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

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Abstract

This paper aims to analyse the systemic risk in the regional BRVM (Bourse Régionale des Valeurs Mobilières) stock exchange in West Africa. This stock market, shared by 8 francophone West Africa countries, has grown over the last decade and is now a valuable source of funding of corporates and governments. This paper seeks to examine the extent to which growing activities in this market generates systemic risk. We cover six economic sectors, namely distribution, finance, industry, agriculture, utility, and transportation. We find strong linkages across all six sectors, but financial and industrial sectors can be seen as the centre of the system around which the other sectors rotate. Financial firms are not the only source of systemic risk in the WAMEU regional stock market, even though they play an important role in the system. Finally, using panel regressions, we find that big firms and high value companies contribute more to systemic risk. In contrast, high level of debt is associated with low systemic risk. Moreover, apart from the agriculture sector in which financial distress risk is negatively correlated with systemic risk, we find opposite results for firms in other sectors. Overall, we find that the determinants of systemic risk depend on the indicator used to assess systemic risk and the sectors in which companies operate. Therefore, the WAEMU financial system is not one-size-fits-all system.

Introduction

The global financial crisis has renewed the interest for systemic risk analysis. Systemic risk is a multiform concept and hard to define, but you know it when you see it. To define the systemic risk, we consider the one suggested by the G10 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". 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).

Systemic risk analysis can be divided into two generations according to the existing literature (e.g., Benoît et al., 2017; Silva et al., 2017; Saidane et al., 2021). The first generation focused on issues related to bank panics and crashes, and 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 which emerged in the aftermath of the 2007 financial crisis 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).

The two generations of research have been instrumental in measuring and understanding systemic risk. Despite the advanced development of our current understanding, little attention has been paid to the contribution of non-financial sector to systemic risk. To what extent does the non-financial sector affect the financial system as a whole and contribute to systemic risk? This question has not been fully studied in the literature. This paper seeks to contribute to this literature.

The recent literature shows that non-financial firms can generate significant spillover effects on the financial system in China (Zhu et al., 2020). For instance, firms operating in the manufacturing, wholesale retail, and real estate are highly correlated with systemic risk in China (Wang et al., 2021). Similarly, Kerste et al. (2015) found that companies in the energy sector trading on Over-the-Counter derivatives market have high contagion risk towards other non-financial sectors as opposed to the banking sector, focusing on the U.S. equity data. Therefore, from these few existing works linking non-financial sector activity and systemic risk, 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 markets, institutions, and their products than other sectors (Van Cauwenberge et al., 2019) and 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).

Overall, these studies highlight the importance of considering the non-financial sector to maintain the overall health and stability of the financial market. In line with this literature, the current paper analyses the contribution of both financial and non-financial sectors to systemic risk in the regional stock exchange in West Africa, that is the BRVM (Bourse Régionale des Valeurs Mobilières). This is a regional market shared by the eight countries of the West African Economic and Monetary Union (WAEMU) countries[1]. The contribution of this paper is twofold. First, as stated above and highlighted in the recent literature, systemic risk is not only centred around financial institutions but should be extended to other sectors. Therefore, this paper considers firms operating in six sectors, namely distribution (retails), finance, industry, agriculture, public utilities, and transportation in order to highlight the connexion between financial institutions and non-financial firms. Second, we focus on a least developed but growing regional stock market in West Africa. The 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 even continue 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.

Therefore, assessing and monitoring systemic risk in such a market is both an economic and political concern. Moreover, it is only recently that some studies have investigated systemic risk on financial systems in Africa (Enoch et al., 2015; Fall, 2017; Khiari and Nachnouchi, 2018; Kouadio et al., 2019; Manguzvane and Mwamba, 2019; Mwamba, 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 markets. Except for Kouadio et al. (2019), the existing studies concentrate on financial institutions and do not include the non-financial institutions. To the best of our knowledge, there are no studies focusing on the systemic risk in the BRVM. Therefore, we do not know how the market behaves in terms of risk and if this risk is systemic in the sense a negative shock to a major company can spread to other companies as well as the economies.

Using 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 within the stock market. We do that

following a two-step methodological approach. The first step consists of estimating systemic risk indicators. The second step focuses on regression analysis to explore the potential determinants of systemic risk.

We find strong linkages across all six sectors, but financial and industrial sectors can be seen as the centre of the system around which the other sectors rotate. Systemic firms belong to the distribution (BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors in the sense that they are more likely to propagate shock to the global market. Also, companies that are more prone to systemic risk belong to distribution (TTLC), finance (SGBC), utility (CIEC, SDCC, SNTS) and agriculture (PALC, SOGC, SPHC) sectors. Therefore, financial firms are not the only source of systemic risk in the WAMEU regional stock market, even though they play an important role in the system. Finally, systemic risk has also a time series dimension. Using panel regressions – second step – we find that big firms and high value companies contribute more to systemic risk. In contrast, high level of debt is associated with low systemic risk. The effect of financial distress risk on systemic risk is mixed. In the agriculture sector, financial distress risk indicator is negatively correlated with systemic risk. Apart from this sector, we find a positive correlation between systemic risk and the financial distress risk indicator in other sectors. Overall, we find that the determinants of systemic risk depend on the indicator used to assess systemic risk and the sectors in which companies operate.

The remainder of this paper is organised as follows. The section 2 presents background information on the BRVM market. The section 3 presents the methodology. The section 4 presents empirical results.

2. Background information on the BRVM market

The BRVM is a regional market created on 18 December 1996 and located in Abidjan. Its main missions are: (i) the organisation of the stock market, (ii) the listing and trading of securities, (iii) the dissemination of stock market information, and (iv) the promotion and development of the market. The regional exchange market is overseen by the *Conseil Régional de l'Epargne Publique et des Marchés Financiers* which plays the same role as the Securities and Exchange Commission in the United States. Other actors of the markets are the Central depository or settlement bank, national or local representatives of the BRVM, brokers, and other participants.

The regional market has two components: equity market and bond market. The stock market has three compartments with different listing conditions described in the Table 1. Only large companies are quoted on the first and second compartments. All companies considered in this paper are listed on these two compartments. The third compartment was introduced on 19 December 2017 to attract small and medium-sized enterprises and companies with high growth potential.

On the bond market, the minimum share to be issued is 25,000 with a total minimum value of XOF 500 million. To issue on this market, all companies must provide a financial rating or a better than investment grade as financial collateral. The bond market is dominated by domestic issuers, especially the public sector: in 2019, the size of the public sector related to the size of the bond market was 72.41%.

The market is relatively dynamic compared to other stock markets on the Africa continent. As a matter of fact, the BRVM was the 6th largest African stock exchange in terms of market capitalization (and stock index performance) in 2013 and in November 2016, it joined the MSCI Frontier Market index. From December 2012 to October 2015, the capitalisation of the BRVM almost doubled, from XOF 4,031 billion to XOF 7,500 billion. The number of listed companies has increased from 6 in 2000 to 46 in 2019. The regional market is now a source of funding of corporates as well as governments.

Table 1: Listing conditions on the BRVM

Criteria	1st compartment	2nd compartment	3rd compartment
Legal form	Limited company	Limited company	Limited company
Minimum capital	XOF 100 million	XOF 100 million	XOF 10 million
Market capitalisation	> XOF 500 million	>XOF 200 million	Not required
Minimum age	5 years	2 years	2 years
Certified account history	5 years	2 years	2 years
Net margin on sales	3% for each of the last three years	Not required	Not required
Minimum distribution of capital to the public (Floating)	20% must correspond to a minimum volume that varies between 2 and 10 million shares, depending on the company's market capitalization		10% must correspond to a minimum of 500,000 shares
Financial reporting	Event-driven, quarterly, semi-annual, annual	Event-driven, quarterly, annual	
Agreement of market animation	Mandatory	Mandatory	Not required
Business Plan	Not required	Not required	Required (over a minimum of 3 years)
Sponsorship Listing	Not required	Not required	Required

Source: BRVM (https://www.brvm.org/fr/comment-etre-cote-la-brvm, accessible on 20 September 2021).

In terms of collaboration, the BRVM and the Casablanca Stock Exchange signed a partnership agreement aimed at increasing the exchange of information, exchanging training processes, and developing the concept of dual listing since December 2013. Moreover, the ongoing collaboration between the BRVM and other stock exchanges in West Africa such as Nigeria Stock Exchange (NSE) and Ghana Stock Exchange (GSX) through the passport mechanism will potentially increase the interconnexion among listed companies and the targeted markets. The international exposure through intense international collaborations and openness, and the growth of the market (in terms of listed companies and capitalisation) 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). That is what this paper attempt to do.

3. Methodology, variables and data

This section describes the methodology, the variables and the data used in this paper.

Methodology

This paper is based on a two-step approach. In the first step, we will estimate a range of systemic risk indicators to assess the level of risk in the stock market. This will allow 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). Indeed, most of the risk indicators used in this paper identify the contribution of each company to the systemic risk. In a second step, we will examine potential determinants of systemic risk. The main purpose is to analyse the extent to which firms' characteristics and aggregate factors contribute to increase the systemic importance of some companies.

Systemic risk indicators

This paper uses existing systemic risk indicators grouped into two main categories. The first category includes "conventional measures" used in the systemic risk literature and known as ***cross-sectional*** measures of systemic risk. We will concentrate on a selective number of indicators[2], namely the Value at Risk (VaR), the expected Shortfall (ES), the Conditional Autoregressive Value-at-Risk (CAViaR), the Conditional Value-at-Risk (CoVaR and ΔCoVaR) and the Marginal Expected Shortfall (MES).

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 at a specified coverage rate, which is fixed at 5% in this paper. More precisely, this is the most that a company loses with 95% confidence. However, VaR gives no information regarding possible exceedances beyond the quantile (Taylor, 2019). The expected shortfall (ES) addresses this constraint by providing more information about the tail of the return distribution than VaR. Formally, the ES is defined as the conditional expectation of the return given that it falls below the VaR. The marginal expected shortfall (MES) shows the contribution of each institution of the financial system to the system-wide risk. It is the losses in the tail of the system's loss distribution.

In addition to these indicators, CAViaR suggested by White et al. (2015) is a multivariate regression quantile model to directly study the degree of tail

interdependence among different assets returns. In this paper, we consider bivariate models, whereby for each of the institutions in the sample, a bivariate CAViaR model is estimated by following White et al. (2015) to avoid 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.

Moreover, the conditional VaR was introduced by Adrian and Brunnermeier (2016) to overcome the limitation of the VaR. A company *i*'s CoVaR relative to the system is defined as the VaR of the whole financial sector conditional on institution *i* being in distress. These authors also suggested the ΔCoVaR which 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.

The second category, based on ***component analysis***, includes absorption ratio, turbulence index, 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 which 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., 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 based on the Mahalanobis distance. According to these authors, during turbulent days, asset prices behave in an uncharacteristic fashion, 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 premia than periods characterized by typical correlations. According to these authors, "days characterized by low correlation surprise are actually 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 company. To assess, the aggregate level of risk, the average value will be calculated. In addition, Allen et al. (2012) suggested a macro index of systemic risk measuring the aggregate level of risk taking in the financial sector (rather than an individual bank's systemic risk exposure) known as CATFIN. This indicator is calculated using the cross-sectional distribution of equity returns of listed firms. This measure is used to predict future real economic downturns (leading indicator).

The systemic risk indicators based on components analysis outlined above do not directly address the issue of connectedness. To this end, Billio et al. (2012) proposed connectedness measures combining principal component 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 a network-based measures of connectedness through five main indicators. Four of these indicators will be 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. These are similar to the number of connections, but they condition on the type of financial institution. The fourth indicator is the eigenvalue centrality which measures the importance of a financial institution in a network by assigning relative scores to financial institutions based on how connected they are to the rest of the network. We complement this network analysis by other centrality measures such as Katz, closeness, degree, betweenness and clustering centrality. The definition of these network indicators will be provided below when describing each of them.

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:

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

where *i* is a listed company, *j* the country in which the company operates, $R_{ij,t}$ a contribution of the company *i* in the country *j* to the risk of the system, $\boldsymbol{X}_{ijt}$ a matrix of company level characteristics, $\boldsymbol{Y}_{jt}$ a matrix of country level characteristics, $\boldsymbol{Z}_t$ a matrix of global factors that affect all companies being listed or not, $\boldsymbol{D}_i$ a matrix of company fixed effects, λ_t is time fixed effects (week-year). α is a scalar and β,γ,ζ are vectors of parameters to be estimated. The list of the variables, their description and the expected signs are presented in the section 3.1.2

Variables

There are two categories of variables. The first category includes the variables used to estimate systemic risk indicators and the second category are composed of potential determinants of systemic risk.

Variables to estimate systemic risk indicators

The systemic indicators described above require four main variables, namely stock prices (returns), market capitalisation, book value of total assets and book value of equity. Stock prices and market capitalisation are daily data, while book values are annual balance sheet data[3]. We also add the stock index of the BRVM calculated for all listed companies in the exchange: the BRVM Composite index.

Variables for the econometric analysis

As explained above, we use firm level variables as well as domestic and global factors.

Firm level variables: Firm level variables are used to evaluate firms' 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)[4]. The literature in developed countries has shown a positive effect of firm size on systemic risk consistent with too-big-to-fail concept. However, Zhu et al. (2020) find a negative effect of size on systemic risk in China. Therefore, the relationship between size and systemic risk is undetermined.
- *Leverage* measured by the ratio between book value of liabilities (total debt) divided by the sum of market capitalisation and book value of liabilities (debt). Highly leverage firms are expected to contribute more to systemic risk (Adrian and Brunnermeier, 2016). Similarly, *debt-to-asset (debt)* ratio is expected to be positively correlated with systemic risk, as this indicator is a book leverage.
- *Book-to-market ratio* is a financial distress risk factor. According to the literature, it is negatively correlated with systemic risk (Qin and Zhou, 2019; Zhu et al, 2020). Indeed, larger book value could provide managers with incentives to have higher capital ratios and to limit risk-taking activities to insure against losses in charter value in case they default (Qin and Zhou, 2019).
- *Tobin-Q* – a measure of firm value – is negatively associated with system risk in the financial sector (Soedarmono and Sitorus, 2017) while 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.

- *ROA* (return on asset) and *OROA* (operating income to asset ratio) are profitability indicators. Profitable companies should contribute less to systemic risk.

Country and global factors: 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 a bust. Therefore, we expect a negative relationship between GDP growth and systemic risk.
- *Gross government debt to GDP ratio* is used as a measure country default risk. High level of debt may negatively affect economic prospect and therefore firms' profit. Through this channel it may affect systemic risk. Stolbov (2017) showed that government debt is a determinant of ΔCoVaR for the sovereign CDS prices.
- Quality of institutions is proxied by the *investment profile,* the *composite risk rating,* and the *political stability and absence of violence:* These variables are used to control for the environment in each country that may affect businesses. We expect a negative effect of each variable on systemic, that is an increase in quality of institutions decreases systemic risk. Similar results have been found in the literature (Kleinow & Nell, 2015).
- *Federal fund rate and shadow rate* are used as global factor and measure the stance of monetary policy in the United States. Colletaz et al. (2018) found a causality from monetary policy to systemic risk in the long run. This result suggests that too loose monetary policy stance may help the progressive build-up of systemic risk. Therefore, we may expect a negative relationship between the stance of monetary policy and systemic risk.
- *Interbank rate* is positively associated with the policy rate. Therefore, we may expect a negative relationship between interbank rate and systemic risk.
- *VIX* is an indicator of the volatility in the US financial market. It uses to proxy global risk. We expect a positive relationship between VIX and systemic risk because the VIX measures investor fear.

Table 2 gives a summary of the variables, their description, and sources of data.

Table 2: Description of the explanatory variables

Variables	Description	Source
Firm level variables		
Size	Logarithm of total market equity for each firm divided by the log of the cross-sectional average of market equity.	BRVM / Own calculation
LEV	Leverage: total debt divided by (market capitalisation plus book value of debt)	BRVM
Debt	Debt-to-asset ratio (book value): Liabilities (debt) divided by total asset	BRVM
ROA	Return on asset: Net income divided by total asset	BRVM
OROA	Operating income divided by total asset	
BMR	Book-to-market ratio: market capitalization divided by book value of equity	BRVM
Tobin-Q	Firm value: market value of equity plus book value of liabilities divided by total asset	BRVM / Own calculation
Country and global factors		
Growth	Real GDP growth	WDI
Gvt Debt	Gross government debt to GDP ratio	WDI
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
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
PS	Political stability and absence of violence/terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. A higher value means lower political risk (higher quality of institutions).	WDI
Interbank	One-week interbank market rate	BCEAO
FFR	Federal fund rates: the stance of monetary policy in the US	Fed
Shadow	Shadow rate: it characterizes the term structure of interest rates. It is not bonded below by 0 and gives the stance of monetary policy even in zero lower bound environment.	Wu and Xia (2016)
VIX	Volatility index	Yahoo Finance

Note: This table presents the variables used in this paper, their definitions, the abbreviations used in empirical results, and the sources of raw data. BRVM is "Bourse Régionale des Valeurs Mobilières". We use companies balance sheet published on the website of the BRVM. BCEAO is the Central Bank of the West African States. ICRG is the International Country Risk Guide and WDI stands for the World Bank's World Development Indicators database. Fed is Federal Reserve System.

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 maximise the number of observations, the sample starts from 1 January 2004 to 31 December 2020. Therefore, 31 companies are considered in this paper. The distribution of these companies by sector is given in the Table 3. The financial sector is composed of 5 companies (16%) and other companies are in the non-financial sector (84%). Companies in the industrial and the distribution sectors dominate the non-financial sector (39% and 19% respectively of the sample).

Table 3: 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' own compilation. The classification is provided by the BRVM.

Table 4 reports the summary statistics of the returns of the sample firms classified by sector. A relatively large kurtosis indicates fat tails and thus relatively high risk; examples are the financial, industrial, utility and agricultural sectors. As explained in the previous sub-section, existing systemic risk indicators will be used to better assess the risk of each sector.

Table 4: Descriptive statistics for the daily returns of the sample firms by sector and of the 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

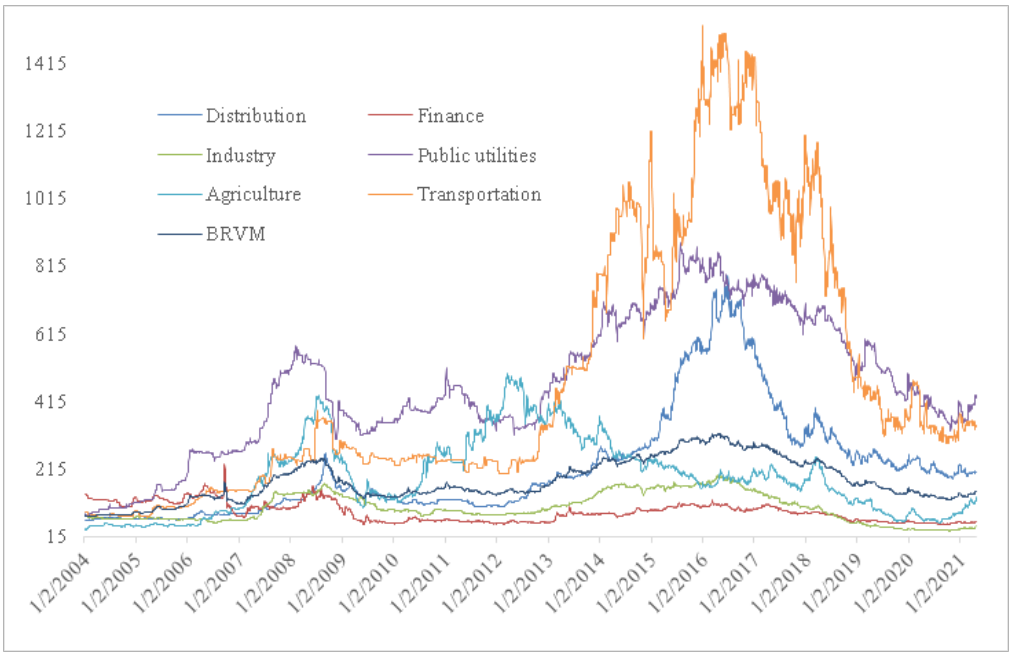
In addition, the Figure 1 shows that each all sectors do not display the same pattern. In fact, transportation, utility, and distribution companies are more volatile compared to the industrial and financial sectors, even though the Table 3 indicates smaller kurtosis for the distribution and transportation 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.

Moreover, Table 5 provides descriptive statistics on abovementioned explanatory variables. Companies listed on the market are similar in terms of size given the low standard deviation[5]. The logarithm of market capitalisation of listed companies – another measure of size not reported in the table – varies between 19.8 and 28.7 with a standard deviation of 1.6. However, they differ in their leverage or debt. Another specific characteristic of companies is their book to market ratio (BMR) which is an indicator of financial distress. Some of companies have a negative BMR, which indicates a negative book value of equity.

Table 5: Descriptive statistics on explanatory variables

	Observations	Mean	Standard deviation	Min	1st quartile	Median	3rd quartile	Max
BMR	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
Debt	130882	0.73	0.30	0.05	0.52	0.75	0.90	2.06
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
Gvt Debt	130882	42.86	10.43	8.37	34.19	41.23	51.24	65.81
PS	130882	-1.27	0.55	-2.26	-1.81	-1.09	-0.98	0.55
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
FFR	130882	1.36	1.64	0.04	0.13	0.40	2.16	5.41
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

Figure 1: Evolution of sectorial and market indices



Source: BRVM, authors' compilation.

For the regressions, appendix Table 20 reports the correlation matrix on explanatory variables. Most of the correlations are generally weak, and especially between global variables and domestic variables, as well as firms' characteristics. However, we find high correlations between quality of institutions variables. Therefore, to avoid multicollinearity issues, we do not include in the same regression variables that exhibit correlation more than 0.6. For example, ROA and OROA will not be included in the same regression, as well as government debt and growth, composite risk indicator and investment profile (IP).

4. Empirical results

This section presents and analyses systemic risk indicators presented in the previous section and is organised around three sub-sections. The first subsection (4.1) focuses on cross-sectional measures. The second (4.2) analyses indicators based on principal component analysis, and the third (4.3) presents regressions results.

Systemic risk indicators based on cross-sectional measures

The first category used to assess systemic risk includes conventional risk indicators. Table 6 reports summary statistics on average systemic risk indicators at 95% level. On average, the most that a company loses with 95% confidence on the market lies between 2.2 and 17.9 percentage points according to the Value at Risk. However, the average expected shortfall (ES), that is the average of returns on days when the portfolio's loss exceeds its VaR limit, varies between -94.5% and -19.6%. The losses in the tail of the system's loss distribution range from 0.1% to 4.9%. But when the market is in its left tail, the average return varies between -0.1% and -4.9%. The average CoVaR at 95% confidence level varies between 1.2% and 2.2% 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.

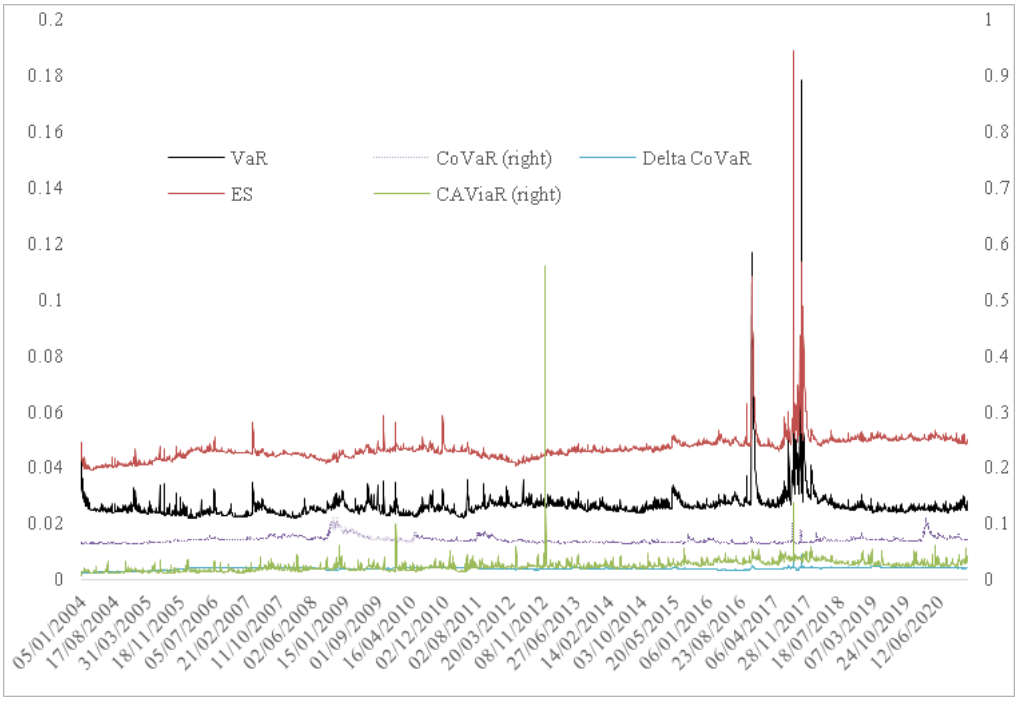
Table 6: Descriptive statistics on average systemic risk indicators at 95% level

	VaR	ES	CAViaR	CoVaR	ΔCoVaR	MES
Mean	0.026	0.234	0.024	0.014	0.004	0.013
Median	0.026	0.231	0.023	0.014	0.004	0.008
Standard Deviation	0.006	0.025	0.013	0.001	0.000	0.011
Kurtosis	277.689	175.415	837.282	7.170	26.095	0.191
Skewness	13.467	8.751	21.018	2.145	0.438	1.127
Minimum	0.022	0.196	0.008	0.012	0.002	0.001
Maximum	0.179	0.945	0.561	0.022	0.012	0.049

The overall market does not seem to show high level of risk, even though losses can be huge some trading days. Because systemic risk has both cross-sectional and time series dimensions, the following analysis concentrates on these two dimensions.

Figure 2 presents the time series of the average systemic risk indicators to trace the time dimension of systemic risks. The figure indicates high risk between 2016 and 2017 in the market, especially in November 2016 and between August and November 2017 when VaR and ES are used as risk indicators. CAViaR also shows 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 have affected the BRVM market.

Figure 2: Time series of the average systemic risk indicators



Systemic risk has also a cross-sectional dimension. Table 7 provides descriptive statistics on the estimated value at Risk at 95% confidence for each listed company. The table reports only companies with non-zero VaR. The highest loss – i.e., a maximum VaR greater than 1 set for convenience – are recorded for the following companies, grouped by sectors: distribution (SHEC), finance (BICC, SGBC), industry (NTLC, SMBC), utility (SDCC, CIEC) and agriculture (SPHC). We cannot conclude that the risk lies solely in one specific sector.

Surprisingly, risk measured by VaR does not vary over time for some companies (BNBC, CFAC, TTLC, TTLC, FTSC, NEIC, SEMC SLBC, STBC and SNTS). Other systemic risk indicators will be used to assess the quality of the VaR.

Table 7:Summary statistics on VaR at 95% level

Firms	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
ABJC	0.047	0.046	0.011	3317.924	56.060	0.046	0.719
BNBC	0.035	0.035	0.000	4221.141	64.967	0.035	0.035
CFAC	0.035	0.035	0.000	4221.750	64.974	0.035	0.035
SHEC	0.051	0.041	0.086	473.671	20.379	0.037	2.586
TTLC	0.040	0.040	0.000	3663.112	59.392	0.040	0.040
BICC	0.033	0.028	0.035	438.102	19.264	0.027	1.084
BOAB	0.020	0.014	0.033	321.657	16.164	0.014	0.893
BOAN	0.029	0.027	0.021	1026.876	29.594	0.027	0.896
SGBC	0.039	0.037	0.028	2589.496	47.313	0.037	1.658
CABC	0.034	0.034	0.011	3123.035	54.320	0.034	0.694
FTSC	0.060	0.060	0.000	4166.228	64.338	0.060	0.060
NEIC	0.026	0.026	0.000	4221.603	64.972	0.026	0.026
NTLC	0.031	0.022	0.052	454.510	19.630	0.018	1.569
SEMC	0.023	0.023	0.000	4221.644	64.973	0.023	0.023
SIVC	0.049	0.048	0.016	2278.220	44.405	0.048	0.935
SLBC	0.016	0.016	0.000	2258.407	46.423	0.016	0.016
SMBC	0.033	0.026	0.032	727.580	22.763	0.024	1.277
STBC	0.036	0.036	0.000	4221.074	64.966	0.036	0.036
UNLC	0.026	0.024	0.008	21.020	3.672	0.020	0.112
UNXC	0.034	0.028	0.042	79.200	8.004	0.015	0.598
CIEC	0.046	0.036	0.060	3196.284	53.049	0.036	3.698
SDCC	0.043	0.038	0.044	231.050	13.792	0.025	1.015
SNTS	0.017	0.017	0.000	4220.738	64.962	0.017	0.017
PALC	0.049	0.048	0.021	14.630	2.584	0.014	0.220
SOGC	0.053	0.053	0.000	4213.297	64.877	0.053	0.064
SPHC	0.049	0.040	0.036	822.209	23.545	0.034	1.510

Note: Only companies with non-zero VaR are reported. VaR for PRSC, SAFC STAC, SICC and SVOC is 0.

To provide a broader view of the systemic risk in the market, Table 8 provides summary statistics of other indicators. High risk companies (top 10) are presented in bold in the table. Given this ranking, high risk companies[6] belong to distribution (TTLC), finance (SGBC), utility (CIEC, SDCC, SNTS) and agriculture (PALC, SOGC, SPHC) sectors. This classification is close to the one obtained by using the VaR. In addition to these companies, SLBC has a large contribution to the system-wide risk according to CoVaR and ΔCoVaR.

These companies are more prone to systemic risk and contribute more to system wide risk (systemic risk). How connected are these companies to the others? The next section will address the issue of connectedness.

Table 8: Systemic risk indicators at 95% 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**	0.013	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

continued next page

Table 8 Continued

	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**
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

Note: SD stands for standard deviation. High risk companies are in bold for each indicator.

Systemic risk indicators based on principal component analysis

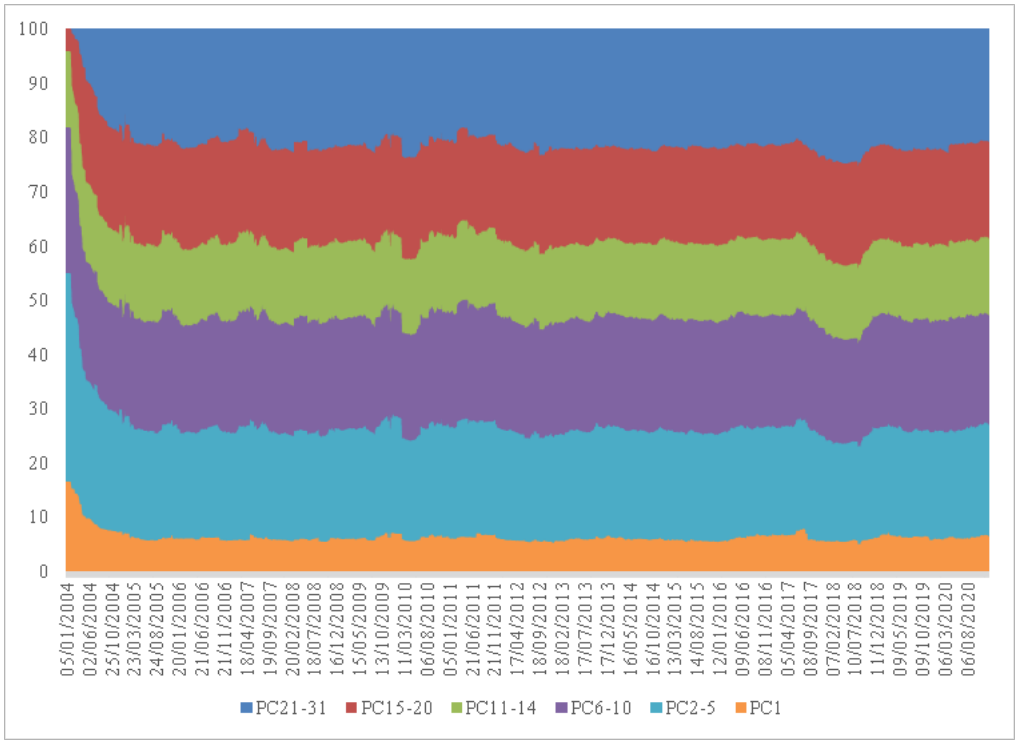
The idea of the principal component analysis (PCA) is that, when the system is highly interconnected, a small number of principal components can explain most of the volatility in the system. Figure 3 shows the cumulative risk fraction (i.e., the fraction of the volatility explained by a limited number of principal components) slightly varies over time. The 20 first principal components capture most of the return's variation during the period of the analysis. Excluding 2004, the variance explained by the first 20 factors fluctuates between 77.0% and 84.2% during the period 2005-2020 (Table 9). When the variance explained by a limited number of factors increases, it is associated with an increased interconnectedness among listed companies.

Table 9: Variance explained Summary statistics for PCAs

	Summary statistics on PC1-20				Average cumulative Risk Fraction (%)			
	Min	Mean	SD	Max	PC1	PC1-5	PC1-10	PC1-20
2004	80.8	89.3	6.8	100.0	10.2	37.1	58.9	89.3
2005	78.1	79.5	1.2	84.2	6.1	26.8	47.3	79.5
2006	77.7	78.8	0.7	80.3	6.0	26.1	46.3	78.8
2007	77.4	79.5	1.4	81.8	5.9	26.4	47.1	79.5
2008	77.2	78.1	0.6	79.4	5.8	25.7	46.3	78.1
2009	77.1	78.7	0.9	80.8	6.1	26.7	47.1	78.7
2010	76.1	78.5	1.5	80.7	6.2	26.3	46.6	78.5
2011	78.6	80.2	0.9	81.8	6.4	27.5	48.8	80.2
2012	76.4	77.9	0.7	79.2	5.6	25.4	45.9	77.9
2013	77.5	78.0	0.2	78.6	5.9	26.0	46.6	78.0
2014	77.3	77.9	0.3	78.6	6.0	26.2	47.0	77.9
2015	77.6	78.2	0.2	78.6	5.6	25.7	46.4	78.2
2016	77.6	78.5	0.3	79.0	6.2	26.4	47.1	78.5
2017	75.8	78.2	1.0	79.8	6.5	26.6	46.9	78.2
2018	74.7	76.3	1.2	78.8	5.7	24.4	44.1	76.3
2019	77.4	77.9	0.4	78.8	6.4	26.2	46.7	77.9
2020	77.0	78.6	0.6	79.5	6.2	26.4	46.9	78.6

Note: this figure displays the cumulative variance explained by the specified number of factors or eigenvectors. For example, PC1-10 is the variance explained by the first 10 factors and PC1-5 is the variance experienced by the first 5 factors.

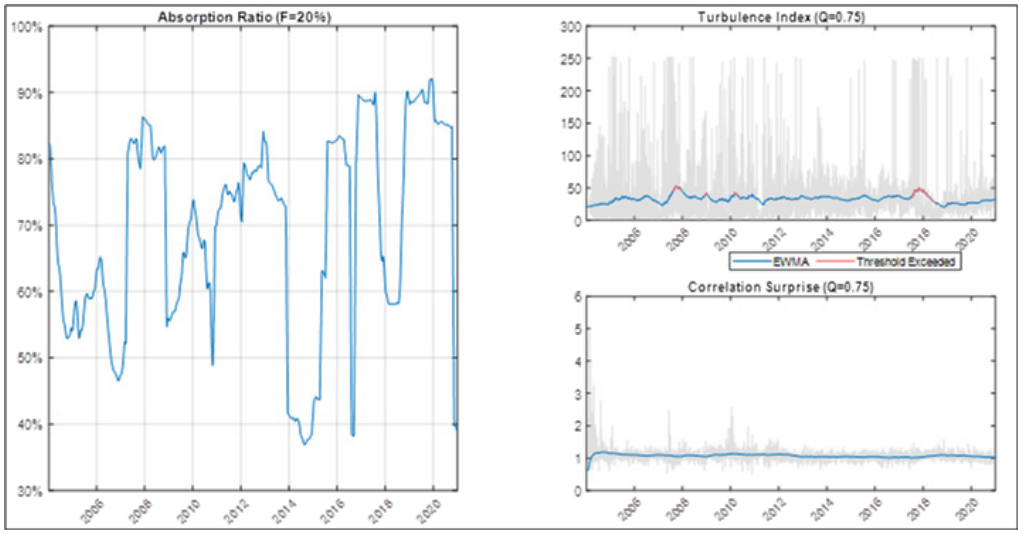
Figure 3: Principal components analysis (explained variance)



Note: this figure displays the cumulative variance explained by the specified number of factors or eigenvectors. For example, PC1-10 is the variance explained by the first 10 factors and PC1-5 is the variance experienced by the first 5 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 per cent the number of assets in our sample as in Kritzman et al. (2011); that is 6 eigenvectors. Figure 4 shows a volatile absorption ratio over the period of 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 post-electoral conflict in Cote d'Ivoire) and November 2012 (during the war in Mali). Probably, the market is sensitive to global factors as well as domestic/ and regional factors. Other high values are recorded throughout the analysis period, especially earlier and during 2020. These results show that the market is unified or tightly coupled, which indicates that the market becomes fragile in the sense that negative shocks can propagate more quickly and widely compared to weakly linked markets.

Figure 4: Absorption ratio, turbulence index and correlation surprise



In addition to the absorption ratio, Figure 4 shows that the BRVM market was turbulent – i.e., the turbulence index was outside the 25 per cent of the distribution or the threshold 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, 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 factors. During turbulent periods, the market experiences lower daily returns as highlighted in the Figure 5 except for two sectors namely public utilities and transportation. Even if the financial sector experiences negative returns, on average, over the period of the analysis, the loss in value is higher during turbulent periods. The results for the public utilities and transportation sectors are counterintuitive and may indicate that those sectors are refuge or "safe haven" sectors.

The correlation surprise does not show a specific pattern, meaning that the market is characterised by low values of the correlation surprise index.

Another interesting indicator of the systemic risk measures category is CATFIN which is defined as the average of two parametric and one non-parametric Value at Risk (VaR) measures. The two parametric VaR measures are based on Generalized Pareto distribution (GPD) and Skewed Generalized Error Distribution (SGED). Figure 6 depicts the daily 5% VaR measures (second row) and the CATFIN measure (first row).

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

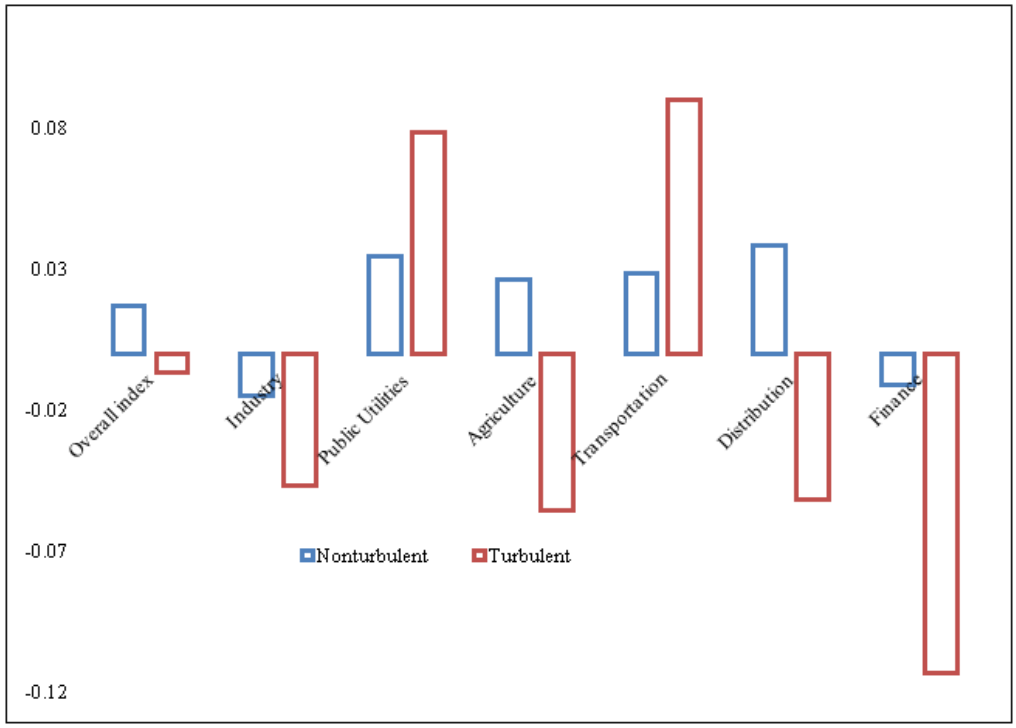
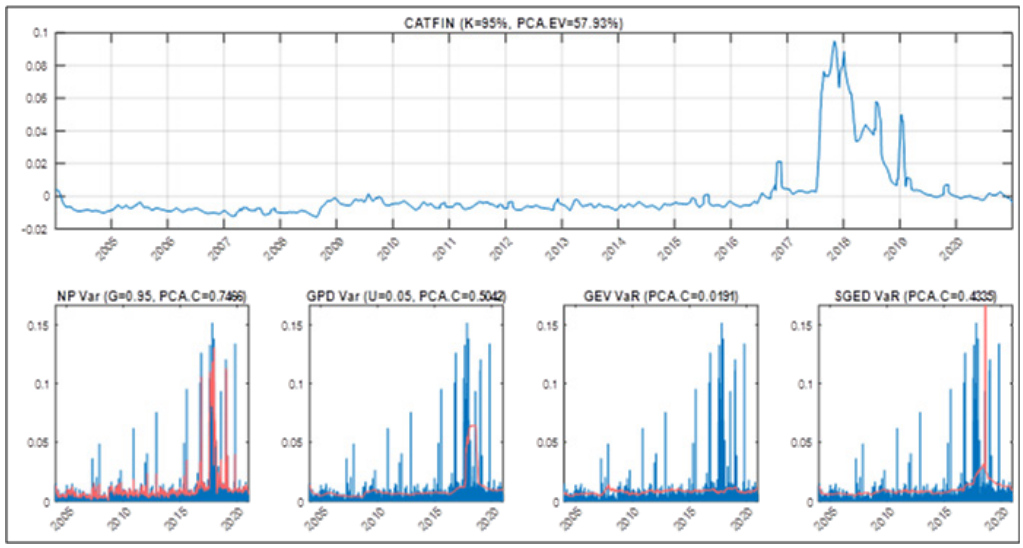


Figure 6: Five per cent Value at Risk (VaR) and the CATFIN



To formally analyse the degree of connections, we follow Billio et al. (2012) and use Granger causality test. Figure 7 presents only those relationships significant at the 5 per cent 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 company of the system, a line is drawn from this company to the other one in the Figure 7. The colours indicate the sector in which each company operates: companies in the distribution are in dark blue, the company in the transportation is in light blue, financial institutions are in orange, yellow colour indicates companies in the industrial sector, public utilities companies are in purple, and companies in the agriculture sector are in green. As shown in the figure below, there are connections among listed companies. On average companies in the distribution sector have between 7 and 21 connections with other institutions, while financial companies' average number of connections is 13 (see Table 10).

Figure 7: Network graph (Granger causality test)

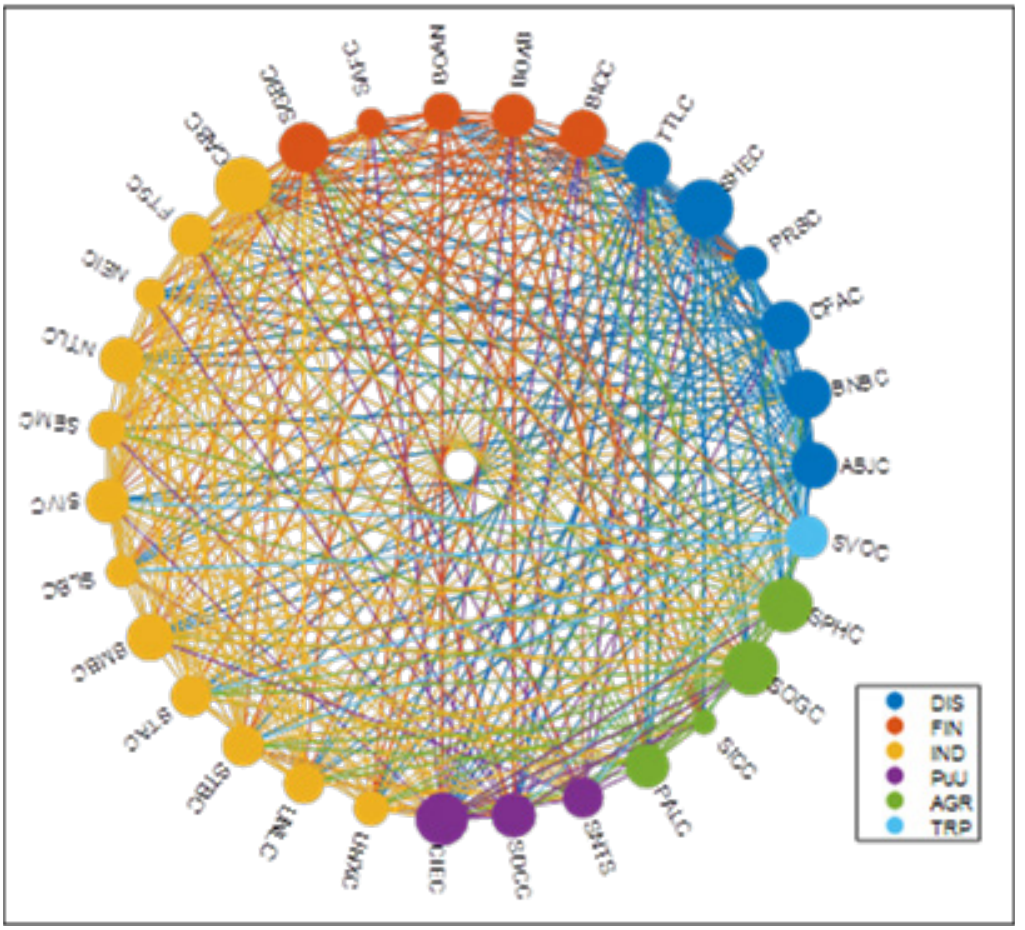


Table 10 also presents the normalised number of connections from one sector to another, that is we divide the number of significant connections from one sector to another by the total possible number of connections. Bold value in the Table 10 indicates intra-sector connections, that is connections from a company operates in a sector to another company operating 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, not only from financial companies.

Table 10: Number of connections from one sector to the system, and to another sector

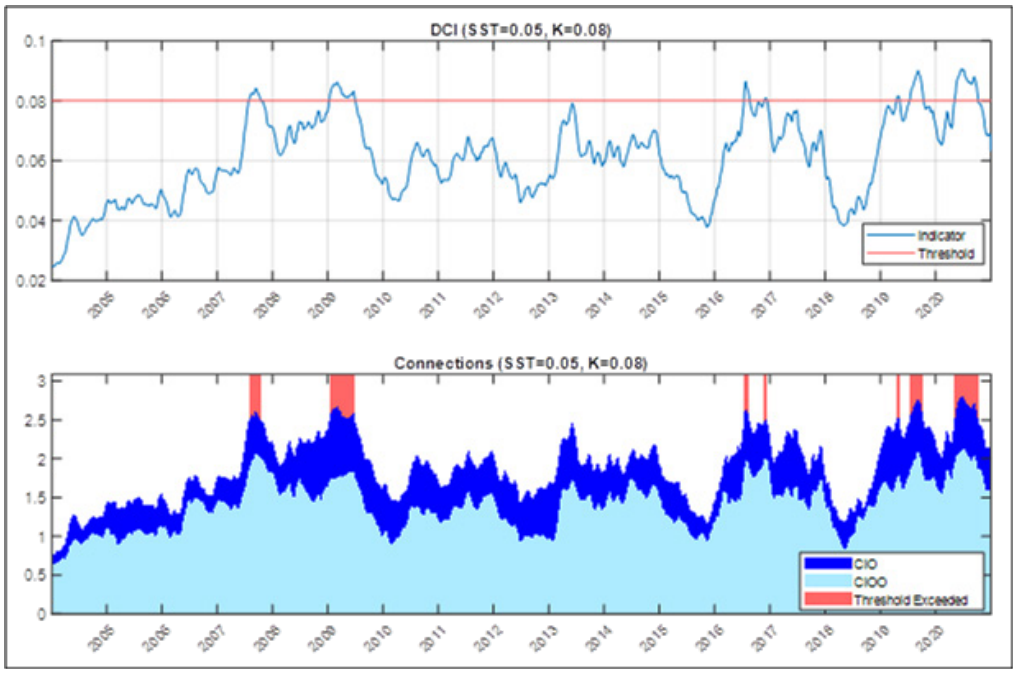
	To the system			To each sector (normalized #)					
From	**Min**	**Mean**	**max**	**Distri-bution**	**Finance**	**Industry**	**Public utilities**	**Agricul-ture**	**Transpor-tation**
Distribution	7	15.83	21	0.73	0.53	0.50	0.56	0.38	0.33
Finance	7	13.2	16	0.37	0.45	0.50	0.40	0.40	0.40
Industry	8	12.25	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 one hand the number of connections from companies operating in one sector to the system. And on the other hand, it shows the normalised number of connections from one sector to another, that is we divide the number of significant connections form one sector to another by the total possible number of connections. There is 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[7] of 0.08 is reported in the first row of Figure 8. The DGC indicates greater connectedness when it exceeds the threshold. According to Figure 8, the number of connections was large and significant during specific periods. The first period which run 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. Increasing in the number of connections are recorded in 2013, 2016, 2017, 2019 and 2020.

The second row of Figure 8 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 normalised number of connections (in and out) between listed companies has evolved over time.

Figure 8: 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 centrality measures to identify systemic companies. Table 11 presents the average centrality measures and highlights to top five or six companies (in bold). By using degree centrality, defined as the number of ties that a vertex has with other vertices, we find that companies in the distribution (BNBC, SHEC), industry (CABC), agriculture (SOGC), and utility (CIEC) sectors are the most importance in the financial market. An extension of the degree centrality is the eigenvector centrality which provides a relative score to each node depending on the type of nodes it is connected to. Companies in the distribution (BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors are the most importance in the financial market according to the eigenvector centrality indicator.

Moreover, examining the closeness centrality which is the average length of the shortest path between the node and all other nodes in the graph, we can conclude that companies in the distribution (ABJC, BNBC, SHEC), industry (CABC) and agriculture (SOGC, PALC) are the most likely to quickly propagating a shock through the network. In fact, 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).

Table 11: 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	0.028	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-five companies are in bold.

Two other interesting indicators are the betweenness centrality and Katz centrality. The betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. Katz centrality measures the relative influence of each node in a given network by taking into account it's immediate neighboring nodes as well as non-immediate neighboring nodes that are connected through immediate neighboring nodes[8].

Based on all centrality measures, the BRVM's systemic firms belong to the distribution (BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors. There are more likely to propagate shock to the global market. All these companies operate in Cote d'Ivoire.

Regression analysis

Full sample analysis

We estimate equation (1) to understand the determinants of systemic risk in WAEMU. The results of the estimates on the full sample are reported in the Table 12. This section concentrates on six cross-sectional systemic risk indicators.

First, book-to-market ratio which, a financial distress indicator, is negatively associated with CAViAR and positively associated with value at risk (VaR) and expected shortfall (ES). Therefore, the effect of book-to-market ratio depends on the metric used to proxy systemic risk.

Second, our results indicate a positive relationship between size and systemic risk consistent with the literature in developed countries[9] and supporting the too-big-to-fail hypothesis. Third, we find counterintuitive results regarding the effect of leverage or debt on systemic risk. In fact, highly leverage or highly indebt firms are expected to contribute more to systemic risk. Our result indicates a negative correlation between debt and systemic risk. 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 reduces 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 results show a disciplinary effect of debt.

Fourth, firm value – proxied by Tobin-Q – is positively associated with system risk as in China (Zhu et al., 2020). Fifth, profitable companies contribute more to systemic risk in contrast to the literature. Firm's marginal contribution to systemic risk increases by one percentage point for a one standard deviation increase in profitability. However, using return on asset or operating income do not provide necessarily the same results, especially for CoVaR and ΔCoVaR.

Table 12: Determinants of systemic risk in the WAEMU (full sample)

	VaR		ES		MES		CoVaR		ΔCoVaR		CAViaR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BMR	0.007***	0.004***	0.015***	0.008**	0.000	0.000	0.000**	-0.000***	0.000***	-0.000***	-0.004***	-0.007***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Size	0.724	3.249***	2.521	6.662***	2.741***	2.527***	-0.054***	0.091***	-0.039**	0.139***	12.194***	11.538***
	(0.588)	(0.457)	(2.193)	(1.603)	(0.122)	(0.078)	(0.017)	(0.013)	(0.016)	(0.012)	(0.465)	(0.290)
LEV	-0.733***		-1.435***		0.031		-0.040***		-0.050***		-0.074	
	(0.082)		(0.293)		(0.022)		(0.003)		(0.003)		(0.073)	
Debt		-0.767***		-2.093***		-0.006		-0.046***		-0.047***		-0.794***
		(0.060)		(0.182)		(0.013)		(0.002)		(0.002)		(0.041)
Tobin-Q	0.015***	0.044***	0.051***	0.131***	-0.000	-0.001	0.001***	0.003***	0.000***	0.002***	-0.006***	0.018***
	(0.002)	(0.003)	(0.009)	(0.010)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
ROA	0.293***		1.324***		0.097***		0.010***		0.012***		1.620***	
	(0.031)		(0.099)		(0.013)		(0.001)		(0.001)		(0.050)	
OROA		-0.077		0.242*		0.124***		-0.014***		-0.010***		1.386***
		(0.048)		(0.147)		(0.016)		(0.002)		(0.002)		(0.053)
Growth	0.006	0.004	-0.014	-0.047	0.011***	0.009**	0.000	0.001***	0.000***	0.001***	-0.007	-0.005
	(0.005)	(0.004)	(0.044)	(0.037)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.011)
IP	-0.012		-0.453***		-0.037***		0.008***		0.001***		0.033**	
	(0.011)		(0.082)		(0.009)		(0.000)		(0.000)		(0.016)	
Composite		0.012***		-0.127***		-0.014***		0.004***		0.001***		0.026***
		(0.004)		(0.037)		(0.003)		(0.000)		(0.000)		(0.007)

continued next page

Table 12 Continued

	VaR		ES		MES		CoVaR		ΔCoVaR		CAViaR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Shadow	0.106	0.105	0.665*	0.664*	-0.005	-0.005	0.019***	0.019***	0.003	0.003	0.094	0.095
	(0.085)	(0.084)	(0.399)	(0.399)	(0.048)	(0.048)	(0.005)	(0.004)	(0.003)	(0.003)	(0.106)	(0.106)
VIX	-0.004	-0.004	-0.011	-0.011	0.000	0.000	0.006***	0.006***	-0.000	-0.000	-0.002	-0.002
	(0.004)	(0.004)	(0.013)	(0.013)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Interbank	0.004	0.004	0.043	0.043	-0.003	-0.003	0.002**	0.002**	0.000	0.000	0.007	0.007
	(0.028)	(0.028)	(0.103)	(0.103)	(0.010)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.027)	(0.026)
Constant	3.903***	0.788	27.456***	28.588***	-1.793***	-1.015***	1.157***	0.851***	0.188***	-0.042**	-11.161***	-11.333***
	(0.791)	(0.761)	(2.592)	(3.037)	(0.239)	(0.260)	(0.026)	(0.025)	(0.023)	(0.021)	(0.544)	(0.554)
Observations	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882
R-squared	0.298	0.298	0.696	0.697	0.210	0.210	0.793	0.794	0.711	0.711	0.480	0.482

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

Pertaining to macroeconomic and global factors, we find mix results for quality of institutions measured by investment profile and composite risk rating. Economic growth, the volatility in the United States financial market and the stance of monetary policy in the United States (shadow rate) and in the WAEMU (interbank rate) seem to contribute to systemic risk in the WAEMU.

Analysis by sector in which companies operate

In addition to the results on the full sample, we rerun the equation (1) by sector to highlight differences between sectors. Table 13 to Table 18 report the estimates of the results.

The new results confirm the positive effect of firms' size on systemic risk indicators with the exception of the distribution sector when MES is used as a systemic risk indicator, the agriculture sector when ES is used as a systemic risk indicator and the financial sector when VaR is used as a systemic risk indicator. For these three sectors, we find a negative effect of size on systemic risk consistent with Zhu et al. (2020) in China.

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

In the full sample, we found a positive association between firm value – measured by Tobin-Q – and with systemic risk. We find a similar positive correlation between firm value and: MES in the utility sector, ΔCoVaR in the industrial sector, CoVaR in the industrial and utility sectors, CAViaR in the distribution sector, ES in the agriculture and industrial sector, VaR in the industrial sector. Apart from these results, we find a negative association between firm value and systemic risk indicators, in line with Soedarmono and Sitorus (2017) for other systemic risk indicators and across the sector.

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 agriculture sector. The same result holds for the distribution sector when CoVaR is used as an indicator of systemic risk. For the remaining indicators and sectors, we find a positive effect of profitability on systemic risk as in the full sample.

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 BMR 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 BMR on systemic risk.

As regards to macroeconomic variables, we find mix results of economic growth and quality of institutions on systemic risk. But we find that high economic growth and better quality of institutions are associated with less risk in the financial sector as expected. A better quality of institutions is associated with low transaction costs which allows 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. The shadow rate is also positively associated with VaR, ΔCoVaR and CAViaR for firms operating in the financial sector. Moreover, the interbank rate plays a role only in the financial sector.

Additional robustness analysis

Additional regressions are performed and reported in the appendix Table 21. The new results confirm the positive effects of size and Tobin-Q, the negative effect of debt and the mix results of BMR and profitability. We also control for government debt and the Federal Fund Rate (FFR) in addition to firm level and other macroeconomic variables. We find that default risk, measured by the level of government debt, is positively associated with ES and MES, while it is negatively associated with CoVAR, ΔCoVaR and CAViaR. Therefore, the effect of government default risk on systemic risk depends on the indicator used to assess risk. FFR is negatively associated with CoVAR, and its effects on other systemic risk indicators are not significantly different from zero. This confirms that too loose monetary policy stance can foster the gradual rise of systemic risk, as highlighted by Colletaz et al. (2018).

Table 13: Determinants of VaR in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.036***	-0.045***	0.003*	0.009***	0.198*	0.009	0.015***	0.014***	0.101	0.169
	(0.001)	(0.002)	(0.002)	(0.002)	(0.106)	(0.107)	(0.002)	(0.002)	(0.185)	(0.204)
Size	10.806***	15.175***	3.784***	6.089***	-2.383**	2.334	0.786	0.528	24.725*	17.371*
	(0.940)	(0.712)	(1.352)	(1.548)	(1.042)	(1.425)	(1.042)	(0.476)	(12.823)	(9.117)
LEV	-0.710***		-1.042***		-0.814*		-0.415**		1.588	
	(0.270)		(0.290)		(0.431)		(0.174)		(1.419)	
Debt		-1.186***		0.316***		-0.858***		-1.067***		0.672
		(0.178)		(0.106)		(0.285)		(0.082)		(2.665)
Tobin-Q	-0.504***	-0.272***	-0.110***	-0.100**	-2.257*	-0.998	0.020***	0.057***	-0.215***	-1.026***
	(0.025)	(0.043)	(0.040)	(0.039)	(1.208)	(1.053)	(0.002)	(0.004)	(0.082)	(0.171)
ROA	-0.073		-0.952***		12.961***		0.438***		28.894***	
	(0.136)		(0.159)		(3.751)		(0.033)		(4.560)	
OROA		-2.229***		0.303***		4.015		-0.060		21.874***
		(0.141)		(0.061)		(2.774)		(0.064)		(7.000)
Growth	0.204	0.181	0.092	0.014	-0.005	-0.016***	0.044	-0.060	0.093***	0.020*
	(0.213)	(0.166)	(0.180)	(0.134)	(0.008)	(0.006)	(0.226)	(0.127)	(0.015)	(0.011)
IP	-0.156		-0.354		-0.070*		-0.853		-0.607***	
	(0.353)		(0.338)		(0.042)		(0.782)		(0.135)	

continued next page

Table 13 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		-0.069		-0.113		0.022**		-0.290		-0.155***
		(0.109)		(0.099)		(0.009)		(0.235)		(0.042)
Shadow	0.008	0.006	0.003	0.003	0.438*	0.436	0.139	0.140	-0.210	-0.210
	(0.217)	(0.216)	(0.104)	(0.103)	(0.265)	(0.265)	(0.122)	(0.122)	(0.384)	(0.385)
VIX	-0.003	-0.003	-0.016	-0.016	-0.000	-0.000	-0.000	-0.000	-0.003	-0.003
	(0.007)	(0.007)	(0.016)	(0.016)	(0.004)	(0.004)	(0.003)	(0.003)	(0.008)	(0.008)
Interbank	0.040	0.040	-0.020	-0.020	0.030	0.030	0.008	0.008	-0.056	-0.056
	(0.062)	(0.060)	(0.096)	(0.096)	(0.047)	(0.047)	(0.037)	(0.037)	(0.061)	(0.063)
Constant	-4.956**	-5.866	2.973	4.488	7.642***	0.383	8.653*	20.931	-16.648	-2.655
	(2.283)	(6.216)	(2.361)	(5.854)	(1.433)	(1.441)	(5.210)	(13.832)	(14.069)	(9.167)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.631	0.634	0.297	0.297	0.327	0.326	0.367	0.370	0.236	0.236

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

Table 14: Determinants of ES in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.086***	-0.110***	0.009	0.032***	1.498**	0.325	0.046***	0.044***	0.199	0.333
	(0.005)	(0.005)	(0.007)	(0.010)	(0.741)	(0.697)	(0.008)	(0.008)	(0.367)	(0.403)
Size	-10.042***	-7.478***	14.219***	20.696***	-10.751	23.891**	6.579**	2.404*	49.239*	34.585*
	(1.977)	(1.617)	(5.154)	(5.203)	(7.409)	(12.071)	(3.064)	(1.270)	(25.380)	(18.040)
LEV	-2.335***		-3.096**		-7.720**		-0.325		3.167	
	(0.449)		(1.313)		(3.634)		(0.557)		(2.810)	
Debt		-5.097***		1.195**		-7.098***		-2.631***		1.338
		(0.315)		(0.490)		(2.143)		(0.228)		(5.273)
Tobin-Q	0.127	1.127***	-0.257	-0.223	-22.920**	-13.830	0.056***	0.146***	-0.428***	-2.037***
	(0.081)	(0.108)	(0.210)	(0.211)	(10.370)	(8.540)	(0.006)	(0.011)	(0.162)	(0.340)
ROA	3.223***		-3.064***		91.011***		1.279***		57.317***	
	(0.274)		(0.543)		(26.890)		(0.102)		(9.038)	
OROA		-1.013***		1.042***		22.564		-0.086		43.375***
		(0.333)		(0.236)		(18.722)		(0.179)		(13.851)
Growth	-0.738	-0.511	0.245	-0.003	-0.053	-0.118**	-0.061	-0.264	0.185***	0.039*
	(0.594)	(0.447)	(0.615)	(0.458)	(0.072)	(0.054)	(0.553)	(0.324)	(0.030)	(0.021)
IP	1.378		-1.127		-0.428		-1.728		-1.204***	
	(1.052)		(1.148)		(0.373)		(1.834)		(0.267)	

continued next page

Table 14 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		0.289		-0.364		0.122		-0.612		-0.307***
		(0.314)		(0.337)		(0.077)		(0.550)		(0.084)
Shadow	0.073	0.070	0.131	0.131	3.210	3.196	0.389	0.391	-0.415	-0.416
	(0.498)	(0.494)	(0.385)	(0.381)	(2.093)	(2.095)	(0.328)	(0.326)	(0.761)	(0.762)
VIX	-0.008	-0.007	-0.051	-0.051	0.002	0.002	-0.001	-0.001	-0.005	-0.005
	(0.012)	(0.012)	(0.055)	(0.055)	(0.027)	(0.027)	(0.011)	(0.011)	(0.017)	(0.017)
Interbank	0.057	0.057	-0.078	-0.078	0.276	0.275	0.047	0.047	-0.111	-0.110
	(0.119)	(0.114)	(0.321)	(0.321)	(0.378)	(0.379)	(0.104)	(0.104)	(0.121)	(0.125)
Constant	15.001**	4.971	34.128***	39.987**	63.826***	12.516	31.764**	62.164*	-25.118	2.699
	(5.872)	(17.294)	(8.207)	(19.929)	(11.496)	(10.980)	(12.359)	(32.349)	(27.844)	(18.137)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.687	0.692	0.604	0.604	0.350	0.349	0.846	0.847	0.601	0.601

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

Table 15: Determinants of MES in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.011***	-0.012***	-0.005***	-0.007***	0.012	0.064***	0.002***	0.002***	-0.018	0.024
	(0.001)	(0.001)	(0.001)	(0.001)	(0.021)	(0.021)	(0.001)	(0.001)	(0.017)	(0.017)
Size	3.709***	4.478***	-5.196***	-3.560***	1.755***	0.942***	1.267***	1.374***	8.478***	-1.454
	(0.400)	(0.284)	(0.472)	(0.378)	(0.255)	(0.257)	(0.227)	(0.130)	(2.971)	(1.534)
LEV	-0.061		-0.314***		0.371***		-0.148***		2.114***	
	(0.129)		(0.067)		(0.059)		(0.029)		(0.681)	
Debt		-0.096		-0.261***		0.243***		-0.306***		2.754***
		(0.086)		(0.044)		(0.062)		(0.016)		(0.891)
Tobin-Q	-0.090***	-0.072***	-0.020***	-0.025***	-0.014	-0.395***	-0.002***	0.009***	0.498***	0.263**
	(0.010)	(0.020)	(0.006)	(0.006)	(0.139)	(0.143)	(0.001)	(0.001)	(0.098)	(0.116)
ROA	-0.031		0.459***		2.312***		0.107***		-0.437	
	(0.052)		(0.056)		(0.710)		(0.013)		(1.540)	
OROA		-0.346***		0.211***		2.121***		-0.063***		2.259
		(0.060)		(0.051)		(0.467)		(0.019)		(1.712)
Growth	0.196*	0.162*	-0.003	0.058	-0.015***	-0.014***	0.063	0.045	0.068***	0.049***
	(0.106)	(0.085)	(0.182)	(0.151)	(0.001)	(0.001)	(0.060)	(0.042)	(0.014)	(0.011)
IP	-0.239		0.421		-0.004		-0.149		-0.157***	
	(0.169)		(0.258)		(0.004)		(0.149)		(0.050)	

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Table 15 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		-0.073		0.134*		-0.013***		-0.053		-0.049***
		(0.052)		(0.078)		(0.001)		(0.045)		(0.015)
Shadow	0.024	0.024	-0.014	-0.014	0.025	0.026	-0.006	-0.006	-0.069	-0.066
	(0.103)	(0.104)	(0.117)	(0.117)	(0.040)	(0.039)	(0.050)	(0.050)	(0.306)	(0.306)
VIX	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.007)	(0.007)
Interbank	0.016	0.016	-0.013	-0.013	0.005	0.005	0.010	0.010	-0.074	-0.073
	(0.020)	(0.019)	(0.021)	(0.021)	(0.008)	(0.008)	(0.009)	(0.009)	(0.068)	(0.069)
Constant	-1.633	0.410	3.082**	-3.640	-1.634***	0.274	0.160	2.335	-7.073*	4.438**
	(1.026)	(2.892)	(1.391)	(4.236)	(0.309)	(0.353)	(0.970)	(2.615)	(3.695)	(2.201)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.378	0.379	0.255	0.255	0.506	0.507	0.140	0.140	0.393	0.393

Note: this table reports regression results of the marginal expected shortfall (MES) on firms, country, and global factors. In all regressions, we control for firms' fixed effects, country fixed effects and week-year (time) effects. Robust standard errors are reported in parentheses. ***p<0.01, ** p<0.05, * p<0.1.

Table 16: Determinants of CoVaR in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.001***	-0.002***	-0.000**	-0.000	0.009**	0.007**	0.000***	0.000***	-0.005	0.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.006)	(0.006)
Size	0.555***	0.702***	0.182***	0.228***	-0.020	0.040	-0.009	0.062***	2.842***	0.794***
	(0.043)	(0.034)	(0.027)	(0.029)	(0.039)	(0.042)	(0.030)	(0.019)	(0.434)	(0.297)
LEV	0.009		-0.025***		-0.005		-0.041***		0.533***	
	(0.012)		(0.005)		(0.010)		(0.004)		(0.052)	
Debt		-0.026***		0.005**		-0.022**		-0.061***		0.979***
		(0.008)		(0.003)		(0.010)		(0.004)		(0.091)
Tobin-Q	-0.022***	-0.018***	-0.003***	-0.002***	-0.063***	-0.055**	0.001***	0.003***	0.019***	0.043***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.022)	(0.022)	(0.000)	(0.000)	(0.003)	(0.007)
ROA	0.005		-0.039***		0.269**		0.011***		1.870***	
	(0.006)		(0.004)		(0.124)		(0.001)		(0.168)	
OROA		-0.099***		-0.014***		0.009		-0.012***		2.256***
		(0.007)		(0.003)		(0.082)		(0.003)		(0.232)
Growth	-0.041***	-0.031***	-0.047***	-0.038***	0.000*	0.000***	-0.046***	-0.040***	0.001*	0.000
	(0.012)	(0.009)	(0.007)	(0.005)	(0.000)	(0.000)	(0.010)	(0.006)	(0.001)	(0.000)
IP	0.075***		0.070***		0.000		0.039		-0.014***	
	(0.019)		(0.011)		(0.001)		(0.033)		(0.005)	

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Table 16 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		0.022***		0.021***		0.000*		0.010		0.010***
		(0.006)		(0.003)		(0.000)		(0.010)		(0.001)
Shadow	0.016	0.016	0.016**	0.016**	0.023**	0.023**	0.022***	0.022***	0.008	0.009
	(0.013)	(0.013)	(0.008)	(0.008)	(0.009)	(0.009)	(0.007)	(0.007)	(0.020)	(0.019)
VIX	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Interbank	0.004	0.004	0.002	0.002	0.002*	0.002*	0.002	0.002	-0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Constant	0.276**	-0.660**	0.599***	-0.234	1.121***	1.052***	1.003***	0.617	-1.957***	-1.022***
	(0.115)	(0.322)	(0.067)	(0.191)	(0.044)	(0.052)	(0.212)	(0.574)	(0.475)	(0.301)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.811	0.812	0.882	0.882	0.822	0.822	0.814	0.815	0.627	0.632

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

Table 17: Determinants of ΔCoVaR in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.001***	-0.002***	0.000*	0.000***	0.008**	0.006**	0.000***	0.000***	0.001	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.006)	(0.006)
Size	0.448***	0.624***	0.056***	0.093***	-0.053	-0.000	0.005	0.137***	1.163***	0.805***
	(0.040)	(0.030)	(0.020)	(0.024)	(0.035)	(0.038)	(0.028)	(0.019)	(0.425)	(0.295)
LEV	-0.027**		-0.017***		-0.001		-0.052***		0.080*	
	(0.012)		(0.004)		(0.009)		(0.004)		(0.048)	
Debt		-0.047***		0.005***		-0.015*		-0.062***		0.034
		(0.008)		(0.002)		(0.009)		(0.004)		(0.086)
Tobin-Q	-0.021***	-0.011***	-0.002***	-0.002***	-0.053**	-0.044**	0.001***	0.003***	-0.010***	-0.040***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.021)	(0.021)	(0.000)	(0.000)	(0.003)	(0.006)
ROA	-0.003		-0.015***		0.268**		0.015***		1.099***	
	(0.006)		(0.002)		(0.122)		(0.001)		(0.167)	
OROA		-0.091***		0.005***		0.104		-0.012***		0.817***
		(0.006)		(0.001)		(0.079)		(0.003)		(0.228)
Growth	0.009	0.008	0.001	0.000	0.000	-0.000	0.000	-0.002	0.003***	0.001
	(0.009)	(0.007)	(0.003)	(0.002)	(0.000)	(0.000)	(0.008)	(0.005)	(0.001)	(0.000)
IP	-0.007		-0.006		-0.001**		-0.021		-0.023***	
	(0.015)		(0.005)		(0.001)		(0.025)		(0.005)	

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Table 17 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		-0.003		-0.002		0.000		-0.008		-0.006***
		(0.005)		(0.002)		(0.000)		(0.008)		(0.001)
Shadow	0.000	0.000	-0.000	-0.000	0.007*	0.007*	0.006	0.006	-0.007	-0.007
	(0.009)	(0.009)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)	(0.013)	(0.013)
VIX	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Interbank	0.002	0.002	-0.000	-0.000	0.001	0.001	0.000	0.000	-0.002	-0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.217**	-0.251	0.066*	0.089	0.155***	0.089**	0.245	0.451	-0.704	-0.100
	(0.097)	(0.263)	(0.036)	(0.090)	(0.036)	(0.044)	(0.167)	(0.450)	(0.464)	(0.297)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.598	0.601	0.552	0.551	0.592	0.592	0.438	0.443	0.767	0.767

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

Table 18: Determinants of CAViaR in the WAEMU by sector

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR	-0.051***	-0.059***	-0.026***	-0.047***	0.324***	0.421***	0.013***	0.012***	-0.284***	-0.327***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.099)	(0.100)	(0.002)	(0.002)	(0.024)	(0.017)
Size	26.775***	28.380***	6.862***	18.175***	2.326	8.793***	22.617***	11.047***	32.970***	41.053***
	(0.574)	(0.533)	(1.554)	(1.212)	(1.995)	(2.185)	(0.843)	(0.335)	(5.042)	(2.198)
LEV	-1.644***		-2.425***		-5.073***		2.216***		-2.945***	
	(0.078)		(0.226)		(0.535)		(0.137)		(1.116)	
Debt		-2.579***		-2.470***		-5.048***		0.229***		-1.457
		(0.064)		(0.153)		(0.407)		(0.053)		(1.213)
Tobin-Q	-0.466***	0.070**	0.142***	0.091***	-6.231***	-5.013***	0.018***	-0.006**	-0.955***	-0.789***
	(0.027)	(0.029)	(0.022)	(0.024)	(1.374)	(1.193)	(0.002)	(0.002)	(0.139)	(0.106)
ROA	-0.067		2.965***		15.040***		1.182***		14.109***	
	(0.092)		(0.197)		(3.420)		(0.060)		(2.123)	
OROA		-1.858***		1.452***		7.169***		1.568***		8.334***
		(0.101)		(0.133)		(2.405)		(0.067)		(2.002)
Growth	-0.950***	-0.388***	-1.041***	-0.601***	-0.040***	-0.054***	-0.785***	-0.323**	0.032**	-0.035*
	(0.203)	(0.146)	(0.266)	(0.205)	(0.012)	(0.011)	(0.182)	(0.139)	(0.014)	(0.020)
IP	3.870***		3.158***		-0.179***		3.268***		-0.385***	
	(0.369)		(0.458)		(0.040)		(0.347)		(0.060)	

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Table 18 Continued

	Agriculture		Distribution		Finance		Industry		Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Composite		1.095***		1.034***		-0.021*		0.947***		-0.012
		(0.106)		(0.136)		(0.011)		(0.104)		(0.013)
Shadow	-0.006	-0.008	-0.025	-0.029	0.470*	0.467*	0.082	0.086	-0.111	-0.118
	(0.193)	(0.188)	(0.274)	(0.278)	(0.267)	(0.269)	(0.154)	(0.155)	(0.233)	(0.233)
VIX	-0.002	-0.002	-0.005	-0.005	-0.001	-0.001	-0.002	-0.002	0.003	0.003
	(0.005)	(0.005)	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Interbank	-0.000	-0.000	-0.021	-0.021	0.058	0.058	0.007	0.007	-0.011	-0.011
	(0.041)	(0.037)	(0.053)	(0.052)	(0.100)	(0.100)	(0.033)	(0.032)	(0.047)	(0.047)
Constant	-43.888***	-85.080***	-20.963***	-71.930***	9.288***	1.795	-39.094***	-61.916***	-26.588***	-37.464***
	(2.111)	(5.978)	(2.876)	(7.594)	(2.680)	(2.652)	(2.134)	(5.824)	(5.955)	(2.562)
Observations	16,888	16,888	25,332	25,332	21,110	21,110	50,664	50,664	12,666	12,666
R-squared	0.829	0.841	0.525	0.526	0.415	0.412	0.581	0.579	0.478	0.478

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

Conclusion

The aim of this paper was to study the systemic risk in the WAEMU regional stock exchange. It focuses on financial and non-financial listed companies grouped into six sectors and uses systemic risk measures suggested in the literature.

We find strong linkages across all six sectors increasing the channels through which a sector-specific shock can propagate to the entire financial sector and other economic sectors. Indeed, there is a dense network among companies operating in the distribution and in agriculture sectors (intra-sectoral network). There is also a dense network between distribution, finance, industry, and utility sectors. Companies operating in the distribution sector are highly connected to those operating in finance, industry, and utility sectors. However financial firms are mostly connected to companies in the industrial sector, and companies in the industrial sector are highly connected to those in the distribution and utility sector. Also, companies operating in the utility sector are strongly connected to financial institutions and firms in the agriculture sector. Furthermore, there is a strong connection from companies operating in the agriculture sector to finance, industry, utility and transportation sectors. Finally, companies operating in the transportation sector are highly connected to those operating to distribution, industry and utility sectors. We can conclude that the financial and industrial sectors can be seen as the centre of the system around which the other sectors rotate.

Nevertheless, systemic firms belong to the distribution (BNBC, SHEC), industry (CABC) and agriculture (PALC, SOGC) sectors in the sense that they are more likely to propagate shock to the global market. This result is consistent with the fact that companies in the distribution and agriculture sectors are strongly connected to firms operating in other sectors.

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. They belong to distribution (TTLC), finance (SGBC), utility (CIEC, SDCC, SNTS) and agriculture (PALC, SOGC, SPHC) sectors. In addition, SLBC (in the industry) has a large contribution to the system-wide risk according to CoVaR and ΔCoVaR. Therefore, financial firms are not the only source of systemic risk in the WAMEU regional stock market, even though they play an important role in the system.

Systemic risk has also a time series dimension. We find that the market was turbulent and therefore subject to high risk (i) during the onset of the global financial

crisis, especially the collapse of the subprime market, (ii) after the Lehman Brothers bankruptcy in September 2008, (iii) at the onset of post-election war in Côte d'Ivoire and (iv) at the start of the war in Mali. Other turbulent periods were identified between July 2017 and June 2018, during the first week of August 2018, and 8/9 January 2019. During turbulent periods, the market experiences negative daily returns on average except for companies operating in the utilities and transportation sectors.

Finally, we perform regression analysis to analyse potential determinants of systemic risk. We find that big firms and high value companies contribute more to systemic risk. In contrast, debt seems to play a disciplinary effect in the sense that high level of debt is associated with low systemic risk. The effects of financial distress and profitability are mixed. Apart from the agriculture sector, financial distress is positively correlated with systemic risk. Overall, we find that the determinants of systemic risk depend on the indicator used to assess systemic risk and the sectors in which companies operate. Therefore, the WAEMU financial system is not one-size-fits-all system.

Although macro-prudential policies can be applied to monitor the stability of the financial system as a whole to prevent the progressive build-up of systemic risk, this paper shows that micro-prudential policies must be used as a complementary tool. First, a single indicator is not sufficient to capture the level of systemic risk in the market. Second, systemic risk should be monitored over time and across firms (cross-sectional and time dimensions). Third, company size, financial distress and value are three key indicators to monitor by the regulator. Fourth, the behaviour of the financial sector should be analysed in relation to global factors such as the stance of monetary policy in the United States as well as the interbank rate in the WAEMU.

Notes

* This paper describes research in progress and is made available to elicit comments and to encourage debate. The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management. All disclaimers apply.

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1. These countries are Benin, Burkina Faso, Guinea- Bissau, Côte d'Ivoire, Mali, Niger, Senegal, Togo.

2. We do not use indicators that required a cut-off on capital-to-asset ratio such as the systemic expected shortfall (SES) by Acharya et al. (2017) and the conditional capital shortfall index (SRISK) by Brownlees and Engle (2017). These measures are more appropriate for financial institutions for which there is a cut-off compared to other sectors that do not have one according to the regulatory framework in the WAEMU region.

3. Quarterly financial reports are not detailed and do not include liabilities, these reports focus on operating results.

4. It is also possible to proxy size by the logarithm of total assets as in Zhu et al. (2020).

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

6. Only companies identified as high risk by 3 or 4 indicators are reported.

7. The threshold corresponds to the 95^{th} percentile of the distribution, which assumes a 5% significance level.

8. These definitions are taken from Zhan et al. (2017).

9. We do not interpret the results on CoVaR and ΔCoVaR because the sign of the variable size changes with the inclusion of leverage even if the correlation between these two variables is slow.

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Appendix

Table 19: 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	Sénégal
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 20: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
BMR (1)	1															
Size (2)	0.17***	1														
Debt (3)	-0.10***	-0.33***	1													
LEV (4)	-0.13***	-0.31***	0.65***	1												
Tobin-Q (5)	0.00	-0.19***	0.48***	-0.04***	1											
ROA (6)	0.07***	0.23***	-0.40***	-0.40***	0.11***	1										
OROA (7)	0.11***	0.29***	-0.41***	-0.48***	0.18***	0.89***	1									
PS (8)	0.01**	0.21***	0.03***	0.04***	-0.05***	0.09***	0.05***	1								
Growth (9)	0.00	0.00	0.06***	-0.05***	-0.06***	-0.01**	-0.04***	0.45***	1							
Gvt Debt (10)	0.00	-0.06***	-0.08***	-0.04***	0.05***	-0.05***	0.00	-0.75***	-0.69***	1						
IP (11)	0.01**	0.09***	0.05***	0.00	-0.06***	0.03***	0.00*	0.76***	0.69***	-0.74***	1					
Composite (12)	0.03***	0.05***	-0.02***	-0.16***	0.03***	0.15***	0.10***	0.69***	0.49***	-0.55***	0.70***	1				
FFR (13)	-0.01***	-0.02***	-0.04***	0.04***	-0.02***	-0.03***	-0.01***	-0.40***	-0.30***	0.48***	-0.45***	-0.32***	1			
VIX (14)	0.00	-0.02***	-0.03***	0.00*	0.04***	0.07***	0.05***	-0.01***	-0.28***	0.09***	-0.24***	-0.09***	-0.25***	1		
Interbank (15)	0.03***	-0.01**	-0.02***	-0.03***	0.01***	0.03***	0.01***	-0.07***	0.01***	0.12***	-0.13***	0.01***	0.28***	0.10***	1	
Shadow (16)	0.01***	-0.01***	-0.05***	0.06***	-0.02***	-0.05***	-0.04***	-0.40***	-0.36***	0.56***	-0.49***	-0.37***	0.93***	-0.12***	0.38***	1

Note: this table reports Pearson correlation coefficients. Stars indicate the significant of each correlation coefficient: ***p<0.01, ** p<0.05, * p<0.1.

Table 21: Determinants of systemic risk by controlling for additional factors

	VaR		ES		MES		CoVaR		ΔCoVaR		CAViaR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BMR	0.004***	0.004***	0.009**	0.007*	0.000	0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Size	3.236***	3.199***	6.264***	6.639***	2.591***	2.605***	0.087***	0.081***	0.139***	0.135***	12.038***	12.134***
	(0.466)	(0.462)	(1.610)	(1.580)	(0.080)	(0.080)	(0.013)	(0.013)	(0.012)	(0.012)	(0.288)	(0.286)
Debt	-0.785***	-0.780***	-2.081***	-2.178***	-0.012	-0.013	-0.048***	-0.046***	-0.049***	-0.048***	-0.806***	-0.794***
	(0.060)	(0.061)	(0.182)	(0.183)	(0.013)	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.041)	(0.042)
Tobin-Q	0.045***	0.045***	0.130***	0.131***	-0.000	-0.000	0.003***	0.003***	0.002***	0.002***	0.024***	0.025***
	(0.003)	(0.003)	(0.010)	(0.010)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
ROA	-0.110***	-0.102***	0.247**	0.136	0.085***	0.082***	-0.016***	-0.014***	-0.013***	-0.012***	1.105***	1.107***
	(0.035)	(0.035)	(0.112)	(0.111)	(0.014)	(0.014)	(0.002)	(0.002)	(0.001)	(0.001)	(0.050)	(0.050)
Growth	0.004		0.028		0.008**		0.000***		0.000***		-0.009	
	(0.004)		(0.039)		(0.004)		(0.000)		(0.000)		(0.011)	
Gvt debt		-0.001		0.051***		0.002**		-0.001***		-0.000***		-0.015***
		(0.001)		(0.010)		(0.001)		(0.000)		(0.000)		(0.001)
PS	0.058**		-1.292***		-0.052***		0.019***		0.008***		0.136***	
	(0.023)		(0.167)		(0.015)		(0.001)		(0.000)		(0.037)	
FFR	0.002	0.002	0.129	0.129	0.028	0.028	-0.019***	-0.019***	-0.001	-0.001	0.023	0.023
	(0.051)	(0.051)	(0.210)	(0.210)	(0.027)	(0.027)	(0.004)	(0.004)	(0.002)	(0.002)	(0.073)	(0.073)

continued next page

Table 21 Continued

	VaR		ES		MES		CoVaR		ΔCoVaR		CAViaR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VIX	-0.004	-0.004	-0.011	-0.011	0.000	0.000	0.006***	0.006***	-0.000	-0.000	-0.002	-0.002
	(0.004)	(0.004)	(0.013)	(0.013)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Interbank	0.003	0.003	0.037	0.037	-0.003	-0.003	0.002*	0.002*	0.000	0.000	0.006	0.006
	(0.028)	(0.028)	(0.103)	(0.103)	(0.010)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.026)	(0.026)
Constant	1.699***	1.689**	19.685***	19.124***	-1.956***	-1.948***	1.146***	1.156***	0.044**	0.047**	-10.000***	-9.579***
	(0.654)	(0.657)	(1.930)	(2.023)	(0.205)	(0.207)	(0.022)	(0.022)	(0.019)	(0.019)	(0.360)	(0.358)
Observations	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882	130,882
R-squared	0.298	0.298	0.697	0.697	0.210	0.210	0.794	0.794	0.711	0.711	0.481	0.482

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

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