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THE AGGREGATED LEVERAGE RATIO AND THE DETECTION OF FINANCIAL VULNERABILITY: EVIDENCE FROM THE UNITED STATES AND EUROPEAN COUNTRIES

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ABSTRACT :

The aim of this paper is to put forward a relevant indicator that could help supervisors to regulate the excessive use of leverage which gives rise to systemic risk. We suggest the aggregated leverage ratio named "Global Aggregated Leverage Ratio" (GALR), which encompasses the activity of commercial and investment banks. We test this indicator through *logit* regressions over the period 2001-2008. We find evidence that the GALR may be a good leading indicator of the build up of financial vulnerabilities then it could be integrated into macro-prudential tools. Moreover, it is costless to compute and consequently easy to implement.

JELCLASSIFICATION : C 52, G21, G24, G28.

KEYWORDS : leverage, securitization, prudential regulation, systemic risk, commercial/investment banks.

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INTRODUCTION

The 2007 summer crisis has emphasized the failure of credit economy based on investments bank "*originate and distribute*" business model. This crisis revealed an excessive use of leverage on behalf of some financial institutions as for example investments bank, SIVs, and *hedge funds*. This excessive leverage is the result of a continuing process of financial innovations which led to an array of new structured products, to the securitization of many loans, and to the extension of market participants. Therefore, it has promoted the emergence of the shadow banking system (Crockett, 2007). This last one is compounded of leveraged financial firms without any deposit base, hence whose funding stems entirely from wholesale money markets (Brunnermeier, 2009).

Given that, leverage can lead to systemic risk mainly because it is pro cyclical as shown in the vicious circle of leverage, it seems crucial for the supervisory authorities to find a way to limit this excessive use of leverage and consequently to control it. What makes leverage excessive and potentially systemic is the fact that these institutions manage their leverage in an active way. That is to say leverage is procyclical (Borio and alii, 2001; Goodhart, 2004). Leverage amplifies in the same time gains and losses depending on the position in the financial cycle. It is a first source of fragility. The second characteristic which makes leverage potentially systemic is related to the fact that each of them rely on short term borrowing. This reliance on short term borrowing makes these institutions more vulnerable to disruption on market liquidity. This huge leverage through fuelled the cumulative process between credit expansion and the increase of asset prices which leads to financial instability and then to a higher systemic risk.

The new finance model has increased the potential for contagion that raises systemic risk. Contagion is the mechanism by which an event may cause a financial crisis as well as a bank run, a credit crunch, a general fall in financial assets prices and the freezing of payment systems (Kashyap and Stein, 2000; Van den Heuvel, 2002). In booming periods, collateralized asset price increases. The more collateralized asset price increases, the more banks have incentives to grant new loans, and the more investors are keen to hold these assets. This process tends to boost the size of these financial institutions' balance sheet and to decrease mechanically their leverage (Kashyap and Stein, 2004; Adrian and Shin, 2008). Financial institutions will buy more assets to reach their target leverage. This will generate an increase of asset prices which will create an additional increase of balance sheet (like positive feed back). It is *vis versa* for downturn periods (Fisher 1933; Bernanke and alii, 1999).

Moreover, the combination of liquidity with derivatives and the leverage they induce is a dangerous formula which can lead to huge difficulties. This combination prevents a crisis and favours the quickly worsening of the crisis. Then, an important deleveraging process will freeze credit markets. The increase in the cost of borrowing can create a slowdown in economic growth. This de-leveraging process illustrates that the crisis has become systemic if supervising institutions don't manage to stop it (Brunnermeier, 2009). The credit guarantees and liquidity lines make links between the sponsoring bank and the SIV sounder (Roubini, 2008).

In reality, the total leverage responsible for the crisis is not captured by the traditional indicators of credit deviation (monetary aggregates, credit growth...). Therefore supervisors are not able to observe the real evolution of the economy indebtedness. To observe credit deviation it can be useful to focus on an aggregated leverage (investment banks, SIVs and hedge funds, commercial banks). Indeed, the institutions of shadow banking can benefit from a huge leverage. Incited by an inflated optimism, they use it acutely to maximize their yield. So in reality, the agents responsible for the excessive leverage are out of the scope of supervisors (Hellwig, 2008). That is why we focus on the leverage of the extended banking system (the so-called shadow banking system). We would like to test if a global aggregated leverage ratio can be a good indicator of credit deviation in the economy. While most of researches focus on the aggregated leverage of each financial institution (Hildebrand, 2008), our paper points out a calculation of a global aggregated leverage.

After the reminder of the current regulation framework on commercial banks and highly leveraged institutions which give rise to regulatory by-pass, we will test the validity of the Global Aggregated Leverage Ratio (GALR) as a macro-prudential tool over the 2001-2008 period through a statistical analysis and logistic regressions. Our results suggest that the GALR may be a good leading indicator of the built-up of financial vulnerabilities. Then, it could be integrated into macro-prudential tools.

The remainder of the paper is organized as follows: in the first section, we propose the global aggregated leverage ratio GALR as a complementary leading indicator of credit deviation. In the second section, we present the data and the methodology used in the empirical analysis. In the third section we analyze and comment the empirical results. And we conclude.

1. TOWARD ENHANCED LEVERAGE MEASUREMENT TOOLS

Leverage fuelled too optimistic anticipations about the continuous rise of asset prices. Hence it is important to control leverage evolution to avoid the likelihood of this vicious cycle to happen due to its detrimental consequences on financial stability and real economy. We will now make a brief recall about the current micro-prudential framework and the perimeter of banking regulators and supervisors to put forward the need for regulatory authorities to develop macro-prudential regulation to really be able to preserve financial stability. The idea is to test if the implementation of a new complementary macro-prudential tool which monitors the evolution of global leverage can improve the detection of financial instability.

Micro-prudential and macro-prudential supervision are clearly intertwined at several levels. But, micro-prudential supervision is traditionally at the core of banking supervisors' attention all around the world. The main objective of micro-prudential supervision is to supervise and to limit individual financial institutions' distress in order to protect the bank's depositors. Prudential authorities thought that by ensuring individual banks' solvency, the risk of a financial crisis to happen was

reduced. So, the preservation of financial stability was an indirect goal of prudential regulation.

Until 2008, the regulatory framework for commercial banks was Basel I. Basel II has come into force in Europe only in 2008 and has been implemented in the United States in 2009 but only for the biggest banks. The objective of the Basel I and the Basel II prudential regulation is to protect depositors and to protect financial stability. The main instrument used to achieve this goal is capital adequacy requirements through a risk-based capital ratio. In the Basel legislations, capital requirements are relative to the bank's exposition to risks. In the U.S., banks are also required to comply with a leverage ratio requirement what represent a significant difference between the two geographical spaces. The leverage ratio interest leans on the fact that it is a simple ratio, publicly, easy to check and consequently hard to manipulate contrary to the risk-based capital ratio which is more complex. The risk-based capital ratio must be equal to 8 % and the US leverage ratio[3] 's limit is set at 2% (Freixas and Parigi, 2007). Banking regulators have begun to draw the lessons of the recent financial crisis and have introduced a leverage ratio in the new Basel 3 package. The limit for the European leverage ratio is set at 3%. Even if some academics consider that this limit is too low, the most important is that things are going in the right direction.

During a long period, supervisors relied only on an indirect regulation for *hedge funds* via their prime brokers. Indeed, most of *hedge funds*' counterparts are regulated. Moreover, they are subjected to market discipline from their investment partners through their trading in equity and debt markets and, supervisors considered that this framework was enough. Consequently, *hedge funds*' regulation only rested on the promotion of standards of good conduct and not on compulsory disclosures. But, regulators have drawn the lessons of the recent financial crisis and, take now into account the systemic feature of *hedge funds*. Indeed, the European Directive *Alternative Investment funds managers* (AIFM) enacted in December 2010 plans to require more information before giving to *hedge funds* the authorization to operate in the European space. It will allow improving hedge funds' transparency. A similar financial plan reform (*financial reform bill*) has been promulgated in July 2010 in the United States for large hedge funds.

Until the current crisis, investment banks are also subject to lower capital and disclosure requirements than commercial banks in the US and in Europe. In the United States, they have to disclose some information to the SEC. These disclosures can be made through two different reporting forms: FOCUS (Financial and Operational Combined Uniform Single Report) or FOGS (Report on Finances and Operations of Government Securities Brokers and Dealers).

Finding information about SIVs is a hard task given their opacity. They do not have disclosure requirement to any supervisory authority. The only information about SIVs is those disclosed to banking regulator at the time of their creation. Besides, some of these SIVs are located in offshore places. This location allows them to benefit a light prudential regulation and favourable accountability rules (Ashman,

[3] The US leverage ratio is the ratio of tier one capital to total assets.

2000). These vehicles don't belong to banks consolidation perimeter then, it is difficult for supervisors to monitor the way these vehicles reallocate risks between geographical and sectorial areas.
Therefore, we observe that most of these highly leveraged financial institutions (investment banks, SIVs and hedge funds) are paradoxically those on which supervisors have less control.

We have seen that it is crucial for supervisors to control leverage to preserve financial stability. We have also note that investment banks, hedge funds and SIVs are amongst the most leveraged financial institutions whereas they are out of the scope of banking regulators. Prudential regulation and supervision should consequently not only focus on commercial banks, but it should encompass all potential systemic institutions as well as nonbank depository corporations and non depository financial intermediaries. The current crisis corroborates this point. Therefore, prudential regulation has to be reconsidered to impose SIVs and hedge funds minimal information disclosures. Consequently, prudential regulation has to be extended to all the financial system participants. This is a crucial turning point in prudential regulation to protect the financial system. The fact that the financial system as a whole may be exposed to common risks is not always fully taken into account. The development of macro-prudential analysis will therefore help to pay more attention to contagious knock-on or feedback effects related to this shadow banking system. The objective of macro-prudential supervision is to limit the distress of the financial system as a whole in order to protect the overall economy from significant losses in term of real output.

Micro-prudential supervision cannot effectively preserve financial stability without adequately taking into account macro-level developments. As far as macro-prudential supervision is concerned, it needs to be strengthened. Lessons from the financial crisis are now drawn and, there is an international consensus emerging on the need to strengthen macro-prudential regulation to reduce the systemic impact of future financial crises (De Larosière Report, 2009). In this part of the paper, we want to demonstrate that a global aggregated leverage ratio may be a good leading indicator for supervisors to detect credit deviation in the financial system.

This need for strengthening macro-prudential supervision had previously been taken into account with the development of early warning systems (EWS) literature. Macro-prudential regulation allows detecting significant vulnerabilities within the financial system. In this regard, there is a consensus on the need to devise an appropriate early warning system to reveal vulnerabilities of the financial system. However, there is no universally accepted set of indicators for monitoring financial markets. International Monetary Fund (IMF) has introduced *Financial soundness indicators* (*FSIs*) which are defined to be indicators compiled to monitor soundness of financial institutions and markets. Moreover, IMF has collaborated with national authorities and other international financial institutions in developing macro prudential indicators (MPIs) and formulating methods in analyzing these indicators of financial soundness. The IMF considers macro-prudential analysis as a key element in designing a policy framework on vulnerability analysis (IMF, 2001). IMF's initial list of MPIs can be divided in three main groups—aggregated micro-prudential indicators, macroeconomic indicators and market-based indicators—to

reflect the health of financial institutions and the broader extent of systemic soundness of the financial system. This paper attempts to propose a new leading macro-prudential indicator (MPI) for monitoring vulnerability in financial markets. The indicator we estimate here is a global aggregated leverage ratio which could belong to the first group of indicators (Bhattacharyay, 2003).
IMF's aggregated micro-prudential indicators are not perfect mainly because the relevance of individual indicators may vary from one country to another country. Indeed, MPIs cannot be used mechanically due to differences in each country's practices. Despite this limitation, aggregated micro prudential indicators can be useful tools at a national level.

2. DATA AND METHODOLOGY

In order to reduce the likelihood of a systemic crisis to happen, we construct a global leverage indicator called the "Global Aggregated Leverage Ratio" (GALR) compounded of commercial and investment banks aggregated leverage. We test if it could be a good indicator of credit deviation. Even if it is crucial to have a representative picture of the global leverage, we don't integrate hedge funds and SIVs in our calculations. The reasons why we do not integrate hedge funds and SIVs in our calculations are the following: First of all, the estimation of hedge funds' leverage is usually done through an approach based on their various strategies. This methodology can't directly be compared with our approach more based on the institutions' balance sheets (Blundell Wignall A., 2007). Moreover, data on hedge funds' equity and assets are not fully available. As far as SIVs are concerned, it is the lack of transparency inherent to these vehicles which don't allow us to obtain the required information for the calculation of the global leverage.

The formula we use to estimate the global aggregated leverage is the ratio of total assets for commercial and investment banks to total equity for commercial and investment banks. With this formula, we are in line with the prudential regulation approach where equity is the pivot variable (Adrian T. and Shin H. S., 2008).

To test the validity of the Global Aggregated Leverage Ratio as a new macro-prudential tool to detect credit deviation, we first compare the boom periods detected by the Global Aggregated Leverage Ratio with the ones detected by traditional indicators of credit deviation. Boom periods are identified through the observation of the deviations of credit series from their long-term trend. The idea is to see if the Global Aggregated Leverage Ratio is a better indicator of credit deviation than traditional indicators. To finish, we perform *logit* regressions to compare through an econometrical methodology the Global Aggregated Leverage Ratio's predictive power with the one of traditional indicators of credit deviation.

We use a sample consisting of a balanced panel of annual data from 2001 to 2008 for a set of European commercial, cooperative, and investment banks established in 12 European countries: Denmark, France, Germany, Italy, Luxembourg, Netherlands, Norway, Ireland, Iceland, Sweden, Switzerland, and Germany. We also consider US commercial and investment banks for the same period. We chose this period of study to capture a complete financial cycle. We begin our study in

2001 because it corresponds to the end of the NITC financial cycle and the beginning of a new one. The year 2008 corresponds to the subprime crisis which ends this cycle. To obtain the aggregated data for European commercial and investment banks we aggregate equity capital and total assets, then we calculate the aggregated leverage ratio. We only consider banks with total assets higher than one billions. We use two distinct statistical sources for US commercial and investment banks over the time period 2001-2008. To obtain data about commercial banks (equity capital, total assets), we use the aggregated annual data produced by the FDIC *(FDIC historical and quarterly banking data)*. As far as US investment banks are concerned, we use Bankscope data as well as for European commercial and investment banks. The final dataset contains 104 observations. The entire dataset is then divided into "in sample" and "out sample" subsets to check the robustness of our results. The "in sample" set contains 78 observations and the "out sample" set 26 observations.

To analyze the effectiveness of the different indicators used to detect credit deviation in the financial system, we compare the boom periods detected by the Global Aggregated Leverage Ratio with the ones detected by traditional indicators of credit deviation. Here, we lean on theories which consider that excessive credit expansion is due to banks' herding behaviour (Kindleberger, 2000). Indeed, worst loans are granted at the peak of the financial cycle (Greenspan, 2001). It means that systemic risk is built-up during the raising phase of the financial cycle (Borio and Lowe, 2001 and, Borio and al, 2001). Boom periods are identified through the observation of the deviations of credit series from their long-term trend. The indicators we consider here are the GALR, and the ratio of credits over the GDP which is the indicator currently used to monitor credit variation. The methodology used in this part of the paper is in line with the papers written by the IMF (2004), by Sa (2006) and more recently by Coudert and Pouvelle (2008), and Mendoza and Terrones (2008). This will allow us comparing the boom periods in the European countries and in the US detected by the GALR and by the indicators traditionally used to detect credit deviation.

We reinforce our analysis with an econometrical analysis. Many studies focus on macroeconomic analysis of systemic banking crisis. Papers which test the ability of Early Warnings Systems (EWS) to predict banking crisis belong to this literature. We can distinguish two main approaches for EWS in the literature: the Signal Extraction approach (Kaminsky and Reinhart, 1999, Kaminsky, 1998, Borio and Lowe, 2002, Borio and Drehmamm, 2009), and the Multivariate Logit approach (Demirgut-Kunt and Detragiache, 1998, 1999, 2005). In this paper we perform *logit* regressions to analyze the GALR's predictive power in comparison with the one of traditional indicators of credit deviation in line with these last studies.

In binomial *logit* regressions, the dependent variable is qualitative and can take two different values (0 or 1) according to the occurrence or not of a specific event. Contrary to what is done in the previous papers, we do not choose systemic banking crisis to define the event but rather stress period in the financial system. This choice is explained by the fact that over our time period (from 1994 to 2008), there is only one systemic banking crisis in the European countries and in the United States which corresponds to the 2007 crisis. It seems important to remind that the

financial system often undergo vulnerabilities outside systemic crisis events. And, these stress periods may threaten the financial system soundness.
To create our dependent variable, we lean on the findings of Kindleberger (2000), and Borio and alii (2001) which establish that it is the increase of excessive optimism observed during the periods just before banking crisis which leads to a higher risk-taking and consequently to a rise of credit supply. And, that is why we construct a stress index to define stress periods combining two variables: the non-performing loans to gross loans ratio, and the domestic credit to GDP ratio. We compute our stress index according the following formula (Hanschel and Monnin, 2008):

$$I_t = \sum_{i=1,..,k} (X_{t,i} - M_i) / \sigma_i$$

where k is the number of variables in the index, M_i is the mean of the variable X_i and σ_i its standard deviation. A positive (negative) value of the index indicates that the variable is above its sample mean and that it indicates more (less) stress to the system than it does on average (Hanschel and Monnin, 2008). We code 1 when index value is positive and 0 otherwise.

The macro approach, which has grown in prominence in recent years, uses macroeconomic variables to explain and ultimately predict systemic bank crises. These studies typically focus on a large sample of countries. A main result of these papers is that macroeconomic variables like GDP growth, inflation rate, real interest rates and M2/Reserves ratio are clearly associated with systemic banking sector problems. In most EWS studies, the explanatory variables used to predict systemic banking crisis are mainly macroeconomic and financial variables. In our model, we use the same kind of independent variables. As far macroeconomics variables are concerned, we choose the real interest rate (R), inflation rate (I), real GDP growth rate (CGPG) and M2/Reserves ratio (M2R) (Demirgut-Kunt and Detragiache, 1998, 1999).

Concerning financial variables, we test respectively the credit growth rate (CG), the money growth (M3G), the commercial bank aggregated leverage (CBL), the investment bank aggregated leverage (IBL) and, our global aggregated leverage ratio (GALR). The data we use for I, CG, GDPG and M2 are taken from IMF international statistics for all the countries. The data we use for R and M3 are provided by national sources for European countries and from IMF international statistics for the UK and the US.

3. RESULTS

Statistical results

We estimate the indicators' long-term trend using a Hodrick-Prescott filter and then, we calculate the deviation of the indicators' value from their long-term trend. We have chosen λ=100 as is typical for annual data. To define the threshold, we choose to use the approach which calculates the threshold by constructing an interval proportional to the standard deviation around the trend (1.75σ). Finally, we compare the deviation from the long-term trend to the threshold to identify boom

credit periods. Whether the spread between the credit indicator and its long term trend is positive, we can conclude that there is a credit boom period. Table 1 reports the boom periods captured in each country according to the different indicators of excessive credit distribution.

TABLE 1. IDENTIFICATION OF CREDIT BOOM PERIODS

	CBL	IBL	ALR	CG	M3G
ITALY				2006;2007	
UK	2008		2002;2003;2008		
FRANCE	2003;2008	2003;2004;2005	2003;2008	2007	2007
GERMANY			2002;2003;2008	2001;2008	2001
USA	2008			2004;2005;2006;20007	
SWEDEN	2001;2002;2007;2008				
DENMARK	2008				2002;2005;2007
NORWAY	2006	2004;2006	2006		2006;2007
ICELAND	2001;2007		2001;2007		2007
GREECE				2005;2007	2001;2007
IRELAND				2004;2005;2006	2001;2004;2005;2006
LUXEMBOURG		2003;2004;2007		2001;2005;2006;2007	2002;2007
SWITZERLAND	2003;2004;2005;2008	2001	2001	2006	2003

Source: authors' calculation.

This statistical approach reveals 73 credit boom observations. The CBL ratio identifies 21.9% credit booms out of the 73 credit booms. The IBL, GALR, CG and M3G respectively identify 11.3%, 16.4%, 26.02% and 23.2% credit booms out of the 73 credit booms.

We note that the credit booms identified by the indicators correspond to stress episodes observed in financial systems in the past. Most of the indicators detect two main credit boom periods: the first one is around 2004 and the second one is around 2007. The year 2004 corresponds to the end of the first part of the financial cycle (the "rising phase") where, as demonstrated by Kindelberger (2005), market participants develop excessive and perverse behavior in order to improve their yields. The year 2007 corresponds to the recent period where, agents increasingly used innovation products in order to restore their profits and to by-pass capital regulation requirements.

So, according to the statistical analysis, CG and M3G appear to better predict the occurrence of stress periods than CBL, IBL and GALR. IBL seems to be the worst indicator for credit boom detection. The CBL and the GALR tend to detect credit booms quite late in comparison with CG and M3G which, react very early. This result can be explained by the fact that the last ones reflect more generally macroeconomic conditions. Indeed, banks and all market participants usually adapt their behavior according to macroeconomic conditions so, their reaction appears ex post. Consequently, even if traditional indicators seem to be more efficient to detect credit deviation, it can be interesting to make further investigation on the GARL indicator.

However, these preliminary results should be moderated for at least two main reasons. The first one is linked to the choice of the calculation method. Calculation

using a Hodrick-Prescott filter often lacks of robustness mainly when the series used are short. This is the case in our analysis for technical reasons (Coudert and Pouvelle, 2008; Banque de France, 2002). The second criticism is related to the fact that a purely statistical approach to estimate the relevance of an indicator can't be enough. Then, it is necessary to complete this analysis with an econometrical approach.

Econometrical results

Table 2 provides summary descriptive statistics of the relevant variables included in our model.

TABLE 2. DESCRIPTIVE STATISTICS

	Obs	Mean	Std. Dev	Min	Max
CBL	100	15,089	6,817	5,064	43,058
IBL	100	16,674	14,594	1,413	82,431
ALR	99	16,769	7,563	3,672	57,240
GDPG	104	0,053	0,033	-0,041	0,138
CG	97	0,114	0,108	-0,145	0,660
M2R	104	21,454	84,736	0,004	491,186
M3G	104	0,094	0,829	-0,214	0,564
I	104	0,027	0,021	-0,018	0,114
R	104	3,770	3,226	0,18	22

Source: authors'calculation.

We first analyze the extent to which the various risk measures convey different information. So, we begin by performing Spearman rank order and Pearson correlations (in brackets) (see table 3).

TABLE 3. PEARSON ORDINARY TEST/SPEARMAN TEST

	CBL	IBL	ALR	CG	M3G
CBL	1	0.101	0.616	0.255	0.112
		(-0.298)	(0.411)	(0.483)	(0.308)
IBL		1	0.617	-0.165	-0.041
			(0.339)	(-0.292)	(-0.136)
ALR			1	-0.011	-0.009
				(0.037)	(-0.033)
CG				1	0.545
					(0.647)
M3G					1

Source: authors' calculation.

The Spearman rank order correlations test reveals weak correlation across the considered indicators (GALR, CG, M3G) what suggest that these indicators convey different information and, consequently, they may be used as complementary tools. Unsurprisingly, GALR is closely linked to CBLR and IBLR because of GALR formula. Moreover, we note a close correlation between CG and M3G. The Pearson correlations give similar results than the Spearman rank order correlations as far as GALR and the two indicators CG and M3G are concerned.

The multivariate *logit* approach allowed Demirguc-Kunt and Detragiache (1998) to relate the likelihood of occurrence or non-occurrence of a stress period to a vector of *n* explanatory variables. The probability that the banking dummy takes a value of one (stress period occurs) at a point in time is given by the value of the logistic cumulative distribution evaluated for the data and parameters at that point in time.

$$\text{Prob}(Y_{it} = 1) = F(\beta\, X_{it}) = \frac{e^{\beta' X_{it}}}{1 + e^{\beta' X_{it}}}$$

where *Yit* is the stress period dummy for country *i* at time *t*, β is the vector of coefficients, *Xit* is the vector of explanatory variables and $F(\beta Xit)$ is the cumulative logistic distribution. The parameters are obtained by maximum likelihood estimation where each possible value of *Yit* contributes to the joint likelihood function so that the log likelihood becomes

$$\log_e L = \sum_{i=1}^{n}\sum_{t=1}^{T}[(Y_{it}\log_e F(\beta' X_{it})) + (1 - Y_{it})\log_e(1 - F(\beta' X_{it}))]$$

The parameters obtained by maximizing this function are not constant marginal effects of *Xi* on the crisis probability since the underlying relationship is non-linear. Rather, the marginal effect of *Xit* on *Yit* is given by the probability of crisis times the probability of no crisis times the coefficient βi. Since the probabilities depend on the values of *Xit*, for a given coefficient, a single explanatory variable can have changing marginal contributions to crisis probability depending on its starting level. The sigmoidal logistic cumulative distribution shows that an explanatory variable.

In *logit* regressions, the dependent variable is qualitative and takes two values 0 or 1 according to the occurrence of a specific event. Our model is an extension of the model of Barell, Davis, Karim and Liadze (2009). They take into account systemic banking crisis detection in OECD countries from 1980 to 2007. Their model is interesting because it focuses on commercial bank leverage. Our contribution is to add investment bank leverage to commercial bank leverage. That is why the indicator we test an aggregated leverage ratio. Contrary to the previous papers, we do not choose systemic banking crisis as event but stress period in the financial system. We perform five *logit* regressions using this panel and we calculate for each model the percentage of stress period correctly predicted of our several indicators.

The first specification includes only macroeconomic variables (model 1). In the two following specifications, we add variables capturing banking sector characteristics

that is to say CG and then M3G (model 2 and model 3). These last ones are generally considered as the traditional excessive credit indicators. In the forth specification, we test our indicator, the GALR (model 4). The idea is to compare the GALR with the previous and to test if GALR is a relevant indicator to explain stress periods. In the two last specifications, we take into account the commercial bank leverage ratio (CBLR) then the investment bank leverage ratio (IBLR) in order to compare them to the GALR (models 4 and 5). The idea is to demonstrate that a global leverage which integrate most of leverage financial institutions give a better excessive credit signal. Table 4 reports the multicollinearity test results.

TABLE 4. MULTICOLLINEARITY TEST

Variable	VIF	SQRT VIF	Tolerance	R-Squared
CBL	2.93	1.71	0.3412	0.6588
IBL	2.23	1.49	0.4487	0.5513
ALR	3.41	1.85	0.2933	0.7067
GDPG	3.30	1.82	0.3032	0.6968
CG	2.76	1.66	0.3618	0.6382
M2R	2.26	1.50	0.4432	0.5568
M3G	1.55	1.25	0.6436	0.3564
I	2.44	1.56	0.4105	0.5895
R	1.81	1.35	0.5513	0.4487
Mean VIF	2.52			

Source: authors'calculation.

We can note that all the VIF (variance inflation factor) are lower than 4 so, there is no sign of multicollinearity between our variables. Now, we perform the *logit* regressions. Table 5 summarizes results of the *logit* estimations.

TABLE 5. LOGIT ESTIMATION (IN-SAMPLE)

STRESS	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
GDPG	2.872	-36.533*	-1.846	8.169*	5.511*	1.373
M2R	-0.000	-0.006	-0.004	-0.002**	-0.002*	-0.000
I	7.708	42.058	10.352	8.259*	4.174	11.520*
R	-0.041	-0.364**	-0.127	-0.100***	-0.076***	-0.124***
CG		13.915**				
M3G			9.365			
GALR				0.029**		
CBL					0.033	
IBL						-0.000
INTERCEPT	-0.307	0.150	-0.565	-0.931*	-0.740	-0.650
% CORRECT	51.28	64	58.97	70.83	64.38	68.06

Source: authors'calculation.

First, we observe that there is a significant relationship between financial institutions leverage (GALR) and the probability of the occurrence of stress periods. One explanation of the strongly significance of the GALR may be that when financial institutions rise their market short term funding, they bear an increasing liquidity and counterparty risk. In case of liquidity freeze, they cannot refund themselves anymore. Then the crisis quickly spreads to the whole financial system.
We also find evidence that introducing information about the evolution of indebtedness enhances the detection of vulnerability periods in financial markets. The percentage of correct prediction for models (2) to (5) is higher than the one of model 1.

According to false alarm criteria, model (4) yields a better ratio of correct predictions than models (2) and (3). We notice that more than 70.83% of stress periods are correctly predicted against respectively 51.28% and 64%. Consequently, GALR seems to be a better expression of credit deviation than CG and M3G.
Another important result is that GALR outperforms CBL and IBL in terms ratio of correct predictions (70.83% against 64.38% and 68.06%). This result suggests that leverage is a better indicator when it takes into account the more financial institutions as possible like investment.

All these results suggest that the GALR may be a good leading indicator of the build up of financial vulnerabilities. Then it could be integrated into macro-prudential tools. This result confirms our intuition that GALR may be a useful complementary indicator to signal the need for supervisory action despite it is a simple ratio. In addition of its simplicity, it is costless to compute and consequently easy to implement. These results are not fully validated by the out-sample results. Even if we can't conclude with certainty that the GALR we propose should be integrated into macro-prudential tools, we note that the results of the three parts of the empirical analysis (statistical analysis, Pearson/Spearman rank order correlation, and *logit* regressions) provide consistent results. We can consequently conclude that the consideration of an aggregated leverage is an interesting trail for supervisors.

CONCLUSION

This paper attempts to propose a leading macro prudential indicator (MPI) for monitoring vulnerability of financial markets. We perform a statistical analysis in which we compare the deviation from the long-term trend to the threshold to identify boom credit periods. According to this analysis, CG and M3G appear to better predict the occurrence of stress periods than CBL, IBL and GALR. IBL appears to be the worst indicator for credit boom detection. The CBL and the GALR tend to detect credit booms quite late in comparison with CG and M3G which, react very early. Then, we perform five *logit* regressions. We observe that there is a significant relationship between financial institutions global leverage (GALR) and the probability of the occurrence of stress periods. We also find evidence that introducing information about the evolution of indebtedness enhances the detection of vulnerability periods in financial markets. The most important result is that GALR seems to be a better expression of credit deviation than CG and M3G and that leverage is a better indicator when it takes into account the more financial institutions as possible like investment.

This result confirms our intuition that GALR may be a useful complementary indicator to signal the need for supervisory action despite it is a simple ratio. In addition of its simplicity, it is costless to compute and consequently easy to implement. These results are not fully validated by the out-sample results. Therefore we can't conclude with certainty that the indicator (GALR), we propose, should be integrated into macro-prudential tools. However, we note that the three methodologies used in our study (statistical, Pearson/Spearman rank order correlation and logit regressions) give consistent results, what suggests that the consideration of the aggregated leverage is an interesting trail for supervisors.

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