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**Systemic Risk Analysis Using  
Forward-Looking Distance-to-Default  
Series**

by Martín Saldías Zambrana



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**Systemic Risk Analysis Using Forward-Looking Distance-to-Default Series**

by Martín Saldías Zambrana

Based on contingent claims theory, 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 DJ STOXX 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; and 3) they produce simultaneously both smooth and informative long-term signals and quick and clear reaction to market distress.

JEL classification: G01, G13, G21.

Keywords: contingent claims analysis, systemic risk, banking crises.

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# 1 Introduction

One of the remarkable 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<sup>1</sup> 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.

The theoretical and empirical details of defining and assessing systemic risk in banking are still in progress. Accordingly, different approaches have emerged in the literature and are either replacing or supplementing existing methodologies that failed to capture vulnerabilities prior to this crisis. Many of these approaches are moving towards sophisticated portfolio models of risk, where the banking system is considered as a whole. These models also aim to capture joint risks and interdependences with the use of market-based information. Recent contributions along these lines are [Adrian and Brunnermeier \(2009\)](#) and [Huang \*et al.\* \(2009, 2010\)](#).

This paper aims to contribute to the literature with a method to monitor systemic risk in the European banking system based on contingent claims theory. Without strong 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 a simple average of individual forward-looking Distance-to-Default, computed using individual equity options. This indicator is standard in the literature and informs about the overall risk outlook in the system. The second series is a portfolio or system Distance-to-Default that aggregates balance sheet information into a single entity and uses the option prices information of the DJ STOXX 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.

The use of index-based option information also incorporates two innovations in the

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<sup>1</sup>See for instance [European Central Bank \(2007b\)](#) for an interesting overview of the research approach in the area conducted by the ECB, the Bank of Japan and the Federal Reserve.

literature. First, it makes use of information from an additional liquid market, the equity index options market. Second, the construction of the indicator avoids arbitrary modelling assumptions or correlation structures among banks in the sample which tend to weaken its information quality. In other words, the information potential of equity index options allow the Distance-to-Default indicators to become a forward-looking analytic tool to monitor systemic risk and interdependences between the banks in the financial system over time.

The series generated in the paper are smooth, 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 increased interdependences. 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.

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 Black-Scholes-Merton model of option pricing, CCA has three principles: 1) the economic value of liabilities<sup>2</sup> is derived and equals the economic value of assets; 2) liabilities in the balance sheet have different priorities (and thus risk); and 3) the company assets distribution follows a stochastic process ([Echeverría et al., 2006](#)).

In this context, as liabilities are viewed as contingent claims against assets with payoffs determined by seniority, equity becomes a 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 the default barrier, the market value of the call option also falls. The distance between market value of asset and the distress barrier is called Distance-to-Default (DD) and constitutes the financial risk indicator used in this paper to assess systemic risk in Europe's banking sector<sup>3</sup>. Distance-to-Default indicates the number of standard deviations at which the market value of assets is away from the default barrier and can be scaled into probabilities of default, if the distribution of assets were known. Details of its derivation and data requirements can be found in Appendix A.

This method has initially been applied to company default risk analysis and disseminated by Moody's KMV -see for instance [Arora et al. \(2005\)](#); [Crosbie and Bohn \(2003\)](#); [Arora and Sellers \(2004\)](#) - proving very effective in prediction of ratings' downgrading and company default. More recently, the CCA approach has been extended to both individual and aggregate financial and non-financial sectors and also to sovereign macrofinancial risk. [Gray and Malone \(2008\)](#) provide a comprehensive review of methodologies and related lit-

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<sup>2</sup>Deposits and senior debt plus equity in the case of banks.

<sup>3</sup>This paper is limited to the development of Distance-to-Default series and their application. The use of the rest of risk indicators derived from this methodology remains for further research.

erature.

DD series and other CCA-derived risk measures are forward-looking, 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.\* \(2004\)](#); [International Monetary Fund \(2009\)](#) and [Tudela and Young \(2003\)](#), inter alia, show also that DD improves and even outperforms other indicators of financial stability including bond or CDS spreads.

However, as the [Financial Stability Board \(2009b\)](#) and the [International Monetary Fund \(2009\)](#) point out, CCA measures also have some shortcomings, common to most market-based financial stability indicators and originated in the input data quality. In particular, they are sensitive to market liquidity and market volatility and also dependant on the accuracy of the market assessment, meaning that it may be possible that in periods of high stress in financial markets, they could not be obtained and even if they could, their signals are unclear. 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](#)).<sup>4</sup>

## 2.2 Aggregation Methods of Individual Distance-to-Default Series

Despite its shortcomings, the CCA approach has been recommended by the [Financial Stability Board \(2009a\)](#) to enhance systemic risk analysis as a tool to identify systemically important financial institutions. The potential to use aggregated DD series to also monitor systemic risk is not negligible and, in the case of the European and other mature banking

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<sup>4</sup>Additional methodological drawbacks not tackled in this paper include the assumption of an ad-hoc default barrier, constant interest rates and constant volatility. [Capuano \(2008\)](#) tackles the first 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.



systems, this potential could even overcome some of the weaknesses cited lines above.

Aggregation of DD is conducted mainly through averages of individual DD and sometimes also calibration of individual data into portfolios of banks, which means treating the system as one large bank (see Appendix B for details). These approaches are not new in the literature and the ECB's Financial Stability Review publishes since 2004 series DD medians and 10th percentiles of global and euro area Large and Complex Banking Groups (LCBG)<sup>5</sup>. The Central Bank of Chile introduced the methodology applied to the Chilean banking system in 2006 (Echeverría *et al.*, 2006) and the IMF used both average and portfolio DD series in country reports for the euro area and the United States (De Nicolò *et al.* (2005); Čihák and Koeva Brooks (2009) and Mühleisen *et al.* (2006)).

The analysis of DD averages (sometimes also medians or other quantiles) is the standard practice in the financial stability publications. Simple averages of individual DD are highly informative of the dynamics of system-wide risks but can be misleading if analyzed alone since they do not take into account bank size differences and risk interdependences. While weighted averages or quantile DD partially solve the bank size problem, they do not tackle the interdependences among banks and therefore fail to react to swings in periods of financial stress (Čihák, 2007; Chan-Lau and Gravelle, 2005). On the other hand, portfolio DD tracks the evolution of the lower bound to the joint probabilities of distress (De Nicolò and Tieman, 2007) and enhances therefore information quality of average DD series, since it takes into account bank size and risk interdependence among banks<sup>6</sup>. The relationship between average and portfolio DD conveys therefore a comprehensive set of instruments to track systemic risk. This joint dynamics works as follows, when the returns correlation increases in times of market distress, showing higher interdependences, both series tend to drop and the gap between them tends to narrow. Since portfolio DD is in general higher than average DD and therefore is a lower bound of distress, the joint movement of DD series contains relevant information about increasing systemic risk.

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<sup>5</sup>See European Central Bank (2005) for the introduction of the indicator in the publication series.

<sup>6</sup>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

The construction of portfolio DD involves an additional assumption, portfolio equity returns volatility require pairwise covariances. If the portfolio DD is built on the base of historical price returns, this does not pose a problem. If individual GARCH-modelled or option implied volatilities are used as inputs, covariances are either neglected or historical or intra-day pairwise covariances are used<sup>7</sup>. In either case, the indicator becomes a coincident one and may fail to detect early signals of market stress ([International Monetary Fund , 2009](#)).

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 a limited extent, and implied volatilities from options on sector-based indices are missing in the literature. The inclusion of individual and index implied volatilities can enhance the information content of average and portfolio DD series without imposing strong methodological assumptions. Sections 3 and 4 show how this methodology can be applied and how it compares to existing use of DD to monitor systemic risk.

### 3 Empirical Application

The empirical approach in this paper consists of two steps. First, individual forward-looking DD series are computed for all banks in sample. These series are then averaged<sup>8</sup> and compared to an also forward-looking portfolio DD. The second series is built from the implied volatilities extracted from the options on the DJ STOXX Banks Index.

Both series are smooth by construction and forward-looking, given the properties of implied volatilities ([Whaley, 2009](#)), and the difference between the two series shows primarily joint risk of distress in the banking system. The two series share a similar long

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<sup>7</sup>Most literature use historical covariance series and [Huang \*et al.\* \(2009, 2010\)](#) propose an innovation using high-frequency intra-day covariances to add a forward-looking dimension to asset return correlation.

<sup>8</sup>This paper reports results using only a simple average. Weighted averages (using individual market capitalization) have been tried without affecting results.

term trend, showing the overall risk profile of the system. In addition, they also react in a clear and timely manner to short-lived events of high market volatility without generating excess noise in the series or affecting the longer term trend.

### 3.1 The Sample

The portfolio of banks includes the largest 24 European listed institutions, 22 of them headquartered in the European Union and two in Switzerland. The selection reference is the Forbes Global 2000 ranking from April 2009<sup>9</sup>. All banks in the sample have also been constituents of the DJ STOXX Banks Index<sup>10</sup> over the whole time span of this analysis and their shares and options are publicly traded in liquid organized exchanges (see Table 1 for details).

[Insert Table 1 here]

In order to justify its systemic importance to represent the whole European banking system, this portfolio choice complies with several of the size, lack of substitutability and interconnectedness criteria listed in a recent report published by request of the G-20 Leaders in April 2009 ([Financial Stability Board, 2009b](#)). The sample also includes non-EU banks because of the pan-European dimension of financial integration.

The bank portfolio accounts for more than 85% of total market value of banks listed in the reference index over the entire time span of this paper; all banks weigh significantly in their respective domestic stock markets in terms of market value and trading volumes, and most banks have multiple listings at major world exchanges. Their aggregated total assets add up to more than 60% of the entire EU-27 banking sector at end-2008 and the composition of assets and liabilities and importance of off-balance sheet activities shows a

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<sup>9</sup>The ranking uses an equally weighted combination of rankings by sales, profits, assets and market capitalization to assign positions. The composition in the top 25 for Europe has remained stable in the last decade, taking into account major M&A transactions.

<sup>10</sup>ING Group belongs to the DJ STOXX Insurance Index due to its bancassurance business model. This institution is however considered as a bank in the Forbes Global 2000 ranking and in most empirical papers on financial stability at EU level. Hypo Real Estate was originally in the sample but then removed due to data quality reasons. The sample was not enlarged in order to keep high quality data of individual implied volatilities.

highly diversified range of businesses.

In addition to the relevant market shares in domestic markets, these banks also operate at a large cross-border scale throughout Europe. 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). Finally, the portfolio of banks constitutes the core of the ECB's LCBG<sup>11</sup>, which means that these banks are not only big and engaged in complex businesses, but also are highly interconnected to each other and to the rest of the financial system, making supervisory oversight more difficult.

In order to estimate individual DD series, both balance sheet and market data are needed between 30 September 2002 and 31 July 2009 (1785 trading days). Balance sheet data comprise annual and interim data on total assets, short-term liabilities and equity. The market-based data include daily observations of risk-free interest rates, market capitalization, euro exchange rates and at-the-money implied volatilities<sup>12</sup>. The risk-free interest rates are 10-year government bond yields in each bank's country of origin. See Table 2 for a description of data and sources.

[Insert Table 2 here]

The calculation of the portfolio DD series requires also daily put and call implied volatilities of options on the DJ STOXX Banks Index under the premise that timely and meaningful implied volatilities call for prices from an active index option market (Whaley, 2009). These series start at the end of the third quarter 2002, which determines the sample start of this paper. The end date is set on 31 July 2009 in order to include second quarter interim reports' information for all banks. The time span therefore includes tranquil times in the beginning, periods of minor stress since 2006, the financial crisis since August 2007

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<sup>11</sup>In addition, Deutsche Bank, Credit Suisse, Barclays, HSBC, Société Générale, UBS, RBS and BNP Paribas were initially included by the Bank of England in the list of Large Complex Financial Institutions (LCFI) due to their important role in the global financial system.

<sup>12</sup>Missing values for Crédit Agricole prior to November 25th 2005 and for Natixis for the whole sample have been replaced for GARCH(1,1) volatility estimates. Infrequent missing values have been replaced for those from the previous trading day.

and the recent markets' recovery and sector restructuring since March 2009.

### 3.2 Calibration of Average and Portfolio Distance-to-Default Series.

Appendices A and B contain a detailed methodological explanation of the procedure followed in this paper to compute both average and portfolio DD series, according to the literature. This section only discusses certain particularities in the data and approach in this paper.

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 yearly frequencies. In this paper, the data were interpolated into daily series using cubic splines. In the second step, daily default barriers are computed using these new series of liabilities. The last step before computing the daily average DD series is to convert put and call implied volatilities into an average implied volatility and then calibrate the individual DD. The closed-form expression for the average DD series is given by:

$$\overline{DD} = \frac{1}{N} \sum DD_i, \text{ where } DD^i = f \left( A_i(E_i), \sigma_i^{A_i}(\sigma_i^{IV_i}), D_i, t, r_i \right)$$

where  $\overline{DD}$  is the simple average of  $N$  individual  $DD_i$   $t$  periods ahead. For each bank  $i$ ,  $A_i$  is the implied value of assets;  $E_i$  is the market value of equity;  $\sigma_i^{A_i}$  is the implied asset volatility;  $\sigma_i^{IV_i}$  is equity price return volatility obtained from individual equity options;  $D_i$  is the distress barrier,  $r_i$  is risk-free interest rate in the respective home market.

Portfolio DD requires aggregation of the balance sheet data. Since they are denominated in different currencies, these figures are converted into euro before interpolation using official bilateral exchange rates. The euro-denominated balance sheet data and daily market values (converted on a daily basis into euros) are aggregated into single series for the whole portfolio. Risk-free interest rates are aggregated using market value as weighting factor.

Finally, implied volatilities of put and call options on the DJ STOXX Banks Index are also transformed into daily averages. Using index implied volatilities means in practice that this paper does not only add a forward looking component to the portfolio DD, comparable to average DD, but also that no covariance structure is assumed. It is taken directly from market data, reflecting market perceptions of joint distress risk in the constituents of the reference index, the European banking system. The expression for the portfolio DD series is given by:

$$DD^P = f\left(A_P(E_P), \sigma_P(\sigma_P^{IV_{Index}}), D_P, t, r_P\right)$$

where  $DD^P$  is the portfolio's DD  $t$  periods ahead. For a given portfolio  $P$  composed of  $N$  banks,  $A_P$  is the implied value of assets;  $E_P$  is the equity market value of the portfolio;  $\sigma_P$  is the implied asset volatility;  $\sigma_P^{IV_{Index}}$  is the portfolio's equity volatility obtained from the index options;  $D_P$  is the portfolio's distress barrier,  $r_P$  is the weighted average of risk-free interest rates in the  $N$  banks' markets.

## 4 Results

The main results focus on the series of average and portfolio DD series and their difference as a tool to monitor systemic risk in Europe's banking system, namely: 1) they focus on the system as a whole and look at interdependences between banks; 2) they are smooth by construction, avoiding low signal-to-noise ratios and fuzzy signals, which allows one to track systemic risk over time; 3) they contain forward-looking signals of distress; and 4) they show quick but short-lived coincident reactions to market events, in other words, their informative properties are not significantly affected by their ability to promptly detect shocks in the markets.

## 4.1 Aggregated Distance-to-Default Series

Figure 1 and Figure 2 plot together the forward-looking average and portfolio DD series, their difference and also the DJ STOXX Banks Index as a reference<sup>13</sup>. As expected, portfolio DD moves along and exceeds average DD over the entire sample and both series provide a good picture of past market assessment and future outlook of the banking system in Europe.

[Insert Figures 1 and 2 here]

Figures 3 and 4 plot together the DD series calculated using only put implied volatilities, since put options are more reactive to market specific events and contain important information regarding the demands for portfolio insurance and market volatility (Whaley, 2009). As DD series obtained using average implied volatilities are smoother, a valued property of market-based indicators in the analysis of systemic risk, the results of this paper focus 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<sup>14</sup>.

[Insert Figures 3 and 4 here]

Distance between average and portfolio DD series tends to narrow when the two indicators are going down (Gray and Malone, 2008). This characteristic is a result of increasing correlation of underlying stocks' returns in times of distress and it holds true for these series as well after February 2007, when the subprime crisis started to unfold, and especially after the start of the credit crunch in August 2007, when the European banking system was no longer perceived as "sound".

In addition, due to different sources of implied volatilities, the difference also narrows for a limited time during episodes of short-lived market distress while the banking system still is in healthy shape and also widens during distressed times in response to positive news. An example of the first case is the credit rating downgrade of General Motors

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<sup>13</sup>Figure 2 shows the series since 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.

<sup>14</sup>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).

and Ford in May 2005, when their difference abruptly tightened even though average and portfolio DD were still at high levels. A second example is the market turbulence in May-June 2006, where global equity markets are hit by a rise in investors' risk aversion. A final example pre-crisis is February 2007, when fears about Asian equity markets and deterioration in the US subprime mortgages hit equity markets. In all cases, the effect would not be perceived if only average DD series were portrayed (see ECB's DD series in Figures 5 and 6). Symmetrically, positive news is also perceived in the series through transitory widening of DD series gap during bad times, as in the late 2008, when capital injections, consolidation and emergency actions were taking place at an unprecedented scale to ensure solvency in the sector.

[Insert Figures 5 and 6 here]

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 (DJ STOXX Banks Index) and long before the DD series computed using historical equity information (ECB's DD series). In addition, they start a downward trend around this date -as noted more clearly in the gap and its 60-day moving average- that only bounces back after the first quarter of 2009. This forward-looking feature provides additional support to the ability in DD of early systemic risk monitoring.

As noted in previous sections, most market-based indicators of financial stability are targets of criticism after the crisis because of their poor performance during the recent 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 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, 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.



## 4.2 Properties of the Indicator of Stress

The smoothness and forward-looking features of my DD series are quite evident in Figures 7 and 8, where I also plot DD series that use volatilities generated by GARCH models. These series are significantly more volatile than the benchmark, even if additional similar assumptions were made for their estimation<sup>15</sup>. GARCH-derived volatilities have the advantage of quick adjustment to changes in the underlying data, but they also tend to overshoot afterwards. 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 1 and 2 and there is more dominance of the short-lived market events.

[Insert Figures 7 and 8 here]

Finally, the forward-looking property of average and portfolio DD series derived from option implied volatilities was econometrically examined running pairwise Granger causality tests vis-à-vis the monthly DD series reported by the ECB in the Financial Stability Review series<sup>16</sup>. Results are reported in Table 3.

[Insert Table 3 here]

Results of Granger tests provide econometric support to the forward-looking feature of our series. Table 3 shows that forward-looking DD indicators Granger cause ECB's median DD series up to two years, as Figures 5 and 6 suggested. More robust results are obtained for longer lags in the test using average DD because of 1) the similar method used

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<sup>15</sup>GARCH(1,1) volatilities were estimated using prices of individual banks' shares and DJ STOXX Banks Index since 31/12/1998, adding an observation as daily closing prices 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.

<sup>16</sup>Average and portfolio DD were previously transformed to match monthly frequency of ECB data and unit root and cointegration tests were conducted prior to the Granger causality tests.

to obtain these series; and 2) the effect of transitory volatility shocks in the portfolio DD indicator is partially cancelled out in averages and median DD series. In spite of this, these results strongly suggest that -even with the ability of a GARCH model to react quickly to changes in volatility- 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 systemic risk analysis.

## 5 Concluding Remarks

This paper proposes a method to monitor systemic risk in the European banking system. The approach relies on contingent claims theory to generate aggregated Distance-to-Default series using option prices information from systemically important banks and the DJ STOXX Banks Index. The analysis extends from 30 September 2002 to 31 July 2009, covering both calm times and the current 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.

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 average and portfolio 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 and joint risk of distress in the system.

Secondly, results in the paper show that the information embedded in option prices endow the series with a forward-looking property, allowing for early signaling 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. It also helps avoid arbitrary assumptions in the model to capture interdependences between banks during times of distress.

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. The research of this paper was conducted while the author was visiting scholar at the Federal Reserve Bank of Cleveland. He thanks helpful comments from its Research Department and especially Ben Craig for his support and encouragement. All remaining errors and views presented here are solely those of the author.

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## Appendix A. Derivation of Distance-to-Default

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

$$\max\{0, A - D\} \quad (\text{A.1})$$

Given the assumption of assets distributed as a Generalized Brownian Motion, the application of the standard Black-Sholes option pricing formula yields the closed-form expression of the Distance-to-Default indicator  $\mathbf{t}$  periods ahead:

$$DD^P = \frac{\ln\left(\frac{A}{D}\right) + \left(r - \frac{1}{2}\sigma_A^2\right)t}{\sigma_A\sqrt{t}} \quad (\text{A.2})$$

where  $\mathbf{r}$  is the rate of growth of the company value (assets) and equals the risk-free interest rate.  $\sigma_A$  is asset volatility.

In practice, implied asset value  $\mathbf{A}$  and volatility  $\sigma_A$  are not observable and must be estimated solving the following system of simultaneous equations by numerical methods:

$$\begin{cases} \mathbf{E} = \mathbf{A}N(d_1) - e^{-rt}DN(d_2) \\ \sigma_E = \frac{A}{E}\sigma_A N(d_1) \end{cases}$$

where  $\mathbf{E}$  is the value of equity,  $\sigma_E$  is the equity price return volatility.  $N(\bullet)$  is the cumulative normal distribution. The values of  $d_1$  and  $d_2$  are expressed as:

$$d_1 = \frac{\ln\left(\frac{A}{D}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)t}{\sigma_A\sqrt{t}} \quad , \quad d_2 = d_1 - \sigma_A\sqrt{t}$$

The calculation of DD in the literature uses market value as the value of equity  $\mathbf{E}$ ; historical, GARCH-derived or option-implied volatilities as equity price return volatility  $\sigma_E$ ; government bond yields as the risk-free interest rate  $\mathbf{r}$  and the face value of short-term liabilities plus half of that of long-term liabilities as the default barrier  $\mathbf{D}$ . The time horizon  $\mathbf{t}$  is usually set at one year.



## Appendix B. Derivation of Portfolio Distance-to-Default

Aggregation of individual market-based and balance sheet data from  $N$  banks into a portfolio DD is given by the following expression:

$$DD^P = \frac{\ln\left(\frac{A^P}{D^P}\right) + \left(r^P - \frac{1}{2}\sigma_P^2\right)t}{\sigma_P\sqrt{t}} \quad (\text{B.1})$$

where:

$A^P = \sum_{i=1}^N A_i$  , is the total value of the portfolio's assets (unobservable).

$D^P = \sum_{i=1}^N D_i$  , is the total value of the portfolio's risky debt.

$E^P = \sum_{i=1}^N E_i$  , is the equity market value of the portfolio.

$r^P = \sum_{i=1}^N w_i r_i$  , is the weighted average of risk-free rates.

$w_i = \frac{E_i}{E^P}$  , or alternatively  $w_i = \frac{A_i}{A^P}$  is bank  $i$ 's weight in the portfolio.

$\sigma_P^2 = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_{ij}$  , is the portfolio's asset variance (unobservable), where  $\sigma_{ij}$  is the asset return covariance of bank  $i$  and  $j$ .

After aggregating individual data and assuming the volatility structure of the portfolio, calibration is conducted solving the system of equations from Appendix A. See [De Nicolò \*et al.\* \(2005\)](#), [De Nicolò and Tieman \(2007\)](#), [Echeverría \*et al.\* \(2006\)](#), [Echeverría \*et al.\* \(2009\)](#), [Gray and Malone \(2008\)](#) and [Vassalou and Xing \(2004\)](#) for applications.

# Tables and Figures

Table 1: Bank Sample

Rank	Bank	Home Country	Exchange	ISIN Code	Datastream Mnemonic	Bankscope Index Number	Revenues Distribution in 2008 (in %)		
							Home	Rest of Europe	Rest of World
1	RBS	United Kingdom	LSE	GB0007547838	RBS	24762, 49494	40.0	35.5	24.5
2	Barclays	United Kingdom	LSE	GB0031348658	BARC	23552, 24158	53.1	15.7	31.2
3	BNP Paribas	France	Euronext (FR)	FR0000131104	F:BNP	10931, 29289	44.9	30.9	24.2
4	HSBC	United Kingdom	LSE	GB0005405286	HSBA	34727, 47424	26.1	11.3	62.6
5	Deutsche Bank	Germany	Xetra (DE)	DE0005140008	D:DBKX	13216, 21723	66.6	14.6	18.8
6	UBS	Switzerland	SIX Swiss Exchange	CH0024899483	S:UBSN	46911, 47584	11.4	33.5	55.1
7	ING	Netherlands	Euronext (NL)	NL0000303600	H:ING	22304, 29199	18.0	17.3	64.7
8	Crédit Agricole	France	Euronext (FR)	FR0000045072	F:CRDA	11948, 17602	49.4	35.4	15.2
9	Société Générale	France	Euronext (FR)	FR0000130809	F:SGE	11150, 29338	50.8	34.5	14.7
10	UniCredit	Italy	Milan	IT0000064854	I:UC	23991, 47295	38.3	58.3	3.4
11	Santander	Spain	SIBE	ES0113900137	E:SCH	23425, 47560	31.7	24.5	43.7
12	Fortis	Belgium	Euronext (BE)	BE0003801181	B:FORT	29010, 45678	28.9	69.2	1.8
13	Credit Suisse	Switzerland	SIX Swiss Exchange	CH0012138530	S:CSGN	29015, 29474	15.2	28.1	56.7
14	Commerzbank	Germany	Xetra (DE)	DE0008032004	D:CBKX	13190, 47032	81.2	9.6	9.2
15	Dexia	Belgium	Euronext (BE)	BE0003796134	B:DEX	29295, 45621	26.7	58.4	15.0
16	BBVA	Spain	SIBE	ES0113211835	E:BBVA	22628, 48331	55.6	2.1	42.3
17	Lloyds Banking Group	United Kingdom	LSE	GB0008706128	LLOY	29227, 43418	100.0	0.0	0.0
18	Danske Bank	Denmark	OMX (DK)	DK0010274414	DK:DAB	10607, 29179	40.4	52.3	7.2
19	Nordea	Sweden	OMX (SE)	SE0000427361	W:NDAB	29305, 49434	20.7	79.3	0.0
20	Natixis	France	Euronext (FR)	FR0000120685	F:KN@F	23951, 39931	44.8	28.0	27.2
21	Intesa Sanpaolo	Italy	Milan	IT00000072618	I:BIN	23687, 28749	81.2	18.8	0.0
22	KBC	Belgium	Euronext (BE)	BE0003565737	B:KKB	29303, 48888	59.6	27.4	13.0
23	Standard Chartered	United Kingdom	LSE	GB0004082847	STAN	24831, 29316	3.9	1.9	94.2
24	SEB	Sweden	OMX (SE)	SE0000148884	W:SEA	29315, 33297	48.9	45.5	5.6

Table 2: Description of Variables

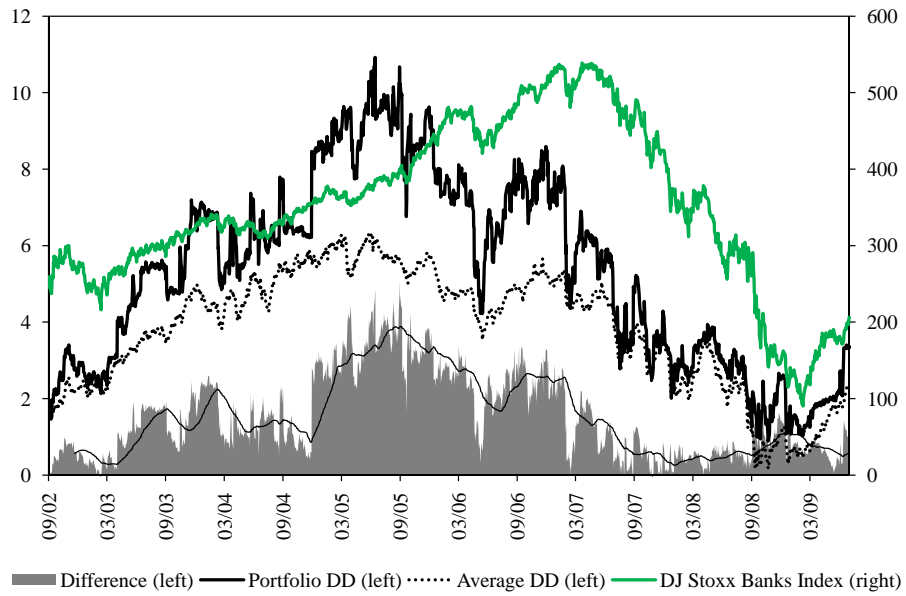
<b>Balance Sheet Variables</b>	
<b>Variable</b>	<b>Definition</b>
Total Assets	As reported in Annual and Interim Reports. Source. Bankscope, code 2025.
Short-term Liabilities	Deposits and Short term funding. Source. Bankscope, code 2030.
Total Equity	As reported in Annual and Interim Reports. Source. Bankscope, code 2055.
<b>Daily Market-based Variables</b>	
<b>Variable</b>	<b>Definition</b>
Risk-free Interest Rate	Benchmark ten-year bond yield of country where the bank in question is headquartered. Source. Thomson Datastream.
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). Source. Thomson Datastream.
Exchange Rates	End-of-day bilateral exchange rates against the euro. Source. European Central Bank.
Equity Implied Volatilities	Daily at-the-money implied volatilities of call and put options on individual bank shares (American style), traded at NYSE Euronext, Eurex and Nasdaq OMX. 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 on the DJ STOXX Banks Index (European style), traded at Eurex. Source. Thomson Datastream, codes DJ6BC.SERIESC for calls and DJ6BC.SERIESP for puts.

Table 3: Granger Causality Tests

Lag	$\overline{DD}$ does not	$DD_{ECB}$ does not	$DD^P$ does not	$DD_{ECB}$ does not
	Granger Cause $DD_{ECB}$	Granger Cause $\overline{DD}$	Granger Cause $DD_{ECB}$	Granger Cause $DD^P$
<b>1</b>	13.5423 <i>0.0004</i>	2.4077 <i>0.1248</i>	12.5345 <i>0.0007</i>	0.9557 <i>0.3313</i>
<b>3</b>	3.3270 <i>0.0244</i>	1.8711 <i>0.1423</i>	3.0514 <i>0.0340</i>	1.1649 <i>0.3293</i>
<b>6</b>	2.0159 <i>0.0769</i>	1.5253 <i>0.1848</i>	0.8912 <i>0.5070</i>	2.9627 <i>0.0131</i>
<b>12</b>	2.6637 <i>0.0089</i>	1.5157 <i>0.1549</i>	1.4473 <i>0.1815</i>	1.8289 <i>0.0727</i>
<b>24</b>	3.9901 <i>0.0242</i>	1.1544 <i>0.4427</i>	1.4198 <i>0.3151</i>	2.1132 <i>0.1371</i>

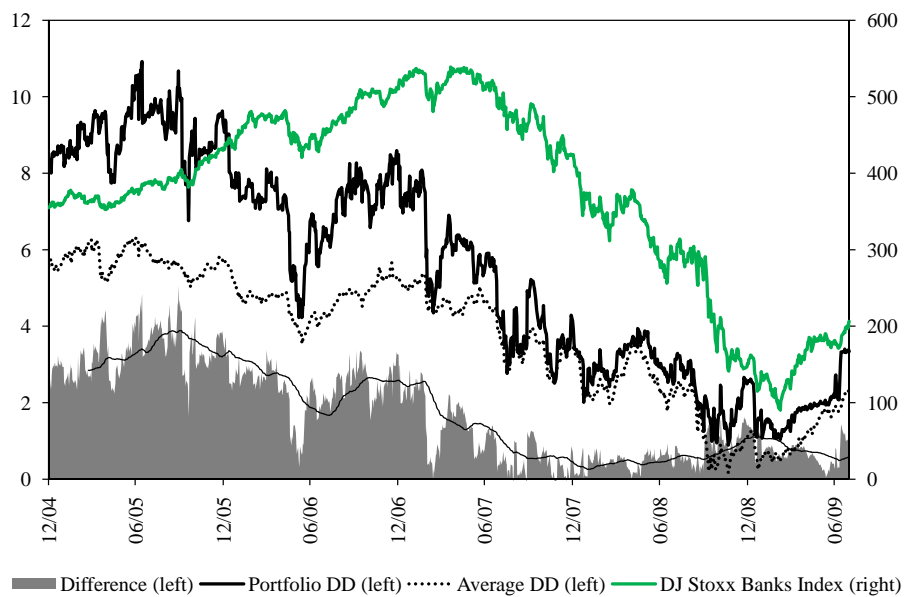
Table reports F-statistics with p-values below. End-of-month data for Average DD ( $\overline{DD}$ ) and Portfolio DD ( $DD^P$ ) series. ECB series are monthly median DD computed for a sample of LCBG. Sample used for test: 30-Sep-2002 to 31-May-2009 due to ECB series data availability.

Figure 1: Forward looking Distance-to-Default series. 30-Sep-2002 - 31-Jul-2009



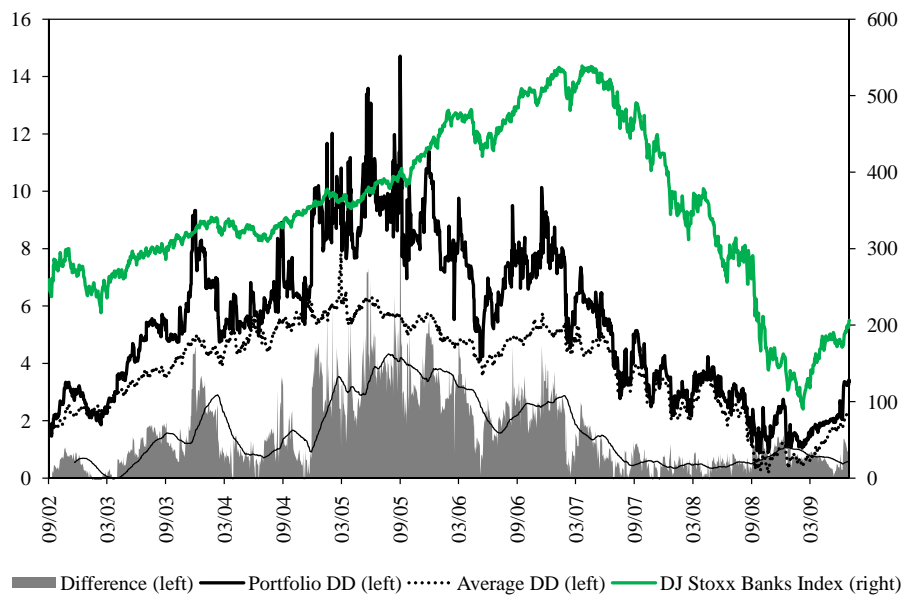
Source. Author's calculations and Thomson Datastream

Figure 2: Forward looking Distance-to-Default series. 31-Dec-2004 - 31-Jul-2009



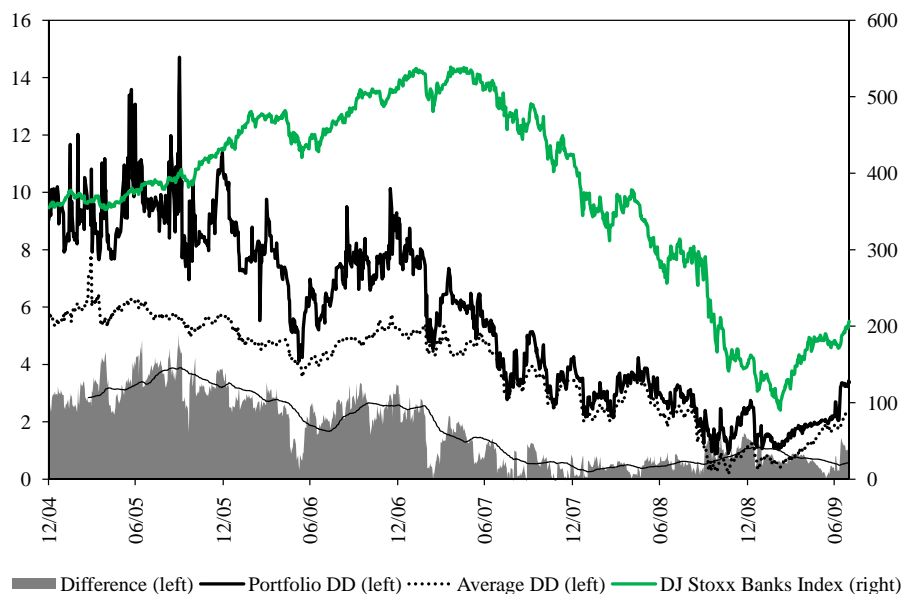
Source. Author's calculations and Thomson Datastream

Figure 3: Put-derived Forward looking DD series. 30-Sep-2002 - 31-Jul-2009



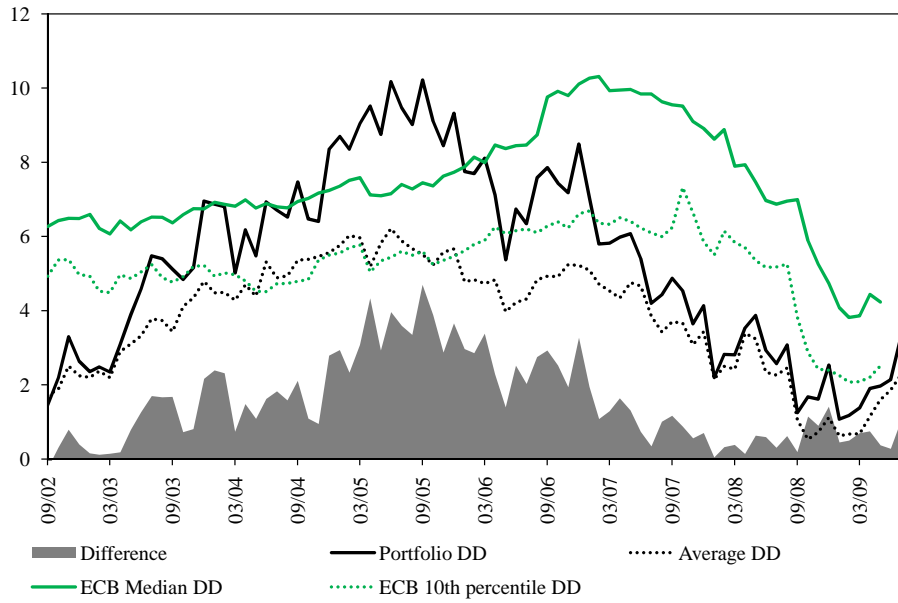
Source. Author's calculations and Thomson Datastream

Figure 4: Put-derived Forward looking DD series. 31-Dec-2004 - 31-Jul-2009



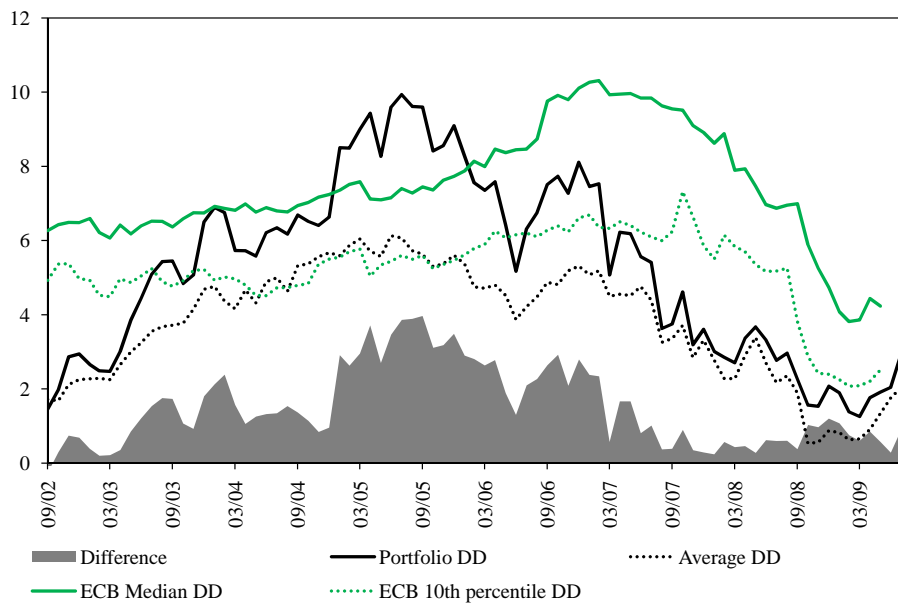
Source. Author's calculations and Thomson Datastream

Figure 5: Forward looking vis--vis historical DD series. End-of-month data.



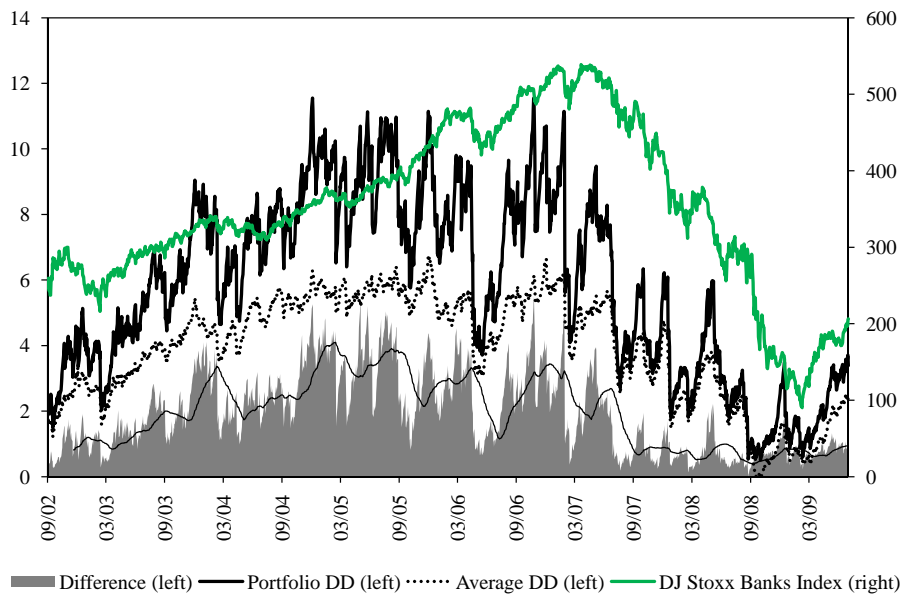
Source. Author's calculations and European Central Bank

Figure 6: Forward looking DD vis--vis historical DD series. Monthly averages.



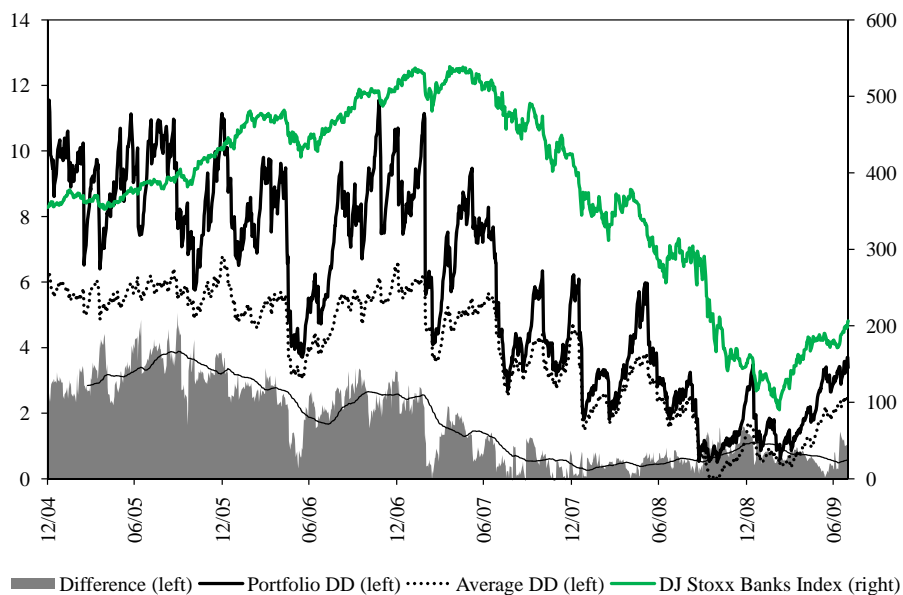
Source. Author's calculations and European Central Bank

Figure 7: GARCH(1,1)-derived DD series. 30-Sep-2002 - 31-Jul-2009



Source. Author's calculations and Thomson Datastream

Figure 8: GARCH(1,1)-derived DD series. 31-Dec-2004 - 31-Jul-2009



Source. Author's calculations and Thomson Datastream