EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 1574 / AUGUST 2013

A MARKET-BASED APPROACH TO SECTOR RISK DETERMINANTS AND TRANSMISSION IN THE EURO AREA

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The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).

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Acknowledgements

The author is grateful to António Antunes, Diana Bonfim, Jörg Breitung, Ben Craig, Frank De Jonghe, Olivier De Jonghe, Jonas Dovern, Salvatore Dell'Erba, Dries Heyman, Peter Pedroni, Ivan Petrella, Andreas Pick, Nuno Ribeiro, Paulo Rodrigues, Elisa Tosetti, Rudi Vander Vennet and participants at the XX International Tor Vergata Conference on Money, Banking and Finance, the 24th Australasian Finance & Banking Conference and at seminars at Banco de Portugal, Bank of England and Banco Central de Chile for helpful comments and suggestions. The views expressed in this paper as those of the author and do not necessarily reflect those of Banco de Portugal or the Eurosystem. All remaining errors those of the author.

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ISSN	1725-2806 (online)
EU Catalogue No	QB-AR-13-071-EN-N (online)

Abstract

In a panel data framework applied to Portfolio Distance-to-Default series of corporate sectors in the euro area, this paper evaluates systemic and idiosyncratic determinants of default risk and examines how distress is transferred in and between the financial and corporate sectors since the early days of the euro. This approach takes into account observed and unobserved common factors and the presence of different degrees of cross-section dependence in the form of economic proximity. This paper contributes to the financial stability literature with a contingent claims approach to a sector-based analysis with a less dominant macro focus while being compatible with existing stress-testing methodologies in the literature. A disaggregated analysis of the different corporate and financial sectors allows for a more detailed assessment of specificities in terms of risk profile, i.e. heterogeneity of business models, risk exposures and interaction with the rest of the macro environment.

JEL classification: G01, G13, C31, C33.
Keywords: Macro-prudential Analysis; Portfolio Credit Risk Measurement; Common Correlated Effects; Contingent Claims Analysis.

Non-technical Summary

The study of interactions and feedback effects between the financial system and the real economy is among the most challenging topics of research on financial stability. Along these lines, this paper presents a framework to analyze distress risk in the financial sector and the non-financial corporate sectors in the euro area. The analysis takes into account their strong sectoral linkages and co-movement across sectors.

In the first part, the paper describes a methodology to compute forward-looking risk indicators at sector-level based on Contingent Claims Analysis with information from balance sheets and prices of stock indices and index options. A sector-wide analysis for the euro area, as opposed to a country-based analysis, emphasizes the increasing degree of integration in financial markets due to the introduction of the euro and also a greater Europeanization of corporate and financial activities.

The second part of the paper analyzes the properties of the resulting Portfolio Distance-to-Default series and sets up an econometric model that incorporates the cross-section dependence of sectoral risk. Cross-section dependence features in the data as a result of the effect of unobserved common factors at place, such as the macroeconomic and financial conditions or unobserved risk spillovers originated in the various forms of "economic proximity". The results show that distress risk in the corporate sector comprises a stationary idiosyncratic component and a non-stationary common factor, which flows around a long-run equilibrium, with temporary deviations caused by shocks in the macro-financial environment, at sector-specific level or as a result of the interplay between sectors.

The econometric results find evidence supporting a more relevant role of sector-specific variables as sectoral risk determinants in the overall corporate sector at the expense of the direct impact from macro-financial variables. The macroeconomic and financial common variables are captured as unobserved common effects, averaged out by heterogeneous affects across sectors 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 interactions. The paper also shows that the effect and magnitude of risk drivers across sectors is highly heterogeneous and that this feature should be taken into account for policy purposes, e.g. the design of stress testing analytical tools.

1. Introduction

Due to the financial and economic crisis that 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 addresses 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 (10 supersectors), 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 the Common Correlated Effects (CCE) estimator from Pesaran (2006) is provided, allowing to study the determinants and 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.

The results show first 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 equilibrium. 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.

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 include in their 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 financial 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 is 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), which provide an additional motivation to this study.

Additionally, the dimension limitations of a traditional VAR model leaves some unobserved effects unaccounted for (Alves, 2005). In a 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 risk transmission between the components of the financial sector (banks and insurance) and additional non-financial corporate sectors and within the non-financial sector is not directly tackled, leaving an important source of risk to be further analyzed.

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, op-

[1]The authors use backward-looking Distance-to-Default series computed for a very large number of individual institutions and aggregate them into series of weighted averages and lower quantiles to compute systemic wide forecasts.

tion prices information. These series become forward-looking and allow for a wide range of stress-testing exercises. 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 rest of this paper is structured as follows. Section 2 introduces the sector-level risk indicator and the methodology to compute it for aggregate sectors. Section 3 describes the sample of sectors and companies included in the analysis and the properties of the sectoral risk indicators. Section 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 5 and Section 6 concludes.

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 balance sheet information of individual companies by sector and market information of their corresponding indices. 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).

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 increasing asset volatility. 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.

[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.

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 contains 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, 2004).

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 unweighed average of DD or EDF series[4] for a large and changing sample of companies. This methodology produces an indicator that highlights the intensity and 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 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 (2009); De Nicolò and Tieman (2007); Mühleisen *et al.* (2006); Echeverría *et al.* (2009); De Nicolò *et al.* (2005) and Saldías (2012). This methodology treats the set of companies by sector as a single entity, it aggregates balance sheet and market data and incorporates the assumed portfolio 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

[3]These assumptions are concerned mainly with those inherent in the Merton-based model (e.g. log-normal distribution of assets, constant asset volatility, etc.) 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.

it does not only capture company size but also interdependencies among the portfolio constituents. It may be considered as 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 and correlation are higher. This feature illustrates quick reaction of the indicator to market events and shows the generalized increase in returns covariance in a sector during distress times, even if fundamentals of portfolio constituents may be solid. Aggregated company fundamentals embedded in the indicator are informative of longer-term trends of sectoral risk (see Saldías (2012) for an extensive discussion).

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 (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 vis-à-vis grouping at Industry level and it is narrow enough not to blur interactions among them, as it is the case at Sector level. An additional and very important reason for this

[5] This paper does not include average DD series computed using option price information as described in Saldías (2012) 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.

[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.

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 C and E describe in detail the company sample by portfolio and all additional assumptions made to ensure the portfolios' accuracy, including exclusions and ad-hoc reclassifications.

3. Sample and Preliminary Analysis

The sample consists of 12 out of the 19 EURO STOXX Supersectors[8]. These sectors are the most relevant by different measures of size, e.g. assets, market value, employment. They have been included in the sample 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[9]; and 2) stock market capitalization of the their corresponding Supersector STOXX Indices at Deutsche Boerse. Table 1 briefly lists them and provides relevant market information.

[Insert Table 1 here]

The dataset comprises monthly observations between December 2001 and October 2009 (95 observations per 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

[8]The remaining seven sectors are Construction & Materials, Travel & Leisure, Personal & Household Goods, Financial Services, Retail, Basic Resources and Real Estate. They were left out of the sample because of two reasons. First, their options series start late in the sample and are comparatively less liquid, with several months without reported trading. In addition, there are breaks in the data. For instance, the STOXX indices shifted methodology from Dow Jones Global Classification Standard to Industry Classification Benchmark (ICB)in September 2004, affecting the composition of the Personal & Household Goods and Travel & Leisure Supersectors and making their corresponding DD series not comparable. In addition, the Real Estate Supersector was elevated to Supersector in 2008, after having been part of the Financial Services Supersector, which constitutes another break in the data.

[9]The DD series were initially 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.

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 as a whole and they provide a first tentative and equity-driven explanation to strong comovement of the series over time, as can be seen in Figure 1.

[Insert Figure 1 here]

Figure 1 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, 2012). 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 2 and 3 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 2 and 3 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 pattern 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 2 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 2 here]

In addition to strong comovement and high correlation among the series, the results in Table 2 suggests that it is very likely to have both observable and unobservable common factors 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 diffusion 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[10]. 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. 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 2 and Appendix A.

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) and further extended in Pesaran and Tosetti (2011) and Chudik *et al.* (2011). 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 (Pesaran and Tosetti, 2011; Chudik *et al.*, 2011). The CCE method also tackles methodological limitations of other

[10] 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.

econometric models when modelling 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 consistent 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 2 and 3.

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

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

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 observed common factors that capture common macroeconomic and financial 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 "neighboring sectors" and other sector-specific variables. All coefficients are allowed to be heterogeneous across sectors[11] 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.

4.1. Macroeconomic and Financial Risk Determinants

A set of five exogenous 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 1 have doc-

[11] 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 distress of corporate sectors, which are defined using the European classification of economic activities (NACE).

umented 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.

The model takes macrofinancial determinants as exogenous and chooses to ignore possible feedback effects to the macrofinancial environment. Examples of this approach and additional explanation for this modelling 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 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 tends to increase with market pessimism, therefore its relationship with DD series is expected to be negative.

4.2. Sector-specific Risk Determinants

4.2.1. Sector-specific Risk Determinants

The model includes four other sector-specific regressors computed for each ICB Supersector Index[12], namely: 1) the annual rate of change of the Price-Earnings Ratio, ΔPE_t; 2) the annual rate of change in Dividend Yields, ΔDY_t, 3) the Return On Assets, $ROA_{i,t}$; and 4) the monthly log excess return on each index's daily price return relative to the EURO STOXX 50 Index, $EXRET_{i,t}$.

Earnings, as measured by Price-Earnings Ratio, and profitability, as measured by ROA, 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). Return

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

On Assets (ROA) incorporates further information about profitability and the ability of the companies in a given sector to generate returns. Dividends traditionally serve to assess and infer corporate performance. Recent work by Charitou *et al.* (2011) 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). Excess returns are a purely market-based measure of relative performance at aggregate level and is motivated by results in Campbell *et al.* (2008).

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.*, 2004).

4.2.2. Neighboring Sectors' Risk Spillovers

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

$$\overline{DD}_{i,t}^{n_i} = \frac{1}{n_i} \sum_{j=1}^{n} DD_{j,t} \tag{2}$$

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

For each sector i, the number of neighbors and weighting of their corresponding DD series are determined by a contiguity matrix (see Table 3) derived from ad-hoc and predefined neighborhood linkages among sectors[13]. Even though the definition of neighboring 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.*, 2011), 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, 2012).

[13]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 neighbors and 0 otherwise. The number of neighbors 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.*, 2011) 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.

In the case of corporate sectors, the literature does not provide a definite metric to determine neighborhood linkages, because sectoral relationships depend both on the choice of sector classification and on the sectoral characteristics to be linked[14]. 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 overlapping dimensions of sectoral interdependencies, 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. 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 3 here]

5. Empirical Results

5.1. Cross-section Dependence and Non-stationarity Analysis

Preliminary analysis in Section 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

[14] 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 (2012) use input-output linkages and analyze the shock propagation across manufacturing sectors.

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[15].

Table 4 reports CD statistics of residuals from ADF(p) regressions of the DD series and the sector-specific variables, including the neighboring sectors' DD series ($\overline{DD}_{i,t}^{n}$). Results detect that DD series and the $\overline{DD}_{i,t}^{n}$ present very high and positive average correlation coefficients, above 60%, whereas correlation for dividend yields' growth and Returns On Assets are also large but in the range of 25% - 40%. Price-Earnings ratio growth show very low correlation across sectors, with a coefficient of around 3%. Excess returns relative to the benchmark index also shows a low, though negative average correlation coefficient of -4% on average. CD test statistics, reported below, are in line with these results and are highest for DD series and neighboring effects, and smaller yet significant for the rest of the variables. These tests confirm the strong cross-section dependence in the data, with arguably the exception of Price-Earnings ratio growth and the relative indexes' excess return.

[Insert Table 4 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 cross-dependence. Accordingly, Table 5 summarizes the CIPS panel unit root tests described in Appendix B.2. IPS test statistics are also reported for robustness check and comparison. Both CIPS and IPS tests reject unit roots in dividend yields' growth, Price-Earnings ratio growth and excess returns and do not reject the null in the case of ROA. Interestingly, the CIPS strongly reject unit roots in the case of DD series and neighboring 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 $I(0)$. These tests also point out to the combination of non-stationary common factors and stationary idiosyncratic components in the sectoral risk[16]. ROA is taken as $I(1)$ and enters the model in first differences.

[15] See Appendix B for technical details of the tests described in this subsection.

[16] The non-stationarity detected in DD series and DD-neighbors using IPS tests comes from the combination of non-stationary common factors and stationary idiosyncratic components. This possibility has been verified by adopting the Panel Analysis of Nonstationarity in the Idiosyncratic and Common components or PANIC approach advanced by Bai and Ng (2004). 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 environment and the cross-sectoral dynamics captured by the CCE method.

Finally, individual ADF(p) unit root tests were run for the macro-financial variables described in Section 4.1 which enter the model as exogenous regressors. Based on the results of these tests reported in Table 6, 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 Tables 5 and 6 here]

5.2. Model Estimation

The results from estimation of Equation (1) are reported in Table 7. Columns [1] to [3] are estimates of naïve OLS Mean Group (MG) models (Pesaran and Smith, 1995) that neglect cross-section dependence (CD). Columns [4] to [6] are Common Correlated Effects (CCE) estimates of these same model specifications, hence more suitable to the CD 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 7 here]

The most relevant finding from the estimation results is the limited relevance of shocks originated in the macroeconomic and financial environment on DD, especially when CD is accounted for. This result has several interpretations and does not necessarily mean that sectoral risk is not affected by the macro-financial environment. First, business cycle volatility is likely to be smoothed out in the construction of DD series or other CCA risk measures (especially EDF). Indeed, as suggested in International Monetary Fund (2011), some high-frequency indicators of distress have the ability to anticipate the cycle, which is very likely in the case of instruments derived from equity and option markets[17]. Marked-based indicators, such as DD, may also be less directly responsive due to non-linearities in their interactions with macroeconomic and financial variables (Sorge and Virolainen, 2006). In addition, 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). Lastly, even

[17]To test this hypothesis, I conducted a simple Granger-causality test using the industrial production growth (PI_t) and the average of DD series and found that indeed the DD series Granger-causes changes in activity up to one trimester.

though sector-specific coefficients may have individual statistically significant signs, they are allowed to be heterogeneous across sectors and the effect across the panel members may be averaged out (Eberhardt and Teal, 2010).

In particular, 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 its effect on overall sectoral risk vanishes. 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 very 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 becomes nil when CD is considered, probably because the unobserved common factors capture it. This result is at odds with findings in Åsberg and Shahnazarian (2009)[18], 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) do not exert any statistically significant effect but in equation [3], when CD is omitted, and none when CD is taken into account. The first result is not entirely at odds with the literature, as Alves (2005) finds that oil prices do not affect but one of the seven sectors he includes in his study. Shocks from industrial

[18] In this paper, the authors analyze effects of macroeconomic shocks on the the median EDF of the whole corporate sector in Sweden in a VEC 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.

production growth (PI_t) are insignificant on DD even when CD is neglected, 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 sector-specific regressors are included in the MG model in two of three cases when CD is controlled for. Its corresponding coefficient equation [6] exerts a positive coefficient. Again, the changing statistical significance in the MG models is a sign of specification failure to account for unobserved common factors appropriately. In turn, lack of statistical significance of these variables with CCE estimates show that the macro-financial effects are very likely to be captured either by the unobserved common effects and/or the set of sector-specific variables more accurately.

Sector-specific regressors on DD display better results in terms of stable and strong statistical significance under CD, which challenges the macro dominant focus in the existing literature of financial stability and highlights the importance of market-based and sector-level information and interactions for policy analysis of systemic risk. Among the set of six sector-specific covariates, the market-based indicators show stronger relevance as distress drivers than those computed using balance-sheet information under alternative econometric methods. In particular, dividend yields' growth ($\Delta DY_{i,t}$) does poorly and shows no statistical significance in all models. The Return On Assets ($\Delta ROA_{i,t}$) and Price-Earnings Ratio, ΔPE_t, show expected positive signs in MG models, equations [2] and [3], but become insignificant when the CCE method is applied, in line with findings in Bernoth and Pick (2011).

Two sector-specific and market-based variables show strong and significant effects regardless the econometric method used, which can be interpreted as evidence of the relevance of market-based information about distress beyond common observed risk drivers. The distress risk persistence, as proxied by the lag of the dependent variable $DD_{i,t-1}$, shows a large and significant positive sign across all models. The CCE estimates show however smaller coefficients as additional regressors are included in the specifications. These 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 illustrates the persistence in idiosyncratic sectoral risk even after controlling for CD. With more economic relevance, the sectoral indices' excess return relative to the EURO STOXX 50 Index, $EXRET_{i,t}$, exerts strong effects on sector-wide distress. This variable shows a positive and significant coefficient sign across all model specifications, illustrating that outperforming sectors relative to the corporate sector as a whole results in higher resilience and thus lower distress risk.

Finally, the neighboring sectors' risk lagged effect on DD[19], $\overline{DD}^{n}_{i,t-1}$, is statistically insignificant in the CCE-estimated model, while MG estimates in Model [3] do exhibit a positive coefficient. 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 is also possible that the ad-hoc definition of neighboring sectors is not sufficiently accurate and other sectoral dimensions than those described in Section 4.2.2 need to be explored to obtain a more reliable contiguity matrix in terms of direct spillovers[20].

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 8 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.

[Insert Table 8 here]

At individual Supersector level, some macro-financial variables do affect DD series but not necessarily with the same sign. As in the aggregate results, oil (OIL_t) and consumer prices (CP_t) are the only macroeconomic variables that fail to show also at individual level any effect on sectoral risk. Interest rates ($R3M_t$) do play a significant role as proxy of borrowing costs and risk premia for the Media (MDI) supersector (-0.502), while shocks from industrial production growth (PI_t) exert a surprisingly negative effect on the idiosyncratic component of risk in the Telecommunications (TLS) supersector (-0.027). The significance of the VIX Index (VIX_t) on distress in the Automobiles & Parts and Industrial Goods & Services sectors with alternating signs, -0.133 and 0.029, respectively, illustrate the possibility of heterogeneous responses at individual level and nil effect on the average.

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

[20] Robustness checks have been conducted using matrices of return and volatility spillovers according to the methodology described in Diebold and Yilmaz (2012) to construct the contiguity matrices. The results did not change for all models' specifications.

As for the sector-specific variables, dividend yields growth, ΔDY_t, and Price-Earnings Ratio growth, ΔPE_t, and Return On Assets ($\Delta ROA_{i,t}$) affect also heterogeneously across Supersectors. For instance, the coefficients associated to dividend yields are significant and surprisingly positive in the Telecommunications and Media sector. Price-Earnings Ratio and Return On Assets growth affects only the Food & Beverages sector with expected positive signs while being 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 no exceptions, while the sectoral indices' excess returns, $EXRET_{i,t}$, are significant for half of the sectors in the sample, with a positive sign in all cases. Finally, the lagged neighboring risk effect, non-significant overall, is a risk driver in two Supersectors, Telecommunications and Media, with positive signs in both cases.

Finally, the econometric estimates worth mentioning is the higher goodness-of-fit of CCE estimates, as measured by the lower Root Mean Squared Errors across all model specifications. As it might be expected, the cross-section dependence test statistics reported below display a remarkable decline when the CCE estimator is applied and there is no significant evidence of remaining CD in the estimation residuals[21]. 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[22]. Finally, the serial correlation tests show that residuals from all estimated models are stationary both individually and jointly.

5.3. Robustness check

Column [7] in Table 7 reports results of a robustness check of model [6] using the Augmented Mean Group (AMG) estimator, which shows very similar properties to CCE and account for cross-section dependence by inclusion of a preassumed single "common dynamic process" in the sector regressions imposed with unit coefficient. AMG estimates provide an alternative estimator under CD and obtain an explicit estimate for the unobserved factors. This estimator has been developed in Eberhardt and Bond (2009) and Eberhardt and Teal (2010) to deal with macro panels and been applied to estimate Total

[21]The CD_P remains high enough not to reject the null of CD at 5%. This is due to the large time series dimension compared to the number of cross-section units.

[22]Although not reported, a closer look at bilateral residual correlations confirms this feature and that this sum drives the value of the statistic, given that $\sqrt{\frac{2T}{N(N-1)}} \approx 1$.

Factor Productivity (TFP) in cross-country production functions (Eberhardt and Teal, 2010) where TFP is the single common dynamic factor.

In our case, there are no priors to assume there is only one common factor driving the idiosyncratic sectoral risk but this exercise serves to stress the robustness of the results in the previous section. The estimates provide support to the previous results in terms of the statistical significance of the lag of the dependent variable $DD_{i,t-1}$, and the sectoral indices' excess return, $EXRET_{i,t}$. In contrast to CCE estimates, the neighboring sectors' risk lagged effect also appears relevant, with a negative coefficient, pointing out to a competing nature of the relationships between sectors. Interestingly, three macroeconomic variable also show statistical significance, namely the shocks from oil prices, industrial production and consumer prices. Overall, these estimates confirm the CCE results, although their goodness-of-fit is relatively lower and the residuals present some degree of serial correlation.

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-Default 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-Default 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, averaged out by heterogeneous affects across sectors 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.

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Tables and Figures

Table 1: 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

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 2: Preliminary Cross-section Dependence Analysis - DD Series

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

Notes: $\bar{\rho}$ and CD_P are computed as detailed in Section B.1 using residuals of regressions on a sector-specific intercept. * indicates the series show cross-section dependence at 5% level.

Table 3: 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: Supersector codes are in Table 1. If element $i, j = 1$, the supersectors in row i and column j are considered neighbours. See Section 4.2.2 for more details.

Table 4: 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
$EXRET_{i,t}$	-0.046	-0.045	-0.040	-0.039	-0.040	-0.038	-0.039
$ROA_{i,t}$	0.266	0.267	0.266	0.265	0.266	0.264	0.246
$\overline{DD}^{n}_{i,t}$	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*
$EXRET_{i,t}$	-3.6*	-3.5*	-3.1*	-3.0*	-3.1*	-2.9*	-3.0*
$ROA_{i,t}$	20.9*	20.9*	20.7*	20.5*	20.5*	20.2*	18.7*
$\overline{DD}^{n}_{i,t}$	56.4*	56.0*	56.0*	55.6*	55.4*	55.2*	54.1*

Notes: pth-order Augmented Dickey Fuller ADF(p) regressions are computed for each Supersector i without cross-section augmentations and for lag orders $p = 0, \dots, 6$ over the whole sample. 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 5: 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***
$EXRET_{i,t}$	-6.18***	-6.06***	-5.00***	-4.57***	-4.31***	-4.14***	-3.90***
$ROA_{i,t}$	-1.49	-1.75	-1.90	-2.24**	-2.31**	-2.36**	-2.28**
$\overline{DD}^{n}_{i,t}$	-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***
$EXRET_{i,t}$	-25.76***	-20.4***	-14.62***	-12.03***	-11.35***	-10.69***	-10.06***
$ROA_{i,t}$	1.79	1.38	1.23	-0.09	-0.26	-0.26	-1.87***
$\overline{DD}^{n}_{i,t}$	-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 6: 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 7: Estimation Results

Dependent Variable $DD_{i,t}$	MG [1]	MG [2]	MG [3]	CCEMG [4]	CCEMG [5]	CCEMG [6]	AMG [7]
Intercept	**0.481****	**0.701****	**0.487****	-0.058	0.024	-0.128	**5.403****
	(0.068)	**(0.134)**	**(0.206)**	(0.136)	(0.164)	(0.156)	**(0.222)**
ΔVIX_t	**-0.083****	**-0.083****	**-0.085****	-0.000	-0.004	-0.004	0.001
	(0.005)	**(0.005)**	**(0.006)**	(0.004)	(0.004)	(0.004)	(0.007)
$\Delta R3M_t$	**0.670****	**0.691****	**0.678****	-0.010	-0.038	-0.066	0.024
	(0.103)	**(0.101)**	**(0.103)**	(0.095)	(0.088)	(0.088)	(0.119)
ΔOIL_t	-0.004	-0.006	**-0.007***	0.000	-0.002	-0.003	**0.111****
	(0.004)	(0.004)	**(0.004)**	(0.003)	(0.003)	(0.004)	**(0.003)**
ΔPI_t	0.000	0.003	-0.002	-0.000	0.001	-0.001	**0.094****
	(0.001)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	**(0.009)**
ΔCP_t	**-0.025***	-0.038	-0.011	0.014	-0.003	0.001	**-0.423****
	(0.011)	(0.026)	(0.032)	(0.021)	(0.017)	(0.017)	**(0.031)**
$\Delta DY_{i,t}$		0.001	0.001		-0.001	-0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)	(0.002)
$\Delta PE_{i,t}$		0.001	**0.002***		0.001	0.000	0.000
		(0.001)	**(0.001)**		(0.001)	(0.001)	(0.003)
$EXRET_{i,t}$		**2.365****	**2.275****		**2.145****	**2.235****	**3.118****
		(0.486)	**(0.478)**		**(0.455)**	**(0.485)**	**(0.626)**
$\Delta ROA_{i,t}$		**0.175****	**0.241***		0.079	0.079	0.062
		(0.072)	**(0.133)**		(0.064)	(0.069)	(0.045)
$DD_{i,t-1}$	**0.921****	**0.883****	**0.767****	**0.740****	**0.668****	**0.652****	**0.417****
	(0.008)	**(0.019)**	**(0.035)**	**(0.042)**	**(0.046)**	**(0.047)**	**(0.076)**
$\overline{DD}^n_{i,t-1}$			**0.141****			0.050	**-0.479****
			(0.035)			(0.037)	**(0.088)**
Observations	1128	1072	1072	1128	1072	1072	1072
$RMSE$	0.562	0.507	0.496	0.360	0.328	0.323	0.438
$\bar{\rho}$	0.424	0.429	0.424	-0.082	-0.080	-0.078	-0.034
CD_P	$33.40^{\ddagger}$	$37.78^{\ddagger}$	$31.50^{\ddagger}$	$-6.48^{\ddagger}$	$-6.07^{\ddagger}$	$-5.89^{\ddagger}$	-2.51
$AR(1)$	$7.396^{\dagger}$	$5.482^{\dagger}$	$7.044^{\dagger}$	1.370	2.129	2.188	$13.128^{\dagger}$

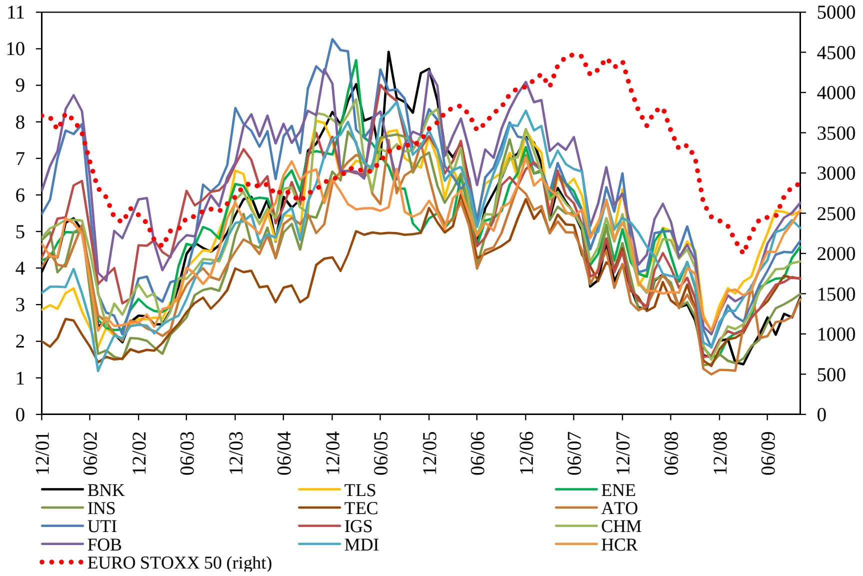
Notes: MG, CCEMG and AUG stand for Mean Group (Pesaran and Smith, 1995), Common Correlated Effects Mean Group (Pesaran, 2006) and and the Augmented Mean Group (Eberhardt and Teal, 2010; Eberhardt and Bond, 2009) estimates respectively. Standard errors are given in parenthesis. *,** denotes significance at 10% and 5%, respectively. CD statistics ($\bar{\rho}$ and CD_P) and panel unit root tests are computed on residuals of each equation. See Appendix B.1 for definitions of the cross-section dependence tests. ‡ indicates rejection of the null hypothesis of cross-section independence at 5% significance level. † indicates rejection of the null of no first-order autocorrelation test described in Drukker (2003).

Table 8: CCE Estimates of all Cross Section Units

$DD_{i,t}$	ICB Supersector											
	BNK	TLS	ENE[(a)]	INS	TEC	ATO	UTI	IGS	CHM	FOB	MDI	HCR
Intercept	**-1.007****	0.175	-0.206	-0.444	-0.095	**-0.726****	-0.394	0.071	-0.213	0.497	-0.227	**1.035****
	(0.480)	(0.346)	(0.642)	(0.367)	(0.213)	**(0.396)**	(0.466)	(0.318)	(0.381)	(0.451)	(0.274)	**(0.456)**
ΔVIX_t	0.010	-0.005	-0.01	0.003	-0.006	**-0.033****	-0.023	**0.029****	-0.006	0.003	0.000	-0.004
	(0.018)	(0.013)	(0.013)	(0.012)	(0.011)	**(0.016)**	(0.018)	**(0.014)**	(0.014)	(0.018)	(0.012)	(0.014)
$\Delta R3M_t$	0.000	0.307	0.000	0.000	-0.022	0.099	0.484	-0.466	0.263	-0.106	**-0.502***	0.305
	(0.000)	(0.301)	(0.000)	(0.000)	(0.250)	(0.366)	(0.431)	(0.313)	(0.334)	(0.43)	**(0.284)**	(0.324)
ΔOIL_t	-0.006	0.01	0.000	-0.015	0.011	-0.010	-0.020	0.005	0.021	-0.022	-0.005	0.000
	(0.013)	(0.01)	(0.000)	(0.010)	(0.009)	(0.013)	(0.015)	(0.011)	(0.012)	(0.015)	(0.010)	(0.011)
ΔPI_t	0.017	**-0.027****	-0.012	0.016	-0.005	-0.008	0.000	0.009	-0.001	-0.009	0.001	0.004
	(0.014)	**(0.014)**	(0.020)	(0.015)	(0.009)	(0.015)	(0.000)	(0.014)	(0.013)	(0.018)	(0.010)	(0.012)
ΔCP_t	0.000	0.000	0.038	0.018	0.002	0.140	0.115	-0.052	0.000	0.105	-0.004	0.000
	(0.000)	(0.000)	(0.111)	(0.067)	(0.066)	(0.103)	(0.118)	(0.076)	(0.000)	(0.115)	(0.069)	(0.000)
$\Delta DY_{i,t}$	0.002	**0.002***	-0.001	-0.003	0.001	-0.001	-0.001	-0.003	-0.002	0.000	**0.003***	-0.004
	(0.004)	**(0.001)**	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.004)	(0.007)	(0.004)	**(0.002)**	(0.004)
$\Delta PE_{i,t}$	0.003	0.001	0.004	0.000	0.000	0.000	-0.009	0.001	0.000	**0.008****	0.000	0.000
	(0.003)	(0.001)	(0.007)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.003)	**(0.004)**	(0.001)	(0.001)
$EXRET_{i,t}$	0.812	**4.341****	**3.090****	-0.793	**1.732****	**3.488****	**4.813****	2.777	1.136	0.907	1.029	**3.486****
	(1.771)	**(1.205)**	**(1.537)**	(1.238)	**(0.803)**	**(1.336)**	**(2.266)**	(1.779)	(1.935)	(1.895)	(1.396)	**(1.369)**
$\Delta ROA_{i,t}$	0.758	-0.019	0.010	-0.226	0.007	-0.069	0.126	0.104	0.048	**0.231****	0.003	-0.021
	(2.002)	(0.042)	(0.123)	(0.414)	(0.044)	(0.190)	(0.245)	(0.098)	(0.056)	**(0.101)**	(0.038)	(0.029)
$DD_{i,t-1}$	**0.519****	**0.484****	**0.728****	**0.640****	**0.837****	**0.399****	**0.711****	**0.843****	**0.423****	**0.736****	**0.843****	**0.664****
	(0.112)	**(0.103)**	**(0.111)**	**(0.088)**	**(0.061)**	**(0.123)**	**(0.092)**	**(0.122)**	**(0.111)**	**(0.09)**	**(0.055)**	**(0.104)**
$\overline{DD}^n_{i,t-1}$	0.033	**0.199***	-0.216	0.033	0.134	0.054	0.108	0.005	-0.025	0.023	**0.296****	-0.040
	(0.133)	**(0.116)**	(0.232)	(0.077)	(0.142)	(0.091)	(0.119)	(0.371)	(0.124)	(0.136)	**(0.15)**	(0.098)

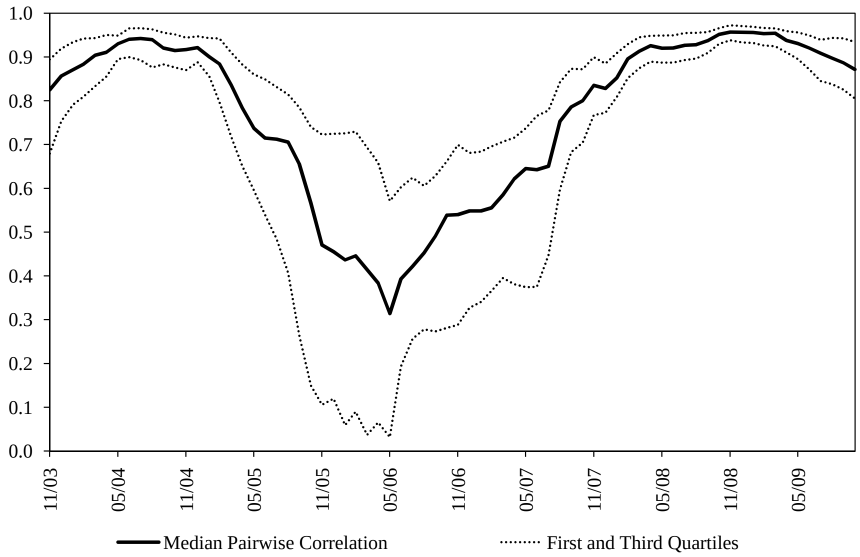
Notes: Individual estimates come from model [6] in Table 7. *,** denotes significance at 10% and 5%, respectively.

Figure 1: Sectoral Distance-to-Default Series. December-2001 - October-2009



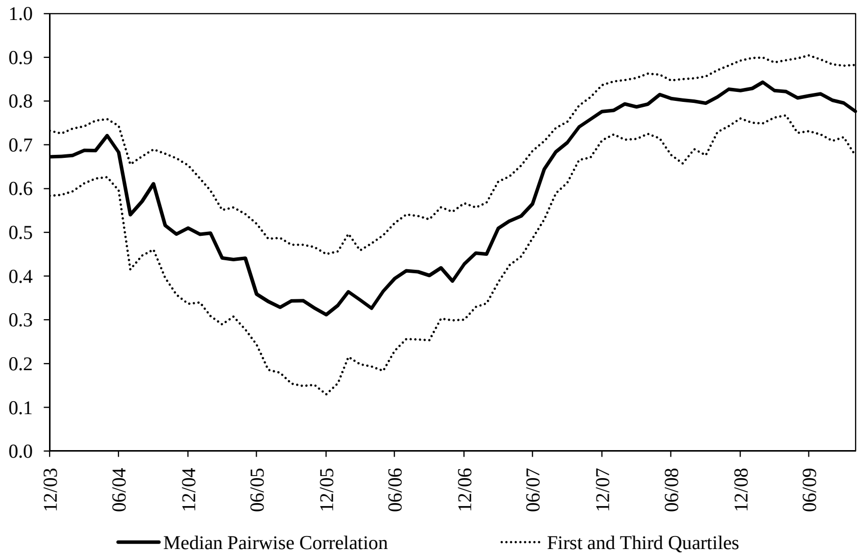
Source. Author's calculations.

Figure 2: Sectoral DD Series Pairwise Correlation



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

Figure 3: 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.

A. Derivation of Portfolio Distance-to-Default

The Portfolio Distance-to-Default treats the portfolio of companies in the sample of each Supersector as a single entity, thus the Merton model assumptions still apply and the calculation method is the same as in the case of a single company with some practical considerations, especially about the difference between the approach in this paper and other applications in the literature, such as De Nicolò *et al.* (2005); De Nicolò and Tieman (2007); Echeverría *et al.* (2006, 2009) and Gray and Malone (2008). As a result, given the three principles in Contingent Claims Analysis (CCA) mentioned in Section 2, the economic value of the portfolio (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).

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

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

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

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

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

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

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

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

The Merton model uses equations (A.2) and (A.5) to obtain the implied portfolio's asset value **A** and volatility σ_A, which are not observable and must be estimated by numerical methods. The portfolio equity volatility σ_E enters as initial value of market value of σ_A in the iteration. The growth rate of the assets in the portfolio is proxied by risk-free interest rate **r** as in Gropp *et al.* (2006) and most papers in the literature. Once a numerical solutions for **A** and σ_A are found, the Portfolio Distance-to-Default DD^P **T** periods ahead is calculated as:

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

D is the total value of the portfolio's risky debt or distress barrier and is obtained by adding up the individual distress barriers across the P constituents in each Supersector, i.e. $D = \sum_{j=1}^{P} D_j$.
r is the instantaneous rate of growth of the portfolio's assets and in general is proxied by a weighted average of individual r_j from government bond yields of each company's home market, i.e. $r = \sum_{j=1}^{P} w_j r_j$. The individual weights w_j are obtained from estimates of implied assets A, thus $w_j = \frac{A_j}{A}$. In this paper, r is proxied by the Eurozone synthetic 10-year government bond yield.
The remaining terms in (A.6), namely the portfolio asset volatility σ_A and the value of the portfolio assets A, should be in principle obtained as in the case of individual companies, solving the system of equations (A.2) and (A.5).
The traditional approach aggregates individual estimates of implied assets A_j, thus $A = \sum_{j=1}^{P} A_j$ and it aggregates the individual estimates of asset volatilities using a asset return based covariance structure, $\sigma_A^2 = \sum_{j=1}^{P}\sum_{k=1}^{p} w_j w_k \sigma_{jk}$, where σ_{jk} is the asset return covariance of companies j and k.
In this paper, the calibration of Portfolio Distance-to-Default do solve equations (A.2) and (A.5) to obtain σ_A and A in each Supersector, hence the equity market value of the portfolio, $E = \sum_{i=1}^{P} E_i$, is obtained directly from the reference Supersector index on a daily basis, and the equity volatility σ_E is obtained from index option implied volatilities. As a result, Portfolio Distance-to-Default do not only capture covariances in σ_A. See Saldías (2012) for more details in the case of banks in Europe.

B. Cross-section Dependence and Panel Unit Root tests

B.1. Cross-section Dependence Tests

The two statistics of cross-section dependence (CD) in panel data used in the paper are based on pairwise correlation coefficients, ρ_{ij}, of regressions' residuals[23]. The **average of cross-correlation coefficients**, $\bar{\rho}$, is applied to provide a first assessment at a descriptive level.

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

The **Pesaran CD statistic**, CD_P, was developed in Pesaran (2004) and is used for panels where series may be either stationary or contain unit roots. This CD statistic shows good properties with dynamic panels but has also a caveat. 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. This statistic takes the following form and distribution.

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

B.2. Unit Root Tests

In addition to the IPS test, **cross-sectionally augmented IPS tests (CIPS)** (Pesaran, 2007) are applied. This test 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 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). It assumes a single unobserved common factor, but is robust to other potential sources of CD, 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.

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + \sum_{l=1}^{p_i} c_{i,l} \Delta y_{i,t-l} + d_i' \bar{z}_t + \nu_{i,t}, \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{B.3}$$

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

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_i \tag{B.4}$$

where $\tilde{t}_i$ is the t-statistic associated to $\hat{b}_i$ in CADF equations.

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

C. 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 1. 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 E.1 through E.14 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).

D. 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 and 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 (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.
- Excess Returns, $EXRET_t$: Monthly log excess return on each index's daily price return relative to the EURO STOXX 50 Index, as constructed in Campbell *et al.* (2008).
- Return On Assets, ROA_t: Bloomberg (ROA), Computed as the ratio of net income to total assets and averaged for all members of a given index. Monthly frequency.

E. Constituents by Supersector

Table E.1: 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 E.2: Supersector Constituents List - Banks (BNK) (cont.)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.3: Supersector Constituents List - Telecommunications (TLS)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.4: Supersector Constituents List - Oil & Gas (ENE)

	Name	**ISIN Code**	**Country**	**Portfolio from:**	**constituent 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 E.5: Supersector Constituents List - Insurance (INS)

	Name	**ISIN Code**	**Country**	**Portfolio from:**	**constituent 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 E.6: Supersector Constituents List - Technology (TEC)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.7: 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 E.8: Supersector Constituents List - Utilities (UTI)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.9: Supersector Constituents List - Industrial Goods & Services (IGS)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.10: Supersector Constituents List - Industrial Goods & Services (IGS) (cont.)

	Name	**ISIN Code**	**Country**	**Portfolio from:**	**constituent 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 E.11: 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 E.12: Supersector Constituents List - Food & Beverage (FOB)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.13: Supersector Constituents List - Media (MDI)

	Name	ISIN Code	Country	Portfolio from:	constituent 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 E.14: Supersector Constituents List - Healthcare (HCR)

	Name	ISIN Code	Country	Portfolio from:	constituent 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.