in countries considered undeveloped; (ii) extend the analysis of systemic risk beyond banks to consider other types of institutions; and (iii) conduct studies that compare the effectiveness of the indicators and methods proposed in the literature.

This paper contributes to the existing literature by attempting to address the three issues raised above. Firstly, we focus on a least developed but growing regional stock market in West Africa, that is, the BRVM (Bourse Régionale des Valeurs Mobilières), located in Abidjan (Côte d'Ivoire), shared by eight countries[*] forming a single monetary zone, with a common currency, the CFA franc, which is pegged to the Euro and with one central bank. Hence a common monetary policy for all the countries of the region. This regional stock market has many imperfections such as the poor governance structure, limitations in financial services, the weak quality of information disclosure, inadequate investor protection mechanisms, large operational risks, substantial delays in payment-delivery processing, etc. (Soumaré et al., 2013). In addition, West Africa has experienced and continues to experience, several cycles of political instability that affect the business environment. In such a regional market, systemic risk stemming from the stock exchange can spread to more than one country. Similarly, an adverse shock affecting one country can impact other countries through the regional stock exchange. Moreover, the ongoing collaboration between the BRVM and other stock exchanges in the African continent through the African Exchanges Linkage Project (AELP),

[*] These countries are Benin, Burkina Faso, Guinea-Bissau, Côte d'Ivoire, Mali, Niger, Senegal and Togo.

the flagship integration initiative of the African Securities Exchanges Association (ASEA) and the African Development Bank, aims to connect the continent's leading exchanges and boost cross-border investment flows. This will potentially increase the interconnection between listed companies and the targeted markets. International exposure through intense collaborations and openness, and the growth of the market (in terms of listed companies and capitalization) can be potential sources of systemic risk that need to be assessed. Even if not all listed companies are involved in risky behaviour, a negative shock to a major company can have repercussions for other firms or the overall regional economy, making the risk systemic in the sense of Adrian and Brunnermeier (2016). Therefore, assessing and monitoring systemic risk in such a market is both an economic and political concern. This paper aims to address this issue and contribute to expanding the existing literature to developing countries.

Secondly, this paper analyses the contribution of both financial and non-financial sectors to systemic risk, extending the analysis of systemic risk beyond banks. Little attention has been paid to the contribution of the non-financial sector to systemic risk. Is systemic risk specific to the financial sector? To what extent does the non-financial sector affect the financial system as a whole and contribute to systemic risk? Regarding the first question, the jury is still out on whether the systemic risk is endogenous (e.g., Farhi and Tirole 2012) or exogenous (e.g., Allen and Wood, 2006) to the financial sector. The financial sector can react to an exogenous shock as well as originate it, reinforcing the need to study the link between the financial and non-financial sectors. This link which is related to the first question has not been fully studied in the literature. The recent literature shows that non-financial firms can generate significant spill over effects on countries' financial systems, for example, Zhu et al. (2020), in the case of China, Kerste et al. (2015) in the U.S. and Van Cauwenberge et al. (2019) for the Dutch economy, underscoring the importance of considering the non-financial sector in maintaining the overall health and stability of the financial system. In line with the recent literature, this paper considers firms operating in six sectors, namely, distribution (retail), finance, industry, agriculture, public utilities, and transportation to highlight the connection between financial institutions and non-financial firms.

Moreover, it is only recently that some studies have investigated systemic risk in financial systems in Africa (Enoch et al., 2015; Fall, 2017; Khiari and Nachnouchi, 2018; Manguzvane and Mwamba, 2019, 2020; Mwamba and Angaman, 2021; Saidane et al. 2021), mainly due to data limitations that make it difficult to calculate systemic risk indicators and the age of most African stock markets. These existing studies concentrate on financial institutions and do not include non-financial institutions. To the best of our knowledge, no study has focused on systemic risk in the BRVM. Therefore, we do not know how the market behaves in terms of risk and if this risk is systemic.

Thirdly, this paper uses a wide range of indicators to assess systemic risk as a one-size-fits-all approach does not always hold. For instance, Benoît et al. (2017) show that the riskiest institutions using Value-at-Risk are not necessarily the most systemically risky when using Delta CoVaR. Our empirical investigation suggests that each indicator measures a specific dimension of systemic risk. As shown below in our results, a single indicator is not sufficient to identify the riskiest firms. Furthermore, we conduct regression analysis to examine the contribution of firms' characteristics and global factors to systemic risk. Following Zhu et al. (2020), we also show that the determinants of systemic risk depend on the indicator used to assess system risk.

This paper uses daily market data and balance sheet data from 2004 to 2020. We estimate a range of systemic risk indicators to identify companies that are more exposed to systemic risk, and those that contribute more to it among the listed firms. We do that following a two-step methodological approach. The first step consists of estimating systemic risk indicators and the second step focuses on panel regression analyses to explore the potential determinants of systemic risk.

We find strong linkages across all six economic sectors where the listed firms operate, with the financial and industrial sectors leading at the center of the system around which the other sectors revolve. Systemically important firms belong to the distribution (BNBC, SHEC), industry (CABC), and agriculture (PALC, SOGC) sectors in the sense that they are more likely to propagate shocks to the global market. Also, companies that are more prone to systemic risk belong to the distribution (TTLC), finance (SGBC), utility (CIEC, SDCC, SNTS), and agriculture (PALC, SOGC, SPHC) sectors. Therefore, financial institutions are not the only source of systemic risk in the WAEMU regional stock market, even though they play an important role in the system. Using panel regressions, we find that big, high-growth and profitable firms contribute more to systemic risk. Overall, we find that the determinants of systemic risk depend on the indicator used to assess it and the sectors in which companies operate.

The remainder of this paper is organized as follows. Section 2 presents a brief literature review. Section 3 presents the methodology. Section 4 presents the empirical results. Section 5 concludes.

2. Related literature

The literature on systemic risk can be divided into two generations (Benoît et al., 2017). The first generation focused on issues related to bank panics and crashes. It shows that bank panics, contagion effects, information asymmetry, liquidity and bank interconnectedness are key factors that can lead to systemic crises (e.g., Bernanke, 1983; Diamond and Dybvig, 1983). The second generation emerged in the aftermath of the 2007 financial crisis and focused on causes, new definitions and measurement tools for predicting systemic risk (e.g., White et al., 2015; Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017).

This section will focus on the second generation of studies which are more up-to-date, and present key measures used to evaluate systemic risk[†]. It will also discuss studies that focus on the contribution of the non-financial sector to systemic risk. Finally, it will survey the analysis of systemic risk in Africa.

2.1. Key measures to assess systemic risk

The existing literature offers two main categories of systemic risk indicators. The first category includes "conventional measures" known as ***cross-sectional*** measures of systemic risk. This presentation focuses on indicators commonly used in empirical studies: Value at Risk (VaR), Expected Shortfall (ES), Marginal Expected Shortfall (MES), Systemic Expected Shortfall (SES), Conditional Capital Shortfall Index (SRISK), Conditional Value-at-Risk (CoVaR and ΔCoVaR), and Conditional Autoregressive Value-at-Risk (CAViaR).

VaR and ES are two standard measures of financial market risk. The VaR measures the potential loss of a given portfolio over a specified holding period for a given confidence level. For example, a confidence level of 95% means that the company will lose more than the VaR amount with a 5% probability. However, VaR does not give much information regarding

[†] There are many other indicators of systemic risk not presented in this paper (see Bisias et al. (2012) for a survey).

possible excesses beyond the VaR quantile (Taylor, 2019). The ES addresses this constraint by providing more information about the tail of the return distribution than the VaR. The ES at q-percent level is the expected return on the portfolio in the worst q percent cases. Going forward, this paper will not present the VaR given its limits but the ES. The MES shows the contribution of each institution of the financial system to the system-wide risk. It corresponds to losses in the tail of the system's loss distribution. The SES is a measure of a financial institution's contribution to a systemic crisis, i.e., its propensity to be undercapitalized when the system is undercapitalized (Acharya et al., 2017). The SRISK measure is defined as the expected capital shortfall of a financial entity conditional on a prolonged market decline (Acharya et al., 2012; Brownlees and Engle, 2017). It depends on the size of the firm, its degree of leverage and its expected equity loss conditional on the market.

This paper will not use SES and SRISK because they require a cut-off on the capital-to-asset ratio. These indicators are more appropriate for financial institutions for which there is a regulatory minimum capital requirement (used as a cut-off) compared to non-financial sectors.

The CoVaR and ΔCoVaR were introduced by Adrian and Brunnermeier (2016). A company i's CoVaR relative to the system is defined as the value at risk (VaR) of the whole financial sector conditional on the institution i being in distress. The ΔCoVaR captures the (cross-sectional) tail-dependency between the whole financial system and a particular institution. More precisely, the ΔCoVaR is the difference between the CoVaR conditional on the distress of an institution and the CoVaR conditional on the median state of that institution. In this paper, we estimate ΔCoVaR based on quantile regression, even though extensions of its estimation method have been proposed in the literature (see Morelli and Vioto (2020) for a discussion).

In addition to these indicators, CAViaR is obtained from a multivariate regression quantile model, to directly study the degree of tail interdependency among different asset returns (White et al., 2015). In this paper, we consider bivariate models, whereby for each institution in the sample, a bivariate CAViaR model is estimated by following White et al. (2015) to avoid the excessive computational burden. In the bivariate model, the first variable is the return on a portfolio of institutions and the second variable is the return on the chosen institution.

The second category of systemic risk indicators is based on ***component analysis*** and includes the absorption ratio, the turbulence index, the correlation surprise, and a macro index called CATFIN. The dynamic principal component analysis helps to assess the degree of linkages among listed companies. The absorption ratio suggested by Kritzman et al. (2011), is an implied systemic risk that equals the fraction of the total variance of a set of asset returns explained by a fixed number of eigenvectors. It captures the extent to which markets are unified or tightly coupled. When a market is tightly coupled (i.e., with a high value of the absorption ratio), it is more fragile in the sense that negative shocks propagate more quickly and broadly compared to a situation when markets are loosely linked. In addition to the absorption ratio, Kritzman and Li (2010), suggest a financial turbulence index by arguing that during turbulent days, asset prices behave uncharacteristically, including extreme price moves, decoupling of correlated assets and convergence of uncorrelated assets.

Apart from these two indicators, the correlation surprise suggested by Kinlaw and Turkington (2013), is used to assess the periods characterized by higher risk and lower returns-to-risk premium than periods characterized by typical correlations. According to these authors, "*days characterized by low correlation surprise are less unusual than the magnitudes of the individual returns alone would suggest*".

All these indicators will help identify potential periods of high risk in the market for each of the listed companies. In addition, Allen et al. (2012) suggest a macro index of systemic risk measuring the aggregate level of risk-taking in the financial sector known as CATFIN. This indicator is calculated using the cross-sectional distribution of equity returns of listed firms. Formally, it is defined as the average of two parametric – based on Generalized Pareto Distribution (GPD) and Skewed Generalized Error Distribution (SGED) – and one non-parametric VaR measure.

The systemic risk indicators, based on the component analysis outlined above, do not directly address the issue of connectedness. To this end, Billio et al. (2012) propose connectedness measures combining principal components analysis and Granger causality. In the spirit of the absorption ratio, the authors argue that when a system is highly connected, a small number of components explain most of the volatility in the system. To investigate the dynamic propagation of shocks to the system, Billio et al. (2012) evaluate the directionality of the degree of connectedness between institutions by using Granger causality. They suggest network-based measures of connectedness through five main indicators. Four of these indicators are used in this paper[‡]. The first indicator is the degree of Granger causality (DGC), which is the fraction of statistically significant Granger-causality relationships among all pairs of financial institutions. The risk of a systemic event is high when DGC exceeds a threshold K estimated as the 95th percentile of the distribution of DGC. The second indicator is the number of connections *out* (i.e., the number of financial institutions that are significantly Granger-caused by a given institution *j*) and *in* (the number of financial institutions that significantly Granger-cause a given institution *j*). In this paper, we will present the sum of the number of connections *in* and *out* to consider two-way causality. The third indicator is sector-conditional connections. This is similar to the number of connections, but it conditions the type of institution. The fourth indicator is eigenvalue centrality which measures the importance of an institution in a network by assigning relative scores to institutions based on how connected they are to the rest of the network.

We complement the network analysis with other centrality measures such as Katz, closeness, degree, betweenness, and clustering centrality[§]. Katz centrality measures the relative influence of each node in a given network by considering its immediate neighbouring nodes as well as non-immediate neighbouring nodes that are connected through immediate neighbouring nodes. The closeness centrality is the average length of the shortest path between the company's node and all other nodes in the graph indicating firms that are the most likely to quickly propagate a shock through the network. This indicator can be regarded as a measure of how much time it takes to spread information into the network from a given vertex (Zhan et al., 2017). The degree of centrality is defined as the number of ties that a vertex has with other vertices. The betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together.

By using a wide range of indicators, we can measure different dimensions of systemic risk.

2.2. Non-financial sector and systemic risk

While most studies on systemic risk focus on banks, the recent literature suggests that considering the non-financial sector provides a better understanding of the sources of risk (Wang et al., 2021). The close linkage between financial and non-financial firms suggests that

[‡] The fifth indicator (the *closeness*) is similar to the *closeness centrality* described later below.
[§] These definitions are taken from Zhan et al. (2017).

the latter can be related to systemic risk. In the U. S., a firm's external financing dependence is one channel through which risk from the financial sector is transmitted to the real economy, Chiu et al. (2015). Zhu et al. (2020) find that non-financial firms can generate significant negative externalities on systemic risk in China as they play a big role in the economy-wide networks. For example, firms operating in manufacturing, wholesale retail, and real estate are highly correlated with systemic risk in China (Wang et al., 2021). Similarly, Kerste et al. (2015), focusing on the U.S. equity data, found that companies in the energy sector trading in the over-the-counter derivatives market have high contagion risk toward other non-financial sectors as opposed to the banking sector. Therefore, from these works, it becomes clear that systemic risk may occur in any sector of the economy. Certain sectors such as energy and construction are likely to be more closely related to financial market institutions and their products rather than other sectors (Van Cauwenberge et al., 2019). They may carry an increased degree of systemic risk compared to other non-financial sectors (e.g., Muns and Bijlsma, 2011; Dungey et al., 2018). In the case of the Dutch economy, non-financial firms within the sectors of administrative and support service, transportation and storage, and construction are among the highest risk contributors (Van Cauwenberge et al., 2019). Dungey et al. (2018) even document that all economic sectors in the U.S. contribute to systemic risk. Along the same line, Samitas et al. (2018) find that no country and sector was immune to spillover effects from the subprime crisis and the European sovereign debt crisis, but certain sectors such as healthcare, telecommunications, utilities and technology, exhibit weak contagion effects.

Consistent with this literature, we consider both the financial and non-financial sectors in our analysis, focusing on Africa where little is known about systemic risk, particularly beyond the financial sector (see section 2.3 below for literature on Africa).

2.3. Systemic risk in Africa: what do we know?

A few studies have been conducted to examine systemic risk in Africa. The limited number of studies is due to data constraints making it difficult to calculate systemic risk indicators and the young age of most African financial markets. The few studies that exist focus mainly on the banking sector (e.g., Saidane et al., 2021). They highlight the role of information asymmetry (Fall 2017) in the WAEMU context, public banks (Khiari and Nachnouchi, 2018) in Tunisia, and the size of banks (Manguzvane and Mwamba, 2019) in South Africa in systemic risk. Manguzvane and Mwamba (2020) and Mwamba and Angaman (2021), show that the insurance sector in South Africa is most systemically risky compared to banks and other financial sectors. In a policy paper, Enoch et al. (2015) discuss the regulatory oversight challenges posed by the rapid expansion of pan-African banks and their cross-border systemic risk threat.

Our study contributes to expanding the literature on African stock markets. As mentioned earlier, it goes beyond the financial sector in a regional setting whereas the existing literature concentrates on financial institutions and/or on a single country. Furthermore, this paper is the first to look at systemic risk in a regional securities market in developing economies. Although we analyse one regional stock market, we cover eight countries providing a regional perspective.

3. Methodology, variables, and data

3.1. Methodology

This paper is based on a two-step approach. In the first step, we estimate a range of systemic risk indicators to assess the level of risk in the stock market. This allows us to identify firms that are more prone to systemic risk and then see among them those that are contributing more to system-wide risk (systemic risk). In the second step, we examine potential determinants of systemic risk. The main purpose is to analyse the extent to which firms' characteristics and aggregate factors contribute to increasing the systemic importance of some companies.

3.1.1. *Systemic risk indicators*

This paper uses a selective number of cross-sectional measures commonly used in empirical studies, namely, the Expected Shortfall (ES), the Marginal Expected Shortfall (MES), the Conditional Value-at-Risk (CoVaR and ΔCoVaR), and the Conditional Autoregressive Value-at-Risk (CAViaR). It also computes indicators based on component analysis. All the systemic risk indicators have been presented in section 2.1.

3.1.2. *Regression analysis exploring potential determinants of systemic risk*

Following the estimation of the systemic risk indicators described above, we then analyse the extent to which firm-level variables, as well as macroeconomic variables, may explain the level of systemic risk. The form of the model to be estimated is as follows:

$$R_{it} = \alpha + \boldsymbol{X}_{it}\beta + \boldsymbol{Y}_{jt}\gamma + \boldsymbol{Z}_t\zeta + \boldsymbol{D}_i + \lambda_t + \varepsilon_t, \#(1)$$

where R_{it} is the contribution of the company *i* to the risk of the system (daily); *i* indexes listed companies; t indicates the time; $\boldsymbol{X}_{it}$ is the matrix of company-level characteristics (daily, except for the annual profitability variables); $\boldsymbol{Y}_{jt}$ are the characteristics of country *j* in which each listed company operates (annual); $\boldsymbol{Z}_t$ is the matrix of global factors that affect all companies being listed or not (daily); $\boldsymbol{D}_i$ is company-level fixed effects; λ_t is the time-fixed effects (week–year); α is a scalar; and β, γ, ζ are vectors of parameters to be estimated. ε_t is the error term. The list of the variables, their description and the expected signs are presented hereunder.

The model is estimated by using the fixed effects technique and the weighted-average least squares technique developed by Magnus et al. (2010). The second estimation technique aims at accounting for uncertainty in the choice of explanatory variables.

3.2. Variables

3.2.1 *Variables used to estimate systemic risk indicators*

The systemic risk indicators described above require four main variables: stock prices (returns), market capitalization, the book value of total assets and the book value of equity. Stock prices and market capitalization are daily data, while book values are annual balance sheet data.[**] We also add the composite stock index of the BRVM calculated for all listed companies in the exchange, called the BRVM Composite index.

3.2.2 *Variables used in the econometric analysis*

We use firm-level variables as well as domestic and global factors. ***Firm-level variables*** are used to evaluate firms' specific characteristics that may affect the level of systemic risk. These variables are:

- *Firm size (Size)* is measured by the logarithm of total market equity for each firm, divided by the log of the cross-sectional average of market equity as in Adrian and Brunnermeier (2016).[††] The literature in developed countries has shown a positive effect of firm size on systemic risk, consistent with the too-big-to-fail concept. However, Zhu et al. (2020) find

[**] Quarterly financial reports are not detailed and do not include liabilities.
[††] It is also possible to proxy size by the logarithm of total assets as in Zhu et al. (2020).

a negative effect of size on systemic risk in China. Therefore, the relationship between size and systemic risk is undetermined.

- *Leverage (LEV) is* measured by the ratio of the book value of liabilities (total debt), divided by the sum of market capitalization and the book value of liabilities (debt). Highly leveraged firms are expected to contribute more to systemic risk (Adrian and Brunnermeier, 2016).
- *Market-to-book ratio (MBR)*, is measured as the market capitalization divided by the book value of equity and is a financial distress risk factor. According to Qin and Zhou (2019), among others, it is negatively correlated with systemic risk. A higher market-to-book ratio signals a lower cost of external equity financing, which should be associated with a lower leverage ratio, thereby contributing to lower systemic risk. At the same time, *Market-to-book ratio* being the firm's growth potential measure, also encompasses the risk dimension associated with high-value creation, and can therefore be positively correlated with systemic risk. Hence, the impact of *MBR* on systemic risk is undetermined and remains to be proven empirically.
- *Tobin-Q*—a measure of firm value is negatively associated with system risk in the financial sector (Soedarmono et al., 2017), but it is positively associated with system risk generated by non-financial firms in China (Zhu et al., 2020). Therefore, the relationship between Tobin-Q and systemic risk is undetermined.
- *Return on asset (ROA)* and *Operating income to asset ratio (OROA*) are profitability indicators. Profitable companies should contribute less to systemic risk.

Country-specific indicators and ***global factors*** are used to control for external factors. These variables are:

- *GDP growth (Growth)*, measured by the growth rate of real gross domestic product (GDP), is used to capture the demand-side effect. GDP growth may affect systemic risk through its effect on profit. We expect companies to be more profitable during economic booms and less during downturns. Therefore, we expect a negative relationship between GDP growth and systemic risk.
- The quality of institutions is proxied by the *Investment profile*, the *Composite risk rating*, and the *Regulatory quality*: These variables are used as a control for the business environment in each country. We expect a negative effect of each institutional quality variable on systemic risk, that is an increase (improvement) in the quality of institutions

decreases systemic risk. Similar results have been found in the literature (e.g., Kleinow and Nell, 2015).

- The *Interbank rate* is positively associated with the policy rate, therefore, we may expect a negative relationship between the interbank rate and systemic risk. This variable is used as a control for domestic financial conditions. Colletaz et al. (2018) found causality from monetary policy to systemic risk in the long run. This result suggests that a too-loose monetary policy stance may help the progressive build-up of systemic risk.
- The *Shadow rate* is used as a global factor and measures the stance of monetary policy in the United States[‡‡]. We may expect a negative relationship between the stance of monetary policy and systemic risk as explained above. Although the BRVM is not fully integrated into the global financial market, the presence of pan-African banks (Enoch et al., 2015) and foreign French banks can create a bridge for global conditions to affect the regional market (Kanga et al., 2021).
- *VIX* is an indicator of the volatility in the US financial market. It is used to proxy global financial market risk. We expect a positive relationship between VIX and systemic risk because VIX measures investor fear.

Table 1 provides a summary of the variables, their description, and sources of data.[§§]

[‡‡] Although the WAEMU currency (CFA franc) is pegged to the Euro, nonetheless, these economies are exposed to global imbalances through the prices of their commodity exports and their imports of goods and services. For robustness check of our results, we run our regressions with the eurozone interest rate alone, and both the eurozone interest rate and the U.S. interest rate, the results provided in Table A4 (Panel A and B) in the appendix remain similar. Overall, our results do not depend on the use of the U.S. interest rate or not.

[§§] The online appendix I provides the detailed and replicable guide to the data and methodology used in this paper.

Table 1: Description of the explanatory variables

Variables	Description	Data source	Literature review
Firm-level variables			
SIZE	The logarithm of total market equity for each firm is divided by the log of the cross-sectional average of market equity.	BRVM / Own calculation	Adrian and Brunnermeier (2016)
LEV	Leverage: Total debt divided by (market capitalization plus book value of debt).	BRVM	Adrian and Brunnermeier (2016)
ROA	Return on asset: Net income divided by the total asset.	BRVM	Morelli and Vioto (2020)
OROA	Operating income is divided by the total asset.	BRVM	Morelli and Vioto (2020)
MBR	Market-to-book ratio: Market capitalization divided by the book value of equity.	BRVM	Qin and Zhou (2019)
Tobin-Q	Firm value: market value of equity plus book value of liabilities divided by the total asset.	BRVM / Own	Zhu et al.

		calculation	(2020)
Country and global factors			
Growth	Real GDP growth.	WDI	Morelli and Vioto (2020)
IP	*Investment profile* is an assessment of factors affecting the risk to investment that are not covered by other political, economic, and financial risk components. A score of 4 equates to very low risk and a score of 0 points to very high risk.	ICRG	Kleinow and Nell (2015)
Composite	*Composite (aggregate) risk rating* is a composite political, financial, and economic risk rating. A score of 100 equates to very low risk and a score of 0 points to very high risk.	ICRG	Kleinow and Nell (2015)
RQ	*Regulatory quality* captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	WGI	Kleinow and Nell (2015)
Interbank	One-week interbank market rate.	BCEAO	Colletaz et al. (2018)
Shadow	*Shadow rate* characterizes the term structure of interest rates. It is not bonded below 0 and gives the stance of monetary policy even in zero lower-bound environments.	Wu and Xia (2016)	Kabundi and De Simone 2020
VIX	Volatility index.	Yahoo Finance	Diebold and Yılmaz (2014).

Notes: This table presents the variables used in this paper, their definitions, the abbreviations used in empirical results, the sources of raw data and authors that used the same indicators in the systemic risk literature. BRVM is "Bourse Régionale des Valeurs Mobilières". We use companies' balance sheets obtained from the BRVM. BCEAO, the abbreviation of "Banque Centrale des États de l'Afrique de l'Ouest", is the Central Bank of West African States. ICRG is the International Country Risk Guide. WDI stands for the World Bank's World Development Indicators database. WGI stands for the World Bank's Worldwide Governance Indicators database.

3.3. Sample and descriptive statistics

Two categories of data are required to calculate the systemic risk indicators, namely, market data and balance sheet data. Because we use market data, only listed companies are considered. To maximize the number of observations, the sample spans from 1st January 2004 to 31st December 2020. On the BRVM market, as of 31 December 2020, 46 companies were listed on its main market, but only 32 were listed on or before 1st January 2004, including one under liquidation. Therefore, we limit our analysis to 31 firms, excluding the company in liquidation for which balance sheet information is no longer available. Table A1 in the appendix provides the list of companies included in our sample. The distribution of these companies by sector is given in Table 2. As per the BRVM sector classification, we have six economic sectors: distribution, finance, industry, public utility, agriculture and transportation. The financial sector is composed of five companies (16%), while the remaining 26 companies are in the non-financial sector (84%). Companies in the industrial and distribution sectors dominate the non-financial sector (39% and 19%, respectively, of the sample).

Table 2: Distribution of companies by sector

Sector	Sector Code	Listed	Sample
Distribution	DIS	7	6
Finance	FIN	15	5
Industry	IND	14	12
Public Utilities	PUU	4	3
Agriculture	AGR	4	4
Transportation	TRA	2	1
Total		**46**	**31**

Source: Authors' compilation. The classification is provided by the BRVM.

Table 3 reports the summary statistics of the daily market returns calculated from the market indices by sector. The transportation, agriculture and financial sectors have the highest standard deviation, in other words, the returns of the stocks in these sectors are highly volatile. Another risk measure is kurtosis, which measures the distribution of losses at the tail. A relatively large kurtosis indicates fat tails and this is the case mainly for the financial, utilities, agricultural, and industrial sectors. Later, we use the systemic risk measures discussed above to better assess the risk of each sector.

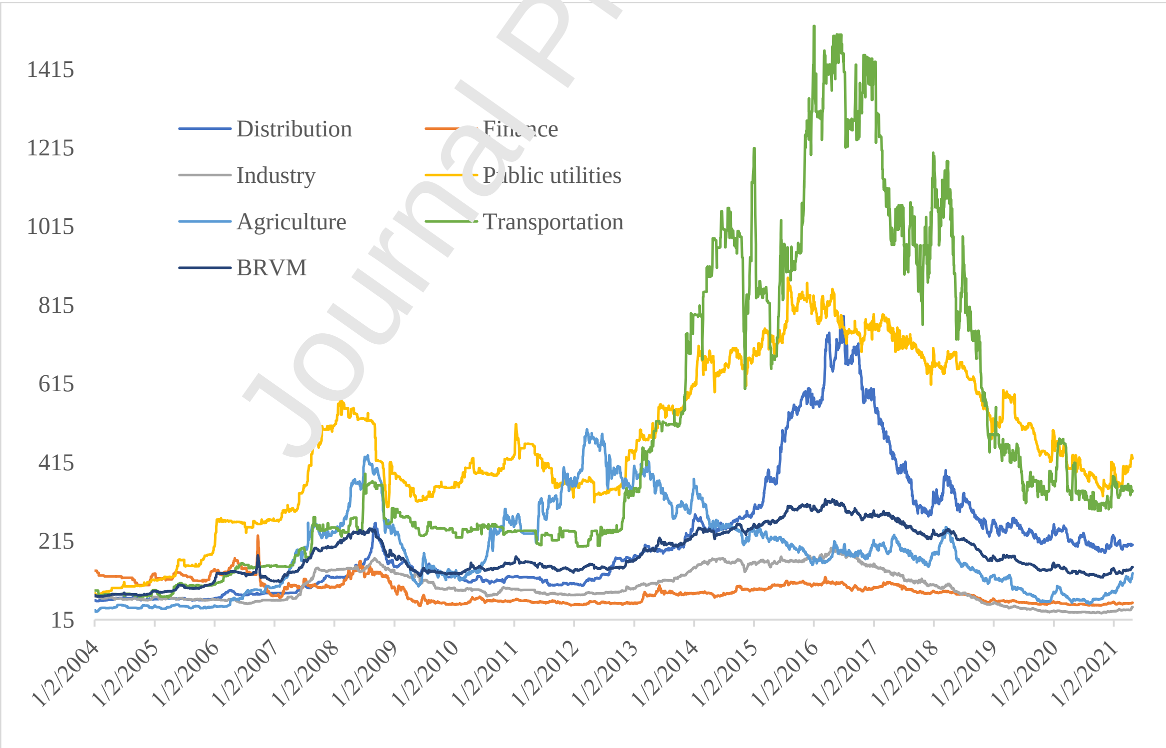
Table 3: Descriptive statistics for the daily market returns by sector and the overall index (BRVM), 2004–2020

	Distribution	Finance	Industry	Public Utilities	Agriculture	Transportation	BRVM
Mean	0.03	-0.01	-0.01	0.05	0.05	0.06	0.02
Standard deviation	1.17	1.66	0.97	1.31	1.87	2.25	0.86
Kurtosis	3.97	20.37	13.57	15.82	14.00	6.21	18.50
Skewness	0.01	0.44	0.31	0.38	0.88	0.20	0.20
Minimum	-6.82	-18.95	-9.35	-13.64	-16.49	-13.72	-10.13
Maximum	9.22	20.86	11.40	14.70	24.99	15.29	9.51
Observations	4303	4303	4303	4303	4303	4303	4303

Source: BRVM; authors' compilation.

Figure 1 shows that all sectors do not display the same pattern in terms of indices. Transportation, utility and distribution companies are more volatile compared to the industrial and financial sectors, even though Table 3 indicates smaller kurtosis for the distribution and transportation sectors. The indices in these three sectors increased and reached their peak around 2017 before falling. This may imply different risk exposure and contribution to the system-wide risk.

Figure 1: Evolution of sectorial and market indices



Source: BRVM; authors' compilation.

Table 4 provides descriptive statistics on the above-mentioned explanatory variables. The listed companies seem to be similar in terms of size, given the low standard deviation and the small gap between the minimum and maximum size.[9] However, they differ in their leverage. Another specific characteristic of companies is their market-to-book ratio (MBR), which is an indicator of financial distress. Some companies have a negative MBR, which indicates a negative book value of equity.

Table 4: Descriptive statistics on explanatory variables

	Observations	Mean	Standard deviation	Min	1st quartile	Median	3rd quartile	Max
MBR	130882	2.20	6.05	-47.10	0.98	1.94	3.60	14.97
Size	130882	0.95	0.06	0.78	0.91	0.96	0.99	1.12
LEV	130882	0.56	0.25	0.01	0.35	0.54	0.80	0.97
Tobin-Q	130882	1.79	2.58	0.50	1.04	1.25	1.79	40.87
ROA	130882	0.05	0.12	-0.87	0.01	0.03	0.09	1.07
OROA	130882	0.07	0.12	-0.65	0.02	0.05	0.12	1.10
Growth	130882	4.54	3.78	-4.86	1.77	3.25	7.36	10.86
RQ	130882	-0.64	0.28	-0.97	-0.90	-0.74	-0.36	0.05
IP	130882	6.64	1.28	5.00	5.00	7.29	8.00	8.50
Composite	130882	60.01	2.71	51.00	58.75	60.00	61.34	65.00
Shadow	130882	0.82	2.19	-2.99	-1.07	0.52	2.13	5.26
VIX	130882	18.87	9.24	9.14	13.08	15.92	21.56	82.69
Interbank	130882	4.15	0.79	2.34	3.52	4.13	4.78	6.00

Source: Raw data are from BRVM, WDI, ICRG, BCEAO, Wu and Xia (2016). Authors' compilation.

Table A2 in the appendix reports the correlation matrix on the explanatory variables. Most of the correlation coefficients are generally low, especially among global variables, country-specific and regional variables, as well as among firms' specific characteristics. However, we find high correlations among the quality of institutions variables. In the regressions, to avoid multicollinearity issues, we do not include the same regression variables that exhibit a correlation of more than 0.6. For example, ROA and OROA will not be included in the same regression.

4. Empirical results

This section analyses the empirical results of systemic risk indicators presented in section 2 and discusses the regression results. It is organized into three subsections. The first subsection focuses on cross-sectional measures of systemic risk. The second subsection analyses systemic risk indicators based on principal component analysis. Finally, the third subsection presents and discusses regressions results of the determinants of systemic risk.

4.1. Systemic risk indicators based on cross-sectional measures

[9] The variable size has the lowest coefficient of variation (not reported) among all firm level variables considered in the analysis.

The first category used to assess systemic risk includes conventional risk indicators. Table 5 reports summary statistics on average systemic risk indicators at a 95% confidence level. The average expected shortfall (ES), that is daily average returns when the portfolio's loss exceeds its value at risk limit, varies between -94.5 and -19.6 percentage points. The losses in the tail of the system's loss distribution, i.e., the MES – range from 0.1 percentage points to 4.9 percentage points. The average CoVaR at a 95% confidence level varies between 1.2 percentage points and 2.2 percentage points with a low average tail-dependency between the whole financial system and a particular institution as measured by ΔCoVaR. On average, there is a limited contribution of each institution to the system-wide risk.

Table 5: Descriptive statistics on average systemic risk indicators at a 95% confidence level

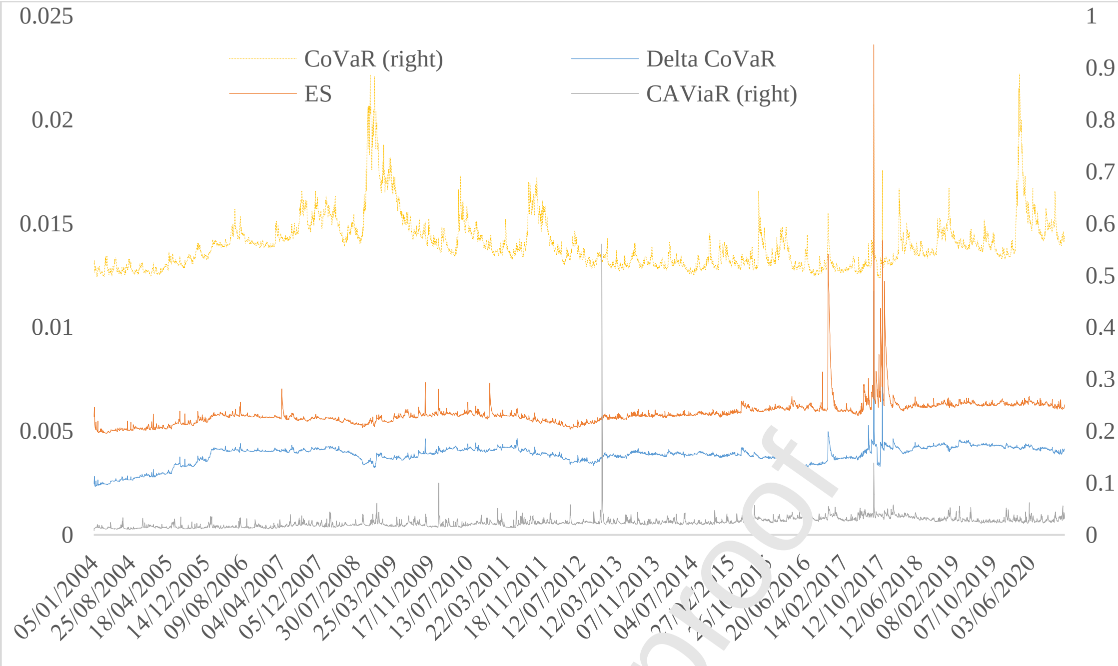
	ES	MES	CoVaR	ΔCoVaR	CAViaR
Mean	0.234	0.013	0.014	0.004	0.024
Median	0.231	0.008	0.014	0.004	0.023
Standard Deviation	0.025	0.011	0.001	$4.5x10^{-4}$	0.013
Kurtosis	175.415	0.191	7.170	26.095	837.282
Skewness	8.751	1.127	2.145	0.438	21.018
Minimum	0.196	0.001	0.012	0.002	0.008
Maximum	0.945	0.049	0.022	0.012	0.561

Source: Raw data are from BRVM. Authors' compilation.

The correlation between CoVaR and ΔCoVaR is 0.61 (Appendix Table A2). Except for these two variables, the systemic risk indicators are not highly correlated, with correlations of less than 0.4. Therefore, each indicator measures a specific dimension of systemic risk.

Because systemic risk has both cross-sectional and time series dimensions, the following analysis concentrates on these two dimensions. Figure 2 presents the average systemic risk indicators to trace the time dimension of systemic risk.

Figure 2: Time series properties of the average systemic risk indicators



Source: Raw data are from BRVM. Authors' compilation.

The figure indicates a high-risk level between 2016 and 2017 in the market, especially in November 2016 and between August and November 2017 when ES is used as a risk indicator. CAViaR also shows a high value of risk in August 2017. In addition, the market was not quiet around the beginning of the global financial crisis (April to June 2007) and in October 2008 after the collapse of Lehman Brothers. Global factors seem to have affected the BRVM market.

In addition to the time dimension, systemic risk has also a cross-sectional dimension. Table 6 provides summary statistics of the cross-sectional systemic risk indicators. The top ten companies with the highest risk values are highlighted in bold. The top risky companies identified as such by at least three indicators are by sector: distribution (TTLC), finance (SGBC), utility (CIEC, SDCC, SNTS) and agriculture (PALC, SOGC, SPHC). In addition to these companies, SLBC contributes significantly to the system-wide risk according to CoVaR and ΔCoVaR.

The companies identified here are more prone to systemic risk and contribute more to system-wide risk (systemic risk) than the others. The next natural question to ask is: how connected are these companies to the others? The next section will address the issue of connectedness.

Table 6: Systemic risk indicators at 95% confidence level, by company

	ES				MES				CAViaR				CoVaR				ΔCoVaR			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
ABJC	**0.350**	0.083	0.347	5.381	0.005	0.003	0.000	0.078	0.033	0.028	0.000	0.162	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.007
BNBC	0.317	0.000	0.317	0.319	0.002	0.002	0.000	0.023	0.027	0.032	0.000	0.484	0.012	0.001	0.011	0.022	0.001	0.000	0.001	0.001
CFAC	**0.526**	0.000	0.526	0.530	**0.005**	0.009	0.000	0.074	0.025	0.037	0.000	0.545	0.012	0.001	0.011	0.022	0.001	0.000	0.001	0.001
PRSC	**0.564**	0.000	0.564	0.567	0.002	0.009	0.000	0.105	0.006	0.026	0.000	0.879	0.012	0.001	0.010	0.021	0.000	0.000	0.000	0.000
SHEC	0.170	0.286	0.124	8.602	0.003	0.004	0.000	0.054	**0.043**	0.024	0.012	0.349	0.012	0.002	0.011	0.052	0.001	0.001	0.001	0.040
TTLC	**0.345**	0.000	0.345	0.347	**0.008**	0.015	0.000	0.073	0.027	0.030	0.000	0.175	**0.013**	0.001	0.012	0.023	**0.002**	0.000	0.002	0.002
BICC	0.173	0.180	0.140	5.641	0.001	0.001	0.001	0.037	0.027	0.016	0.000	0.059	0.012	0.002	0.010	0.022	0.000	0.000	0.000	0.011
BOAB	0.157	0.267	0.111	7.175	0.000	0.002	0.000	0.071	0.017	0.029	0.000	0.500	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.009
BOAN	0.280	0.198	0.263	8.638	0.004	0.006	0.000	0.079	0.023	0.036	0.000	0.639	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.004
SAFC	**0.430**	0.000	0.430	0.433	**0.005**	0.000	0.005	0.005	0.003	0.017	0.000	0.801	0.012	0.001	0.010	0.021	0.000	0.000	0.000	0.000
SGBC	0.206	0.150	0.194	8.772	**0.013**	0.009	0.012	0.534	**0.034**	0.029	0.000	1.337	**0.014**	0.002	0.012	0.105	**0.002**	0.002	0.002	0.095
CABC	**0.481**	0.155	0.476	9.763	**0.018**	0.041	0.000	2.614	0.025	0.020	0.000	0.069	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.001
FTSC	0.079	0.000	0.079	0.079	0.004	0.000	0.000	0.011	**0.054**	0.017	0.027	0.169	0.012	0.001	0.011	0.022	0.001	0.000	0.001	0.001
NEIC	**0.378**	0.000	0.378	0.381	0.000	0.000	0.000	0.000	0.016	0.024	0.000	0.083	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.000
NTLC	0.094	0.161	0.055	4.810	0.001	0.002	0.000	0.017	0.026	0.042	0.000	1.014	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.010
SEMC	**0.444**	0.000	0.444	0.448	0.003	0.006	0.000	0.044	0.017	0.020	0.000	0.076	0.012	0.001	0.011	0.022	0.001	0.000	0.001	0.001
SIVC	0.219	0.072	0.214	4.176	0.002	0.002	0.000	0.074	**0.042**	0.021	0.000	0.068	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.007
SLBC	0.143	0.000	0.143	0.144	0.004	0.000	0.004	0.004	0.017	0.015	0.000	0.048	**0.013**	0.002	0.011	0.023	**0.001**	0.000	0.001	0.001
SMBC	0.077	0.074	0.056	2.937	0.004	0.003	0.000	0.101	0.028	0.024	0.000	0.184	0.013	0.002	0.011	0.051	0.001	0.001	0.001	0.040
STAC	**0.583**	0.000	0.583	0.588	0.002	0.003	0.000	0.021	0.014	0.017	0.000	0.073	0.012	0.002	0.010	0.022	0.000	0.000	0.000	0.000
STBC	**0.319**	0.000	0.319	0.321	0.002	0.003	0.000	0.048	**0.033**	0.027	0.009	0.560	0.012	0.001	0.010	0.022	0.000	0.000	0.000	0.000
UNLC	0.092	0.029	0.070	0.399	0.004	0.003	0.000	0.051	0.024	0.019	0.000	0.131	0.012	0.001	0.011	0.022	0.001	0.000	0.001	0.003
UNXC	0.092	0.112	0.039	1.609	0.004	0.009	0.000	0.286	0.024	0.024	0.000	0.080	**0.013**	0.003	0.011	0.043	**0.002**	0.002	0.001	0.032
CIEC	0.092	0.119	0.071	7.313	**0.006**	0.008	0.000	0.158	**0.049**	0.001	0.031	0.061	**0.013**	0.002	0.011	0.126	**0.001**	0.002	0.001	0.116
SDCC	0.086	0.088	0.049	2.014	0.004	0.004	0.000	0.028	**0.037**	0.028	0.000	0.927	**0.013**	0.002	0.011	0.049	**0.002**	0.002	0.001	0.039
SNTS	0.278	0.000	0.278	0.280	**0.020**	0.021	0.000	0.080	0.017	0.022	0.000	1.167	**0.015**	0.001	0.014	0.022	**0.006**	0.000	0.006	0.007
PALC	0.060	0.026	0.017	0.267	**0.009**	0.005	0.000	0.080	**0.045**	0.022	0.000	0.084	**0.014**	0.002	0.011	0.025	**0.002**	0.001	0.001	0.009
SICC	0.108	0.050	0.071	0.354	0.000	0.000	0.000	0.004	0.011	0.014	0.000	0.082	0.012	0.001	0.010	0.021	0.000	0.000	0.000	0.000
SOGC	0.179	0.001	0.179	0.216	**0.007**	0.006	0.000	0.029	**0.045**	0.017	0.001	0.229	**0.013**	0.001	0.012	0.023	**0.002**	0.000	0.002	0.002
SPHC	0.078	0.058	0.054	2.424	**0.014**	0.018	0.000	0.795	**0.050**	0.012	0.007	0.079	**0.014**	0.002	0.012	0.075	**0.002**	0.002	0.001	0.065
SVOC	0.126	0.046	0.088	0.424	0.000	0.001	0.000	0.010	0.008	0.008	0.000	0.034	0.012	0.001	0.010	0.021	0.000	0.000	0.000	0.000

Notes: SD stands for standard deviation. Companies with high risk are in bold for each indicator.

4.2. Systemic risk indicators based on principal component analysis

The idea behind a principal component analysis (PCA), based systematic risk indicator is that, when the system is highly interconnected, a small number of principal components can explain most of the volatility in the system. As shown in Table 7, excluding 2004, the variance explained by the first 14 factors fluctuates between 55.9% and 65.7% during the period 2005–2020. Therefore, the first 14 principal components capture about two-thirds of the returns' variations during the period of the analysis. When the variance explained by a limited number of factors increases, it is associated with an increased interconnectedness among listed companies.

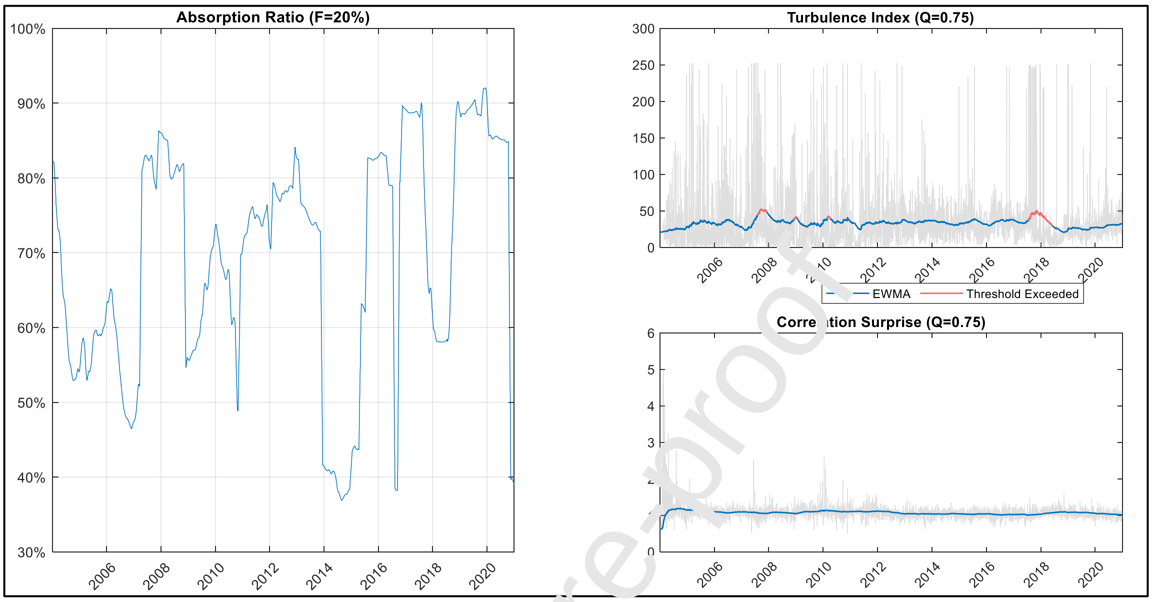
Table 7: Variance explained – Summary statistics for PCAs

	PC1-5			PC1-10			PC1-14			PC1-15			PC1-20		
	Min	Max	SD	Min	Max	SD	Min	Max	SD	Min	Max	SD	Min	Max	SD
2004	28.6	55.0	8.3	48.4	81.9	10.4	62.2	95.9	10.9	65.5	97.6	10.5	80.8	100.0	6.8
2005	25.4	29.9	1.0	45.8	51.1	1.2	59.7	65.7	1.3	63.0	69.0	1.3	78.1	84.2	1.2
2006	25.4	27.1	0.5	45.1	47.8	0.7	59.1	62.1	0.8	62.5	65.4	0.8	77.7	80.3	0.7
2007	25.2	28.1	0.8	45.3	49.1	1.0	59.1	63.1	1.2	62.3	66.5	1.2	77.4	81.8	1.4
2008	24.8	26.5	0.5	45.3	47.3	0.6	58.9	61.6	0.7	62.1	64.9	0.8	77.2	79.4	0.6
2009	25.3	29.4	0.9	45.1	49.9	0.9	58.9	63.6	0.9	62.2	66.8	0.9	77.1	80.8	0.9
2010	24.1	28.8	1.5	43.5	49.1	1.9	57.5	63.2	2.0	60.8	66.4	1.9	76.1	80.7	1.5
2011	26.3	28.2	0.5	47.0	50.2	0.9	61.0	64.8	1.1	64.1	67.9	1.0	78.6	81.8	0.9
2012	24.4	26.3	0.5	44.5	47.1	0.7	58.4	61.2	0.7	61.6	64.4	0.7	76.4	79.2	0.7
2013	25.0	27.4	0.6	45.7	48.0	0.6	59.6	61.7	0.5	62.9	64.8	0.5	77.5	78.6	0.2
2014	25.5	27.2	0.4	46.2	48.0	0.4	60.1	61.7	0.4	63.2	64.8	0.4	77.3	78.6	0.3
2015	25.1	26.2	0.3	45.7	47.3	0.3	59.9	61.7	0.3	63.2	64.8	0.3	77.6	78.6	0.2
2016	25.2	27.1	0.4	45.8	48.1	0.5	60.0	61.9	0.5	63.2	65.1	0.5	77.6	79.0	0.3
2017	24.2	28.4	0.9	43.7	48.7	1.1	57.3	62.7	1.2	60.6	65.9	1.2	75.8	79.8	1.0
2018	23.0	26.7	1.0	42.1	47.7	1.6	55.9	61.5	1.7	59.2	64.7	1.7	74.7	78.8	1.2
2019	25.5	27.4	0.4	45.8	48.0	0.5	59.7	61.8	0.5	62.9	64.9	0.5	77.4	78.8	0.4
2020	25.5	27.6	0.5	46.1	47.8	0.5	59.8	61.8	0.5	62.9	65.0	0.5	77.0	79.5	0.6

Note: This table displays the cumulative variance explained by the specified number of factors or eigenvectors. For example, PC1-10 is the variance explained by the first ten factors, and PC1-5 is the variance explained by the first five factors.

Based on the principal component analysis, four different systemic risk measures have been suggested for this first category: the absorption ratio, the turbulence index, the correlation surprise, and the CATFIN. To estimate the absorption ratio, we fix the number of eigenvectors at 20% of the number of firms in our sample as in Kritzman et al. (2011), that is, six eigenvectors. Figure 3 shows a volatile absorption ratio throughout the analysis. It increases to its highest value in November 2007 during the global financial crisis. The same trend is observed between November 2010, (the beginning of the post-electoral conflict in Côte d'Ivoire) and November 2012, (during the war in Mali, which we assumed had begun in January 2012). Probably, the market is sensitive to global factors as well as domestic/regional factors. Other high values are recorded throughout the analysis period especially earlier and during 2020. When the absorption ratio becomes high, the market is unified which indicates that the market becomes fragile in the sense that negative shocks can propagate more quickly and widely compare to weakly linked markets.

Figure 3: Absorption ratio, turbulence index, and correlation surprise

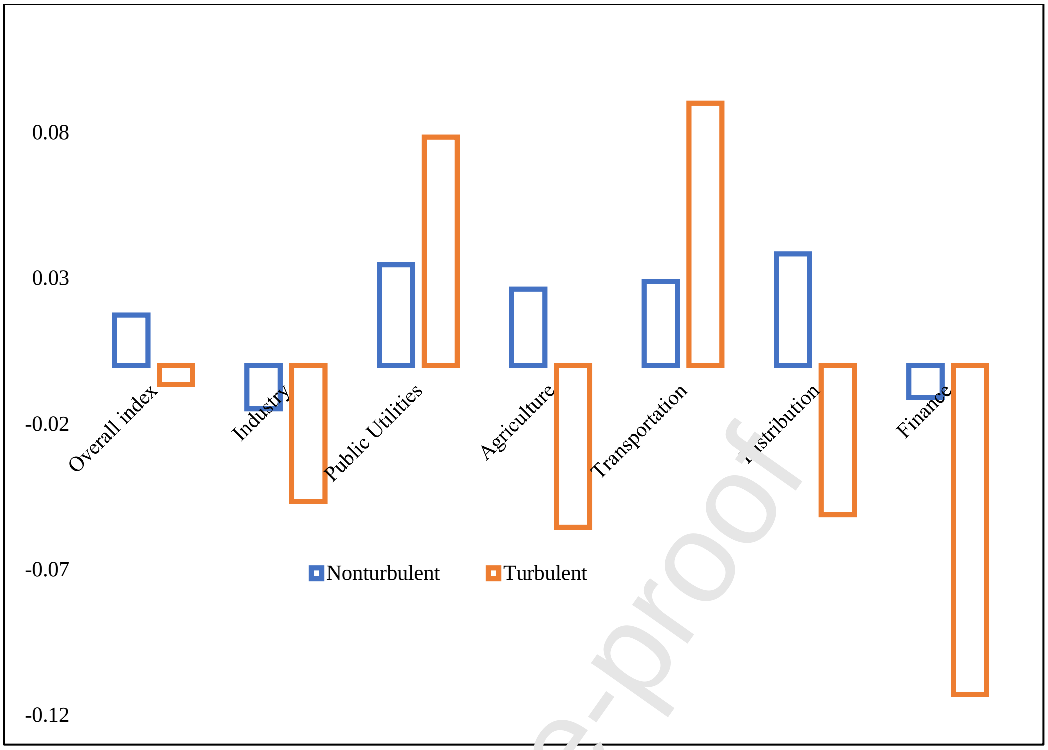


Source: Raw data are from BRVM. Authors' compilation.

In addition to the absorption ratio, Figure 3 shows that the BRVM market was turbulent, i.e., the turbulence index was outside the 25% of the distribution, or the threshold was exceeded during the following periods: between August 2007 and December 2007, in December 2008, between February and April 2010, between July 2017 and June 2018, the first week of August 2018 and 8–9 January 2019. The BRVM is not a quiet market and is sensitive to global factors, such as the global financial crisis, as well as domestic/regional factors. During turbulent periods, the market experiences lower daily returns as highlighted in Figure 4, except for two sectors namely, public utilities and transportation for which the average daily returns are higher during turbulent periods compared to non-turbulent periods. Even if the financial sector experiences negative returns, on average, throughout the analysis, the loss in value is higher during turbulent periods. The high average daily returns for the public utilities and the transportation sectors are counterintuitive; this may indicate that those sectors are refuge or "safe haven" sectors.

The correlation surprise does not show specific patterns, the market is characterized by low values of the correlation surprise index.

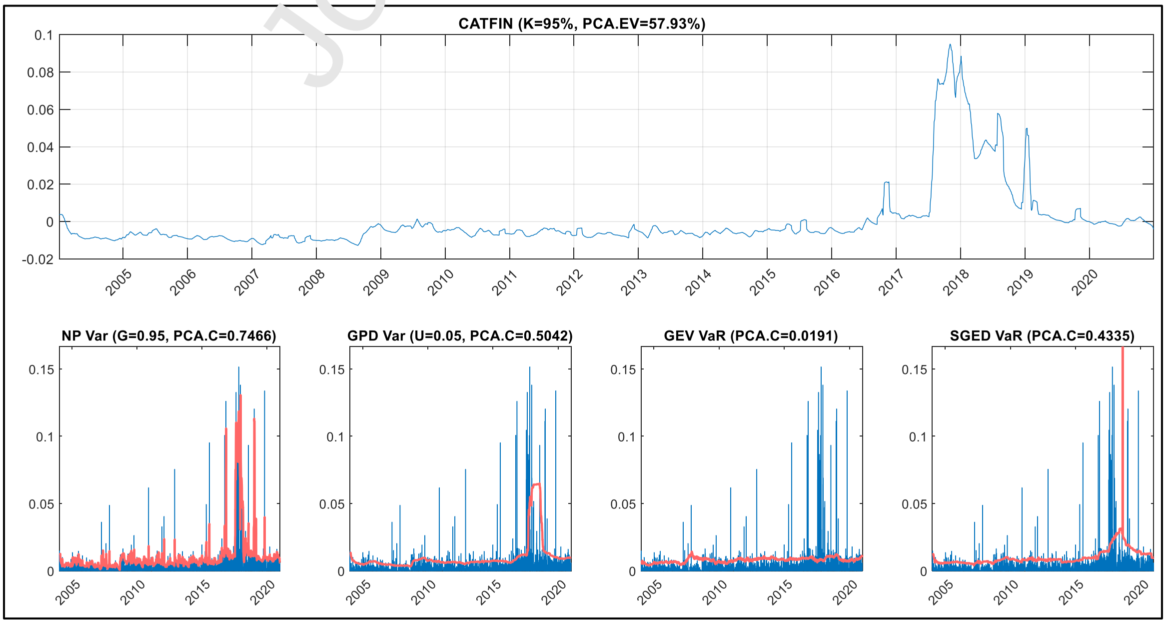
Figure 4: Average daily returns (in %) during turbulent and non-turbulent periods



Source: Raw data are from BRVM. Authors' compilation.

Another interesting indicator of systemic risk is CATFIN highlighted in the first row of Figure 5. CATFIN increases slightly over the year and sharply from 2017 to reach its highest value in August 2018. This is consistent with the results of the turbulence index presented before.

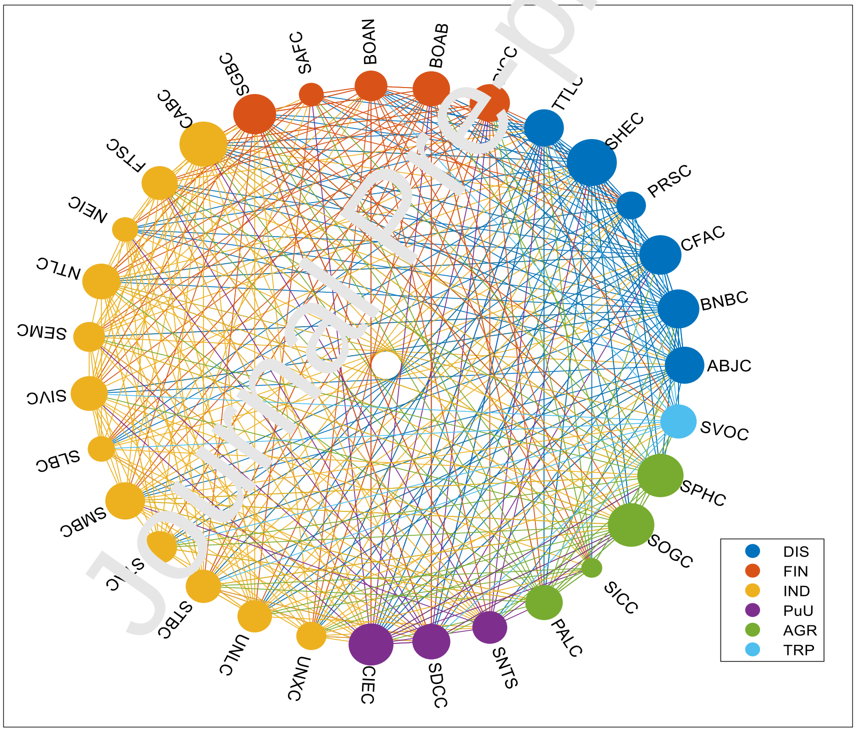
Figure 5: Value at Risk (VaR) at 5% and the CATFIN



Source: Raw data are from BRVM. Authors' compilation.

To formally analyse the degree of connections, we follow Billio et al. (2012) and use the Granger causality test. Figure 6 presents only those relationships significant at the 5% level. Granger-causality relationships are represented by straight lines connecting two institutions, that is, the institution at date t which Granger causes the returns of another institution at date $t + 1$. When there is a significant connection between a company and another one in the system, a line is drawn from this company to the other one. The colours indicate the sector in which each company operates (see notes at the bottom of Figure 6). As shown in the figure, there are connections among the listed companies in our sample. On average, companies in the distribution sector have between seven and 21 connections with other institutions, while financial companies' average number of connections is 13 (see Table 8).

Figure 6: Network graph (Granger-causality test)



Note: This figure displays the connections among companies. The colour represents the sectors in which companies operate: the distribution sector companies are in dark blue, the transportation in light blue, financial institutions are in orange, yellow colour indicates companies in the industrial sector, public utility companies are in purple, and companies in the agriculture sector are in green

Table 8 also presents the normalized number of connections from one sector to another, that is, we divide the number of significant connections from one sector to another by the total possible number of connections. The bold value in Table 8 indicates intra-sector connections, i.e., connections from a company operating in a specific sector to another company in the same sector.

We find a dense network among companies operating in the distribution and agriculture sectors. It is also interesting to notice that the risk can originate from any company listed on the stock market, and not only from financial companies.

Table 8: Number of connections from one sector to the system, and another sector

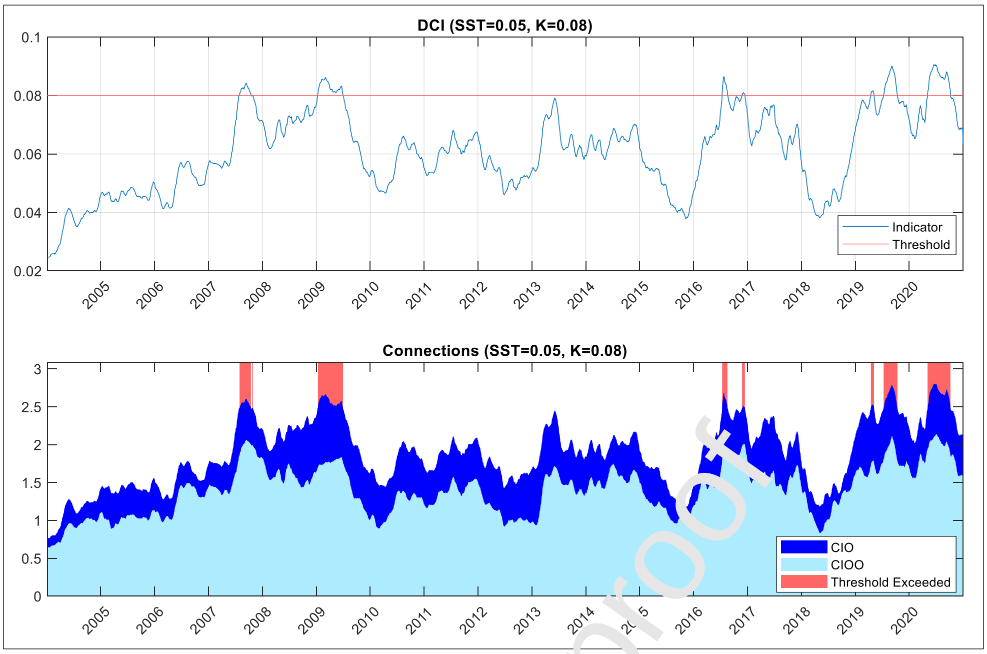
	To the system			*To* each sector (normalized #)					
From	Min	Mean	max	Distribution	Finance	Industry	Public Utilities	Agriculture	Transportation
Distribution	7	15.83	21	**0.73**	0.53	0.50	0.56	0.38	0.33
Finance	7	13.2	16	0.37	**0.45**	0.50	0.40	0.40	0.40
Industry	8	12.25	22	0.51	0.30	**0.37**	0.61	0.35	0.33
Public Utilities	9	12.33	15	0.39	0.53	0.36	**0.50**	0.50	0.00
Agriculture	8	15	18	0.42	0.50	0.50	0.50	**0.67**	0.50
Transportation		15		0.67	0.40	0.50	0.67	0.25	-

Note: This table reports, on the one hand, the number of connections from companies operating in one sector to the system; and on the other hand, it shows the normalized number of connections from one sector to another, that is, we divide the number of significant connections from one sector to another by the total possible number of connections. Note that there is only one company in the transportation sector.

The time series of the number of connections as a percentage of connections of all possible connections known as, the degree of Granger causality (DGC) against a threshold[1] of 0.08 is reported in the first row of Figure 7. The DGC indicates greater connectedness when it exceeds the threshold. According to Figure 7, the number of connections was large and significant during specific periods. The first period, which runs from the last week of July to November 2007, coincides with the beginning of the global financial crisis, especially the collapse of the subprime market. The second period begins in October 2008 and ends in July 2009, probably due to the consequences of the Lehman Brothers' bankruptcy in September 2008. Increases in the number of connections are recorded in 2013, 2016, 2017, 2019 and 2020. The second row of Figure 7 corroborates the finding of the first row by indicating in red the periods over which the threshold has been exceeded. In addition, it shows the extent to which the normalized number of connections (*in* and *out*) between companies has evolved.

[1] The threshold corresponds to the 95th percentile of the distribution, which assumes a 5% significance level.

Figure 7: Connectedness measures



Note: Dynamic causality index (DCI) is the same as the degree of Granger causality. CIO denotes the sum of *in* and *out* connections and CIOO stands for the number of sector-conditional connections.

Finally, we use the centrality measures associated with the connectedness indicator to identify systemic companies. Table 9 presents the average centrality measures. The top six companies are highlighted in bold. By using degree centrality, we find that companies in the distribution (ABJC, BNBC, SHEC), industry (CABC), agriculture (SOGC) and utility (CIEC) sectors are the most important in the financial market. Companies in the distribution (ABJC, BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors are the most important in the financial market according to the eigenvector centrality indicator.

Moreover, examining the closeness centrality, we can conclude that companies in the distribution (ABJC, BNBC, SHEC), industry (CABC) and agriculture (SOGC, PALC) are the most likely to quickly propagate a shock through the network.

Based on all centrality measures, the BRVM's systemic firms belong to the distribution (ABJC, BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors. These firms are more likely to propagate shocks to the whole market. It is interesting to see that all these companies operate in Côte d'Ivoire, the first economic power of the WAEMU monetary region. Surprisingly, these companies are not part of the 10 percent well-capitalized companies among the listed companies based on end-of-December 2019 data.

Table 9: Centrality measures

	Betweenness	Closeness	Degree	Eigenvector	Katz	Clustering
ABJC	0.040	**0.714**	**1.067**	**0.043**	**0.246**	**0.147**
BNBC	0.043	**0.750**	**1.100**	**0.048**	**0.274**	**0.161**
CFAC	0.049	0.652	1.000	0.036	0.194	0.102
PRSC	0.022	0.566	0.733	0.016	0.044	0.039
SHEC	**0.077**	**0.769**	**1.267**	**0.052**	**0.305**	**0.142**
TTLC	**0.050**	0.667	1.033	0.036	0.188	0.096
BICC	0.035	0.682	0.933	0.037	0.198	0.131
BOAB	0.042	0.682	0.933	0.036	0.186	0.123
BOAN	0.039	0.652	0.833	0.031	0.155	0.127
SAFC	0.014	0.556	0.567	0.013	0.015	0.055
SGBC	0.050	0.638	1.033	0.031	0.153	0.075
CABC	**0.069**	**0.789**	**1.267**	**0.050**	**0.287**	**0.142**
FTSC	0.020	0.588	0.833	0.023	0.109	0.073
NEIC	0.018	0.566	0.667	0.017	0.055	0.063
NTLC	0.047	0.638	0.933	0.028	0.131	0.083
SEMC	0.017	0.638	0.733	0.035	0.196	**0.190**
SIVC	0.032	0.612	0.867	0.026	0.118	0.071
SLBC	0.020	0.600	0.667	0.024	0.113	0.111
SMBC	0.037	0.625	0.900	0.030	0.157	0.093
STAC	0.035	0.612	0.767	0.023	0.140	0.107
STBC	0.035	0.638	0.933	0.031	0.153	0.101
UNLC	0.023	0.625	0.767	0.027	0.123	0.132
UNXC	0.040	0.638	0.833	0.030	0.148	0.117
CIEC	**0.062**	0.667	**1.133**	0.034	0.176	0.074
SDCC	0.037	0.638	0.933	0.030	0.151	0.093
SNTS	0.031	0.588	0.800	0.025	0.130	0.083
PALC	0.037	**0.714**	0.933	**0.045**	**0.264**	**0.206**
SICC	0.020	0.577	0.600	0.020	0.077	0.092
SOGC	**0.059**	**0.714**	**1.100**	**0.046**	**0.270**	0.139
SPHC	**0.051**	0.682	1.000	0.038	0.205	0.126
SVOC	0.027	0.667	0.833	0.034	0.172	0.140

Note: For each measure (column), the high top-six companies are highlighted in bold.

4.3. Regression analysis

This section presents the results of the estimates of equation (1) to understand the determinants of systemic risk in WAEMU by using the full sample (section 4.3.1) and by sector (section 4.3.2). In addition, we discuss the issue of endogeneity and use an alternative regression technique to account for uncertainty about the choice of the explanatory variables (section 4.3.3). Given the high variance of the principal components in 2004, data for the regression analyses begin in 2005. We concentrate also on five cross-sectional systemic risk indicators, namely: ES, MES, CoVaR, ΔCoVaR and CAViaR.

4.3.1. Full sample analysis

The results of the estimates on the full sample are reported in **Error! Reference source not found.**. First, the market-to-book ratio, which is a financial distress indicator, has a significant positive impact on almost all systemic risk indicators, except CAViaR where its coefficient is negative. Second, our results indicate a positive relationship between size and three systemic risk measures (ES, MES, CAViaR) at a 5% confidence level, consistent with the literature in developed countries (e.g., Adrian and Brunnermeier, 2016; Bostandzic and Weiß, 2018) and supporting the too-big-to-fail hypothesis. With the CoVaR and ΔCoVaR indicators, the coefficients of size although negative are not significant in all regressions.

Third, the impact of the leverage ratio (LEV) is inconclusive since its coefficient is positive with two of the systemic risk metrics and negative with the three others. One would have expected highly leveraged firms to contribute more to systemic risk, this is the case with the MES and CAViaR measures, but not with the ES, CoVaR and ΔCoVaR indicators. This may be explained by the fact that, from a capital structure perspective, debt is a mitigation instrument in the sense that it reduces agency costs of free cash flows (Jensen, 1986). Debt can help reduce the amount of free cash available to divert, and it gives debtholders the option to force liquidation if cash flows are poor. Moreover, if bankruptcy is costly for managers, then debt can create an incentive for managers to behave in ways that reduce the likelihood of bankruptcy (Grossman and Hart, 1982). Therefore, our seemingly counterintuitive results show a disciplinary effect of debt necessary in this kind of poor corporate governance environment.

Fourth, the effect of firm value proxied by Tobin-Q, depends on the metric used to proxy systemic risk. At a 5% confidence level, Tobin-Q has a positive significant impact on three systemic risk indicators, and only CAViaR is negatively affected. This positive relationship result is consistent with the existing literature in China related to non-financial institutions (e.g., Zhu et al., 2020).

Fifth, profitability measures, (ROA and OROA), have significant positive effects on systemic risk indicators at a 5% confidence level, meaning that profitable companies contribute to systemic risk. A firm's marginal contribution to systemic risk increases by one percentage point for a one standard deviation increase in profitability. One explanation may be that profitable firms take too many risks and stick to their culture of risk-taking which increases their exposure and contribution to systemic risk (Bierth et al., 2015).

Table 10: Determinants of systemic risk in the WAEMU (full sample)

	ES			MES			ΔCoVaR			CoVaR			CAViaR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MBR	1.942***	1.927***	1.980***	0.034*	0.035*	0.038**	0.013***	0.013***	0.013***	0.011***	0.012***	0.013***	-0.378***	-0.310**	-0.320***
	(0.395)	(0.394)	(0.393)	(0.019)	(0.019)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.123)	(0.123)	(0.123)
Size	5.213**	6.650***	4.574*	2.817***	2.938***	2.796***	-0.031*	-0.029	-0.018	-0.032	-0.048**	-0.055***	11.826***	12.890***	13.173***
	(2.513)	(2.469)	(2.440)	(0.134)	(0.132)	(0.128)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.500)	(0.502)	(0.502)
LEV	-1.202***	-0.915***	-1.157***	0.066***	0.078***	0.061***	-0.048***	-0.047***	-0.046***	-0.035***	-0.037***	-0.038***	0.050	0.164**	0.200**
	(0.311)	(0.318)	(0.313)	(0.023)	(0.024)	(0.023)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.076)	(0.079)	(0.078)
Tobin-Q	0.057***	0.060***	0.057***	-0.001*	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.013***	-0.004**	-0.004*
	(0.009)	(0.009)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
ROA		1.583***	1.561***		0.116***	0.114***		0.013***	0.013***		0.010***	0.011***		1.862***	1.861***
		(0.112)	(0.113)		(0.015)	(0.015)		(0.001)	(0.001)		(0.001)	(0.001)		(0.058)	(0.058)
OROA	1.269***			0.137***			0.011***			0.007***			1.994***		
	(0.126)			(0.015)			(0.002)			(0.002)			(0.057)		
Growth	-0.031	-0.008	0.009	0.011***	0.014***	0.013***	0.000***	0.000***	0.000**	0.000	-0.000	0.002***	-0.002	-0.007	-0.020*
	(0.039)	(0.047)	(0.029)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.010)	(0.010)
Composite	-0.187***			-0.015***			0.001***			0.004***			-0.014*		
	(0.042)			(0.003)			(0.000)			(0.000)			(0.008)		
IP		-0.441***			-0.038***			0.001***			0.009***			-0.005	
		(0.085)			(0.009)			(0.000)			(0.000)			(0.015)	
RQ			-3.125***			-0.228***			0.014***			0.007***			0.312***
			(0.657)			(0.042)			(0.002)			(0.002)			(0.109)
Shadow	0.694	0.693	0.694	-0.011	-0.011	-0.011	0.003	0.003	0.003	0.019***	0.019***	0.019***	0.073	0.073	0.073
	(0.424)	(0.424)	(0.424)	(0.050)	(0.050)	(0.050)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.110)	(0.110)	(0.110)
VIX	-0.011	-0.011	-0.011	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.006***	0.006***	0.006***	-0.002	-0.002	-0.002
	(0.013)	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Interbank	0.132	0.132	0.132	0.006	0.006	0.006	0.001	0.001	0.001	0.003**	0.003**	0.003**	0.008	0.009	0.009
	(0.186)	(0.186)	(0.186)	(0.014)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.043)	(0.043)	(0.043)
Constant	26.989***	17.538***	14.670***	-1.45[illegible]***	-2.202***	-2.451***	0.098***	0.129***	0.136***	0.832***	1.041***	1.097***	-9.501***	-11.266***	-11.297***
	(3.823)	(2.942)	(2.966)	(0.28[illegible])	(0.208)	(0.201)	(0.023)	(0.021)	(0.020)	(0.028)	(0.024)	(0.024)	(0.781)	(0.635)	(0.625)
Observations	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039
R-squared	0.683	0.683	0.683	0.206	0.206	0.206	0.702	0.702	0.702	0.791	0.791	0.791	0.471	0.471	0.471

Notes: This table reports regression results of each systemic risk indicator on firm-specific characteristics and country/regional and global factors. In all regressions, we control for firms' fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

Sixth, concerning macroeconomic and global factors, we find mixed results for the quality of institutions[11] on CAViaR, i.e., the institutional quality indicator *Composite* impacts CAViaR negatively at the 10% level, whereas, the indicator *RQ* has a positive impact on it at the 1% level. Good institutions are associated with lower systemic risk measured by ES and MES, while they are positively associated with CoVaR and ΔCoVaR.

Finally, economic growth, the volatility in the United States' financial market and the stance of monetary policy in the United States (shadow rate) and the WAEMU (interbank rate) seem to contribute to systemic risk in the WAEMU financial system at 5% confidence level as expected.

Given the currency peg of the WAEMU to the Euro, we check if our results are sensitive to the use of the U.S. interest rate. We re-run equation (1) using the eurozone shadow rate on the one hand, and using both the eurozone and U.S. interest rates on the other hand. The results reported in Table A4 in the appendix are similar to that reported in Table 10. We also found that the eurozone interest rate is positively correlated with ES. Therefore, our results are not dependent on the use of the U.S. interest rate.

4.3.2. Analysis by sector in which companies operate

In addition to the results on the full sample presented and discussed above, we rerun Equation (1) by sector to highlight differences between sectors. Panels A, B, and C of Table 11 report the estimation results. We do not report the results for the transportation section which includes only one company.

The new results confirm the positive effect of firms' size on systemic risk indicators except for the distribution sector when MES is used as a systemic risk indicator and the agriculture sector when ES is used as a systemic risk indicator. For these two sectors, we find a negative effect of size on systemic risk consistent with Zhu et al. (2020) in China. In the financial and industrial sectors, we do not find a significant effect of size on CoVaR and ΔCoVaR.

Leverage harms systemic risk as before, with two main exceptions. First, we find a positive effect of leverage on ES, MES, CoVaR and ΔCoVaR for companies operating in the utility sector. The same result is found in the financial sector when MES is used as the systemic risk indicator and in the industrial sector when CAViaR is used as the systemic risk indicator. Second, the effects of leverage on ES are not significantly different from zero for companies

[11] We kept the investment profile and economic growth in the same equation despite the correlation of 0.69. Appendix Table A3 shows that the inclusion of these variables separately does not alter our results.

operating in the industrial, distribution and financial sectors. We find the same results for the agriculture sector when MES and ΔCoVaR are used as systemic risk indicators, as well as for the financial sector when CoVaR and ΔCoVaR are used as systemic risk indicators.

In the full sample, we found a positive association between firm value measured by Tobin-Q, and systemic risk. We find a similar positive correlation between firm value and ES in the agriculture and industrial sectors, MES in the utility sector, ΔCoVaR in the industrial sector, CoVaR in the industrial and utility sectors, and CAViaR in the distribution and industrial sectors. Apart from these results, we find a negative association between firm value and systemic risk indicators in the other regressions, in line with Soedarmono et al. (2017), except when ES is used as a risk indicator in the distribution and financial sectors. The effect of profitability on systemic risk also depends on the sector in which the company operates and the indicator used to assess systemic risk. We find that profitable firms contribute less to systemic risk in the distribution sector for all systemic risk indicators except for MES and CAViaR. Profitability is not significantly associated with MES in the agriculture sector. For the remaining indicators and sectors, we find a positive effect of profitability on systemic risk as in the full sample.

The financial distress indicator, (book-to-market ratio), has both positive and negative effects on systemic risk depending on the sector and the indicator used to proxy risk. For companies operating in the agriculture sector, we find a negative correlation between MBR and systemic risk. The same result holds for companies operating in the distribution sector when MES, CoVaR and CAViaR are used as systemic risk measures. For the remaining sectors, the new results confirm the positive effect of MBR on systemic risk.

With respect to the macroeconomic variables, we find that high economic growth and better quality of institutions are associated with less risk in the financial sector as expected when CAViaR and MES are used as systemic risk indicators. A better quality of institutions is associated with low transaction costs which allow banks to increase lending without taking excessive risk.

The monetary stance in the United States, measured by the shadow rate, is positively associated with CoVaR in the distribution, financial and industrial sectors. Moreover, the interbank rate plays a role only in the financial and agriculture sectors when CoVaR is used as a systemic risk indicator.

Table 11: Determinants of systemic risk in the WAEMU, by sector

A. Regression results for ES and MES, by sector

	ES					MES				
	Agriculture	Distribution	Finance	Industry	Utility	Agriculture	Distribution	Finance	Industry	Utility
MBR	-8.295***	0.901	58.848	5.572***	24.589	-1.028***	-0.446***	6.321***	0.242***	-0.011
	(0.472)	(0.681)	(79.623)	(0.822)	(37.860)	(0.058)	(0.060)	(2.413)	(0.058)	(1.671)
Size	-4.655**	20.268***	11.544	10.347***	65.114**	2.575***	-5.473***	1.143***	1.492***	1.007
	(2.259)	(6.125)	(8.725)	(3.534)	(27.805)	(0.427)	(0.499)	(0.280)	(0.233)	(3.082)
LEV	-1.878***	-2.133	-3.289	0.215	5.152*	-0.066	-0.369***	0.307***	-0.115***	1.441**
	(0.465)	(1.359)	(3.132)	(0.622)	(2.929)	(0.133)	(0.072)	(0.081)	(0.032)	(0.681)
Tobin-Q	0.172**	-0.252	-18.250	0.065***	-1.619***	-0.073***	-0.021***	-0.268*	-0.002***	0.321**
	(0.081)	(0.211)	(11.521)	(0.006)	(0.294)	(0.010)	(0.006)	(0.158)	(0.001)	(0.128)
ROA	3.331***	-2.867***	102.696***	1.372***	59.739***	0.049	0.466***	2.089***	0.110***	-1.675
	(0.288)	(0.539)	(25.657)	(0.118)	(7.777)	(0.055)	(0.056)	(0.753)	(0.017)	(1.386)
Growth	-0.748	-0.143	-0.081	-0.792**	-0.126***	0.110	0.048	-0.015***	0.022	0.058***
	(0.488)	(0.605)	(0.056)	(0.310)	(0.036)	(0.0[illegible]4)	(0.152)	(0.001)	(0.046)	(0.012)
Composite	0.751**	0.147	0.085	0.577**	-0.660***	0.012	0.138	-0.011***	-0.021	-0.025
	(0.371)	(0.335)	(0.062)	(0.234)	(0.102)	(0.072)	(0.085)	(0.002)	(0.036)	(0.018)
Shadow	0.119	0.168	3.233	0.402	-0.374	0.040	-0.012	0.018	-0.003	-0.149
	(0.523)	(0.408)	(2.230)	(0.344)	(0.796)	(0.110)	(0.124)	(0.041)	(0.053)	(0.316)
VIX	-0.008	-0.051	0.002	-0.000	-0.004	0.000	0.000	-0.000	-0.000	0.001
	(0.012)	(0.055)	(0.028)	(0.012)	(0.017)	(0.003)	(0.003)	(0.001)	(0.002)	(0.007)
Interbank	0.138	-0.042	0.464	0.152	-0.098	0.040	-0.010	0.014	0.024	-0.089
	(0.165)	(0.601)	(0.674)	(0.154)	(0.168)	(0.029)	(0.034)	(0.012)	(0.017)	(0.092)
Constant	-25.686	12.037	16.997	17.252	-16.421	-1.390	-2.034	-0.060	0.181	0.525
	(20.826)	(19.410)	(14.071)	(13.591)	(31.795)	(4.082)	(4.760)	(0.395)	(2.044)	(3.752)
Observations	15,876	23,814	19,845	47,628	11,907	15,876	23,814	19,845	47,628	11,907
R-squared	0.675	0.590	0.339	0.839	0.589	0.373	0.254	0.495	0.135	0.401

Notes: This table reports regression results of ES and MES on firms, country, and global factors. In all regressions, we control for firms' fixed effects and week–year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

B. Regression results for CoVaR and ΔCoVaR, by sector

	ΔCoVaR					CoVaR				
	Agriculture	Distribution	Finance	Industry	Utility	Agriculture	Distribution	Finance	Industry	Utility
MBR	-0.128***	0.004*	0.617*	0.036***	0.210	-0.123***	-0.014**	0.780**	0.040***	-0.784
	(0.006)	(0.002)	(0.349)	(0.004)	(0.605)	(0.007)	(0.006)	(0.362)	(0.0[illegible]4)	(0.607)
Size	0.278***	0.083***	-0.010	0.039	1.465***	0.419***	0.216***	0.029	0.02[illegible]	2.556***
	(0.043)	(0.024)	(0.038)	(0.032)	(0.462)	(0.047)	(0.031)	(0.044)	(0.0[illegible]4)	(0.470)
LEV	-0.016	-0.012***	0.011	-0.047***	0.116**	0.028**	-0.020***	0.01[illegible]	0.03[illegible]***	0.460***
	(0.012)	(0.004)	(0.013)	(0.004)	(0.050)	(0.012)	(0.005)	(0.014)	(0.005)	(0.053)
Tobin-Q	-0.016***	-0.002***	-0.044*	0.001***	-0.031***	-0.017***	-0.003***	-0.05[illegible]**	0.001***	0.074***
	(0.001)	(0.001)	(0.023)	(0.000)	(0.005)	(0.001)	(0.001)	(0.024)	(0.000)	(0.006)
ROA	0.017***	-0.014***	0.309**	0.015***	1.121***	0.026***	-0.03[illegible]***	0.308**	0.009***	0.979***
	(0.006)	(0.002)	(0.130)	(0.001)	(0.145)	(0.00[illegible])	(0.0[illegible]4)	(0.133)	(0.002)	(0.149)
Growth	0.003	-0.000	-0.000*	-0.009*	-0.003***	-0.03[illegible]***	-0.039***	0.000	-0.050***	-0.002***
	(0.008)	(0.003)	(0.000)	(0.005)	(0.001)	(0.010)	(0.007)	(0.000)	(0.006)	(0.001)
Composite	0.006	0.000	0.000	0.008**	-0.012***	0.[illegible]32***	0.025***	0.001**	0.035***	0.010***
	(0.006)	(0.001)	(0.000)	(0.003)	(0.0[illegible]2)	(0.009)	(0.005)	(0.000)	(0.005)	(0.002)
Shadow	0.002	0.000	0.005	0.006	-0.006	0.017	0.016*	0.022**	0.022***	0.009
	(0.009)	(0.002)	(0.004)	(0.005)	(0.014)	(0.013)	(0.008)	(0.010)	(0.008)	(0.021)
VIX	-0.000	-0.000	0.000	-0.00[illegible]	-0.000	0.006***	0.006***	0.006***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)	(0.0[illegible]0)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Interbank	0.004	-0.000	0.002	0.001	-0.002	0.006*	0.002	0.004**	0.003	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Constant	-0.480	-0.019	0.054	-0.423**	-0.531	-0.998**	-0.472	0.947***	-0.838***	-2.397***
	(0.366)	(0.085)	(0.043)	(0.198)	(0.519)	(0.493)	(0.297)	(0.059)	(0.283)	(0.532)
Observations	15,876	23,814	19,845	47,628	11,907	15,876	23,814	19,845	47,628	11,907
R-squared	0.597	0.539	0.580	0.436	0.758	0.812	0.880	0.820	0.814	0.621

Notes: This table reports regression results of CoVaR and ΔCoVaR on firms, country, and global factors. In all regressions, we control for firms' fixed effects, and week–year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

C. Regression results for CAViaR, by sector

	Agriculture	Distribution	Finance	Industry	Utility
MBR	-4.632***	-2.416***	10.412	1.416***	-29.064***
	(0.146)	(0.203)	(11.552)	(0.225)	(2.290)
Size	21.349***	5.452***	8.149***	22.608***	36.573***
	(0.663)	(1.666)	(2.364)	(0.939)	(6.002)
LEV	-1.730***	-2.332***	-4.512***	2.196***	-2.800**
	(0.082)	(0.246)	(0.530)	(0.151)	(1.295)
Tobin-Q	-0.374***	0.152***	-4.858***	0.020***	-0.797***
	(0.027)	(0.023)	(1.530)	(0.002)	(0.114)
ROA	0.355***	3.201***	16.204***	1.423***	8.259***
	(0.094)	(0.201)	(3.326)	(0.072)	(2.201)
Growth	-0.187	-0.497**	-0.029**	-0.220	-0.076***
	(0.168)	(0.236)	(0.012)	(0.146)	(0.018)
Composite	0.561***	0.688***	-0.058***	0.681***	-0.088***
	(0.140)	(0.188)	(0.011)	(0.112)	(0.024)
Shadow	-0.004	-0.030	0.368	0.080	-0.141
	(0.199)	(0.291)	(0.269)	(0.159)	(0.242)
VIX	-0.002	-0.005	-0.001	-0.002	0.003
	(0.005)	(0.008)	(0.006)	(0.004)	(0.005)
Interbank	0.001	-0.034	0.079	0.018	-0.047
	(0.054)	(0.090)	(0.174)	(0.047)	(0.060)
Constant	-47.071***	-39.920***	3.075	-58.203***	-24.978***
	(7.964)	(10.678)	(3.314)	(6.318)	(6.140)
Observations	15,876	23,814	19,845	47,628	11,907
R-squared	0.823	0.514	0.412	0.572	0.470

Notes: This table reports regression results of CAViaR on firms, country, and global factors. In all regressions, we control for firms' fixed effects and week–year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

4.3.3. Endogeneity issue and alternative regression model

Endogeneity: As in all empirical studies, we are not immune to endogeneity bias. Endogeneity can arise from firm-level variables and country and global factors. We use the lag of all explanatory variables to reduce the reverse causality issue. The results of the estimates are presented in Table A5 in the appendix. Our main results hold with the exception that size is no longer significantly associated with ES.

While this approach helps to reduce endogeneity arising from reverse causality, we acknowledge that we are not immune to endogeneity due to omitted variables or measurement errors. Therefore, we interpret all our results in terms of correlation and not causality.

Alternative estimation technique: To consider the uncertainty about the choice of the explanatory variables, we re-run equation (1) by using the weighted-average least squares technique developed by Magnus et al. (2010) and implemented by De Luca and Magnus

(2011). This alternative approach aims to identify regressors that are robustly associated with systemic risk indicators. The setup distinguishes between focus regressors, i.e., variables that are always included in the model and auxiliary regressors of which we are less certain. This technique consists of computing a weighted average of the conditional estimates across all possible models because each of them provides some information about the focus regression parameters. In the spirit of the Bayesian inference, the weight given to each model and the conditional estimates of its parameters are determined based on data and priors. To apply this technique, we assume that all explanatory variables are auxiliary variables since we do not have clear theories stating the key determinants of systemic risk. An auxiliary regressor is robustly correlated with the outcome if the *t*-ratio on its coefficient is greater than one in absolute value[12]. We also use the Subbotin prior as in Kumar and Magnus (2013).

Table 12 reports the results of the estimates with *t*-ratios in parentheses. The effects of the explanatory variables depend on the metric used to proxy systemic risk as before. But leverage, firm size, and profitability are robustly associated with systemic risk across all regressions. Firm value (Tobin-Q) and financial distress (market-to-book ratio) are robustly associated with all systemic risk indicators, except MES. The quality of institutions is also important in analysing systemic risk. Shadow rate, VIX, and the interbank rate are robustly associated with CoVaR only as before. All in all, these robustness regressions confirm our previous findings for the full sample.

[12] The *t-ratio* statistics does not follow standard Student (or normal) distribution.

Table 12: Estimation results from the weighted-average least squares technique, full sample

	ES			MES			CoVaR			ΔCoVaR			CAViaR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MBR	2.132	1.771	1.779	0.049	0.038	0.043	0.011	0.013	0.014	0.014	0.012	0.012	-0.378	-0.285	-0.274
	(4.538)	(3.188)	(3.148)	(0.976)	(0.858)	(0.944)	(3.060)	(2.932)	(4.046)	(3.525)	(3.303)	(3.018)	(-4.241)	(-2.643)	(-2.672)
Size	3.695	5.139	3.443	2.694	2.796	2.713	-0.021	-0.037	-0.053	-0.029	-0.029	-0.018	11.688	12.742	13.033
	(1.943)	(2.439)	(1.430)	(11.963)	(12.502)	(12.053)	(-1.189)	(-2.003)	(-2.818)	(-1.658)	(-1.669)	(-1.039)	(27.395)	(29.832)	(29.920)
LEV	-1.298	-1.191	-1.336	0.058	0.074	0.057	-0.035	-0.038	-0.037	-0.046	-0.046	-0.045	0.027	0.135	0.179
	(-3.806)	(-3.043)	(-2.953)	(1.403)	(1.797)	(1.372)	(-10.665)	(-11.211)	(-10.701)	(-14.4[illegible]0)	(-1[illegible].124)	(-13.949)	(0.345)	(1.713)	(2.219)
Tobin-Q	0.059	0.055	0.056	-0.000	0.000	-0.000	0.001	0.001	0.001	0.001	0.001	0.001	-0.013	-0.004	-0.004
	(3.817)	(3.534)	(3.560)	(-0.167)	(0.011)	(-0.232)	(6.798)	(6.077)	(5.979)	(4.55[illegible])	(4.628)	(4.934)	(-5.179)	(-1.617)	(-1.221)
ROA		1.697	1.519		0.113	0.113		0.011	0.011		0.013	0.014		1.843	1.843
		(5.636)	(5.065)		(3.625)	(3.581)		(3.956)	(4.[illegible]45)		(5.335)	(5.469)		(31.976)	(29.953)
OROA	1.401			0.142			0.009			0.011			2.003		
	(4.598)			(4.229)			(3.401)			(4.272)			(35.441)		
Growth	-0.011	-0.023	-0.014	0.009	0.012	0.012	0.000	-0.000	0.001	0.000	0.000	0.000	-0.000	-0.005	-0.017
	(-0.393)	(-0.772)	(-0.457)	(2.613)	(3.311)	(3.622)	(0.05[illegible])	(-0.056)	(6.259)	(1.960)	(1.630)	(1.042)	(-0.052)	(-1.086)	(-2.679)
Composite	-0.189			-0.013			0.004			0.001			-0.011		
	(-5.714)			(-4.004)			(10.674)			(3.958)			(-1.802)		
IP		-0.389			-0.032			0.008			0.001			-0.003	
		(-4.580)			(-3.493)			(12.707)			(2.743)			(-0.235)	
RQ			-2.836			-0.204			0.008			0.014			0.329
			(-7.333)			(-5.369)			(2.904)			(6.564)			(4.502)
Shadow	0.327	0.324	0.338	-0.009	-0.010	-0.013	0.015	0.015	0.017	0.001	0.001	0.001	-0.018	-0.017	-0.014
	(0.500)	(0.488)	(0.499)	(-0.1[illegible]5)	(-0.184)	(-0.240)	(2.105)	(2.109)	(2.575)	(0.268)	(0.282)	(0.278)	(-0.125)	(-0.121)	(-0.098)
VIX	-0.018	-0.021	-0.018	-0.000	-0.000	0.000	0.006	0.006	0.006	-0.000	-0.000	-0.000	-0.002	-0.002	-0.002
	(-1.215)	(-1.385)	(-1.195)	(-0.020)	(-0.083)	(0.149)	(36.226)	(36.600)	(36.080)	(-0.571)	(-0.549)	(-0.553)	(-0.652)	(-0.795)	(-0.671)
Interbank	0.190	0.168	0.137	0.010	0.010	0.012	0.003	0.004	0.003	0.001	0.001	0.001	0.005	0.002	0.005
	(0.949)	(0.822)	(0.561)	(0.477)	(0.477)	(0.501)	(1.724)	(1.912)	(1.741)	(0.808)	(0.874)	(0.899)	(0.120)	(0.052)	(0.105)
Constant	0.698	0.812	1.439	0.100	0.120	0.188	0.056	0.050	0.061	0.009	0.008	0.005	1.249	1.206	1.058
	(0.707)	(0.808)	(1.289)	(1.007)	(1.164)	(1.744)	(5.063)	(4.500)	(5.788)	(1.082)	(1.019)	(0.632)	(5.405)	(5.228)	(4.598)
Observations	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039

Notes: This table reports regression results using the weighted-average least squares technique. *t*-stat is reported in parentheses. In all regressions, we control for firms' fixed effects and week–year (time) effects not reported to save space.

4.4. Additional robustness checks

In the analysis so far, we have considered 31 companies over a long period (2004-2020). In this section, we extend the analysis to 41 listed companies over the period 2017-2020, representing 89% of the listed companies (see Table 13).

Table 13: Distribution of companies by sector

Sector	Sector Code	Listed	Previous sample	New Sample
Distribution	DIS	7	6	7
Finance	FIN	15	5	12
Industry	IND	14	12	12
Public Utilities	PUU	4	3	4
Agriculture	AGR	4	4	4
Transportation	TRA	2	1	2
Total		**46**	**31**	**41**

Source: Authors' compilation. The classification is provided by the BRVM.

By shortening the period of the analysis, we can consider many of the newly listed companies. The purpose of these additional analyses is to check the extent to which the previous results are still true when considering almost all listed companies in the most recent period. The new sample now includes all listed companies in the distribution, utilities, agriculture and transportation sectors. Only a few firms are missing in the finance sector (3) and industry sector (2). The results of these additional analyses with this revised sample are provided in the online appendix II.

5. Conclusion

This paper aimed to study systemic risk in the WAEMU regional stock exchange. The analysis focuses on financial and non-financial listed companies grouped into six sectors and uses systemic risk measures suggested in the literature.

First, we find strong linkages across all six sectors, hence increasing the channels through which a sector-specific shock can propagate to the entire financial sector and other economic sectors. The financial and industrial sectors appear as the center of the system around which the other sectors revolve. Second, we find systemic firms to belong to the distribution (BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors, in the sense that, they are more likely to propagate shocks to the global market. This result is consistent with the fact that, in the WAEMU region like many other developing economies, companies in the distribution and agriculture sectors are strongly connected to firms operating in other sectors. Moreover, over recent years, ABJC (distribution), BOA a pan-African banking group, and UNXC (industry) greatly contributed to systemic risk. Therefore, financial firms are not the only source of systemic risk in the WAEMU regional stock market, even though they play an important role in the system, particularly, with the rise of pan-African banking groups.

Third, the analysis allows us to identify companies most exposed to systemic risk, i.e., those that are likely to experience significant negative returns in the event of turbulence. These firms are TTLC in the distribution sector, SGBC in the financial sector, CIEC, SDCC and SNTS in the utility sector, PALC, SOGC and SPHC in the agriculture sector and finally, SLBC in the industry sector.

Fourth, systemic risk also has a time series dimension. We find that the market was turbulent, and therefore subject to high risk (i) at the onset of the global subprime financial crisis in 2007, (ii) after the Lehman Brothers collapse in September 2008, (iii) at the beginning of the post-election war in Côte d'Ivoire in 2010, and (iv) at the start of the war in Mali in 2012. Other turbulent periods were also identified between July 2017 and June 2018, during the first week of August 2018 and 8–9 January 2019. During turbulent periods, the market experienced negative daily returns on average, except for companies operating in the utilities and transportation sectors.

Finally, we perform a regression analysis to analyse potential determinants of systemic risk within the regional stock market. We find that big, high-value, and profitable firms contribute more to systemic risk than others although, the effects of these firm-specific characteristics are heterogeneous across sectors. Overall, we find that the determinants of systemic risk depend on the indicators used to assess systemic risk and the sectors in which companies operate. Therefore, the WAEMU financial system is not a one-size-fits-all system.

Although macro-prudential policies can be applied to monitor the overall stability of the financial system as a whole to prevent the progressive build-up of systemic risk, this paper recommends that micro-prudential policies must be used as complementary tools. First, a single indicator is not sufficient to capture the overall level of systemic risk in the market. Second, systemic risk should be monitored over time and across sectors. Third, company size, growth potential, and profitability are three key firm-specific indicators to be monitored by the regulator. Fourth, the behaviour of the financial sector should be analysed in relation to global factors, as well as regional ones.

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APPENDIX

Table A1: List of companies included in the analysis

Sector	Code	Name	Country
Distribution	ABJC	SERVAIR ABIDJAN COTE D'IVOIRE	Côte d'Ivoire
Distribution	BNBC	BERNABE COTE D'IVOIRE	Côte d'Ivoire
Distribution	CFAC	CFAO MOTORS COTE D'IVOIRE	Côte d'Ivoire
Distribution	PRSC	TRACTAFRIC MOTORS COTE D'IVOIRE	Côte d'Ivoire
Distribution	SHEC	VIVO ENERGY COTE D'IVOIRE	Côte d'Ivoire
Distribution	TTLC	TOTAL COTE D'IVOIRE	Côte d'Ivoire
Finance	BICC	BICI COTE D'IVOIRE	Côte d'Ivoire
Finance	BOAB	BANK OF AFRICA BENIN	Benin
Finance	BOAN	BANK OF AFRICA NIGER	Niger
Finance	SAFC	SAFCA COTE D'IVOIRE	Côte d'Ivoire
Finance	SGBC	SOCIETE GENERALE COTE D'IVOIRE	Côte d'Ivoire
Industry	CABC	SICABLE COTE D'IVOIRE	Côte d'Ivoire
Industry	FTSC	FILTISAC COTE D'IVOIRE	Côte d'Ivoire
Industry	NEIC	NEI-CEDA COTE D'IVOIRE	Côte d'Ivoire
Industry	NTLC	NESTLE COTE D'IVOIRE	Côte d'Ivoire
Industry	SEMC	CROWN SIEM COTE D'IVOIRE	Côte d'Ivoire
Industry	SIVC	AIR LIQUIDE COTE D'IVOIRE	Côte d'Ivoire
Industry	SLBC	SOLIBRA COTE D'IVOIRE	Côte d'Ivoire
Industry	SMBC	SMB COTE D'IVOIRE	Côte d'Ivoire
Industry	STAC	SETAO COTE D'IVOIRE	Côte d'Ivoire
Industry	STBC	SITAB COTE D'IVOIRE	Côte d'Ivoire
Industry	UNLC	UNILEVER COTE D'IVOIRE	Côte d'Ivoire
Industry	UNXC	UNIWAX COTE D'IVOIRE	Côte d'Ivoire
Public Utilities	CIEC	CIE COTE D'IVOIRE	Côte d'Ivoire
Public Utilities	SDCC	SODE COTE D'IVOIRE	Côte d'Ivoire
Public Utilities	SNTS	SONATEL SENEGAL	Senegal
Agriculture	PALC	PALM COTE D'IVOIRE	Côte d'Ivoire
Agriculture	SICC	SICOR COTE D'IVOIRE	Côte d'Ivoire
Agriculture	SOGC	SOGB COTE D'IVOIRE	Côte d'Ivoire
Agriculture	SPHC	SAPH COTE D'IVOIRE	Côte d'Ivoire
Transportation	SVOC	MOVIS COTE D'IVOIRE	Côte d'Ivoire

Table A2: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ES (1)	1																	
MES (2)	0.16***	1																
CoVaR (3)	0.01***	0.24***	1															
ΔCoVaR (4)	0.03***	0.39***	0.61***	1														
CAViaR (5)	-0.01**	0.18***	0.15***	0.23***	1													
MBR (6)	0.02***	0.01***	0.03***	0.05***	0.03***	1												
Size (7)	-0.27***	0.21***	0.30***	0.57***	0.16***	0.17***	1											
LEV (8)	-0.11***	-0.12***	-0.13***	-0.23***	-0.09***	-0.13***	-0.31***	1										
Tobin-Q (9)	0.24***	-0.04***	-0.01***	-0.06***	-0.09***	0.00*	-0.19***	-0.04***	1									
ROA (10)	0.04***	0.09***	0.16***	0.18***	0.10***	0.07***	0.23***	-0.40***	0.11***	1								
OROA (11)	0.08***	0.14***	0.18***	0.26***	0.07***	0.11***	0.29***	-0.48***	0.18***	0.89***	1							
RQ (12)	0.03***	0.12***	-0.02***	0.22***	0.35***	-0.01***	0.12***	0.05***	-0.08***	0.02***	-0.03***	1						
Growth (13)	0.02***	0.03***	-0.23***	0.01***	0.22***	0.00*	0.00*	-0.05***	-0.06***	-0.01**	-0.04***	[illegible]	1					
IP (14)	0.02***	0.08***	-0.16***	0.14***	0.28***	0.01**	0.09***	0.00*	-0.06***	0.03***	0.00*	[illegible]	0.69***	1				
Composite (15)	0.02***	0.09***	0.01**	0.19***	0.26***	0.03***	0.05***	-0.16***	0.03***	0.15***	0.10***	0.62***	0.49***	0.70***	1			
VIX (16)	-0.02***	0.00*	0.74***	-0.01***	-0.04***	0.00*	-0.02***	0.00*	0.04***	0.07***	0.05***	-0.14***	-0.28***	-0.24***	-0.09***	1		
Interbank (17)	0.02***	0.01***	0.12***	0.02***	0.08***	0.03***	-0.01**	-0.03***	0.01***	[illegible]	0.01***	0.04***	0.01***	-0.13***	0.01***	0.10***	1	
Shadow (18)	0.00*	-0.01***	-0.02***	-0.01***	-0.09***	0.01***	-0.01***	0.06***	[illegible]	[illegible]	-0.04***	-0.10***	-0.36***	-0.49***	-0.37***	-0.12***	0.38***	1

Notes: This table reports Pearson correlation coefficients. '*' indicates the significance level of each correlation coefficient: ***p<0.01, ** p<0.05, and * p<0.1.

Table A3: Regression analysis (full sample) – Growth and Investment profile (IP)

	ES		MES		ΔCoVaR		CoVaR		CAViaR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MBR	1.891***	1.927***	0.031*	0.035*	0.013***	0.013***	0.013***	0.012***	-0.311**	-0.310**
	(0.394)	(0.394)	(0.019)	(0.019)	(0.002)	(0.002)	(0.003)	(0.003)	(0.123)	(0.123)
Size	7.326***	6.654***	2.997***	2.932***	-0.031*	-0.029	-0.061***	-0.048**	12.898***	12.893***
	(2.466)	(2.473)	(0.132)	(0.132)	(0.018)	(0.018)	(0.019)	(0.019)	(0.500)	(0.501)
LEV	-0.815**	-0.914***	0.086***	0.075***	-0.047***	-0.047***	-0.039***	-0.037***	0.166**	0.166**
	(0.318)	(0.320)	(0.024)	(0.024)	(0.003)	(0.003)	(0.003)	(0.003)	(0.078)	(0.078)
Tobin-Q	0.060***	0.060***	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	-0.004**	-0.004**
	(0.009)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
ROA	1.555***	1.584***	0.113***	0.113***	0.013***	0.013***	0.011***	0.010***	1.862***	1.863***
	(0.113)	(0.113)	(0.015)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.058)	(0.058)
Growth	-0.105***		0.005		0.001***		0.002***		-0.008	
	(0.039)		(0.003)		(0.000)		(0.000)		(0.009)	
IP		-0.453***		-0.019**		0.002***		0.009***		-0.016
		(0.073)		(0.007)		(0.000)		(0.000)		(0.015)
Shadow	0.693	0.693	-0.011	-0.011	0.003	0.003	0.019***	0.019***	0.073	0.073
	(0.424)	(0.424)	(0.050)	(0.050)	(0.003)	(0.003)	(0.005)	(0.005)	(0.110)	(0.110)
VIX	-0.011	-0.011	0.000	0.000	-0.000	-0.000	0.006***	0.006***	-0.002	-0.002
	(0.013)	(0.013)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Interbank	0.132	0.132	0.006	0.006	0.001	0.001	0.003**	0.003**	0.009	0.009
	(0.186)	(0.186)	(0.014)	(0.014)	(0.001)	(0.001)	(0.002)	(0.002)	(0.043)	(0.043)
Constant	14.702***	17.579***	-2.448***	-2.271***	0.136***	0.127***	[illegible]	1.042***	-11.300***	-11.229***
	(2.964)	(2.907)	(0.201)	(0.208)	(0.020)	(0.021)	(0.024)	(0.024)	(0.625)	(0.639)
Observations	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039
R-squared	0.683	0.683	0.206	0.206	0.702	0.702	0.791	0.791	0.471	0.471

Notes: This table reports regression results of each systemic risk indicator on firm-specific characteristics and country/regional and global factors. In all regressions, we control for firms' fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

Table A4: Regression analysis (full sample) – with alternative interest rates

Panel A. Eurozone interest rate as control

	ES			MES			ΔCoVaR			CoVaR			CAViaR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MBR	1.942***	1.927***	1.980***	0.034*	0.035*	0.038**	0.013***	0.013***	0.013***	0.011***	0.012***	0.013***	-0.378***	-0.310**	-0.320***
	(0.395)	(0.394)	(0.393)	(0.019)	(0.019)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.123)	(0.123)	(0.123)
Size	5.217**	6.655***	4.579*	2.817***	2.938***	2.796***	-0.031*	-0.029	-0.018	-0.0[illegible]1	0.048**	-0.055***	11.826***	12.890***	13.173***
	(2.513)	(2.470)	(2.440)	(0.134)	(0.132)	(0.128)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.500)	(0.502)	(0.502)
LEV	-1.201***	-0.915***	-1.156***	0.066***	0.078***	0.061***	-0.048***	-0.047***	-0.046***	-0.0[illegible]5***	-0.037***	-0.038***	0.050	0.164**	0.200**
	(0.311)	(0.319)	(0.313)	(0.023)	(0.024)	(0.023)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.076)	(0.079)	(0.078)
Tobin-Q	0.057***	0.060***	0.057***	-0.001*	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.013***	-0.004**	-0.004*
	(0.009)	(0.009)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
ROA		1.583***	1.561***		0.116***	0.114***		0.013***	0.013***		0.010***	0.011***		1.862***	1.861***
		(0.112)	(0.113)		(0.015)	(0.015)		(0.001)	(0.001)		(0.001)	(0.001)		(0.058)	(0.058)
OROA	1.269***			0.137***			0.011***			0.007***			1.994***		
	(0.126)			(0.015)			(0.002)			(0.002)			(0.057)		
Growth	-0.031	-0.008	0.009	0.011***	0.014***	0.013***	0.000***	0.000***	0.000**	0.000	-0.000	0.002***	-0.002	-0.007	-0.020*
	(0.039)	(0.047)	(0.029)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.010)	(0.010)
Composite	-0.187***			-0.015***			0.001***			0.004***			-0.014*		
	(0.042)			(0.003)			(0.000)			(0.000)			(0.008)		
IP		-0.441***			-0.038***			0.001***			0.009***			-0.005	
		(0.085)			(0.009)			(0.000)			(0.000)			(0.015)	
RQ			-3.124***			-0.228***			0.014***			0.007***			0.312***
			(0.657)			(0.042)			(0.002)			(0.002)			(0.109)
Shadow (ECB)	0.577*	0.577*	0.577*	0.014	0.014	0.014	0.002	0.002	0.002	0.012***	0.012***	0.012***	-0.004	-0.004	-0.004
	(0.295)	(0.295)	(0.295)	(0.034)	(0.034)	(0.034)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.084)	(0.084)	(0.084)
VIX	-0.012	-0.012	-0.012	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.006***	0.006***	0.006***	-0.002	-0.002	-0.002

	(0.013)	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Interbank	0.119	0.119	0.119	0.006	0.006	0.006	0.001	0.001	0.001	0.003*	0.003*	0.003*	0.008	0.008	0.008
	(0.186)	(0.186)	(0.186)	(0.014)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.043)	(0.043)	(0.043)
Constant	27.731***	18.278***	15.413***	-1.515***	-2.258***	-2.507***	0.101***	0.132***	0.139***	0.858***	1.067***	1.123***	-9.294***	-11.061***	-11.092***
	(3.807)	(2.824)	(2.788)	(0.260)	(0.175)	(0.167)	(0.022)	(0.019)	(0.019)	(0.025)	(0.021)	(0.021)	(0.739)	(0.590)	(0.581)
Observations	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039
R-squared	0.683	0.683	0.683	0.206	0.206	0.206	0.702	0.702	0.702	0.791	0.791	0.791	0.471	0.471	0.471

Notes: This table reports regression results of each systemic risk indicator on firm-specific characteristics and country/regional and global factors. In all regressions, we control for firms' fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

Panel B. Eurozone and US interest rates as control

	ES			MES			ΔCoVaR			CoVaR			CAViaR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MBR	1.942***	1.927***	1.980***	0.034*	0.035*	0.038**	0.013***	0.013***	0.013***	0.011***	0.012***	0.013***	-0.378***	-0.310**	-0.320***
	(0.395)	(0.394)	(0.393)	(0.019)	(0.019)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.123)	(0.123)	(0.123)
Size	5.216**	6.653***	4.577*	2.817***	2.938***	2.796***	-0.031*	-0.029	-0.018	-0.031	-0.048**	-0.055***	11.826***	12.890***	13.173***
	(2.513)	(2.469)	(2.440)	(0.134)	(0.132)	(0.128)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.500)	(0.502)	(0.502)
LEV	-1.201***	-0.915***	-1.156***	0.066***	0.078***	0.061***	-0.048***	-0.047***	-0.046***	-0.03[illegible]***	-0.037***	-0.038***	0.050	0.164**	0.200**
	(0.311)	(0.319)	(0.313)	(0.023)	(0.024)	(0.023)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.076)	(0.079)	(0.078)
Tobin-Q	0.057***	0.060***	0.057***	-0.001*	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.013***	-0.004**	-0.004*
	(0.009)	(0.009)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
ROA		1.583***	1.561***		0.116***	0.114***		0.01[illegible]***	0.[illegible]13***		0.010***	0.011***		1.862***	1.861***
		(0.112)	(0.113)		(0.015)	(0.015)		(0.001)	(0.001)		(0.001)	(0.001)		(0.058)	(0.058)
OROA	1.269***			0.137***			0.011***			0.007***			1.994***		
	(0.126)			(0.015)			(0.00[illegible])			(0.002)			(0.057)		
Growth	-0.031	-0.008	0.009	0.011***	0.014***	0.01[illegible]***	0.000***	0.000***	0.000**	0.000	-0.000	0.002***	-0.002	-0.007	-0.020*
	(0.039)	(0.047)	(0.029)	(0.004)	(0.004)	(0.0[illegible]4)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.010)	(0.010)
Composite	-0.187***			-0.015***			0.001***			0.004***			-0.014*		
	(0.042)			(0.00[illegible])			(0.000)			(0.000)			(0.008)		
IP		-0.441***			-0.038***			0.001***			0.009***			-0.005	
		(0.085)			(0.009)			(0.000)			(0.000)			(0.015)	
RQ			-3.124***			-0.228***			0.014***			0.007***			0.312***
			(0.657)			(0.042)			(0.002)			(0.002)			(0.109)
Shadow (US)	0.549	0.548	0.549	-0.015	-0.015	-0.015	0.002	0.002	0.002	0.016***	0.016***	0.016***	0.076	0.076	0.076
	(0.422)	(0.421)	(0.422)	(0.051)	(0.051)	(0.051)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.116)	(0.115)	(0.115)
Shadow (ECB)	0.525*	0.525*	0.525*	0.015	0.015	0.015	0.002	0.002	0.002	0.011***	0.011***	0.011***	-0.012	-0.012	-0.011
	(0.295)	(0.295)	(0.295)	(0.034)	(0.034)	(0.034)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.087)	(0.087)	(0.087)
VIX	-0.012	-0.012	-0.012	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.006**	0.006**	0.006**	-0.002	-0.002	-0.002

										*	*	*			
	(0.013)	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Interbank	0.123	0.123	0.123	0.006	0.006	0.006	0.001	0.001	0.001	0.003*	0.003*	0.003*	0.009	0.009	0.009
	(0.186)	(0.187)	(0.187)	(0.014)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.043)	(0.043)	(0.043)
Constant	26.348***	16.896***	14.029***	-1.478***	-2.221***	-2.469***	0.095***	0.126***	0.133***	0.819***	1.028***	1.084***	-9.487***	-11.252***	-11.283***
	(3.921)	(3.072)	(3.095)	(0.289)	(0.214)	(0.207)	(0.023)	(0.020)	(0.020)	(0.027)	(0.024)	(0.023)	(0.782)	(0.639)	(0.630)
Observations	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039	123,039
R-squared	0.683	0.683	0.683	0.206	0.206	0.206	0.702	0.702	0.702	0.791	0.791	0.791	0.471	0.471	0.471

Notes: This table reports regression results of each systemic risk indicator on firm-specific characteristics and country/regional and global factors. In all regressions, we control for firms' fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

Table A5: Regression analysis (full sample) – with lagged explanatory variables

	ES			MES			DeltaCoVaR			CoVaR			CAViaR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
L.MBR	1.920***	1.898***	1.944***	0.035	0.035	0.038*	0.013***	0.013***	0.013***	0.010***	0.012***	0.013***	-0.371***	-0.304**	-0.313**
	(0.463)	(0.462)	(0.461)	(0.023)	(0.023)	(0.023)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.143)	(0.142)	(0.142)
L.Size	-0.349	1.252	-0.600	2.790***	2.917***	2.771***	-0.049**	-0.047**	-0.037*	-0.052**	-0.067***	-0.075***	11.508***	12.616***	12.885***
	(2.629)	(2.553)	(2.481)	(0.154)	(0.153)	(0.146)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.578)	(0.575)	(0.581)
L.LEV	-1.703***	-1.393***	-1.608***	0.077***	0.091***	0.075***	-0.048***	-0.047***	-0.046***	-0.036***	-0.038***	-0.039***	0.046	0.167*	0.200**
	(0.295)	(0.302)	(0.289)	(0.026)	(0.026)	(0.025)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.088)	(0.090)	(0.090)
L.Tobin-Q	0.045***	0.047***	0.045***	-0.001*	-0.000	-0.001	0.000***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.013***	-0.004*	-0.004
	(0.006)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)
L.ROA		1.633***	1.612***		0.116***	0.113***		0.013***	0.013***		0.010***	0.011***		1.884***	1.884***
		(0.129)	(0.129)		(0.017)	(0.018)		(0.001)	(0.001)		(0.001)	(0.001)		(0.066)	(0.066)
L.OROA	1.325***			0.132***			0.011***			0.007***			2.018***		
	(0.146)			(0.017)			(0.002)			(0.002)			(0.065)		
L.Growth	-0.009	0.003	0.016	0.013***	0.016***	0.015***	0.000***	0.000***	0.000**	0.000	-0.000	0.002***	0.006	-0.002	-0.013
	(0.049)	(0.059)	(0.036)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.011)	(0.009)
L.Composite	-0.200***			-0.017***			0.001***			0.004***			-0.019**		
	(0.051)			(0.004)			(0.000)			(0.000)			(0.009)		
L.IP		-0.417***			-0.044***			0.001***			0.009***			-0.001	
		(0.098)			(0.010)			(0.000)			(0.000)			(0.018)	
L.RQ			-2.837***			-0.243***			0.013***			0.006***			0.305***
			(0.714)			(0.048)			(0.002)			(0.002)			(0.103)
L.Shadow	0.603	0.602	0.603	0.011	0.011	0.011	0.005	0.005	0.005	0.005	0.005	0.005	0.020	0.020	0.019
	(0.627)	(0.626)	(0.626)	(0.086)	(0.086)	(0.086)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.179)	(0.179)	(0.179)
L.VIX	-0.005	-0.005	-0.005	0.001	0.001	0.001	-0.000	-0.000	-0.000	0.016***	0.016***	0.016***	-0.002	-0.002	-0.002
	(0.016)	(0.016)	(0.016)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
L.Interbank	0.248	0.248	0.248	0.012	0.012	0.012	0.001	0.001	0.001	0.001	0.001	0.001	0.027	0.027	0.027
	(0.257)	(0.258)	(0.258)	(0.018)	(0.018)	(0.018)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.058)	(0.058)	(0.058)
Constant	33.054***	22.601***	19.879***	-1.432***	-2.267***	-2.551***	0.112***	0.139***	0.146***	0.762***	0.967***	1.023***	-8.931***	-10.978***	-10.980***
	(4.543)	(3.340)	(3.340)	(0.367)	(0.291)	(0.284)	(0.028)	(0.025)	(0.025)	(0.030)	(0.026)	(0.026)	(0.975)	(0.816)	(0.807)
Observations	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488	94,488
R-squared	0.705	0.705	0.705	0.197	0.197	0.197	0.727	0.727	0.727	0.825	0.825	0.825	0.479	0.479	0.479

Notes: This table reports regression results of each systemic risk indicator on firm-specific characteristics and country/regional and global factors. In all regressions, we control for firms' fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, and * p<0.1.

ONLINE APPENDIX:

I. DETAILED AND REPLICABLE GUIDE IN DATA AND METHODOLOGY

This section provides a detailed and replicable guide to the data and methodology used in the paper. It explains how source data are collected, systemic risk indicators are estimated, and regression analysis is performed.

1. Variables and data

Two categories of variables are used in the paper: firm-level variables and country/global factors (macro variables).

1.1 Firm-level variables

Data for stock market prices and indices are from the BRVM, which publishes this information daily in the "*Bulletin Officiel de la Cote"* (BOC): https://www.brvm.org/fr/bulletins-officiels-de-la-cote). Historical data are available upon request from the BRVM (https://www.brvm.org/fr/donnees-historiques).

Data for firm-level structural variables (book value of debt, book value of equity, net income, book value of assets, and book value of liabilities) are published by the BRVM on annual basis (https://www.brvm.org/fr/rapports-societes-cotees). As mentioned in the paper, quarterly financial reports are available, but they are not detailed and do not include liability data.

It is worth noting that all information is available in PDF format. Therefore, we first convert the raw PDF format data to Excel and then check for the consistency of the data.

1.2 Macro-variables

The sources of macroeconomic and global factors are listed in the paper. The information is freely available, except for the ICRG variables.

2. Systemic risk indicators

Systemic risk indicators are estimated by using Matlab code provided by Tommaso Belluzzo and freely downloadable at: https://www.mathworks.com/matlabcentral/fileexchange/62482-systemic-risk. This software code provides step-by-step guidance with templates for estimating the indicators of the paper and more.

We use Matlab R2021b to compute the indicators used in the paper.

3. Regression analysis

All regressions are performed by using Stata 17. Regression table 14 is produced by using the Stata command *wsls* provided by De Luca and Magnus (2011)[1]. All other regression tables are produced using *areg* command with the *robust* option to estimate standard errors.

4. Data availability

Data and code will be made available upon request.

[1] De Luca, G., & Magnus, J. R. (2011). Bayesian model averaging and weighted-average least squares: Equivariance, stability, and numerical issues. *The Stata Journal*, 11(4), 518-544.

II. ADDITIONAL ROBUSTNESS CHECKS

In the main analysis, we have considered 31 companies over a long period (2004-2020). Here, we extend the analysis to 41 listed companies over the period 2017-2020, representing 89% of the listed companies. The new sample now includes all listed companies in the distribution, utilities, agriculture, and transportation sectors. Only a few firms are missing in the finance sector (3 out of 15) and industry sector (2 out of 14) as shown in Table 13.

Cross-sectional systemic risk indicators

Table O1 provides summary statistics of the cross-sectional systemic risk indicators calculated on the new sample. The top ten risky companies for each indicator are indicated in bold. As previously, TTLC (distribution) and SGBC (finance) have been identified among the top risky companies identified as such by at least three indicators. In addition, we identify the following companies by sector: industry (UNXC, SCRC), utilities (SNTS, ONTBF), and transportation (SDSC). The difference with the previous results is that CIEC, SDCC, PALC, SOGC, and SPHC are no longer among the top-risky companies across systemic risk indicators. However, these companies are among the top risky companies if we look at specific risk indicators, except SDCC.

Table O1: Summary statistics of cross-sectional systemic risk indicators calculated at a 95% confidence level, by company

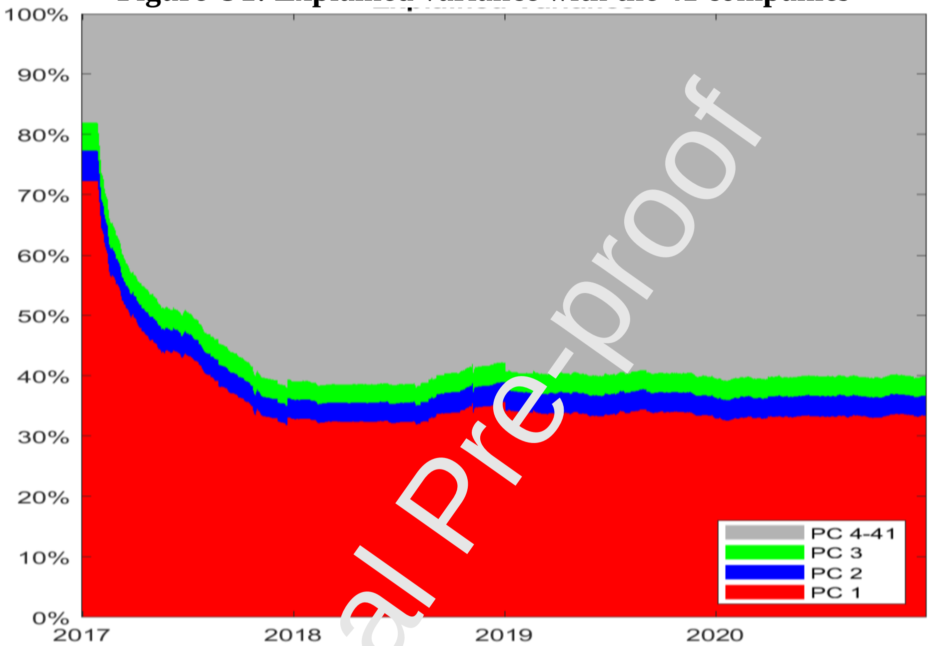
	ES				MES				CoVaR				ΔCoVaR				CAViaR			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
ABJC	0.044	0.011	0.029	0.083	0.007	0.003	0.000	0.028	0.013	0.001	0.010	0.016	0.002	0.000	0.001	0.003	**0.061**	0.009	0.044	0.093
BNBC	0.636	0.000	0.636	0.637	0.003	0.009	0.000	0.066	0.012	0.001	0.008	0.013	0.000	0.000	0.000	0.000	0.059	0.010	0.035	0.087
CFAC	**1.094**	0.000	1.094	1.096	0.016	0.028	0.000	0.157	0.013	0.001	0.011	0.015	0.002	0.000	0.002	0.002	0.058	0.008	0.034	0.082
PRSC	**1.052**	0.000	1.052	1.054	0.004	0.013	0.000	0.109	0.011	0.001	0.010	0.013	0.000	0.000	0.000	0.000	0.025	0.017	0.007	0.072
SHEC	0.055	0.014	0.038	0.100	0.009	0.004	0.002	0.023	0.014	0.001	0.011	0.016	0.002	0.001	0.001	0.004	0.056	0.014	0.032	0.101
TTLC	0.097	0.117	0.067	2.576	**0.021**	0.017	0.000	0.266	**0.018**	0.009	0.015	0.200	**0.007**	0.009	0.005	0.189	**0.067**	0.007	0.056	0.094
TTLS	0.505	0.000	0.505	0.506	0.013	0.019	0.000	0.086	0.014	0.001	0.011	0.016	0.002	0.000	0.002	0.002	0.046	0.011	0.037	0.201
BICC	0.113	0.182	0.067	3.476	0.000	0.003	0.000	0.106	0.012	0.001	0.008	0.013	0.000	0.000	0.000	0.000	0.057	0.016	0.033	0.408
BOAB	0.553	0.000	0.553	0.554	0.008	0.012	0.000	0.079	0.013	0.001	0.011	0.015	0.002	0.000	0.002	0.002	0.040	0.021	0.010	0.398
BOAN	0.524	0.000	0.524	0.525	0.014	0.020	0.000	0.104	0.013	0.001	0.008	0.015	0.002	0.000	0.002	0.002	0.047	0.019	0.038	0.623
SAFC	**0.842**	0.000	0.842	0.843	**0.020**	0.000	0.020	0.020	0.012	0.001	0.008	0.013	0.000	0.000	0.000	0.000	0.022	0.006	0.016	0.114
SGBC	0.538	0.000	0.538	0.539	**0.017**	0.000	0.017	0.017	**0.015**	0.001	0.014	0.017	**0.004**	0.000	0.004	0.004	0.036	0.051	0.018	1.384
BOABF	0.538	0.000	0.538	0.539	0.013	0.016	0.000	0.065	0.012	0.001	0.010	0.013	0.000	0.000	0.000	0.000	0.042	0.027	0.026	0.553
BOAC	0.536	0.000	0.536	0.537	0.006	0.008	0.000	0.044	0.012	0.001	0.010	0.014	0.001	0.000	0.001	0.001	0.048	0.012	0.026	0.080
BOAM	0.316	0.000	0.316	0.316	0.007	0.007	0.000	0.052	0.013	0.001	0.010	0.014	0.001	0.000	0.001	0.001	0.047	0.024	0.019	0.535
BOAS	0.561	0.000	0.561	0.562	0.011	0.014	0.000	0.083	**0.015**	0.001	0.010	0.017	**0.004**	0.000	0.004	0.004	0.044	0.025	0.026	0.542
CBIBF	0.397	0.000	0.397	0.397	**0.036**	0.010	0.002	0.064	0.013	0.001	0.011	0.015	0.002	0.000	0.002	0.002	0.022	0.007	0.012	0.036
ETIT	0.045	0.026	0.001	0.107	0.010	0.009	0.000	0.038	0.015	0.002	0.008	0.020	**0.004**	0.002	0.000	0.009	0.051	0.021	0.000	0.078
SIBC	0.358	0.000	0.358	0.359	0.005	0.008	0.000	0.042	[illegible]	0.001	0.011	0.014	0.001	0.000	0.001	0.001	0.033	0.009	0.022	0.087
CABC	**0.857**	0.000	0.857	0.858	**0.071**	0.026	0.000	0.240	0.012	0.001	0.010	0.013	0.000	0.000	0.000	0.000	0.060	0.008	0.047	0.076
FTSC	0.212	0.000	0.212	0.212	0.010	0.001	0.000	[illegible]	**0.015**	0.001	0.014	0.016	0.003	0.000	0.003	0.003	**0.067**	0.005	0.060	0.123
NEIC	**0.704**	0.000	0.704	0.705	0.009	0.016	[illegible]	0.090	0.013	0.001	0.011	0.014	0.001	0.000	0.001	0.001	**0.072**	0.003	0.066	0.077
NTLC	**0.654**	0.000	0.654	0.656	0.001	0.002	0.000	0.008	0.011	0.001	0.007	0.013	0.000	0.000	0.000	0.000	0.058	0.006	0.036	0.075
SEMC	**0.866**	0.000	0.866	0.868	0.009	0.015	0.000	0.075	0.014	0.001	0.012	0.016	0.002	0.000	0.002	0.002	0.052	0.015	0.025	0.080
SIVC	0.457	0.000	0.457	0.458	0.000	0.000	0.000	0.000	0.011	0.001	0.009	0.013	0.000	0.000	0.000	0.000	**0.065**	0.012	0.013	0.347
SLBC	0.028	0.010	0.012	0.059	[illegible]	0.002	0.000	0.011	0.013	0.001	0.011	0.015	0.002	0.001	0.001	0.003	0.036	0.017	0.008	0.086
SMBC	0.185	0.000	0.185	[illegible]	0.006	0.002	0.000	0.021	0.015	0.001	0.013	0.016	0.003	0.000	0.003	0.003	**0.061**	0.007	0.050	0.086
STAC	**1.110**	0.000	1.110	1.112	[illegible]	0.019	0.000	0.125	0.013	0.001	0.010	0.015	0.001	0.000	0.001	0.001	0.042	0.017	0.016	0.076
STBC	**0.684**	0.000	0.684	0.685	0.000	0.000	0.000	0.000	0.011	0.001	0.009	0.013	0.000	0.000	0.000	0.000	0.055	0.007	0.047	0.138
UNXC	0.083	0.129	0.047	2.407	**0.020**	0.015	0.000	0.145	**0.017**	0.009	0.014	0.181	**0.006**	0.009	0.004	0.170	0.058	0.010	0.046	0.088
SCRC	0.218	0.000	0.218	0.219	0.016	0.006	0.000	0.048	**0.016**	0.001	0.010	0.017	**0.005**	0.000	0.005	0.005	**0.062**	0.012	0.047	0.200
CIEC	0.652	0.000	0.652	0.654	0.015	0.023	0.000	0.109	**0.015**	0.001	0.012	0.017	**0.005**	0.000	0.005	0.005	0.057	0.018	0.043	0.398
SDCC	0.466	0.000	0.466	0.467	0.000	0.000	0.000	0.000	0.012	0.001	0.009	0.013	0.000	0.000	0.000	0.000	0.060	0.013	0.047	0.266
SNTS	0.040	0.020	0.028	0.205	**0.026**	0.015	0.012	0.149	**0.016**	0.004	0.011	0.045	**0.008**	0.004	0.005	0.039	0.020	0.010	0.009	0.067
ONTBF	0.102	0.015	0.099	0.543	**0.017**	0.008	0.000	0.038	**0.016**	0.001	0.015	0.037	**0.005**	0.001	0.005	0.027	0.040	0.018	0.019	0.252
PALC	0.080	0.000	0.080	0.080	0.010	0.004	0.000	0.035	0.014	0.002	0.011	0.017	0.003	0.000	0.003	0.003	**0.065**	0.007	0.051	0.089
SICC	0.064	0.025	0.032	0.135	0.000	0.001	0.000	0.009	0.011	0.001	0.009	0.012	0.000	0.000	0.000	0.000	0.029	0.026	0.000	0.096
SOGC	0.467	0.000	0.467	0.467	0.009	0.012	0.000	0.051	0.013	0.001	0.010	0.015	0.001	0.000	0.001	0.001	**0.060**	0.003	0.045	0.095
SPHC	0.059	0.074	0.042	2.271	**0.019**	0.023	0.014	0.722	0.012	0.001	0.011	0.032	0.001	0.001	0.000	0.020	0.060	0.010	0.038	0.078
SVOC	0.060	0.062	0.004	0.265	0.000	0.000	0.000	0.000	0.012	0.001	0.009	0.013	0.000	0.000	0.000	0.000	0.011	0.013	0.000	0.063
SDSC	**0.908**	0.000	0.908	0.909	**0.017**	0.028	0.000	0.150	**0.016**	0.001	0.014	0.018	**0.005**	0.000	0.005	0.005	**0.062**	0.009	0.042	0.084

Notes: SD stands for standard deviation. Companies with high risk are in bold for each indicator.

Systemic risk indicators based on principal component analysis

The principal component analysis displayed in Figure O1 shows that the first three components explain on average about 40% of the volatility in the system. This indicates that the market has become highly connected since the first five components explained less than 30% of the volatility in the system in the previous analysis. Therefore, the concentration on the recent years provides another look at the recent development of the market.

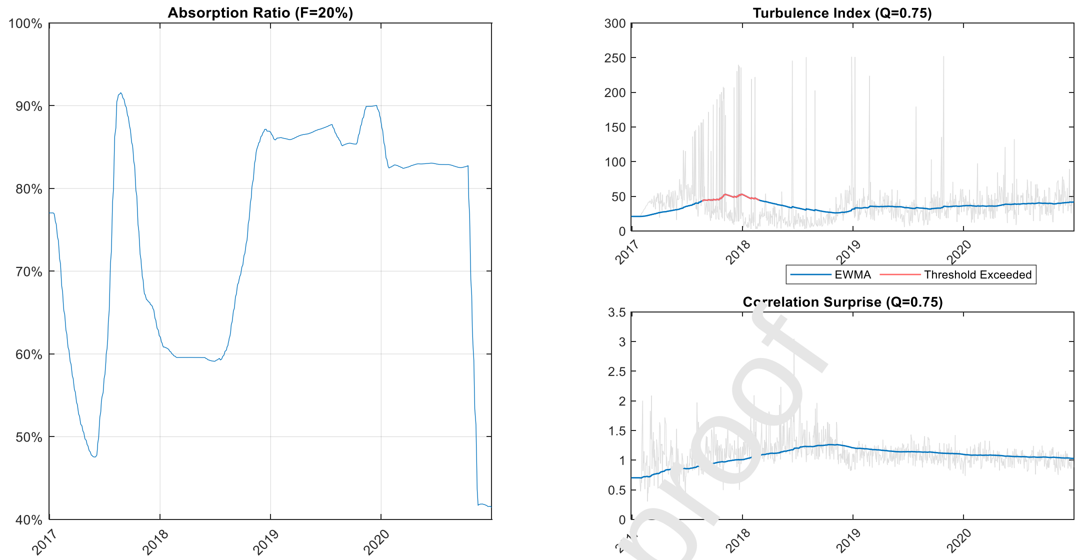
Figure O1: Explained variance with the 41 companies



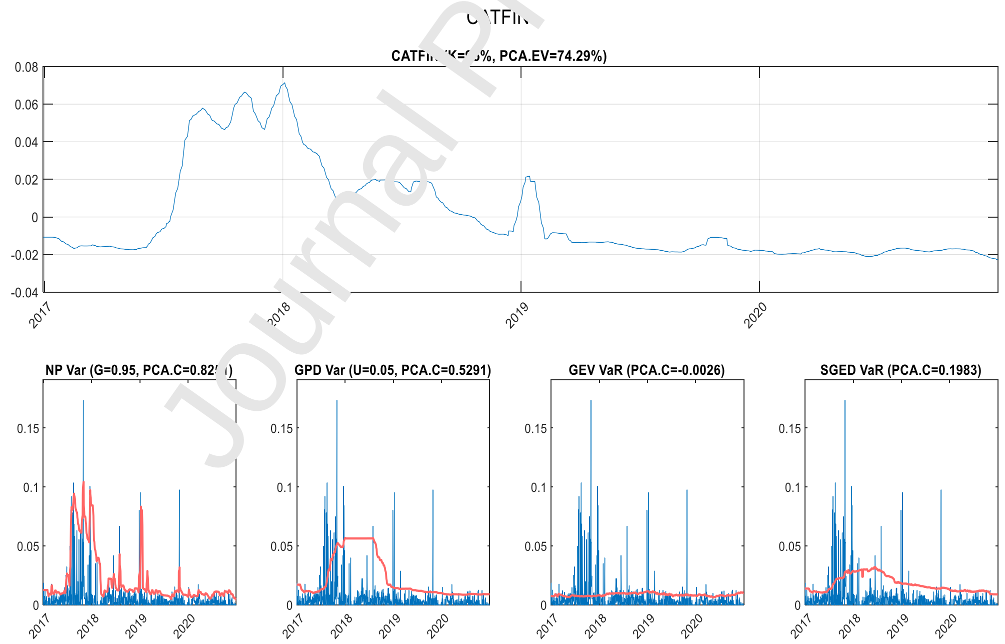
We construct the absorption ratio, the turbulence index, the correlation surprise, and the CATFIN as before. The results are presented in Panels A and B of Figure O2. As previously found, the absorption ratio was high between 2019 and 2020, confirming the fact that the market becomes fragile. In addition, the BRVM market was turbulent between end-August 2017 and end-February 2018. Furthermore, the CATFIN increases slightly from mid-2017 to reach its highest value in end-October 2017 during the turbulence period.

Figure O2: Systemic risk indicators based on principal component analysis – 41 companies

(A) Absorption ratio, turbulence index, and correlation surprise



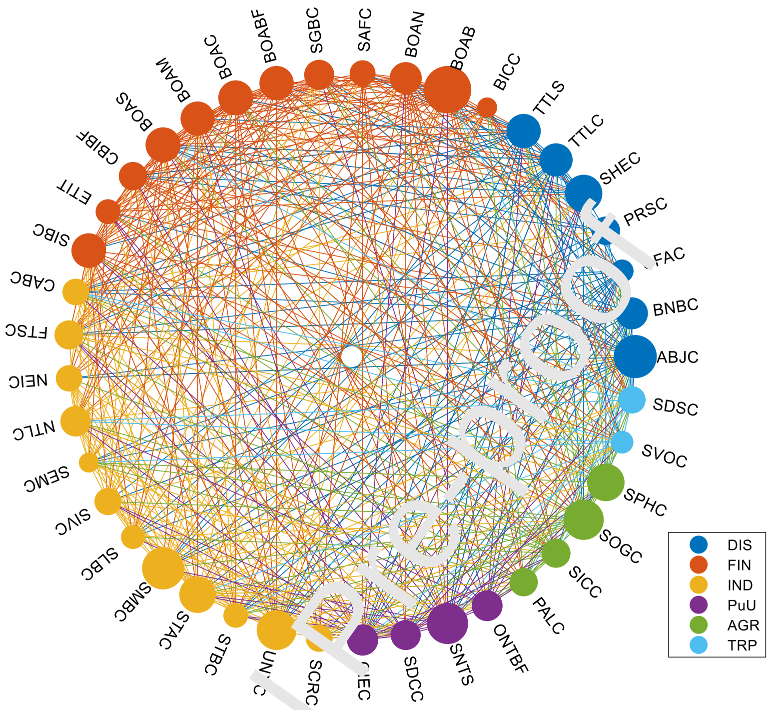
(B) Value-at-Risk (VaR) at 5% and the CATFIN



Degree of connections

We use the Granger-causality test to assess the degree of connections as before (see Figure O3).

Figure O3: Network graph (Granger-causality test) – 41 companies



As shown in Table O2, the number of connections has increased considerably in recent years with the listing of new companies. We find a dense network among companies operating in finance and agriculture. As before, the risk can originate from any company listed on the stock market, not only from financial companies.

Table O2: Number of connections from one sector to the system, and another sector (41 companies)

	To the system			*To* each sector (normalized #)					
From	Min	Mean	Max	Distribution	Finance	Industry	Public Utilities	Agriculture	Transportation
Distribution	10	13.29	19	**0.38**	0.30	0.37	0.43	0.18	0.29
Finance	9	15.50	23	0.37	**0.48**	0.35	0.27	0.40	0.42
Industry	5	11.92	20	0.31	0.31	**0.31**	0.31	0.21	0.25
Public Utilities	11	14.50	16	0.46	0.25	0.40	**0.42**	0.44	0.25
Agriculture	13	16.50	21	0.43	0.38	0.40	0.38	**0.50**	0.38
Transportation	11	11.00	11	0.21	0.13	0.33	0.38	0.38	**1.00**

Note: This table reports, on the one hand, the number of connections from companies operating in one sector to the system; and on the other hand, it shows the normalized number of connections from one sector to another, that is, we divide the number of significant connections from one sector to another by the total possible number of connections. There is only one company in the transportation sector.

Centrality measures

Finally, we compute the centrality measures and report the results in Table O3. For each measure, the top six companies are highlighted in bold. The top risky companies identified as such by at least three indicators are, by sector: distribution (ABJC), finance (BOAB, BOABF, BOAC, BOAM), industry (UNXC), and agriculture (SPHC). As we could see, one pan-African banking group (Bank of Africa - BOA) is identified as systemically important in the region. This finding is consistent with the existing literature showing that the expansion of pan-African banks into the WAEMU banking system supports the *competition-fragility* hypothesis (e.g., Kanga et al., 2021).

Table O3: Centrality measures – 41 companies

	Betweenness	Closeness	Degree	Eigenvector	Katz	Clustering
ABJC	**0.079**	**0.656**	**0.950**	0.032	0.199	0.078
BNBC	0.035	0.588	0.725	0.021	0.108	0.064
CFAC	0.024	0.597	0.650	0.021	0.112	0.082
PRSC	0.020	0.571	0.450	0.018	0.095	0.082
SHEC	0.025	0.580	0.600	0.021	0.113	0.067
TTLC	0.046	0.606	**0.875**	0.025	0.152	0.061
TTLS	0.024	0.597	0.650	0.024	0.146	0.100
BICC	0.007	0.556	0.425	0.014	0.051	0.110
BOAB	0.053	**0.702**	**0.975**	**0.040**	**0.270**	**0.123**
BOAN	0.042	0.645	0.775	0.032	0.214	0.114
SAFC	0.023	0.571	0.575	0.020	0.108	0.067
SGBC	0.027	0.571	0.625	0.018	0.088	0.055
BOABF	0.019	0.645	0.700	**0.036**	**0.259**	**0.181**
BOAC	**0.061**	**0.667**	**0.900**	**0.036**	**0.238**	0.103
BOAM	0.040	0.635	0.800	**0.034**	**0.236**	**0.118**
BOAS	0.043	0.635	**0.900**	0.030	0.197	0.079
CBIBF	0.037	0.597	0.675	0.025	0.149	0.074
ETIT	0.028	0.606	0.600	0.026	0.159	**0.127**
SIBC	**0.065**	0.615	0.850	0.026	0.149	0.054
CABC	0.018	0.541	0.550	0.012	0.043	0.043
FTSC	0.036	0.606	0.750	0.024	0.140	0.074
NEIC	0.012	0.526	0.525	0.010	0.034	0.021
NTLC	0.032	0.558	0.675	0.020	0.101	0.070
SEMC	0.016	0.533	0.500	0.012	0.042	0.042
SIVC	0.022	0.588	0.575	0.020	0.105	0.089
SLBC	0.019	0.548	0.550	0.015	0.059	0.041
SMBC	0.039	0.625	0.750	0.029	0.179	0.091
STAC	0.036	**0.667**	0.800	0.032	0.197	**0.128**
STBC	0.023	0.556	0.575	0.015	0.068	0.040
UNXC	**0.077**	**0.656**	**0.950**	**0.036**	**0.244**	0.085
SCRC	0.022	0.597	0.575	0.020	0.101	0.085
CIEC	0.033	0.615	0.700	0.027	0.160	0.103
SDCC	0.041	0.625	0.700	0.028	0.172	0.097
SNTS	**0.055**	0.625	0.850	0.029	0.186	0.080
ONTBF	0.020	0.571	0.550	0.020	0.108	0.084
PALC	0.027	0.597	0.650	0.022	0.120	0.094
SICC	0.020	0.606	0.625	0.023	0.123	0.115
SOGC	**0.059**	0.645	0.850	0.030	0.185	0.086
SPHC	0.034	**0.678**	0.775	**0.037**	**0.251**	**0.159**
SVOC	0.028	0.571	0.600	0.019	0.101	0.080

SDSC	0.024	0.580	0.625	0.019	0.091	0.065

Note: For each centrality measure (column), the high top six companies are highlighted in bold.

We have no actual or potential conflict of interest of any form.

CRediT author statement

Désiré KANGA: Conceptualization, Methodology, Software, Data curation, Validation, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing.

Issouf SOUMARÉ: Supervision, Conceptualization, Methodology, Validation, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing.

Edoh AMENOUNVÉ: Supervision, Conceptualization, Methodology, Writing- Reviewing and Editing.

- We investigate the systemic risk in the WAEMU stock exchange (BRVM)
- We find strong linkages across all economic sectors of listed firms
- Financial institutions are not the only source of systemic risk in the WAEMU region
- Big, high-growth and profitable firms contribute more to systemic risk than the others
- The determinants of systemic risk depend on the indicator used to assess it and the sectors