Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Document de Treball 2014/21 1/32
Working Paper 2014/21 1/32

"Forward Looking Banking Stress in EMU Countries"

Marta Gómez-Puig, Manish K. Singh and Simon Sosvilla-Rivero

Institut de Recerca en Economia Aplicada | Research Institute of Applied Economics

Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics
Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

WEBSITE: www.ub.edu/irea/ • CONTACT: irea@ub.edu

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Abstract

Based on contingent claims analysis (CCA), this paper tries to estimate the systemic risk build-up in the European Economic and Monetary Union (EMU) countries using a market based measure \distance-to-default" (DtD). It analyzes the individual and aggregated series for a comprehensive set of banks in each eurozone country over the period 2004-Q4 to 2013-Q2. Given the structural di_erences in _nancial sector and banking regulations at national level, the indices provide a useful indicator for monitoring country speci_c banking vulnerability and stress. We _nd that average DtD indicators are intuitive, forward-looking and timely risk indicators. The underlying trend, uctuations and correlations among indices help us analyze the interdependence while cross-sectional di_erences in DtD prior to crisis suggest banking sector fragility in peripheral EMU countries.

JEL classification: G01, G21, G28
Keywords: contingent claim analysis, distance-to-default, systemic risk

Marta Gómez-Puig: Department of Economic Theory & Riskcenter-IREA, Universitat de Barcelona (Barcelona, Spain) (marta.gomezpuig@ub.edu).

Manish K. Singh: Department of Economic Theory & Riskcenter-IREA, Universitat de Barcelona (Barcelona, Spain) (manish.singh@barcelonagse.eu).

Simón Sosvilla-Rivero: Department of Quantitative Economics, Universidad Complutense de Madrid (Madrid, Spain) (sosvilla@ccee.ucm.es).

Acknowledgements

We are very grateful to Analistas Financieros Internacionales for kindly providing the credit rating dataset. We also thank Scott R. Baker and Raquel Lopez and Eliseo Navarro for nicely providing datasets built up by themselves. This paper is based upon work supported by the Government of Spain under grant numbers ECO2011-23189 and ECO2013-48326. Simon Sosvilla-Rivero thanks the Universitat de Barcelona and RFA-IREA for their hospitality. Responsibility for any remaining errors rests with the authors.

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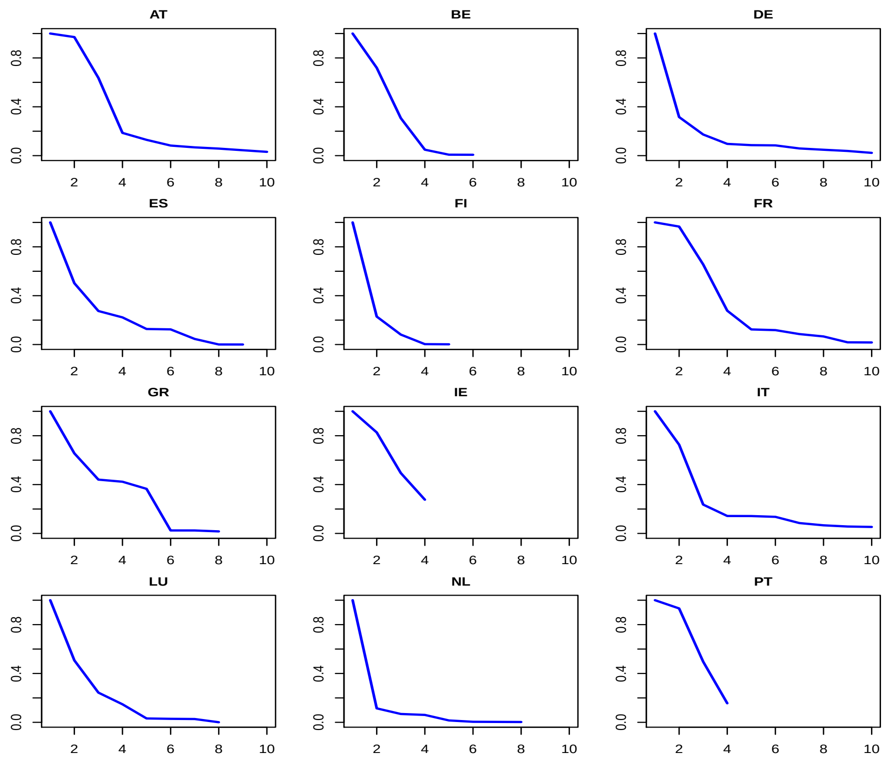
1 Introduction

The 2007-08 financial crisis and the subsequent European sovereign debt crisis has exacerbated the need to understand and monitor the systemic risk. The eurozone case is especially interesting given the diverse set of countries and the nature of the European Economic and Monetary Union (EMU).

With the advent of euro, the EMU saw a rapid growth in the financial sector fostered by the monetary policy convergence. But the structure of the financial sector within countries has its own legacies and varies considerably. In the case of Germany, Finland and the Netherlands, the total banking assets are quite concentrated, while in Italy, Greece, France and Austria, the assets are distributed quite equitably. Figure 1 suitably summarizes this information by plotting the relative size of financial institutions (by total assets) for all EMU countries, where the size of the biggest firm is normalized to one.

Figure 1 Size distribution of banks in individual countries

AT: Austria, BE: Belgium, DE: Germany, ES: Spain, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, LU: Luxembourg, NL: The Netherlands, PT: Portugal. Datasource: Bankscope



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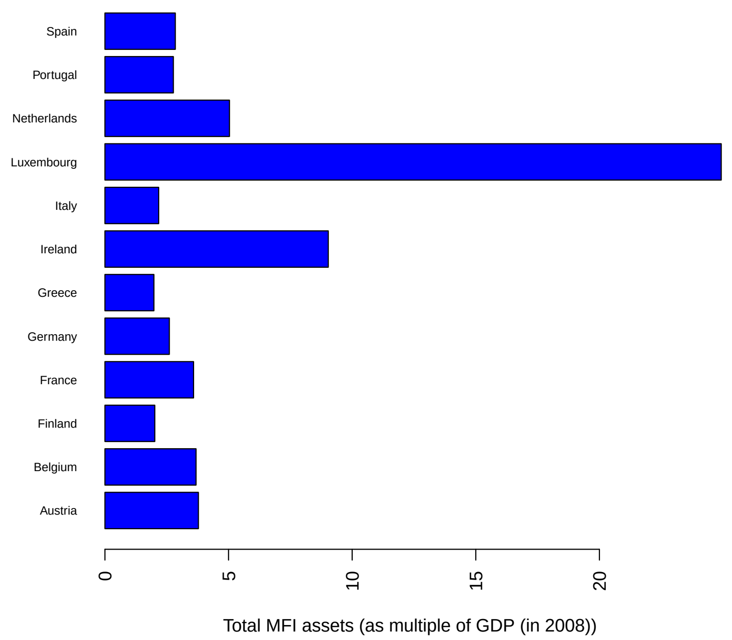
In some countries, all financial services are only provided by banks, while other have specialized mortgage banks, pension and insurance companies. The economic dependence on financial sector and total assets managed also varies drastically within EMU countries (Figure 2). Consider the case of Luxembourg, where the total financial assets under management is roughly twenty five times the GDP[1] while, in Greece, Italy and Finland, this multiple is less than three. Given the existence of deposit insurance at country level, bank defaults can transfer huge contingent liabilities on sovereign's balance sheets.

Figure 2 MFI total assets as multiple of GDP

MFI: Monetary Financial Institution as classified by OECD. Datasource: OECD, National Central Banks



It is also important from the point of view of EMU structure. As banks use sovereign bonds for repurchase agreements with the ECB but their governments only partially back up any losses, in case the banks are unable to repurchase the bonds. This can shift additional liability to sovereign's balance sheets in case of domestic bank failure. The banking regulation is currently at the national level and governments have political incentives to save domestic banks.

[1]Gross Domestic Product (at current prices)

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The basic idea of the paper is to take one structural market-based forward looking indicator and gauge its performance in a cross sectional setting. This basic risk indicator should: (1) identify the existing balance sheet mismatch; (2) incorporate uncertainty using some forward looking market measure and (3) provide quantifiable risk indicators to measure risk exposures (Gapen et al. (2005)) It is possible, had regulators paid greater attention to these country specific buildup of risk which this paper focuses, they might have done better and earlier to mitigate the extent and impact of crisis.

We use data for a representative set of listed financial firms in each EMU country from the end of 2004 till mid 2013, documenting the evolution of one standard CCA market-based risk measure -"distance-to-default" (DtD) - and examining its performance in cross-sectional econometric models of sovereign and banking sector performance and their linkages. The central questions addressed here are (i) does this systemic risk measure provide useful information on the buildup of risk in financial sector?; (ii) does it disentangle the structural differences in financial sector across countries?; (iii) does there exist a strong interlink between sovereigns financial stress?; (iv) does it provide useful insight about the market sentiments? and (v) can it perform better as a forecasting indicator than regulatory and accounting based measures of prudential risk?

As it turns out, DtD is a quite simple, convenient and intuitive forward looking risk measure. The level of DtD does not extricate the countries based on the structural differences in their financial sectors, but provides a good measure of inter-linkage. The market sentiments indicators are highly correlated with DtD, but Granger causality test reveals no systemic component.

The contribution of this paper is four fold: (1) we use one of the most comprehensive representative databases for EMU financial sector; (2) the study tries to understand the link between country specific buildup of systemic risk with country specific market sentiments; (3) we are not neglecting the banking sector of smaller countries, which may not be relevant at EMU level but will be relevant at country level; and (4) this simple one-period contingent claim model helps us understand the changes in capital structure of banking sector which in turn will suggest the risk-shifting behavior of banks and the readiness of sovereigns to stand sudden catastrophe.

The paper is organized as follows. Section 2 reviews prior literature that employs similar contingent claims framework to assess bank fragility and buildup of systemic risk. Section 3 offers a detailed account of the methodology used to construct, analyze and interpret the DtD indicator. Section 4 describes the sample data and calibration of individual and aggregate DtD series. Section 5 first documents the behavior of returns, volatility and DtD for each EMU country. It then analyzes the joint behavior of returns, volatility and DtD in the whole EMU financial sector and presents some cross-sectional econometric analysis to gauge the predictive ability of the aggregate DtD indicator in measuring the build-up of financial stress and market sentiments. Section 6 draws conclusions.

2 Literature survey

The traditional approach to assess the financial health of a firm has been based on balance sheet based information. Certain accounting ratios were identified that could measure and differentiate the financial well being of firms (Altman (1968); Ohlson (1980); Zmijewski (1984)). These papers typically employ multivariate discriminant analysis and multinomial choice models to estimate the default probability. However the consensus on the accuracy and prediction achieved is relatively low (see Altman and Katz (1976); Kaplan and Urwitz (1979); Blume et al. (1998)). These models have generally been criticized on three grounds: (1) the absence of a underlying theoretical model; (2) the timeliness of information[2] and (3) the lack of uncertainty or forward looking component. The methodology also introduces sample selection bias generating inconsistent coefficient estimates (Shumway (2001); Chava and Jarrow (2004); Susan et al. (2012)).

The contingent claims model of Merton (1974) answers some of these criticisms. It provides a structural underpinning and combines market-based and accounting information to obtain a comprehensive set of company financial risk indicators, e.g: DtD, probabilities of default, credit spreads, etc. The basic model is based on the priority structure of balance sheet liabilities and uses standard Black-Scholes option pricing formula to value the junior claims as call option on firms' value with the value of senior claims as default barrier. It has been widely applied for assessing the ability of corporates, banks and sovereigns to service their debt. Banking applications follow CCA by interpreting a bank's equity a call option on bank's value given the limited liability of shareholders. This approach was further refined by Vasicek (1984) and Crosbie and Bohn (2003) and is applied professionally at Moody's KMV to predict default.

Several papers have examined the usefulness of DtD as a tool for predicting corporate and bank failure (Kealhofer (2003); Oderda et al. (2003); Vassalou and Yuhang (2004); Gropp et al. (2006); Harada et al. (2010); Susan et al. (2012)). They found DtD as a powerful measure to predict bankruptcy and rating downgrades. In parallel, comparative analysis of accounting based measures and DtD (Hillegeist et al. (2004) and Agarwal and Taffler (2008)),

[2]These models use financial statements information which are based on past performance and are available only at either a quarterly or an annual frequency, thus fail to capture changes in the financial conditions of the borrowing firm.

suggest that the DtD can be a powerful proxy to determine default. Campbell et al. (2008) and Bharath and Shumway (2008) incorporate a hazard modeling approach using both accounting as well as market variables in their estimation. They find that the DtD measure has relatively little explanatory power once they include other variables in their models. Campbell et al. (2011) identify an alternative set of market measures such as price levels, volatility of returns, equity to book ratio and profitability that enhance the predictive power of the models to match real world probabilities of default.

Systemic risk and CCA

Systemic risk was first investigated in the early 1990s and since then it has been the focus of many studies. OFR[3] and De Bandt and Hartmann (2000) provide a very comprehensive survey of the literature that addresses systemic risk. The CCA approach has been widely cited and reviewed by the IMF[4], ECB and OFR as a tool to enhance systemic risk analysis. A number of applications of this approach have been studied to analyze different dimensions of systemic risk.

This literature can be classified in three broad categories: (1) to define systemic risk (Bartholomew and Whalen (2005); Goldstein (1995); Kaufman (1995)); (2) to investigate what may cause changes in the level of systemic risk, for example, changes in the level of inter-bank lending (Rochet and Tirole (1996)), financial system consolidation (De Nicolo and Kwast (2002)), VaR - induced herding behavior in bank trading patterns (Jorion (2006)), and the opaque and largely unregulated hedge funds (Chan et al. (2006); Kambhu et al. (2007)) and (3) to develop systemic risk measures for monitoring purposes. We intend to advance the third strand of literature with our current study. This approach will help supplement the existing methodologies that failed to capture vulnerabilities prior to this crisis.

In practice, the extension of DtD series as system wide indicator suffer two major issues: (1) how individual banks data can be aggregated as system wide representation and (2) at what level they should be aggregated? We follow Harada and Ito (2008) and Harada et al. (2010) which provided empirical evidence of DtD usefulness to detect bank default risks. The systemic risk indicator in this case was an average of individual DtD series. This approach offers relative risk measures and is very attractive in terms of policy advise. However, this aggregation method ignores the joint distribution properties. In Gray et al. (2007), Gray and Jobst (2010), Duggar and Mitra (2007), Gray et al. (2010) and Gray and Jobst (2013)), authors provide further extensions to incorporate inter-linkages using rolling correlations or extreme value theory and developed extensions to analyze a wide range of

[3] Office of Financial Research, US Treasury

[4] International Monetary Fund

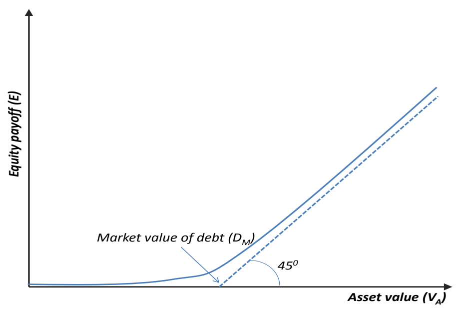
macro-financial issues. This paper will remain silent on these issues. Instead we will try to investigate the linkages based on the weighted and unweighted average DtD indicators.

In recent literature, Gray and Malone (2008) and Saldias (2013) have argued that option based volatility can improve the performance of DtD and overcome some of the shortcomings originated in its assumptions on the returns distributions. Given that we want to discriminate the banking structure among EMU countries, we will shy away from using index volatility. Instead, we will construct our own measure of volatility based on historical returns series for each country. This ignores information based on index options (future correlations and skews) but is more appropriate for our analysis.

3 Contingent claim analysis

Contingent claim analysis has its genesis in Merton's general derivative pricing model (Merton (1974)) in a framework that combines market based and balance sheet information to obtain a set of financial risk indicators. In this context, the liabilities are viewed as contingent claims against assets with payoff determined by seniority. Since equity has limited liability and has the residual claim on the assets after all other obligations have been met, it becomes an implicit call option on the market value of assets with strike price defined by the debt barrier. Figure 3 shows this relationship graphically.

Figure 3 Equity as call option



To understand the key relationship between the value of total assets and the promised payments, Figure 4 plots the probability distribution of assets value at time t_1 assuming that the asset return process is $dA/A = \mu_A dt + \sigma_A \epsilon \sqrt(t)$, where μ_A is the drift rate or asset return, σ_A is equal to the standard deviation of the asset return, and ϵ is normally distributed, with zero mean and unit variance. Default occurs when assets fall to or below

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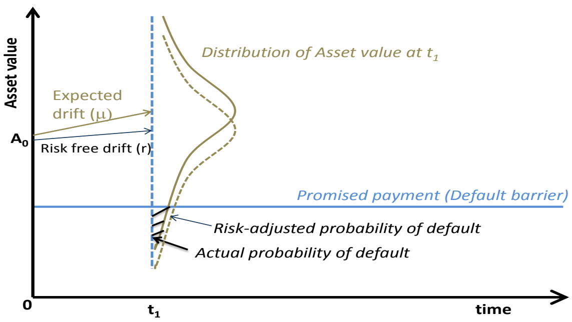
the promised payments. The probability that the assets value will be below the promised payments is the area below the promised payments and is the "actual" default probability.

But the asset-return probability distribution used to value contingent claims is not the "actual" one but the "risk-adjusted" or "risk-neutral" probability distribution, which substitutes the risk-free interest rate for the actual expected return in the distribution. This risk-neutral distribution is the dashed line in Figure 4 with expected rate of return r, the risk-free rate. Thus, the "risk-adjusted" probability of default calculated using the "risk-neutral" distribution is larger than the actual probability of default for all assets which have an actual expected return (μ) greater than the risk-free rate r (that is, a positive risk premium).

Figure 4 Risk-adjusted probability of default



3.1 Derivation of individual DtD

Given this background, DtD cannot be measured directly. Rather it is recovered implicitly from observed measures of bank liabilities and of the market prices of those liabilities. Since equity is a junior claim to debt, the former can be modeled and calculated as a standard call option on the assets with exercise price equal to the value of risky debt (also known in the literature as distress barrier or default barrier).

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

Given the assumption of assets distributed as a Generalized Brownian Motion, the application of the standard Black-Scholes option pricing formula

(Black and Scholes (1973)) yields the closed-form expression of equity E as an European call option on the bank's assets A at maturity T:

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

where r is the risk-free rate under risk-neutrality, and N(∗) is the cumulative normal distribution. The values of d_1 and d_2 are expressed as

$$d_1 = \frac{ln(\frac{A}{D}) + (r + 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{3}$$

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

We use an additional equation that links the asset volatility σ_A to the volatility of the bank's equity σ_E by applying Ito's Lemma:

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

The Merton model uses Eqs. 2 and 5 to obtain the implied asset value A and volatility σ_A , which are not observable and must be estimated by inverting the two relationships. Once a numerical solutions for A and σ_A are found, the DtD is calculated as:

$$DtD = \frac{V_A - D}{\sigma_A V_A} \tag{6}$$

Using this model to quantify DtD requires some practical compromises. Real debt contracts are not all written with a single terminal date. To overcome this problem, a common procedure used by Moody's KMV and also employed here, is to adopt a one year horizon T, but to weight longer term debt of maturity greater than one year at only 50% of face value. We also use the market value of firms' equity, average quarterly historical volatilities as equity price return volatility and 10-year government bond yields as the risk-free interest rate.

3.2 Sensitivity of DtD

DtD can be interpreted as how many standard deviations the asset value of the firm is away from the debt of the firm. Three key inputs to calculating the DtD for a firm are market capitalization, debt level, and the volatility of equity. This implies that the DtD is influenced by the leverage ratio and volatility of the firm. A lower value of DtD can be obtained either because the leverage of the firm is high or because the volatility is high or both.

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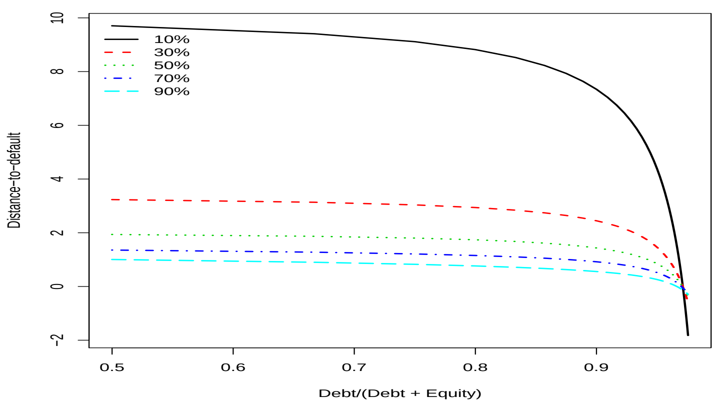
Figure 5 shows the sensitivity of DtD to each of these inputs across varying levels of leverage and equity volatility.

It should be noted that when overall market volatility is high, it is likely that even small changes in the leverage will cause large changes in the DtD. Thus, in episodes of distress when systemic volatility reached peak levels, the DtD react much more sharply to even small changes in leverage. Whereas the same amount of change during calm period would decrease DtD slightly (Susan et al. (2012)).

Figure 5 Sensitivity of distance-to-default



4 Data

This section introduces the bank sample used to compute the individual firm specific and aggregate country specific DtD time series. For the analysis, we will consider countries which share the common currency Euro from the very start (1999) except for Greece which joined in 2001. This choice will ensure that the selected banks share the same accounting currency. It doesn't mean that they have similar exchange rate risk profile since the level of foreign currency exposure will depend on the asset profile of their respective banks.

4.1 The sample

The sample used to compute the DtD and aggregate DtD series is based on all monetary financial institutions listed in EMU countries. This includes all monetary firms whose share are publicly listed and traded between the last quarter of 2004 till the second quarter of 2013. We have also considered firms which got listed/delisted in the reference period. The idea is to create a comprehensive list of institutions which can be used as one of the best reference of the European financial sector covering almost all dimensions of European banking integration in terms of systemic risk and for the purpose of this research.

The data selection methodology is as follows: Firstly, an exhaustive list of all listed/delisted financial institution are selected from Bankscope which provides a comprehensive balance sheet data for banking companies. We got a total of 199 firms in western Europe. Secondly, banks based in countries which are not part of this study have been dropped out. Thirdly, we removed credit institutions which are pure-play insurance, pension or mortgage banks. To formalize this decision, we have used Datastream as an additional source of information. Finally, firms which got listed, delisted, nationalized or suffered any other relevant corporate actions have been considered in the data set till they stopped trading at public exchanges.

Table 1 summarizes the list of countries and total number of banks considered for the DtD analysis. One should note that due to the varying number of bankruptcy, M&A, nationalization or other corporate actions, the number of firms in the sample will change year-on-year, both for the full sample and for each individual country (Figure 6). The comprehensive list of firms used in this analysis is summarized in Table 2. The period for which each firm got traded is also available but is not documented to save space. This information is available upon request.

Table 1 Countries and banks considered for the analysis

Country	Year of joining the Euro	No. of Banks Selected
Austria	1999	3
Belgium	1999	2
Germany	1999	15
Spain	1999	9
Finland	1999	3
France	1999	21
Greece	2001	7
Ireland	1999	5
Italy	1999	22
Netherlands	1999	6
Portugal	1999	5
Total		**98**

Table 2 List of banks (by country)

Name	Status	ISIN
Austria		
UniCredit Bank Austria AG	Delisted	AT0000995006
Erste Group Bank AG	Listed	AT0000652011
Raiffeisen Bank International AG	Listed	AT0000606306
Germany		

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Name	Status	ISIN
Landesbank Berlin Holding AG	Delisted	DE0008023227
Hypothekenbank Frankfurt AG	Delisted	DE0008076001
UniCredit Bank AG	Delisted	DE0008022005
Oldenburgische Landesbank	Listed	DE0008086000
Deutsche Postbank AG	Listed	DE0008001009
UmweltBank AG	Listed	DE0005570808
Hypo Real Estate Holding AG	Delisted	DE0008027707
HSBC Trinkaus & Burkhardt AG	Listed	DE0008115106
Deutsche Bank AG	Listed	DE0005140008
Commerzbank AG	Listed	DE000CBK1001
Wustenrot & Wurttembergische	Listed	DE0008051004
Comdirect Bank AG	Listed	DE0005428007
Net-M Privatbank 1891 AG	Delisted	DE0008013400
Merkur-Bank KGaA	Listed	DE0008148206
Quirin Bank AG	Listed	DE0005202303
Spain		
Banco Santander SA	Listed	ES0113900J37
Banco Bilbao Vizcaya Argentaria SA	Listed	ES0113211835
Caixabank, S.A.	Listed	ES0140609019
Bankia, SA	Listed	ES0113307021
Banco de Sabadell SA	Listed	ES0113860A34
Banco Popular Espanol SA	Listed	ES0113790226
Caja de Ahorros del Mediterraneo CAM	Listed	ES0114400007
Bankinter SA	Listed	ES0113679I37
Renta 4 Banco, S.A.	Listed	ES0173358039
France		
Credit Agricole Sud Rhone Alpes	Listed	FR0000045346
Paris Orleans SA	Listed	FR0000031684
Credit Agricole de la Touraine et du Poitou	Listed	FR0000045304
Credit Agricole Alpes Provence	Listed	FR0000044323
Credit Agricole Nord de France	Listed	FR0000185514
Credit Agricole d'Ile-de-France	Listed	FR0000045528
Credit Agricole Loire Haute-Loire	Listed	FR0000045239
Credit Industriel et Commercial	Listed	FR0005025004
Banque Tarneaud	Delisted	FR0000065526
Credit agricole mutuel de Normandie-Seine	Listed	FR0000044364
Credit Agricole Mutuel du Languedoc	Listed	FR0010461053
Natixis	Listed	FR0000120685
Credit Agricole de l'Ille-et-Vilaine	Listed	FR0000045213
Credit Agricole d'Aquitaine	Delisted	FR0000044547
Societe Generale	Listed	FR0000130809
Credit Agricole S.A.	Listed	FR0000045072
BNP Paribas	Listed	FR0000131104
Boursorama	Listed	FR0000075228
Credit Agricole du Morbihan	Listed	FR0000045551
Credit Agricole Brie Picardie	Listed	FR0010483768
Societe Alsacienne de Dveloppement et d'Expansion	Delisted	FR0000124315
Belgium		
Dexia	Listed	BE0003796134
KBC Groep NV	Listed	BE0003565737
Finland		
Pohjola Bank Plc	Listed	FI0009003222

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Name	Status	ISIN
Aktia Bank Plc	Listed	FI4000058870
Alandsbanken Abp-Bank of Aland Plc	Listed	FI0009001127
Ireland		
Depfa Bank Plc	Delisted	IE0072559994
Irish Bank Resolution Corporation Limited-IBRC	Delisted	IE00B06H8J93
Permanent TSB Plc	Delisted	IE0004678656
Bank of Ireland	Listed	IE0030606259
Allied Irish Banks plc	Listed	IE0000197834
Italy		
UniCredit SpA	Listed	IT0004781412
Intesa Sanpaolo	Listed	IT0000072618
Banca Monte dei Paschi di Siena SpA	Listed	IT0001334587
Unione di Banche Italiane Scpa	Listed	IT0003487029
Banco Popolare - Societa Coop.	Listed	IT0004231566
Mediobanca SpA	Listed	IT0000062957
Banca popolare dell'Emilia Romagna	Listed	IT0000066123
Banca Popolare di Milano SCaRL	Listed	IT0000064482
Banca Carige SpA	Listed	IT0003211601
Banca Popolare di Sondrio Societa Coop. per Azioni	Listed	IT0000784196
Credito Emiliano SpA-CREDEM	Listed	IT0003121677
Credito Valtellinese Soc Coop	Listed	IT0000064516
Banca popolare dell'Etruria e del Lazio Soc. coop.	Listed	IT0004919327
Credito Bergamasco	Listed	IT0000064359
Banco di Sardegna SpA	Listed	IT0001005070
Banco di Desio e della Brianza SpA	Listed	IT0001041000
Banca Ifis SpA	Listed	IT0003188064
Banca Generali SpA	Listed	IT0001031084
Banca Intermobiliare di Investimenti e Gestioni	Listed	IT0000074077
Banca Popolare di Spoleto SpA	Listed	IT0001007209
Banca Profilo SpA	Listed	IT0001073045
Banca Finnat Euramerica SpA	Listed	IT0000088853
The Netherlands		
SNS Reaal NV	Delisted	NL0000390706
RBS Holdings NV	Delisted	NL0000301109
ING Groep NV	Listed	NL0000303600
Delta Lloyd NV-Delta Lloyd Group	Listed	NL0009294552
Van Lanschot NV	Listed	NL0000302636
BinckBank NV	Listed	NL0000335578
Portugal		
Montepio Holding SGPS SA	Delisted	PTFNB0AM0005
Banco Comercial Portugues, SA	Listed	PTBCP0AM0007
Banco Espirito Santo SA	Listed	PTBES0AM0007
Banco BPI SA	Listed	PTBPI0AM0004
BANIF - Banco Internacional do Funchal, SA	Listed	PTBAF0AM0002

4.2 Calibration of DtD series

To compute individual DtD, we used information on the risk-free rate, the market value of equity, and short-term liability (book value). Default barrier was calculated as the sum of 100% of deposits and short term debt and

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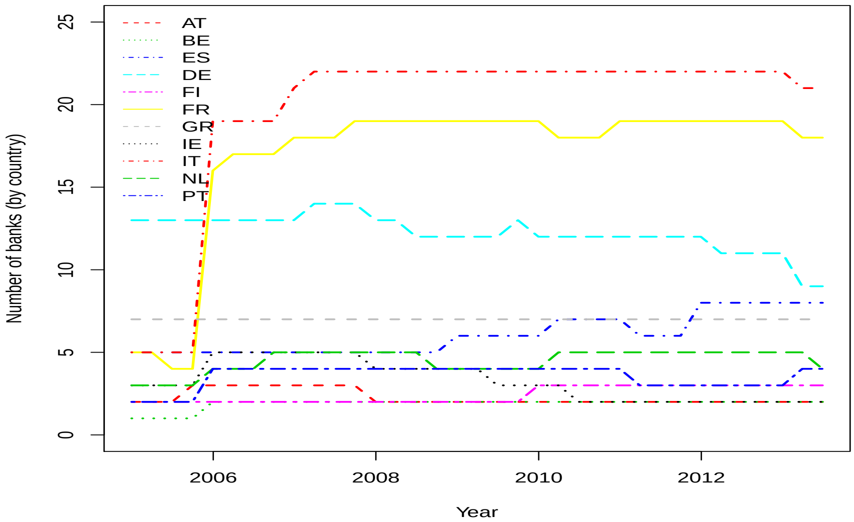
Figure 6 No of banks used every period for each country



50% of long term liability. Daily share price data and number of shares for each firm were downloaded from Datastream, and used to compute market capitalization and volatility. Volatility was calculated as the standard deviation of logarithmic returns for the past 66 trading days (3 months) prior to each accounting date. Share prices and interest rates were all downloaded in the currency used by each bank for its annual reporting.

Calculations of distance to default were made on a quarterly basis. While most of the institutions report their numbers quarterly, many other institutions only reported on a half-yearly basis for most of the period $2004-2013$. To have data consistency, balance sheet variables are interpolated for intermediate dates using cubic splines. The list of variable used for the analysis are summarized in Table 3.

4.3 Aggregating DtD series

The unweighted average DtD ($aDtD$) is obtained by taking the simple average across all credit institutions headquartered in a particular country and is computed as:

$$aDtD_t = (1/N)\sum_{j=1}^{N} DtD_{j,t} \tag{7}$$

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Table 3 Description of variables

Balance sheet variables		
Variable	Definition	Source
Total assets	As reported in annual/interim reports	Bankscope (Code 2025)
Short-term liabilities	Deposits and short term funding	Bankscope (Code 2030)
Total equity	As reported in annual/interim reports	Bankscope (Code 2055)

Daily market based variables		
Variable	Definition	Source
Risk-free interest rate	Benchmark 10Y bond yield of country where the bank headquarter is based	Thomson Datastream
Market capitalization	Daily closing share price multiplied by total outstanding share in public	Thomson Datastream

where $DtD_{j,t}$ is the DtD of firm j at time t .

The aggregate weighted average DtD ($wDtD$) is based on the market capital weighted average of DtD for all credit institutions headquartered in a particular country and is represented as:

$$wDtD_t = \sum_{j=1}^{N} w_{j,t} DtD_{j,t} \tag{8}$$

where $DtD_{j,t}$ is thel DtD of firm j and $w_{j,t}$ is the individual market-capital weights at time t.

5 Analysis

To put the data into perspective, we summarize the behavior of returns, volatility and DtD at country level for all EMU countries under study. Figure 7 plots the index level based on average logarithmic returns of all firms in the sample for a particular country. Firms which dropped out (due to some corporate action) during a particular quarter have been removed from the average calculations at the next period. This methodology creates an upward bias in the returns index level and should be interpreted carefully. To check the variation in data, Figure 8 shows the evolution of market capitalization weighted returns index at country level. Both indices are normalized to 100 for all countries at the end of the third quarter in 2004.

The returns level suggests that the indices have fallen very substantially for all countries. The first period of rapid decline started around mid 2007 but saw some recovery during 2009. The second period of decline started during the sovereign debt crisis at the end of 2009 which still continues for some countries. For half of the sample, the index level at the end of 2012 is below the index value in 2004. Greece, Belgium, Ireland, Portugal and Italy witnessed the highest drop while Finland and Austria sailed quietly. In some countries (like Portugal and Ireland) the index level shows a dramatic recovery post crisis. These spikes are because of the sudden drop in sample size due to firms failures and hence is more exaggerated for small countries.

Figure 7 Average index return

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

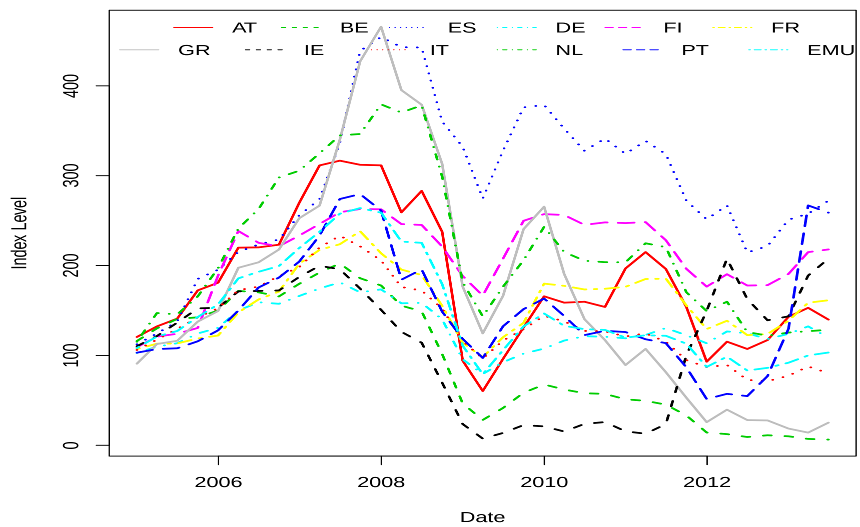

Figure 9 presents unweighted equity price volatility[5] aggregated at country level for all EMU countries under study. As can be seen, the market volatility was quite stable till mid 2008 but saw a knee jerk reaction once Lehman Brothers collapsed. Interestingly, the price decline started from the beginning of 2008 but the market volatility remained stable. Some of the countries (Ireland, Belgium, Austria, Germany, Greece and the Netherlands) saw huge spikes, while the peripheral countries registered a relatively calm period. One possible reason of the excess volatility may be the higher integration and exposure to international financial markets.

[5] The volatility is calculated as the standard deviation of previous 66 days daily logarithmic returns and is annualized by multiplying it with $\sqrt{252}$.

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Figure 8 Market capital weighted index returns

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

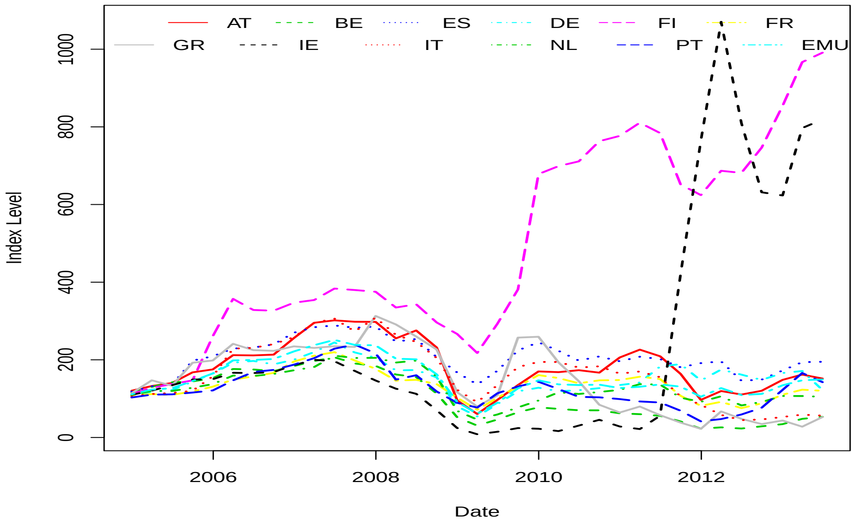

Table 4 Summary statistics - Average returns volatility

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
AT	20.89	26.84	30.94	42.19	48.56	127.90
BE	13.40	21.89	40.66	56.83	79.71	203.90
ES	12.01	18.72	26.34	30.59	41.59	63.79
DE	19.06	25.92	30.58	34.51	36.65	87.09
FI	12.92	19.53	26.36	28.39	33.06	60.04
FR	15.07	19.85	23.93	27.30	34.99	52.87
GR	19.55	30.86	56.57	59.68	75.66	150.60
IE	15.55	22.65	69.49	75.61	102.20	220.80
IT	12.81	21.39	28.01	31.12	40.66	56.91
NL	16.96	23.67	27.86	35.08	43.72	90.09
PT	11.86	20.69	31.57	33.16	46.27	69.39
EMU	17.82	23.15	37.77	41.31	54.94	88.72

Average volatility level of small countries (Greece, Portugal, Ireland, the Netherlands and Austria) are relatively high in general. Table 4 provides the summary statistics for average volatility at country level. Post 2009, the volatility dropped for most EMU countries but has not yet reached its

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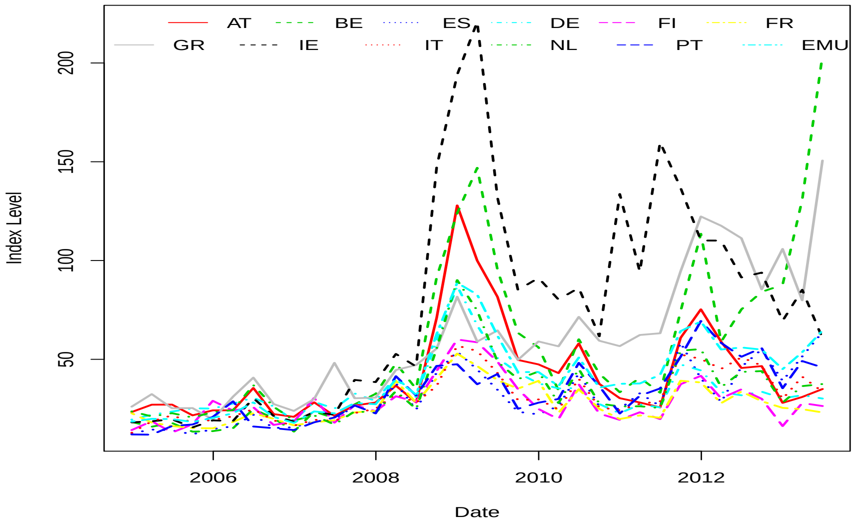
Figure 9 Average returns volatility

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union



pre-crisis level. European sovereign debt crisis and loss of market confidence may be some possible explanation why the average volatility in peripheral countries remains relatively high. The shift in the mean volatility level also need to be interpreted cautiously. Analysis based on market capitalization weighted volatility suggests similar findings.

Figure 10 show the behavior of unweighted and weighted average DtD for each country while Table 5 reports the summary statistics. It should be noted that average level of DtD is quite low for Greece and Ireland which suggests their vulnerability to sudden and unexpected shocks. Any increase in market volatility will lead to insolvency very fast. Together these series show a downward trend from 2004 till 2009 and then stay at the same level. Given that the returns started collapsing at the start of 2008 and volatility was quite stable till mid 2008, this plots suggest that DtD might be a leading indicator of distress.

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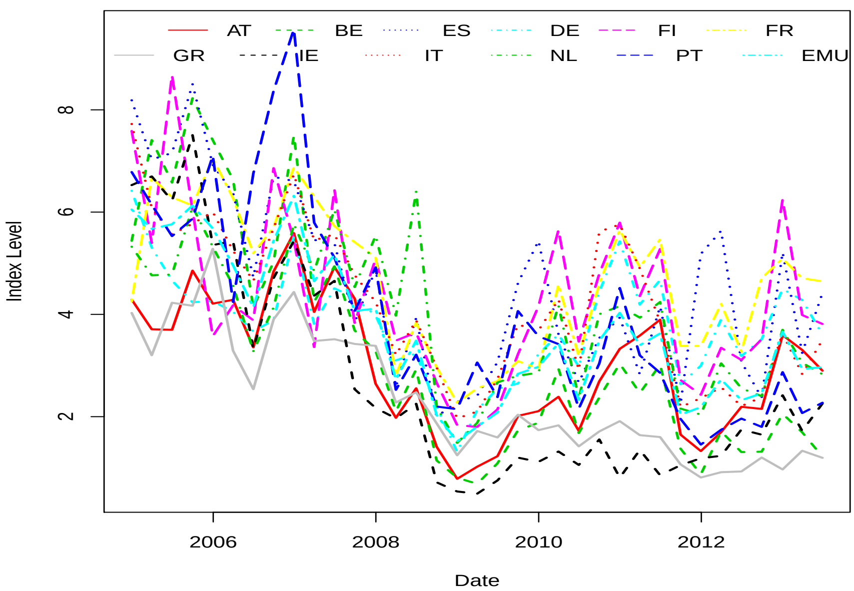
Figure 10 aDtD and wDtD

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

aDtD



wDtD

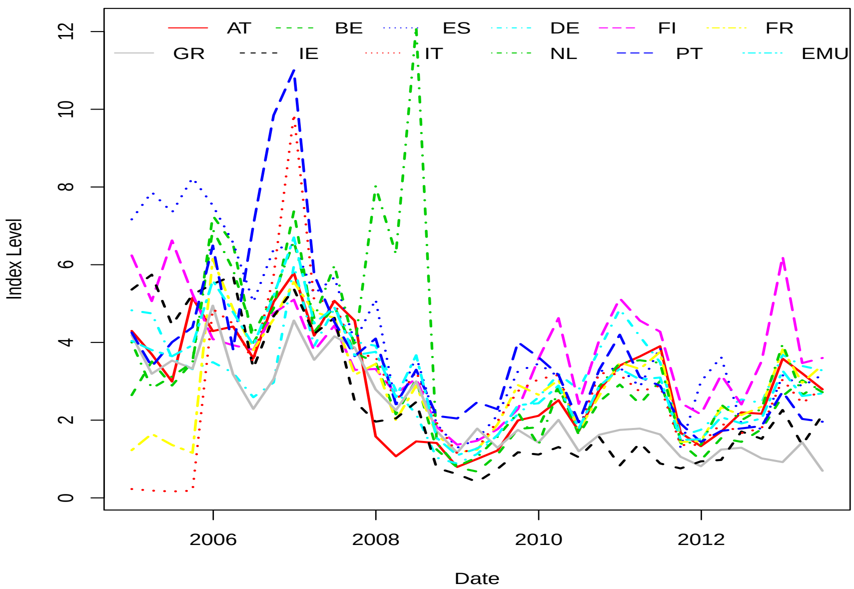


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Table 5 Summary statistics - aDtD and wDtD

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			aDtD			
AT	0.78	2.00	2.90	2.98	3.97	5.59
BE	0.69	1.53	2.46	3.25	4.59	8.23
ES	2.00	3.07	4.42	4.58	5.54	8.50
DE	1.31	3.14	3.89	3.80	4.38	6.42
FI	1.80	3.35	3.88	4.34	5.42	8.68
FR	2.27	3.33	4.71	4.63	5.67	7.05
GR	0.81	1.38	1.87	2.35	3.40	5.28
IE	0.49	1.15	1.75	2.69	4.51	7.50
IT	1.97	2.87	3.89	4.20	5.57	7.72
NL	1.49	2.74	3.98	3.83	4.77	6.40
PT	1.45	2.23	3.21	3.96	5.32	9.58
EMU	1.52	2.59	3.49	3.69	4.81	6.32
			wDtD			
AT	0.80	1.69	2.79	2.92	4.04	5.79
BE	0.68	1.70	2.72	2.93	3.51	7.38
ES	1.29	2.61	3.36	4.04	5.46	8.23
DE	0.88	2.34	3.22	3.11	3.86	5.97
FI	1.37	2.56	3.60	3.71	4.59	6.62
FR	1.16	1.70	2.89	2.88	3.62	6.15
GR	0.70	1.29	1.78	2.27	3.19	4.95
IE	0.41	1.01	1.71	2.48	4.33	5.74
IT	0.17	1.69	2.75	2.79	3.38	9.87
NL	0.81	2.10	3.12	3.67	4.42	12.12
PT	1.44	2.08	3.30	3.67	4.15	11.00
EMU	1.10	2.06	3.05	3.13	3.87	6.70

5.1 Preliminary results

To visualize aDtD as a potential indicator of future financial stress, we examine the variation in aDtD with the broad market indicators of returns and volatility. Figure 11-12 plot aDtD, average returns and average volatility for each EMU country. The left axis represents the returns index level while the right axis represents the annualized volatility in percentage. The level of aDtD is scaled to show the general trend and variation with time.

The graphs suggest that aDtD started deteriorating for most countries between 2006-07, except for France and the Netherlands. It should be noted that aDtD started declining when average returns were showing an upward trend. It also indicates very strong correlations with the average volatility which does undermine its predictive ability. A similar graph based on weighted indices suggests analogous findings, which encourages us to test its

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predictive ability.

Figure 11 Country-wise indices

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France.

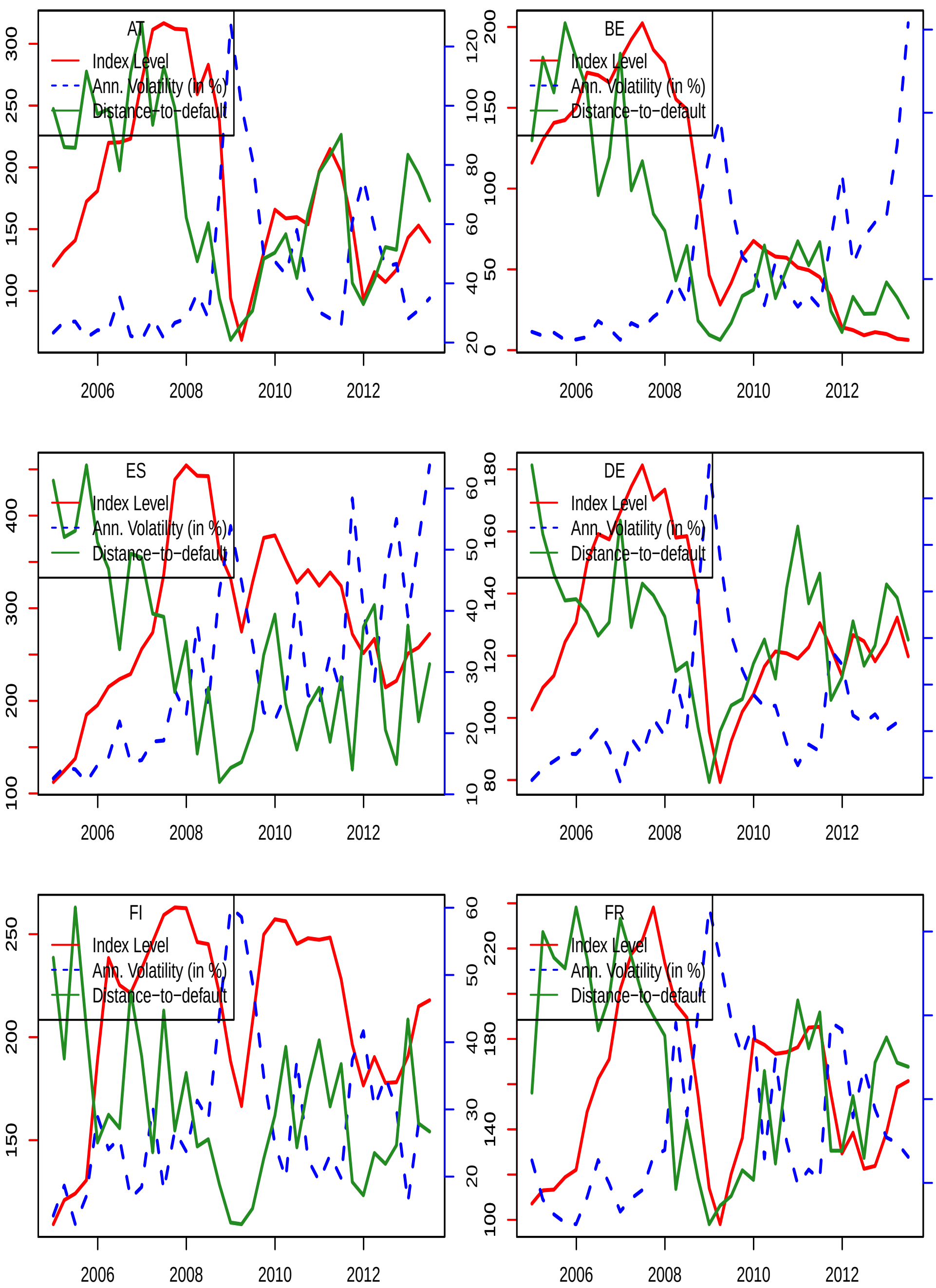
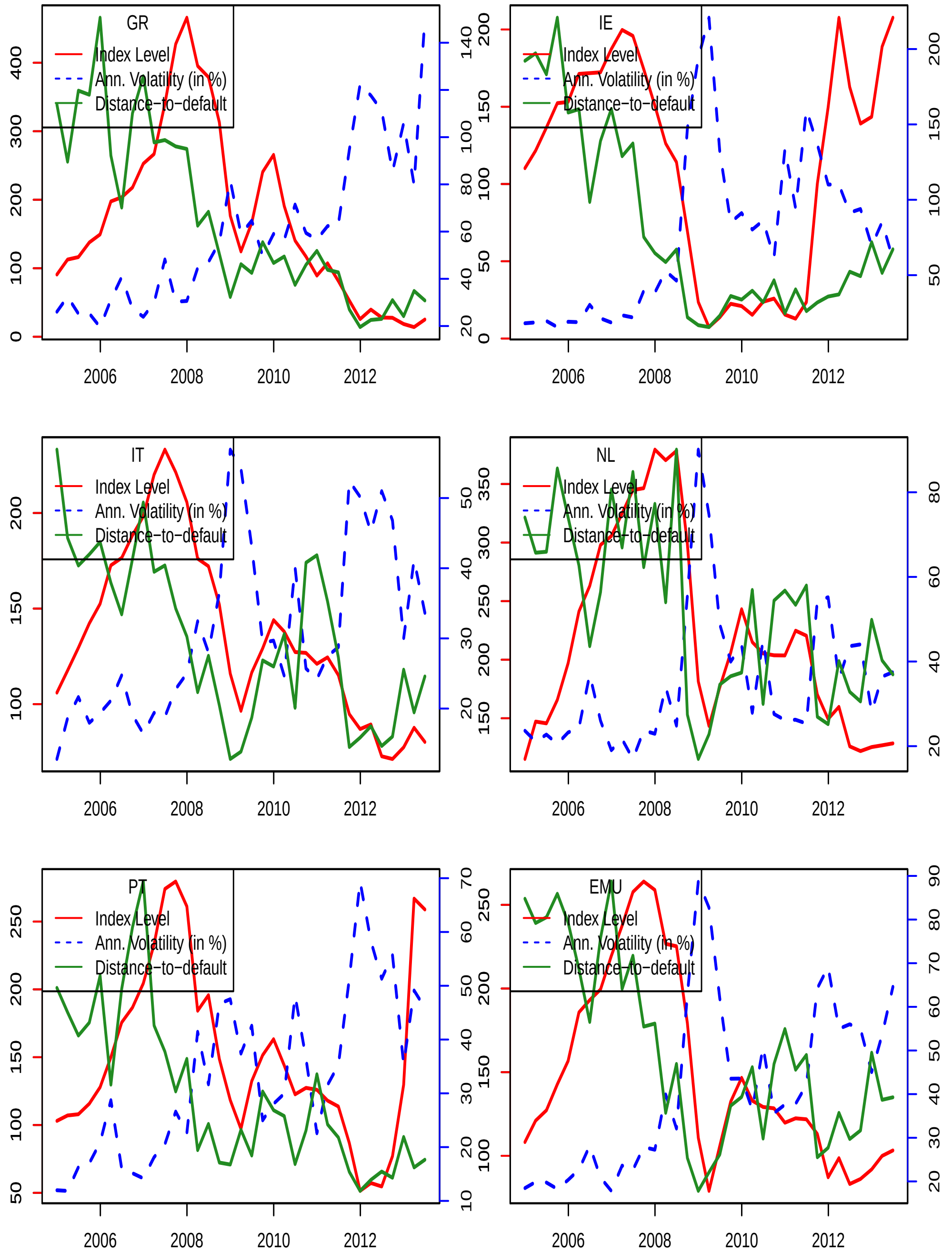


Figure 12 Country-wise indices

Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union.



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5.2 Correlations

We use three correlations measures (parametric: Pearson, and non-parametric: Spearman and Kendell) in our analysis to avoid any bias rising from potential non-linear dependencies and to ascertain the robustness of our findings. Since the Pearson measure is the most commonly used, we report our findings based on Pearson correlations only, but they are also robust based on the Spearman and Kendell correlations as well.

For each correlations measure, we first estimate the pair-wise correlations among all the aggregated sovereign DtD series (Table 6) and then take the mean and median of these pair correlations to obtain some inferences. The average correlation among indices is very high which suggests a common risk factor. This may also be because of the small sample that contains two crisis episodes. To understand the time varying correlation dynamics, a sighed rank test is applied to test the null hypothesis that the mean and median correlations are equal if we divide the time period in two half (pre and post crisis). The results remain consistent for varying sample periods.

Table 6 Correlations among aDtD and wDtD indices

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

aDtD

Country	AT	BE	ES	DE	FI	FR	GR	IE	IT	NL	PT	EMU
AT	1.00	0.83	0.70	0.79	0.71	0.88	0.74	0.78	0.84	0.79	0.77	0.91
BE	0.83	1.00	0.83	0.66	0.63	0.83	0.89	0.93	0.84	0.79	0.84	0.95
ES	0.70	0.83	1.00	0.65	0.66	0.67	0.72	0.86	0.75	0.65	0.73	0.87
DE	0.79	0.66	0.65	1.00	0.78	0.75	0.51	0.62	0.81	0.69	0.58	0.80
FI	0.71	0.63	0.66	0.78	1.00	0.62	0.53	0.63	0.74	0.65	0.58	0.77
FR	0.88	0.83	0.67	0.75	0.62	1.00	0.69	0.74	0.76	0.72	0.70	0.86
GR	0.74	0.89	0.72	0.51	0.53	0.69	1.00	0.84	0.81	0.78	0.88	0.88
IE	0.78	0.93	0.86	0.62	0.63	0.74	0.84	1.00	0.78	0.71	0.77	0.92
IT	0.84	0.84	0.75	0.81	0.74	0.76	0.81	0.78	1.00	0.80	0.84	0.93
NL	0.79	0.79	0.65	0.69	0.65	0.72	0.78	0.71	0.80	1.00	0.67	0.85
PT	0.77	0.84	0.73	0.58	0.58	0.70	0.88	0.77	0.84	0.67	1.00	0.88
EMU	0.91	0.95	0.87	0.80	0.77	0.86	0.88	0.92	0.93	0.85	0.88	1.00

wDtD

Country	AT	BE	ES	DE	FI	FR	GR	IE	IT	NL	PT	EMU
AT	1.00	0.80	0.75	0.77	0.73	0.62	0.68	0.77	0.51	0.33	0.69	0.85
BE	0.80	1.00	0.74	0.65	0.51	0.83	0.79	0.80	0.74	0.64	0.77	0.95
ES	0.75	0.74	1.00	0.62	0.71	0.38	0.82	0.92	0.23	0.45	0.64	0.83
DE	0.77	0.65	0.62	1.00	0.78	0.51	0.60	0.60	0.45	0.40	0.51	0.76
FI	0.73	0.51	0.71	0.78	1.00	0.31	0.48	0.63	0.15	0.30	0.45	0.66
FR	0.62	0.83	0.38	0.51	0.31	1.00	0.46	0.43	0.88	0.56	0.66	0.76
GR	0.68	0.79	0.82	0.60	0.48	0.46	1.00	0.84	0.43	0.61	0.69	0.85
IE	0.77	0.80	0.92	0.60	0.63	0.43	0.84	1.00	0.32	0.49	0.65	0.85
IT	0.51	0.74	0.23	0.45	0.15	0.88	0.43	0.32	1.00	0.52	0.74	0.69
NL	0.33	0.64	0.45	0.40	0.30	0.56	0.61	0.49	0.52	1.00	0.46	0.69
PT	0.69	0.77	0.64	0.51	0.45	0.66	0.69	0.65	0.74	0.46	1.00	0.84
EMU	0.85	0.95	0.83	0.76	0.66	0.76	0.85	0.85	0.69	0.69	0.84	1.00

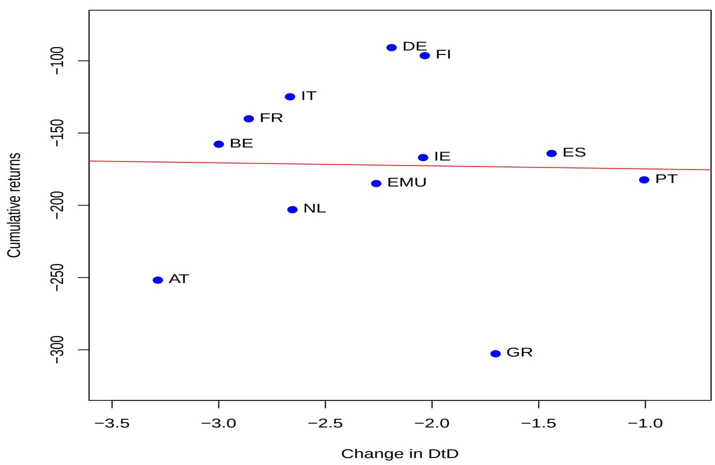
5.3 Market returns and DtD during the crisis

Figure 13 summarizes the behavior of country specific returns and of aggregate DtD during the financial crisis. As a potential indicator of future financial stress, we examine the possibility by comparing the cumulative returns from 2007-Q2 and 2008-Q2 to 2009Q1 with the fall in DtD. As this makes clear, most of the fall in DtD was between 2007-Q2 and 2008-Q2 which shows a direct and obvious prediction of vulnerability prior to the crisis. On the other hand, the total drop in returns shows no correlation with the drop in DtD.

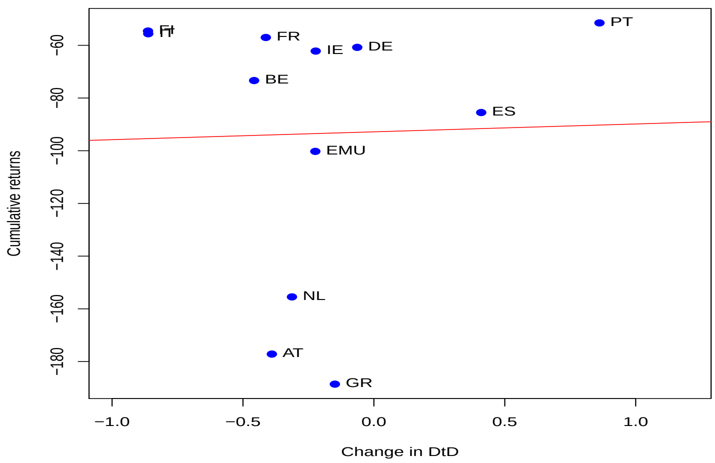
Figure 13 Cumulative returns vs DtD

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

2007-Q2 to 2009-Q1



2008-Q2 to 2009-Q1

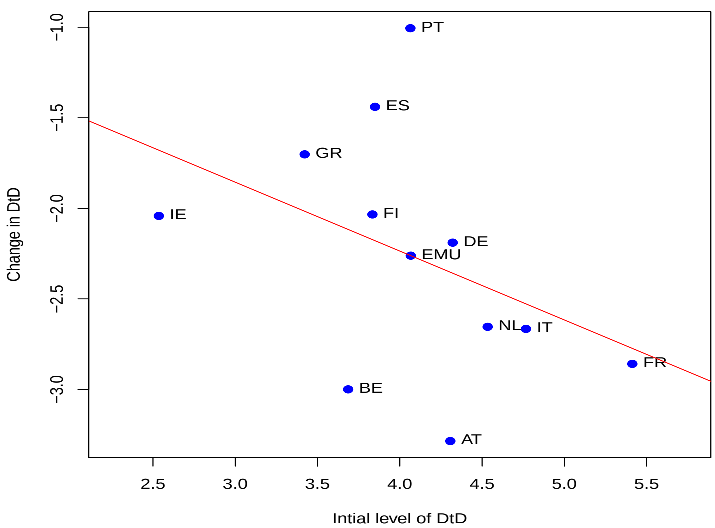


When we look at the initial level of DtD with the drop in DtD during the crisis (Figure 14), the relationship seems to be positive. This suggests that the higher level of DtD experiences a relatives higher correction during this period. The average level of DtD for most EMU countries was around four. For a subset of countries - Austria, France and Italy - DtD fell quite sharply between 2007-Q2 and 2009-Q1. While for Portugal, Spain and Greece, the corrections were less than expected.

Figure 14 Scatter plot with trend line

AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union

2007-Q2 to 2009-Q1



6 Conclusion

By analyzing the behavior and fluctuations of a market based indicator for individual EMU countries, we find that average DtD is an intuitive, simple and convenient forward looking systemic risk measure. It shows some predictive ability 12-18 months prior to the global financial crisis for most of the countries and captures the trend as well as fluctuations in the financial markets. Moreover, it also presents very strong correlations with quarterly average historical volatility which undermines its usefulness.

The average level of risk measure suggests some cross sectional differences across the financial industry. The average DtD indicator shows synchronized movements in all countries with very strong correlations, which suggests the existence of common risk factors across EMU countries. The sudden dip in average DtD for countries during time of stress can be explained by increased global volatility.

To conclude, there are various reasons for considering structural market based indicators alongside accounting/regulatory risk measure. As statistical theory suggests, when faced with two estimators for the same underlying variable, it is optimal to combine the two. Tracking country specific indices does provide some additional information related with the average risk level and the ability to withstand sudden and unexpected disruptions.

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Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

WEBSITE: www.ub.edu/irea/ • **CONTACT:** irea@ub.edu