Bank risk behavior and connectedness in EMU countries

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Abstract

Given the structural differences in banking sector and financial regulation at national level in EMU, this paper tries to estimate the banking sector risk behavior at country level. Based on contingent claim literature, it computes "Distance-to-default (DtD)" at bank level and analyses the aggregate series at country level for a representative set of banks over the period 2004-Q4 to 2013-Q2. The indices provide an intuitive, forward-looking and timely risk measure having strong correlations with national/regional market sentiment indicators. An underlying trend exists but causality tests suggest no systemic component. Cross-sectional differences in DtD suggests fragility in EMU countries 12-18 months prior to the crisis and better predictive ability than the regulatory index based on large and complex banking institutions at European level. Furthermore, we explore the reasons for this divergence using VAR estimates.

Keywords: contingent claim analysis, Distance-to-default, banking risk
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1. Introduction

The 2007-08 financial crisis and the subsequent European sovereign debt crisis have exacerbated the need to understand and monitor the bank risk behavior. Renewed attention is being focused at the global scale to enhance

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and extend risk measurement methodologies. The eurozone is no exception and the twin objective of the European Central Bank (ECB) - price and financial system stability - places a strong emphasis on Systemically Important Financial Institutions (SIFI) but relies on individual countries' central banks to supervise smaller financial institutions.

This paper deviates from this current and in our view excessive focus and attention on detecting and monitoring risk at European banking level. We take a step backward and introduce a micro approach to document and monitor the buildup of banking sector risk at country level. Based on contingent claims literature, we calculate "Distance-to-default (DtD)" at bank level and analyze the aggregate series at country level for a representative set of banks over the period 2004-Q4 to 2013-Q2. Conceivably, if regulators pay greater attention to country-specific buildups of risk and their connectedness, they might take actions earlier to mitigate the extent and impact of future crisis.

There are many reasons for this choice. First, the structure of the banking sector within EMU countries varies considerably. In the case of Germany, Finland and the Netherlands, total banking assets are relatively concentrated, while in Italy, Greece, France and Austria, they are distributed quite equitably. Figure 1 summarizes this information by plotting the relative size of banking firms (by total assets in 2010) in individual EMU countries, where the total asset of the biggest banking firm in a particular country is normalized to one. Excessive asset concentration lowers regulatory cost but makes countries vulnerable to the actions of individual institutions.

[Figure 1 about here.]

Second, countries economic dependence on the banking sector varies drastically.[1] Consider the case of Luxembourg, where the total financial assets under management is roughly 25 times the GDP[2] while, in Greece, Italy and Finland, this multiple is less than three (Figure 2). In some countries, all financial services are provided by banks, while in others there are specialized mortgage, pension and insurance companies. Given the existence of deposit insurance at the national level, governments implicitly or explicitly guarantee bank deposits; which in times of stress, can transfer huge contingent

[1]We consider total asset managed by banking firms as a proxy for relative economic dependence.

[2]Gross Domestic Product (at current prices).

liabilities onto sovereign's balance sheets and bailing out may lead to the weakening of government's own position.

[Figure 2 about here.]

Third, the excessive home bias in European banks' asset portfolios (Figure 3) creates a vicious circle for risk transfer between banks and sovereigns, which creates perverse economic and political incentives for government to save domestic banks. The existence of financial regulation at national level provides governments with the means to pursue their own national interests. "The Financial Trilemma"noted by Schoenmaker (2013, xi) apply aptly to the current crisis in the euro area context.[3] Neighborhood effects, close connectedness with certain countries and cross country differences in bailout strategy also indicate a need for monitoring bank risk at country level.

[Figure 3 about here.]

Given this background, the main objective of this paper is to document the evolution of country wise DtD indices. The central questions addressed here are:

- Does this risk measure provide useful information on the buildup of risk in the banking sector?;
- Does it render utile insights into market sentiments?; and
- Can it perform better than regulatory measure of prudential risk?

As it turns out, national DtDs are simple, convenient and intuitive forward-looking risk measures. The level of DtD differentiates countries based on the structural differences in their financial sectors. It shows strong correlations with indicators of national and regional market sentiment and performs better than aggregate index based on SIFI at European level. Our results indicate that causal relationships run from national DtDs to Euro wide aggregate indicators. To test the improved informational content and reasons for divergence, we explore the cross sectional linkages and dependence using correlation, connectedness and causality measures.

[3] *"financial stability and national policies for supervision and resolution cannot be combined in an open economy with international banks"*

This paper contributes to the literature in several ways: (1) we use a novel bottom-up approach to understanding systemic risk buildup in the banking sector and risk-shifting behavior in EMU countries; (2) we use one of the most comprehensive representative databases for the EMU financial sector; (3) we do not neglect the banking sector of smaller countries, which may not be relevant at EMU level but will be relevant at country level; and (4) to our knowledge, this is the first paper which tries to establish a link between country-specific buildup of financial risk with euro-wide aggregate risk indicators and national and regional market sentiments.

The rest of the paper is organized as follows. Section 2 reviews the prior literature that used different frameworks to understand bank fragility and justifies our selection of DtD as banking risk indicator. Section 3 describes the sample data used to construct, analyze and calibrate the individual and aggregate DtD series. Section 4 first documents the behavior of returns, volatility and DtD for each EMU country; it then analyses these behaviors jointly and presents some cross-sectional econometric analysis to gauge the relative predictive ability of the country-specific DtD indicators. Section 5 tests the additional information content of DtD indices at EMU level while section 6 explores the reason for divergence among bank risk behavior using different connectedness measures. Section 7 draws conclusions.

2. Choice of risk indicator

Based on the survey of the existing measures of bank risk, we employed three basic criteria for indicator selection. It should: (1) identify the existing balance sheet fragility; (2) incorporate uncertainty using forward looking market measure; and (3) provide quantifiable risk indicators to measure risk exposures (Gapen et al. (2005)). A comprehensive survey suggest that most of bank risk indicators can be classified into two broad categories: (1) pure market based; and (2) pure balance sheet based ratios. However the consensus on the accuracy and stress prediction ability of these indicators is relatively low (see Altman and Katz (1976); Kaplan and Urwitz (1979); Blume et al. (1998) among others).

These models have generally been criticized on three grounds: (1) the absence of a underlying theoretical model; (2) the timeliness of the information[4] and (3) the lack of uncertainty or a forward-looking component.

[4]These models use information from financial statements which are based on past per-

These methodologies also introduce sample selection bias, generating inconsistent coefficient estimates (e.g., Shumway (2001); Chava and Jarrow (2004); Thomas et al. (2012)).

The contingent claims model of Merton (1974) answers some of these criticisms. The basic model is based on the priority structure of balance sheet liabilities and uses the 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 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.

Additionally, this measure captures the current period instability (using volatility), a forward-looking component (using stock prices) and balance sheet mismatch (using capital structure), in accordance with our requirements. It has been widely applied to assess the ability of corporates, banks and sovereigns to service their debt. Banking applications follow CCA by interpreting a bank's equity as a call option on its value given the limited liability of shareholders. This approach was further refined by Vasicek (1984) and Crosbie and Bohn (2003) and is applied professionally in Moody's KMV to predict default.

The DtD approach has been widely cited and reviewed by the International Monetary Fund (IMF), European Central Bank (ECB) and Office of Federal Research (OFR) as a tool for enhancing banking sector risk analysis. A number of applications of this approach have been studied to analyze different dimensions of risk. 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); Thomas et al. (2012)). They have found DtD to be 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)), suggests that 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 and market variables in their estimation; they find that the

formance and are available only at a quarterly or an annual frequency; thus, they fail to capture changes in the financial conditions of the borrowing firm.

DtD measure has relatively little explanatory power when 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.

Note that here we don't intend to improve the existing risk measurement methodologies or aggregation techniques (like CoVaR, SRISK etc.) but aim to use them more effectively in order to capture the existing fragility. 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 a system wide indicator has two major difficulties: (1) how can individual banks' data be aggregated as a system-wide representation?; and (2) at what level should they be aggregated? We follow Harada and Ito (2008) and Harada et al. (2010) which provided empirical evidence of the usefulness of DtD to detect bank default risks. The systemic risk indicator in this case was an average of individual DtD series of "sound" banks. This approach offers relative risk measures and is very attractive in terms of policy advice. 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)), the authors provide further extensions to incorporate inter-linkages using rolling correlations or extreme value theory and develop extensions to analyze a wide range of macro-financial issues. This paper will remain silent on these issues. Instead, we will try to investigate the linkages based on the aggregate DtD indicators.

In recent literature, Gray and Malone (2008) and Saldias (2013) have argued that option based implied volatility can improve the performance of DtD and overcome some of the shortcomings caused by the assumptions about return distributions. Given that we want to discriminate between the banking structures in 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.

2.1. Calculation method

The foundation for this model lies with the structural model of default developed by Black and Scholes (1973) and Merton (1974). Since equity is a junior claim to debt, it 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).

The model uses no arbitrage conditions and assumes a frictionless market. The stochastic process generating the firm's assets return are described by the diffusion process with a constant variance per unit time (σ_A). Following standard literature, we assume that financial distress and bankruptcy are costless.[5] A firm has a simple capital structure with N shares of common stock with market capital E and zero coupon bonds with a face value of D with time to maturity T. The estimation methodology is as follows.

We use the value conservation equation:

$$A = E + D \tag{1}$$

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:

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

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:

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

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

The Merton model uses 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:

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

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 numerical solutions for A and σ_A are found, the T periods ahead DtD is calculated as:

[5] Here we assume that equity market price will reflect the cost of bankruptcy.

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

3. Data

3.1. The sample

The data selection methodology is as follows: First, an exhaustive list of all listed and delisted monetary financial institutions is selected from Bankscope database.[6] We obtain a total of 199 firms in western Europe. Secondly, only firms whose shares were publicly listed and traded between the last quarter of 2004 till the second quarter of 2013 and are headquartered in EMU countries are selected. Third, credit institutions which are pure-play insurance, pension or mortgage banks are removed. The major reason for this exclusion is the difference in liability structure and business model compared to banks. However it doesn't mean that they are less risky to the financial system. To formalize this decision, we use Datastream as an additional source of information.

Firms which were listed, delisted, nationalized or suffered any other relevant corporate actions are considered in the data set until they stopped trading on public exchanges. This choice also ensures that the selected banks share the same accounting currency. However, it does not mean that they have a similar exchange rate risk profile, since the level of foreign currency exposure will depend on their respective asset profiles. The market-based data include daily observations of risk-free interest rates, daily stock price and total outstanding share in public. The risk free interest rates are 10-year government bond yields in each banks country of origin. The list of variables and data sources used for the above analysis are summarized in Table 1.

[Table 1 about here.]

Figure 4 summarizes graphically the number of banks considered for the analysis in each country at different time intervals. One should note that due to the varying number of bankruptcies, mergers and acquisitions, 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

[6] It provides a comprehensive balance sheet data for financial companies.

country. The comprehensive list of firms used in this analysis is summarized in Table ??.[7] This comprehensive list of firms represents one of the best references for the EMU banking sector.

[Figure 4 about here.]

[Table 2 about here.]

3.2. Computation of individual DtD

DtD is not measured directly; it is recovered implicitly from the observed measures of bank liabilities and of the market prices of those liabilities. Individual *DtD* series have quarterly frequency. In practical terms, this means that the balance sheet information has to be modified from its original quarterly, half-yearly or, in few cases, yearly frequencies. In this paper, the original data were interpolated into quarterly series using cubic splines. Also the 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 ($T = 1$), but to weight longer term debt of maturity greater than one year at only 50% of face value. So in the second step, debt barriers (the face value of short-term liabilities plus half of that of long-term liabilities) are computed using these new series of quarterly balance sheet items.

The last step before computing the quarterly *DtD* series is to calculate the market value of firms' equity and volatility. We use the average quarterly historical volatilities based on log-return of equity prices. The individual *DtD* is then calibrated by solving the nonlinear system of equations (2 and 5) and substituting the value of firm and asset volatility in equation (6).

3.2.1. Interpreting DtD across firms

DtD can be interpreted as how many standard deviations the asset value of the firm is away from the debt of the firm. The standardisation by both the size of the firm and volatility of the firm value means that the *DtD* can be used to rank firms in terms of their credit quality. Thus, even when data on actual defaults or bankruptcies are not readily observed, the *DtD* retains its usefulness as a relative measure of credit worthiness of firms in a given

[7] The period for which each firm was traded is also available but is not presented here in order to save space. This information is available from the authors upon request.

sample. At any given point in time, across firms in a sample, the closer DtD of a firm is to zero, the closer the firm is to default compared to firms whose DtD values are further from zero.

3.2.2. Interpreting DtD across input variable characteristics

Three key inputs to calculating the DtD for a firm are market capitalization, debt, and the volatility of equity. This implies that the DtD is infuenced by the leverage - ratio of debt to the sum of equity and debt - and volatility of the firm. A higher value of DtD can be obtained either because the leverage of the firm is low or because the volatility is low or both.

In this section, we evaluate the sensitivity of DtD to each of these inputs by drawing Iso-DtD curves, across varying levels of leverage and equity volatility. We plot Iso-DtD curves for nine different values of DtD in Figure 5. The graph shows that at a fixed level of volatility and low levels of leverage, DtD changes are small and insignificant for changes in leverage. DtD only starts changing (dropping towards zero) significantly only for much higher levels of leverage (beyond 80 percent). For a constant level of leverage, DtD shows much sharper drops for changes in equity volatility. This implies that more than leverage, it is equity volatility that has a greater influence in driving large changes in DtD.

[Figure 5 about here.]

This has some interesting implications for interpreting and using the market based DtD as a measure of credit quality. 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 such as the financial crisis of 2008, when systemic volatility reached peak levels, the market reacted much more strongly to even small changes in leverage. Whereas these same changes in leverage during systemically calm periods would have generated smaller decreases in DtDs. Thus, the interpretation of changes in DtDs have different implications on changes in firm credit quality during periods of high and low volatility.

3.3. Aggregating DtD series

Once individual banks' DtD are calculated, we aggregate the indicators at country level. Following Harada et al. (2010), we consider the banking risk indicators as the simple average of individual DtD series of all banks headquartered in a particular country. The simple average DtD for country i at time t is represented by $aDtD_{i,t}$:

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

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

To test the robustness of our results, we also did the analysis based on banks' market capital (total asset) weighted average DtD ($wDtD_{i,t}$) risk indicators for all firms headquartered in a particular country and is represented by:

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

where $DtD_{j,t}$ is the individual DtD for firm j and w_j is the weight based on market capital (total asset) of firm j at time t. The evolution of all these indicators is quite similar. However, given the structure of the banking sector in individual EMU countries, $aDtD$ seems to capture the general trend and fluctuation better and avoids sudden jumps due to the bankruptcy (or nationalization) of a particular firm with excessive weight. This is why our analysis will focus on the $aDtD$ indicator.

4. Analysis

To visualize the country-wise banking risk behavior, we plot the $aDtD$ for individual EMU countries (Figure 6). As can be seen, the level of $aDtD$ (Table 3) differs considerably across countries. Though these series together show a trend, the variability across time is high. The pre-crisis level of $aDtD$ is relatively low for Austria, Greece and Netherlands, while Ireland, Portugal and Belgium show a huge drop in levels during crisis period.

[Figure 6 about here.]

[Table 3 about here.]

4.1. As potential indicator

As banking stress indicators, we compare the evolution of $aDtD$ with banking sector equity and volatility indices.[8] Figure 7 plots $aDtD$, bank equity index and volatility for each EMU country separately. The left axis represents the equity 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. Notably, it started declining when bank index level showed an upward trend while volatility was quite stable.[9]

[Figure 7 about here.]

The returns level suggests that the bank equity prices have fallen substantially for all countries. The first period of rapid decline started around mid 2007, though some recovery was seen in 2009. The second period of decline started during the sovereign debt crisis at the end of 2009, and still continues for some countries. For almost half of the sample, the index level at the end of 2012 is below the index value at the end of 2004. Greece, Belgium, Ireland, Portugal and Italy witnessed the highest drop while Finland and Austria were largely unaffected. In some countries (like Portugal and Ireland) the index level shows a dramatic recovery post crisis. These spikes are due to the sudden drop in sample size due to bank failures and are therefore more notable for small countries having fewer banks.

The volatility of small countries (Greece, Portugal, Ireland, the Netherlands and Austria) is relatively high in general. Post 2009, the volatility dropped for most EMU countries but has not yet returned to its pre-crisis level. European sovereign debt crisis, loss of market confidence and the

[8] The country wise bank equity index is based on average logarithmic returns of all publicly traded banking firms headquartered in a particular country and are normalized to 100 for all countries at the beginning of the last quarter in 2004. The volatility is equal weighted annualized equity price volatility based on the standard deviation of daily logarithmic returns of the previous quarter. This methodology creates an upward (downward) bias in the returns (volatility) indices due to bank failures and should be interpreted carefully.

[9] It also indicates strong correlations with the average volatility, which undermines its effectiveness.

need for continuous monetary support to banking sector may be explanations for the relatively high average volatility in peripheral countries. Given the changes in the sample size in a few peripheral countries, the shift in the mean volatility level needs to be interpreted with caution.

4.2. Equity index vs aDtD during the crisis

To compare the performance of equity indices with $aDtD$ during the crisis, we analyze the country-wise behavior of market returns with $aDtD$ during the financial crisis. As a predictive indicator of future health, we examine the possibility by comparing the cumulative returns from 2007-Q2 and 2008-Q2 to 2009Q1 with the fall in level of $aDtD$ indicator in each country. Figure 8 summarizes this information aptly. As can be seen, most of the fall in DtD occurred between 2007-Q2 and 2008-Q2, indicating a direct obvious prediction of vulnerability prior to the crisis. However, the total drop in returns shows no correlation with the drop in DtD.

Whether or not the initial level of $aDtD$ matters, we plot the initial level of $aDtD$ with the drop in $aDtD$ during the crisis (Figure 9) and find a positive relationship. This suggests that higher initial levels of $aDtD$ experienced higher corrections during this period. The $aDtD$ for most EMU countries averaged between 4 to 5 prior to the crisis. During the crisis (between 2007-Q2 and 2009-Q1), it fell sharply for Austria, France and Italy while for Portugal, Spain and Greece, the corrections were lower than expected.

[Figure 8 about here.]

[Figure 9 about here.]

4.2.1. Comparison with regulatory risk indicator of bank stress

We examine how country-wise $aDtD$ perform with respect to the European SIFI based aggregate banking risk indicator ($ECBDtD$) used by the European Central Bank. To see whether each country's banking risk indicator has better predictive ability, we plot the countries' DtDs with $ECBDtD$ indicator based on large and complex banking institutions. The graphical evidence (Figure 10) suggests that $aDtD$s do suggest the deteriorating market conditions in most peripheral EMU countries (Spain, Ireland, Greece, Italy) and some central countries (Germany, Belgium and Finland) prior to the crisis.

[Figure 10 about here.]

4.2.2. Association with market sentiments

Here we explore the association of *aDtD* with a selection of indicators covering broad market sentiments and sectoral bank indices collected from independent agencies, professional market data providers and other academic authors.

- *At country level:* We consider six variables as proxy for market sentiment: a consumer confidence indicator (CCI), stock returns (RET), the credit rating (RAT), a fiscal stance indicator (FSI), stock volatility (VOL), rating (RAT) and an index of economic policy uncertainty (EPU). As for the national bank indices, we examine two sectoral equities indices covering banks and financial services (Table 4).

  Table 5 shows that for the individual countries we find a positive association between *aDtD*, CCI and RET. In 7 out of 11 cases we detect a strong connection between our indicator and CCI, while for the RET we obtain a moderate or strong relationship in 6 out of 11. We also find a relatively moderate negative association with RAT and EPU and a strong negative correlation with VOL. For FSI we obtain mixed results. For the sectoral bank indices, regardless of the *DtD* indicator, our results suggest a moderate positive association with both DSBANKS and DSFIN. The findings suggest that *aDtD*s are capturing the underlying trends that generate differences in risk perceptions of national banking system.

  [Table 4 about here.]

  [Table 5 about here.]

- *At regional (Eurozone) level:* Table 6 presents the regional financial indicators we have considered while Table 7 examines the relationship with *aDtDs*. As can be noted, we find a strong positive association between *aDtD*s and the regional consumer confidence indicator (EMUCCI) and a strong negative relationship with regional economic policy uncertainty (EMUEPU) and regional financial market volatility (EMUVSTOXX); their associations with the indicator of credit quality in the EMU corporate market (EMUCREDSPR) and regional fiscal stance (EMUFSI) are moderate and positive and mix their connection with regional interest rate volatility (EIRVIX1Y) is mixed. Regarding the regional sectoral bank indices, there is evidence of a strong association with national DtDs in most cases. Interestingly, the *aDtD*s in the peripheral countries strongly influence all EMU bank indices (both PIIGS and non-PIIGS), suggesting that the close links between banks within EMU left them progressively more exposed to the risk of shocks in other banks.

[Table 6 about here.]

[Table 7 about here.]

5. Additional information content

An additional dimension of considering comprehensive list of banks for each country is the increased informational content. To test whether this has a significant effect, we explore the relationship of our EMU DtDs with the EMU macroeconomic uncertainty indicators compiled by the European Central Bank (2013) from a set of diverse sources: (1) measures of uncertainty perceived by economic agents about the future economic situation based on surveys; (2) measures of uncertainty or of risk aversion based on financial market indicators; and (3) measures of economic policy uncertainty (see Table 8). As far as the EMU banking risk measure is concerned, we use the *DtD* for large and complex banking groups examined by the European Central Bank (2012).

Regarding the measures of uncertainty related to future economic outcomes, we use the degree of disagreement about the projections for activity between professional forecasters measured as the standard deviation of the projections from Consensus Economics for annual real GDP growth in the following calendar year (ECBANY), the average "aggregate uncertainty"from the ECB's Survey of Professional Forecasters (ECBBAVE), combining both disagreement between forecasters and individual uncertainty, and an indicator capturing the uncertainty of private households (ECBCHOU) and enterprises (ECBCBUS) based on the European Commission's Business and Consumer Surveys.

To assess financial market uncertainty or risk aversion measures, we use an average of a set of financial market indicators (implied bond and stock market volatility, implied EUR/US dollar volatility and CDS spreads over government bond yields) and a number of systemic stress indicators (exchange rate volatility, equity market volatility, bond market volatility, money market volatility, financial intermediation and a composite systemic stress indicator) (ECBDAVE).

With respect to economic policy uncertainty, we use an index based on the newspaper coverage of policy-related economic uncertainty and the disagreement between forecasters with regard to the outlook for inflation and budget balances: These components are aggregated using weights of 50% for the former and 25% for each of the dispersion measures (ECBEAVE). Additionally, we make use of an indicator that combines all the individual sets of series by principal component analysis (ECBFPC). We select these measures of uncertainty because they show a significant negative correlation with key macroeconomic variables, such as quarterly growth rates of real GDP, total investment, private consumption and, in particular, total employment.

[Table 8 about here.]

We compute EMU-aDtD by calculating the simple average of all aDtDs at the country-level. Table 9 summarizes the correlations of these indicators with ECB regulatory indicators. As can be seen, we find a significant and negative association between our indicators of EMU banking systemic risk based on DtD and the various measures of macroeconomic uncertainty, suggesting that higher banking systemic risk (signalled by a reduction in DtD) will increase macroeconomic uncertainty and, as a consequence, adversely affect macroeconomic events.

To test the predictive ability of this indicator with respect to the regulatory indicators, we assessed the possible existence of Granger-causality. As can be seen in Table 10, with the sole exception of ECBCHOU, we find a significant unidirectional Granger-causality relationship running from our indicators of EMU banking systemic risk to both the various measures of macroeconomic uncertainty and the banking risk indicator used by the ECB. This result gives further support to the hypothesized interconnection between *DtD*s and macroeconomic uncertainty and banking risk.

[Table 9 about here.]

[Table 10 about here.]

6. Inter-linkages

To explore the possible causes for the improved performance of country wise *aDtD*, we explore the linkages between *aDtD* using a cross country connectedness measures. We use three ways to measure the connectedness: (1) Correlations; (2) Granger causality; and (3) Diebold-Yilmaz connectedness index (DYCI) based on the variance decomposition of forecast errors.

6.1. Correlation measures

To understand the co-movement properties, we use three correlation measures (parametric: Pearson, and non-parametric: Spearman and Kendell) in our analysis.[10] 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 other measures.

[Table 11 about here.]

For each measure of correlations, we first estimate the pair-wise correlations between the aDtD (Table 11). As can be seen, we find a strong correlation[11] between indices, which suggests a common risk factor. This may also be due to the small sample, which contains two crisis episodes. To understand the time varying correlation dynamics, we tested for correlations using pre-/post crisis windows and apply a signed rank test to evaluate the null hypothesis that the mean and median correlations are equal if we divide the time period in two half (pre and post 2009-Q4).

[Figure 11 about here.]

The results suggest that except Germany and Finland, all other countries shows very strong correlations with EMU average. This also suggest a common risk factor which we test in the next section. Belgium, Greece, Italy and Portugal have strong inter-linkages and connections across the board. Belgian banking sector shows strong connections with all EMU countries except Germany and the Netherlands. Germany is strongly connected with only Italy and moderately to France, Austria and Finland. For other peripheral countries, Germany has weak correlations (Figure 11).

[10]This avoids any bias arising from potential non-linear dependencies and confirms the robustness of our findings.

[11]We use the adjective "strong" when the absolute value of the cross-correlation is above 0.8, "moderate"when it is between 0.7-0.8, and "weak" when it is between 0.6-0.7

6.2. Granger causality

The graphic behavior of the countries' *aDtD* series suggests an underlying trend. It may be due to an increase in the systemic risk of global financial industry due to cross linkages, increased volatility or investment in correlated assets. To understand this spillover within the EMU banking sector, we run Granger causality tests for each pair-wise country *aDtD*s. We find very weak evidence of causality running from a particular country towards the rest of the countries (Figure 12), which suggests that the banking risk captured by countries' *aDtD*s remains idiosyncratic.

[Figure 12 about here.]

6.3. Diabold-Yilmaz connectedness measure

To explore further the reasons for divergence among *aDtD* indices, we use VAR[12] based measure of connectedness. The connectedness is based on the decomposition of the forecast error variance, which is briefly described here. For a multivariate time series, the forecast error variance decomposition works as follows:

- First, we fit a standard vector autoregressive (VAR) model to the series;
- Secondly, using series data up to, and including, time t, establish an H period ahead forecast (up to time $t + H$); and
- Finally, decompose the forecast error variance for each component with respect to shocks from the same or other components at time t.

Consider an N-dimensional covariance-stationary data-generating process (DGP) with orthogonal shocks:

$$x_t = \Theta(L)u_t, \Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + ..., E(u_t, u_t^{'}) = I$$

Note that Θ_0 need not be diagonal. All aspects of connectedness are contained in this very general representation. Contemporaneous aspects of connectedness are summarized in Θ_0 and dynamic aspects in $\Theta_1, \Theta_2, ...$ Transformation of $\Theta_1, \Theta_2, ...$ via variance decompositions in needed to reveal and compactly summarize connectedness. Let us denote by d_{ij}^H the ij-th H-step

[12]Vector auto regression methodologies.

variance decomposition component (i. e., the fraction of variable i's H-step forecast error variance due to shocks in variable j). The connectedness measures are based on the "non-own", or "cross", variance decompositions, $d_{ij}^{H}, i, j = 1, ..., N, i \neq j$.

Diebold and Yilmaz (2014) propose several connectedness measures built from pieces of variance decompositions in which the forecast error variance of variable i is decomposed into parts attributed to the various variables in the system. Here we provide a snapshot of their connectedness index. They proposed a connectedness table such as Table 12 to understand the various connectedness measures and their relationships. Its main upper-left NxN block, that contains the variance decompositions, is called the "variance decomposition matrix," and is denoted it by $D^H = [d_{ij}]$ The connectedness table augments D^H with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

[Table 12 about here.]

The off-diagonal entries of D^H are the parts of the N forecast-error variance decompositions of relevance from a connectedness perspective. In particular, the *gross pairwise directional connectedness* from j to i is defined as follows:

$$C_{i \leftarrow j}^{H} = d_{ij}^{H}$$

Since in general $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$ the *net pairwise directional connectedness* from j to i, can be defined as:

$$C_{ij}^{H} = C_{j \leftarrow i}^{H} - C_{i \leftarrow j}^{H}$$

Regarding the off-diagonal row sums in Table 12, they give the share of the H-step forecast-error variance of variable x_i coming from shocks arising in other variables (all other, as opposed to a single other), while the off-diagonal column sums provide the share of the H-step forecast-error variance of variable x_i going to shocks arising in other variables. Hence, the off-diagonal row and column sums, labeled "from" and "to" in the connectedness table, offer the total directional connectedness measures. In particular, *total directional connectedness* from others to i is defined as

$$C^H_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{N} d^H_{ij}$$

The *total directional connectedness* to others from i is defined as

$$C^H_{\bullet\leftarrow i} = \sum_{j=1,j\neq i}^{N} d^H_{ji}$$

We can also define *net total directional connectedness* as

$$C^H_i = C^H_{\bullet\leftarrow i} - C^H_{i\leftarrow\bullet}$$

Finally, the grand total of the off-diagonal entries in D^H (equivalently, the sum of the "from" column or "to" row) measures *total connectedness*:

$$C^H = \frac{1}{N} \sum_{i,j=1,j\neq i}^{N} d^H_{ij}$$

For the case of non-orthogonal shocks the variance decompositions are not easily calculated as before because the variance of a weighted sum is not an appropriate sum of variances; in this case methodologies for providing orthogonal innovations like traditional Cholesky-factor identification may be sensitive to ordering. So, following Diebold and Yilmaz (2014), a generalized VAR decomposition (GVD), invariant to ordering, proposed by Koop et al. (1996) and Pesaran and Shin (1998) will be employed. The H-step generalized variance decomposition matrix is defined as $D^{gH} = [d^{gH}_{ij}]$, where

$$d^{gH}_{ij} = \frac{\sigma^{-1}_{ij} \sum_{h=0}^{H-1} (e'_i \Theta_h \sum e_j)}{\sum_{h=0}^{H-1} (e'_i \Theta_h \sum \Theta'_h e_j)}$$

In this case, e_j is a vector with j^{th} element unity and zeros elsewhere, Θ_h is the coefficient matrix in the infinite moving-average representation from VAR, $\sum$ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, σ_{ij} being its j^{th} diagonal element. In this GVD framework, the lack of orthogonality makes it so that the rows of do not have sum unity and, in order to get a generalized connectedness index $\tilde{D^g} = [\tilde{d^g_{ij}}]$, the following normalization is necessary: $\tilde{d_{ij}^g} = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$, where by construction $\sum_{j=1}^N \tilde{d_{ij}^g} = 1$ and $\sum_{i,j=1}^N \tilde{d_{ij}^g} = N$

The matrix $\tilde{D^g} = [\tilde{d_{ij}^g}]$ permits us to define similar concepts as defined before for the orthogonal case, that is, *total directional connectedness, net total directional connectedness and total connectedness.*

Table 13-14 shows the net connectedness of $aDtD$ based on 6 months and 1 year horizon while Figure 13 shows the highest connectedness based on the top three deciles (black, red and orange respectively). As can be seen, the Netherlands shows very weak connectedness while Germany and Italy shows linkages only with Finland and Portugal respectively. Spain, Belgium, Portugal and Austria have high connectedness with most EMU countries except the Netherlands, Italy and Germany. Even for changing horizon, the results remain quite consistent. In most cases, the effects seem to dry out but the connectedness pair remain the same. Finally, we observe a value of 73.67% for the total connectedness between $aDtD$ in a horizon of 6 months and value 76.72% for a year, in line with the values of 78.3% obtained by Diebold and Yilmaz (2014) for US financial institutions.

[Table 13 about here.]

[Table 14 about here.]

[Figure 13 about here.]

7. Conclusion

By analyzing the behavior and fluctuations of a market based banking risk indicator for individual EMU countries, we find that $aDtD$ is an intuitive, simple and convenient forward looking risk measure. It shows some predictive ability 12-18 months prior to the crisis for most of the peripheral EMU countries and captures trends as well as fluctuations in the financial markets. However its sensitivity to volatility also generates strong correlations with quarterly average historical volatility.

The level of $aDtD$ varies with country suggesting cross-sectional structural differences across the banking sector. The country-level $aDtD$ indicators shows strong co-movements across countries but the test for a systemic component reveals negative results. Analysis of the crisis period suggest that the initial level of $aDtD$ matters but that the change in $aDtD$ is more pronounced for countries with a higher initial level. The correlations analysis suggests inter-linkage across country banking stress but low inter-linkage between core and peripheral EMU countries.

When compared with risk measures, average EMU DtDs shows better predictive ability together with very high correlations with market uncertainty and sentiment measures. The Granger causality test reveals the direction of causality running from EMU DtD to Eurozone risk indicators (and not the other way round) suggesting better information content. The strong association between $aDtD$s and regional (Eurozone) market sentiment/sectoral banking indices shows better explanatory power.

Our results may be beneficial to policymakers since, given the current structure of financial markets and market regulations, it makes sense to track systemic risk indicators at the national level. Following the systemic risk indicators based on large, complex EU-wide financial institution may delay the prediction of risk buildup.

To conclude, there are various reasons for considering country-wise risk indicators alongside regional market and other risk measures. As the statistical theory suggests, when faced with two estimators for the same underlying variable, it is optimal to combine the two. Tracking country specific indices provide additional information related to the average risk level and their ability to forecast the risk buildup cannot be ignored.

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Table 1: Description of variables

Balance sheet variables		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		
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

Table 2 List of banks (by country)

Name	Status	ISIN
Austria (AT)		
UniCredit Bank Austria AG	Delisted	AT0000995006
Erste Group Bank AG	Listed	AT0000652011
Raiffeisen Bank International AG	Listed	AT0000606306
Belgium (BE)		
Dexia	Listed	BE0003796134
KBC Groep NV	Listed	BE0003565737
Germany (DE)		
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

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Name	Status	ISIN
Comdirect Bank AG	Listed	DE0005428007
Net-M Privatbank 1891 AG	Delisted	DE0008013400
Merkur-Bank KGaA	Listed	DE0008148206
Quirin Bank AG	Listed	DE0005202303
	Spain (ES)	
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
	Finland (FI)	
Pohjola Bank Plc	Listed	FI0009003222
Aktia Bank Plc	Listed	FI4000058870
Alandsbanken Abp-Bank of Aland Plc	Listed	FI0009001127
	France (FR)	
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

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Name	Status	ISIN
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
Greece (GR)		
National Bank of Greece SA	Listed	GRS003003019
Piraeus Bank SA	Listed	GRS014003008
Eurobank Ergasias SA	Listed	GRS323003004
Alpha Bank AE	Listed	GRS015013006
Marfin Investment Group	Listed	GRS314003005
Attica Bank SA-Bank of Attica SA	Listed	GRS001003003
General Bank of Greece SA	Listed	GRS002003010
Ireland (IE)		
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 (IT)		
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

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Name	Status	ISIN
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 (NL)		
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 (PT)		
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

Table 3: Summary statistics - aDtD

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	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

Table 4: National financial indicators

Market sentiment indicators

Variable	Description	Source
Consumer Confidence Indicator (CCI)	This index is built up by the European Commission which conducts regular harmonized surveys of consumers in each country.	European Commission (DG ECFIN)
Stock Returns (RET)	Differences between logged stock indices prices of the last and the first day of the quarter for each country.	Datastream
Rating (RAT)	Credit rating scale built up from Fitch, Moodys, S&P ratings for each country. Following Blanco (2001), we built up a quarterly scale to estimate the effect of investor sentiment based on the rating offered by these three rating agencies.	Bloomberg
Index of Fiscal Stance (FSI)	This indicator compares a target level of the debt-GDP ratio at a given point in the future with a forecast based on the government budget constraint. It was built by Polito and Wickens (2011, 2012).	Provided by the authors
Stock Volatility (VOL)	Quarterly average of monthly standard deviation of the daily returns of each country's stock market general index	Datastream
Index of Economic Policy Uncertainty (EPU)	This index draws on the frequency of newspaper references to policy uncertainty; it was built for Germany, France, Italy, Spain and EMU by Baker et al. (2013).	www.policyuncertainty.com

Sectoral bank indices

Variable	Description	Source
DSBANKS	DataStream Equity Index-Banks	DataStream
DSFIN	DataStream Equity Index-Financial Services	DataStream

Table 5: Correlations between *aDtD*s and national financial indicators

	aDtD							
	Market sentiment indicators						**Sectoral bank indices**	
	CCI	RET	RAT	FSI	VOL	EPU	DSBANKS	DSFIN
AT	0.87	0.08	-	-0.55	-0.86	-	0.70	0.49
BE	0.80	-0.03	-0.34	-0.64	-0.94	-	0.58	0.90
DE	0.71	0.40	-	-0.83	-0.92	-0.51	0.44	0.53
ES	0.58	-0.03	0.22	-0.31	-0.69	-0.30	0.49	0.29
FI	0.53	0.05	-	0.17	-0.88	-	0.31	-
FR	0.76	0.56	-0.10	-0.64	-0.94	-	0.47	0.90
GR	0.79	0.67	-0.60	0.65	-0.88	-	0.81	0.41
IE	0.87	0.75	-0.58	0.87	-0.83	-	0.82	0.24
IT	0.68	0.53	-0.61	0.04	-0.92	-0.64	0.60	0.66
NL	0.59	0.51	-	0.35	-0.87	-	0.70	0.66
PT	0.24	0.06	-0.34	-0.36	-0.95	-	0.21	0.23

Table 6: Regional financial indicators

	Market sentiment indicators	
Variable	Description	Source
EMUCCI	Consumer Confidence Indicator.	European Commission (DG ECFIN)
EMUCREDSPR	Difference between the yields of the iBoxx indices containing BBB-rated European corporate bonds against the yields of the respective iBoxx indices of AAA-rated European corporate bonds.	Datastream
EMUEPU	This index draws on the frequency of newspaper references to policy uncertainty; it was built for Germany, France, Italy, Spain and EMU by Baker et al. (2013)	Provided by the authors
EMUFSI	Index of Fiscal stance, based on comparing a target level of the debt-GDP ratio at a given point in the future with a forecast based on the government budget constraint. It was built by Polito and Wickens (2011, 2012).	Provided by the authors
EIRVIX1Y	1-year interest rate volatility index for the Eurozone based on the implied volatility quotes of caps (floors). This index was created by Lopez and Navarro (2013) for the period 2004:1-2012:4.	Provided by the authors
EMUVSTOXX	Eurostoxx-50 implied stock market volatility index	www.stoxx.com
	Sectoral bank indices	
Variable	Description	Source
EUROSTOXX	Europe Total Market Banks	Datastream
EMUBANKS	EMU Banks	Datastream
EMUPIIGSBANKS	PIIGS Banks	Datastream
EMUNOPIIGSBANKS	EMU excluding PIIGS Banks	Datastream

Table 7: Cross correlation of national DtDs with regional financial indicators

	aDtD									
	Market sentiment indicators						**Sectoral bank indices**			
	EMUCCI	EMUCREDSPR	EMUEPU	EMUFSI	EIRVIX1Y	EMUVSTOXX	EUROSTOXX	EMUBANKS	EMUPIIGS--BANKS	EMUNOPIIGS--BANKS
AT	0.80	0.46	-0.80	0.42	-0.27	-0.83	0.75	0.67	0.56	0.68
BE	0.89	0.46	-0.85	0.39	-0.43	-0.81	0.79	0.73	0.63	0.69
DE	0.69	0.61	-0.67	0.11	-0.06	-0.80	0.43	0.34	0.26	0.38
ES	0.43	0.32	-0.73	0.30	-0.14	-0.80	0.61	0.53	0.43	0.49
FI	0.56	0.53	-0.60	0.10	-0.15	-0.75	0.44	0.38	0.30	0.38
FR	0.73	0.45	-0.75	0.37	-0.16	-0.83	0.67	0.58	0.44	0.57
GR	0.55	0.15	-0.84	0.64	-0.47	-0.78	0.89	0.86	0.80	0.82
IE	0.46	0.17	-0.80	0.51	-0.28	-0.77	0.75	0.67	0.56	0.63
IT	0.69	0.54	-0.82	0.26	-0.27	-0.88	0.73	0.69	0.61	0.66
NL	0.70	0.38	-0.78	0.48	-0.39	-0.82	0.74	0.72	0.69	0.74
PT	0.55	0.23	-0.80	0.47	-0.38	-0.74	0.82	0.78	0.71	0.74

Table 8: Regulatory indicators

Variable	Explaination	Based on
	Macroeconomic uncertainty indicators	
ECBANY	Disagreement about the projections for annual GDP growth at the following year	Consensus Economics
ECBBAVE	Average uncertainty over GDP, HICP and unemployment over four time horizons (current year, one year ahead, two years ahead and long term)	ECB's Survey of Professional Forecasters
ECBCHOU	Heterogeneity of responses by private households	European Commission's Business and Consumer Surveys
ECBCBUS	Heterogeneity of responses by enterprises	European Commission's Business and Consumer Surveys
ECBDAVE	Average of a set of financial market indicators and systemic stress indicators	ECB financial market database
ECBEAVE	Economic policy uncertainty indicator	Baker, Bloom and Davis (2013)
ECBFPC	Summary measure of economic, financial market and economic policy uncertainty	ECB staff calculations.
	Banking risk indicators	
Variable	Explaination	Based on
ECBEMUDD	Aggregate DtD for large and complex EMU banking groups	ECB staff and Moody's KMV calculation

Table 9: Cross correlation of EMU DtDs with ECB indicators

	EMU-aDtD	EMU-wDtD
Macroeconomic uncertainty indicators		
ECBANY	-0.62	-0.61
ECBBAVE	-0.66	-0.68
ECBCHOU	-0.64	-0.52
ECBCBUS	-0.53	-0.59
ECBEAVE	-0.85	-0.85
ECBFPC	-0.85	-0.84
Banking risk indicators		
	EMU-aDtD	EMU-wDtD
ECBEMUDD	0.67	0.61

Table 10: Granger causality between EMU DtDs and ECB indicators

Null Hypothesis	F-Stats	Prob.	Significant at	Null Hypothesis	F-Stats	Prob.	Significant at
EMU-aDtD							
Macroeconomic uncertainty indicators							
ECBANY does not Granger Cause EMUADTD	2.29	0.12		EMUADTD does not Granger Cause ECBANY	5.08	0.01	5%
ECBBAVE does not Granger Cause EMUADTD	0.28	0.76		EMUADTD does not Granger Cause ECBBAVE	8.76	0.00	1%
ECBCHOU does not Granger Cause EMUADTD	1.97	0.16		EMUADTD does not Granger Cause ECBCHOU	0.64	0.53	
ECBCBUS does not Granger Cause EMUADTD	1.39	0.27		EMUADTD does not Granger Cause ECBCBUS	4.00	0.03	5%
ECBEAVE does not Granger Cause EMUADTD	0.40	0.67		EMUADTD does not Granger Cause ECBEAVE	2.93	0.07	10%
ECBFPC does not Granger Cause EMUADTD	0.32	0.73		EMUADTD does not Granger Cause ECBFPC	7.51	0.00	1%
Banking risk indicators							
ECBEMUDD does not Granger Cause EMUADTD	0.12	0.89		EMUADTD does not Granger Cause ECBEMUDD	6.53	0.0047	1%

Table 11: Correlations among aggregate DtD 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						
	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

Table 12: Schematic connectedness table

	x_1	x_2	...	x_N	From others
x_1	d^H_{11}	d^H_{12}	...	d^H_{1N}	$\sum j = 1^N d^H_{1j}, j \neq 1$
x_2	d^H_{21}	d^H_{22}	...	d^H_{2N}	$\sum j = 1^N d^H_{2j}, j \neq 2$
..	..	...	..	..	
..	..	...	..	..	
x_N	d^H_{N1}	d^H_{N2}	...	d^H_{NN}	$\sum j = 1^N d^H_{Nj}, j \neq N$
To others	$\sum i = 1^N d^H_{i1}$ $i \neq 1$	$\sum i = 1^N d^H_{i2}$ $i \neq 2$	...	$\sum i = 1^N d^H_{iN}$ $i \neq N$	$\frac{1}{N} \sum i, j = 1^N d^H_{iN}$ $i \neq N$

Table 13: Connectedness among country-wise banking risk - aDtD and Horizon 6 months

Country	AT	BE	ES	DE	FI	FR	GR	IE	IT	NL	PT	EMU	From
AT	19.35	3.76	1.30	4.95	22.30	5.47	5.09	4.76	3.66	3.77	13.15	12.42	80.65
BE	6.50	7.58	5.72	5.94	18.18	4.45	9.81	3.30	6.00	3.43	17.13	11.95	92.42
ES	5.59	4.14	16.78	3.52	13.77	4.51	9.09	4.65	10.14	6.01	10.00	11.81	83.22
DE	8.22	2.54	1.63	38.97	14.19	9.51	7.12	5.48	5.62	1.10	0.58	5.04	61.03
FI	12.77	3.57	2.39	5.72	33.04	4.54	3.97	3.85	8.15	3.12	6.18	12.70	66.96
FR	10.20	3.38	1.45	14.28	14.95	27.47	4.37	5.41	2.82	5.33	2.23	8.13	72.53
GR	4.77	3.91	3.79	6.58	6.77	2.98	28.52	1.55	4.13	5.19	24.74	7.07	71.48
IE	13.42	3.84	2.88	10.71	15.96	10.95	2.69	15.06	5.18	4.38	6.67	8.26	84.94
IT	4.68	4.89	6.76	5.43	10.28	2.28	3.99	2.23	20.16	6.21	18.98	14.12	79.84
NL	5.45	2.85	3.12	1.57	6.95	6.14	5.22	0.85	9.37	42.32	5.39	10.77	57.68
PT	4.85	4.40	4.16	4.80	4.54	1.20	4.56	0.96	6.52	2.50	51.65	9.87	48.35
EMU	9.04	5.51	4.74	4.39	16.52	4.93	5.07	3.31	9.44	6.35	15.66	15.06	84.94
To	81.54	84.95	69.34	63.54	81.38	67.47	68.13	70.70	77.89	52.83	70.03	88.16	**73.67**

Table 14: Connectedness among country-wise banking risk - aDtD and Horizon 1 year

Country	AT	BE	ES	DE	FI	FR	GR	IE	IT	NL	PT	EMU	From
AT	18.15	3.91	1.66	4.70	21.34	4.67	5.87	4.35	4.50	4.31	13.71	12.84	81.85
BE	7.34	7.68	3.98	5.09	17.00	3.34	10.12	3.31	7.00	4.04	17.14	13.96	92.32
ES	6.81	5.37	9.81	2.66	16.15	2.85	12.03	3.66	9.14	8.12	10.93	12.47	90.19
DE	6.68	3.71	1.74	32.04	12.82	6.68	9.46	3.96	7.22	1.49	6.52	7.67	67.96
FI	12.47	3.73	2.03	5.48	30.61	4.47	4.93	4.27	8.81	3.26	6.20	13.74	69.39
FR	8.19	4.71	1.86	11.02	13.89	19.95	6.14	3.34	4.14	6.11	9.12	11.54	80.05
GR	7.71	3.86	1.51	7.18	8.71	2.77	29.04	3.02	1.87	5.57	23.03	5.71	70.96
IE	13.90	5.12	2.28	9.76	18.35	5.00	5.47	11.37	4.77	3.64	10.50	9.85	88.63
IT	6.26	5.65	4.54	7.11	14.99	2.93	5.36	2.36	16.47	5.78	16.10	12.44	83.53
NL	7.42	3.69	2.25	2.44	7.74	8.80	7.81	1.43	6.69	38.76	3.28	9.66	61.24
PT	5.80	4.87	2.54	6.51	6.13	2.16	5.46	1.19	3.82	2.83	50.67	8.01	49.33
EMU	10.17	6.07	3.17	4.91	17.69	4.76	6.60	3.19	7.70	5.49	15.45	14.82	85.18
To	83.64	86.85	73.75	67.61	83.49	70.83	73.18	74.98	79.95	56.64	72.26	88.83	**76.72**

Figure 1: Size distribution of banks in individual countries

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

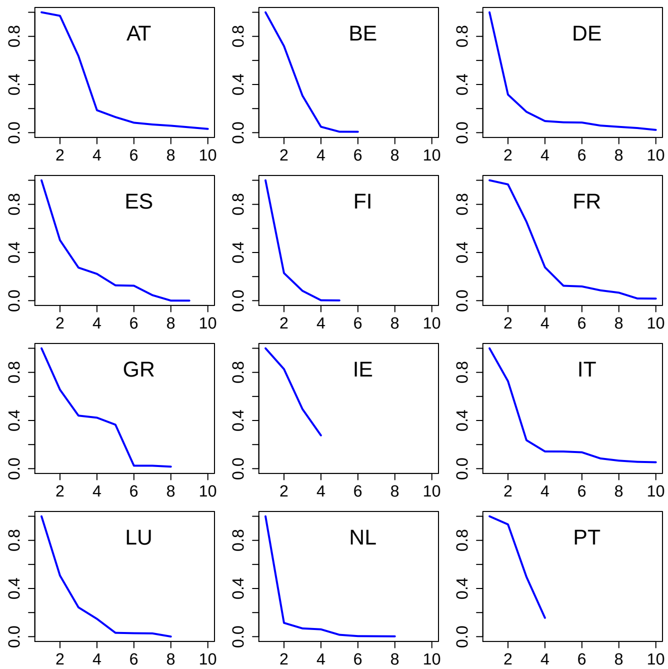


Figure 2: MFI total assets as multiple of GDP

MFI: Monetary Financial Institution as classified by Organization for International Co-operation and Development (OECD). Datasource: OECD, National Central Banks.

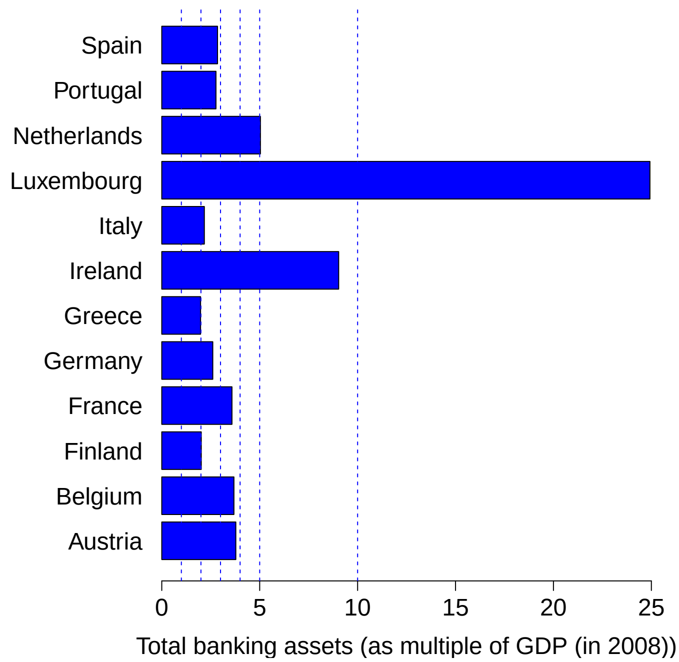


Figure 3: Banks' holding of their own sovereign bonds in notional terms (as % of total notional outstanding)

Source: European Bank Authority stress test 2011 and Eurostat.

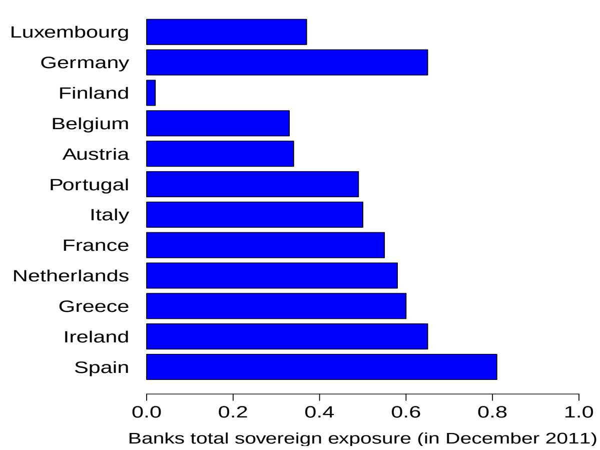


Figure 4: No of banks used every period for each country

AT: Austria, BE: Belgium, DE: Germany, ES: Spain, FI: Finland, FR: France, GR: Greece, IR: Ireland,

IT: Italy, LU: Luxembourg, NL: The Netherlands, PT: Portugal. Datasource: Bankscope.

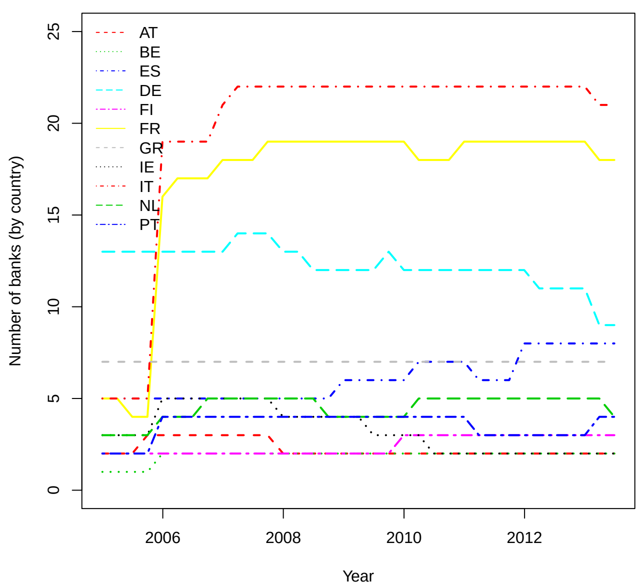


Figure 5: ISO-DtD curves

The figure shows simulated iso-DtD curves for nine different values of DtD with respect to leverage and equity volatility. One can clearly see that DtD is much more sensitive to equity volatility than the leverage even at low levels.

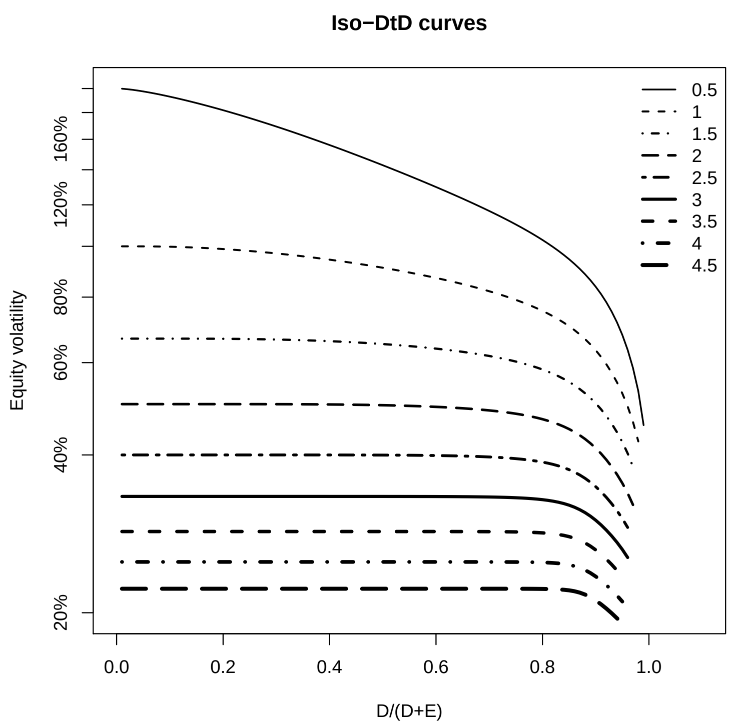


Figure 6: Average DtD

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.

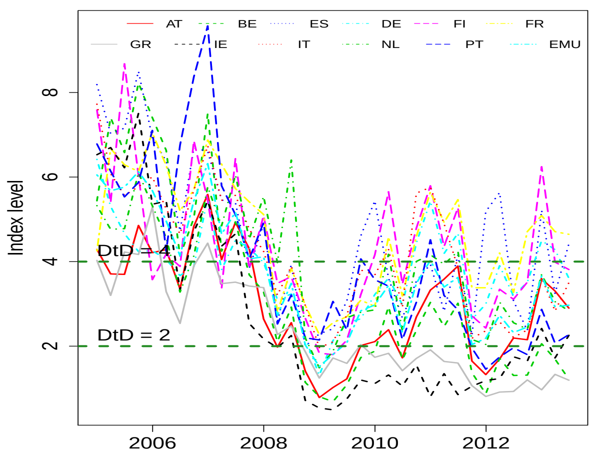


Figure 7: Country-wise indices

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. The blue, green and red line represent volatility, $aDtD$ and equity index level respectively.

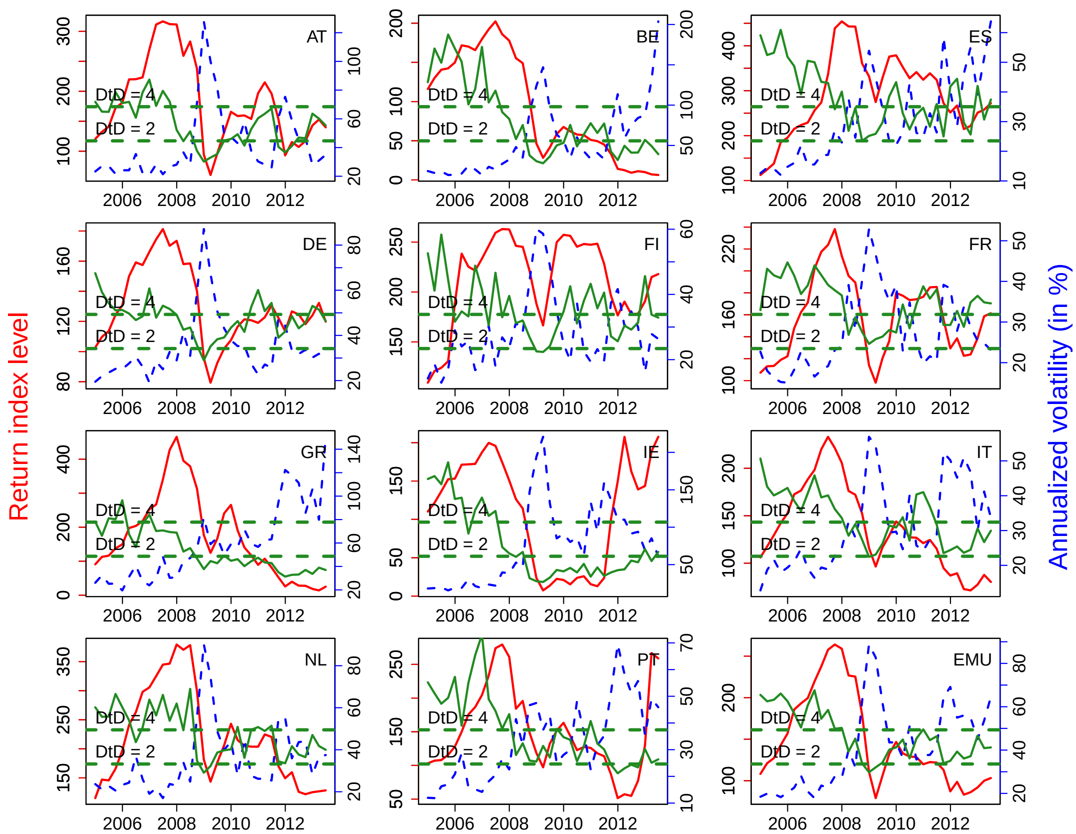
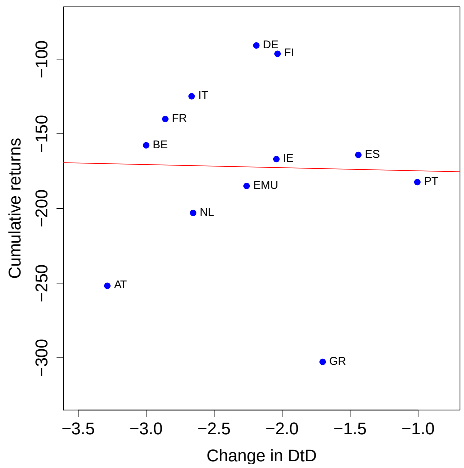
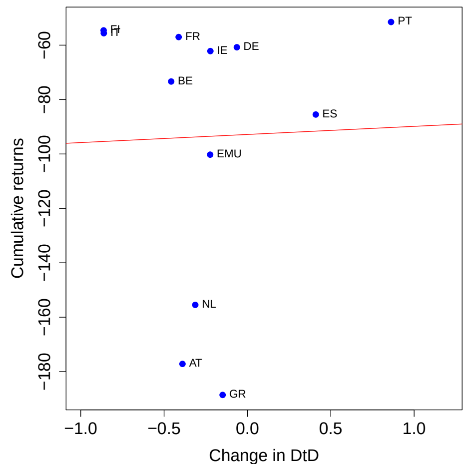


Figure 8: Cumulative returns vs DtD

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.



(a) 2007Q2-2009Q1



(b) 2008Q2-2009Q1

Figure 9: Scatter plot with trend line (2007-Q2 to 2009-Q1)

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.

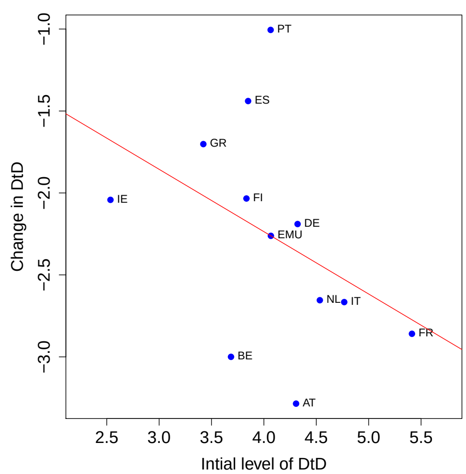


Figure 10: National DtD vs ECB DtD

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

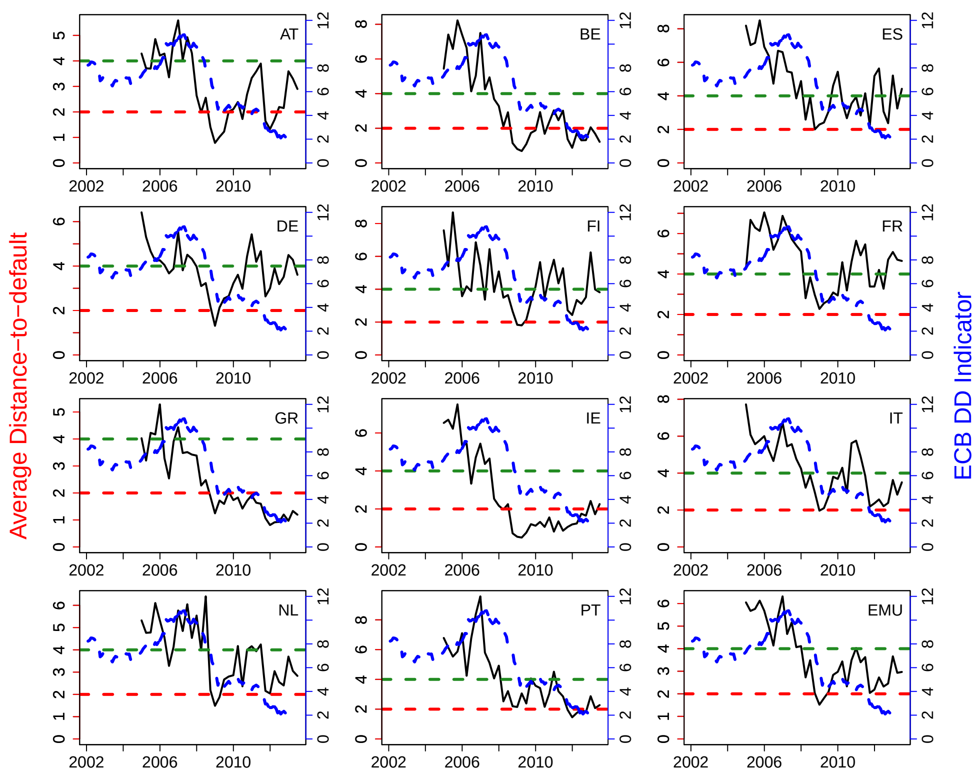
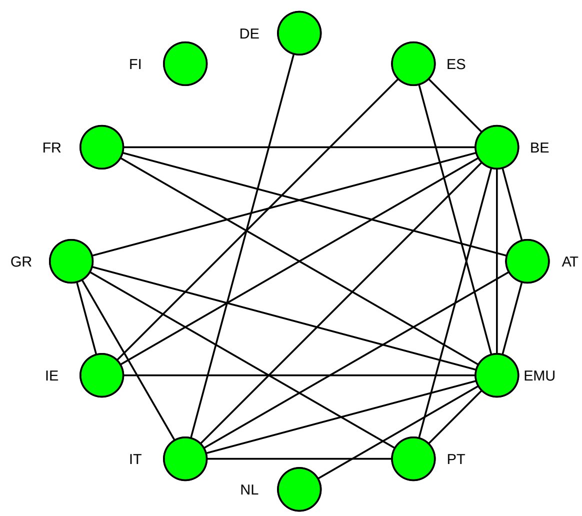
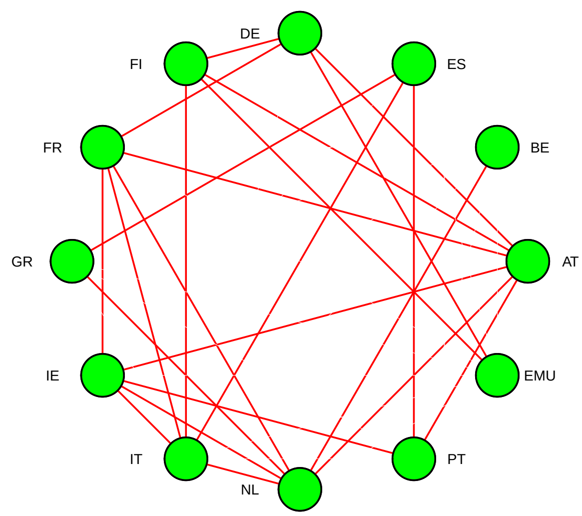


Figure 11: Correlations among aDtDs

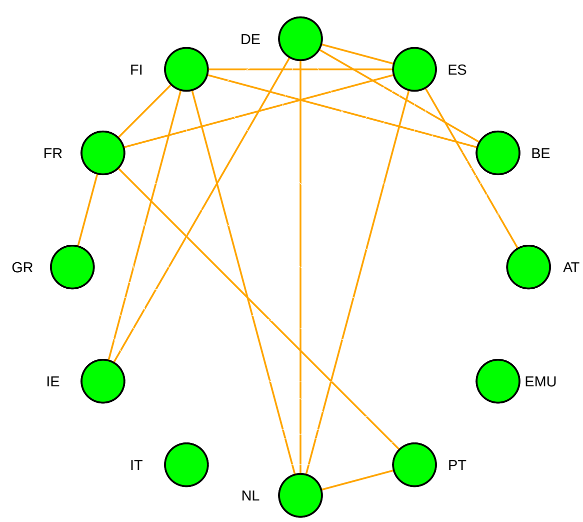
AT: Austria, BE: Belgium, ES: Spain, DE: Germany, FI: Finland, FR: France, GR: Greece, IE: Ireland, IT: Italy, NL: The Netherlands, PT: Portugal, EMU: European Economic and Monetary Union.



(a) Strong



(b) Moderate



(c) Low

Figure 12: Linkages based on Granger causality tests
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. Red and orange lines represent significance at 10% and 5% level respectively.

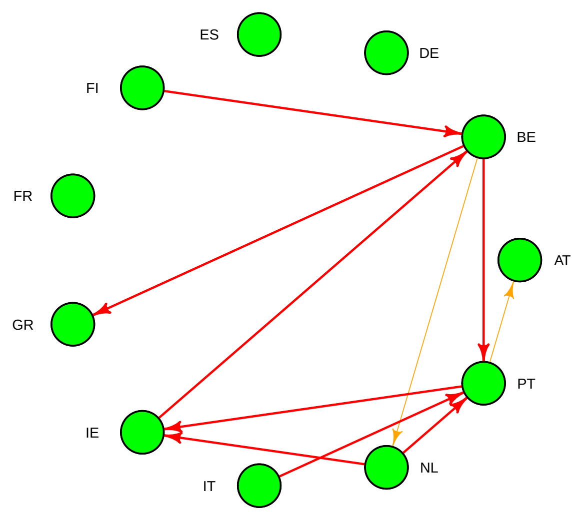
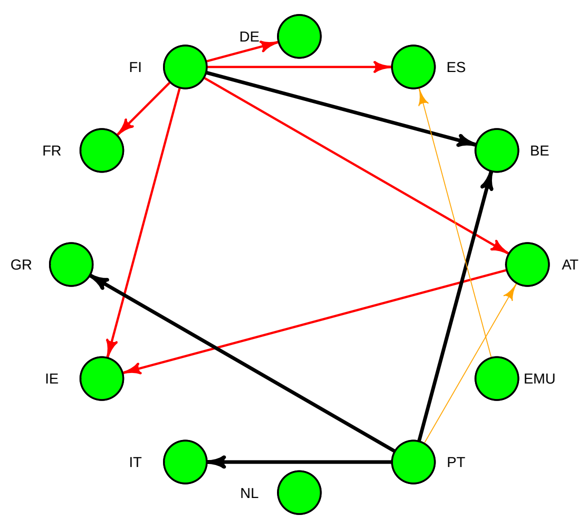
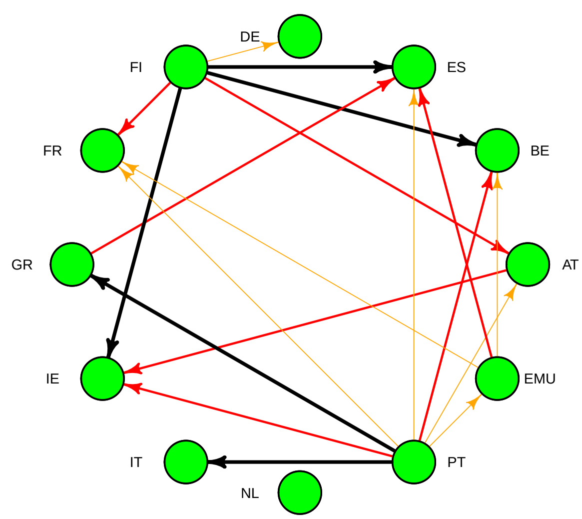


Figure 13: Net directional connectedness among $aDtD$s

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. Black, red and orange lines represent the first, second and third deciles based on net directional connectedness.



(a) Horizon 6 months



(b) Horizon 1 year