Essays on Market-Based Analysis of Financial Stability

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To Cristina, always

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Chapter 1

Introduction

The mechanisms designed to safeguard financial stability, namely crisis prevention and crisis management and resolution, have gone through great development in the last decades and have been further spurred by the subprime crisis and its consequences. As financial stability has become a policy priority far-reaching reforms are taking place these days at an unprecedented scale of international coordination. These reforms aim to strengthen the international financial architecture and are also designed to cope with the increasing complexity, integration and interdependences of financial systems around the globe.

On the crisis prevention front, in particular in macroprudential supervision, public authorities are pursuing improved regulatory and supervisory policies, comprising a wider range of financial markets, asset classes and stakeholders. Along these lines, an overhaul to the current framework to monitor risks in banks and the rest of the financial system is also taking place, since the existing financial stability analytic toolbox has been target of strong criticism due to its failure to detect early signals of distress and to anticipate channels of transmission and contagion after the adverse events had occurred.

Among other shortcomings, techniques of financial stability measurement have suffered from two significant weaknesses. First, the informational properties of most indicators -mostly balance-sheet based and also some market-based-did a poor job in allowing policymaking to react timely to growing risks in banks' balance sheets and the rest of the financial system. Some did even not provide but fuzzy signals and suffered market freezes. Even though crises are hardly predictable, early signals of market stress should provide public authorities with some room for manoeuvre to take corrective actions. In other words, robust financial stability indicators need to contain forward-looking signals of stress and should also adapt promptly to new information from the market.

Secondly, some risk measures -mostly market-based-did provide some alerts, such as booming housing prices, excess liquidity indicators and low interest rates. However, increasing systemic risk was not well perceived because most macro financial models overlooked default risk exposures and channels of credit risk transmission between banks and other financial institutions and between the real and the financial sectors.

This dissertation addresses these two limitations in existing literature of financial stability assessment and develops market-based methods to assess distress risk at individual bank level, systemic risk in developed banking systems and, finally, risk exposures and interactions between the financial and nonfinancial sectors.

Being entirely empirical, the chapters below explore the informational potential of market-based data, i.e. securities and option market series, and recent market-based analytic approaches. In particular, the theoretical framework is largely based on contingent claims analysis (CCA) and techniques to extract information from option prices. CCA is an analytic framework based on the Black-Scholes-Merton model of option pricing to generate a number of credit risk indicators from balance-sheets and equity prices. CCA has been initially developed to cover the main elements of company risk, namely asset returns, asset volatility and leverage.

This analysis has been extended in this research to portfolios of companies to evaluate the risk profile of an entire corporate sector. The thesis also adds to the literature the information embedded in option prices of individual stocks and sector indices. Option prices are an underexplored source of information about individual banks and portfolios of companies. Option prices produce high frequency information about expectations of market participants and prove very efficient to endow market-based indicators, such as distance-to-default series or debt spreads, with a forward-looking component. In my analysis of individual banks, options cannot only streamline the CCA indicators properties but they can also provide expected distributions of the equity prices and contribute to assess stress scenarios and extreme events. Applied to entire sectors, option prices information introduce a proxy for risk co-movements and develop a framework to assess systemic risk in a timely manner.

Finally, the use of CCA measures with option prices information can be applied to assess risk profiles of entire sectors through time and see how the risk profiles of companies and sectors with some degree of economic proximity react to shocks within the sector and to exogenous shocks originated in the financial or any other sector. Given the forward-looking properties of option prices, this analysis produces a new and powerful tool for stress testing exercises and complements emerging analytical techniques such as network analysis.

Chapter 2

Option-implied Distributions: Incorporating Information from Option Prices to the Assessment of Bank Fragility

Contents

2.1 Introduction

The 2007-2009 financial crisis has highlighted the importance of early detection of stress and vulnerabilities in individual banks that can turn into a systemic crisis. Standard Financial Soundness Indicators, specially those based on balance sheet information, have proved unable to detect ex-ante higher default risk and many market-based indicators have behaved at best as coincident with the individual and systemic events triggered in August 2007 (International Monetary Fund , 2009a; Borio and Drehmann, 2009a). Some of these indicators have swiftly reacted to distress, but few have shown the ability to provide additional information about uncertainty or probabilities of extreme movements in asset prices. This evidence urges to explore robust instruments of early detection of financial stress.

To this end, this paper contributes to the empirical literature of quantitative tools for financial stability assessment with the analysis of the information embedded in option prices of banks. In particular, this study draws from the literature of option implied Probability Density Functions (PDF) to compute high-frequency distributions of individual banks' share prices and their moments. The properties of this set of indicators are then analyzed in terms of market expectations about uncertainty, asymmetry and extreme movements for supervisory purposes. In addition, using PDF-derived implied volatilities, I compute an adaptation of the Distance-to-Default indicator of stress and assess its forward-looking properties vis-à-vis CDS spreads, an increasingly used measure of distress and even systemic risk.

Information from option prices have been extracted and analyzed to guide policy makers about aggregate market expectations of financial and economic variables, such as interest rates, commodity prices or foreign exchange rates. Their informative content has been tested in terms of market anticipation or reaction to relevant unexpected market events, such as elections, wars, etc. Many studies have also applied option prices to predict future changes and movements or distributions of financial assets in the future.

The development of market-based indicators from option prices is encouraged by the large development of derivative markets as well. Options on different financial instruments have been available and increasingly liquid since the nineties, but markets for single equity options have emerged later and only the trading volumes can be considered liquid enough in the last decade to implement the PDF estimation approach followed in this paper. Therefore, this paper contribution is also pioneering the application of option-based PDF to single equity options.

The use of option prices for financial stability analysis has not been explored extensively and it has been limited thus far to studies of aggregated equity indices or the properties of model-based implied volatilities (IV) at individual level. Swidler and Wilcox (2002) pioneered in this area of research and their study focuses on signals from options implied volatilities and their ability to forecast future share prices volatilities. They found strong common movements across banks IV, which could be interpreted as systemic risk, and also between IV and other bank-specific risk measures. The authors find additionally that IV information contain additional risk warnings than those embedded in share prices or subordinated debt spreads.

More recently, Coffinet *et al.* (2010) also explore the usefulness of IV extracted from option prices for micro-prudential supervision under a different analytical approach. The authors apply survival models to a large sample of US banks and financial services firms to assess the occurrence of financial distress, narrowly measured by dividend cuts and omissions, which usually lead to default, bankruptcy or restructuring. Their results show that option prices considerably improve the accuracy to detect time-to-failure of distressed firms and perform at least as well as other indicators used in bank default models. In both cases, the IV series were model based [1]

The contribution of this paper is twofold. First, it outlines a method to compute PDF from option prices for financial stability monitoring and provides a comprehensive analysis of the properties of selected statistics of uncertainty, asymmetry and extreme movements derived from the option-implied PDF estimates. This analysis is useful for policy makers and bank supervisors, as it bundles together market expectations of future risk in the banking sector in few measures.

Results of this research show that option-implied PDF provide a set of indicators with rich and complementary information. Their signals share common trends and react accurately to significant market events. They also show common trends across financial institutions and other market based indicators, which provides a first notion of systemic risk. The uncertainty and asymmetry measures show a relatively stable behaviour along the timespan, while the extreme movement risk indicator is more irregular. This may likely be due to data issues, but the information content of this indicator is also partially detected by the former two. Finally, the Distance-to-Default adaptation using the IV estimate from the PDF shows that this indicator shares similar information with CDS spreads and leads it in many, if not most, cases analyzed. This result advocates for a joint use of alternative market-based indicators to monitor risk at individual banks.

The remaining of the paper is structured as follows. Section 2.2 summarizes the methodology used to compute the constant-maturity PDF and their summary statistics, with some remarks regarding the case of PDF applied to American-style equity options. In section 2.3, I describe the dataset and estimation strategy. The main results are discussed in Section 2.4 and Section 2.5 introduces and application of the Distance-to-Default series that include PDF-derived IV. Section 2.6 concludes.

[1] Coffinet *et al.* (2010) use at-the-money interpolated IV from a Cox-Ross-Rubinstein binomial tree model to take into account dividends and the possibility of early exercise, whereas Swidler and Wilcox (2002) use a slightly different approach and apply an interpolated IV from near-the-money options, which is a method used by the Chicago Board Options Exchange (CBOE) to compute the VIX Index.

2.2 Constant-maturity Option-implied PDF

Methods to estimate option implied PDF have developed extensively since the mid-nineties and have been applied to many different financial instruments but scarcely to individual equity options, mainly due to data liquidity issues and other methodological constraints. This study applies this technique for individual banks options thanks to the continuous development of exchange-traded options in recent years. This section provides a brief review of the literature and describes the adjustments needed to achieve the objectives of this paper.

Option implied risk-neutral probability density functions are analytic tools designed to exploit the information potential of options prices. They represent and allow retrieving the whole probability distribution of different outcomes of underlying assets and tracking expectations of market participants of these outcomes. The information embedded in PDF has proven very useful in several applications, ranging from assessment of market events or policy actions to case studies in different markets. Bu and Hadri (2007), Liu *et al.* (2007) and Lynch and Panigirtzoglou (2008) provide a comprehensive review of PDF applications under different methods and purposes.

Several methods to estimate option-implied risk-neutral PDF in the literature are based on the Cox and Ross (1976) pricing model for European style options, which defines call option prices as the risk-neutral expected payoff of the option at maturity, discounted back at the risk-free rate and holding volatility constant.

$$C = e^{-rt} \int_{S_T=K}^{\infty} (S_T - K)\, f(S_T)\, dS_T \tag{2.1}$$

where S_T is the underlying asset price at maturity T; $f(S_T)$ is the risk-neutral PDF; K is the strike price and r is the continuously compounded risk-free rate[2].

Both parametric and non-parametric techniques have been developed to approximate the PDF. A popular parametric technique is the mixture of log-normal functions discussed in Bahra (1997) and Melick and Thomas (1997). This technique assumes a weighted average of two or more log-normal PDF as the functional form $f(S_T)$ and fits the observed put and call prices to predicted prices via non-linear least squares. This method is flexible and captures the features of distributions, adapting to different stochastic processes of the underlying asset and thus different shapes, e.g. fat tails, skewness and bi-modality.

This technique also produces parsimonious estimates and it is relatively computationally efficient in terms of the optimization routines. The main drawback for the purposes

[2] A similar expression can be derived for put options: $P = e^{-rt} \int_{-\infty}^{S_T=K} (K - S_T)\, f(S_T)\, dS_T$. See Bahra (1997) for details.

of this paper is the existence of spikes when one of the lognormal PDF collapses, which is frequent in times of financial stress. This is a result of lack or bad quality of data and makes difficult to compare PDF and their summary statistics over time. An additional drawback that prevents an efficient application of this method in this case are the limited degrees of freedom given the large number of parameters to estimate, specially when dealing with single equity options.

Instead, this paper applies a non-parametric technique introduced in Shimko (1993) and described in depth in Bliss and Panigirtzoglou (2004, 2002); Cooper (2000) and Panigirtzoglou and Skiadopoulos (2004). This technique is based on the Breeden and Litzenberger (1978) result, which states that the PDF can be recovered by differentiating Equation 2.1 with respect to the strike price K twice. Differentiating it a single time provides the cumulative density function (CDF).

$$\frac{\partial C\left(K\right)}{\partial K^{2}}=e^{-rt}f\left(S_{T}\right) \tag{2.2}$$

At any given trading day, only a discrete and reduced number of options are traded and therefore a direct application of Breeden and Litzenberger (1978) result becomes unfeasible. However, as pointed out by Shimko (1993) and Malz (1995, 1997), a continuous of strikes and corresponding call prices can be obtained according to the following method. First, strikes and observed option prices are converted into delta values and implied volatilities. Then, implied volatilities are smoothly interpolated using a cubic spline across the delta-space and the results are converted back into continuous of strikes and call prices. The CDF and PDF are obtained differentiating numerically. This method stands out for its flexibility and easy implementation[3].

The result of this process are daily PDF and CDF of logarithmic changes of the underlying asset, banks' equity prices in this case, over a given horizon determined by the options contract maturity. Following Lynch and Panigirtzoglou (2008), these functions allow to compute summary statistics that provide market expectations of uncertainty, asymmetry and extreme movements.

Some remarks about this method before its application to the current dataset. First, Breeden and Litzenberger (1978) result was derived for options European-style options but is applied in this study for American-style options. Panigirtzoglou and Skiadopoulos (2004) show that the Barone-Adesi and Whaley quadratic approximation (Barone-Adesi and Whaley, 1987) can be used to compute implied volatilities in order to capture the early exercise premium of the American-style options. The conversion between strike-call price and delta - BAW implied volatility spaces is then computed using the Black-Scholes

[3]See Galati *et al.* (2007) for an illustrative diagram of this method

formula[4].

Second, the smoothed implied volatility smile method does not assume any stochastic process of the underlying price, the Black-Scholes formula is used only to map data from one space to another. Finally, the interpolation across delta-space, introduced by Malz (1997), is preferred to the strike price space, since delta space is bound and away-from-the-money options are put closely to the near-the-money options and it enables a greater variation in shape of the PDF near the at-the-money point, where data are more reliable (Bliss and Panigirtzoglou, 2004).

2.3 Data and Estimation

2.3.1 The Dataset

The dataset comprises daily exchange-traded equity American-style options from nine banks categorized as Large Complex Financial Institutions[5]. The data covers trading days between January 2, 2004 and December 30, 2008 for banks with options traded at Euronext and CBOE and between January 2, 2004 and June 30, 2009 for banks with options traded at Eurex[6]. This allows to assess the behaviour of the PDF summary statistics during the worst part of the crisis and the slow and incipient recovery in early 2009.

All contracts have maturity dates on every third Friday of the expiration month. The option cycle is March, June, September, and December, all banks in the sample have up to 60 contract months with a contract size set at 100. Table 1 summarizes general features of the sample.

[Insert Table 1 here]

The banks in the sample were chosen according to the following criteria. First, all banks in the sample are very large for any size metric, diversified and, as we know now, highly interconnected with the rest of the financial system. They conduct operations around the globe and across most, if not all, financial activities[7]. Second, they are diversified across geographies, which is useful to detect the degree of comovement of their summary statistics across crountries also in option prices. Third, banks were chosen according to a preliminary analysis of liquidity of their associated options. Bank equity options are the

[4] Some examples of this approach can be found in Bliss and Panigirtzoglou (2004) and Cincibuch (2004). As an alternative, Carlson *et al.* (2005) and Healy *et al.* (2007) chose to ignore altogether the early exercise premium, since it only affects too-deep-in-the-money options (Dupont, 2001), that are normally excluded from estimation.

[5] Due to data quality, HSBC was dropped from the sample.

[6] Dr. Torsten Lüdecke, at Universität Karlsruhe, kindly provided additional data.

[7] The LCFI categorization combines size metrics and the involvement in the following markets: equity, bonds, syndicated loans, interest rate derivatives, foreign exchange, assets custody.

most liquid across sectors on aggregate, but at individual bank level, trading varies and is generally concentrated within a smaller set of institutions. Finally, as the timespan includes extreme events, such as bankruptcies (Lehman Brothers), nationalization (RBS) or major restructuring and bailouts (Citigroup), the option data of some institutions are distorted and therefore produce breaks in the data should be removed for a long term analysis.

Underlying equities' data are daily closing prices, retrieved from Bloomberg, traded at the exchanges linked to the option contracts[8], corrected for dividends[9] and denominated in domestic currencies. Corporate actions affect the option series, such as corporate restructuring and equity splits or reverse splits. For instance, UBS and Lehman Brothers made effective a share split 2-for-1 on 10 July 2006 and 2 May 2006, respectively, while RBS announced a stock split on 8 May 2007, changing permanently their underlying prices and making necessary an adjustment in the strike prices and other characteristics of existing option contracts.

The interest rates used to estimate PDF are 3-month money market rates, i.e. EURIBOR for euro area banks, LIBOR USD-, GBP- and CHF-denominated rates for American, British and Swiss banks, respectively. A maturity mismatch is inevitable when using these rates instead of a term structure of interest rates. Option market makers usually price options with term structures customized by their treasury departments or generated by financial data providers. However, 3-month money market rates were chosen because they fit well the time horizon of the PDF; they are good proxies of borrowing costs, are less prone to be affected by monetary policy actions, are highly liquid and have little effect in the PDF estimation methodology (Bliss and Panigirtzoglou, 2004)[10].

Raw option data must be filtered before estimation because daily trading is concentrated around a narrow set of near-the-money strikes (Clews *et al.*, 2000) and settlement prices are less informative of market expectations if strikes deviate too much, especially in the case of too deep in-the-money options. Quotes of less frequently traded options only may reflect previous days' traded prices and models from which the notional prices are derived. Accordingly, all in-the-money options were first discarded, keeping only at- and out-of-the money calls and puts.

Additionally, this dataset has been filtered to ensure informative PDF. The exclusion criteria followed in this paper lead to exclude: 1) options with greater than 20% absolute moneyness[11], 2) options with less than five and more than 120 days to maturity; 3) op-

[8]Multiple-listing may be distortive due to liquidity effects and therefore must be addressed to ensure reliable estimates. Options may also be multiple-listed but only options traded in main markets were included in the sample.

[9]As a result, the underlying shares are treated as non-dividend paying stocks for matter of simplicity.

[10]Money market rates were retrieved from Thomson Reuters Datastream

[11]Absolute moneyness is defined as $\left|\frac{K}{S} - 1\right|$. The threshold in Bliss and Panigirtzoglou (2004) and

tions for which Barone-Adesi Whaley implied volatilities were not possible to compute, 4) option prices that violated the monotonicity and convexity properties[12]; and 5) options with deltas equal or greater than 0.99 or less than or equal to 0.01.

2.3.2 Constant-maturity PDF

After obtaining a filtered dataset with liquid option quotes for each bank, the BAW implied volatilities are fitted across the delta space from 0.99 to 0.01 with the smoothing cublic spline method for each trading day and for each one of the active contracts. No fitting is conducted if there are less than three delta points (from corresponding strikes) per contract and no pseudo-data points are added to extrapolate horizontally as in Bliss and Panigirtzoglou (2004) and Lynch and Panigirtzoglou (2008)[13].

These interpolated implied volatilities could already be converted into strike-price space but are subject to suffer from the time-to-maturity effect. This effect occurs when the underlying price decreases as maturity approaches and estimates of volatility in PDF decrease without real changes in uncertainty about the asset. In order to correct for this, I followed the methodology described in Clews *et al.* (2000) and applied in Lynch and Panigirtzoglou (2008). Accordingly, for each trading day, I interpolate across the implied volatilities of splines with the same delta but with different maturities[14]. From this interpolation across maturities, I choose the resulting 30-day constant-maturity interpolated implied volatilities to generate daily 30-day constant PDF and derive their summary statistics.

2.3.3 PDF Summary Statistics

For each 30-day constant-maturity PDF estimated applying the method described above, I compute weekly summary statistics[15] that provide market expectations in terms of uncertainty, asymmetry and extreme movements risk[16]. The uncertainty statistic is the 30-day **at-the-money implied volatility**, **IV**, which is obtained directly from the spline interpolation. This is a model-free statistic that increases if higher uncertainty is perceived in the market.

Dumas *et al.* (1998) is 10% and in Glatzer and Scheicher (2005) is 25%. Other papers filter by time-adjusted moneyness $\left|\frac{K}{S}-1\right|\frac{1}{\sqrt{T}}$.

[12]Monotonicity requires call(put) prices to strictly decrease(increase) with the strike. Convexity requires a positive butterfly spread at a particular strike.

[13]These authors add three pseudo strike points at each end of the volatility smile in order to avoid negative or implausible large implied volatilities. For robustness check, I tested this approach but found no significantly different results.

[14]This is an additional reason to interpolate across the delta space.

[15]Averages of the available daily estimates, in order to reduce noise in the data for graphical analysis.

[16]Lynch and Panigirtzoglou (2008) provide a large set of additional statistics that can be included in the analysis. However, since they are highly correlated among them and their information may become redundant, I report only one statistic of uncertainty, asymmetry and extreme movements.

The asymmetry measure is the **standardized risk reversal**, **SRR**, which is computed as the difference between the 25-delta call and 75-delta call implied volatilities, divided by the at-the-money (50-delta) implied volatility. This measure informs about the slope of the volatility smile and is adjusted for changes in overall uncertainty. Even though Rubinstein (1994) and other authors have largely documented that equity options tend to show a steep volatility smile after the Crash of October 1987, also called "Crashophobia", this statistic has additional signals of fear in the market and expectations of fat tails[17].

Finally, the statistic of extreme movement risk is the **standardized strangle**, **SS**, which measures the degree of fatness of tails if the corresponding option implied PDF. To compute it, I take the difference between the 25-delta call IV and the at-the-money IV, the difference between the 75-delta call IV and the at-the-money IV, and divide the average of the resulting differences by the at-the-money IV in order to adjust it for changes in uncertainty[18].

2.4 Behaviour of PDF and Summary Statistics

This section describes the behaviour and properties of the PDF summary statistics introduced in Section 2.3.3. I start with the main properties of PDF implied volatilities across banks and over time. Figure 1 shows the PDF 30-day implied volatilities (PDF-IV) for each of the nine banks in the sample. As anticipated, some discontinuities are found at the beginning of the sample due to less liquidity of option contracts during that early period of development of these instruments, although is limited to specific banks, e.g. Lehman Brothers (LEH).

[Insert Figure 1 here]

More importantly, the charts show the common movement of these series over the whole timespan, with very high correlation coefficients, over 65%, in all cases and with no distinctive correlation pattern in terms of country of origin or exchange where the corresponding options are traded. This result is in line with findings in Hawkesby *et al.* (2005) about the high interconnection of LCFI across frontiers and gives an illustration of systemic risk specially since 2007. See Tables 3 and 2for pairwise correlation coefficients for both levels and first differences.

[Insert Tables 3 2 here]

Table 4 reports the historical properties of the PDF-IV series by bank. The pattern of IV across banks is very similar. The average IV is around 33% and does not differ much

[17] For reference, a lognormal PDF has a zero standardized risk reversal.

[18] A lognormal PDF has a zero standardized strangle.

across banks with the exceptions of Lehman Brothers (LEH) and BNP Paribas (BN1), with mean IV's of 40.4% and 28.4%, respectively. The latter and the second French bank in the sample, Société Générale (GL1), stand out for having the lowest dispersion in spite of the large jumps in IV at the end of the sample. Large skewness and kurtosis coefficients for IV indicate that the expectations of equity uncertainty for all banks tend to be higher than the median and that the market participants are prone to make significant changes in their risk perceptions.

[Insert Table 4 here]

Combining the summary information and the chart, we can observe that the maximum values of the IV for each bank are found in 2008. RBS shows the largest value (196.8%), and it coincides with rumours of nationalization in mid October 2008. The second largest value corresponds to Deutsche Bank (DBK), also post-Lehman Brothers collapse. The series for Lehman Brothers (LEH) are relatively shorter at the end of the sample due to its bankruptcy, whereas the IV values for Citigroup show more discontinuities at the end of the sample at the time of the Federal bail-out. Needless to say, these extremely large values of IV are a result of a full-blown financial crisis and the dataset only allows us to observe a mild slowdown in early 2009, after large-scale government actions in the cases of Deutsche Bank, UBS and Credit Suisse.

In addition to these systemic events, it is important to note that all IV series start an upward trend in early 2007, as hedge funds were being closed due to subprime-related losses and large default risks were only building up. Finally, graphical inspection of the IV estimates allows us to detect accurately particular events for each bank. For instance, IV series of Deutsche Bank report a sharp increase in mid-2006, as the bank was affected by the downgrade of bonds of General Motors and Ford, and for Barclays in December 2007, as this institution sued Bear Stearns for hidden losses on investments in a fund.

Figure 2 shows the **standardized risk reversals,** the measure of asymmetry. As expected for equity options, historical values of standardized risk reversal tend to be negative, pointing out to a steep volatility smirk and higher valuation of significant bank share prices drops. However, with arguably the exception of Citigroup, the charts show that, simultaneously with increasing uncertainty, large and negative standard risk reversals indicated since the beginning of 2007 an anticipated and extended market perception of fear of a large collapse in bank equity prices, as it effectively happened. The charts also show that this indicator becomes very large during specific market events, such as Bear Stearns and Lehman Brothers bankruptcies.

The charts corresponding to Deutsche Bank, UBS and Credit Suisse show that during the first half of 2009 the fear perception, though still large, stabilized. This fact, in combination with a still high degree of uncertainty perception, as measured by the IV series, indicates that market participants in options markets did not rule out further deterioration in banks risk profiles.

[Insert Figure 2 here]

Finally, Figure 3 plots the **standardized strangle** statistic. From the chart, it is very noticeable that this indicator is highly irregular in time and heterogeneous across banks. This result is not entirely surprising and was also found in Lynch and Panigirtzoglou (2008) for equity indices. Positive values of this indicator point out to fat tails and clearly coincide in this sample with periods of extreme stress in the sector. This evidence goes in line with the previous discussion of the distribution of IV from Table 4 but fails to give further insights.

2.5 Empirical Application: Distance-to-Default

So far, the analysis of option-implied PDF statistics dealt with bank risks in terms of future movements in share prices returns. Although this approach is highly relevant from a supervisory point of view, it does not cover additional risk elements such as levelage or bank asset risks. Accordingly, in this section I explore the usefulness of the PDF statistics as inputs in other market based indicators of bank fragility. In particular, this application introduces the estimates of PDF implied volatilities into the Distance-to-Default indicator and compares the resulting indicator to the 1-year CDS spreads of the banks in the sample using traditional pairwise Granger Causality tests, following the approach described in Kim and Chan-Lau (2004).

Distance-to-Default (DD) is a market based risk indicator based on the Contingent Claims Analysis. It is an indicator of stress based on option theory that assumes that company value, represented by its assets, is the sum of its risky debt and equity. As 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).

In practical terms, the computation of Distance-to-Default[19] requires the equity volatility as an input, normally taken from historical share prices, in addition to market value of equity and balance sheet information about the assets and the liabilities to compute the distress barrier. Accordingly, for this application, I will introduce the PDF estimates of IV in the DD calibration in order to endow this indicator with forward-looking properties and assess its performance vis-à-vis CDS spreads[20]. It is worth noticing that the option

[19]The rest of data inputs were obtained from: Bankscope for balance sheet data; Thomson Reuters Datastream for market capitalization and risk-free interest rates.

[20]CDS data correspond to daily quotes (averaged into weekly data) from 1-year Senior contracts, obtained from Thomson Reuters Datastream.

implied PDF and CDF described above also allow to create scenarios according to the distribution of banks share prices at a given trading day, but this falls out of the scope of this complementary exercise.

First, DD series are displayed in Figure 4 and show interesting properties. Same as in the case of the PDF summary statistics, the DD series show common trends across banks and start a steep downward trend in 2007. In fact, they start to show a downward trend in mid-2005 but this result is therefore driven by the rest of DD inputs, namely increasing leverage. Some banks hit the zero barrier, which is a synonym of bankruptcy, and Lehman Brothers and RBS go deep into negative values of the indicator. This is mainly explained by the large IV estimates and exacerbated by the falling market value of equity. A zero DD does not mean that a bank becomes insolvent, it means that if short-term liabilities are not rolled over and extra profits are not suddenly boosted, the bank will exhaust assets within a one year horizon and would become insolvent even faster in case of a bank run. Negative DD means that the failure is very highly.

[Insert Figure 4 here]

Before assessing the forward-looking properties of DD and CDS rates, I compute a correlation matrix by bank. Table 5 displays these results and shows that these series are highly and negatively correlated across all banks. As the larger the DD, the greater the distance of a company from the default point and the less risk or probability of default, the distress risk of CDS is measured in the inverse scale.

[Insert Table 5 here]

Finally, Table 6 show the results of the pairwise Granger Causality tests[21] for different lags. Overall, I find that the DD indicator that includes estimates of IV from the PDF lead at least in most cases and for different lags the CDS spreads. For some banks (BNP Paribas or RBS) this is not the case, which can be interpreted as complementary information about bank risk from different market-based indicators[22]. This exercise illustrate the importance of combining the current set of indicators with other alternative measures of risk that incorporate additional sources of information, in this case, expectations from option prices.

[Insert Table 6 here]

2.6 Concluding Remarks

This paper develops a method to extract risk-neutral Probability Density Functions (PDF) from option prices for a set of nine banks categorized as Large Complex Financial Institu-

[21] Previous analyisis of unit roots and cointegration was conducted but is not reported.

[22] French banks also provide only half-yearly statements, which may also distort the forward-looking properties of the indicator.

tions. The resulting PDF are used to build a set of three indicators that monitor financial stability at individual bank level in terms of uncertainty, asymmetry and extreme movements. The time span runs between January 2004 and December 2008 and June 2009, for some banks. This period covers tranquil times and a full-blown financial crisis.

The analysis of properties of the PDF summary statistics show that option-implied PDF provide a set of indicators with very rich complementary information. The three resulting statistics show common trends across financial institutions and other market based indicators. They react accurately to significant market events and are able to detect idiosyncratic risk elements. In particular, the uncertainty and asymmetry measures behave relatively stable along the timespan, while the extreme movement risk indicator is more irregular due to data issues, but its information content is also detected by the other two.

Finally, an application of this methodology adapts the Distance-to-Default risk indicator using the IV estimate from the PDF and compares its performance with the CDS of the corresponding bank. Using Granger causality tests, results of this application show that this indicator shares similar information with CDS spreads and leads them in many, if not most, cases analyzed. This result advocates for a joint use of alternative market-based indicators to monitor risk at individual banks and provides useful analytic tools for policy makers and bank supervisors, as it bundles together market expectations of future risk in the banking sector in few measures.

Chapter 3

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

Contents

3.1 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[1] and was driven by last decade's financial innovation, liberalization and development. However, the dynamics

[1]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.

of this financial crisis has triggered renewed attention and operational focus.

The theoretical and empirical work 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 and where the contribution to systemic risk becomes . 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 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 3.2 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 3.3, 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 3.4 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 3.5 concludes.

3.2 Theoretical Underpinnings

3.2.1 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[2] 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[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 probabilities of default, if the distribution of assets were known. Details of its derivation and data requirements can be found in Annex 1.

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

[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. The use of the rest of risk indicators derived from this methodology remains for further research.

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 literature.

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.* (2004a); International Monetary Fund (2009b) 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 (2009b) 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, 2009b).[4]

3.2.2 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 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

[4]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.* (2009a) 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.

the system as one large bank (see Annex 2 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)[5] . 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 (Annett *et al.* (2005); Čihák and Koeva Brooks (2009a) 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[6]. 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.

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[7]. In either case, the indicator becomes a coincident one and may fail to detect early signals of market stress (International Monetary Fund , 2009b).

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

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

[6]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

[7]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.

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 3.3 and 3.4 show how this methodology can be applied and how it compares to existing use of DD to monitor systemic risk.

3.3 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[8] 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 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.

3.3.1 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[9]. All banks in the sample have also been constituents of the DJ STOXX Banks Index[10] over the whole time span of this analysis and their shares and options are publicly traded in liquid organized exchanges (see Table 7 for details).

[Insert Table 7 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

[8] This paper reports results using only a simple average. Weighted averages (using individual market capitalization) have been tried without affecting results.

[9] 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.

[10] 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.

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 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[11], 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[12]. The risk-free interest rates are 10-year government bond yields in each bank's country of origin. See Table 8 for a description of data and sources.

[Insert Table 8 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

[11] 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.

[12] 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.

in the beginning, periods of minor stress since 2006, the financial crisis since August 2007 and the recent markets' recovery and sector restructuring since March 2009.

3.3.2 Calibration of Average and Portfolio Distance-to-Default Series.

Appendices 1 and 2 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 portofolio. 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; σ_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.

3.4 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.

3.4.1 Aggregated Distance-to-Default Series

Figure 5 and Figure 6 plot together the forward-looking average and portfolio DD series, their difference and also the DJ STOXX Banks Index as a reference[13]. 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 5 and 6 here]

Figures 7 and 8 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[14].

[Insert Figures 7 and 8 here]

[13]Figure 6 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.

[14]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).

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 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 9 and 10). 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 9 and 10 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.

3.4.2 Properties of the Indicator of Stress

The smoothness and forward-looking features of my DD series are quite evident in Figures 11 and 12, 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[15]. 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 11 and 12 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[16]. Results are reported in Table 9.

[Insert Table 9 here]

Results of Granger tests provide econometric support to the forward-looking feature of our series. Table 9 shows that forward-looking DD indicators Granger cause ECB's median DD series up to two years, as Figures 9 and 10 suggested. More robust results are obtained for longer lags in the test using average DD because of 1) the similar method used 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

[15] 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 3.3. 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.

[16] 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.

constructed in this paper have therefore an important advantage as a tool of systemic risk analysis.

3.5 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 interdepences 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.

Appendix A. Derivation of Distance-to-Default

Given the three principles in CCA mentioned in Section 3.2.1, 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 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).

$$\max\{0, A - D\}$$

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 **t** periods ahead:

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

where **r** is the rate of growth of the company value (assets) and equals the risk-free interest rate. σ_A is asset volatility.
In practice, implied asset value **A** and volatility σ_A are not observable and must be estimated solving the following system of simultaneous equations by numerical methods:

$$\begin{cases} \mathrm{E}{=}\mathrm{AN}(\mathrm{d}_1) - e^{-rt}DN(d_2) \\ \sigma_E = \frac{A}{E}\sigma_A N(d_1) \end{cases}$$

where **E** is the value of equity, σ_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 **E**; historical, GARCH-derived or option-implied 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.

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:

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

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 σ_{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 Annett *et al.* (2005), De Nicolò and Tieman (2007), Echeverría *et al.* (2006), Echeverría *et al.* (2009a), Gray and Malone (2008) and Vassalou and Xing (2004a) for applications.

Chapter 4

A Market-based Approach to Sector Risk Determinants and Transmission in the Euro Area

Contents

4.1 Introduction

Due to the financial and economic crisis started in Summer 2007, research on financial stability is facing new challenges and embarked on a growing agenda. There is a consensus to develop new and enhanced measures to understand global financial networks and to provide policy making with improved analytic tools (Financial Stability Board, 2010). The growing literature on financial stability has been urged to expand the focus and to incorporate the interaction between the financial system and the rest of the economic agents and sectors.

This paper adresses the importance of heterogeneity in terms of risk determinants and risk transmission across corporate sectors in the euro area. I propose a model where risk in the corporate sector, comprising the financial sector (banks and insurance companies) and the non-financial corporate sector, is determined by general economic and financial markets conditions and by sector-specific risk drivers. The first step in this paper consists in generating forward-looking sector-level risk indicators based on Contingent Claims Analysis, a market-based indicator. Then, an analytic framework using Common Correlated Effects (CCE) estimator from Pesaran (2006) is provided, allowing to study the diffusion of risk across sectors and over time, in addition to those coming from other sector-specific determinants and also from the macroeconomic environment and the financial markets.

A large amount of the emerging literature has focused mainly on the effects of macroeconomic shocks on banking stability, while some work also addresses vulnerabilities in the corporate sector at aggregate level. These studies vary significantly in terms of the empirical methods applied, the sectors and macroeconomic variables of study, and the assumptions about the direction of shocks, but they all show this strong macro analytic focus. As an example, De Graeve *et al.* (2008) develop a model of shocks and feedback effects between the real sector (through monetary policy shocks) and the financial system with no prior assumptions about the direction of shocks. On the same topic, Castrén *et al.* (2009) propose a model to assess effects from macroeconomic variables, with no feedback, on credit risk measures of Large and Complex Banking Groups (LCBG) in the euro area.

Focusing on the interdependence between macro variables and the non-financial corporate sector, Åsberg and Shahnazarian (2009) use an error correction model to assess sensitivity in the aggregate Swedish corporate sector to shocks in variables such as industrial production, interest rates and consumer prices. Carling *et al.* (2007) use a panel data model to assess empirically the impact of macroeconomic and firm-specific shocks on default probabilities also in the Swedish corporate sector. Bruneau *et al.* (2008) analyze links in both directions between non-financial companies and macroeconomic variables, including financial shocks, for the French economy. Castrén *et al.* (2010) expand their previous work and study global macro and financial shocks on the same credit risk measures of the euro area financial and corporate sectors separately, using satellite-GVAR models. Castrén and Kavonius (2009) propose a different approach and they include in the analysis the linkages among the rest of economic sectors, e.g. households, government and rest of the world, using a network of balance sheet exposures and risk-based balance sheets.

Even though the assessment of the effects of general economic conditions on overall corporate risk is highly relevant for finacial stability, understanding also the credit risk relationships within the corporate sector with a less macro focus is certainly not negligible, yet it has not been extensively studied. As credit risk events at individual firm level are linked via sector-specific and general economic conditions (Zhou, 2001), so is risk propagation across corporate sectors through a number of complex channels. In addition, sectoral risk features and responses to common shocks are heterogeneous, hence neglecting this heterogeneity may be misleading in terms of overall credit risk management (Hanson *et al.*, 2008), financial stability analysis and policy decisions.

During the Asian crisis in 1997, an over-leveraged and poorly profitable corporate sector put the Asian financial system on the verge of collapse and triggered a deep economic crisis (Pomerleano, 2007). The current crisis has highlighted the role of banks in heterogeneous risk transmission to the corporate sector in developed economies either directly through credit constraints or indirectly through higher financing costs, less investment counterparts or even second round effects on demand. Castrén and Kavonius (2009) show that the bilateral linkages between the financial system and the corporate sector in euro area (measured by balance sheets gross exposures) are the most significative and take place through both the credit channel and the securities markets. In addition, the degree of correlation and default transmission between non-financial corporate sectors is high due to complementary or similar business lines, e.g. Telecoms and Technology, Utilities and Oil & Gas.

Sectoral risk relationships and their dynamics have previously been analyzed using market-based indicators in Alves (2005) with a VAR approach and in Castrén and Kavonius (2009) using network analysis. Their results highlight important cross-dynamics across sectors in addition to the impacts viewed as systemic and generated by macroeconomic variables. However, the high degree of aggregation in these papers are likely to have neglected important linkages within the corporate sector and with the financial system (Castrén and Kavonius, 2009) and may also have ignored sector-specific elements of default risk (Chava and Jarrow, 2004).

Additionally, the dimension limitations of a traditional VAR model leaves some unobserved effects unaccounted for (Alves, 2005). In a very recent paper, Bernoth and Pick (2011) model linkages between the insurance and banking sectors and forecast their default risk in presence of unobserved linkages and other common shocks using the CCE estimator[1]. The determinants of default risk are presented and discussed as subproducts, since the paper focus are mainly forecasting techniques, hence the authors do not tackle the issue of risk transmission between the financials and the non-financial corporate sector,

[1]The authors use backward-looking Distance-to-Default series computed for a very large number of individual institutions and aggregate them into simple average series to compute systemic wide forcasts.

potentially overlooking an important source of risk in their sample.

For these reasons, this paper exploits recent techniques to deal with panel data in presence of cross-section dependence (CD) and unobserved factors using the Common Correlated Effects (CCE) estimator introduced in Pesaran (2006). This study generates the following contributions to the literature. First, it proposes a methodology to build sectoral risk indicators using balance sheet, market-based and, most notably, option prices information. These series become forward-looking and allow for a wide range of stress-testing execises. Then, the paper provides an analytic framework to study risk determinants and transmission at sector level in the euro area by taking into account both the cross-section dimension as well as the time series dimension of risk, which has been long neglected in the literature due to lack of a suitable multivariate methodology.

The results show that aggregate corporate default risk comprises a stationary idiosyncratic factor and a non-stationary common element that drives the deviations of the former from a long-term steady state. Results of the econometric model show that shocks originated in the macroeconomic and financial environment have limited relevance on idiosyncratic sectoral risk when cross-section dependence is accounted for and the common element is filtered out. This result is partly driven by the market-base nature of the risk indicator under analysis and more importantly because sectoral risk responds more significantly to sector-specific shocks, including proximity-driven risk spill-overs. Results also reveal a high degree of heterogeneity in terms of sensitivity and direction of the effects both from macro-financial variables and from sector-specific risk-drivers. These results show that a macro-only focus of the analysis of financial stability would be misleading for policy if cross-section dependence and sectoral heterogeneity is ignored.

The rest of this paper is structured as follows. Section 4.2 introduces the sector-level risk indicator and the methodology to compute it for aggregate sectors. Section 4.3 describes the sample of sectors and companies included in the analysis and the properties of the sectoral risk indicators. Section 4.4 describes the analytic framework of risk determinants and diffusion using the CCE estimator and other panel data methods applied in the empirical analysis. The results of the former are explained in Section 4.5 and Section 4.6 concludes.

4.2 Sectoral Risk Measure for the Euro Area's Financial and Corporate Sectors

The risk measures chosen in this paper to analyze sector-level stress in the euro area are Portfolio Distance-to-Default (DD) series, namely forward-looking DD series built using aggregated information of individual companies by sector. *DD* series make part of the set of risk indicators based on Contingent Claims Analysis (CCA)[2]. *DD* series were initially developed and disseminated for commercial purposes by Moody's KMV using market-based and balance sheet information to assess credit risk in individual companies (Crosbie and Bohn, 2003; Arora and Sellers, 2004).

They indicate the number of standard deviations at which the market value of assets is away from a default barrier defined by a given liabilities structure. A decrease in *DD* reflects a deteriorating risk profile, as a result of the combination of the following factors: lower expected profitability, weakening capitalization and/or incresing asset volatility (Annett *et al.*, 2005; De Nicolò and Tieman, 2007). Variants of this indicator are increasingly used to analyze credit risk of aggregated corporate and macro sectors. Gray and Malone (2008) provide a comprehensive overview of techniques and applications.

At aggregate corporate sector-level exclusively, *DD* signals the probability of generalized distress or joint failure in a given sector or industry. Despite strong modelling assumptions[3], empirical research has shown that aggregate *DD* dynamics contain informational signals of market valuation of distress and therefore *DD* is a valuable monitoring tool of the risk profile in the financial and non-financial corporate sectors (Gropp *et al.*, 2009; Vassalou and Xing, 2004b).

Since the same principles of CCA can be applied to aggregation of firms, the analysis of an entire corporate sector becomes the analysis of a portfolio of companies. In empirical terms, individual company information needs to be aggregated together into a single, tractable and highly representative indicator by corporate sector, where its composition must be clearly defined.

As for aggregation, most papers in the literature compute the median or either the weighted or unweighted average of *DD* or EDF series[4] for a large and changing sample of companies. This methodology produces an indicator that highlights the overall risk outlook in the sector but may overemphasize the large players or may partially neglect interdependencies among portfolio constituents (Alves, 2005). Examples of this approach are found in Alves (2005); Bernoth and Pick (2011); Carlson *et al.* (2008); Castrén and

[2]Contingent Claims Analysis (CCA) is an analytic framework whereby a comprehensive set of financial risk indicators is obtained by combining balance sheet and market-based information including expected loss, probability of distress, expected recovery rate and credit spread over the benchmark risk-free interest rate. It is based on the Black-Scholes-Merton model of option pricing and has three principles: 1) The economic value of liabilities is derived and equals the economic value of assets, where liabilities equals debt plus equity; 2) Liabilities in the balance sheet have different priorities and risk; and 3) The assets distribution follows a stochastic process.

[3]These assumptions are concerned mainly with those inherent in the Merton-based model (e.g. lognormal distribution of assets) and also the liability structure.

[4]Expected Default Frequency (EDF) is a credit measure based on CCA and adapted by Moody's KMV to reflect actual default distributions.

Kavonius (2009); Castrén *et al.* (2009, 2010) and Åsberg and Shahnazarian (2009).

By contrast, this paper's aggregation approach are Portfolio DD series, following research on financial systemic risk in Čihák and Koeva Brooks (2009b); De Nicolò and Tieman (2007); Mühleisen *et al.* (2006); Echeverría *et al.* (2009b); Annett *et al.* (2005) and Saldías (2010). This methodology treats the set of companies by sector as a single entity, it aggregates balance sheet and market data and incorporates the assumed portofolio volatility before computing the DD series. Appendix A contains a complete explanation of Portfolio DD's derivation and data requirements.

The Portfolio DD series obtained using this methodology have several interesting features. Portfolio DD enhances the informational properties of average DD series, since it does not only capture company size but also interdependencies among the portfolio constituents. It may be considered the upper bound of joint distance to distress (the lower bound in terms of joint probabilities of distress) in normal times (De Nicolò and Tieman, 2007) but it tends to converge with the average DD in times of stress, when equity market volatility is higher. This feature illustrates quick reaction of the indicator to market events and shows the generalized increase in returns correlation in a sector during distress times, even if fundamentals of portolio constituents may be solid (Saldías, 2010). Aggregated company fundamentals embdedded in the indicator are informative of longer-term trends of sectoral risk.

Finally, since aggregation of company information is conducted before computing the risk indicator, calibration of Portfolio DD also allows to add more easily forward-looking properties from option markets via option implied volatilities from EURO STOXX indices, which also circumvent assumptions about constituents' returns correlations. Portfolio DD acquires more responsiveness to early signs of sector-level distress and hence serves to stress scenarios[5].

The second empirical issue deals with the sector classification and the selection of constituent companies in the Portfolio DD. Research based on median and average DD series tackles only the former issue[6] and then picks the largest sample available with breaks in sample composition. This approach is however likely to be affected by spurious variation due to classification changes affecting large companies (Alves, 2005) or due to relevant corporate events, including M&A, spin-offs or delistings.

This paper choice for sector classification is the Industry Classification Benchmark

[5] This paper does not include average DD series computed using option price information as described in Saldías (2010) since there are not enough single equity options traded for all companies in this large sample.

[6] In general, they adopt systems linked to those used for National Accounting.

(ICB) at Supersector level[7]. ICB is a widely used and comprehensive company classification system jointly developed by FTSE & Dow Jones Indexes to aggregate traded companies according to their main sources of revenue, as reported in audited accounts and directors' reports. The grouping at Supersector level is wide enough to ensure a large degree of homogeneity in business models and sectoral characteristics in each portfolio and it is narrow enough not to blur interactions among them. An additional yet very important reason for this grouping criterion is the fact that Portfolio DD are built so they include option-based information and the most liquid option market for sector indices are the EURO STOXX options on ICB-based Supersectors traded at Eurex.

Constituent lists in each Supersector Index are revised every quarter and reclassifications take place whenever relevant corporate events occur. In order to minimize possible spurious variation in the risk indicator, the portfolio constituents take into account these changes and make some assumptions when required. Appendices B and C describe in detail the company sample by portfolio and all additional assumptions made to ensure the portfolios' accuracy, including exclusions and ad-hoc reclassifications.

4.3 Sample and Preliminary Analysis

The sample consists of 12 out of the 19 EURO STOXX Supersectors. These sectors are the most relevant by different measures of size, e.g. assets, market value, employment. They have been chosen according to two main criteria in order to ensure the best informative quality of their market-based indicators, namely: 1) availability and liquid trading volume of their associated Eurex Index options quotes[8]; and 2) stock market capitalization of the their corresponding Supersector STOXX Indices at Deutsche Boerse. Table 10 briefly lists them and provides relevant market information.

[Insert Table 10 here]

The dataset comprises monthly observations between December 2001 and October 2009 (95 observations by Supersector). This period is characterized by an increasing degree of integration in European financial markets due to the introduction of the euro and a greater europeanization of corporate activities (Véron, 2006). Recent trends and findings suggest that equity markets integration has lead to a reduction of home bias and to an increase of sector-based equity allocation strategies at the expense of country-based strategies (European Central Bank, 2010; Cappiello *et al.*, 2010). These developments give support to the aggregation of company risk indicators into portfolios for the euro area

[7]Even though Industries, Supersectors and Sectors are clearly differentiated as ICB Categories, the use of these terms in this paper will uniquely refer to Supersectors.

[8]The DD series were initally computed on a daily basis and then averaged to obtain monthly data. Volatilities from a GARCH(1,1) model applied to the respective Supersector index were used to complete the volatilities series when unavailable.

as a whole and they provide a first temptative and equity-driven explanation to strong comovement of the series over time, as can be seen in Figure 13.

[Insert Figure 13 here]

Figure 13 displays together the 12 sectoral DD series and the EURO STOXX 50, the benchmark stock index in the euro area. Being a market-based indicator, DD series move along together with the stock market benchmark. In fact, they visibly lead it. This feature serves to illustrate the forward-looking properties of the DD series from option prices as inputs (Saldías, 2010). The DD series anticipate turning points along the entire period of analysis. During the recent crisis, they reach their bottom at the end of 2008 while the EURO STOXX 50 only picks up after the end of the first quarter of 2009.

[Insert Figures 14 and 15 here]

The DD series do not show a clear linear trend but they suggest a high degree of comovement along the whole time span and correlation among them is very high on average and statistically significant both in levels and in first differences. Figures 14 and 15 show the median and quartile regions of bilateral correlation coefficients across sectors using 24-month moving windows of DD series levels and first differences in order to illustrate the changing patttern of cross-section sectoral risk correlation over time. Median correlation is high in the entire sample but it shows greater dispersion in tranquil times where idiosyncratic drivers of sector risk dominate. However, median correlation increases and its dispersion across sectors narrows significantly in episodes of higher stress in financial markets, e.g. in the aftermath of the dot-com bubble burst in 2002; after the subprime crisis start in August 2007; and especially in the third quarter of 2008, after Lehman Brothers' collapse. At the end of the sample, median risk correlation across sectors remains high, but there is greater dispersion suggesting somehow a moderation in the role of sector-wide risk drivers.

Table 11 reports preliminary cross-section dependence tests applied to levels and first differences of DD series regressed on sector intercepts. High values of all these statistics reject the null hypothesis of cross-section independence and confirm the results of graphical inspection: DD series show a high degree of cross-section dependence even if the series are differentiated.

[Insert Table 11 here]

Strong comovement and high correlation among the series suggests first that both observable and unobservable factors must be at place. Variables from the macroeconomic environment and from financial markets are strong candidates as common factors and induce strong cross-section dependence across sectors (Alves, 2005; Holly *et al.*, 2010).

Additionally, this particular dynamics in DD series may also be caused by risk difusion across sectors, which in turn may come in form of "economic proximity" and additional unobserved factors. Risk transmission is likely to be variant across sectors and change in time and the nature of sectoral economic proximity comes from many sources. Similarity of business lines is a first source of this type of relationship and it includes common customer base and competition relationships. Financial linkages are another source of shock spillovers and take place not only between the financial sector and the non-financial corporates, but also between non-financial companies through credit chains and counterparty risk relationships. See results in Couderc *et al.* (2008); Das *et al.* (2007); Jarrow and Yu (2001) and Veldkamp and Wolfers (2007) for in depth discussions of these relationships[9]. Finally, other complementarity relationships are also relevant. They can take place through technological linkages (Raddatz, 2010) or collateral channels of risk through the securities channel (Benmelech and Bergman, 2011).

4.4 The Econometric Model

This section describes in detail the econometric model to analyze the risk determinants and transmission across the euro area's financial and corporate sectors using the Portfolio Distance-to-Default series constructed following the methodology presented in Section 4.2 and Appendix A. It also summarizes additional cross-section dependence and panel unit root tests used in the model specification and inference.

Under the potential presence of cross-section dependence in the DD series, a suitable econometric method is the Common Correlated Effects (CCE) estimator introduced in Pesaran (2006). CCE is a consistent econometric panel data method in presence of different degrees of cross-section dependence coming from common observed and single or multiple unobserved factors and from proximity-driven spillover effects. The CCE method also tackles methodological limitations of other econometric models when modeling interrelationships across sectors due to large N dimension, e.g. VAR (Pesaran *et al.*, 2004).

This method is computationally simple and has satisfactory small sample properties even under a substantial degree of heterogeneity and dynamics, and for relatively small time-series and cross-section dimensions ($N = 12$ and $T = 95$ in this case). It is also consis-

[9] Bernoth and Pick (2011) also explore spatial effects in risk diffusion between banking and insurance sectors using DD series of individual institutions from Asia, North America and Europe. In this paper, the spatial component is not relevant since portfolios are constructed bundling together only euro area companies.

tent in presence of stationary and non-stationary unobserved common factors (Kapetanios *et al.*, 2011) and more suitable for this dataset than a SURE model due to the possible presence of time-variant correlation patterns, as suggested for this case in Figures 14 and 15.

The general model specification is a dynamic panel and takes the following form:

$$DD_{i,t} = \alpha_i d_t + \beta_i X_{i,t} + u_{i,t}, \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{4.1}$$

where $DD_{i,t}$ is the Distance-to-Default of sector i at time t. The vector d_t includes the intercepts and a set of common observed factors that capture common macroeconomic and systemic market shocks. $X_{i,t}$ is the vector of sector-specific regressors, including lags of i's own Distance-to-Default, the direct risk spill-overs from "neighbouring sectors" and other sector-specific variables. All coefficients are allowed to be heterogeneous across sectors[10] and all remaining factors omitted in the specification and other idiosyncratic risk drivers are captured in the error term $u_{i,t}$.

The CCE estimator can be computed by OLS applied to sector-individual regressions where the observed regressors are augmented with cross-sectional averages of the dependent variable and the individual-specific regressors. The CCE estimator provides two versions, namely the CCE Pooled estimator (CCEP) and the CCE Mean Group estimator, of which only the latter will be reported because of slope heterogeneity and no need for CCEP efficiency gains in this case.

4.4.1 Macroeconomic and Financial Risk Determinants

A set of five exogeneous variables is included in the model in order to control for determinants originated in the macroeconomic environment and to capture risk sensitivity to common shocks in financial markets. A number of papers quoted in Section 4.1 have documented the explanatory power of macroeconomic and financial variables in corporate default risk, thus their omission could bias the results of the parameter estimation in the model. In addition, CCE literature suggests that common shocks tend to be one of the main sources of strong cross-section dependence.

The model takes macrofinancial determinants as exogeneous and chooses to ignore possible feedback effects to the macrofinancial environment. Examples of this approach and additional explanation for this modeling decision can be found in Castrén *et al.* (2010) and Castrén *et al.* (2009). Accordingly, the econometric specification first includes the annual rate of change of the Industrial Production Index (ΔPI_t) and the Harmonised Index of

[10]See for instance results in Castrén *et al.* (2010) for a more detailed, yet not strictly comparable, discussion of heterogeneous impact of macro variables on corporate sectors, which are defined using European national accounting (NACE) methodology.

Consumer Prices (ΔCP_t) in the euro area, in order to capture the effect of demand shocks. Brent Oil (1-Month Forward Contract) prices changes denominated in euro (OIL_t) detect supply shocks. The short-term benchmark interest rate is also included using the 3-Month Euribor Rate ($R3M_t$), which also reflects developments in the money market affecting the financial sector and serves as a reference for corporate debt yields and borrowing. They also are linked to corporate asset return growth Finally, the Chicago Board Options Exchange Volatility Index (VIX_t) is included to gauge global equity market sentiment. The VIX index tends to be low when markets are on an upward trend and tend to increase with market pessimism, therefore it's relationship with DD series is expected to be negative.

4.4.2 Sector-specific Risk Determinants

Sector-specific Risk Determinants

The model includes two other sector-specific regressors computed for each ICB Supersector Index[11], namely the annual rate of change of the Price-Earnings Ratio, ΔPE_t, and the annual rate of change in Dividend Yields, ΔDY_t.

Earnings are studied extensively in the corporate bankruptcy literature. Indeed, results in Shumway (2001); Beaver *et al.* (2005) and Chava and Jarrow (2004) show that higher earnings are traditionally associated with lower distress probabilities, in spite of a weaker informational ability detected in recent years due to higher frequency in earnings restatements and the possibility of data manipulation (Dechow and Schrand, 2004). Dividends traditionally serve to assess and infer corporate performance. Recent work by Charitou *et al.* (2010) shows that dividend payment initiations or increases tend to reduce corporate default and tend to raise the assets returns for several subsequent periods. However, specially in the financial sector, aggressive dividend policies may also encourage risk-taking and erode the capital base of a company or sector (Acharya *et al.*, 2011).

No additional firm-level information or sector specific indicator are included in the model since the DD construction already includes either directly or indirectly the most relevant variables of sector risk, i.e. market-implied assets' returns and volatility and aggregated leverage (Bernoth and Pick, 2011; Gropp *et al.*, 2004b).

Neighbouring Sectors' Risk Spillovers

The risk spill-over across sectors is studied using DD series from neighbouring sectors. For a given sector i, the neighbouring effect is defined by:

$$\overline{DD}_{i,t}^{n_i} = \frac{1}{n_i}\sum_{j=1}^{n} DD_{j,t} \tag{4.2}$$

[11] See Appendix D for details of these determinants and the rest of macro-financial variables.

$\overline{DD}^n_{i,t}$ is a simple average of the DD series of the n "neighbours" ($DD_{j,t}$) of sector i.

For earch sector i, the number of neighbours and weighting of their corresponding DD series are determined by a contiguity matrix (see Table 12) derived from ad-hoc and predefined neighbourhood linkages among sectors[12]. Even though the definition of neighbouring sectors and cross-sectional dependence in the literature comes largely from spatial proximity (Holly *et al.*, 2011, 2010; Pesaran and Tosetti, 2011; Chudik *et al.*, 2010), other measures of proximity, from economic or social networks, are also used in recent research (Conley and Topa, 2002; Conley and Dupor, 2003; Holly and Petrella, 2010).

In the case of corporate sectors, the literature does not provide a definite metric to determine neighbourhood linkages, because sectoral relationships depend both on the choice of sector classification and on the sectoral characteristics to be linked[13]. Pesaran *et al.* (2004) argue that the aggregation error in this type of exercises can be minimized if the cross-section units, i.e. sectors in this case, are similar and the weights are chosen carefully.

As a result, the approach in this model is ad-hoc and market-based. It relies on similarity of business lines embedded in the ICB methodology and covers important and ovelapping dimensions of sectoral interdependences, namely: balance-sheet exposures, financial linkages, common accounting practices, technological linkages, etc.

Supersectors are first assumed to be neighbours if they belong to the same Industry, an upper level of aggregation to Supersectors in the ICB methodology structure. For instance, the Industry of Consumer Goods links the Supersectors of Automobiles & Parts and Foods & Beverages while Banks and Insurance Supesectors are bundled together as Financials.

The second proximity criterion used to aggregate series into neighbours is also based on the ICB methodology but it relies on the most frequent company reclassifications across Supersectors within or outside a given Industry during the time span used in the paper. Under multiple business lines, company reclassifications take place mainly due to changes in the main business line and also due to corporate actions such as spin-offs or M&A.

[12]The contiguity matrix W is an $N \times N$ nonnegative matrix, whose $w_{i,j}$ element is 1 if sectors i and j are considered neighbours and 0 otherwise. The number of neighbours for sector i is the sum of elements along row i. Although weighting criteria is not likely to affect the properties of the econometric approach (Chudik *et al.*, 2010) and a valid alternative in this case could weigh DD series by implied assets from the calibration, this paper assumes equal weights in the neighborhood average ($1/n$) because the nature of the business in each sector affects considerably the asset sizes, hence, asset-based weights could introduce distortion. In addition, there is no only and unambiguous way to determine relative importance of sectors among each other.

[13]Most studies deal with manufacturing sectors data, excluding financials. For example, Conley and Dupor (2003) study sectoral synchronization of output and productivity growth using factor demand linkages as a metric for economic distance for US corporates and define the sectors of study using the SIC system. Holly and Petrella (2010) use input-output linkages and analyze the shock propagation across manufacturing sectors.

Examples of this were frequent in supersectors such as Industrial Goods & Services, Oil & Gas and Utilities, which do not belong to the same ICB Industries.

[Insert Table 12 here]

4.4.3 Cross-section Dependence Tests

This section makes a brief review of the three statistics of cross-section dependence (CD) in panel data used in the paper for model specification and inference. All of them are based on pairwise correlation coefficients, ρ_{ij}, of regressions' residuals[14]. The average of cross-correlation coefficients, $\bar{\rho}$, is applied to provide a first assessment at a descriptive level.

$$\bar{\rho} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N-1} \rho_{ij} \tag{4.3}$$

The second statistic is the Lagrange Multiplier (LM) CD test proposed by Breusch and Pagan (1980), CD_{LM}, in the context of seemingly unrelated regression equation (SURE) framework with N fixed and T large ($T \to \infty$). Under the null hypothesis of no CD (and the assumption of no serial correlation of the residuals), the CD_{LM} statistic takes the following form and distribution:

$$CD_{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}^2 \xrightarrow{d} \chi^2_{N(N-1)/2} \tag{4.4}$$

Finally, the third statistic is the Pesaran (2004) CD statistic, CD_P, developed for cases where the N dimension becomes larger and the CD_{LM} tends to suffer from size distorsions and bias. It is a test for panels where series may be eithe stationary or contain unit roots. This statistic takes the following form and distribution.

$$CD_P = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \xrightarrow{d} N(0,1) \tag{4.5}$$

This CD statistic shows good properties with dynamic panels but has also a ceveat. Since it involves the sum of pairwise correlation coefficients instead of the sum of squared correlations, the CD_P statistic might miss out CD where there are alternating signs of correlations in the residuals. For this reason, these three CD statistics are reported with the preliminary analysis and estimation results.

[14] $\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} \hat{u}_{it}\hat{u}_{jt}}{\sqrt{\sum_{t=1}^{T} \hat{u}_{it}^2}\sqrt{\sum_{t=1}^{T} \hat{u}_{jt}^2}}$, where $\hat{u}_{it}$ and $\hat{u}_{jt}$ are residuals from equation (4.1) or individual series' ADF(p) or cross-sectionally augmented ADF(p) regressions, CADF(p).

4.4.4 Unit Root Tests

In addition to the IPS test proposed by Im *et al.* (2003), cross-sectionally augmented IPS test (CIPS) from Pesaran (2007) are applied to test for unit roots in the dataset and hence to ensure a correct model specification. This test also allows for individual unit root processes and for different serial correlation properties across units. It is more suitable in the presence of cross-section dependence in the series, since the traditional IPS may lead to spurious inference.

The CIPS test statistic is computed using the average of the individual p^{th} order cross-sectionally Augmented Dickey-Fuller (ADF) regressions' statistics (CADF). The test assumes a single unobserved common factor, but is robust to other potential sources of cross-section dependence, such as spill-over effects (Baltagi *et al.*, 2007). This assumed factor structure is accounted for by adding the averages of lagged levels and first-differences of the dependent variable to each standard ADF regression.

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + \sum_{l=1}^{p_i} c_{i,l} \Delta y_{i,t-l} + d_i' \bar{z}_t + \nu_{i,t}, \qquad i = 1, \dots, N; t = 1, \dots, T \tag{4.6}$$

where $\bar{z}_t = (\bar{y}_{t-1}, \Delta\bar{y}_t, \Delta\bar{y}_{t-1}, \dots, \Delta\bar{y}_{t-p})'$. Under the null hypothesis of non-stationarity against the possibly heterogeneous presence of unit roots across i, the CIPS statistic takes the following form.

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_i \tag{4.7}$$

where $\tilde{t}_i$ is the t-statistic associated to $\hat{b}_i$ in CADF equations. The joint asymptotic limit of the CIPS statistic is nonstandard and critical values can be found in Pesaran (2007) for various numbers of cross-section units N and time series lengths T.

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4.5 Empirical Results

4.5.1 Cross-section Dependence and Non-stationarity Analysis

Preliminary analysis in Section 4.3 detected a high degree of comovement in DD series in levels and first differences. This section takes a step further and extends the CD tests to the rest of sector-specific variables in the panel allowing for different degrees of serial correlation in the data. It also conducts stationarity analysis of the data for correct model specification, taking into account the potential presence of CD.

Table 13 reports CD statistics of residuals from ADF(p) regressions of the DD series and the sector-specific variables, namely Dividend Yields growth ($\Delta DY_{i,t}$), Price-Earnings ratio growth ($\Delta PE_{i,t}$) and the neighbouring sectors' DD series ($\overline{DD}^{n}_{i,t}$). The regressions are run without cross-section augmentations for lag orders $p = 0, \ldots, 6$ over the whole sample. Results are robust to the lag order choice p and detect that DD series and the $\overline{DD}^{n}_{i,t}$ present very high and positive average correlation coefficients, above 60%, whereas correlation for dividend yields' growth area also large but in the range of 30% - 40%. Price-Earnings ratio growth show very low correlation across sectors, with a coefficient of around 3%. CD test statistics, reported below, are in line with these results and are highest for DD series and neighbouring effects, and smaller yet significant for the rest of the variables. These tests confirm the high cross-section dependence in the data, with arguably the exception of Price-Earnings ratio growth.

[Insert Table 13 here]

In line of the results of CD tests, panel unit root tests for the DD series and the sector-specific regressors need to take into account the cross-dependence. Accordingly, Table 14 summarizes the CIPS panel unit root tests introduced in Section 4.4.4. IPS test statistics are also reported for robustness check and comparison. Both CIPS and IPS tests reject unit roots in dividend yields' growth and Price-Earnings ratio growth. Interestingly, the CIPS strongly reject unit roots in the case of DD series and neighbouring effects for all lag orders p, whereas IPS tests seem to suggest non-stationarity in most cases tested. Given the substantial degree of cross-section dependence detected in these series, the CIPS tests provide a more reliable inference and these variables are also taken as $I(0)$.

[Insert Table 14 here]

However, it is relevant to check for the robustness of these panel unit root results and to explore the source of non-stationarity in the DD and in neighbouring-DD series when CD is omitted. Table 15 reports CIPS test statistics for different orders of serial correlation were one Supersector at a time is removed from the panel. Results are similar to those presented in Table 14 and indicate also that non-stationarity in $DD_{i,t}$ and $\overline{DD}^{n}_{i,t}$ series must be rejected.

[Insert Table 15 here]

Given these results, the non-stationarity detected using IPS tests may likely come from the combination of non-stationary common factors and stationary idiosyncratic components in DD series and DD-neighbouring effects. This possibility is checked this by adopting the Panel Analysis of Nonstationarity in the Idiosyncratic and Common components or PANIC approach advanced by Bai and Ng (2004). First, the common factors can be well approximated by the cross-section averages of the series ($\overline{DD}_t$, $\overline{\overline{DD}}^{n}_{t}$), under the CCE model assumptions detailed in Section 4.4. Idiosyncratic components are obtained from the residuals from the OLS regressions of the individual series DD_{it} and $\overline{DD}^n_{i,t}$, $i = 1, \ldots, 12$, on these cross-section averages. Then, unit root tests for these series are conducted using individual ADF unit root tests for the cross-section averages (common components) and IPS tests for the residuals (idiosyncratic components). Results of these tests are displayed in Table 16 and confirm that non-stationarity in the series is indeed due to the common factor while the idiosyncratic sectoral risk components are stationary. This result is consistent with findings in Alves (2005), and provides empirical support to the notion that aggregate sectoral risk evolves to a long-run equilibrium, which is in turn affected temporarily by the macro-financial enviroment and the cross-sectoral dynamics captured by the CCE method.

[Insert Table 16 here]

Finally, individual ADF(p) unit root tests were run for the macro-financial variables described in Section 4.4.1 which enter the model as exogeneous regressors. Based on the results of these tests reported in Table 17, the annual rates of change of the Industrial Production Index (ΔPI_t) and the Harmonised Index of Consumer Prices (ΔCP_t) enter the model as $I(0)$ variables, while Brent Oil prices (OIL_t), the 3-Month Euribor Rate ($R3M_t$) and the VIX Volatility Index (VIX_t) are previously differentiated to enter the model.

[Insert Table 17 here]

4.5.2 Model Estimation

The results from estimation of Equation (4.1) are reported in Table 18. Columns [1] to [3] are estimates of naïve OLS Mean Group (MG) models that neglect cross-section dependence (CD) induced by unobserved common factors. Columns [4] to [6] are Common Correlated Effects (CCE) estimates of these same specifications, hence more consistent given the data properties analyzed in the previous section. Although MG estimates are likely to be biased, they serve as a benchmark for the CCE estimates and also put into context the relevance of CD in the model specification. They also serve to compare these results with previous studies on determinants of aggregate sectoral risk.

[Insert Table 18 here]

The first result worth mentioning is the limited relevance, overall, of shocks originated in the macroeconomic and financial environment on DD, specially when CD is accounted for. Sorge and Virolainen (2006) tackled this issue and found that marked-based indicators, such as DD, are less responsive due to non-linearities in their interactions with macroeconomic and financial variables. Additionally, the authors suggest that business cycle volatility has been smoothed out in the construction of DD series or other CCA risk measures (specially EDF). Macro-financial effects may impact sectoral DD in a more indirect way, via market news already embedded in the DD inputs and/or through cross-dynamics transmitting risk across industries (Alves, 2005).

In paticular, the VIX Volatility Index (VIX_t), a measure of investors' risk sentiment, is statistically significant at five percent across all the MG estimates and shows a stable and expected negative sign, indicating an increase in sector-wide risk, i.e. a drop in DD, when equity markets become more volatile. However, in all models estimated using the CCE method, [4] to [6], its effect on overall sectoral risk tends to vanish. This is not a surprising result, as Bernoth and Pick (2011) report that the VIX Index is absent in their CCE-based models when forecasting DD at firm-level for banks and insurance companies. A plausible explanation in this case is that option implied volatilities from index options endow the sectoral DD with the forward-looking information embedded in the VIX Index.

The same holds true for the 3-month Money Market (Euribor) Rate, $R3M_t$, which shows statistical significance at five percent level and a positive and stable coefficient only if CD is ignored. The effect of short-term interest rates on sectoral risk was expected to be negative if we consider them as a proxy of borrowing costs and risk premia. However, since short-term interest rates are closely linked to the risk-free rate used to capture sectoral assets return growth in the DD computation via the yield curve, this feature is likely to be dominant in the estimates in this case. In addition, several empirical studies link the short-term interest rates to higher performance and make an empirical case for the positive sign. This positive effect (0.6) becomes nil when CD is included, probably because the unobserved common factors capture it. This result is at odds with findings in Åsberg and Shahnazarian (2009)[15], where the authors use a single risk indicator for the whole corporate sector, but consistent with those from Castrén *et al.* (2010), where short-term interest rates are in general insignificant across several corporate sectors studied individually.

Shocks from oil prices (OIL_t) and industrial production growth (PI_t) are insignificant on DD even when CD is negleted, whereas growth in consumer prices (CP_t) affects negatively, as expected, on overall sectoral risk in only one of the MG specifications, equation [1]. This impact becomes insignificant when more regressors are included in the model and in all cases when CD is controlled for. As for the statistical insignificance of the first two variables, this result is somehow surprising but not entirely inconsistent with previous findings in the empirical literature. For instance, Alves (2005) finds that oil prices do not affect but one of the seven sectors he includes in his study, whereas the effects of inflation are likely to be captured either by the unobserved common effects or the set of sector-specific variables more accurately. Bernoth and Pick (2011) find a positive effect on

[15] In this paper, the authors analyze effects of macroeconomic shocks on the the median EDF of the whole corporate sector in Sweden in a cointegrated VAR model. This series is a I(1) variable, in line with the findings described in the stationarity analysis of this paper, but this analysis does not take into account the heterogeneity across sectors and the cross-section dependence is ignored.

inflation on DD series of banks and negative one on insurance companies.

Sector-specific regressors on DD show much better results in terms of statistical significance under CD, which challenges the macro dominant focus in the existing literature of financial stability and highlights the importance of sector-level information and interactions for policy analysis of systemic risk. In particular, dividend yields' growth by Supersector ($\Delta DY_{i,t}$) do not have statistical significance when CD is omitted but exert a significant yet surprisingly negative effect on DD when CD is taken into account. The opposite sign was expected, but this result is not entirely in conflict with previous findings using this method, since Bernoth and Pick (2011) report also that the impact of dividends' growth may vary across sectors, being negative for the insurance sector and positive for banks. One possible theoretical explanation is the positive link between risk taking and aggressive dividend policies across companies and sectors (Acharya *et al.*, 2011). The Price-Earnings Ratio, ΔPE_t, shows an expected positive sign in equation [3], significant at 10% level, but becomes insignificant when the CCE method is applied, in line with findings in Bernoth and Pick (2011).

The lag of the dependent variable, $DD_{i,t-1}$, shows a large and significant positive coefficient regardless the estimation method. The CCE estimates show however smaller coefficients as additional regressors are included in the specifications. This MG coefficients are larger, close to one, probably because MG estimates capture also the non-stationary common components. The strong significance of this regressor confirms results in the literature (Alves, 2005; Bernoth and Pick, 2011) and illustrate the persistence in idiosyncratic sectoral risk even after controlling for CD.

Finally, the neighbouring sectors' risk lagged effect on DD[16], $\overline{DD}^{n}_{i,t-1}$, is statistically insignifficant in the CCE-estimated models, overall, while MG estimates do exhibit the expected positive coefficient (0.123). This result implies that the risk impact in sectors with strong linkages on other sectors does not work directly but is mainly captured as unobserved common factor. It may also be possible that the ad-hoc definition of neighbouring sectors is not sufficiently accurate and other sectoral dimensions than those described in Section 4.4.2 need to be explored to obtain a more reliable contiguity matrix.

Some of the overall results described so far are expected to vary across sectors due to heterogeneous effects of the regressors and also possibly because unobserved cross-sectoral and complex shocks alter the relationships with them. As the CCE modelling approach allows to shed some light on this, Table 19 reports the results of model [6] at individual sector-level. To recap, this model is the most comprehensive and includes all variables described in Section 4.4. Its overall estimates showed that none of the macroeconomic or

[16]Contemporary effects were not gauged do the risk of dealing with potential strong endogeneity and limited possibilities to find valid instruments for this regressor.

financial variables is statistically significant. Only the lag of DD (0.591) and the growth in dividend yields, with a negative sign (-0.002), are the main drivers of idiosyncratic sectoral risk, after controlling for cross-section dependence.

[Insert Table 19 here]

However, at individual Supersector level, macro-financial variables do affect DD in some Supersectors and with not necessarily the same sign. For instance, oil prices (OIL_t) do exert a statistically significant impact on the Insurance (INS) supersector (-0.015) and, as expected, a positive effect on the Oil & Gas (ENE) supersector (0.022), which is linked to the nature of its business line and performance. Interest rates ($R3M_t$) do play a significant role as proxy of borrowing costs and risk premia for the Media (MDI) supersector (-0.550), while the VIX Index (VIX_t) has a surprisingly positive effect on the idiosyncratic component of risk in the Industrial Goods & Services supersector (0.026), which is in turn the only Supersector where the lag of DD is irrelevant. Industrial production growth and consumer prices inflation stand out as the only macroeconomic variables that fail to show also at individual level any effect on sectoral risk.

As for the sector-specific variables, dividend yields growth, ΔDY_t, and Price-Earnings Ratio growth, ΔPE_t, affect also heterogeneously across Supersectors. The coefficients associated to dividend yields are significant and surprisingly positive in the Telecommunications and Media sector, in contrast to the negative significant sign overall. Price-Earnings Ratio growth affect only the Food & Beverages sector with an expected positive sign but is also irrelevant for the rest of Supersectors.

Mirroring aggregated results, the lag of the dependent variable, $DD_{i,t-1}$, is highly significant also at individual level, for all supersectors with the only exception of the Industral Goods & Services sector. Finally, the lagged neighbouring risk effect, non-significant overall, is a risk driver in two Supersectors, Industral Goods & Services and Media, but with a negative and positive signs, respectively. The divergence in signs are informative of the nature of relationships of these sectors with their neighbours, as defined by the contiguity matrix constructed in this study.

As might be expected, the cross-section dependence test statistics at the bottom of Table 18 display a remarkable decline when the CCE estimator is applied and there is no significant evidence of remaining CD in the estimation residuals. It is however noticeable the negative sign in all $\bar{\rho}$ and CD_P statistics for CCE estimates. Since these indicators are based on the sum of pairwise correlation coefficients, the sign indicates that negative correlation coefficients are more frequent and sizable after controlling for CD[17]. Finally,

[17] Although not reported, a closer look at bilateral residual correlations shows that this is indeed the case and that this sum drives the value of the statistic, given that $\sqrt{\frac{2T}{N(N-1)}} \approx 1$. The CD_{LM} statistic remains relatively high because of the large time series dimension compared to the number of cross-section units

the IPS and CIPS unit root test statistics, and additional serial correlation tests, show that residuals from all estimated models are stationary both individually and jointly.

4.6 Concluding Remarks

This paper presents a framework to analyze risk in the corporate sector that takes into account their strong sectoral linkages and comovement. In a first part, the paper describes a methodology to compute comprehensive forward-looking risk indicators at sector-level based on Contingent Claims Analysis with information from balance sheets, equity markets and, more importantly, index option prices. The second part of the paper analyzes the properties of the resulting Distance-to-Default series and sets up an econometric model that incorporates the cross-section dependence of sectoral risk. This model allows to study the determinants and diffusion of risk across sectors, including sector-specific drivers, the macroeconomic and financial markets environment and proximity-driven risk spill-overs.

In particular, the paper computes forward-looking Distance-to-Deafult DD series, a market-based indicator, for 12 of the 19 financial and corporate sectors in the euro area as defined by the EURO STOXX indices between December 2001 and October 2009. These series show very good properties in terms of capturing cycles and episodes of distress. The econometric analysis relies on the Common Correlated Effects estimator of Pesaran (2006) in order to stress the importance of cross-section dependence (CD) in the risk series over time, which is driven by common observed and unobserved factors.

Controlling for cross-section dependence among the Distance-to-Deafult series, the first result of this analysis shows that sectoral risk comprises a stationary idiosyncratic component and a non-stationary common factor. This result provides empirical support to the notion that aggregate sectoral risk evolves to a long-run equilibrium, with temporary deviations caused by the macro-financial environment, sector-specific shocks and the cross-sectoral dynamics.

Results of the econometric model estimation using the Common Correlated Effects (CCE) method find evidence supporting a more relevant role of sector-specific variables as sectoral risk determinants in the corporate sector overall at the expense of the impact from macro-financial variables. The sector-specific drivers include risk persistence, measures of overall sectoral performance and also direct risk spill-overs from risk in related sectors. The macroeconomic and financial common variables are either captured as unobserved common effects or smoothed out by construction of the Distance-to-Default series. This empirical finding challenges much of the literature that focuses mainly on macroeconomic risk drivers and tends to ignore sector-specific characteristics and specially interactions either explicitly or implicitly through an aggregate analysis of the whole corporate sector.

This study also provides empirical evidence of the high degree of heterogeneity as concerns the relevance and responsiveness to the risk drivers used in the model, both in macro-terms as in sector-specific terms. These results show that a macro-only focus of the analysis of financial stability would be misleading for policy if cross-section dependence and sectoral heterogeneity is ignored. These results make a case for a more disaggregated analysis of risk across sectors without neglecting the inherent interactions that take place among them. Subjects for further research include the inclusion of non-linearities in the interaction of risk across sectors and exploring more accurate metrics to assess the direct risk intersectoral linkages in order to extend the model to conduct stress tests.

Appendix A. Derivation of Portfolio Distance-to-Default

Given the three principles in Contingent Claims Analysis (CCA) mentioned in Section 4.1, 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 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).

$$\max\{0, A - D\}$$

For a given portfolio of I companies, individual company information is aggregated in the following form:

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

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

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

Given that CCA principles apply for the portfolio and 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 Portfolio Distance-to-Default indicator **t** periods ahead:

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

where **r** is the rate of growth of the porfolio assets value and equals the risk-free interest rate for the euro area. σ_A is portolio asset volatility.
In practice, implied portfolio asset value A^P and volatility σ_A are not observable and must be estimated solving the following system of simultaneous equations by numerical methods:

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

where E^P is the value of portfolio equity, σ_E is the equity index price return volatility. $N(\bullet)$ is the cumulative normal distribution. The values of d_1 and d_2 are expressed as:

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

The calculation of DD in the literature uses market value as the value of equity **E**; historical, GARCH-derived or option-implied 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.

Appendix B. Sample Selection Methodological Notes

The analysis in the paper covers 12 out of 19 Supersectors, as classified by STOXX. The list of Supersectors is found in Table 10. The companies included in a given Supersector Index are part of the STOXX Europe 600, which represents large, mid and small capitalization companies across 18 European countries. Since the composition list of the STOXX Europe 600 is revised periodically, mostly according to changes in market capitalization or relevant corporate actions, the list of companies in each Supersector portfolio is revised accordingly and updated.

Since the most relevant changes take place at the bottom of the ranking, some companies do not stay long in the Supersector Indices and may only add noise to the series. Therefore, some small companies were excluded from the sample under the assumption that their low weight in their respective index would not affect the aggregation of company information by Supersector during the calibration of DD series. In addition, some companies are reclassified and should therefore be assigned to one Supersector only according to the time listed in a given supersector. See Tables 20 through 33 for individual cases. The list of exclusions from the sample by Supersector is below.

Banks: Banque Nationale de Belgique (BE0003008019), Banca Antonveneta (IT0003270102), IKB (DE0008063306), Rolo Banca 1473 (IT0001070405), Crédit Agricole Île-de-France (FR0000045528), Emporiki Bank Of Greece (GRS006013007), Banco Pastor (ES0113770434), Marfin Financial Group (GRS314003005), Depfa Bank (IE0072559994), Banca Fideuram (IT0000082963), Finecogroup Spa (IT0001464921), First Active (IE0004321422), KBC Ancora (BE0003867844).

Oil & Gas: Fortum (FI0009007132), Royal Dutch Petroleum (NL0000009470, excluded due to incorporation in the UK with a primary listing on the London Stock Exchange), Enagás (ES0130960018).

Insurance: Fortis (BE0003801181), Nürnberger Beteiligungs (DE0008435967), Irish Life & Permanent (IE00B59NXW72).

Utilities: SolarWorld (DE0005108401).

Technology: SAFRAN (FR0000073272), Eutelsat Communication (FR0010221234), Amadeus Global Travel Distribution (ES0109169013), Terra Networks (ES0178174019), Infogrames Entertainment (FR0000052573), Wanadoo (FR0000124158), Riverdeep Group (IE0001521057), Tiscali (IT0001453924), Equant (NL0000200889).

Industrial Goods & Services: Linde (DE0006483001), Pirelli & Co. (IT0000072725), Gamesa (ES0143416115), Wendel Investissement (FR0000121204), Q-Cells (DE0005558662), Indra Sistemas (ES0118594417), Ackermans & Van Haaren (BE0003764785), Altran Technologies (FR0000034639), Aixtron (DE0005066203), CGIP (FR0000121022), Eurotunnel (FR0000125379), Snecma (FR0005328747), Rexel (FR0000125957), ASF (FR0005512555), Aurea (ES0111847036).

Chemicals: Altana (DE0007600801), Degussa (DE0005421903), Celanese (DE0005753008).

Food & Beverage: Parmalat Finanziaria (IT0003121644), IAWS Group (IE0004554287).

Media: RTL Group (LU0061462528), Premiere (DE000PREM111), Gestevisión Telecinco (ES0152503035), Tele Atlas (NL0000233948), Fox Kids Europe (NL0000352524).

Healthcare: Fresenius Medical Care (DE0005785802), Alapis (GRS322003013), Altana (DE0007600801), Schwarz Pharma (DE0007221905), Omega Pharma (BE0003785020), Instrumentarium(FI0009000509).

Appendix C. Data Sources

The structure of balance sheets varies by sector. Companies are classified into the following sectors: Banks, Insurance Companies and Industrials.

Balance-sheet Information,Obtained at quarterly/half-yearly frequence from Annual and Interim Reports.

- Total Assets. For banks, Bankscope (code 2025); for Insurance Companies, Thomson Worldscope (code WC02999); for Industrials, Thomson Worldscope (code WC02999A).
- Short-term Liabilities: For banks, Bankscope (Deposits and Short Term Funding, code 2030); for Insurance Companies, Thomson Worldscope (code WC03051A); for Industrials, Thomson Worldscope (code WC03101A).
- Total Equity: For banks, Bankscope (Deposits and Short Term Funding, code 2055); for Insurance Companies and Industrials, Difference between Total Assets (Thomson Worldscope, code WC02999A) and Total Liabilities (Thomson Worldscope, code WC03351A).

Market Information.

- Sector Index Tickers. Thomson Datastream (codes DJESBNK, DJESTEL, DJESEGY, DJESINS, DJESTEC, DJESAUT, DJESUSP, DJESIGS, DJESCHM, DJESFBV, DJESMED, DJESHTC).
- Market Capitalization. Thomson Datastream (code MV).
- Price Indices. Thomson Datastream (code PI).
- Index Options Implied Volatilities: Thomson Datastream (codes DJBXC.SERIESC, DJCXC.SERIESC, DJEXC.SERIESC, DJIXC.SERIESC, DJTXC.SERIESC, DJAXC.SERIESC, DJUXC.SERIESC, DJIGC.SERIESC, DJCMC.SERIESC, DJFBC.SERIESC, DJMXC.SERIESC, DJHXC.SERIESC, DJBXC.SERIESP, DJCXC.SERIESP, DJEXC.SERIESP, DJIXC.SERIESP, DJTXC.SERIESP, DJAXC.SERIESP, DJUXC.SERIESP, DJIGC.SERIESP, DJCMC.SERIESP, DJFBC.SERIESP, DJMXC.SERIESP, DJHXC.SERIESP).
- Interest rates. Thomson Datastream (code EMBRYLD).

Macro-Financial Variables and Sector-specific Variables.

- VIX Volatility Index, VIX_t: Chicago Board Options Exchange.
- Money Market Rate, $R3M_t$: Three-month Euribor Rate, ECB.
- Oil Price, OIL_t, Brent Crude 1-Month-Forward Price, ECB, level.
- Euro Area Industrial Production Index, ΔPI_t: ECB, Annual rate of change, working day and seasonally adjusted.
- Euro Area Inflation Rate, ΔCP_t: ECB, HICP Overall index, Annual rate of change, Neither seasonally nor working day adjusted.
- Price-Earnings Ratio, ΔPE_t: Thomson Datastream (PE). Weighted average of PERs of index constituents, Annual rate of change.
- Dividend Yield, ΔDY_t: Thomson Datastream, Market-value weighted average of individual DYs of index constituents, Annual rate of change.

Tables and Figures

Table 1: Banks Sample - PDF

	Bank	Symbol[1]	Data Source	Underlying ISIN Code	Data Availability
1	Citigroup	CITI	CBOE	US1729671016	02/01/2004-30/12/2008
2	Lehman Brothers	LEH	CBOE	US5249081002	02/01/2004-30/12/2008
3	Deutsche Bank	DBK	Eurex	DE0005140008	02/01/2004-30/06/2009
4	UBS	UBSN	Eurex	CH0024899483	02/01/2004-30/06/2009
5	Credit Suisse	CSGN	Eurex	CH0012138530	02/01/2004-30/06/2009
6	BNP Paribas	BN1	Euronext	FR0000131104	02/01/2004-30/12/2008
7	Société Générale	GL1	Euronext	FR0000130809	02/01/2004-30/12/2008
8	Barclays	BBL	Euronext	GB0031348658	02/01/2004-30/12/2008
9	RBS	RBS	Euronext	GB0007547838	02/01/2004-30/12/2008

Notes: (1) As defined by the corresponding exchanges.

Table 2: Correlation Matrix - PDF Implied Volatilities (levels)

	CITI	**LEH**	**DBK**	**UBSN**	**CSGN**	**BN1**	**GL1**	**BBL**
CITI								
LEH	0.876							
DBK	0.780	0.679						
UBSN	0.941	0.871	0.793					
CSGN	0.861	0.777	0.867	0.909				
BN1	0.871	0.759	0.882	0.873	0.887			
GL1	0.890	0.757	0.858	0.912	0.907	0.944		
BBL	0.945	0.860	0.791	0.921	0.866	0.873	0.898	
RBS	0.939	0.872	0.767	0.917	0.859	0.854	0.886	0.966

Notes: Computed on weekly averages of daily observations over the whole timespan.

Table 3: Correlation Matrix - PDF Implied Volatilities (first differences)

	CITI	LEH	DBK	UBSN	CSGN	BN1	GL1	BBL
CITI								
LEH	0.516							
DBK	0.422	0.420						
UBSN	0.632	0.379	0.480					
CSGN	0.500	0.539	0.486	0.610				
BN1	0.325	0.133	0.445	0.395	0.407			
GL1	0.468	0.334	0.536	0.492	0.419	0.595		
BBL	0.491	0.527	0.528	0.462	0.544	0.403	0.531	
RBS	0.359	0.391	0.383	0.454	0.458	0.202	0.303	0.548

Notes: Computed on weekly averages of daily observations over the whole timespan.

Table 4: Historical Distribution of PDF Implied Volatilities

	Observations	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
CITI	218	0.300	0.183	1.477	0.104	0.243	2.205	8.457
LEH	192	0.404	0.272	1.654	0.119	0.294	2.083	6.975
DBK	283	0.335	0.249	1.845	0.099	0.243	2.618	10.983
UBSN	264	0.352	0.218	1.520	0.108	0.269	1.520	4.579
CSGN	277	0.343	0.252	1.151	0.146	0.224	1.859	5.598
BN1	254	0.284	0.230	1.140	0.113	0.172	2.807	11.691
GL1	258	0.311	0.240	1.360	0.146	0.195	2.672	11.589
BBL	224	0.375	0.267	1.698	0.165	0.261	2.437	9.599
RBS	239	0.330	0.210	1.968	0.136	0.285	2.879	13.020

Notes: Computed on weekly averages of daily observations over the whole timespan.

Table 5: Correlation Matrix: CDS - Distance-to-Default series (levels)

CDS/DD	CITI	LEH	DBK	UBSN	CSGN	BN1	GL1	BBL	RBS
CITI	-0.812	-0.740	-0.539	-0.773	-0.735	-0.698	-0.724	-0.757	-0.771
LEH	-0.734	-0.694	-0.525	-0.697	-0.662	-0.635	-0.639	-0.693	-0.699
DBK	-0.865	-0.789	-0.599	-0.806	-0.772	-0.747	-0.772	-0.815	-0.834
UBSN	-0.783	-0.720	-0.526	-0.748	-0.714	-0.676	-0.705	-0.733	-0.740
CSGN	-0.772	-0.705	-0.525	-0.707	-0.686	-0.645	-0.673	-0.706	-0.717
BN1	-0.798	-0.716	-0.520	-0.751	-0.719	-0.688	-0.724	-0.748	-0.764
GL1	-0.782	-0.736	-0.534	-0.752	-0.720	-0.679	-0.705	-0.734	-0.742
BBL	-0.859	-0.787	-0.578	-0.810	-0.767	-0.745	-0.771	-0.807	-0.827
RBS	-0.824	-0.751	-0.556	-0.778	-0.748	-0.712	-0.742	-0.773	-0.787

Notes: Computed on weekly averages of daily observations over the whole timespan.

Table 6: DD-CDS Granger Causality Tests (levels)

	DD does not cause CDS	CDS does not cause DD	DD does not cause CDS	CDS does not cause DD	DD does not cause CDS	CDS does not cause DD	DD does not cause CDS	CDS does not cause DD
	Lag=1	Lag=1	Lag=2	Lag=2	Lag=3	Lag=3	Lag=4	Lag=4
CITI	9.93*	3.50	8.77*	1.49	3.95*	0.74	3.33*	1.29
LEH	3.95*	2.88	1.98	0.99	2.09	0.79	1.69	0.49
DBK	4.71*	26.38*	3.11*	9.46*	2.30	4.58*	2.26	4.17*
UBSN	4.01*	0.79	3.14*	0.75	2.35	1.10	1.85	0.88
CSGN	5.96*	3.33	4.50*	2.22	3.17*	1.67	2.32	1.21
BN1	2.83	6.74*	3.18*	3.52*	2.29	3.06*	1.39	2.20
GL1	4.00*	4.82*	2.63	1.88	2.09	1.78	1.48	1.19
BBL	6.86*	6.34*	5.64*	3.37*	3.27*	2.00*	2.15	1.30
RBS	2.61	25.76*	10.65*	15.72*	3.68*	12.58*	5.02*	14.21*

Notes: * indicates rejection of the null at 5%.

Table 7: Bank Sample - Portfolio DD

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	ES0113900J37	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. 31398	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:NDA	29305, 49434	20.7	79.3	0.0
20	Natixis	France	Euronext (FR)	FR0000120685	F:KN@F	23951, 39931. 45333	44.8	28.0	27.2
21	Intesa Sanpaolo	Italy	Milan	IT0000072618	I:BIN	23687, 28749. 46616	81.2	18.8	0.0
22	KBC	Belgium	Euronext (BE)	BE0003565737	B:KB	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 8: 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.
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 9: Granger Causality Tests

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

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.

Notes: Series of implied volatilities start dates:(1) 25-Sep-01 ,(2) 31-Jul-02,(3) 23-Sep-02,(4) 19-May-03. Supersector codes are assigned according to the ICB methodology prior to September 2004.(a) Portfolio size does not include companies' predecessors, for more details, see Appendix C. (b) Average monthly volume over the whole timespan. (c) Year-end average over the whole time span in thousands of euros.

Table 10: Supersectors Sample

	ICB Supersector	Supersector Code	ICB Industry	Portfolio Size[a]	Options Volume[b]	Market Capitalization[c]
1	Banks[1]	BNK	Financials	40	24894.6	490278.1
2	Telecommunications[1]	TLS	Telecommunications	17	5439.5	245011.1
3	Oil & Gas[2]	ENE	Oil & Gas	19	5130.3	272077.1
4	Insurance[2]	INS	Financials	17	5406.9	233824.6
5	Technology[1]	TEC	Technology	21	2952.7	233154.2
6	Automobiles & Parts[2]	ATO	Consumer Goods	13	3161.0	117228.1
7	Utilities[3]	UTI	Utilities	22	2536.2	216164.7
8	Industrial Goods & Services[4]	IGS	Industrials	56	412.6	108511.6
9	Chemicals[4]	CHM	Basic Materials	14	162.1	147751.8
10	Food & Beverage[4]	FOB	Consumer Goods	13	677.4	94878.9
11	Media[3]	MDI	Consumer Services	25	620.0	87118.6
12	Health Care[1]	HCR	Health Care	17	116.7	100830.1

Table 11: Preliminary Cross-section Dependence Analysis - DD Series

	$\bar{\rho}$	CD_P	CD_{LM}
$DD_{i,t}$	0.843	66.7*	4486.4*
$\Delta DD_{i,t}$	0.595	46.9*	2245.4*

Notes: $\bar{\rho}$, CD_P and CD_{LM} are computed as detailed in Section 4.4.3 using residuals of regressions on a sector-specific intercept. * indicates the series show cross-section dependence at 5% level.

Table 12: Contiguity Matrix

	BNK	**TLS**	**ENE**	**INS**	**TEC**	**ATO**	**UTI**	**IGS**	**CHM**	**FOB**	**MDI**	**HCR**
BNK	0	0	0	**1**	0	0	0	0	0	0	0	0
TLS	0	0	0	0	**1**	0	0	0	0	0	0	0
ENE	0	0	0	0	0	0	**1**	**1**	0	0	0	0
INS	**1**	0	0	0	0	0	0	0	0	0	0	0
TEC	0	**1**	0	0	0	0	0	**1**	0	0	**1**	0
ATO	0	0	0	0	0	0	0	**1**	0	**1**	0	0
UTI	0	0	**1**	0	0	0	0	0	0	0	0	0
IGS	0	0	**1**	0	**1**	**1**	0	0	**1**	0	**1**	0
CHM	0	0	0	0	0	0	0	**1**	0	0	0	**1**
FOB	0	0	0	0	0	**1**	0	0	0	0	0	0
MDI	0	0	0	0	**1**	0	0	**1**	0	0	0	0
HCR	0	0	0	0	0	0	0	0	**1**	0	0	0

Notes: If element $i, j = 1$, the supersectors in row i and column j are considered neighbours. See Section 4.4.2 for more details.

Table 13: Residual Cross-section Dependence of ADF(p) Regressions

Average cross-correlation ($\bar{\rho}$)							
	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)	ADF(5)	ADF(6)
$DD_{i,t}$	0.605	0.603	0.608	0.608	0.610	0.610	0.596
$\Delta DY_{i,t}$	0.383	0.350	0.352	0.348	0.346	0.342	0.322
$\Delta PE_{i,t}$	0.030	0.023	0.024	0.021	0.040	0.036	0.034
$\overline{DD}^n_{i,t}$	0.716	0.715	0.719	0.718	0.719	0.720	0.710
Pesaran test (CD_P)							
	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)	ADF(5)	ADF(6)
$DD_{i,t}$	47.6*	47.2*	47.4*	47.1*	47.0*	46.7*	45.4*
$\Delta DY_{i,t}$	27.6*	25.1*	25.3*	25.0*	24.9*	24.6*	23.2*
$\Delta PE_{i,t}$	2.2*	1.7*	1.8*	1.5	2.9*	2.6*	2.4*
$\overline{DD}^n_{i,t}$	56.4*	56.0*	56.0*	55.6*	55.4*	55.2*	54.1*
LM test (CD_{LM})							
	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)	ADF(5)	ADF(6)
$DD_{i,t}$	2315.2*	2274.8*	2289.7*	2263.9*	2253.7*	2226.6*	2109.7*
$\Delta DY_{i,t}$	946.6*	812.3*	813.1*	795.4*	777.6*	762.9*	685.1*
$\Delta PE_{i,t}$	157.7*	127.3*	135.9*	159.2*	151.3*	154.2*	154.2*
$\overline{DD}^n_{i,t}$	3268.3*	3221.9*	3220.8*	3175.5*	3148.6*	3124.7*	3007.4*

Notes: pth-order Augmented Dickey Fuller ADF(p) regressions are computed for each Supersector i. Tests for $\Delta DY_{i,t}$ and $\Delta PE_{i,t}$ are based on a reduced sample $N = 11$, excluding the Oil & Gas Supersector due to short series length. No linear trend is included. ***** indicates rejection of the the null hypothesis of no error cross-sectional dependence at 5% level.

Table 14: Panel Unit Root Tests

CIPS Panel Unit Root Tests							
	CADF(0)	CADF(1)	CADF(2)	CADF(3)	CADF(4)	CADF(5)	CADF(6)
$DD_{i,t}$	-3.49***	-3.41***	-2.92***	-2.77***	-2.62***	-2.66***	-2.44***
$\Delta DY_{i,t}$	-2.19*	-2.29**	-2.73***	-2.79***	-2.77***	-2.61***	-2.59***
$\Delta PE_{i,t}$	-4.29***	-3.32***	-2.83***	-3.19***	-2.81***	-2.56***	-2.51***
$\overline{DD}^n_{i,t}$	-3.65***	-2.29***	-2.73***	-2.79***	-2.77***	-2.61***	-2.59***
IPS Panel Unit Root Tests							
	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)	ADF(5)	ADF(6)
$DD_{i,t}$	-1.34*	-1.68**	-0.80	-0.66	-0.40	-0.55	-0.45
$\Delta DY_{i,t}$	-0.43	-2.29***	-3.91***	-4.39***	-3.82***	-4.11***	-5.94***
$\Delta PE_{i,t}$	-9.97***	-6.39***	-4.8***	-5.96***	-4.84***	-4.26***	-4.81***
$\overline{DD}^n_{i,t}$	-1.05	-1.39*	-0.47	-0.33	-0.14	-0.18	-0.14

Notes: Tests for $\Delta DY_{i,t}$ and $\Delta PE_{i,t}$ are based on a reduced sample $N = 11$, excluding the Oil & Gas Supersector due to short series length. No linear trend is included. *****,**,*** indicate rejection of the the null hypothesis of unit root at 1%, 5% and 10% levels, respectively.

Table 15: Panel Unit Root Tests

Sensitivity analysis: CIPS Panel Unit Root Tests							
Excluded Supersector	CADF(0)	CADF(1)	CADF(2)	CADF(3)	CADF(4)	CADF(5)	CADF(6)
	$DD_{i,t}$						
BNK	-3.41	-3.44	-2.96	-2.81	-2.65	-2.74	-2.49
TLS	-3.59	-3.50	-2.97	-2.84	-2.66	-2.62	-2.44
ENE	-3.56	-3.45	-2.89	-2.74	-2.53	-2.63	-2.34
INS	-3.37	-3.23	-2.90	-2.76	-2.55	-2.60	-2.38
TEC	-3.63	-3.52	-3.03	-2.89	-2.73	-2.74	-2.52
ATO	-3.26	-3.16	-2.78	-2.65	-2.51	-2.65	-2.42
UTI	-3.46	-3.36	-2.81	-2.69	-2.52	-2.60	-2.40
IGS	-3.56	-3.45	-2.94	-2.77	-2.64	-2.71	-2.53
CHM	-3.26	-3.32	-2.83	-2.65	-2.55	-2.50	-2.32
FOB	-3.49	-3.32	-2.88	-2.68	-2.60	-2.67	-2.40
MDI	-3.62	-3.54	-3.02	-2.91	-2.76	-2.73	-2.51
HCR	-3.59	-3.51	-3.01	-2.83	-2.68	-2.71	-2.52
	$\overline{DD}_{i,t}^{n}$						
BNK	-3.52	-3.39	-3.15	-3.00	-2.79	-2.74	-2.54
TLS	-3.79	-3.66	-3.28	-3.14	-2.99	-2.91	-2.66
ENE	-3.72	-3.63	-3.13	-3.01	-2.84	-2.84	-2.61
INS	-3.53	-3.62	-3.16	-3.01	-2.86	-2.89	-2.62
TEC	-3.72	-3.63	-3.15	-3.01	-2.88	-2.78	-2.54
ATO	-3.72	-3.57	-3.16	-3.01	-2.86	-2.85	-2.63
UTI	-3.74	-3.61	-3.13	-3.02	-2.81	-2.81	-2.51
IGS	-3.75	-3.61	-3.22	-3.09	-2.95	-2.89	-2.68
CHM	-3.66	-3.57	-3.14	-2.95	-2.78	-2.76	-2.56
FOB	-3.39	-3.29	-2.96	-2.85	-2.69	-2.73	-2.50
MDI	-3.71	-3.57	-3.11	-2.99	-2.84	-2.81	-2.56
HCR	-3.50	-3.48	-3.06	-2.90	-2.79	-2.67	-2.48

Notes: No linear trend is included. All statistics reject the null hypothesis of unit root at 5%.

Table 16: Unit Root Tests - PANIC Method

Variable	**Common Factor** ADF statistic	**Idiosyncratic Factor** IPS $W_{\bar{t}}$-statistic
$DD_{i,t}$	-1.574	-7.324*
$\overline{DD}_{i,t}^{n}$	-1.566	-8.661*

Notes: ADF and IPS $W_{\bar{t}}$ test statistics' lag lengths are determined by SIC criterion. * indicate rejection of the the null hypothesis of unit root. Results of IPS test are robust to equal lag lengths for $p = 1, \ldots, 6$.

Table 17: Unit Root Tests - Macroeconomic and Financial Risk Variables

Variable	**Level**	**First Difference**
VIX_t	-2.07	-7.78***
$R3M_t$	-1.73	-3.92***
OIL_t	-2.11	-6.09***
ΔPI_t	-2.79*	-2.60*
ΔCP_t	-6.00***	-4.77***

Notes: Intercept included only in levels, lag length determined by AIC and HQ criteria. *****,**,*** indicate rejection of the the null hypothesis of unit root at 1%, 5% and 10% levels, respectively. Results are robust to inclusion of trend and seasonal dummies; and also to structural breaks in two cases (ΔPI_t, ΔCP_t).

Table 18: Estimation Results

Dependent Variable $\text{DD}_{i,t}$	MG [1]	MG [2]	MG [3]	CCEMG [4]	CCEMG [5]	CCEMG [6]
Intercept	**0.481****	**0.612****	**0.402****	-0.058	0.033	-0.008
	(0.068)	**(0.101)**	**(0.183)**	(0.136)	(0.182)	(0.196)
ΔVIX_t	**-0.083****	**-0.081****	**-0.082****	0.000	-0.001	0.000
	(0.005)	**(0.005)**	**(0.005)**	(0.004)	(0.003)	(0.004)
$\Delta R3M_t$	**0.670****	**0.617****	**0.614****	-0.010	0.004	-0.004
	(0.103)	**(0.086)**	**(0.089)**	(0.095)	(0.086)	(0.083)
ΔOIL_t	-0.004	-0.003	-0.005	0.000	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
ΔPI_t	0.000	0.001	-0.003	0.000	0.002	0.000
	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
ΔCP_t	**-0.025****	-0.021	0.002	0.011	-0.004	0.003
	(0.011)	(0.019)	(0.026)	(0.021)	(0.019)	(0.022)
$\Delta DY_{i,t}$		0.000	0.000		**-0.002****	**-0.002***
		(0.001)	(0.001)		**(0.001)**	**(0.001)**
$\Delta PE_{i,t}$		0.002	**0.002***		0.001	0.000
		(0.001)	**(0.001)**		(0.001)	(0.001)
$DD_{i,t-1}$	**0.921****	**0.897****	**0.798****	**0.740****	**0.672****	**0.591****
	(0.008)	**(0.014)**	**(0.026)**	**(0.042)**	**(0.050)**	**(0.056)**
$\overline{DD}^n_{i,t-1}$			**0.123****			0.013
			(0.039)			(0.074)
Observations	1128	1072	1072	1128	1072	1072
$\bar{\rho}$	0.424	0.431	0.434	-0.082	-0.081	-0.077
CD_P	33.4	33.2	33.4	-6.5	-6.3	-5.9
CD_{LM}	1207.0	1202.0	1208.0	176.7	195.0	175.4
IPS $W_{\bar{t}}$-stat	-31.724	-31.306	-31.486	-31.197	-31.590	-31.127
CIPS-stat	-6.19	-6.19	-6.19	-6.19	-6.19	-6.19

Notes: MG and CCEMG stand for OLS Mean Group and Common Correlated Effects Mean Group estimates respectively. Standard errors are given in parenthesis. *,** denotes significance at 10% and 5%, respectively. CD statistics ($\bar{\rho}$, CD_{LM} and CD_P) and panel unit root tests are computed on residuals of each equation. See Section 4.4.3 and Section 4.4.4 for definitions, respectively.

Table 19: CCE Estimates of all Cross Section Units

	ICB Supersector											
$DD_{i,t}$	BNK	TLS	ENE[(a)]	INS	TEC	ATO	UTI	IGS	CHM	FOB	MDI	HCR
Intercept	**-1.280****	**0.600****	0.386	-0.393	-0.098	**-0.698****	-0.234	0.384	-0.292	0.697	-0.341	**1.175****
ΔVIX_t	0.004	0.013	-0.001	0.003	-0.014	-0.021	-0.008	**0.026****	-0.008	0.001	-0.001	0.005
$\Delta R3M_t$	-0.362	0.248	-0.030	-0.010	0.105	0.318	0.331	-0.270	0.314	-0.151	**-0.550****	0.007
ΔOIL_t	-0.012	0.006	**0.022***	**-0.015***	0.009	-0.008	-0.011	0.009	0.019	-0.016	-0.006	0.000
ΔPI_t	0.005	-0.008	0.018	0.014	-0.005	-0.012	-0.010	-0.002	-0.006	-0.006	-0.006	-0.006
ΔCP_t	-0.016	-0.038	-0.069	0.015	-0.017	0.132	0.080	-0.047	0.029	0.112	-0.001	-0.140
$\Delta DY_{i,t}$	0.001	**0.002****		-0.003	-0.001	-0.002	-0.004	-0.005	-0.003	0.000	**0.003****	-0.005
$\Delta PE_{i,t}$	0.001	0.001		0.000	0.000	0.000	-0.008	0.001	0.000	**0.011****	0.000	0.000
$DD_{i,t-1}$	**0.420****	**0.555****	**0.796****	**0.646****	**0.846****	**0.299****	**0.761****	0.334	**0.370****	**0.688****	**0.784****	**0.591****
$\overline{DD}^{n}_{i,t-1}$	0.034	0.168	**0.121***	0.046	0.160	-0.045	0.029	**-0.838***	0.020	0.057	**0.433****	-0.039

Notes: Individual estimates come from model [6] in Table 18. *,** denotes significance at 10% and 5%, respectively. (a) Oil & Gas Supersector's equation excludes $\Delta DY_{i,t}$ and $\Delta PE_{i,t}$ due to short series length.

Table 20: Supersector Constituents List - Banks (BNK)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Deutsche Bank	DE0005140008	DE	31-Dec-01	31-Oct-09
2	BNP Paribas(1)	FR0000131104	FR	31-Dec-01	31-Oct-09
→	Fortis(2)(3)	BE0003801181	BE	31-Dec-01	21-Sep-09
→	Banca Nazionale del Lavoro(2)	IT0001254884	IT	31-Dec-01	22-May-06
3	Crédit Agricole	FR0000045072	FR	18-Mar-02	31-Oct-09
→	Crédit Lyonnais(2)	FR0000184202	FR	31-Dec-01	19-Jun-03
4	Société Générale	FR0000130809	FR	31-Dec-01	31-Oct-09
5	UniCredit	IT0000064854	IT	31-Dec-01	31-Oct-09
→	Capitalia(2)(4)	IT0003121495	IT	31-Dec-01	1-Oct-07
→	HypoVereinsbank(2)(5)	DE0008022005	DE	31-Dec-01	19-Jun-06
→	Bank Austria(2)	AT0000995006	AT	24-Oct-03	5-Dec-05
6	Santander(6)	ES0113900J37	ES	31-Dec-01	31-Oct-09
→	ABN Amro(7)	NL0000301109	NL	31-Dec-01	2-Nov-07
7	Dexia(8)	BE0003796134	BE	31-Dec-01	31-Oct-09
8	Commerzbank(9)	DE0008032004	DE	10-Aug-07	31-Oct-09
9	Intesa Sanpaolo(10)	IT0000072618	IT	31-Dec-01	31-Oct-09
→	San Paolo IMI(2)	IT0001269361	IT	31-Dec-01	2-Jan-07
10	Natixis	FR0000120685	FR	19-Apr-05	31-Oct-09
11	BBVA	ES0113211835	ES	31-Dec-01	31-Oct-09
12	KBC	BE0003565737	BE	31-Dec-01	31-Oct-09
→	Almanij(2)	BE0003703171	BE	31-Dec-01	3-Mar-05
13	Deutsche Postbank	DE0008001009	DE	20-Sep-04	31-Oct-09
14	Erste Group Bank(11)	AT0000652011	AT	31-Dec-01	31-Oct-09
15	Bank Of Ireland	IE0030606259	IE	31-Dec-01	31-Oct-09
16	Banca Monte dei Paschi di Siena(12)	IT0001334587	IT	31-Dec-01	31-Oct-09
17	Allied Irish Banks	IE0000197834	IE	31-Dec-01	31-Oct-09

Notes: (1) Increase in share capital and free float change on 19-May-09. (2) Takeover. (3) Also constituent prior to 21-Jun-04. (4) Formerly Banca di Roma. (5) Also constituent between 24-Nov-05 and 19-Jun-06 after takeover. (6) Increase in share capital due to takeover of Abbey on 16-Nov-04. (7) Takeover by Royal Bank of Scotland, Fortis and Santander. (8) Increase in share capital on 8-Jan-09. (9) Increase in share capital on 23-Jul-09. (10) Banca Intesa is the predecessor company. Increase in free float on 19-Apr-04. (11) Increase in share capital on 31-Jan-06. (12) Increase in share capital due to takeover of Banca Agricola Mantovana and Banca Toscana on 31-Mar-03.

Table 21: Supersector Constituents List - Banks (BNK) (cont.)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
18	Banco Popolare(13)	IT0004231566	IT	2-Jul-07	31-Oct-09
→	Banca Popolare Italiana	IT0000064300	IT	31-Dec-01	2-Jul-07
→	BP di Verona e Novara	IT0003262513	IT	4-Jun-02	2-Jul-07
→	BP di Novara	IT0000064508	IT	31-Dec-01	4-Jun-02
→	BP di Verona	IT0001065215	IT	31-Dec-01	4-Jun-02
19	UBI Banca(14)	IT0003487029	IT	2-Apr-07	31-Oct-09
→	Banca Lombarda e Piemontese	IT0000062197	IT	31-Dec-01	2-Apr-07
→	BP di Bergamo	IT0000064409	IT	31-Dec-01	1-Jul-03
→	BP Commercio e Industria	IT0000064193	IT	31-Dec-01	1-Jul-03
20	Banco Popular Español	ES0113790531	ES	31-Dec-01	31-Oct-09
21	Anglo Irish Bank(15)	IE00B06H8J93	IE	31-Dec-01	26-Jan-09
22	National Bank Of Greece	GRS003013000	GR	31-Dec-01	31-Oct-09
23	BCP	PTBCP0AM0007	PT	31-Dec-01	31-Oct-09
24	Raiffeisen International	AT0000606306	AT	20-Jun-05	31-Oct-09
25	Banco Sabadell(16)	ES0113860A34	ES	31-Dec-01	31-Oct-09
26	EFG Eurobank Ergasias	GRS323013003	GR	31-Dec-01	31-Oct-09
27	Banco Espirito Santo	PTBES0AM0007	PT	31-Dec-01	31-Oct-09
28	Mediobanca(17)	IT0000062957	IT	31-Dec-01	31-Oct-09
29	Alpha Bank	GRS015013006	GR	31-Dec-01	31-Oct-09
30	Bank Of Greece	GRS004013009	GR	14-Aug-03	31-Oct-09
31	Bankinter	ES0113679I37	ES	31-Dec-01	31-Oct-09
32	BP dell'Emilia Romagna(18)	IT0000066123	IT	31-Dec-01	31-Oct-09
33	Piraeus Bank(19)	GRS014013007	GR	31-Dec-01	31-Oct-09
34	BP di Milano	IT0000064482	IT	31-Dec-01	31-Oct-09
35	Banco BPI(20)	PTBPI0AM0004	PT	31-Dec-01	31-Oct-09
36	Banca Carige	IT0003211601	IT	20-Jun-05	31-Oct-09
37	Pohjola Bank	FI0009003222	FI	18-Sep-06	31-Oct-09
38	Banco de Valencia	ES0113980F34	ES	23-Jun-03	31-Oct-09
39	BP di Sondrio(21)	IT0000784196	IT	31-Dec-01	31-Oct-09
40	Credito Valtellinese	IT0000064516	IT	22-Dec-08	31-Oct-09

Notes: (13) Merger on 2-Jul-07 between BP Italiana (IT0000064300, formerly BP di Lodi) and BP di Verona e Novara (IT0003262513, merger between BP di Novara and BP di Verona in June 2002). (14) Merger on 2-Apr-07 between Banche Popolare Unite (predecessor) and Banca Lombarda e Piamontese. The former was formed by the merger between BP di Bergamo, BP Commercio e Industria and BP di Ruino e di Varese (no data) on 1-Jul-03. (15) Previous ISIN IE0001987894, nationalized. (16) Increase in share capital on 15-Mar-04. (17) Also constituent prior to 23-Dec-02. (18) Temporary deletion between 22-Dec-03 and 10-Sep-09. (19) Increase in share capital on 2-Jan-04. (20) Also constituent prior to 24-Mar-03. (21) Temporary deletion between 22-Dec-03 and 21-Sep-09.

Table 22: Supersector Constituents List - Telecommunications (TLS)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Deutsche Telekom	DE0005557508	DE	31-Dec-01	31-Oct-09
2	Telefónica	ES0178430E18	ES	31-Dec-01	31-Oct-09
→	Telefónica Móviles(1)	ES0178401016	ES	31-Dec-01	28-Jul-06
3	France Telecom	FR0000133308	FR	31-Dec-01	31-Oct-09
→	Orange(2)	FR0000079196	FR	31-Dec-01	20-Oct-03
4	Telecom Italia	IT0003497168	IT	4-Aug-03	31-Oct-09
→	Telecom Italia(3)	IT0001127429	IT	31-Dec-01	04-Aug-03
→	Olivetti	IT0001137311	IT	31-Dec-01	04-Aug-03
→	TIM(4)	IT0001052049	IT	31-Dec-01	30-Jun-05
5	KPN(5)	NL0000009082	NL	31-Dec-01	31-Oct-09
6	Portugal Telecom	PTPTC0AM0009	PT	31-Dec-01	31-Oct-09
7	OTE	GRS260333000	GR	31-Dec-01	31-Oct-09
→	Cosmote Mobile(6)	GRS408333003	GR	22-Sep-03	14-Dec-07
8	Telekom Austria	AT0000720008	AT	18-Mar-02	31-Oct-09
9	Belgacom	BE0003810273	BE	21-Jun-04	31-Oct-09
10	Elisa Corporation(7)	FI0009007884	FI	31-Dec-01	31-Oct-09
11	Mobistar	BE0003735496	BE	19-Jun-03	31-Oct-09
12	Neuf Cegetel(8)	FR0004166072	FR	14-Nov-07	25-Jun-08
13	Fastweb(9)	IT0001423562	IT	22-Dec-03	24-Sep-07
14	Eircom Group(10)	GB0034341890	IE	21-Jun-04	18-Aug-06
15	Vodafone-Panafon Hellenic(11)	GRS307333005	GR	31-Dec-01	28-Jan-04
16	Vodafone Telecel(11)	PTTLE0AM0004	PT	31-Dec-01	07-Apr-03
17	Sonera(12)	FI0009007371	FI	31-Dec-01	09-Dec-02

Notes: (1) Telefónica takes over Telefónica Móviles. (2) France Telecom takes over Orange. (3) Olivetti takes over Telecom Italia and is renamed to Telecom Italia. (4) Telecom Italia takes over TIM. (5) KPN increases share capital on 26-Mar-02. (6) OTE takes over Cosmote Mobile. (7) Elisa Corporation increases share capital on 18-Nov-05. (8) Taken over by SFR. (9) Formerly e.Biscom, taken over by Swisscom. (10) Taken over by Babcock & Brown Capital. (11) Taken over by Vodafone Group. (12) Taken over by Telia.

Table 23: Supersector Constituents List - Oil & Gas (ENE)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Total(1)	FR0000120271	FR	31-Dec-01	31-Oct-09
2	ENI	IT0003132476	IT	31-Dec-01	31-Oct-09
3	Repsol YPF	ES0173516115	ES	31-Dec-01	31-Oct-09
4	OMV	AT0000743059	AT	31-Dec-01	31-Oct-09
5	SAIPEM	IT0000068525	IT	31-Dec-01	31-Oct-09
6	CEPSA(2)	ES0132580319	ES	31-Dec-01	22-Jun-09
7	Technip	FR0000131708	FR	31-Dec-01	31-Oct-09
8	GALP Energia	PTGAL0AM0009	PT	10-Aug-07	31-Oct-09
9	CGGVeritas(3)	FR0000120164	FR	19-Jun-06	31-Oct-09
10	Neste Oil(4)	FI0009013296	FI	19-Apr-05	31-Oct-09
11	Gamesa(5)	ES0143416115	ES	18-Nov-03	31-Oct-09
12	Saras	IT0000433307	IT	23-Mar-09	21-Sep-09
13	Bourbon(6)	FR0004548873	FR	19-Dec-05	31-Oct-09
14	SBM Offshore(7)	NL0000360618	NL	31-Dec-01	31-Oct-09
15	Q-Cells(8)	DE0005558662	DE	31-Jul-06	31-Oct-09
16	SolarWorld(9)	DE0005108401	DE	20-Mar-06	31-Oct-09
17	FUGRO	NL0000352565	NL	20-Mar-06	31-Oct-09
18	Maurel & Prom(10)	FR0000051070	FR	21-Mar-05	31-Oct-09
19	Dragon Oil	IE0000590798	IE	23-Jun-08	22-Dec-08

Notes: (1) Decreased weighting on 18-May-06 due to spin-off of Arkema. (2) Temporary deletion between 18-Jun-07 and 22-Dec-08. (3) CGG takes over Veritas DGC and increases share capital on 17-Jan-07. (4) Spun-off from Fortum on 19-Apr-05. (5) Classified as Industrial Goods & Services between 18-Nov-03 and 22-Sep-08. (6) Also constituent between 19-Dec-05 and 20-Mar-06. (7) IHC Caland N.V. (NL0000360584) prior to May 05. (8) Also constituent between 31-Jul-06 and 22-Sep-08. (9) Also constituent between 20-Mar-06 and 22-Sep-08. (10) Temporary deletion between and 19-Mar-07 and 22-Jun-09.

Table 24: Supersector Constituents List - Insurance (INS)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	ING(1)	NL0000303600	DE	31-Dec-01	31-Oct-09
2	Allianz	DE0008404005	DE	31-Dec-01	31-Oct-09
→	RAS(2)	IT0000062825	IT	31-Dec-01	16-Oct-06
3	AXA(3)	FR0000120628	DE	31-Dec-01	31-Oct-09
4	Assicurazioni Generali	IT0000062072	IT	31-Dec-01	31-Oct-09
→	Alleanza Assicurazioni(2)	IT0000078193	IT	31-Dec-01	1-Oct-09
→	AMB Generali Holding(2)	DE0008400029	DE	31-Dec-01	18-Sep-06
5	AEGON	NL0000303709	NL	31-Dec-01	31-Oct-09
6	CNP Assurances	FR0000120222	FR	31-Dec-01	31-Oct-09
7	Munich Re	DE0008430026	DE	31-Dec-01	31-Oct-09
8	Fondiaria-SAI	IT0001463071	IT	7-Jan-03	31-Oct-09
→	La Fondiaria Assicurazioni(2)(4)	IT0001062097	IT	31-Dec-01	7-Jan-03
9	Unipol Gruppo Finanziario(5)	IT0001074571	IT	22-Sep-03	31-Oct-09
10	MAPFRE(6)	ES0124244E34	ES	23-Jun-03	31-Oct-09
11	Hannover Re	DE0008402215	DE	5-Jan-04	31-Oct-09
12	Vienna Insurance(7)	AT0000908504	AT	25-Mar-08	31-Oct-09
13	SCOR(8)	FR0010411983	FR	31-Dec-01	31-Oct-09
14	Mediolanum	IT0001279501	IT	31-Dec-01	21-Aug-07
15	Sampo	FI0009003305	FI	31-Dec-01	31-Oct-09
16	Cattolica Assicurazioni	IT0000784154	IT	31-Dec-01	31-Oct-09
17	AGF	FR0000125924	FR	31-Dec-01	7-May-07

Notes: (1) Also constituent prior to 24-Jun-02. (2) Takeover. (3) Increased weighting due to takeover of FINAXA on 22-Dec-05 and decreases share share capital on 9-Jan-06. (4) SAI is the predecessor company. (5) Alternate listing of ordinary and preference shares (IT0001074589). Temporary deletion between 22-Mar-04 and 19-Dec-05. (6) Increase in share capital on 7-Mar-07 and on 14-Jul-08. (7) Increase in share capital on 13-May-08. (8) Temporary deletion between 23-Dec-02 and 22-Mar-04. Increase in share capital on 30-Jun-05, 29-May-07 and 10-Aug-07 (takeover of Converium). (9) Temporary deletion between 22-Jun-09 and 21-Sep-09.

Table 25: Supersector Constituents List - Technology (TEC)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Nokia	FI0009000681	FI	31-Dec-01	31-Oct-09
2	Alcatel Lucent(1)	FR0000130007	FR	31-Dec-01	31-Oct-09
3	SAP	DE0007164600	DE	31-Dec-01	31-Oct-09
→	Business Objects(2)	FR0004026250	FR	31-Dec-01	11-Feb-08
4	STMicroelectronics	NL0000226223	IT	31-Dec-01	31-Oct-09
5	Capgemini	FR0000125338	FR	31-Dec-01	31-Oct-09
6	Infineon Technologies	DE0006231004	DE	31-Dec-01	31-Oct-09
7	Atos Origin(3)	FR0000051732	FR	31-Dec-01	31-Oct-09
8	ASML Holding	NL0006034001	NL	31-Dec-01	31-Oct-09
9	Indra Sistemas(4)	ES0118594417	ES	31-Dec-01	31-Oct-09
10	Dassault Systems	FR0000130650	FR	31-Dec-01	31-Oct-09
11	Neopost	FR0000120560	FR	24-Jun-02	31-Oct-09
12	Iliad	FR0004035913	FR	22-Sep-08	31-Oct-09
13	Wincor Nixdorf	DE000A0CAYB2	DE	19-Jun-06	31-Oct-09
14	United Internet	DE0005089031	DE	19-Mar-07	31-Oct-09
15	Software	DE0003304002	DE	23-Mar-09	31-Oct-09
16	Aixtron	DE000A0WMPJ6	DE	21-Sep-09	31-Oct-09
17	Tom Tom	NL0000387058	NL	24-Sep-07	22-Dec-08
18	Tietoenator	FI0009000277	FI	31-Dec-01	24-Sep-07
19	Getronics	NL0000355915	NL	22-Mar-04	18-Sep-06
20	Océ	NL0000354934	NL	31-Dec-01	19-Jun-06
21	T-Online International	DE0005557706	DE	31-Dec-01	20-Mar-06

Notes: (1) Increase in share capital on 4-Dec-06 due to takeover of Lucent Technologies. (2) Takeover by SAP. (3) Increase in share capital on 2-Feb-04. (4) Increase in share capital on 1-Feb-07, also constituent prior to 31-Dec-03.

Table 26: Supersector Constituents List - Automobiles & Parts (ATO)

	Name	**ISIN Code**	**Country**	**Portfolio from:**	**constituent to:**
1	Volkswagen(1)	DE0007664005	DE	31-Dec-01	31-Oct-09
2	Daimler	DE0007100000	DE	31-Dec-01	31-Oct-09
3	BMW	DE0005190003	DE	31-Dec-01	31-Oct-09
4	Renault(2)	FR0000131906	FR	31-Dec-01	31-Oct-09
5	Peugeot	FR0000121501	FR	31-Dec-01	31-Oct-09
6	Fiat(3)	IT0001976403	IT	31-Dec-01	31-Oct-09
7	Porsche	DE000PAH0038	DE	31-Dec-01	31-Oct-09
8	Continental(4)	DE0005439004	DE	31-Dec-01	17-Sep-08
9	Michelin	FR0000121261	FR	31-Dec-01	31-Oct-09
10	Pirelli & C.(5)	IT0000072725	IT	19-Dec-05	31-Oct-09
11	Valeo	FR0000130338	FR	31-Dec-01	31-Oct-09
12	Rheinmetall	DE0007030009	DE	14-Jul-05	31-Oct-09
13	Nokian Tyres(6)	FI0009005318	FI	9-May-05	31-Oct-09

Notes: (1) Free-float decrease due to changes in shareholder structure on 28-Dec-08. (2) Renault increases share capital on 8-Apr-02. (3) Fiat increases share capital on 15-Nov-05. (4) Taken over by Schaeffler Group. (5) Also constituent between 31-Dec-01 and 19-Dec-05. Increases share capital on 9-Jun-03. Takes over Pirelli on 4-Aug-03. (6) Temporary deletion between 18-Sep-06 and 7-May-07.

Table 27: Supersector Constituents List - Utilities (UTI)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	EDF	FR0010242511	FR	31-Dec-01	31-Oct-09
2	E.ON	DE000ENAG999	DE	31-Dec-01	31-Oct-09
3	Enel	IT0003128367	IT	31-Dec-01	31-Oct-09
→	Endesa(1)	ES0130670112	ES	31-Dec-01	31-Oct-09
4	GDF Suez	FR0010208488	FR	19-Sep-05	31-Oct-09
→	Suez(2)	FR0000120529	FR	31-Dec-01	22-Jul-08
→	Electrabel(3)	BE0003637486	BE	31-Dec-01	10-Jul-07
5	RWE	DE0007037129	DE	31-Dec-01	31-Oct-09
6	Iberdrola	ES0144580Y14	ES	31-Dec-01	31-Oct-09
7	Veolia Environnement	FR0000124141	FR	31-Dec-01	31-Oct-09
8	EDP Energias de Portugal	PTEDP0AM0009	PT	31-Dec-01	31-Oct-09
9	Fortum(4)	FI0009007132	FI	20-Sep-04	31-Oct-09
10	Iberdrola Renovables	ES0147645016	ES	23-Jun-08	31-Oct-09
11	Gas Natural	ES0116870314	ES	31-Dec-01	31-Oct-09
→	Unión Fenosa(5)	ES0181380710	ES	31-Dec-01	28-Apr-09
12	Public Power Corporation	GRS434003000	GR	23-Jun-03	31-Oct-09
13	A2A(6)	IT0001233417	IT	31-Dec-01	31-Oct-09
14	SNAM Rete Gas	IT0003153415	IT	18-Mar-02	31-Oct-09
15	Terna	IT0003242622	IT	20-Sep-04	31-Oct-09
16	EDP Renováveis	ES0127797019	PT	7-Jan-09	31-Oct-09
17	Verbund	AT0000746409	AT	19-Dec-05	31-Oct-09
18	Red Eléctrica Corporation	ES0173093115	ES	9-Oct-03	31-Oct-09
19	Edison	IT0003152417	IT	1-Aug-03	18-Nov-05
20	Acea	IT0001207098	IT	31-Dec-01	23-Jun-03
21	Hera	IT0001250932	IT	25-Mar-08	21-Sep-09
22	Enagás(7)	ES0130960018	ES	23-Sep-02	31-Oct-09

Notes: (1) Enel and Acciona take over Endesa on 5-Oct-2007. Deleted between 5-Oct-07 and 22-Sep-08. (2) Suez merges with GDF on 22-Jul-08. (3) Suez takes over Electrabel on 10-Jul-07. (4) Classified as Utilities also between 20-Sep-04 and 19-Apr-05. (5) Gas Natural takes over Unión Fenosa on 28-Apr-09. (6) AEM merges with ASM and AMSA on 2-Jan-08 and changes name to A2A. (7) Classified as Utilities also betweenn 23-Sep-02 and 19-Dec-05.

Table 28: Supersector Constituents List - Industrial Goods & Services (IGS)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Deutsche Post(1)	DE0005552004	DE	31-Dec-01	31-Oct-10
2	Siemens	DE0007236101	DE	31-Dec-01	31-Oct-10
3	EADS	NL0000235190	NL	31-Dec-01	31-Oct-10
4	ThyssenKrupp	DE0007500001	DE	31-Dec-01	31-Oct-10
5	Finmeccanica	IT0003856405	IT	31-Dec-01	31-Oct-10
6	Schneider Electric	FR0000121972	FR	31-Dec-01	31-Oct-09
7	Alstom	FR0010220475	FR	31-Dec-01	31-Oct-09
8	Abertis Infraestructuras	ES0111845014	ES	31-Dec-01	31-Oct-09
9	Suez Environnement	FR0010613471	FR	22-Sep-08	31-Oct-09
10	Thales	FR0000121329	FR	31-Dec-01	31-Oct-09
11	Safran(2)	FR0000073272	FR	23-Sep-02	31-Oct-09
12	Man	DE0005937007	DE	31-Dec-01	31-Oct-09
13	Atlantia	IT0003506190	IT	31-Dec-01	31-Oct-09
14	Cintra	ES0118900010	ES	31-Dec-01	31-Oct-09
15	Groupe Eurotunnel	FR0010533075	FR	22-Dec-08	31-Oct-09
16	ADP	FR0010340141	FR	19-Mar-07	31-Oct-09
17	TNT	NL0000009066(3)	NL	31-Dec-01	31-Oct-09
18	Legrand	FR0010307819	FR	18-Sep-06	31-Oct-09
19	Fraport	DE0005773303	DE	9-Dec-05	31-Oct-09
20	Vallourec	FR0000120354	FR	10-Aug-05	31-Oct-09
21	Metso	FI0009007835	FI	31-Dec-01	31-Oct-09
22	Randstad	NL0000379121	NL	31-Dec-01	31-Oct-09
→	Vedior(4)	NL0006005662	NL	31-Dec-01	16-May-08
23	GEA Group	DE0006602006	DE	31-Dec-01	31-Oct-09
24	Nexans	FR0000044448	FR	13-Feb-07	31-Oct-09
25	Wartsila	FI0009003727	FI	20-Jun-05	31-Oct-09
26	MTU Aero Engines	DE000A0D9PT0	DE	18-Aug-06	31-Oct-09
27	Prysmian	IT0004176001	IT	23-Jun-08	31-Oct-09
28	Andritz	AT0000730007	AT	24-Sep-07	31-Oct-09
29	Zodiac Aerospace	FR0000125684	FR	31-Dec-01	31-Oct-09
30	Bekaert	BE0003780948	BE	2-Oct-08	31-Oct-09
31	Tognum	DE000A0N4P43	DE	24-Dec-07	31-Oct-09
32	Kone	FI0009013403	FI	31-Dec-01	31-Oct-09
33	Vopak	NL0000393007	NL	23-Jun-08	31-Oct-09
34	Imtech	NL0006055329	NL	23-Jun-08	31-Oct-09
35	DCC	IE0002424939	IE	23-Dec-02	31-Oct-09
36	Bureau Veritas	FR0006174348	FR	30-Apr-08	31-Oct-09
37	Gemalto	NL0000400653	NL	23-Jun-08	31-Oct-09

Notes: (1). Also constituent before 23-Dec-02. (2) Also constituent before 19-Sep-05. (3) Also constituent before 19-Nov-02. (4) takeover.

Table 29: Supersector Constituents List - Industrial Goods & Services (IGS) (cont.)

	Name	**ISIN Code**	**Country**	**Portfolio constituent from:**	**to:**
38	SGL Carbon	DE0007235301	DE	7-Aug-07	31-Oct-09
39	Konecranes	FI0009005870	FI	24-Dec-07	31-Oct-09
40	Zardoya Otis	ES0184933812	ES	31-Dec-01	31-Oct-09
41	Brisa	PTBRI0AM0000	PT	31-Dec-01	31-Oct-09
42	Österreichische Post	AT0000APOST4	AT	19-Jan-09	21-Dec-09
43	SAPRR	FR0006807004	FR	3-Mar-05	19-Mar-07
44	Corporate Express	NL0000852861	NL	22-Dec-03	24-Dec-07
45	Heidelberg(5)	DE0007314007	DE	31-Dec-01	23-Jun-08
46	AGFA Gevaert(6)	BE0003755692	BE	24-Jun-02	24-Dec-07
47	Cargotec Corporation	FI0009013429	FI	1-Jun-05	22-Sep-08
48	Hagemeyer(7)	NL0000355477	NL	31-Dec-01	12-Mar-08
49	Grafton	IE00B00MZ448	IE	22-Sep-03	22-Sep-08
50	Huhtamaki	FI0009000459	FI	31-Dec-01	18-Dec-06
51	Stork	NL0000390672	NL	19-Sep-05	19-Mar-07
52	Epcos	DE0005128003	DE	31-Dec-01	20-Dec-04
53	Outotec	FI0009014575	FI	4-Oct-07	22-Dec-08
54	Medion	DE0006605009	DE	31-Dec-01	20-Sep-04
55	Singulus Technologies	DE0007238909	DE	31-Dec-01	22-Mar-04
56	Buderus	DE0005278006	DE	31-Dec-01	7-Jul-03

Notes: (5) Temporary deletion between 24-Mar-03 and 23-Jul-04. (6) Also constituent before 22-Sep-03. (7) Temporary deletion between 22-Sep-03 and 14-Jun-06.

Table 30: Supersector Constituents List - Chemicals (CHM)

	Name	ISIN Code	Country	Portfolio from:	constituent to:
1	Bayer	DE000BAY0017	DE	31-Dec-01	31-Oct-09
2	BASF	DE0005151005	DE	31-Dec-01	31-Oct-09
3	Linde(1)	DE0006483001	DE	31-Dec-01	31-Oct-09
4	Air Liquide	FR0000120073	FR	31-Dec-01	31-Oct-09
5	AkzoNobel	NL0000009132	NL	31-Dec-01	31-Oct-09
6	Solvay	BE0003470755	BE	31-Dec-01	31-Oct-09
7	DSM	NL0000009827	NL	31-Dec-01	31-Oct-09
8	Arkema	FR0010313833	FR	18-May-06	31-Oct-09
9	Wacker Chemie	DE000WCH8881	DE	19-Mar-07	31-Oct-09
10	Lanxess	DE0005470405	DE	31-Jan-05	31-Oct-09
11	K+S	DE0007162000	DE	25-Jun-04	31-Oct-09
12	Umicore	BE0003884047	BE	2-Jan-04	31-Oct-09
13	Symrise	DE000SYM9999	DE	10-Oct-07	31-Oct-09
14	Rhodia(2)	FR0010479956	FR	9-Mar-06	23-Mar-09

Notes: (1) Classified as Chemicals also before 23-Dec-02. (2) Temporary deletion between 22-Dec-03 and 9-Mar-06.

Table 31: Supersector Constituents List - Food & Beverage (FOB)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Anheuser-Busch InBev	BE0003793107	BE	31-Dec-01	31-Oct-09
2	Unilever	NL0000009355	NL	31-Dec-01	31-Oct-09
3	Danone	FR0000120644	FR	31-Dec-01	31-Oct-09
→	Royal Numico(1)	NL0000375616	NL	31-Dec-01	14-Nov-07
4	Pernod Ricard	FR0000120693	FR	31-Dec-01	31-Oct-09
5	Heineken Holding(2)	NL0000008977	NL	31-Dec-01	31-Oct-09
→	Heineken NV	NL0000009165	NL	31-Dec-01	31-Oct-09
6	Suedzucker(3)	DE0007297004	DE	23-Sep-02	31-Oct-09
7	Coca-Cola HBC	GRS104003009	GR	31-Dec-01	31-Oct-09
8	Parmalat	IT0003826473	IT	20-Mar-06	31-Oct-09
9	Kerry Grp	IE0004906560	IE	31-Dec-01	31-Oct-09
10	Ebro Puleva(4)	ES0112501012	ES	23-Dec-02	31-Oct-09
11	Nutreco(5)	NL0000375400	NL	22-Sep-08	31-Oct-09
12	CSM	NL0000852549	NL	31-Dec-01	31-Oct-09
13	C&C Group	IE00B010DT83	IE	19-Sep-05	22-Dec-08

Notes: (1) Takeover. (2) Dual-listed. (3) Temporary deletion between 19-Mar-07 and 23-Mar-09. (4) Temporary deletion between 24-Dec-07 and 22-Dec-08. (5) Also constituent before 23-Dec-02.

Table 32: Supersector Constituents List - Media (MDI)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Vivendi	FR0000127771	FR	31-Dec-01	31-Oct-09
2	Lagardère	FR0000130213	FR	31-Dec-01	31-Oct-09
3	Publicis Groupe	FR0000130577	FR	31-Dec-01	31-Oct-09
4	SES	LU0088087324	LU	31-Dec-01	31-Oct-09
5	Mediaset	IT0001063210	IT	31-Dec-01	31-Oct-09
6	Wolters Kluwer	NL0000395903	NL	31-Dec-01	31-Oct-09
7	Eutelsat Communication	FR0010221234	FR	12-Mar-08	31-Oct-09
8	JCDecaux	FR0000077919	FR	23-Dec-02	31-Oct-09
9	TF1	FR0000054900	FR	31-Dec-01	31-Oct-09
10	Sanoma	FI0009007694	FI	22-Sep-03	31-Oct-09
11	Teleperformance	FR0000051807	FR	22-Sep-08	31-Oct-09
12	M6 Métropole TV(1)	FR0000053225	FR	31-Dec-01	31-Oct-09
13	Reed Elsevier	NL0006144495	NL	31-Dec-01	31-Oct-09
14	Zon Multimedia	PTZON0AM0006	PT	24-Dec-07	31-Oct-09
15	Pagesjaunes	FR0010096354	FR	20-Sep-04	31-Oct-09
16	Prisa	ES0171743117	ES	31-Dec-01	20-Mar-06
→	Sogecable(2)	ES0178483139	ES	31-Dec-01	15-May-08
17	ProSiebenSat.1 Media	DE0007771172	DE	22-Dec-03	23-Jun-08
18	Thomson(3)	FR0000184533	FR	31-Dec-01	22-Sep-08
19	Havas	FR0000121881	FR	31-Dec-01	19-Jun-06
20	RCS Mediagroup	IT0003039010	IT	31-Dec-01	19-Dec-05
21	Independent Newspapers	IE0004614818	IE	31-Dec-01	24-Dec-07
22	Mondadori Group	IT0001469383	IT	31-Dec-01	19-Dec-05
23	Antena 3	ES0109427734	ES	20-Dec-04	19-Mar-07
24	SEAT Pagine Gialle	IT0001389920	IT	31-Dec-01	23-Jun-08
25	VNU	NL0000389872	NL	31-Dec-01	14-Jun-06

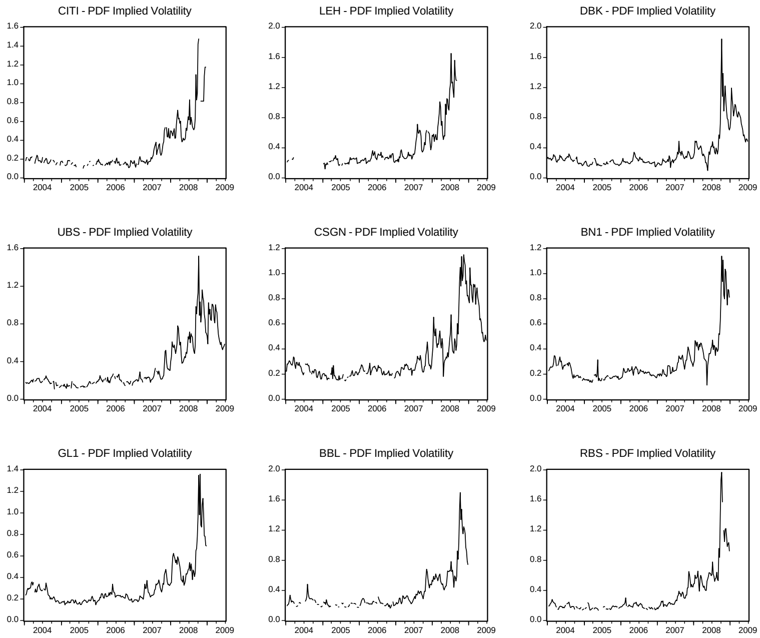
Notes: (1) Temporary deletion between 24-Jun-02 and 8-Apr-04 and between 24-Sep-07 and 23-Mar-09. (2) Takeover. (3) Also constituent prior to 19-Sep-05.

Table 33: Supersector Constituents List - Healthcare (HCR)

	Name	ISIN Code	Country	Portfolio constituent from:	to:
1	Sanofi-Aventis	FR0000120578	FR	31-Dec-01	31-Oct-09
→	Aventis(1)	FR0000130460	FR	31-Dec-01	28-Jul-04
2	Fresenius(2)	DE0005785638	DE	31-Dec-01	31-Oct-09
3	Merck	DE0006599905	DE	31-Dec-01	31-Oct-09
4	UCB	BE0003739530	BE	31-Dec-01	31-Oct-09
5	Essilor International	FR0000121667	FR	31-Dec-01	31-Oct-09
6	STADA Arzneimittel	DE0007251803	DE	23-Dec-02	31-Oct-09
7	Rhoen Klinikum	DE0007042301	DE	26-Jun-07	31-Oct-09
8	Qiagen	NL0000240000	NL	31-Dec-01	31-Oct-09
9	Biomerieux	FR0010096479	FR	22-Dec-08	31-Oct-09
10	Elan Corporation	IE0003072950	IE	31-Dec-01	31-Oct-09
11	Grifols	ES0171996012	ES	4-Apr-07	31-Oct-09
12	Orion(3)	FI0009014377	FI	22-Dec-08	31-Oct-09
13	Crucell	NL0000358562	NL	23-Mar-09	31-Oct-09
14	Intercell	AT0000612601	AT	22-Sep-08	31-Oct-09
15	Schering	DE0007172009	DE	31-Dec-01	18-Sep-06
16	Faes Farma	ES0134950F36	ES	19-Mar-07	21-Sep-09
17	Zeltia	ES0184940817	ES	31-Dec-01	20-Mar-06

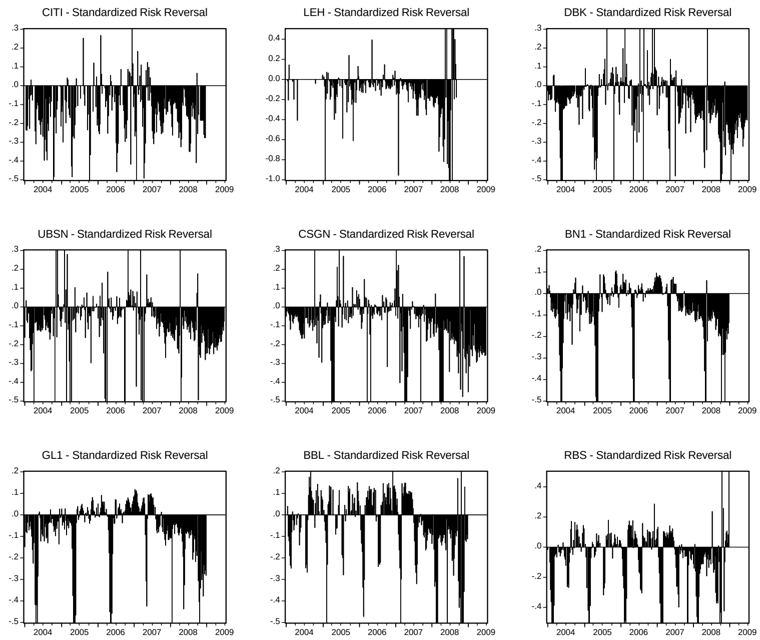
Notes: (1) Takeover by Sanofi-Synthélabo and renamed Sanofi-Aventis. (2) Fresenius Medical Care is also listed but partially owned by Fresenius. (3) B Shares, also constituent between 23-Dec-02 and 22-Sep-03 and between 28-Jul-05 and 18-Sep-06.

Figure 1: PDF At-the-money Implied Volatilities.



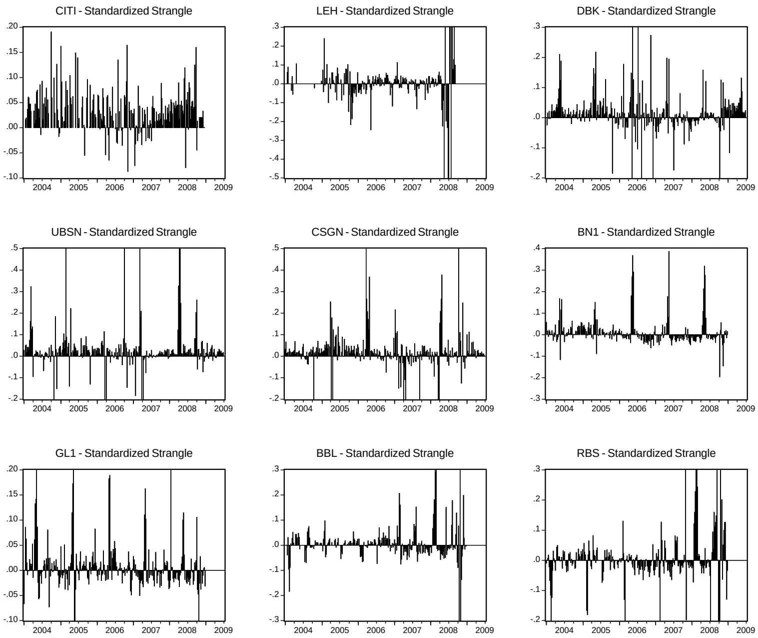
Note. Weekly averages of daily observations.

Figure 2: PDF Standardized Risk Reversal.



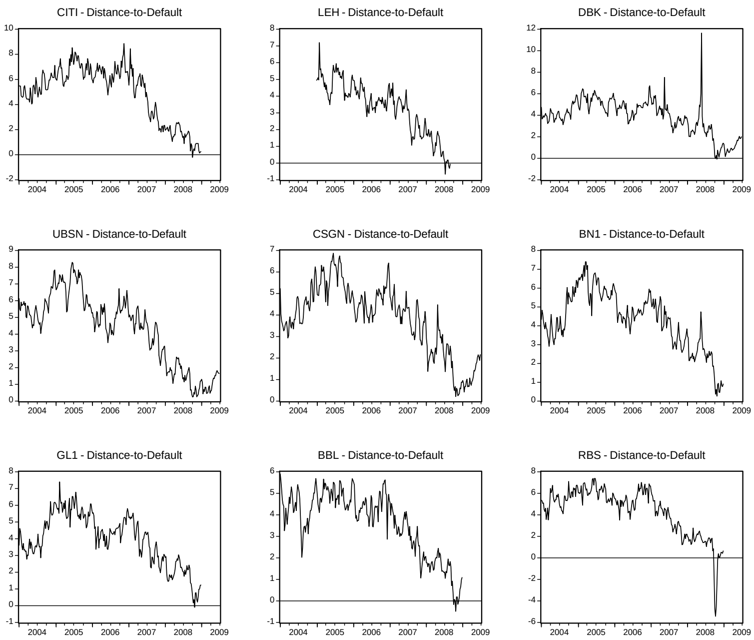
Note. Weekly averages of daily observations.

Figure 3: PDF Standardized Strangle.



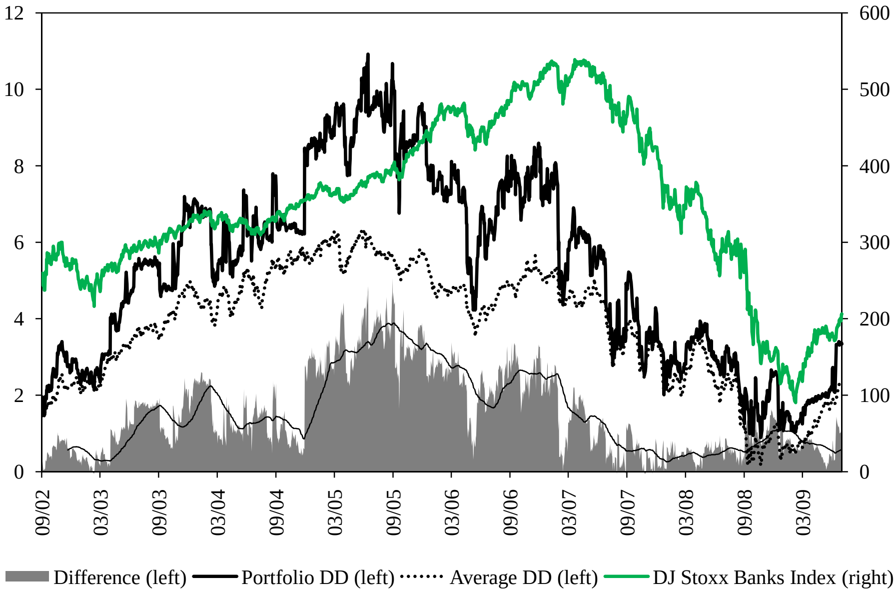
Note. Weekly averages of daily observations.

Figure 4: Distance-to-Default based on Option-implied IV.



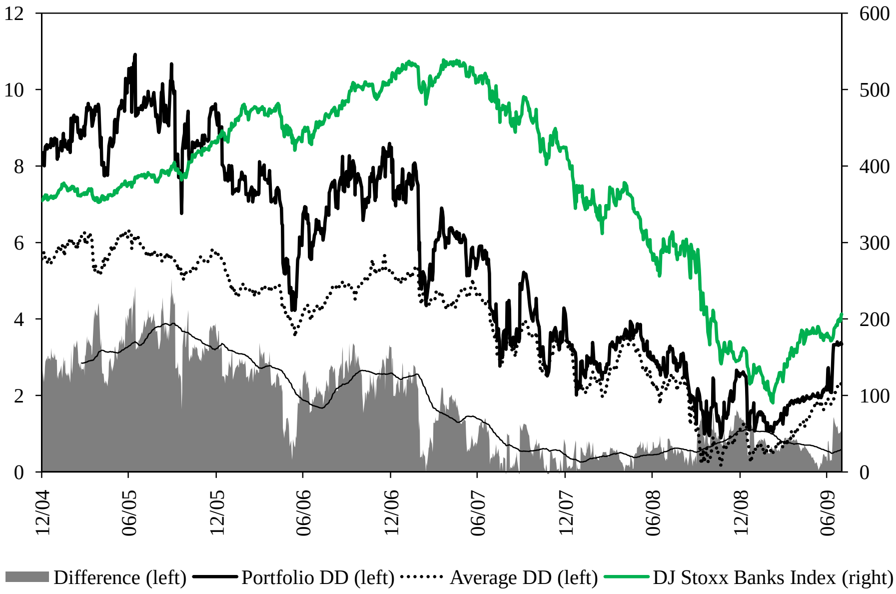
Note. Weekly averages of daily observations.

Figure 5: Forward looking Distance-to-Default series. 30-Sep-2002 - 31-Jul-2009



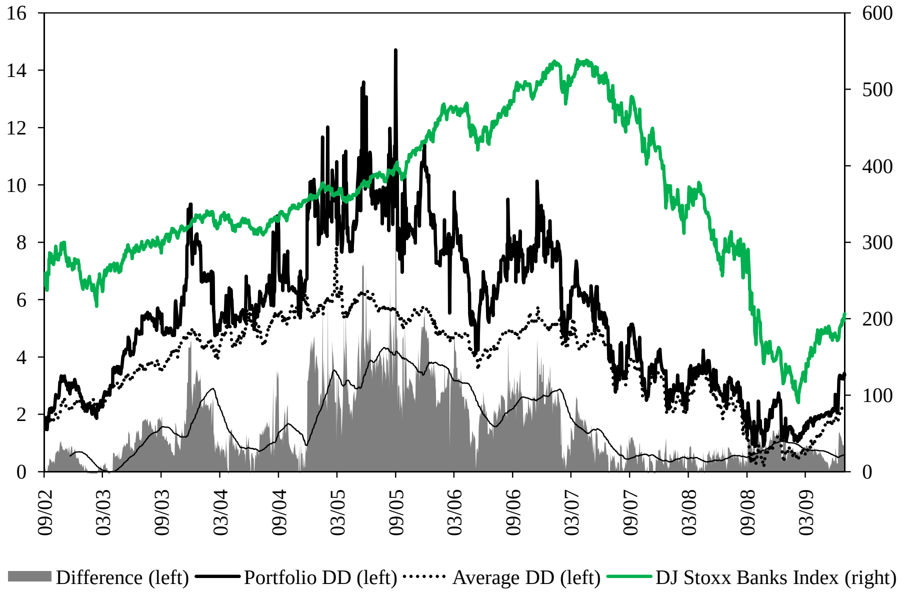
Source. Author's calculations and Thomson Datastream

Figure 6: Forward looking Distance-to-Default series. 31-Dec-2004 - 31-Jul-2009



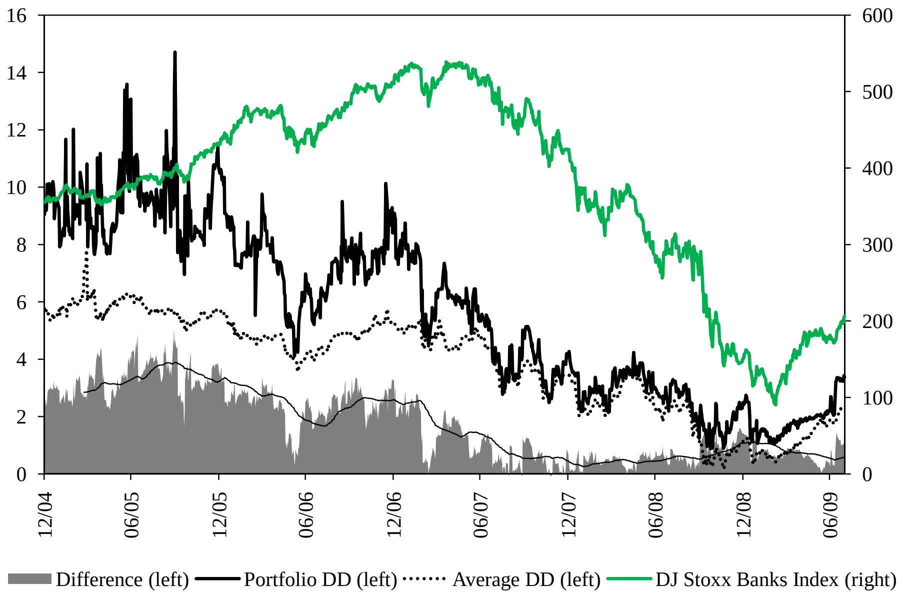
Source. Author's calculations and Thomson Datastream

Figure 7: Put-derived Forward looking DD series. 30-Sep-2002 - 31-Jul-2009



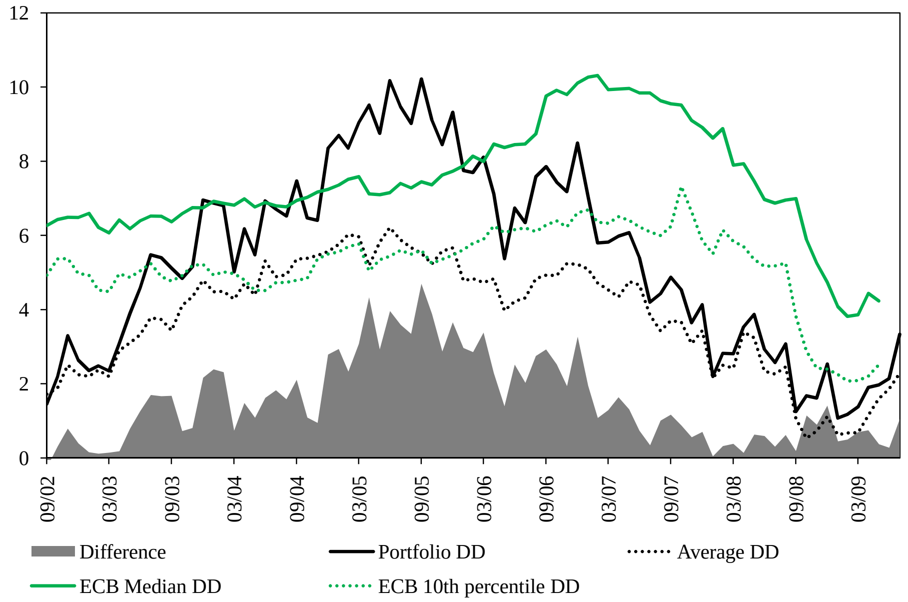
Source. Author's calculations and Thomson Datastream

Figure 8: Put-derived Forward looking DD series. 31-Dec-2004 - 31-Jul-2009



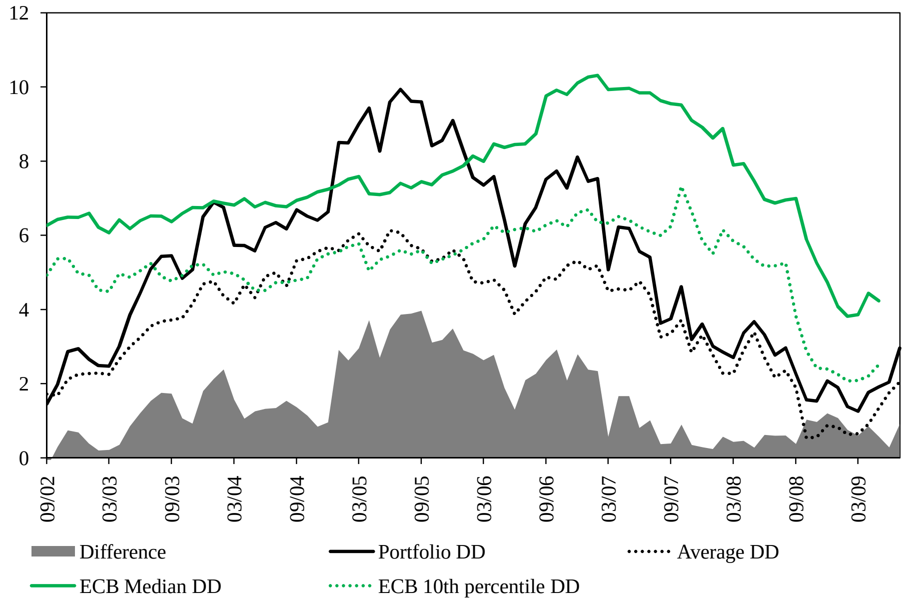
Source. Author's calculations and Thomson Datastream

Figure 9: Forward looking vis--vis historical DD series. End-of-month data.



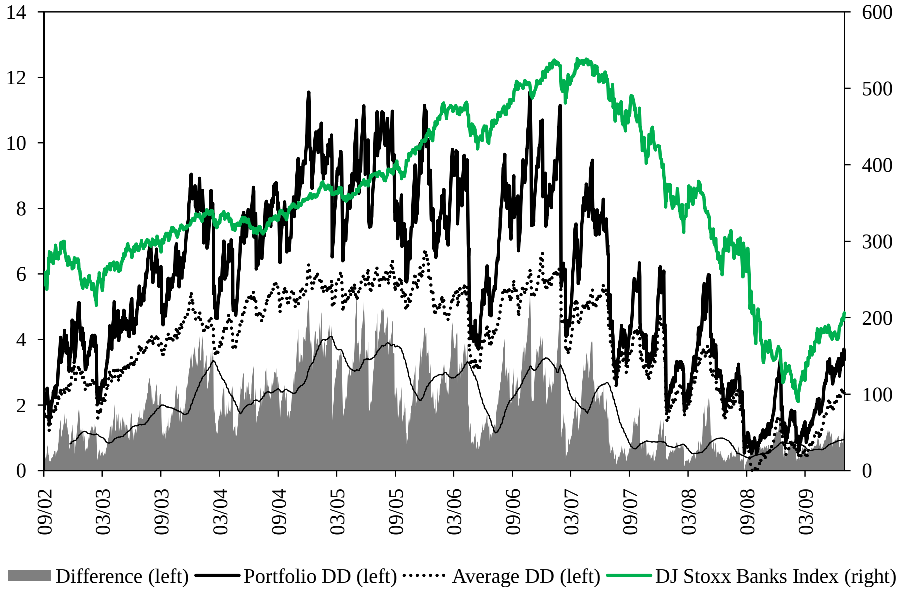
Source. Author's calculations and European Central Bank

Figure 10: Forward looking DD vis--vis historical DD series. Monthly averages.



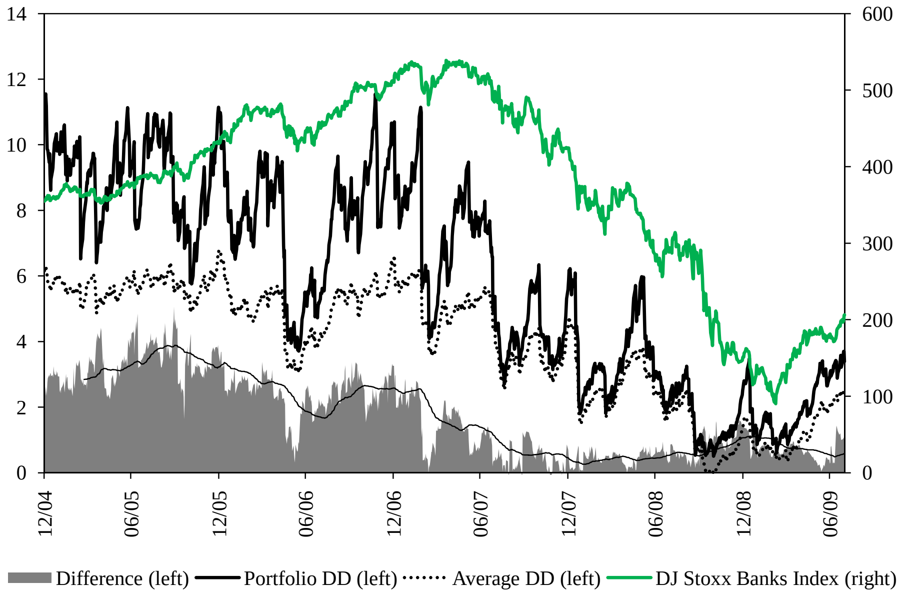
Source. Author's calculations and European Central Bank

Figure 11: GARCH(1,1)-derived DD series. 30-Sep-2002 - 31-Jul-2009



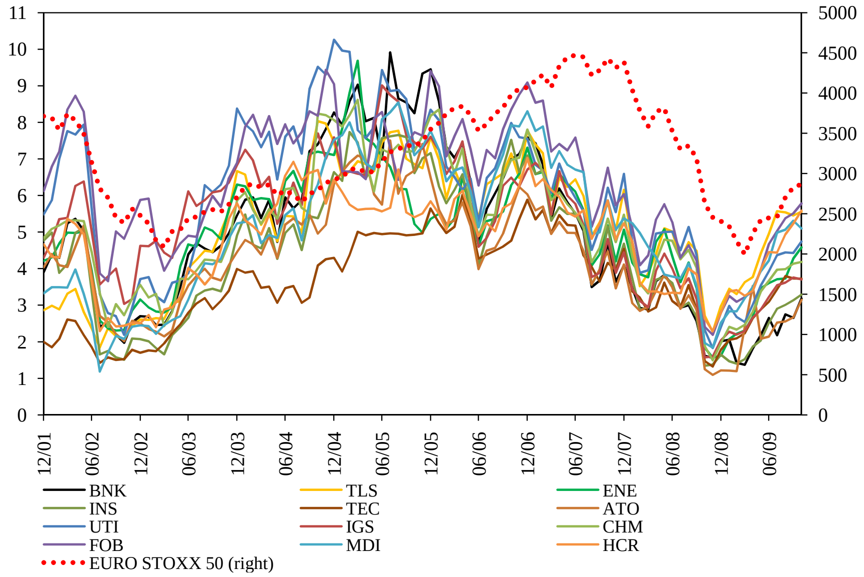
Source. Author's calculations and Thomson Datastream

Figure 12: GARCH(1,1)-derived DD series. 31-Dec-2004 - 31-Jul-2009



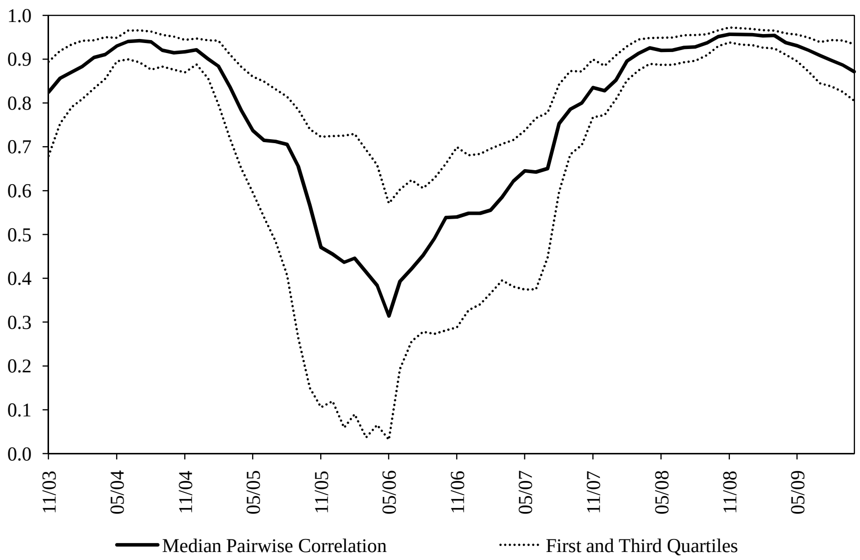
Source. Author's calculations and Thomson Datastream

Figure 13: Sectoral Distance-to-Default Series. December-2001 - October-2009



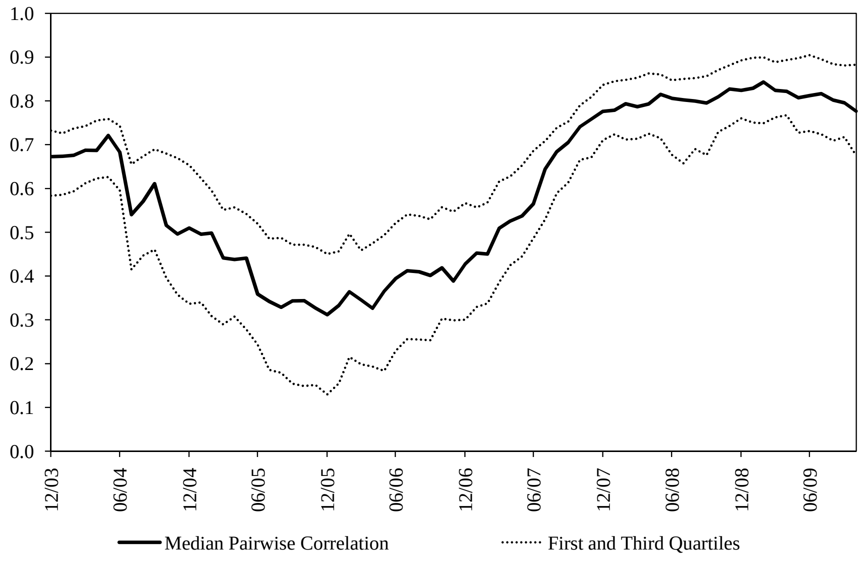
Source. Author's calculations.

Figure 14: Sectoral DD Series Pairwise Correlation



Source. Author's calculations. Correlation is calculated using a 24-month moving window.

Figure 15: Sectoral DD Series Pairwise Correlation (series in first differences)



Source. Author's calculations. Correlation is calculated using a 24-month moving window of series in first differences.

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