SYSTEMIC RISK ANALYSIS USING FORWARD-LOOKING DISTANCE-TO-DEFAULT SERIES

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Systemic Risk Analysis using Forward-looking Distance-to-Default Series

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Abstract

Based on Contingent Claims Analysis, this paper develops a method to monitor systemic risk in the European banking system. Aggregated Distance-to-Default series are generated using option prices information from systemically important banks and the STOXX Europe 600 Banks Index. These indicators provide methodological advantages in monitoring vulnerabilities in the banking system over time: 1) they capture interdependences and joint risk of distress in systemically important banks; 2) their forward-looking feature endow them with early signaling properties compared to traditional approaches in the literature and other market-based indicators; 3) they produce simultaneously smooth and informative long-term signals and quick and clear reaction to market distress and 4) they incorporate additional information through option prices about tail risk and correlation breaks, in line with recent findings in the literature.

Contents

1 Introduction

One of the key lessons from the financial crisis generated in the US subprime mortgage market is the need to enhance and extend the systemic risk's analytic toolbox to guide policymaking. The interest in systemic risk analysis is not that new[1] and was driven by last decade's financial innovation, liberalization and development. However, the dynamics of this financial crisis has triggered renewed attention and operational focus at a global scale.

The theoretical and empirical work of defining and assessing systemic risk in banking is making great progress (de Bandt *et al.*, 2009). As far as empirical research is concerned, different approaches have emerged in the literature 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 supplementing existing methodologies that failed to capture vulnerabilities prior to this crisis.

This paper introduces a method to detect and monitor systemic risk in the European banking system based on Contingent Claims Analysis. Without strong additional modelling assumptions, this paper generates two series of aggregated Distance-to-Default indicators based on data from balance sheets, equity markets and option markets. The first series is the Average Distance-to-Default (ADD), a simple average of individual forward-looking Distance-to-Default series, computed using individual equity options. This indicator is standard in the literature and informs about the overall risk outlook in the system and the intensity of systemic distress. The second series is a Portfolio Distance-to-Default (PDD) that aggregates balance sheet information into a single entity and uses the equity and option prices information of the STOXX Europe 600 Banks Index. This indicator supplements the information of the Average Distance-to-Default, outlining the joint risk of distress and embedding interrelations between the banks in the system, and also the dynamics between the bank index and its core constituents under

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[1]See for instance European Central Bank (2007b) for an overview of the early research approach in this area conducted by the ECB, the Bank of Japan and the Federal Reserve.

tail risk events and possible correlation breaks. In option pricing theory terms, these two indicators are a basket of options (ADD) and an option on a basket (PDD), where their difference is primarily (yet not only) driven by interdependence among their constituents.

Other models are similar to mine in that they aim to capture and quantify joint risks and interdependences with the use of market-based information and include risk drivers such as leverage, size, interbank linkages or maturity mismatch. Recent and popular contributions and their extensions along these lines are found in Adrian and Brunnermeier (2011), Acharya *et al.* (2010), Brownlees and Engle (2011), Diebold and Yilmaz (2009), Huang *et al.* (2009, 2012), Drehmann and Tarashev (2011b) and Tarashev *et al.* (2010); Drehmann and Tarashev (2011a). Galati and Moessner (2011) provide a comprehensive review of this literature and their relative performance. The approach in this paper is based on Contingent Claims Analysis and it is therefore closer to the work reviewed in Gray and Malone (2008) and extended in Gray and Jobst (2010a) and Gray *et al.* (2010) to include sovereign risk. Compared to the literature cited above, the CCA approach produces time-varying point estimates of risk indicators that can be periodically updated, becoming more comprehensive than alternative (conditional) measurement approaches to systemic risk (Gray and Jobst, 2010b).

Recent contributions in the CCA literature include multivariate density estimations, like the Systemic CCA measure in Gray and Jobst (2010b), in order to assess the marginal contribution of financial institutions to systemic risk. In contrast to the approach in this paper, this methodology introduces formally the dependence structure of the financial institutions in the system to assess systemic tail risk and to capture systemic risk contributions. The aim in this paper is limited to set up the framework of a monitoring device that incorporates the information from different market sources with a strong forward looking component and ability to adapt to changing market conditions. As a result, the dependence structure among the banks in the financial system embedded in PDD and ADD series is purely data-based and come from the differences between the benchmark bank index and its constituents, especially in the case of options.

The use of individual and index option information incorporates two innovations in the literature. First, it makes use of information from an additional liquid market, the single equity and equity indices options markets. Second, the construction of the indicator avoids arbitrary or strong modeling assumptions or dependence structures among banks in the sample which tend to weaken its information quality and rely on past information that hinders its ability to anticipate events of high systemic risk. In other words, the information potential of individual equity and equity index options allow the Distance-to-Default indicators to become a forward-looking analytic tool to monitor systemic risk, interdependences between the banks and extreme events in the financial system over time.

The series generated in the paper show a lower noise-to-signal ratio, and allow one to tracking the build-up of risks in the system with a long-term perspective. They are computable on a daily basis and incorporate up-to-date market sentiment from option prices. In doing so, they react quickly to specific market events, when volatility of the components of the system increases and correlations tend to reveal changing interdependences and stock prices moving in tandem. The option prices information also enhances significantly the forward-looking properties of the series and makes their signals timelier than in either literature of market-based indicators or alternative specifications similar to mine in employing comparisons between a portfolio and an average of its components. Finally, information about tail-risk events and correlation breaks are detected through option prices as market events affecting the whole of the banking system have heterogeneous effects on individual banks.

The rest of the paper is structured as follows. Section 2 first reviews the Contingent claims analysis' main features and applications -the supporting theory of this approach-then makes reference to a specific application of the literature that is a standard tool of systemic risk analysis. In Section 3, the paper provides a detailed description of the method which produces individual and aggregated series of forward-looking Distance-to-

Default (DD) indicators using the information of the European banking system and its core systemic components. Section 4 reports the main results of the DD series, highlighting its main attributes as a systemic risk indicator and its advantages when compared to possible alternative specifications in the related literature. Section 5 concludes.

2 Theoretical Underpinnings

2.1 Contingent Claims Analysis

Contingent Claims Analysis (CCA) is a framework that combines market-based 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, expected losses on senior debt, etc. Based on the Merton (1974) approach to credit risk, CCA has three principles: 1) the economic value of liabilities[2] is derived and equals the economic value of assets (which reflect the present value of future income); 2) liabilities in the balance sheet have different priorities (i.e. senior and junior claims) and associated risk); and 3) the company assets distribution follows a stochastic process (Echeverría *et al.*, 2006; Gray *et al.*, 2010).

In this context, as 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 default barrier is called Distance-to-Default (DD) and constitutes the financial risk indicator used in this paper to assess and monitor systemic risk in Europe's banking sector[3]. 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

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[2]Deposits and senior debt plus equity in the case of banks.

[3]This paper is limited to the development of Distance-to-Default series and their application as a systemic risk monitoring tool. The use of the rest of risk indicators derived from this methodology remains for further research. The indicator is also known as Distance-to-Distress in some applications in order to highlight the fact that, especially in the financial sector, actual defaults seldom occur. I chose not to make that distinction even though the indicators in the paper are designed to detect and monitor distress.

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probabilities of default, if the distribution of assets were known.

This method has initially been applied to company default risk analysis and disseminated by Moody's KMV[4], proving very effective in prediction of ratings' downgrading and company default. Gray and Malone (2008) provide a comprehensive review of methodologies and related literature. The CCA-based indicators are attractive in that they combine different sources of information, thus making stress detection in the banking system more comprehensive compared to indicators based on a single source[5].

DD series and other CCA-derived risk measures incorporate forward-looking expectations and are easy and data-efficient to compute at high-frequencies. They are also good indicators of market sentiment, relatively less affected by government interventions and they incorporate most relevant elements of credit risk. Results in Gropp *et al.* (2004, 2006); International Monetary Fund (2009) and Tudela and Young (2003), inter alia, show also that DD improves and may even outperform other indicators of financial stability including bond or CDS spreads. More recently, the International Monetary Fund (2011) reports that aggregated Distance-to-Default series computed for the US banking system did a good job in forecasting systemic extreme events and in detecting early turning points near systemic events in the last decade, even though these series were computed using historical equity information.

Having these advantages into consideration, it is also important to consider that, as other market-based financial stability indicators, DD series may also be exposed to some methodological shortcomings originated in the quality of input data (International Monetary Fund , 2009; Financial Stability Board, 2009b). In particular, DD series may be sensitive to market liquidity and market volatility and also exposed to the accuracy of the market assessment, meaning that it may be possible that in periods of high stress in financial markets or market freezes, the computation may not be possible to implement

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[4]See for instance Arora *et al.* (2005); Arora and Sellers (2004); Crosbie and Bohn (2003); Dwyer and Qu (2007).

[5]As an example, Krainer and Lopez (2008) show that informational properties of equity and bond markets vary according to the state of stress and the proximity of corporate default.

and/or the DD indicators may produce unclear signals. At worst, even if stress signals from DD series were available, the indicator could at best be coincident with market events, leaving little margin for policy makers to react (Borio and Drehmann, 2009)[6].

2.2 CCA and Systemic Risk Analysis

The CCA approach has been cited and reviewed by the Financial Stability Board (2009a) 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, a number of applications of this approach have been implemented to analyze different dimensions of systemic risk in banking as well as in a broader context. In practical terms, the extensions of DD series and other CCA-based indicators into system-wide indicators for systemic risk analysis entail an aggregation issue of individual banks' data into a representative portfolio indicator and also modelling assumptions about the interdependence across the financial institutions. The indicators developed in this paper provide two complementary ways to aggregate individual bank information and the dependence structure is not explicitly modelled but embedded in the data from index options.

For instance, Harada and Ito (2008) and Harada *et al.* (2010) provided empirical evidence of DD usefulness to detect bank default risks and to assess the effects of mergers in crisis periods in Japan comparing individual DD series of distressed banks to aggregate DD series built as benchmark of the entire banking system. The systemic

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[6]As discussed in Gray and Malone (2008), the framework is flexible enough to introduce modeling variants and relax some of the assumptions, such as an ad-hoc default barrier, constant interest rates and constant volatility. As a result, several extensions in the literature have been developed in recent years. In particular, Capuano (2008) tackles the ad-hoc default barrier issue proposing an endogenously determined default barrier that rapidly incorporates market sentiment about the developments of the balance sheets, while Chan-Lau and Sy (2006) introduce modifications in the ad-hoc default barrier to capture pre-default regulatory actions, such as Prompt-Corrective-Actions frameworks, a common feature in the case of financial institutions. Findings in Echeverría *et al.* (2009) show that the choice of risk-free interest rates does not affect the estimates of DD significantly but their selection has to be adjusted to the specificities of the institutions and markets of analysis (see Blavy and Souto (2009) for a detailed discussion in the case of the Mexican banking system). Finally, as for constant volatility, this assumption is relaxed in some models that introduce time varying -generally GARCH(1,1)- volatility series. Research in Echeverría *et al.* (2006) and Gray and Walsh (2008) are good examples of this approach.

risk indicator is in this case an average of individual DD series of "sound" banks. This approach is very attractive in terms of policy advise and provides empirical support to apply aggregated DD for monitoring systemic risk overall and compare relative risk performance of individual entities. However, this simple aggregation method implicitly chooses to omit their joint distributions' properties. In another application, Duggar and Mitra (2007) construct DD series for individual Irish and other international banks, then compute rolling correlation series and finally apply a multinomial logit model to assess cross-border contagion and interdependences under different degrees of stress. Finally, Gray and Walsh (2008) compute DD series for largest institutions in the Chilean banking system and assess the heterogeneous effects of macroeconomic factors on default risk of banks[7].

Recently, Gray *et al.* (2007) and Gray and Jobst (2010a) developed further extensions of the CCA framework to analyze a wider range of macro-financial issues and systemic risk[8]. These authors emphasize the role of inter-linkages through of risk-adjusted balance sheets. These model extensions stress the importance of aggregation of univariate CCA models of institutions or sectors into a multivariate framework that can track the interdependences and linkages. In Gray *et al.* (2010); Gray and Jobst (2010b), the authors stress that conventional correlation measures based on realized data become unreliable in presence of fat tails, especially in times of crisis, and therefore develop a method where they account for both linear and non-linear dependence via extreme value theory techniques.

The potential to use aggregated DD series to monitor systemic risk is not negligible and, in the case of the European and other mature banking systems, this potential could overcome some of the modelling limitations and signal quality weaknesses cited above via the properties of option prices of both individual bank equities and bank equity indices.

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[7]In this application, the authors treat the banking system as a "big bank" and thus aggregate the individual balance sheet and equity data and model equity volatility with a GARCH(1,1) model applied to aggregate market capitalization.

[8]In particular, the authors address issues such as sovereign risk, economic output, risk transmission across sectors and quantification of systemic risk contributions

In particular, Gray and Malone (2008) argue that the inclusion of external volatility such as the option-based volatility index VIX improves the performance of the Merton (1974) model and overcomes some of the shortcomings originated in its assumptions on the returns distributions. Fleming (1998) and Yu *et al.* (2010) find empirical evidence of the index options predictive power of future volatility, while Becker *et al.* (2009) provide evidence of the ability of index options to reflect incremental information about jumps in volatility that model-based forecasts do not. Bollen and Whaley (2004) show that index options tend to have information about hedging strategies while stock options are mostly affected by bullish sentiment. Kelly *et al.* (2011) analyze the differences between options on a portfolio and options on its constituents and find public policy-driven sources of divergence in addition to the correlation component. Avellaneda *et al.* (2002) report that index option prices contain information about future correlations and about correlation skews. The methodology described in the following section aims to include all these properties from single equity end equity indices option markets into the DD series and improve their performance for systemic risk analysis, while avoiding additional and probably more restrictive assumptions in the Merton (1974) model with respect to the joint distribution features and dynamics of risk in the banking system.

2.3   Aggregation Methods and Properties of Distance-to-Default Series

This section introduces the two CCA indicators used as systemic risk monitoring tools, i.e. the Average Distance-to-Default (ADD) and the the Portfolio-Distance-to-Default (PDD) series. In terms of the underlying option pricing theory, these two indicators can be seen as proxies of a basket of options (ADD) and an option on a basket (PDD), where their wedge is primarily driven by interdependence among their constituents. In this empirical application, additional differences in this gap are originated in specific properties of options on individual bank stock prices and on the reference index.

Most CCA applications aggregating individual DD into system-wide indicators uses simple or weighted averages of individual DD series as standard practice, sometimes also DD medians or other DD quantiles. For instance, the ECB's Financial Stability Review

publishes since 2004 series of DD medians and 10th percentiles of global and euro area Large and Complex Banking Groups (LCBG) or Global Systemically Important Financial Institutions (GSIFIs)[9]. Very few applications use the PDD approach, i.e. calibration of individual data into portfolios of banks, which means treating the system as one large bank. The Central Bank of Chile introduced formally this methodology applied to the Chilean banking system in 2006 (Echeverría *et al.*, 2006). The IMF published both ADD and PDD series in country reports for the euro area and the United States (Annett *et al.*, 2005; Čihák and Koeva Brooks, 2009; Mühleisen *et al.*, 2006). All of these CCA applications have traditionally relied on backward-looking information, especially when modelling pairwise asset returns covariances for PDD computation, and none of them have yet used the information of option prices information of both bank stocks and banks indices before.

The analysis of ADD series (including DD medians or other DD quantiles) is highly informative of the build-up, dynamics and intensity of system-wide distress risk. It can though be misleading if analyzed alone since ADD series do not take into account bank heterogeneity, size differences, risk interdependences and sector-wide tail risks, especially in stress times. ADD implicitly assumes perfect correlation across assets in the banking system. While weighted averages or quantile DD partially solve the bank 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; Chan-Lau and Gravelle, 2005).

PDD series tracks the evolution of the lower bound of joint probabilities of distress (De Nicolò and Tieman, 2007) and enhances therefore information quality of ADD series, since it takes into account bank size and tackle risk interdependence among banks[10]. Given that PDD series are usually computed using realized pairwise asset covariances and volatilities based on historical equity returns, as described in Appendix B and in De Nicolò

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[9]See European Central Bank (2005) for the introduction of the indicator in the publication series.

[10]This holds true in spite of the fact that aggregation of individual balance sheet data does not fully take into consideration the crossed exposures, i.e. the portfolio balance sheet data are similar to unconsolidated bank figures.

and Tieman (2007), the joint dynamics works primarily as follows: when comovement in banks' assets increases in times of market distress, showing higher interdependences, the gap between them tends to narrow and both series also tend to drop in case of deteriorating fundamentals and market capitalization. Since PDD is in general higher than ADD and therefore is a lower bound of distress, the joint movement of ADD and PDD series contains relevant information about increasing comovement and hence systemic risk. As illustration, Figure 1 shows the ADD and PDD series based on this methodology, where 1-year historical volatility enters the calibration as equity volatility and 1-year rolling windows are used to compute asset covariances. The figure also shows the cases when perfect and nil correlation across implied assets are assumed. ADD and the PDD series under perfect asset correlation are almost identical, while PDD tends to fluctuate between the latter and the PDD series under asset independence. As a result, the wedge between PDD and ADD fluctuates with the realized asset correlation, while the levels of the ADD and PDD series are affected by the rest of risk drivers and therefore provide information of the distress risk outlook of the system.

[Insert Figure 1 here]

Alternatively, in empirical applications where individual GARCH-modelled or option implied volatilities are used as inputs instead of realized volatilities, the ADD series acquires more reaction to market events. Covariances required for the computation of PDD in this framework may either be neglected or historical or intra-day pairwise covariances may be used instead[11]. In either case, the PDD indicator is still likely to become a coincident one and may fail to detect early signals of market stress (International Monetary Fund , 2009) even if option prices information of the portfolio constituents is used.

The information potential of aggregated DD series has not been fully exploited, given the rich data available in mature markets where option markets are active and deep. Indeed, standard implied volatilities of options on individual bank stocks are used only to

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[11]Most literature use historical covariance series and Huang *et al.* (2009, 2012) propose an innovation using high-frequency intra-day covariances to add a forward-looking dimension to asset return correlation.

a limited extent, and implied volatilities from options on sector-based indices are barely analyzed in the literature[12], even though index options are known to contain specific views of the market direction, which is a relevant feature for systemic risk monitoring. The inclusion implied volatilities of an index and of index components in the model can thus enhance the information content of Average and Portfolio DD series without imposing modelling assumptions about the covariance and dependence structure. Sections 3 and 4 show how this methodology is applied and how it compares to existing use of DD to monitor systemic risk.

More important, when using option implied volatilities, the difference between Portfolio and Average DD conveys important information about systemic risk and include additional elements to the dependence structure found in the literature, namely tail risk dependence, correlation skews and the effects of public guarantees in system-wide risk perception. Langnau and Cangemi (2011) show 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, i.e. in times of crises. 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. In addition, Kelly *et al.* (2011) provide empirical evidence of the diminishing effect of public guarantees on market-wide risk. Roughly speaking, public guarantees to the financial sector make artificially cheap the index options and thus lowers their implied volatility, while individual options may show high implied volatilities even though there is high correlation of returns. These features would not be traceable using realized volatilities and covariances and therefore make a strong case for the use of index and individual equity option prices information in the calibration of DD series.

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[12]Castrén and Kavonius (2009) provide one of the few applications where implied volatilities of indices are used to calibrate sectoral DD series, although the authors do not compute either PDD or ADD in the strict sense from this paper but use the implied volatilities instead as a proxy for sectoral equity volatility, combined with balance sheets from the euro area financial accounts.

3   Empirical Application

This section introduces the bank sample used to compute ADD and PDD series. Then, Sections 3.2 and 3.3 discuss some relevant particularities in the data and methodological approach in this paper. A detailed explanation of the Merton (1974) model, the numerical procedure to compute ADD and PDD and other relevant technical discussions of the method can be found in Appendices A and B.

3.1   The Sample

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 between the Third Quarter of 2002 and the Fourth Quarter of 2011. This sector-based index includes the largest and most widely traded shares of banks from 17 countries headquartered in the Eurozone, Iceland, Norway, Switzerland and the United Kingdom. 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 paper in that there are liquid exchange-traded option prices on the corresponding index[13] available since 2002.

The sample used to compute the PDD series includes 95 (out of 99) banks belonging to the STOXX Europe 600 Banks Index over the timespan, taking into account quarterly index composition and updates in the broader STOXX Europe 600 Index due to M&A, nationalizations, bankruptcy, reclassifications and other relevant corporate actions. The full list of banks in the sample and other related methodological notes are presented in Tables 1 to 3.

[Insert Tables 1 to 3 here]

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

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[13]Additionally, options on the EURO STOXX Banks Index are also available for the analysis of the banking system in the Eurozone.

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[14]. Ideally, the PDD and ADD samples should match perfectly, but the availability of liquid option prices acts as a practical constraint. Accordingly, an initial sample of 52 banks, for which option implied volatilities were available, was filtered according to the individual option data length and quality[15]. As additional criterion, the banks in the ADD subsample had to be constituents of the index at the beginning and during at least 70% of the trading days included in the analysis.

Table 4 lists the resulting 34 banks in this subsample. 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 excluded from the reference index in December 2011.

[Insert Table 4 here]

The resulting ADD banks are the largest in terms of free-float market capitalization in the reference index, with an aggregate weight over 80% at the beginning of the sample and nearly 95% in the First Quarter of 2012[16].

These banks are regarded as systemically important since this portfolio complies 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 (Financial

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[14]According to the Industry Classification Benchmark (ICB) methodology, ING Group belongs to the STOXX 600 Insurance Index due to its bancassurance business model. This institution is however considered a bank in most bank rankings, most empirical research on financial stability and even EU-wide stress tests conducted by the European Banking Authority (EBA).

[15]This discrepancy becomes less as the number of constituents in the index decreases in time and several M&A take place within the ADD banks in sample. Alternatively, I could have included the implied volatility information of predecessor banks, with the possible risk of introducing noise in the data.

[16]This notable weight increase was mainly driven by the consolidation process in the European banking sector and, to a lesser extent, to resulting M&A and other post-crisis restructuring.

Stability Board, 2009b) and more recently detailed in a report published by the Basel Committee of Banking Supervision (2011). With the exceptions of Natixis[17], Mediobanca, Standard Chartered and the two large Swiss banks (UBS and Credit Suisse), all of them were participating banks in the 2011 EBA's EU-wide stress tests.

In terms of size, an accurate approximation of systemic importance (Drehmann and Tarashev, 2011a,b), these banks rank highest in the region by total assets[18] and according to other size-based classifications, such as the Forbes 2000 list[19]. All these banks weigh significantly in their respective domestic stock markets in terms of market value and trading volumes, and most of them have multiple listings at major world exchanges and liquid options traded[20]. By the end of 2008 and 2009, these banks represented around 70% of the total assets of the EU-27 banking system[21].

In addition to the relevant market shares in domestic markets, these banks also operate at a large cross-border scale throughout Europe and in the rest of the world, which illustrates their large cross-jurisdictional activity and complexity. On average, around 30% of their total revenues was generated in a European country other than the home market and over 25% of total revenues was generated outside Europe in 2008 (Posen and Véron, 2009). Geographical distribution of assets and liabilities shows similar characteristics.

This portfolio of banks constitutes the core of the ECB's LCBG and the seed of the Global Systemically Financial Institutions (G-SIFI) list. Eight of these banks appeared in the Bank of England's list of 15 Large Complex Financial Institutions (LCFI) due

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[17]Technically, Natixis did participate, but as the corporate and investment banking arm of Groupe BPCE.

[18]Based on 2009 end-of-year Bankscope data, fourteen of them are among the Top-3 by assets in their respective home countries and seven are in the Top-20 in the World Rank.

[19]This ranking uses an equally weighted combination of rankings by sales, profits, assets and market capitalization to assign positions. The composition in the top 30 for Europe has remained stable in the last decade, taking into account major M&A transactions.

[20]The fact that these banks have options on their stocks adds an additional source of comovement, compared to banks without traded options, which is relevant in terms of systemic risk analysis (Agyei-Ampomah and Mazouz, 2011).

[21]Based on data from Bankscope and European Central Bank (2010)

to their important role in the global financial system and their engagement in complex businesses and high interconnections with the rest of the financial system[22], making supervisory oversight more difficult. More recently, Acharya *et al.* (2011) cites 14 of these institutions as the European financial institutions considered systemically risky by the Financial Stability Board.

3.2 Calibration of Average Distance-to-Default Series.

The Average Distance-to-Default (ADD) is represented in (1) below and is obtained by taking the simple average across $N = 34$ individual bank DD series[23].

$$ADD_t = \frac{1}{N} \sum DD_{i,t} \tag{1}$$

where is the individual DD_i T periods ahead[24]. As presented in (2) below, for each bank $i = 1, \ldots, 34$, $DD_{i,t}$ is a function of a distress barrier $D_{i,t}$, obtained from the banks' balance sheet data; the rate of growth of its assets –approximated by the risk-free interest rate in the respective home market, $r_{i,t}$[25]– and two unobservable variables, namely the implied value of assets $A_{i,t}$ and the implied assets volatility $\sigma_{i,t}^A$. The latter two variables are estimated with standard iterative techniques[26] using the market value of equity $E_{i,t}$ and equity price return volatility $\sigma_{i,t}^E$, obtained in this paper from individual equity options as explained in Appendix A.

$$DD_{i,t} = f\left(A_{i,t}(E_{i,t}, \sigma_{i,t}^E), \sigma_{i,t}^A(E_{i,t}, \sigma_{i,t}^E), D_{i,t}, T, r_{i,t}\right) \tag{2}$$

Balance sheet and market data were obtained for the period between 30 September

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[22]Deutsche Bank, Credit Suisse, Barclays, HSBC, Société Générale, UBS, RBS and BNP Paribas. The rest of banks in the list are not European. This list covers several measures of interconnectedness, substitutability and complexity.

[23]In the benchmark model, all calculations are conducted with data reported in the currency of the bank's home market. DD series with bank data previously converted into euro were also computed with very little differences on the aggregate outcome.

[24]Set at one year, as standard practice in the literature.

[25]This assumption entails risk neutrality and therefore the associated asset return probability distribution is very likely to differ from the actual asset return probability distribution. The European soverign debt crisis may have introduced some distortions to the risk-free assumption, but sensitivity to this input is minor in the results. Gray (2009) provides a thorough discussion of this difference.

[26]Newton-Raphson method with two equations and two unknowns in this application.

2002 and 31 December 2011 (2437 trading days)[27]. Balance sheet data comprise annual and interim data on total assets, short-term liabilities and equity obtained from Bankscope. 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[28]. The risk-free interest rates are 10-year government bond yields in each bank's country of origin. See Table 5 for a description of data and sources.

Individual DD series have daily frequency. In practical terms, this means the balance sheet information has to be modified from its original quarterly, half-yearly or, in few cases, yearly frequencies[29]. In this paper, the original data were interpolated into daily series using cubic splines. 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.

[Insert Figure 2 here]

3.3 Calibration of Portfolio Distance-to-Default Series.

The expression for the PDD series is the following:

$$PDD_t = f\left(A_{P,t}(E_{P,t}, \sigma^E_{P,t}), \sigma^A_{P,t}(E_{P,t}, \sigma^E_{P,t}), D_{P,t}, T, r_{P,t}\right) \tag{3}$$

where PDD_t is the Portfolio Distance-to-Default T periods ahead. The definition of the inputs in the PDD case are the same as in (2). However, as the PDD assumes that individual banks are regarded as a big bank, some relevant methodological changes are worth pointing out to highlight the methodological contributions of this paper and

[27]DD series corresponding to Dexia, Fortis, HBOS and Alliance & Leicester stop on 18 November 2011, 21 September 2009, 16 January 2009 and 10 October 2008, respectively.

[28]Missing values for Natixis prior to 29 September 2010 have been replaced for volatility estimates from a GARCH(1,1) model. Infrequent missing values have been replaced for those from the previous trading days.

[29]In general, French and British banks issue semi-annual financial reports, while the rest of banks provide quarterly information. Yearly data were more frequent in the first years of the sample and under Local GAAP accounting standards. Since 2005, most of the banks in the sample report under IFRS.

in terms of option pricing theory. The calibration of (3) requires the aggregation of balance sheet data into a single series. Hence, the individual annual and interim data on total assets, short-term liabilities and equity are first converted into euro using bilateral exchange rates against the euro and then added up across the actual constituents from the portfolio, $P = 95$, 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 Eurozone synthetic 10-year government bond yield[30].

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 $\sigma_{P,t}^A$, was conducted using the equity market value of the portfolio $E_{P,t}$, directly taken as the euro-denominated market value of the reference index, and the portfolio's equity volatility obtained directly from the index options $\sigma_{P,t}^E$.

The daily put and call implied volatilities of options on the STOXX Europe 600 Banks Index are included under the premise that timely and meaningful implied volatilities call for prices from an active index option market (Whaley, 2009). These series start on 30 September 2002, which determines the sample start of this paper. The end date is set on 31 January 2012 in order to include 2011 annual reports' information for all banks. The time span therefore covers the slow recovery from the dot-com bubble in the beginning, tranquil times alternated with periods of minor stress between 2004 and 2006, the financial crisis since August 2007, and the periods of market recovery and sector-wide recapitalization combined with the emergence of the European sovereign debt crisis and its policy responses. Implied volatilities of put and call options on the STOXX Europe 600 Banks Index are also transformed into daily averages.

In contrast to other PDD applications in the literature (Annett *et al.*, 2005; De Nicolò and Tieman, 2007; Echeverría *et al.*, 2006, 2009; Gray and Malone, 2008), where the

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[30]This series was obtained from Thomson Reuters Datastream. Alternatively and following previous research, a market-cap weighted average of risk-free interest rates in the corresponding home markets has been examined but did not affect the results.

implied assets $A_{i,t}$ of the banks in the sample are used to compute covariances and the portfolio volatility (see Appendix B), using implied volatilities from the reference index and its main constituents means in practice that this paper does not only add a 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 . In terms of option pricing theory, a basket option usually uses a basket volatility based in the correlation matrix across returns, which makes the model unable to capture correlation breaks and skew[31]. Equity volatility is taken directly from options market data, introducing market perceptions of correlation breaks, joint distress risk and their features under extreme events.

4 Results

This section reports the results of the calibration of ADD and PDD series described in the previous section. It focuses on the properties of the Average Distance-to-Default (ADD) and Portfolio Distance-to-Default (PDD) series and their difference as a tool to monitor systemic risk in Europe's banking system, namely 1) the three series allow to monitor the banking system as a whole and look at interdependences between banks over time; 2) they are capable of identifying long term dynamics and build-up of risk in the sector, while showing a quick and short-lived reaction to specific market events seen as results of market sentiment and fluctuations; 3) they are smooth, avoiding low signal-to-noise ratios and fuzzy signals, which allows one to track systemic risk over time and during crisis and non-crisis episodes; 4) 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; and 5) the convey richer information of system-wide tail risk, correlation breaks and other market-wide policy actions via the relationship between the reference index and the constituents.

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[31]The analytical expression –very similar to the one used to compute the Average Implied Correlation– is expressed as follows: $\sigma_{Index} \approx \sqrt[2]{\sum_{i=1}^{P} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{P} \sum_{j=1, j \neq i}^{P} w_i w_j \rho_{i,j} \sigma_i \sigma_j}$. (Avellaneda *et al.*, 2002) and Fengler *et al.* (2012) provide further discussions on this topic.

4.1 Distance-to-Default Series Dynamics and Systemic Risk Outlook

Figure 3 plots together 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. Table 6 provides the summary statistics of these DD series, denoted as benchmark model, and those of other DD series computed with alternative specifications to be described below[32]. These three series 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 also shows a higher standard deviation and positive skewness compared to the ADD series. The first feature illustrates the quick reaction of the PDD series to new information and their effect on comovement across the sample, while the second feature shows 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 in response to specific market events of high volatility during easily identifiable and short periods, well illustrated by the reference equity index. The difference tends to stay narrow for longer periods under high volatility regimes in the market and when there is a high degree of joint distress in the sector, as anticipated in the simulation in Figure 1. 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, when a wide range of policy measures were implemented at an unprecedented scale to ensure solvency in the sector under a high degree of uncertainty in the markets.

[Insert Table 6 here]

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 and the effects of the exposure

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[32]Figure 4 shows the series starting in 2005 to account for the generalized adoption of IFRS accounting standards that might have introduced a break in the series due to revaluation of balance sheet items, see European Central Bank (2006) and Rapp and Qu (2007) for further discussion.

of many European banks to the Argentinean crisis, under a high volatility regime. The series show an upward trend and an increasing PDD-ADD gap afterwards until the end of 2005, reaching a maximum PDD-ADD gap on 8 August, as financial markets become less volatile and the sector becomes more profitable yet increasingly levered.

During this time span however, there are some specific and short-lived events where the PDD-ADD gap narrows significantly. A first example is the period between April and May 2004, where markets experienced corrections as they anticipated earlier and more pronounced monetary policy tightening in the US. In April-May 2005, there is another episode of turbulence in both equity and option markets due to uncertainties about the monetary policy stance in the Eurozone and the US and especially due to the downgrade of the credit ratings of GM and Ford, which drove a sharp widening in yield spreads in debt markets also in October 2005, after Delphi's (a GM's subsidiary) bankruptcy. In mid-2006, the series also reflect a market-wide correction in global equity markets, while in February 2007, the gap narrows for a relatively longer period as the subprime crisis was starting to unfold. All these events took place in a low market volatility regime and during a period where bank profitability was continuously increasing. Another interesting feature of the reported DD series is the fact that they 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. This downward trend was mainly caused by the increasing leverage.

[Insert Figures 3 and 4 here]

Since August 2007, the subprime crisis drove the DD series and especially the gap to very low levels, setting a new regime of high volatility, decreasing stock returns and high return comovement across banks, with exceptional periods of wider gaps due to temporary good news. 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 (Echeverría *et al.*, 2009). The DD series continued to

plummet until the Lehman Brothers collapse and the first round of stress-tests in the US. The round of capital injections at global scale produced an upturn in the DD series while the gap remained close to zero.

At the end of the sample, the ADD and PDD series show an upward trend, reflecting deleveraging and, arguably, improving 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 the series of capital injections across all Europe coupled with a high volatility regime in financial markets that makes contagion very likely and fast. The late interruptions in recovery (including the marginal upturn as a consequence of the LTRO credit infusion) are a consequence of the European sovereign debt crisis (especially in the last quarter of 2010 and Summer 2011). All these developments are consistent with related findings in the literature Brownlees and Engle (2011); Diebold and Yilmaz (2009); Yilmaz (2011) about returns spillovers and volatility spillovers.

As noted in previous sections, most market-based indicators of financial stability were targets of criticism because of their poor performance during the crisis and their failure to detect early signals of distress in major banking institutions. Indeed, the ECB's Financial Stability Review reports the decline of their DD series only in the second quarter 2007 and equity markets remained somewhat stable even after the liquidity squeeze took place (European Central Bank, 2007a). Even if the forward-looking DD series presented in this section had no predictive power at the time, the figures described above make a strong argument for the combined use of forward-looking DD series based on option prices information to monitor the general build-up of risk in systemically important banks in Europe and to detect regimes of high volatility and contagion in the market.

Figures 5 and 6 plot together the series computed for banks headquartered in the Eurozone and Table 6 provides a comparison of their summary statistics vis-à-vis the benchmark model. As expected, the three series look very similar to those computed for all Europe and with respect to the reference equity index (EURO STOXX Banks Index).

Compared to the series covering the entire bank sample, the DD series in the Eurozone are slightly more volatile and skewed. The main difference is at the end of the sample, where the sovereign debt crisis affected harder the Eurozone banks and drove the gap into negative values for longer periods of time between October and November 2010. This event means that, given high volatility in the market and high expected comovement of stock returns, the perception of risk in the financial system as a whole is more pessimistic than the aggregation of case-by-case assessments and is mainly driven by the difference between the option implied and equity volatility information on the reference index and on its constituents.

[Insert Figures 5 and 6 here]

4.2 Smoothness Properties

Figures 7 and 8 show the DD series using put implied volatilities and volatilities from a GARCH(1,1) model in the calibration of both ADD and PDD series, respectively. Their summary statistics are reported in Table 6. The model assumptions for these specifications are the same as in the benchmark model with the only difference in the data source of equity volatility used for calibration. The results are robust to this variation as regards the ability of the indicator to detect build-up of stress and monitor its dynamics but they serve to illustrate the smoothness of the original series with respect to other possible but slightly different model specifications. However, as put options are more reactive to market specific events and contain important information regarding the demands for portfolio insurance and market volatility (Whaley, 2009), DD series obtained using average implied volatilities are smoother, which is a valued property of market-based indicators in the analysis of systemic risk, and provide lower standard deviations. The results of this paper focus therefore on them only, although it is desirable that the analysis of short term market distress takes into account the information potential of put-derived DD series[33].

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[33]Put options are extensively used for insurance purposes, i.e. hedgers buy puts if they have concerns about a potential drop in the markets (Whaley, 2009). Kelly *et al.* (2011) show the usefulness of put options pricing to evaluate government bailout guarantees.

DD series based on GARCH(1,1) model volatilities are plotted in Figure 8. They have larger standard deviations than the benchmark DD series and look clearly and significantly more volatile and with more swings along the sample and thus convey a low and undesired signal-to-noise ratio[34]. GARCH-modeled volatilities have the advantage of quick adjustment to changes in the underlying data, but they also tend to overshoot. This feature means more noise in the DD indicator, which leads in practice to a difficult interpretation of its signals and more frequent false positives in the series of DD differences. As a result, reliability of this approach is reduced in terms of monitoring systemic risk compared to both the benchmark series and even DD series constructed with historical volatilities. In addition, the trends in the GARCH-derived DD series are not as clear as those depicted in Figures 3 and 4 and there is more dominance of the short-lived market events.

[Insert Figures 7 and 8 here]

4.3 Forward-looking Properties

Figures 9, 10 and 11 compare the forward-looking DD series and their gap to those computed with historical volatilities and published by the European Central Bank (2009, 2012). In particular, the three series in Figures 9, 10 and 11 are the weighted average of Distance-to-Default series of Global Large and Complex Banking Groups (DD_{LCBG}), the median of Distance-to-Default series of a sample of large EU banks ($DD_{EUmedian}$) and the weighted average of Distance-to-Default series for Large and Complex Banking Groups in the euro area (DD_{EURO}), respectively. 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.

[Insert Figures 9, 10 and 11 here]

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[34]GARCH(1,1) volatilities were estimated using prices of individual banks' shares and STOXX Europe 600 Banks Index since 31/12/1998, adding an observation as daily closing prices (denominated in local currency) become available in order to generate more realistic data series. The DD series followed the same estimation methodology described in Section 3. In terms of the Portfolio DD, this means that GARCH volatilities are estimated for the index and covariances are neglected. Although not reported, Granger causality tests were conducted for average, portfolio and differences series, showing rejection of the null hypothesis that main DD do not cause GARCH-generated DD for 5, 10 and 20 day lags, especially for the Average DD.

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 and compute the Quandt-Andrews breakpoint tests on the persistence en level of these series vis-à-vis these backward-looking monthly DD series[35]. Results are reported in Tables 7 and 8

[Insert Tables 7 and 8 here]

Results of Granger tests provide econometric support to the forward-looking feature of our series. Table 7 shows that forward-looking DD indicators and also their difference Granger cause backward-looking DD series up to two years, as the graphs suggested. Slightly 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 transitory volatility shocks and changes in correlation in the PDD indicator is partially cancelled out in averages and median DD series. The results are also more robust in the case of the series computed for the Eurozone banks, since the sample is more likely to concide[36]. 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.

The forward-looking DD series were compared also to other two market-based indicators of systemic financial stress which do not share the same modelling assumptions. These indicators are the IMF's Systemic Financial Stress indicator (SFS) and the Diebold-Yilmaz Connectedness Index ($DYCI$), plotted in Figures 12 and 13, respectively. They are based on stock prices information and thus do not include either balance-sheet data or market sentiment embedded in option prices. The Systemic Financial Stress indicator was replicated for all banks in the ADD sample following the methodology in International Monetary Fund (2011). This indicator is based on stock returns and is bound by construc-

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[35]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.

[36]Unfortunately, the ECB publications do not disclose their portfolio composition, which may affect the tests results marginally.

tion between 0 and 1. It measures the fraction of financial institutions in the European banking system that experience large negative abnormal returns relative to the market benchmark on a given day as well as negative abnormal returns for two weeks following that day[37]. The performance of this indicator is tested (International Monetary Fund , 2011) vis-à-vis other ten indicators in the literature[38], including a backward-looking version of the Distance-to-Default, in terms of its relative ability to forecast systemic stress, extreme events and early turning points. This indicator captures very well the intensity and scope of financial distress but embeds to a lesser extent interconnectedness among the banks in the sample besides the simultaneity of large negative returns, as it is an aggregation of individual signals of distress.

[Insert Figures 12 and 13 here]

The Diebold-Yilmaz Connectedness Index ($DYCI$) introduced in Diebold and Yilmaz (2009) and applied for a set of 14 European banks[39] in Yilmaz (2011) is based on the decomposition of forecast error variances from a vector autoregression model. It is also 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. Compared to the SFS indicator, the $DYCI$ provides a better picture of time varying cross-section effects of stock return volatility, i.e. comovement and contagion, but it does not provide signals of increasing risk from higher leverage in banks' balance sheets. Figure 13 clearly shows that spikes of this indicator (plotted on inverted scale to facilitate comparison) correspond to those short-lived episodes where the gap between PDD and ADD narrows significantly.

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[37]In the European case, the speed of transmission of stress can somehow lower than in the US due to the country-specific circumstances at play and therefore the occurrence of negative abnormal can be slightly less frequent than in the US case. The reference index to compute market stock returns is the STOXX Europe 600 Index. See International Monetary Fund (2011) for a more detailed explanation of the indicator's construction, properties and its application to the US banking system using data from 17 financial institutions.

[38]Namely time-varying and rolling CoVaR series (Adrian and Brunnermeier, 2011), Joint Probability of Distress (Segoviano and Goodhart, 2009) , LIBOR-OIS spread, Diebold-Yilmaz Connectedness Index (Diebold and Yilmaz, 2009), Credit Suisse Fear Barometer, VIX Index, Systemic Liquidity Risk Indicator (Severo, 2011), the yield-curve and backward-looking DD series.

[39]Dexia, KBC, Credit Suisse, UBS, Commerzbank, Deutsche Bank, Crédit Agricole, BNP Paribas, Société Générale, Intesa Sanpaolo, Unicredit, ING, BBVA and Santander

The lower two panels in Table 7 show the results of the Granger Causality tests applied to these two additional systemic risk measures. They show that the forward-looking series developed in this paper provide a better performance in terms of early systemic stress detection. In particular, the PDD series Granger causes the SFS in the short run while the ADD series precede its signals up to 24 months. This result is largely driven by the similar type of systemic risk elements captured by the ADD series and the SFS indicator. The results of the tests applied to the $DYCI$ provide an additional insight. While the PDD and ADD series do not seem to Granger cause this indicator independently, the PDD-ADD difference Granger cause the $DYCI$ up to three months, which illustrates the information content of PDD-ADD gap series about comovement, correlation shifts, contagion and joint distress, which is relatively less perceptible in ADD series compared to its ability to assess the intensity of financial distress or PDD, as it includes both measures. The forward-looking DD series do not Granger cause the $DYCI$ for longer lags probably due to the modelling ability of this indicator to incorporate quickly new information about joint stress, including tail events.

Following the analysis of early turning points in International Monetary Fund (2011), Table 8 shows that the DD series constructed in this paper have also the earliest turning points in levels and persistence terms based on the dates of their most likely structural breaks, as early as of the first quarter of 2005, which is in line of the graphical inspection of the Figures above, which adds further support to their early-warning properties[40].

4.4 The PDD–ADD Difference

Thus far, the section has stressed the ability of the forward-looking Distance-to-Default series and their difference to assess the risk outlook in the banking system in Europe over time and to provide early systemic stress detection vis-à-vis alternative specifications of

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[40]An *ad-hoc* analysis of forecasting extreme events to test the forward-looking properties of these indicators could be also an alternative, in line with several applications in the literature (see for instance Blix Grimaldi (2010) or Campbell *et al.* (2008)). However, those tests are in general based on a rather arbitrary or subjective selection of distress events *ex-post*, while the tests described above provide a good comparison of the features of the indicators as a monitoring tool.

Distance-to-Default and other market-based indicators. This subsection gives a closer look at the difference between the PDD and ADD series and its properties besides the prevalence of expected comovement changes across bank returns implied by the differences between the index implied volatility and the implied volatilities of its constituents, as introduced in Section 2.3.

As described in Section 2.3, the difference between PDD and ADD series embeds to a large extent the comovement and correlation structure of banks' equity and asset returns. In the case of series where calibration relies on realized pairwise covariances from the individual calibrations, it is a full reflection (see Figure 1). In the case of the series computed with individual and index option implied volatilities, the role of expected correlation on the DD gap remains very important but it also includes additional elements of sector-wide tail risks in extreme times due to volatility and correlation skews Fengler *et al.* (2012) present in options. In addition, the PDD-ADD gap also depends on the volatility regime in the equity markets. During crisis times, there is stronger effect of the comovement component 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 on their level.

In order to illustrate these points, Figure 14 shows the empirical exceedance correlations[41] between standardized PDD and ADD series following the methodology described in Ang and Chen (2002) and Longin and Solnik (2001) superimposed with exceedance correlations for the bivariate normal distribution with the same correlation coefficient ($\rho = 0.9478$). This figure documents the presence of asymmetric and nonlinear dependence between the series, which is in turn determined by the correlation skew, the volatility regime and the relative relevance of the data inputs in the calibration. First, the left of the distribution shows as expected significantly larger correlation than the right of the distribution. However, correlations in the left are not strictly decreasing, showing that co-

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[41]Exceedance correlations show the correlations of the two standardized DD series as being conditional on exceeding a p threshold. $\tilde{\rho} \equiv Corr[PDD, ADD | PDD \leq Q_{PDD}(p)$ and $ADD \leq Q_{ADD}(p)]$, for $p \leq 0.5$ and $\tilde{\rho} \equiv Corr[PDD, ADD | PDD > Q_{PDD}(p)$ and $ADD > Q_{ADD}(p)]$ for $p > 0.5$, where $Q_{PDD}(p)$ and $Q_{ADD}(p)$ and are the pth quantiles of the standardized PDD and ADD series, respectively.

movement of the PDD and ADD series are not replicating that frequent empirical finding in the literature about equity returns.

[Insert Figure 14 here]

Figure 15 shows the difference between the implied volatility of the STOXX Europe 600 Banks Index and the (market-cap) weighted average of implied volatilities across the ADD sample. This spread has been time-varying but negative and 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 the overall regular behavior of this gap, compared to the larger movements described in the forward-looking DD series difference. Figure 16 plots this difference versus the PDD-ADD difference to provide evidence of the nonlinear relationship between these variables. Even though the relationship becomes stronger when the DD gap is smaller, the relevance of the volatility component when DD series are close this figure suggests that the implied volatilities differences play a different role under different volatility levels.

[Insert Figures 15 and 16 here]

In order to add further insights, Figure 17 shows a scatter plot where the PDD and ADD difference is displayed against the Average Implied Correlation. The Average Implied Correlation (AIC) is a weighted difference of the STOXX Europe 600 Banks Index implied volatility and the weighted average of the implied volatilities of the banks in sample. This is a measure of the markets expectation of the future correlation of the index components and was generated following the CBOE S&P 500 Implied Correlation Index methodology[42] and also analyzed in Skintzi and Refenes (2005).

[Insert Figure 17 here]

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[42]See http://www.cboe.com/micro/impliedcorrelation/ImpliedCorrelationIndicator.pdf for details.

Figure 17 shows a negative and nonlinear relationship between the DD differences and the AIC series, with a large Spearman correlation coefficient rho of -0.88 and a Kendall's tau of -0.70[43], which illustrates the correlation component of the gap between Portfolio DD and Average DD.

Yet, as in the previous case, the relationship is stronger when the gap between PDD and ADD is low but it allows large AIC fluctuations under very narrow DD gap. The relationship flattens out as these DD series diverge more, where idiosyncratic bank risk components dominate and the other risk DD inputs play a stronger role in the DD calibration. The solid red data points in the graph show the period after August 2007. As in the case of simple differences between the implied volatilities, the relationship between DD differences and AIC becomes very steep but it includes also narrow gaps of the DD series and, more strikingly low comovement regimes. 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 and correlation breaks.

5   Concluding Remarks

This paper proposes 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 portfolio of banks comprises the largest financial institutions in Europe, characterized by a high degree of complexity and close linkages to the rest of the financial system. This approach is applicable to mature economies, where option markets are active and liquid in both individual equity and equity index option contracts.

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[43]Similar values for the subsamples before and after August 2007.

The generated series revealed several methodological advantages with respect to traditional approaches in the literature and other market-based indicators of financial stability. Firstly, the analysis of systemic risk is notably enhanced if both Portfolio and Average and Distance-to-Default series and their gap are used to monitor vulnerability in the banking system over time. The aggregated series encompass the analysis of both overall, joint risk of distress in the system and even tail risk events and correlation breaks.

Secondly, results in the paper show that the information embedded in option prices endow the series with a forward-looking property, allowing for early signalling of distress, which is not perceived by many other market based indicators of financial stability or even by backward-looking specifications of similar indicators. The use of implied volatilities from options on the sector index also helps circumvent assumptions about equity prices correlations and the use of historical data, which would turn the indicator into a coincident one and may neglect the sudden shifts in correlation structures. It also helps avoid arbitrary assumptions in the model to capture interdependence between banks during times of distress and additional signals of risk in addition to the expected asset and return correlation component.

Finally, the aggregated Distance-to-Default series are smooth and show quick and clear reaction to short-lived market events without weakening their longer-term informational content. In other words, they incorporate very quickly market expectations via option prices that do not distort the overall risk outlook in the financial system.

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Tables and Figures

Table 1: Bank sample based on the STOXX Europe 600 Banks Index

	Name	ISIN Code	Country	Constituent from	to
1	RBS*	GB0007547838	GB	Q3-02	Q4-11
2	Barclays*	GB0031348658	GB	Q3-02	Q4-11
3	BNP Paribas*	FR0000131104	FR	Q3-02	Q4-11
→	Fortis*	BE0003801181	BE	Q3-02	Q1-09
→	BNL	IT0001254884	IT	Q3-02	Q1-06
4	HSBC*	GB0005405286	GB	Q3-02	Q4-11
5	Deutsche Bank*	DE0005140008	DE	Q3-02	Q4-11
→	Deutsche Postbank	DE0008001009	DE	Q3-04	Q4-10
6	UBS*	CH0024899483	CH	Q3-02	Q4-11
7	ING*(1)	NL0000303600	NL	Q3-02	Q4-11
8	Crédit Agricole*	FR0000045072	FR	Q3-02	Q1-11
→	Crédit Lyonnais	FR0000184202	FR	Q3-02	Q1-03
→	Emporiki Bank	GRS006013007	GR	Q3-02	Q2-06
9	Société Générale*	FR0000130809	FR	Q3-02	Q4-11
10	UniCredit*	IT0000064854	IT	Q3-02	Q4-11
→	Bank Austria Creditanstalt	AT0000995006	AT	Q4-03	Q3-05
→	HypoVereinsbank	DE0008022005	DE	Q3-02	Q1-06
→	Capitalia	IT0003121495	IT	Q3-02	Q3-07
11	Santander*	ES0113900J37	ES	Q3-02	Q4-11
→	Abbey National	GB0000044551	GB	Q3-02	Q3-04
→	Banca Antonveneta	IT0003270102	IT	Q3-02	Q1-06
→	ABN Amro	NL0000301109	NL	Q3-02	Q3-07
→	Bradford & Bingley	GB0002228152	GB	Q2-05	Q3-08
→	Alliance & Leicester*	GB0000386143	GB	Q3-02	Q3-08
12	Credit Suisse*	CH0012138530	CH	Q4-02	Q4-11
13	Commerzbank*	DE0008032004	DE	Q3-02	Q4-11
14	Dexia*	BE0003796134	BE	Q3-02	Q4-11
15	BBVA*	ES0113211835	ES	Q3-02	Q4-11
16	Lloyds Banking Group*	GB0008706128	GB	Q3-02	Q4-11
→	HBOS*	GB0030587504	GB	Q3-02	Q4-08
17	Danske Bank *	DK0010274414	DK	Q3-02	Q4-11
18	Nordea*	SE0000427361	SE	Q3-02	Q4-11
19	Natixis*	FR0000120685	FR	Q3-02	Q4-11
20	Intesa Sanpaolo*	IT0000072618	IT	Q3-02	Q4-11
→	San Paolo IMI	IT0001269361	IT	Q3-02	Q4-06
21	KBC*	BE0003565737	BE	Q3-02	Q4-11
→	Almanij	BE0003703171	BE	Q3-02	Q4-04
22	Standard Chartered*	GB0004082847	GB	Q3-02	Q4-11

Notes: → denotes acquisition by the nearest numbered bank listed above. * Also in the sample of the Average Distance-to-Default series. (1) Constituent of the STOXX 600 Insurance Index.

Table 2: Bank sample based on the STOXX Europe 600 Banks Index (cont.)

	Name	ISIN Code	Country	Constituent from	to
23	SEB*	SE0000148884	SE	Q3-02	Q4-11
24	DnB NOR*	NO0010031479	NO	Q3-02	Q4-11
→	Gjensidige NOR	NO0010149354	NO	Q3-02	Q3-03
25	Svenska Handelsbanken*	SE0000193120	SE	Q3-02	Q4-11
26	Erste Group*	AT0000652011	AT	Q3-02	Q4-11
27	Swedbank*	SE0000242455	SE	Q3-02	Q4-11
28	Banca Monte dei Paschi di Siena*	IT0001334587	IT	Q3-02	Q4-11
29	Banco Popular Español*	ES0113790531	ES	Q3-02	Q4-11
30	Mediobanca*	IT0000062957	IT	Q4-02	Q4-11
31	Bankinter*	ES0113679I37	ES	Q3-02	Q4-11
32	Raiffeisen Bank International	AT0000606306	AT	Q2-05	Q4-11
33	National Bank of Greece	GRS003013000	GR	Q3-02	Q4-11
34	Alpha Bank	GRS015013006	GR	Q3-02	Q4-11
35	Bank of Ireland	IE0030606259	IE	Q3-02	Q4-11
36	Banco de Sabadell	ES0113860A34	ES	Q3-02	Q4-11
37	UBI Banca	IT0003487029	IT	Q3-02	Q4-11
→	Banca Lombarda e Piemontese	IT0000062197	IT	Q3-02	Q1-07
→	BP di Bergamo	IT0000064409	IT	Q3-02	Q2-03
→	BP Commercio e Industria	IT0000064193	IT	Q3-02	Q2-03
38	Jyske Bank	DK0010307958	DK	Q3-02	Q4-11
39	Bank of Piraeus	GRS014013007	GR	Q3-02	Q4-11
40	EFG Eurobank Ergasias	GRS323013003	GR	Q3-02	Q4-11
41	Banca Popolare di Milano	IT0000064482	IT	Q3-02	Q4-11
42	Banco Popolare	IT0004231566	IT	Q3-02	Q4-11
→	Banca Popolare Italiana	IT0000064300	IT	Q3-02	Q3-07
→	BP di Verona	IT0001065215	IT	Q3-02	Q1-02
→	BP di Novara	IT0000064508	IT	Q1-02	Q1-02
43	Banco Comercial Portugus	PTBCP0AM0007	PT	Q3-02	Q4-11
44	Banco Espirito Santo	PTBES0AM0007	PT	Q3-02	Q4-11
45	Allied Irish Banks	IE0000197834	IE	Q3-02	Q2-10
46	Banco de Valencia	ES0113980F34	ES	Q2-03	Q4-11
47	Anglo Irish Bank	IE00B06H8J93	IE	Q3-02	Q4-08
48	Valiant(2)	CH0014786500	CH	Q1-03	Q4-06
49	Bank of Greece	GRS004013009	GR	Q3-03	Q1-10
50	Banco BPI	PTBPI0AM0004	PT	Q1-03	Q1-09
51	Sydbank	DK0010311471	DK	Q2-05	Q4-11
52	Banca Carige	IT0003211601	IT	Q2-05	Q4-11
53	Northern Rock	GB0001452795	GB	Q3-02	Q3-07
54	Pohjola Bank	FI0009003222	FI	Q3-06	Q4-11

Notes: → denotes acquisition by the nearest numbered bank listed above. * Also in the sample of the Average Distance-to-Default series. (2) Also constituent between Q1-08 and Q1-11.

Table 3: Bank sample based on the STOXX Europe 600 Banks Index (cont.)

	Name	ISIN Code	Country	Constituent from	to
55	BP Emilia Romagna(3)	IT0000066123	IT	Q3-02	Q3-03
56	BP Di Sondrio(3)	IT0000784196	IT	Q3-02	Q3-03
57	Close Brothers	GB0007668071	GB	Q4-02	Q2-05
58	Investec	GB00B17BBQ50	GB	Q4-02	Q2-05
59	Credito Valtellinese	IT0000064516	IT	Q4-08	Q4-10
60	Landsbanki	IS0000000156	IS	Q1-07	Q3-08
61	Kaupthing	IS0000001469	IS	Q1-07	Q3-08
62	Julius Baer	CH0102484968	CH	Q4-09	Q4-11
→	GAM Holding	CH0102659627	CH	Q3-02	Q2-05
63	EFG International	CH0022268228	CH	Q3-08	Q1-09
64	Depfa Bank	IE0072559994	DE	Q3-03	Q3-07
65	Banco Pastor	ES0113770434	ES	Q1-06	Q2-08
66	Crédit Agricole d'Île-de-France	FR0000045528	FR	Q4-02	Q4-04
67	Banque Nationale de Belgique	BE0003008019	BE	Q1-03	Q4-03
68	Banque Cantonale Vaudois	CH0015251710	CH	Q3-11	Q4-11
69	Caixabank	ES0140609019	ES	Q3-11	Q4-11
70	Bankia	ES0113307039	ES	Q4-11	Q4-11

Notes: → denotes acquisition by the nearest numbered bank listed above. (3) Also constituent between Q3-09 and Q1-11. Marfin Financial Group (GRS314003005, GR), Glitnir Banki (IS0000000131, IS), KBC Ancora (BE0003867844, BE) and First Active (IE0004321422, IE) were excluded from the sample due to data quality reasons. In all these cases, their corresponding index weights did not exceed 0.2%.)

Table 4: Bank Sample: Average Distance-to-Default

Bank Name	Code	Home Country	Exchange	ISIN Code	Datastream Mnemonic	Bloomberg Mnemonic	Bankscope Index Number	Weight in Index (in %)
RBS	RBS	United Kingdom	LSE	GB0007547838	RBS	RBS LN Equity	24762, 49494	2.9
Barclays	BARC	United Kingdom	LSE	GB0031348658	BARC	BARC LN Equity	23552, 24158	4.1
BNP Paribas	BNP	France	Euronext (FR)	FR0000131104	F:BNP	BNP FP Equity	10931, 29289	6.7
HSBC	HSBA	United Kingdom	LSE	GB0005405286	HSBA	HSBA LN Equity	34727, 47424	13.8
Deutsche Bank	DBK	Germany	Xetra (DE)	DE0005140008	D:DBKX	DBK GY Equity	13216, 21723	4.2
UBS	UBS	Switzerland	SIX Swiss Exchange	CH0024899483	S:UBSN	UBSN VX Equity	46911, 47584	5.2
ING(1)	ING	Netherlands	Euronext (NL)	NL0000303600	H:ING	INGA NA Equity	22304, 29199	
Santander	SAN	Spain	SIBE	ES0113900J37	E:SCH	SAN SQ Equity	23425, 47560	7.4
UniCredit	UCG	Italy	Milan	IT0000064854	I:UC	UCG IM Equity	23991, 47295	3.6
Société Générale	GLE	France	Euronext (FR)	FR0000130809	F:SGE	GLE FP Equity	11150, 29338	3.7
Crédit Agricole	ACA	France	Euronext (FR)	FR0000045072	F:CRDA	ACA FP Equity	11948, 17602	3.0
Credit Suisse	CSGN	Switzerland	SIX Swiss Exchange	CH0012138530	S:CSGN	CSGN VX Equity	29015, 29474, 31398	5.0
Commerzbank	CBK	Germany	Xetra (DE)	DE0008032004	D:CBKX	CBK GY Equity	13190, 47032	0.8
BBVA	BBVA	Spain	SIBE	ES0113211835	E:BBVA	BBVA SQ Equity	22628, 48331	4.1
Lloyds Banking Group	LLOY	United Kingdom	LSE	GB0008706128	LLOY	LLOY LN Equity	29227, 43418	4.8
Danske Bank	DANSKE	Denmark	OMX (DK)	DK0010274414	DK:DAB	DANSKE DC Equity	10607, 29179	1.6
Nordea	NDA	Sweden	OMX (SE)	SE0000427361	W:NDA	NDA SS Equity	29305, 49434	3.4
Natixis(2)	KN	France	Euronext (FR)	FR0000120685	F:KN@F	KN FP Equity	23951, 39931, 45333	1.2
Intesa Sanpaolo	ISP	Italy	Milan	IT0000072618	I:BIN	ISP IM Equity	23687, 28749, 46616	2.7
KBC	KBC	Belgium	Euronext (BE)	BE0003565737	B:KB	KBC BB Equity	29303, 48888	1.0
Standard Chartered	STAN	United Kingdom	LSE	GB0004082847	STAN	STAN LN Equity	24831, 29316	4.6
SEB	SEB	Sweden	OMX (SE)	SE0000148884	W:SEA	SEBA SS Equity	29315, 33297	1.5
DnB NOR	DNBNOR	Norway	Oslo	NO0010031479	N:DNB	DNBNOR NO Equity	48594, 16637	1.9
Svenska Handelsbanken	SHBA	Sweden	OMX (SE)	SE0000193120	W:SVK	SHBA SS Equity	30723, 29362	1.5
Erste Group	EBS	Austria	XETRA (AT)	AT0000652011	O:ERS	EBS AV Equity	48560, 46146	1.4
Swedbank	SWEDA	Sweden	OMX (SE)	SE0000242455	W:SWED	SWEDA SS Equity	23639, 31268	1.2
Banca Monte dei Paschi di Siena	BMPS	Italy	Milan	IT0001334587	I:BMPS	BMPS IM Equity	29352, 21413	0.5
Banco Popular Español	POP	Spain	SIBE	ES0113790531	E:POP	POP SM Equity	23654, 22724	0.6
Mediobanca	MB	Italy	Milan	IT0000062957	I:MB	MB IM Equity	39478, 45296	0.7
Bankinter	BKT	Spain	SIBE	ES0113679137	E:BKT	BKT SM Equity	29587, 22713	0.2
Dexia	DEXB	Belgium	Euronext (BE)	BE0003796134	B:DEX	DEXB BB Equity	29295, 45621	0.5
Fortis	FORB	Belgium	Euronext (BE)	BE0003801181	B:FORT	FORB BB Equity	29010, 45678	
HBOS	HBOS	United Kingdom	LSE	GB0030587504	HBOS	HBOS LN Equity	17577, 28839	
Alliance & Leicester	AL	United Kingdom	LSE	GB0003586143	AL	AL/ LN Equity	46576, 22683	

Table 5: Description of Variables

Balance Sheet Variables

Variable	Definition
Total Assets	As reported in Annual and Interim Reports. Source. Bankscope, code 2025.
Short-term Liabilities	Deposits and Short term funding. Source. Bankscope, code 2030.
Total Equity	As reported in Annual and Interim Reports. Source. Bankscope, code 2055.

Daily Market-based Variables

Variable	Definition
Risk-free Interest Rate	Benchmark ten-year bond yield of country where the bank in question is headquartered. Source. Thomson Datastream, codes: Austria (OEBRYLD), Belgium (BGBRYLD), Denmark (DKBRYLD), Eurozone, synthetic (EMBRYLD), France (FRBRYLD), Germany (BDBRYLD), Italy (ITBRYLD), Netherlands (NLBRYLD), Norway (NWBRYLD), Spain (ESBRYLD), Sweden (SDBRYLD), Switzerland (SWBRYLD), UK (UKMBRYD).
Market Capitalization	Total market value measured by close share price multiplied by the ordinary number of shares in individual issue. Expressed in thousands of domestic currency (converted into euro at official ECB exchange rates when required). Source. Bloomberg, code CUR_MKT_CAP. Codes for banks available in Table 4.
Index Market Capitalization	Total market value measured as the sum of individual total market values of the constituents. Expressed in thousands of euro. Source. Bloomberg, code CUR_MKT_CAP for the data field and SX7P Index for STOXX Europe 600 Banks Index and SX7E Index for the EURO STOXX Banks Index.
Exchange Rates	End-of-day bilateral exchange rates against the euro. Source. Datastream, codes: Danish Krone (DKECBSP), Icelandic Krona (ICECBSP), Norwegian Krone (NWECBSP), Swedish Krona (SDECBSP), Swiss Franc (SWECBSP), British Pound (UKECBSP), US Dollars (USECBSP).
Equity Implied Volatilities	Daily at-the-money implied volatilities of call and put options on individual bank shares (American style), traded at Borsa Italiana, Eurex, NYSE Euronext, MEFF, Nasdaq OMX and Oslo Børs. Source. Bloomberg, codes HIST_CALL_IMP_VOL for calls and HIST_PUT_IMP_VOL for puts.
Index Implied Volatilities	Daily at-the-money implied volatilities of call and put options (European style) on the STOXX Europe 600 Banks Index (SX7P Index) and the EURO STOXX Banks Index (SX7E Index), traded at Eurex. Source. Bloomberg, codes HIST_CALL_IMP_VOL for calls and HIST_PUT_IMP_VOL for puts.

Table 6: Summary Statistics

	Benchmark Model			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
Minimum	0.893	0.339	-0.472	0.958	0.410	-0.826
Std. Dev.	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
Jarque-Bera Statistic	166.9*	100.8*	429.9*	188.4*	113.2*	788.6*
Observations	2437	2437	2437	2437	2437	2437

	PUT-based Model			GARCH(1,1)-based Model		
	PDD	ADD	$PDD - ADD$	PDD	ADD	$PDD - ADD$
Mean	4.665	3.528	1.137	5.260	3.645	1.615
Median	3.940	3.351	0.749	4.797	3.623	1.192
Maximum	12.484	7.281	6.999	11.951	6.532	5.702
Minumum	0.768	0.362	-0.530	0.494	0.046	-0.157
Std. Dev.	2.257	1.446	1.057	2.646	1.502	1.268
Skewness	0.586	0.011	1.488	0.297	-0.189	0.891
Kurtosis	-0.475	-0.992	2.542	-0.996	-0.885	-0.189
Jarque-Bera Statistic	162.5*	100.0*	1550.2*	136.6*	94.1*	325.7*
Observations	2437	2437	2437	2437	2437	2437

Notes: This table presents some summary statistics of the DD estimates under alternative choices of the equity volatility in the DD calibration. The **benchmark model** uses the average of put and all implied volatilities. The model for the **Eurozone banks** applies the same methodology, using the call and put implied volatilities, but to a smaller sample of banks, based on the EURO STOXX Banks Index, for both ADD and PDD series. The **PUT-based model** uses only implied volatilities from put options on the index, while the **GARCH(1,1)-based model** uses volatilities from a GARCH(1,1) model applied on returns. The sample period runs from 30-Sep-2002 to 31-Jan-2012, yielding 2,437 daily observations in total. More details about the models are in Section 4.2. An asterisk (*) indicates a rejection of the null hypothesis at the 0.05 level.

Table 7: Granger Causality Tests

X	PDD	DD_{LCBG}	ADD	DD_{LCBG}	$PDD-ADD$	DD_{LCBG}	Lags
Y	DD_{LCBG}	PDD	DD_{LCBG}	ADD	DD_{LCBG}	$PDD-ADD$	
	7.9336**	0.0102	8.2765**	0.1288	3.8197*	1.4651	1
	3.8135**	2.0846	3.5111**	2.2373	3.7108**	1.0431	2
	2.8826**	2.1302	2.4579*	1.5477	3.1143**	1.7228	3
	0.6712	2.6501**	1.1358	1.3101	1.1929	2.3867**	6
	0.7876	1.3684	1.4378	1.1014	1.0369	1.3524	12
	1.4565	1.1442	1.6916*	1.3567	1.1700	1.883**	24
X	PDD	$DD_{EUmedian}$	ADD	$DD_{EUmedian}$	$PDD-ADD$	$DD_{EUmedian}$	Lags
Y	$DD_{EUmedian}$	PDD	$DD_{EUmedian}$	ADD	$DD_{EUmedian}$	$PDD-ADD$	
	9.8082**	1.9012	11.5817**	3.4081*	4.4287**	0.0868	1
	4.1214**	1.4960	4.5748**	1.4610	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	1.3560	12
	1.0517	2.0360	1.9579	2.1533	0.9604	0.6808	24
X	PDD_{EURO}	DD_{EURO}	ADD_{EURO}	DD_{EURO}	$PDD-ADD_{EURO}$	DD_{EURO}	Lags
Y	DD_{EURO}	PDD_{EURO}	DD_{EURO}	ADD_{EURO}	DD_{EURO}	$PDD-ADD_{EURO}$	
	12.0901**	0.1533	12.7067**	0.3116	6.711**	0.2247	1
	7.2846**	0.2402	6.9198**	0.6822	4.6798**	0.0404	2
	4.0849**	0.2359	3.9127**	0.4158	2.5229*	0.0410	3
	1.3111	0.1872	1.9358*	0.5163	1.8215	0.3625	6
	2.1935**	0.2291	1.7342*	0.6053	2.4618**	0.4108	12
	2.3065**	0.3845	2.9459**	0.7641	1.5578	0.8148	24
X	PDD	SFS	ADD	SFS	$PDD-ADD$	SFS	Lags
Y	SFS	PDD	SFS	ADD	SFS	$PDD-ADD$	
	4.8648**	1.4453	7.4226**	1.4009	1.4568	1.0035	1
	2.379*	0.9928	4.2189**	0.6379	0.9264	0.5109	2
	1.1459	0.9117	2.0562	0.4609	0.3932	1.0396	3
	0.9443	0.9382	2.8947**	0.4240	0.5490	0.7998	6
	0.7924	0.5214	1.8622*	0.3666	0.4092	0.5986	12
	1.0484	0.5052	1.6501*	0.7743	0.5164	0.3289	24
X	PDD	$DYCI$	ADD_{14}	$DYCI$	$PDD-ADD_{14}$	$DYCI$	Lags
Y	$DYCI$	PDD	$DYCI$	ADD_{14}	$DYCI$	$PDD-ADD_{14}$	
	2.1428	0.4533	0.4523	2.6550	2.6054	5.3437**	1
	2.1824	1.2656	1.5263	1.4025	3.9766**	1.3962	2
	1.4306	0.9498	1.0738	1.2834	2.5429*	1.2729	3
	1.1377	0.6783	0.6658	0.7600	1.3122	1.0396	6
	0.9087	1.3461	0.5207	1.0292	1.2092	0.9366	12
	0.5593	1.0129	1.3084	1.4016	1.1403	0.5385	24

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 the null at 5% and 10% levels, respectively. Averages are used to transform ADD, PDD, ADD_{EURO} and PDD_{EURO} series into monthly frequencies. $DD_{EU-median}$, DD_{LCBG} and DD_{EURO} are obtained from European Central Bank (2009) and European Central Bank (2012). The Diebold-Yilmaz Connectedness Index, $DYCI$, is obtained from http://www.financialconnectedness.org. Test samples, subject to data availability: Sep-2002 to May-2009 for $DD_{EU-median}$; Sep-2002 to Jan-2012 for DD_{LCBG}, DD_{EURO} and SFS; and Jan-2004 to Jan-2012 for $DYCI$. ADD_{14} is a subsample of banks that matches the $DYCI$ banks sample.

Table 8: Early turning points: Quandt-Andrews breakpoint tests

Indicator	Break date in mean	Break date in persistence process
PDD	Aug-05	Jun-05
ADD	Mar-05	Aug-10
$PDD - ADD$	Sep-05	Nov-05
PDD_{EURO}	Aug-05	Jul-04
ADD_{EURO}	Mar-05	Feb-08
$PDD - ADD_{EURO}$	Jan-06	Aug-05
SFS	Dec-08	Sep-09
$DYCI$	Sep-10	Feb-06
DD_{LCBG}	Feb-07	Feb-09
$DD_{EU-median}$	Mar-07	Jun-08

Notes: This table presents the most likely breakpoint locations based on autoregressive regressions of each indicator with three lags and 15% trimming percentage, testing the breaks in both the constant term (mean) and lagged coefficients in the AR(3) term (persistence process). Test samples, subject to data availability: Sep-2002 to May-2009 for $DD_{EU-median}$; Jan-2004 to Jan-2012 for $DYCI$; Sep-2002 to Jan-2012 for all other variables.

Figure 1: Calibration of Distance-to-Default series.
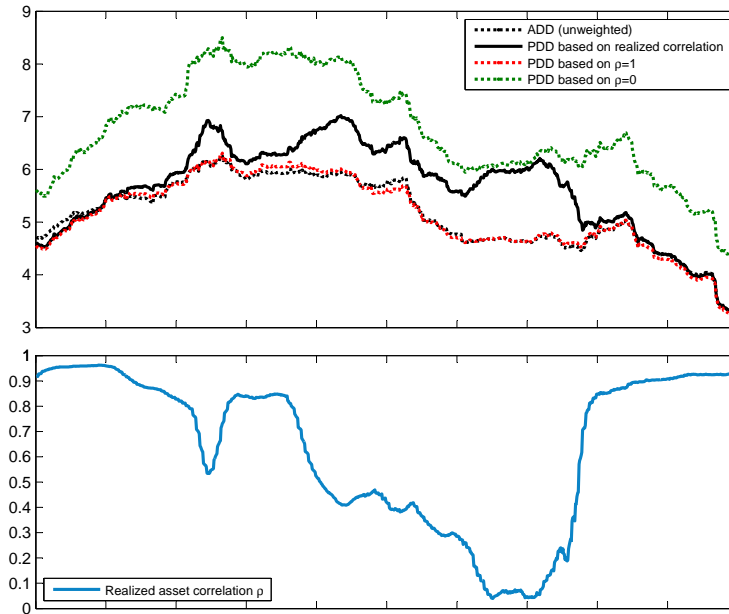
Source. Author's calculations. The portfolio is built using daily data from BNP Paribas and KBC covering 1000 trading days of the sample used in the paper. One-year rolling windows were used to compute equity volatilities and pairwise asset covariances. The ADD using asset-weighed averages were also computed but did not change the results.

Figure 2: Calibration of Distance-to-Default series.
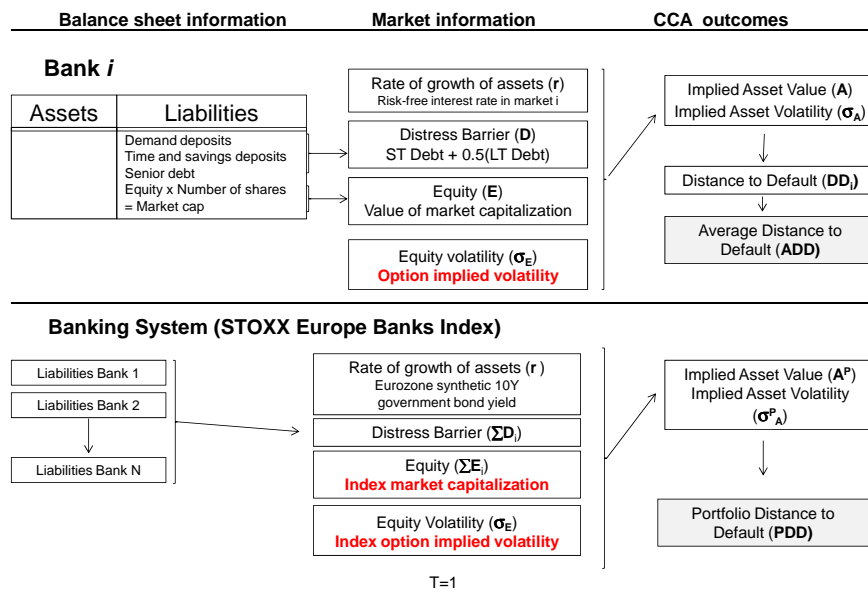
Figure 3: Forward looking Distance-to-Default series. 30-Sep-2002 - 31-Jan-2012
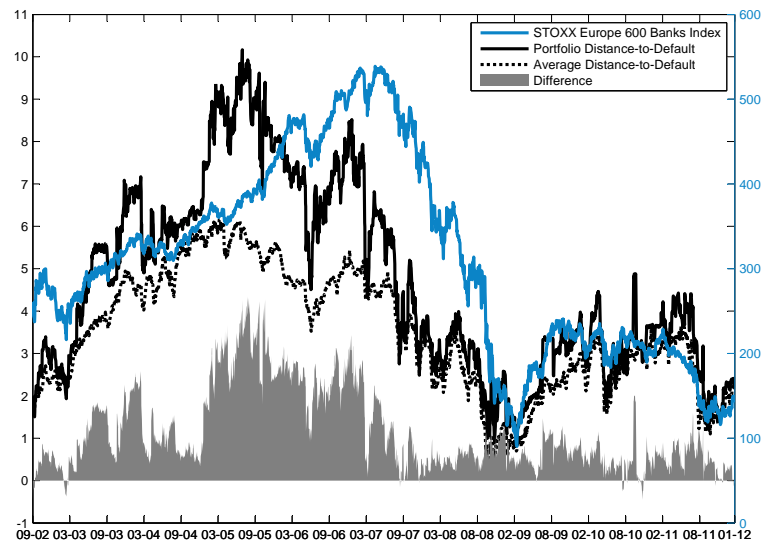
Source. Author's calculations and Bloomberg.

Figure 4: Forward looking Distance-to-Default series. 31-Dec-2004 - 31-Jan-2012
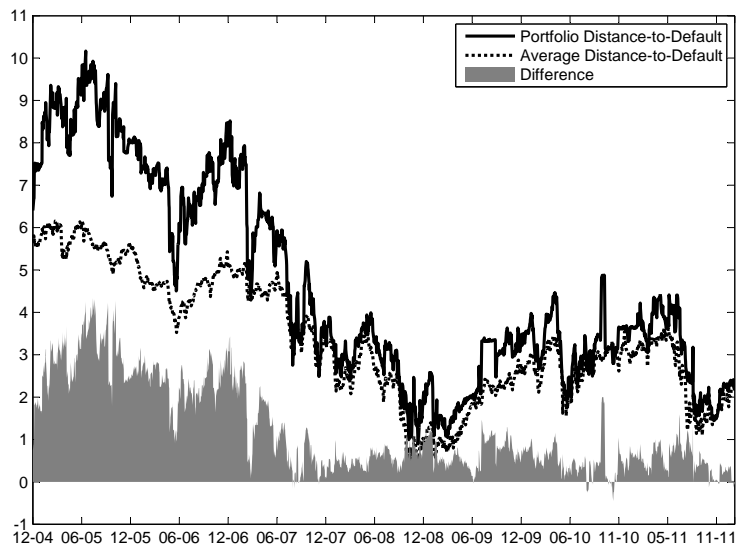
Source. Author's calculations.

Figure 5: EURO Forward looking DD series. 30-Sep-2002 - 31-Jan-2012
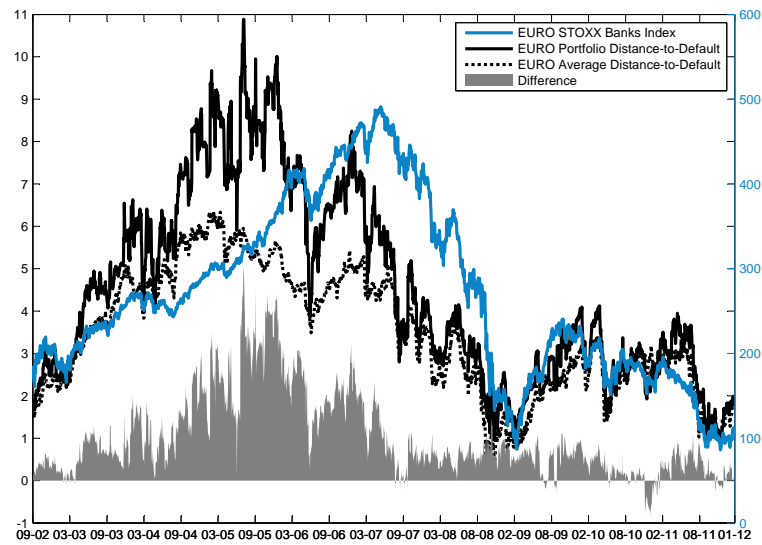
Source. Author's calculations and Bloomberg.

Figure 6: EURO Forward looking DD series. 31-Dec-2004 - 31-Jan-2012
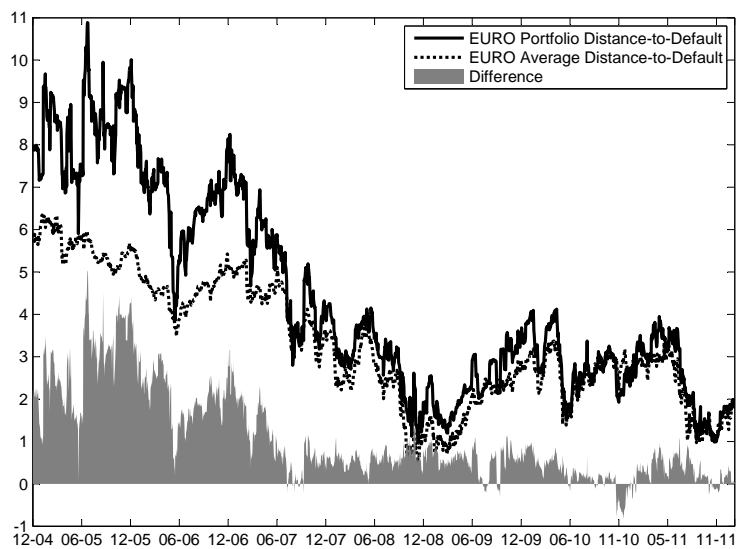
Source. Author's calculations.

Figure 7: Distance-to-Default series. 30-Sep-2002 - 31-Jan-2012
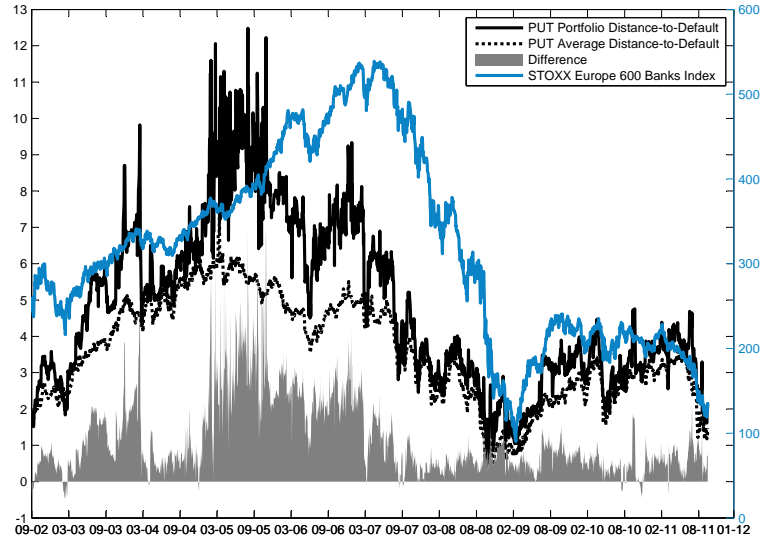
Source. Author's calculations, using PUT implied volatilities in DD calibration, and Bloomberg.

Figure 8: Distance-to-Default series - GARCH(1,1). 30-Sep-2002 - 31-Jan-2012
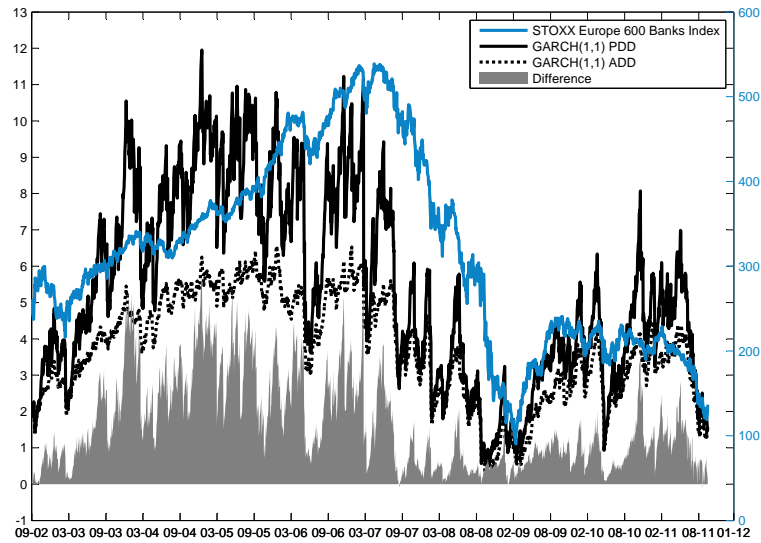
Source. Author's calculations, using volatilities derived from a GARCH(1,1) model in DD calibration, and Bloomberg.

Figure 9: Forward looking DD series vis-à-vis historical LCBG's DD series
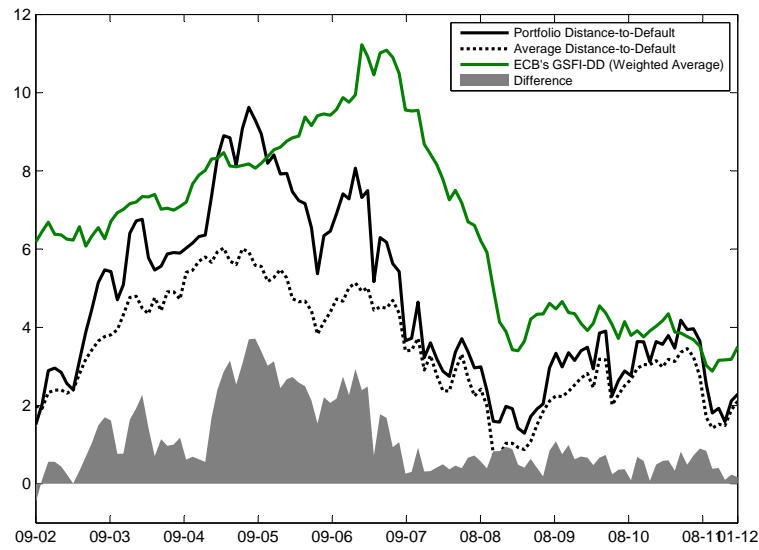
Source. Author's calculations and European Central Bank (2012). Monthly averages for DD series.

Figure 10: Forward looking DD series vis-à-vis historical EU banks' DD series
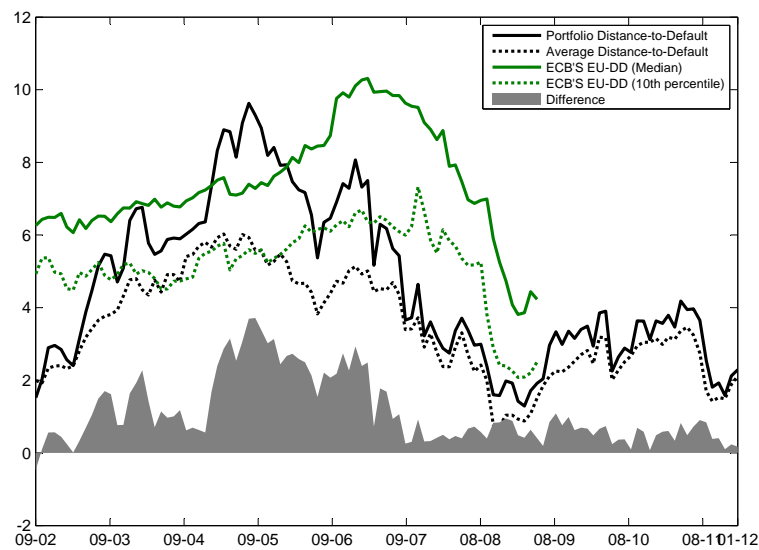
Source. Author's calculations and European Central Bank (2009). Monthly averages for DD series.

Figure 11: Forward looking DD series vis-à-vis historical Eurozone banks' DD series
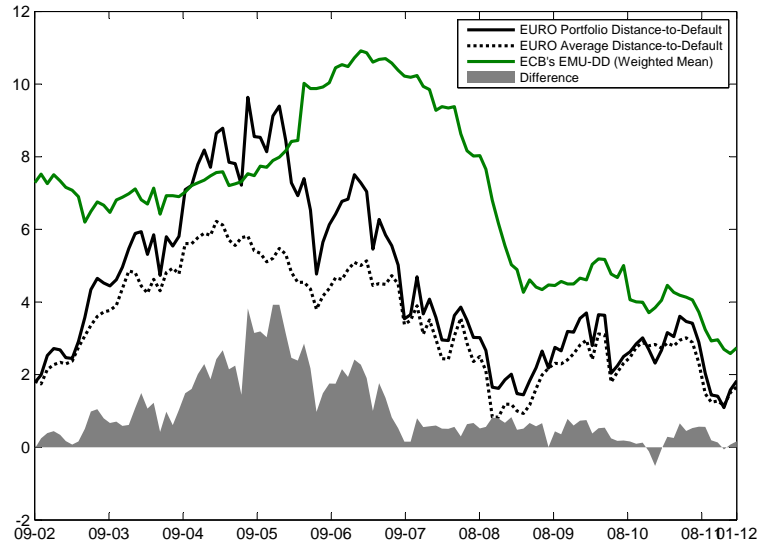
Source. Author's calculations and European Central Bank (2012). Monthly averages for DD series.

Figure 12: Forward looking DD series vis-à-vis Systemic Financial Stress indicator
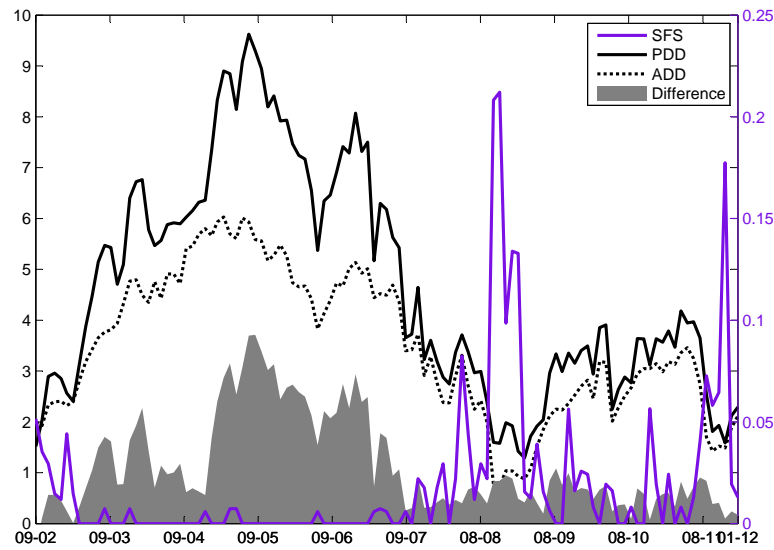
Source. Author's calculations, using monthly averages from daily series.

Figure 13: Forward looking DD series vis-à-vis Diebold-Yilmaz Connectedness Index
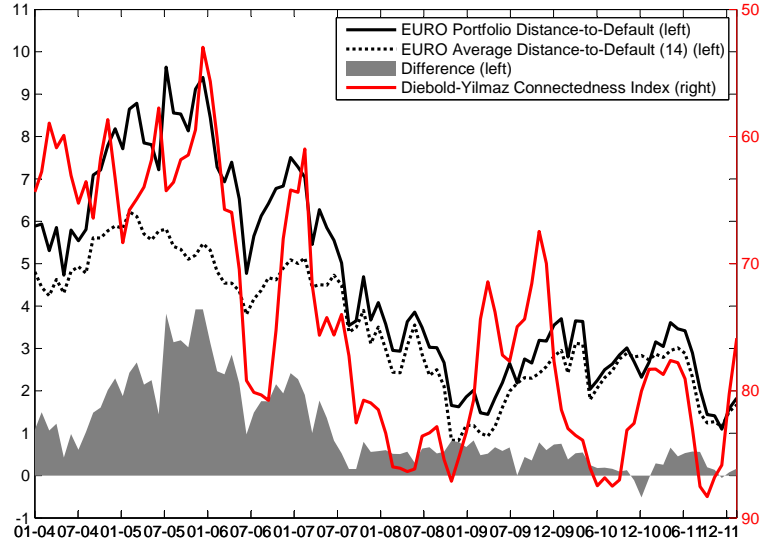
Figure 14: PDD and ADD exceedance correlations
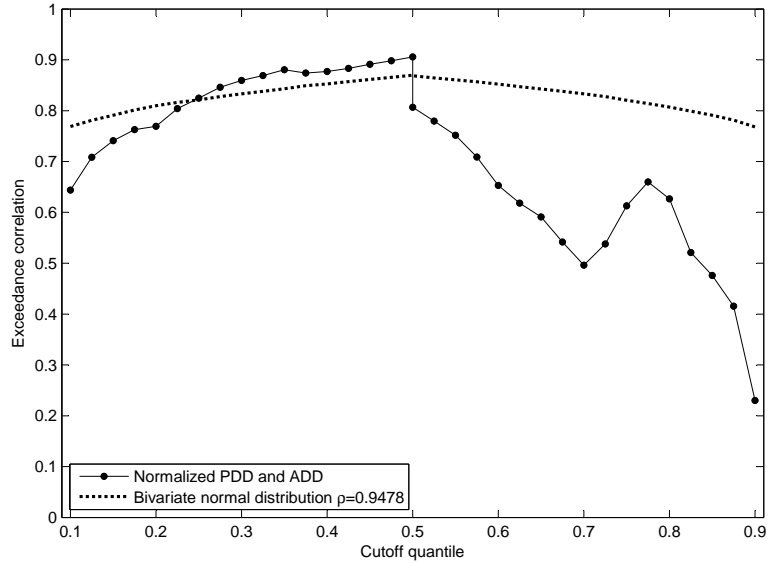
Figure 15: Portfolio and Weighted Average Implied Volatilities
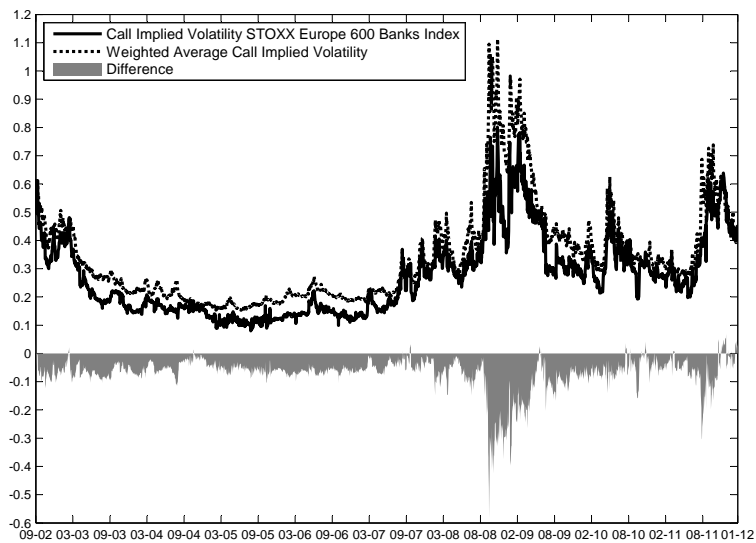
Source. Author's calculations and Bloomberg.

Figure 16: Differences: DD and Implied Volatilities
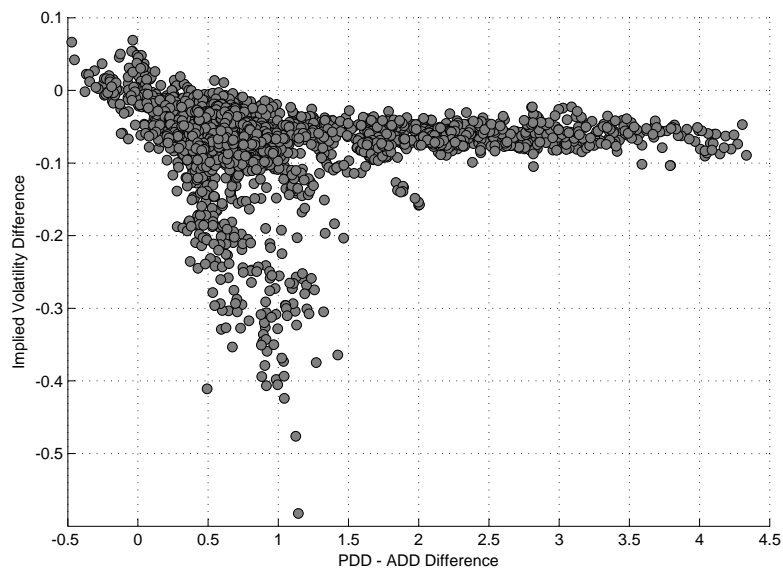
Source. Author's calculations and Bloomberg.

Figure 17: Average Implied Correlation
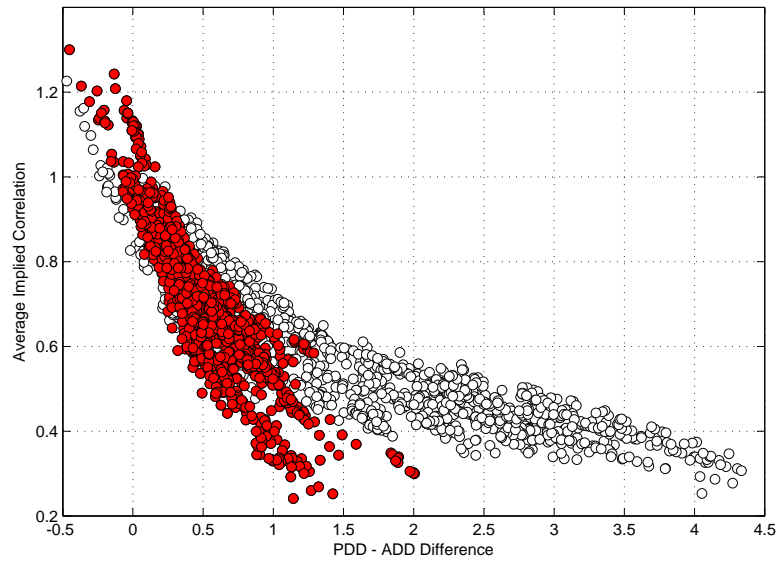
Source. Author's calculations

A   Derivation of Individual Distance-to-Default Series

Given the three principles in CCA mentioned in Section 2.1, company value (represented by its assets, **A**) is the sum of its risky debt (**D**) and equity (**E**). Since equity is a junior claim to debt, the former can be modeled and calculated as a standard call option on the assets with exercise price equal to the value of risky debt (also known in the literature as distress barrier or default barrier).

$$E = \max\{0, A - D\} \tag{A.1}$$

Given the assumption of assets distributed as a Generalized Brownian Motion, the application of the standard Black-Scholes option pricing formula yields the closed-form expression of equity **E** as a European call option on the bank's assets **A** at maturity **T**:

$$E = AN(d_1) - e^{-rT}DN(d_2) \tag{A.2}$$

where r is the instantaneous rate of growth of assets, generally approximated by the risk-free rate under risk-neutrality, and $N(\bullet)$ is the cumulative normal distribution. The values of d_1 and d_2 are expressed as:

$$d_1 = \frac{\ln\left(\frac{A}{D}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \tag{A.3}$$

$$d_2 = d_1 - \sigma_A\sqrt{T} \tag{A.4}$$

where σ_A is the is asset volatility. The Merton model uses an additional equation that links the former to the volatility of the bank's equity σ_E by applying Itô's Lemma:

$$E\sigma_E = A\sigma_A N(d_1) \tag{A.5}$$

The Merton model uses equations (A.2) and (A) to obtain the implied asset value **A** and volatility σ_A, which are not observable and must be estimated by numerical methods (Newton-Raphson method with two equations and two unknowns in this application). Using Equation , the equity volatility σ_E is transformed to enter as initial value of market value of σ_A in the iteration. The initial value for the implied asset value **A** is set to the sum of the default barrier (**D**) and market equity (**E**). The growth rate of the assets is proxied by risk-free interest rate **r** as in Gropp *et al.* (2006) and most papers in the literature. Once a numerical solutions for **A** and σ_A are found, the Distance-to-Default **T** periods ahead is calculated as:

$$DD = \frac{\ln\left(\frac{A}{D}\right) + \left(r - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \tag{A.6}$$

The implementation of (A.6) uses in general market value as the value of equity **E**; historical volatilities as equity price return volatility σ_E; government bond yields as the risk-free interest rate **r** and the face value of short-term liabilities plus half of that of long-term liabilities as the default barrier **D**. The time horizon **T** is usually set at one year.

In this paper, the equity volatility is obtained from individual bank equity option implied volatilities. For comparison (see Section 4), I use also volatilities estimated with a GARCH(1,1) with price return series starting in January 1998. Frequent examples of this approach cited in the literature, with some implementation differences and discussions, are found in Bharath and Shumway (2008); Crosbie and Bohn (2003); Gray and Malone (2008); Gropp *et al.* (2006) and Vassalou and Xing (2004).

Alternatively, Duan (1994, 2000) and Duan *et al.* (2004) propose a computation method where **A** and σ_A are obtained based on a maximum likelyhood (ML) estimation and a one-to-one relationship between asset value **A** and equity value **E**, yielding accurate estimates even in relatively small samples (Lando, 2004). Although estimates tend not to differ much, this approach provides also distributions of the estimates for testing hypotheses, which is an advantage compared to the method used in this paper. However, the application of the maximum likelyhood estimation would unable this work to profit from the information potential from option prices. In addition, Duan *et al.* (2004) and Gropp *et al.* (2006) argue that one of the reasons why the ML is more attractive is the fact that historical volatilities tend to understimate DD in periods of increasing stock prices and to do the opposite during downturns. This issue is not present in the case of option implied volatilities, as they are market-determined expectations of future volatility.

B Derivation of Portfolio Distance-to-Default Series

The Portfolio Distance-to-Default treats the portfolio of P banks in the sample as a single entity, thus the Merton (1974) model assumptions still apply and the calculation method is the same as explained in Appendix A. Under these assumptions, the calibration of the PDD requires some additional practical considerations, especially about the difference between the approach in this paper and other applications in the literature, such as Annett *et al.* (2005); De Nicolò and Tieman (2007); Echeverría *et al.* (2006, 2009) and Gray and Malone (2008).

In particular, the closed-form expression of PDD **T** periods ahead is represented by the following expression:

$$PDD = \frac{\ln\left(\frac{A^P}{D^P}\right) + \left(r^P - \frac{1}{2}\sigma_P^2\right)T}{\sigma_P\sqrt{T}} \tag{B.1}$$

D^P is the total value of the portfolio's risky debt or distress barrier and is obtained by adding up the individual distress barriers across the P banks in the sample, i.e. $D^P = \sum_{i=1}^{P} D_i$.

r^P is the instantaneous rate of growth of the portfolio's assets and in general is proxied under risk-neutrality by a weighted average of individual r_i from government bond yields of each bank's home market, i.e. $r^P = \sum_{i=1}^{P} w_i r_i$. The individual weights w_i are obtained from estimates of implied assets A_i, thus $w_i = \frac{A_i}{A^P}$. In this paper, r^P is proxied by the Eurozone synthetic 10-year government bond yield.

The remaining terms in (B.1), namely the portfolio asset volatility σ_P and the value of the portfolio assets A^P, should be in principle obtained as in the case of individual banks, solving the system of equations (A.2) and (A).

The traditional approach aggregates individual estimates of implied assets A_i, thus $A^P = \sum_{i=1}^{P} A_i$ and it aggregates the individual estimates of asset volatilities using a asset return based covariance structure, $\sigma_P^2 = \sum_{i=1}^{P} \sum_{j=1}^{p} w_i w_j \sigma_{ij}$, where σ_{ij} is the asset return covariance of banks i and j.

In this paper, the calibration of PDD does solve equations (A.2) and (A) to obtain σ_P and A^P, hence the equity market value of the portfolio, $E^P = \sum_{i=1}^{P} E_i$, is obtained directly from the reference index on a daily basis, and the equity volatility σ_E is obtained from index option implied volatilities. As a result, PDD is not computed using backward-looking data and the difference between the PDD and the ADD is not based on the covariance term in σ_P, but on additional signals from the individual stocks' and index option markets about volatility and interdependence.

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