SYSTEMIC RISK ANALYSIS AND OPTION-BASED THEORY AND INFORMATION*

*Martín Saldías***

ABSTRACT

This article describes the methodology to compute and the properties of aggregated and forward-looking Distance-to-Default series. These are a set of two market-based indicators to monitor systemic risk in the European banking system based on Contingent Claims Analysis and constructed using information of banks' balance sheets and equity and option quotes. These indicators are generated using information from systemically important banks and the STOXX Europe 600 Banks Index and provide methodological advantages in monitoring vulnerabilities in the banking system over time.

1. INTRODUCTION

The financial crisis started in 2007 triggered a renewed attention and operational focus as concerns research on systemic risk in banking. The emerging theoretical[1] and empirical work in this area is making great progress and has produced a wide range of methodologies to detect, to measure systemic risk and to attribute systemic risk to individual institutions in the financial system.

These new approaches are either replacing or enhancing existing methodologies that failed to capture vulnerabilities prior to this crisis. They rely on a variety of sources of information and they are also designed to incorporate new features of the phenomenon as they materialize, such as shared exposures to other economic sectors or market segments, different channels of distress transmission, extreme dependence or other complex elements of systemic risk.[2]

This article highlights one of the recent contributions in this area and describes an application of Contingent Claims Analysis (CCA) to the early detection and monitoring of systemic risk in European banking system. Portfolio and Average Distance-to-Default series are generated using information from individual banks' balance sheets and information from individual and index equity and option markets from systemically important banks based on the STOXX Europe 600 Banks Index.

These indicators contain several attractive features of other systemic risk indicators and also provide methodological advantages in monitoring vulnerabilities in the banking system over time. First, the inclusion of information from option markets, in addition to balance sheet and equity markets information, endows the indicators with forward-looking properties that enable them to detect signs of overall distress in the

---

1 See de Bandt *et al.* (2009) for a comprehensive discussion of the concept of systemic risk.

2 Galati and Moessner (2011) and Rodríguez-Moreno and Peña (2012) provide a detailed literature review of recent and widely cited work on systemic risk and their relative performance, including inter alia the contributions by Acharya *et al.* (2010), Adrian and Brunnermeier (2011), Segoviano and Goodhart (2009) and Huang *et al* (2010). Other relevant contributions include Brownlees and Engle (2011), Drehmann, and Tarashev, (2011a, b) and Schwaab *et al.* (2011).

banking sector earlier than traditional approaches in the literature and than other market-based indicators.

Due to the inclusion of equity index information in addition to individual banks' data, these series also are able to capture interdependences and joint risk of distress in systemically important banks without turning to explicitly model the dependence structure among individual banks. It also allows detecting tail risk through the differences in equity and option prices of the index and its constituents. Being point estimates, the series produce quick and clear reaction to market distress while keeping smooth and informative long-term signals from fundamentals.

The rest of the article is structured as follows. Section 2 reviews the features of CCA and its applications to systemic risk analysis. Section 3 introduces the banks' sample and discusses the methodological approach in this article. In Section 4 the results of the model calibration are presented and I discuss the properties of the PDD and ADD series and their difference as a tool of systemic risk monitoring. Section 5 concludes.

2. CONTINGENT CLAIMS ANALYSIS AND SYSTEMIC RISK

Contingent Claims Analysis (CCA) is a modelling framework that applies option pricing theory to corporate default. This framework combines market-based –normally stock prices– and balance sheet information to obtain a comprehensive set of company financial risk indicators, e.g: Distance-to-Default, probabilities of default, risk-neutral credit risk premia, etc.

Based on the Merton (1974) model of credit risk[3], company liabilities are viewed as contingent claims against assets with payoffs determined by seniority. Equity becomes an implicit call option on the market value of assets with strike price defined by the default or distress barrier (determined by the risky debt). As company assets decline and move closer to a default barrier, the market value of the call option also falls. The normalized distance between market value of asset and the distress barrier is called Distance-to-Default (DD) and constitutes the financial risk indicator used in this article to assess and monitor systemic risk in Europe's banking. Distance-to-Default indicates the number of standard deviations at which the market value of assets is away from the default barrier and can be scaled into probabilities of default, if the distribution of assets were known.

The CCA approach has been cited and reviewed by the Financial Stability Board (2009) as a tool to enhance systemic risk analysis and to identify systemically important financial institutions and help establish a regulatory framework that can cope with risk arising from systemic linkages. Accordingly, several applications of this approach based on aggregated data have been implemented to analyze different dimensions of systemic risk in banking and further extensions have been developed for wider range of macro-financial issues and systemic risk, such as sovereign risk, economic output, risk transmission across sectors and quantification of systemic risk contributions.[4]

In most CCA literature thus far, the bottom-up approach of aggregation of individual DD into system-wide indicators has been conducted through simple averages, ADD series, and occasionally also through calibration of individual data into portfolios of banks based on historical return information and pairwise covariances, *i.e.* the basic version of PDD series, which means treating the system as one large bank.

Even though ADD series based on individual DD are highly informative of the dynamics and intensity of

---

3 See Gray and Malone (2008) for comprehensive technical review of this and extended methodologies as well as related literature.

4 Empirical applications of CCA to assess systemic risk in banking can be found in Duggar and Mitra (2007), Gray and Walsh (2008), Harada and Ito (2008) and Harada *et al.* (2010 Gray *et al.* (2007) and Gray and Jobst (2010) provide in detail discussions of further extensions of the CCA to analyze a wider range of macro-financial issues. See Antunes and Silva (2010) for the case of the Portuguese banking system and Silva *et al.* (2011) for an extension of systemic risk to the analysis of Portuguese macro-financial sectors.

system-wide risks, they can also be misleading if analyzed alone since they do not take into account bank heterogeneity, size differences, risk interdependences and sector-wide tail risks. While other measures of central tendency, such as weighted averages or quantile DD, partially solve the size problem, they are more useful when distress correlations are low and thus do not tackle well the interdependences among banks and fail to react to swings in periods of financial stress (Čihák, 2007).

PDD series enhances the information quality of ADD series, since it additionally takes into account bank size and tackles risk interdependence among banks and also tracks the evolution of the lower bound to the joint probabilities of distress. The resulting joint dynamics of PDD and ADD series works primarily as follows: when the banks' returns comovement increases in times of market distress, showing higher interdependences, both series tend to drop and the gap between them tends to narrow. Since PDD is in general higher than ADD and therefore is a lower bound of distress, the joint movement of DD series contains relevant information about increasing comovement, volatility spillovers and hence systemic risk. PDD may however become coincident indicator when computed using realized data and thus may fail to detect early signals of market stress.

In recent CCA applications, the importance of aggregation of univariate CCA models of institutions into a multivariate framework has been addressed in order to account for both linear and non-linear dependence and to track the interdependences and linkages within and across institutions, given that conventional correlation measures based on realized data become unreliable in presence of fat tails, especially in times of crisis.

In this context, the forward-looking Distance-to-Default series discussed in this article provide two innovations to this literature that tackle the issues of dependence structure among banks and early warning signals of distress. First, the inclusion of information of the reference equity index, the STOXX Europe 600 Banks Index, avoids arbitrary or explicit modeling assumptions or dependence structures among banks in the sample which tend to weaken its information quality and hinder its ability to anticipate events of high systemic risk. Instead, the PDD and ADD series will retain their forward looking properties and their difference will largely reflect the information differences embedded in the implied volatilities of the reference index and its constituents. As information from options on equity indices has not been fully exploited, this feature endows these indicators with an additional signal of distress in the banking sector.

Option implied volatilities from the bank index and its constituents convey also important information about tail risk dependence and the effects of public guarantees in system-wide risk perception.[5] The difference between the downside risks of a portfolio and that of its constituents is a crucial feature in terms of systemic risk when assets tend to have high correlation. There is a higher degree of tail dependence that is not a result of the combination of fat tails of the constituents of a basket.

3. Calibration of Portfolio and Average Distance-to-Default series

The samples used to compute the Portfolio Distance-to-Default (PDD) and Average Distance-to-Default (ADD) series are based on the constituents of the STOXX Europe 600 Banks Index and on those of the EURO STOXX Banks Index, a subset of the former, for the analysis of the banking system in the Euro area between the Third Quarter of 2002 and the Fourth Quarter of 2011.

This sector-based index includes the largest and most widely traded banks' stocks headquartered in 17 countries in Europe. It is probably the best reference of the European banking sector, reflecting the pan-European dimension of financial integration. It has an additional key feature for the purposes of this analysis in that there are liquid exchange-traded option prices on the corresponding index.

---

[5] See Kelly *et al.* (2011) and Langnau and Cangemi (2011) for more insights.

The changing sample used to compute the PDD series includes 96 (nearly all) banks belonging to the STOXX Europe 600 Banks Index over the complete time span, taking into account changes in the quarterly index composition and updates in the broader STOXX Europe 600 Index due relevant corporate actions.[6] The bank sample used to compute the ADD series is a subset of the former. These banks are considered the core of the European banking system in terms of systemic risk and for the purposes of this research. This subsample consists of 34 large systemically important financial institutions, i.e. the largest 33 banks in the PDD sample plus the ING Group. Ideally, the PDD and ADD samples should perfectly match, but the availability of liquid option prices acts as a practical constraint.[7]

Table 1 lists the resulting 34 banks in this subsample.[8]

These banks are regarded as systemically important as they comply with several of the size, cross-jurisdictional activity, interconnectedness, substitutability and complexity criteria listed initially by request of the G-20 leaders in April 2009 and more recently by the Financial Stability Board. They constitute the core of the ECB's Large and Complex Banking Groups and the seed of the Global Systemically Financial Institutions (G-SIFI) list.

As for the models used to calibrate the DD series, at each point in time t, the Average Distance-to-Default (ADD) is represented in equation (1) below and is obtained by taking the simple average across the N individual bank DD series.

$$ADD_t = \frac{1}{N}\sum_{i=1}^{N}DD_{i,t}$$

(1)

Table 1

AVERAGE DISTANCE-TO-DEFAULT SAMPLE BANKS				
	Bank	**Country**	**Bank**	**Country**
1	RBS	United Kingdom	18 Natixis	France
2	Barclays	United Kingdom	19 Intesa Sanpaolo	Italy
3	BNP Paribas	France	20 KBC	Belgium
4	HSBC	United Kingdom	21 Standard Chartered	United Kingdom
5	Deutsche Bank	Germany	22 SEB	Sweden
6	UBS	Switzerland	23 DNB ASA	Norway
7	ING	Netherlands	24 Svenska Handelsbanken	Sweden
8	Crédit Agricole	France	25 Erste Group	Austria
9	Société Générale	France	26 Swedbank	Sweden
10	UniCredit	Italy	27 Banca Monte dei Paschi di Siena	Italy
11	Santander	Spain	28 Banco Popular Español	Spain
12	Credit Suisse	Switzerland	29 Mediobanca	Italy
13	Commerzbank	Germany	30 Bankinter	Spain
14	BBVA	Spain	31 Dexia[a]	Belgium
15	Lloyds Banking Group	United Kingdom	32 Fortis[a]	Belgium
16	Danske Bank	Denmark	33 HBOS[a]	United Kingdom
17	Nordea	Sweden	34 Alliance & Leicester[a]	United Kingdom

Source: Saldías (2010).

Notes: (a) The exit dates from the sample for Alliance & Leicester, HBOS, Fortis and Dexia, are October 2008, January 2009, September 2009 and November 2011, respectively.

6 See the updated version of Saldías (2010) for the full list of banks in the sample.

7 This mismatch is reduced as the end of the sample includes several banks that resulted from M&A in earlier periods. At the end of the sample, the ADD sample includes 30 out of the 49 banks from the PDD sample and over 95% of market capitalization. See Saldías (2010) for more details.

8 There are four special cases worth pointing out. Fortis, HBOS and Alliance & Leicester were large and established banks in the sample until they were taken over by other large financial institutions from the sample, BNP Paribas, Lloyds Banking Group and Santander, respectively. As these acquisitions took place late in the sample, the banks were constituents since the start and had liquid option prices, these three banks were not dropped from the ADD sample. Dexia was deleted from the reference index in November 2011 after being broken-up due to its losses in the most acute period of the Greek debt crisis thus far.

where $DD_{i,t}$ is the individual DD of bank i for a one-year horizon T, as it is standard practice in the literature. As presented in equation (2) below, for each bank i, $DD_{i,t}$ is a function of a distress barrier $D_{i,t}$, obtained from the banks' balance sheet data; the rate of growth of its assets $r_{i,t}$ – approximated by the risk-free interest rate in the respective home market, and two unobservable variables, namely the implied value of assets $A_{i,t}$ and the implied assets volatility σ_A. The latter two variables are estimated with standard iterative techniques using the market value of equity $E_{i,t}$ and equity price return volatility σ_A, obtained in this article from individual exchange-traded equity options.[9]

$$DD_{i,t} = \frac{\ln\left(\dfrac{A_{i,t}}{D_{i,t}}\right) + \left(r_{i,t} - \dfrac{1}{2}\sigma_{A,t}^2\right)T}{\sigma_{A,t}\sqrt{T}} \qquad (2)$$

Balance sheet and market data were obtained for the period between 30 September 2002 and 31 January 2012 (2437 trading days). Balance sheet data comprise annual and interim data on total assets, short-term liabilities and equity. The market-based data include daily observations of risk-free interest rates, market capitalization, euro exchange rates and at-the-money calls and puts implied volatilities. The risk-free interest rates are 10-year government bond yields in each bank's country of origin.

Individual DD series have daily frequency. In practical terms, balance sheet information had to be modified from its original quarterly, half-yearly or, in few cases, yearly frequencies using cubic splines to interpolate into daily data. In a second step, daily default barriers (the face value of short-term liabilities plus half of that of long-term liabilities) are computed using these new series of daily balance sheet items. The last step before computing the daily average DD series is to convert put and call implied volatilities into an average implied volatility and then calibrate the individual DD.

The expression for the PDD series is the following:

$$PDD_t = \frac{\ln\left(\dfrac{A_{P,t}}{D_{P,t}}\right) + \left(r_{P,t} - \dfrac{1}{2}\sigma_{P,A}^2\right)T}{\sigma_{A,t}\sqrt{T}} \qquad (3)$$

where PDD_t is the Portfolio Distance-to-Default T periods ahead at day t. The definition of the inputs in the PDD case is the same as in equation (2). However, as the PDD assumes that individual banks are regarded as a big bank, some relevant methodological changes are worth pointing out. The calibration of PDD in equation (3) requires the aggregation of balance sheet data of the PDD banks into a single series. Hence, the individual annual and interim data on total assets, short-term liabilities and equity are first converted into euro and then added up across the actual constituents from the portfolio to compute quarterly portfolio's distress barrier $D_{P,t}$, before daily interpolation. The rate of growth of the portfolio assets $r_{P,t}$ is proxied by the Euro area synthetic 10-year government bond yield. Finally, the estimation of the unobservable variables, namely the portfolio's implied value of assets $A_{P,t}$ and the portfolio's implied asset volatility σ_A, was conducted using the equity market value of the portfolio $E_{P,t}$, directly taken as the euro-denominated market value of the reference equity index, and the portfolio's equity volatility obtained from the index options $\sigma_E = \sigma_{Index}$.

As mentioned lives above, using implied volatilities from the reference index and its main constituents means in practice that this paper does not only keep the forward looking component to the ADD and PDD series, but also that no covariance structure is assumed in the calibration of the aggregated data, which constitutes an important difference with existing applications of PDD. Equity volatility is taken directly from options market data, introducing market perceptions of joint distress risk and its features under extreme events.

---

[9] For technical details of these computations, see Saldías (2010).

4. RESULTS

This section reports the results from the calibration of the PDD and ADD series described lines above and focuses on their properties and those embedded in their difference as tools to monitor systemic risk in Europe's banking system.

4.1. *DD* Series Dynamics and Systemic Risk Outlook

Chart 1 plots together on the left hand panel the forward-looking Average Distance-to-Default (ADD) and Portfolio Distance-to-Default (PDD) series, their difference and also the STOXX Europe 600 Banks Index as a reference. The right hand panel shows the PDD and ADD series computed for the Euro area-based banks with the EURO STOXX banks index as a reference.

These charts serve to illustrate that the dynamics of these three series – PDD, ADD and PDD-ADD gap– provide a good picture of the market assessment and risk outlook of the banking system in Europe. As expected, PDD moves along and above ADD over the entire sample, with some exceptional periods where ADD exceeds PDD. The PDD series shows a higher standard deviation and large positive skewness (see Table 2 for summary statistics) compared to the ADD series. The first feature illustrates the quick reaction of the PDD series to new information and their effect on returns comovement across the sample, while the differences in terms of skewness show the role of ADD and PDD as lower and higher bounds of joint distress indicators, respectively.

Given a specific trend direction in the series, the difference between PDD and ADD narrows suddenly in response to specific events of high market volatility. These events take place during easily identifiable and short periods and are well illustrated by the reference equity indices. The differences tend to stay narrow for longer periods of high market volatility and when there is a high degree of joint distress in the sector. Symmetrically, positive market news are also perceived in the series through transitory widening of DD series gap during bad times, i.e. low levels of the PDD and ADD series and a continuous and narrow gap. An example of this latter case can be found in late 2008, during wide range recapitalizations in large banks, such as RBS.

The ADD and PDD series start at very low levels and with a very narrow gap in the aftermath of the WorldCom / Enron accounting scandals under a high volatility regime. The series show an upward trend

Chart 1

FORWARD LOOKING DISTANCE-TO-DEFAULT SERIES FOR EUROPE AND THE EURO AREA |
30-SEP-2002 - 31-JAN-2012
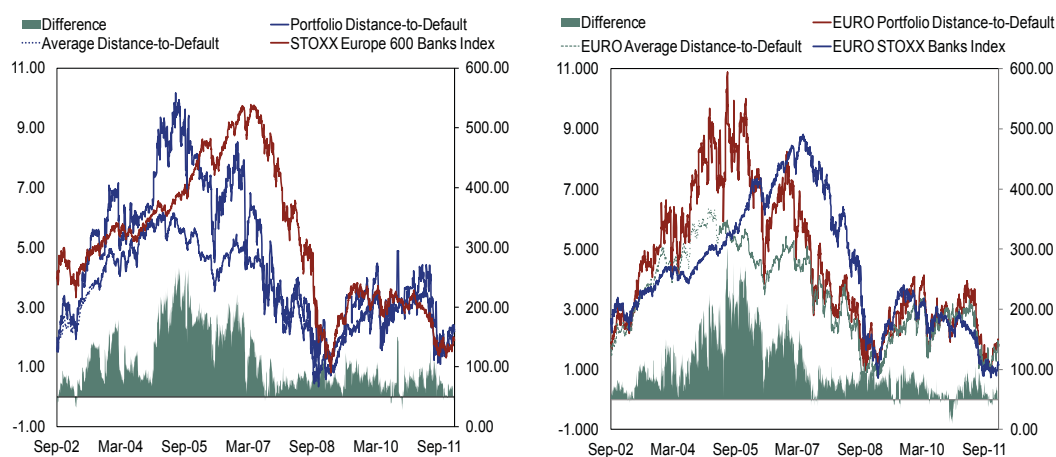
Sources: Bloomberg and author's calculation.

Chart 2

SUMMARY STATISTICS						
	European Banks			**Eurozone Banks**		
	PDD	*ADD*	*PDD-ADD*	*PDD*	*ADD*	*PDD-ADD*
Mean	4.655	3.504	1.151	4.486	3.466	1.020
Median	3.948	3.338	0.767	3.789	3.257	0.667
Maximum	10.168	6.163	4.334	10.887	6.343	5.047
Minumum	0.893	0.339	-0.472	0.958	0.410	-0.826
Std. Deviation	2.215	1.425	0.976	2.267	1.451	0.991
Skewness	0.470	-0.008	1.028	0.557	0.045	1.271
Kurtosis	-0.872	-0.996	0.119	-0.783	-1.052	1.151
Observations	2437	2437	2437	2437	2437	2437

Source. Author calculations.

and an increasing PDD-ADD gap afterwards until the end of 2005, reaching a maximum PDD-ADD gap in August, as financial markets become less volatile and the sector becomes more profitable yet increasingly levered. During this time span of low market volatility and increasing bank profitability, there are some specific and short-lived events where the PDD-ADD gap narrows significantly.[10]

Another noteworthy feature in the charts is the fact that the DD series reach their peak in 2005, long before our equity markets' benchmark reached theirs. They start a downward trend around this date, which only bounces back after the first quarter of 2009. Since August 2007, the subprime crisis drove the DD series and especially the gap to very low levels, setting a new period of high volatility, decreasing stock returns and high return comovement across banks. In this new phase, expected stock return volatility, approximated by the options implied volatilities, becomes dominant in the calibration of DD, as the elasticities of DD to changes in the default-barrier and implied asset value is decreasing with changes in the implied asset volatility. The DD series continued to plummet until the Lehman Brothers collapse and the release of the results of the first round of stress-tests in the US in May 2009. The ensuring capital injections at global scale produced an upturn in the DD series while the gap remained close to zero.

The post-Lehman period is characterized by a weak upward trend in the series, reflecting deleveraging and, arguably, better capitalization in banks' balance sheets, but the gap between them stays at very low levels, showing that transmission of volatility shocks remains high. This feature illustrates on one hand the series of capital injections across all Europe coupled with a high volatility regime in financial markets that makes contagion very likely and fast. In addition, there are significant interruptions in recovery as the European sovereign debt crisis hurt the recovery significantly between October and November 2010 and in the Summer of 2011, hitting the euro area banks DD series harder. The very end of the sample shows a marginal upturn as a consequence of the LTRO credit infusion.

4.2. Forward-looking Properties

Chart 2 compare the forward-looking DD series and their gap to those computed with realized historical volatilities and published by the ECB. In particular, the forward-looking DD series are compared in the left hand side panel with the median of Distance-to-Default series of a sample of large EU banks and in the right hand side panel with the weighted average of Distance-to-Default series of Global Large and Complex Banking Groups. A simple graphical inspection of these figures suggests that turning points of forward-looking DD series precede those of the DD series based on historical volatilities along the whole time span.
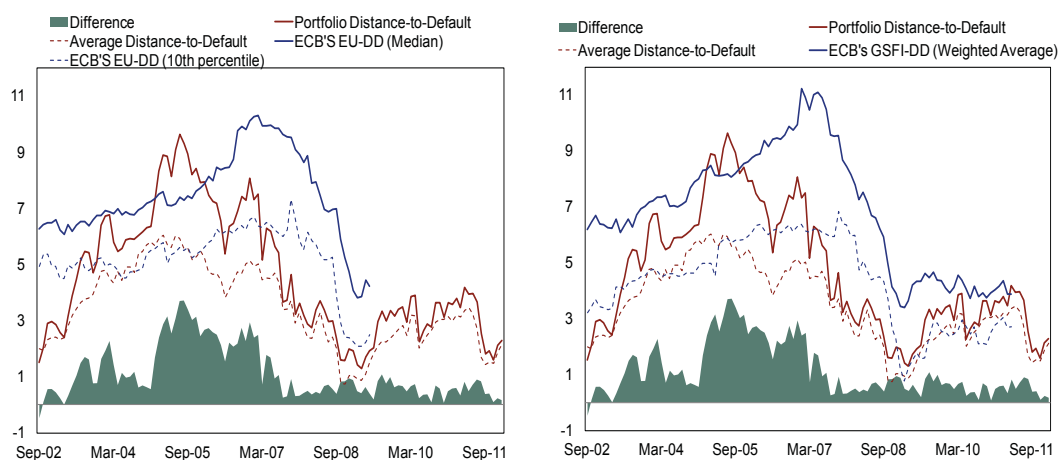
---

10 These episodes include events of significant monetary policy tightening (April and May 2004, May 2005) or strong market corrections (mid-2006, February 2007).

Chart 2

| FORWARD LOOKING DISTANCE-TO-DEFAULT SERIES FOR EUROPE AND THE EURO AREA |
| SEPTEMBER 2002 – JANUARY 2012 |

Source. Author calculations.

In order to test econometrically this forward-looking feature of Average and Portfolio DD series derived from option implied volatilities and their difference, I run pairwise Granger causality tests vis-à-vis these backward-looking monthly DD series.[11]

Results are reported in Table 3 and provide econometric support to the forward-looking feature of our series. They show that forward-looking DD indicators and also their difference Granger cause ECB's DD series up to two years, as the graphs suggested. More robust results are obtained for longer lags in the test using ADD because of the similar method used to obtain these series and because of the effect of

Table 3

GRANGER-CAUSALITY TESTS						
X	PDD	DD_{LCBG}	ADD	DD_{LCBG}	$PDD\text{-}ADD$	DD_{LCBG}	**Lags**
Y	DD_{LCBG}	PDD	DD_{LCBG}	ADD	DD_{LCBG}	$PDD\text{-}ADD$	
	9.2960**	0.3409	9.9358**	1.448	4.3131**	0.5886	1
	4.6203**	2.157	4.1809**	3.1928**	3.6260**	0.6386	2
	3.3685**	2.3546*	2.8266**	2.8647**	2.9027**	1.5599	3
	0.8942	2.7027**	1.4522	1.1849	1.1	2.4833**	6
	0.7975	1.4975	1.569	1.0343	0.9672	1.4936	12
	1.5336	1.0367	2.161**	1.124	1.0934	1.7115*	24
X	PDD	$DD_{EUmedian}$	ADD	$DD_{EUmedian}$	$PDD\text{-}ADD$	$DD_{EUmedian}$	**Lags**
Y	$DD_{EUmedian}$	PDD	$DD_{EUmedian}$	ADD	$DD_{EUmedian}$	$PDD\text{-}ADD$	
	9.8082**	1.9012	11.5817**	3.4081*	4.4287**	0.0868	1
	4.1214**	1.496	4.5748**	1.461	2.5346*	0.9063	2
	1.9776	0.8844	2.2155*	1.4751	1.4611	0.6109	3
	0.5576	1.3161	1.2194	1.3442	0.9657	0.7811	6
	1.1634	1.3623	1.8172*	1.3476	1.1521	1.356	12
	1.0517	2.036	1.9579	2.1533	0.9604	0.6808	24

Source: Author calculations.

Notes: The table reports F-statistics of the Granger Causality Tests where the null hypothesis is "X does not Granger cause Y". **,* indicate rejection of the null at 5% and 10% levels, respectively. Averages are used to transform ADD and PDD series into monthly frequencies. $DD_{EUmedian}$ and DD_{LCBG} series obtained from European Central Bank's Financial Stability Reviews. Test samples, subject to data availability: Sep-2002 to May-2009 for $DD_{EUmedian}$; Sep-2002 to Apr-2011 for DD_{GSIFI}.

11 ADD and PDD series were previously transformed to match monthly frequency of ECB data and unit root and cointegration tests were conducted prior to the Granger causality tests. Saldías (2010) also includes Granger causality tests for the Euro area DD series. Unfortunately, the ECB publications do not disclose their portfolio composition, which may affect the tests results marginally.

transitory volatility shocks in the PDD indicator is partially cancelled out in averages and median DD series. These results strongly suggest that there is still a backward-looking component embedded that is not present in the DD series that incorporate option price information. The DD series constructed in this paper have therefore an important advantage as a tool of early detection of systemic risk.

4.3. Comovement and Risk Dependence

This subsection gives a closer look at the relationship between the PDD and ADD series and its properties in terms of expected comovement changes across bank returns and tail risk dependence.

The difference between PDD and ADD series embeds the comovement and correlation structure of banks' returns. In the case of series where calibration relies on realized pairwise covariances, it is a full reflection. However, when DD series are computed with individual and index option implied volatilities, the role of expected correlation on the DD gap remains important but also includes additional elements of sector-wide tail risks in extreme times. In addition, the PDD-ADD gap depends on the volatility regime in the equity markets, which means that there is a non-linear dependence structure determined by options and other data inputs. In particular, there is stronger effect of the comovement component during crisis times while under low volatility regimes, the other DD inputs, i.e. relative difference in terms of leverage and return growth, play a more relevant role.

In order to illustrate these points, Chart 3 compares the forward-looking DD series for Euro area banks to the Diebold-Yilmaz Connectedness Index (DYCI), introduced in Diebold and Yilmaz (2009). This indicator is constructed using stock prices information and is based on the decomposition of forecast error variances from a vector autoregression model. It is bound by construction between 0 and 100 and it measures the fraction of forecast error variances of banks in the sample that is explained by shocks to other bank stocks. The DYCI provides a good picture of time varying cross-section effects of stock return volatility, *i.e.* comovement and contagion, even though it does not contain signals of increasing risk from higher leverage in banks' balance sheets.

Chart 3

FORWARD LOOKING DISTANCE-TO-DEFAULT SERIES AND DIEBOLD-YILMAZ INTERCONNECTEDNESS INDEX | JANUARY 2004 – JANUARY 2012
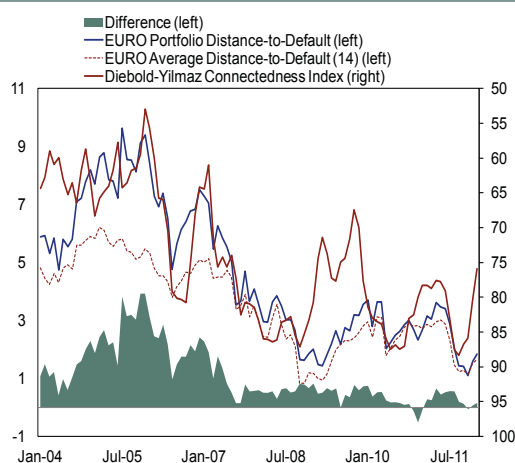
Sources: Author calculations and www.financialconnectedness.org.

Notes: Monthly observations. EURO Average Distance-to-Default (14) is a subsample of banks that matches the DYCI banks sample.

As suggested by Figure 3, the forward-looking DD series, especially the PDD series, are highly correlated with the DYCI[12], which illustrates the ability of the DD series to track comovement and contagion. In addition, the spikes detected in the DYCI indicator (plotted on inverted scale to facilitate comparison) also illustrate the short-lived episodes where the gap between PDD and ADD narrows significantly

Charts 4 and 5 illustrate an additional feature of the PDD and ADD series. The PDD-ADD gap embeds presence of asymmetric and nonlinear dependence between the series, which is in turn determined by the volatility regime, the relative relevance of the data inputs in the calibration, and the presence of elements of tail dependence.

Chart 4 plots together the call and put implied volatilities of the STOXX Europe 600 Banks Index and the (market-cap) weighted average of implied volatilities across the ADD sample. The spread between these two series spread has been time-varying but negative and in reality bound between 20 and 30 percentage points for most of the time until the Lehman Brothers bankruptcy. Then, this spread widened remarkably until it receded since May 2009. The implied volatilities went back to similar levels from the early days of the financial crisis, *i.e.* August 2007 - September 2008, and the spread below 20 percentage points up to the end of 2011. This figure shows that implied volatilities gap shows an overall regular behavior, compared to the larger movements described in the forward-looking DD series difference.

Chart 5 plots this difference versus the PDD-ADD difference to provide evidence of the nonlinear relationship between these variables.[13] Even though the relationship becomes stronger when the DD gap is smaller, the relevance of the volatility component when DD series are converging suggests that the implied volatilities differences play a different role under different volatility levels.

This evidence is in line with recent findings in the literature and illustrate that options prices endow the DD series with richer information than alternative specifications that are highly relevant for systemic risk and are not only related to correlation or comovement, but also with tail events. The modeling framework also allows incorporating the information from fundamentals to track longer-term trends and systemic risk build-up.

Chart 4

PORTFOLIO AND WEIGHTED AVERAGE IMPLIED VOLATILITIES | SEPTEMBER 2002 – JANUARY 2012
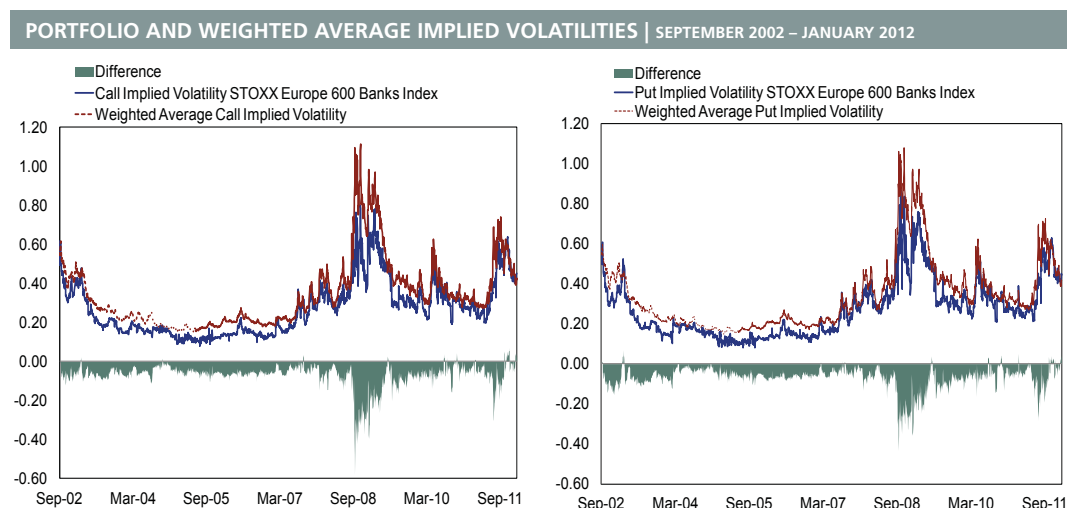
Sources: Bloomberg and author's calculations.

---

12 The PDD and DYCI pairwise Pearson, Kendall and Spear man correlation coefficients are -0.795, -0.516 and -0.722, respectively. These coefficients vis-à-vis the ADD series are -0.760, -0.505 and -0.712, respectively. Saldías (2010) also tests Granger-causality between the series and provide further evidence early systemic stress in the DD series, especially in the case of PDD series.

13 Saldías (2010) provides additional insights about the presence of asymmetric and nonlinear dependence between the DD series using empirical exceedance correlations and the Average Implied Correlation (AIC) indicator.

Chart 5
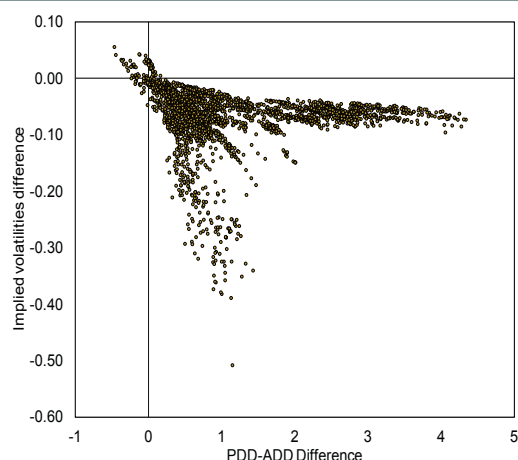
Sources: Bloomberg and author's calculations.

Note: The Implied Volatility difference uses the average of put and call index implied volatilities.

5. CONCLUSIONS

This article reviewed a method to monitor systemic risk in the European banking system. The approach relies on Contingent Claims Analysis to generate aggregated Distance-to-Default series using option prices information from systemically important banks and the STOXX Europe 600 Banks Index. The analysis extends from 30 September 2002 to 31 January 2012, covering both calm times and the financial crisis.

The three series allow monitoring the banking system as a whole and look at interdependences between banks over time. They are capable of identifying long term trends of build-up of risk in the sector based on the fundamentals, while showing a quick and short-lived reaction to specific market events seen as results of market sentiment and fluctuations. They are smooth in spite of being point in time estimates and thus avoid low signal-to-noise ratios and fuzzy signals. This feature allows one to track systemic risk over time and during crisis and non-crisis episodes

Due to the inclusion of option implied volatilities, they contain forward-looking signals of distress compared to other specifications of the indicator that contain past information and to other alternative market-based indicators based only on stock prices. Finally, they convey richer information of system-wide tail risk and other market-wide policy actions via the relationship between the reference index and the constituents.

References.

Acharya, V. V., L. Pedersen, Philippon, Thomas and M. Richardson (2010), "Measuring Systemic Risk", FRB of Cleveland *Working Paper* No. 2010-02.

Adrian, T. and M. Brunnermeier (2011), "CoVaR", NBER *Working Papers* 17454, National Bureau of Economic Research.

Antunes, A. and N. Silva (2010), "An Application of Contingent Claim Analysis to the Portuguese Banking System", *Financial Stability Report* Article, Banco de Portugal, May.

Brownlees, C. T. and R. Engle (2011), "Volatility, Correlation and Tails for Systemic Risk Measurement", *Working paper*, NYU Stern School of Business.

Čihák, M. (2007), "Systemic Loss: A Measure of Financial Stability", *Czech Journal of Economics and Finance*, vol. 57 no 1-2: pp. 5 – 26.

de Bandt, O., P. Hartmann and J. Pedró, J. (2009), "Systemic Risk in Banking: an Update", in Berger, A., P. Molyneux and J. Wilson (Ed.) *Oxford Handbook of Banking*, Oxford University Press.

Diebold, F. X. and K. Yilmaz, K. (2009), "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets", *The Economic Journal*, vol. 119 no 534: pp. 158 – 171.

Drehmann, M. and N. Tarashev, N. (2011a), "Measuring the Systemic Importance of Interconnected Banks", BIS *Working Papers* 342, Bank for International Settlements.

Drehmann, M. and N. Tarashev (2011b), "Systemic Importance: Some Simple Indicators", BIS *Quarterly Review*.

Duggar, E. and S. Mitra (2007), "External Linkages and Contagion Risk in Irish Banks", IMF *Working Papers* 07/44, International Monetary Fund.

Financial Stability Board (2009), "Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations", *Report to G20 Finance Ministers and Governors*, October 2009.

Galati , G. and R. Moessner (2011), "Macroprudential policy - a literature review", BIS *Working Papers* 337, Bank for International Settlements.

Gray, D., A. Jobst and S. Malone (2010), "Quantifying Systemic Risk and Reconceptualizing the Role of Finance for Economic Growth", *Journal of Investment Management*, vol. 8 no 2: pp. 90 – 110.

Gray, D. and A. Jobst (2010), "Systemic CCA: A Model Approach to Systemic Risk", in *Deutsche Bundesbank / Technische Universität Dresden Conference: Beyond the Financial Crisis: Systemic Risk, Spillovers and Regulation*, Dresden.

Gray, D. and S. Malone (2008), *Macrofinancial Risk Analysis*, Wiley & Sons Inc., Chichester, West Sussex, UK.

Gray, D. and J. Walsh (2008) "Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System", IMF *Working Papers* 08/89, International Monetary Fund.

Harada, K. and T. Ito, T. (2008) "Did Mergers Help Japanese Mega-Banks Avoid Failure? Analysis of the Distance to Default of Banks", *Working Paper* 14518, National Bureau of Economic Research.

Harada, K., T. Ito and S. Takahashi (2010), "Is the Distance to Default a Good Measure in Predicting Bank Failures? Case Studies", *Working Paper* 16182, National Bureau of Economic Research.

Huang, X, H. Zhou and H. Zhu (2010) "Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis", BIS *Working Papers* 296, Bank for International Settlements.

Kelly, B., H. Lustig and S. Van Nieuwerburgh (2011) "Too-Systemic-To-Fail: What Option Markets Imply About Sector-wide Government Guarantees", *Working Paper* 17149, National Bureau of Economic Research.

Langnau, A. and D. Cangemi (2011) "Marking Systemic Portfolio Risk with the Merton Model", *Risk Magazine*.

Merton, R. (1974) "On the pricing of corporate debt: the risk structure of interest rates", *Journal of Finance*, vol. 24 no 2: pp 449 – 470.

Rodríguez-Moreno, M. and J. I. Peña (2012), "Systemic Risk Measures: The Simpler the Better?", Universidad Carlos III de Madrid *working paper.*

Saldías, M. (2010), "Systemic Risk Analysis using Forward-looking Distance-to-Default Series", *Working Paper* 1005, Federal Reserve Bank of Cleveland.

Schwaab, Bernd, S. J. Koopman and A. Lucas (2011), "Systemic Risk Diagnostics: Coincident Indicators and Early Warning Signals", ECB *Working Paper* No. 1327.

Segoviano, M and C. Goodhart (2009), "Banking Stability Measures", IMF *Working Paper*, January.

Silva, N., N. Ribeiro and A. Antunes (2011) "Towards a CCA-based Systemic Risk Indicator", Banco de Portugal, *Financial Stability Report*, November.