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ABSTRACT

CDS spreads are often used as market's view of credit risk. There is no popular alternative to it; perhaps only the distance-to-default measure based on Merton (1974) comes close to it. In this paper we investigate the relationship between these two measures for large European banks in post subprime crises era. The analysis makes use of conventional Granger causality test statistics for individual banks and for the whole panel data. As for the results, we find that the lead-lag relationship between these variables varies over time and over different banks and economic regimes. The lead of distance-to-default is stronger for banks in problem countries (PIGS), during European debt crises, for relatively small banks and when there are large changes in CDS spread. These results suggest that we may have predictive power by not only using the CDS spread, but also other measures such as the distance-to-default.

JEL Classification: G01, G14, G21, G32, G33

Keywords: financial stability, European banks, distance-to-default, credit default swap, lead-lag relationship

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1 Introduction

The recent financial turmoil that started from the subprime crises and spread to European banks and ultimately escalated to a sovereign debt crises, has increased the interest on stability of the banking system. The bailouts of Goldman Sachs, Morgan Stanley and many European banks has raised the question of markets failure to anticipate the credit risk of those banks. The knowledge of a variable leading a commonly used market based credit risk measure like the credit default swap (CDS) spread, would suggest that in addition to market's view also other measures have predictive power and should be used as an early warning indicator alongside the CDS price in credit risk assessment. We investigate, if the popular distance-to-default measure based on Merton (1974) signals the changes in credit risk of banks in a more timely manner than the CDS spread.

A lead of distance-to-default over CDS spread can be motivated with the possible inefficiency of the CDS markets, which has been studied in many previous papers. As majority of the results from these studies[1] support the efficiency of CDS markets, there has been evidence of other measures leading CDS spreads. Tolo, Jokivuolle & Viren (2015) find that the average overnight borrowing rate (AOR) leads the CDS spread at least by one day. The lead is stronger for relatively small banks, banks with weak ratings, during turmoil days and for banks in problem countries. Acharya & Johnson (2007) find that also equity leads CDSs. The selection of distance-to-default as the baseline measure to the comparison with the "leading" market-based measure is based on it's popularity[2] in corporate default prediction. Also the theoretical background of distance-to-default and the fact that it uses corporate balance sheet data in addition to market data makes it an appealing alternative to CDS spreads in analysing credit risk. Distance-to-default has also been proven to have some success in default prediction[3] and is often used as a control for credit risk instead of credit ratings[4].

In our empirical analysis we use a panel of 37 large European banks with monthly observations spanning from January 2008 to December 2013. Due to bank defaults etc. the panel is unbalanced so that the observations for individual banks are between 32 and 72 for a total of 2374 observations in the dataset. We test the lead-lag relationship between the two measures with conventional Granger causality analysis for the whole panel and for individual banks in levels and differences. The lead is assumed to be one month, but longer leads were also a analyzed. Cointegration analysis was omitted, because both variables are stationary according to panel unitroot tests. From a theoretical point of view it would be counter-intuitive, if a credit risk measure would be non-stationary or have a deterministic linear trend. In panel level we use fixed bank effects in the VAR-model to control for

[1]See e.g. Zhang & Zhang (2013) and Blanco, Brennan & Marsh (2005).

[2]Credit rating agency Moodys' analytical service KMV has commercialized this measure with their own estimation method using historical default data to extract default probabilities from D2D.

[3]See Bharath & Shumway (2008).

[4]See e.g. Ahmed, Anderson & Zarutskie (2015) and Acharya, Lochstoer & Ramadorai (2013).

bank specific heterogeneity and we find that the Granger causality is bidirectional[5], which means that both variables have predictive power over the future values of the other measure. At individual bank level distance-to-default leads CDS spreads for a subset of eight banks. Majority of these banks are from the so called PIIGS-countries. By using conditional dummy variable interaction terms in the panel VAR-model, we find that the direction and magnitude of this lead-lag relationship varies over time, general market conditions, banks domicile country and bank specific characteristics. The lead of distance-to-default is significantly stronger during the European debt crises, when there are large changes in the CDS spread and if the banks domicile is in the PIGS-countries[6]. There is also some evidence - though not statistically significant - that the lead is stronger for smaller banks.

These results can all be related to CDS market inefficiency. During the European debt crises and large changes in CDS spreads the amount of CDS contracts would decline, because of the hardened credit assessment by the seller and buyer of CDS contract. Declined transaction volume could affect the price discovery process and these markets would not be as informative. Also banks in problem countries have usually lower credit quality and the CDSs of smaller banks are traded seldom. All these aspects might produce 'thin' markets and affect the information content of the CDS spread. Distance-to-default uses also market data, but this is from stock markets, that are probably far more liquid and thus more efficient. The fact that CDSs are bilateral contracts traded over-the-counter mainly by large institutional investors supports this claim as the CDS markets would be rather 'thin' when compared with stock markets.

This papers main contribution is to show that during crises times, large upward changes in credit risk implied by the CDS spread, for banks in 'problem' countries and for banks that are relatively small the distance-to-default should be used along side the 'leading' market-based measure CDS spread in credit risk assessment of banks. Distance-to-default is a better early warning indicator of a change in banks creditworthiness than CDS spread when these criteria are met, because it's lead in a sense that it Granger causes CDS spread is stronger in those cases. Credit risk assessment is vital for banks, investors, global institutions like IMF etc., which is why the knowledge of one measure leading the other is useful from the aspect of financial stability in general.

This paper is organized as follows: in section 2 we discuss the calculation and specifics of distance-to-default and CDS spread as credit risk measures. In section 3 the dataset for empirical analysis is introduced. Section 4 explains the empirical methodology used in the paper to study the relationship between the two measures. The empirical results and their economic implications are also discussed in the same section. Finally section 5 concludes.

[5]The result holds with both levels and differences.

[6]Portugal, Ireland, Greece and Spain.

2 Distance-to-default and Credit default swaps

2.1 Distance-to-Default

Distance-to-default is a credit risk measure derived from Merton (1974) theoretical credit risk model, which treats firm's equity E as a call option on the firm's assets A. This means that equity holders get the rest of the value of assets after bondholders have gotten their debt D at the maturity T of the debt. This way the equity value can be presented as $E_T = max(V_T - D, 0)$. Distance-to-default is simply the distance between the expected value of assets A and the default point, which is the value of debt D. In other words, the firm is expected to default if its assets fall below the level of debt.

$$D2D = \frac{log(\frac{A}{D}) + (\mu - \frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A \sqrt{T-t}} \tag{1}$$

From the D2D formula in equation 1 one can see that a higher leverage ratio gives a larger D2D value, when other parameters are kept unchanged. Same effect is with larger expected return and higher volatility of the assets when the numerator of equation 1 is positive. This makes sense as we would expect the likelihood of a default for a more leveraged firm to be higher. Also when firm's expected return of assets has risen, then the likelihood that it can pay its debts must be higher. Intuitively the more volatile the returns are, the more likely it is that the assets fall below debt level. The critical assumptions of the model are

- debt D is homogeneous with maturity T
- there are no market frictions
- firm's capital structure is $A = D + E$
- firm's asset value A follows a geometric Brownian motion $dA_t = \mu A_t dt + \sigma_A dS_t$, where μ is the drift of the asset value and S_t is a standard Brownian motion
- Economic agents are also assumed to be risk neutral, which makes the estimation much simpler as μ can be replaced with r in formula 1.

The problem in the formula is that we can not observe the value of assets A or its volatility σ_A. Due to the option interpretation of the firm's equity, we can present the value of the firm's equity at time t with the Black & Scholes (1973) option pricing formula:

$$E_t = A_t \phi(d_1) - e^{-r(T-t)} D \phi(d_2) \tag{2}$$

$$\sigma_E = \frac{A}{E} \frac{\partial E}{\partial A} \sigma_A \tag{3}$$

here $d_1 = \frac{log(\frac{A}{D})+(r-\frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A\sqrt{T-t}}$ and $d_2 = d_1 - \sigma_A\sqrt{T-t}$. The unobservable asset value and its volatility can be solved from the system of nonlinear equations consisting of equation 2 and the relationship between asset and equity volatility in equation 3. Before we can obtain the asset value and volatility, we must collect the debt value from the firms balance sheet, risk-free rate and equity value and volatility from stock price data. One of the most often used application of D2D is Moody's KMV method where the debt maturity T is set as 1 year and the debt variable is constructed as the sum of short term debt and one half of long term debt. This is justified by historical data from KMV's default database, which indicates that typically firms default when asset are somewhere between total debt and short term debt[7]. This is also the method used in this paper.

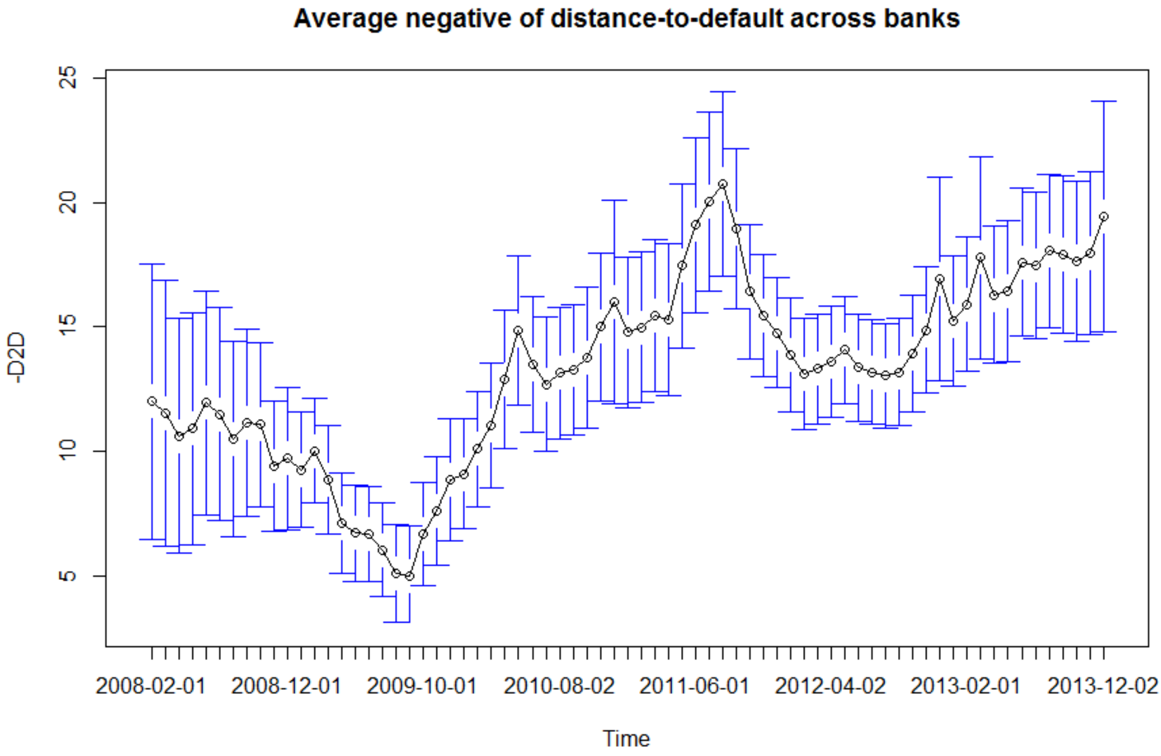


Figure 1: Average negative of distance-to-default for 37 large European banks from 2008 to 2014

The calculation of distance-to-default for banks has few problems, when compared to non-financial firms. Firstly financial regulators usually take action before the actual default occurs, because of the larger effect bank defaults have to the economy due to the collapse of credit supply. Sy & Chan-Lau (2006) introduced a modified measure called distance-to-capital, which corrects the leverage ratio of D2D with the statutory minimum capital adequacy ratio. The other more severe problem with banks D2D derivation is the divergence of financial firms balance sheet from the one of a non-financial firm. Banks

[7]Crosbie and Bohn (2003).

have different kind of deposits, derivative and trading liabilities in their balance sheets. It is hard to define the maturity of these liabilities. In this paper we use a capital adequacy ratio of 12% to correct the leverage ratio and define deposits as short term debt and exclude derivative and trading liabilities[8].

2.2 Credit defaults swaps

Credit default swaps (CDS) are usually used as protection from credit risk. If an investment bank wants to hedge from the default risk of a corporation whose 5-year maturity bond the bank holds, the bank can buy a 5-year maturity CDS contract from a third party. These CDS contracts are usually traded in over-the counter (OTC) markets. Then the bank will pay annual fees to the CDS seller in exchange to the repayment of the rest of the debt if a default occurs before the maturity of the bond. This annual fee is referred as the CDS price or CDS spread, which is expressed in basis points. The payments to the seller are usually done more frequently e.g. quarterly. If the corporation doesn't default during those five years, then the seller keeps the annual fees as profit from the default risk he has borne on behalf of the bank. If default occurs before the maturity of the CDS contract, then the seller keeps the fees he has collected from the buyer and compensates the credit loss to the bank. This compensation is usually done by physically delivering a reference asset or by a cash settlement. Because of the full protection the buyer of the CDS receives against the credit risk of the reference entity, there is a very close relationship between the CDS price and bond's spread[9]. This relationship has been investigated in numerous papers[10], because of the possible arbitrage opportunity between the two financial instruments.

In addition to hedging from credit risk, CDS spreads are also used as early warning indicators of bank's bad state. A rapid decline in bank's creditworthiness raises the CDS spread as the insurer of the reference entity or the seller of the CDS demands a larger fee against the bigger risk that he has to compensate the credit losses of the CDS buyer. It is possible to extract default probabilities from the CDS spread as it is seen as a function of default probability and the recovery value. This recovery value is usually assumed to be a constant, but some authors[11] have stressed that this assumption is not correct in all circumstances. There are few aspects why CDS spread might not reflect purely a banks credit risk. Firstly the very popular post-2008 research subject of bank's that are too-big-to-fail. Vlz & Wedow (2011) found that CDS spreads of large banks are distorted, because they are thought as too-big-to-fail. This might affect the CDS spread in a downgrading way. Secondly the liquidity of a CDS contract may have an effect on the price. The results in the papers investigating the direction of this effect are mixed,

[8]Keeping derivative and trading liabilities in the calculation either as short term or long term didn't seem to affect the results significantly.

[9]Bond spread or credit spread is the difference between the bonds rate and the risk-free rate.

[10]See Blanco et al. (2005).

[11]See Duffie (1999).

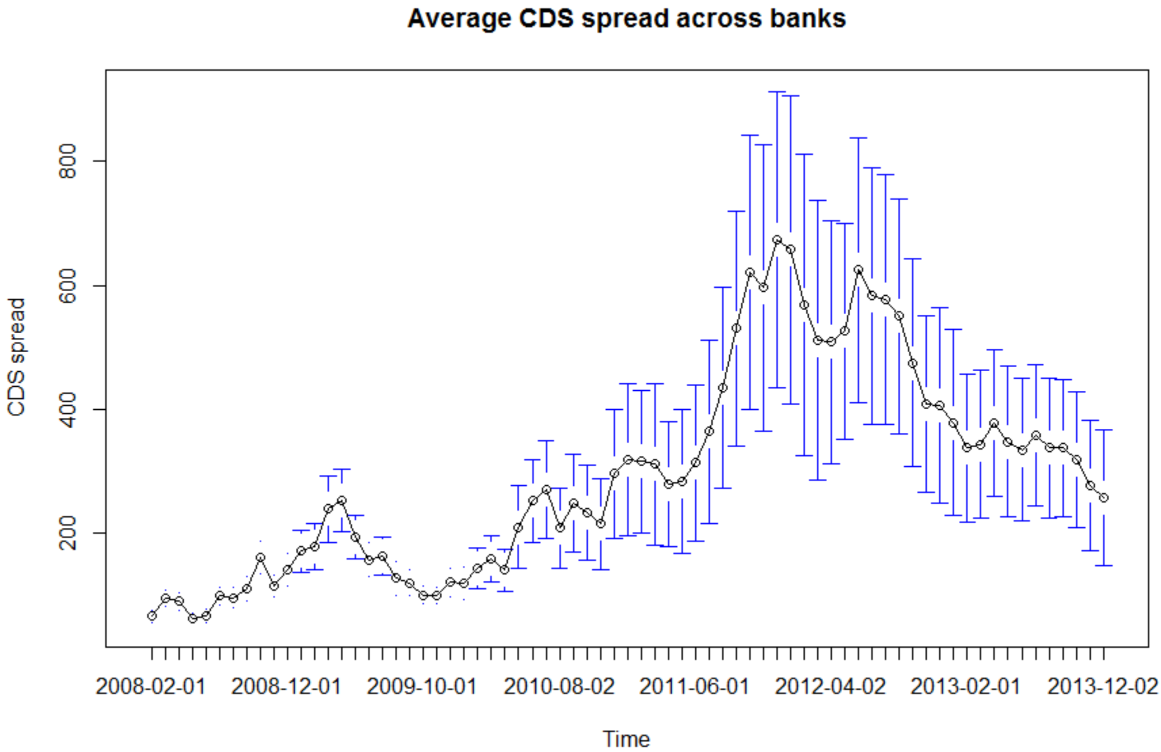


Figure 2: Average CDS spread for 37 large European banks from 2008 to 2014

but a higher liquidity is usually expected to lower the CDS price. Lastly the restructuring of the debt is also seen as a default event for the CDS contracts in Europe. This means that a cheapest-to-deliver option is also included in the CDS spread, because a physical settlement can be done with some reference entities with discounts.

3 Data description

The dataset used in this paper is monthly data for 37 large European banks spanning from January 2008 to December 2013. Originally we had balance sheet data for over 90 banks, but the ones that were not listed had to be dropped, because stock prices are needed to calculate distance-to-default. The list of banks got even smaller, because CDS transaction data was available only for an even smaller subset. We use monthly credit default swap spreads that are averaged over daily transaction prices from Datastream. The CDS contracts are of senior five year maturity, that is the most liquid traded maturity. The data started for some banks as early as 2003, but the majority could be collected as late as 2008 or even later. Because of this the number of monthly observations varies across banks from 32 to 72, so that the total number of observations is 2374.

The variables that were needed to calculate the monthly distance-to-default were mainly assembled from Macrobond. The market capitalization averaged from daily observations was used as the value of equity and the annualized volatility calculated with a

Table 1: **List of banks**

Bank	Country	Obs	Default* date	Bank	Country	Obs	Default* date
Danske Bank	Denmark	71		Royal Bank of Scotland Group	United Kingdom	71	2008-10
BNP paribas	France	71		Svenska Handelsbanken	Sweden	71	
Societe generale	France	71		Swedbank	Sweden	71	
Credit agricole	France	71		HSBC Holdings	United Kingdom	70	
Commerzbank	Germany	71		DNB Bank	Norway	70	
Deutsche bank	Germany	71		Alpha Bank	Greece	71	2012-8
IKB	Germany	36		National bank of Greece	Greece	61	2012-6
UBI Banca	Italy	71		Lloyds Banking Group	United Kingdom	71	2012-6
Allied Irish Banks	Ireland	71	2010-9	Mediobanca	Italy	71	2008-11
Bank of Ireland	Ireland	32	2010-9	Dexia	Belgium	71	2008-9 and 2011-10
Banca Popolare di Milano	Italy	32		Banco BPI	Portugal	32	
Banco popolare societa cooperativa	Italy	71		Erste Group	Austria	71	
ING Groep	Netherlands	71		Intesa Sanpaolo	Italy	65	
Banco Comercial Portugus	Portugal	71		UniCredit	Italy	42	
Banco Bilbao Vizcaya argentaria	Spain	32		Banco Santander	Spain	71	
Bankinter	Spain	71		Nordea	Sweden	71	
Banco popular espanol	Spain	66		Eurobank Ergasis	Greece	71	2011-7 and 2012-6
Banco de Sabadell	Spain	68		Banca Monte dei Pachi di Siena	Italy	72	
Barclays	United Kingdom	71					

Note: *We count mergers, bailouts, nationalizations and separations from the main bank as defaults.

12 month rolling window from daily stock returns as volatility of equity. Annual balance sheet data was collected from Bankscope and used with the same value for all months of that year. Semi annual or quarterly data would have been available for a large portion of the banks, but only for the last couple of years. Annual balance sheet data might be an issue, because the other variables have new information at daily frequency, which is then aggregated to monthly frequency. This problem would in all likelihood appear as large movements in the distance-to-default value at every January when the new information replaces the assumed old information of the later months of that year. We did not observe this kind of general behaviour in the values so we proceeded to further analysis with the same data. The debt variable of a bank is the sum of short term (< 1 year) debt and one half of long term debt (> 1 year).

Table 2: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	Max
CDS spread in basis points	2,374	293	374	15	2,646
D2D	2,374	−13	9	−67	28
Market capitalization in millions	2,374	80,985	388,319	39	7,120,000
Volatility of returns	2,374	0.234	0.132	0.067	1.381
12 month euribor in %	2,374	1.835	1.374	0.478	5.495
S-T liabilities and deposits in millions	2,374	323,162	321,002	19,799	1,261,480
L-T liabilities in millions	2,374	88,035	86,586	708	718
Total liabilities in millions	2,374	604,669	629,040	22,456	2,423,755

Some of the conditional dummy variables e.g. HIGH CDS was constructed by taking the median of each months CDS spread across all 37 banks and if the bank had a higher CDS spread than the median of that month then it got the value one for HIGH CDS that month. In a similar manner were constructed most of the other variables. TURMOIL was one for bank i at month h, if it had a higher CDS spread than the ITRAXX index, which is an index of CDS spreads for large European financial firms. The bank default information to assemble the BANK DEFAULT dummy was mainly collected from Failed Bank Tracker[12], which lists bank bailouts, nationalizations, mergers, bankruptcies, defaults etc..

4 Empirical analysis

4.1 Long-term relationship between D2D and CDS spreads

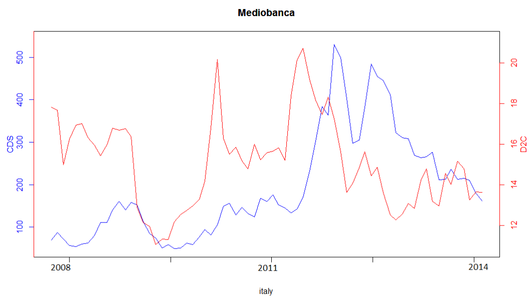
Because both CDS spread and distance-to-default are measures of credit risk, then despite the presence of some short-term deviations there should be some kind of equilibrium relationship between the two in the long run. To study this possible long-term relationship between the two credit risk measures, we test for co-integration at panel and individual bank level. Fisher panel unitroot test with individual Augmented Dickey-Fuller or Phillips-Perron unitroot tests reject the null of a unitroot in the distance-to-default series at a 1 % significance level. The results remain the same whether an individual constant or a linear trend is assumed in the test specification for each cross-section. It would be quite counter intuitive, if distance-to-default or CDS spreads would have a linear trend in the long-run, although this can be detected in some of the graphs of individual banks.

This is of course due to our dataset's time-interval which is from 2008 to 2014, that is from the sub-prime crisis through the ongoing European sovereign debt crises when credit risk was generally rising in European banks[13]. From theoretical point of view it would be hard to see why either of the measures would be non-stationary or have a linear trend in general. Linear trend in the series would indicate that the credit risk for each bank would just rise to infinity in the long-run and all the banks would go bankrupt. The results for the CDS spread series are pretty much the same, null of a unitroot is rejected at a 1 % significance level with a constant in the series, but not with a linear trend. Here we exercise some judgement and conclude that CDS spreads are stationary at panel level given the theoretical and intuitive reason mentioned earlier.

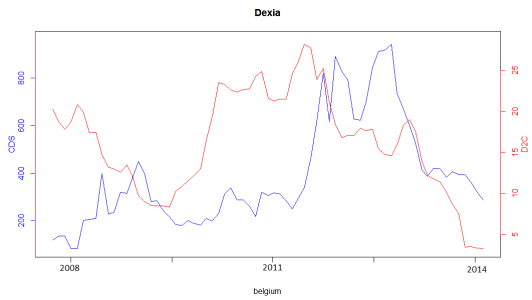
Hypothesis 1. *Credit default swap spread and distance-to-default have a linear time-invariant relationship.*

These results deny the use of co-integration analysis in panel level. Although ADF and PP tests indicated unitroots in both series at individual bank level for some cross-sections, the intuitive assumption of stationarity of the two credit risk measures in general

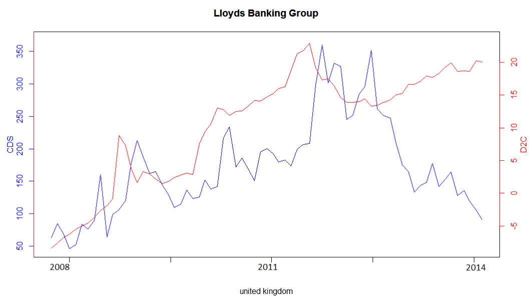
[12]See http://openeconomics.net/failed-bank-tracker/.
[13]See figures 1 and 2.



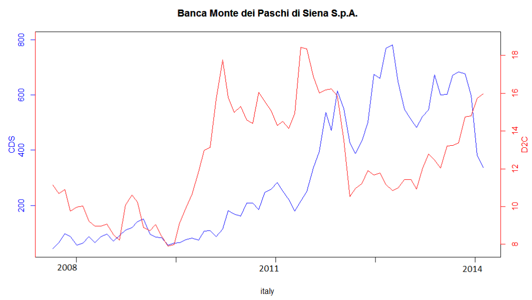
(a) Mediobanca



(b) Dexia



(c) Lloyds



(d) Banca Monte dei Paschi di Siena

Figure 3: CDS spreads and negative of distance-to-default

makes this approach not a preferable option to study the relationship between the two variables. Instead of co-integration analysis, we estimate a panel fixed effects regression with fixed bank effects for the levels of the variables to test hypothesis 1. The fixed bank effects take into account the unobserved heterogeneity of each bank. This way we can observe, if there is a general statistically significant linear relationship between the two default risk measures. The formal definitions of fixed effects and two-way effects models can be seen in equations 4 and 5. If also individual time effects are needed in the model, then the relationship between the variables changes across time. From the results in table 3, we can see as expected that a simple pooled model without individual bank effects is not a sufficient specification as it has a positive sign for the coefficient of D2D against intuition. This would mean that a rise in D2D would raise CDS spreads. The coefficient of determination is also very low when compared to the specification with fixed bank effects that also has a highly statistically significant negative coefficient.

$$CDS_{i,t} = \alpha_i + \beta * D2D_{i,t} + \epsilon_{i,t} \tag{4}$$

$$CDS_{i,t} = \alpha_i + \gamma_t + \beta * D2D_{i,t} + \epsilon_{i,t} \tag{5}$$

We find that fixed time effects are also needed to the model[14] in addition to individ-

[14]Breusch-Pagan Lagrange multiplier test for the need of time effects is used. The null of no need for time effects is rejected at 1% significance level.

ual bank effects, which we interpret as violation of hypothesis 1. The coefficient stays negative, significant and the model has clearly the highest adjusted R-squared. The fact that CDS spread is a price in basis points and distance-to-default is a value of how many standard deviations away a possible default is, makes a non linear relation between the two measures a justifiable alternative that needs to be checked. Quadratic and cubic formulations were also fitted, but the results didn't change as time effects were still needed in addition to bank effects. Also the coefficient of determination didn't change much[15], which is why we stick to the assumption of a linear relationship in further analysis.

4.2 Lead-lag relationship

A long-term relationship between the two measures in its own would not be surprising or even not that interesting result as the two should measure the same thing - credit risk. It would be more interesting to see, if one of the measures would lead the other. To study this possible lead-lag relationship, we assume this lead means that one of the variables Granger causes the other variable, but not the other way around. This relationship is assumed to be short term (one month), although longer periods were also studied. The one month lag could be motivated by the hypothesis of CDS market inefficiency, but it would be hard to believe that the inefficiency would result in a longer lead e.g. four months. A longer lead could be explained with the theoretical background of distance-to-default, which would give an advantage for this measure when compared to just the market's view in the CDS price. We follow the methodology of Tolo et al. (2015), as we try to find evidence for hypothesis 2 by estimating a simple panel vector autoregression model with different fixed effects specifications. The formal definition of the model is $Y_t^i = \alpha_{0,i,t} + \beta y_{t-1}^i + \epsilon_t^i$, where $\alpha_{0,i,t}$ represents either a constant for the pooled model or the fixed effects of different specifications, vector β holds the coefficients of the panel regression and finally vector Y_t^i contains the CDS spread and distance-to-default for bank i at month t. The coefficients are estimated with OLS, which is shown to give consistent estimators for dynamic panel models with macroeconomic data that has a rather large T and small N. We use heteroskedasticity and autocorrelation robust inference in the results.

The short term results for the panel VAR-model where the variables are in levels can be seen in table 4. The lead coefficient of both variables in each other's equations are negative in all models except with fixed time effects.

Hypothesis 2. *Credit default swap and distance-to-default have a lead-lag relationship in a sense that that the other measure Granger causes the other one.*

Also the lead coefficient of CDS doesn't change much between model specifications, but the lead coefficient of D2D over CDS changes pretty dramatically. With pooled and

[15]The adjusted R-squared for the quadratic specification was 0.82 and for the linear model 0.80.

fixed bank models the Granger causality is bidirectional. The results are very similar for the differenced variables as seen in table 5. This implies that there might be an exogenous variable that should be controlled or that the direction of Granger causality varies between banks with different characteristics. The latter option seems to be the case, because when the same analysis is done for differenced series for individual banks, Granger causality is found for a large subset of the 37 banks. These results can be seen in table 13. Distance-to-default Granger causes CDS prices for a subset of eight banks. Seven of these eight banks are from the so called PIIGS countries and one is simply a problem bank from Austria. If the significance level for the Granger causality test would have been set to 10 %, then also Eurobank Ergasis - another Greek bank - would be in this group. The results for levels in table 12 are pretty much the same: D2D Granger causes CDS spreads for three Italian, two Spanish, one Greek, one Portuguese and one Belgian bank. Again there is a major representation of banks from so called 'problem' countries in this lead subset. Only bank that didn't have a domicile in PIIGS was Dexia, which was bailed out in 2008 and finally in 2011 went through a resolution process due to its major losses from Greek government bonds. This might suggest that the information on the problem banks or the banks in problem countries was not entirely reflected in the CDS prices. The fact that CDS markets are rather "thin" compared with stock markets could explain the lead of D2D that uses information from the latter. The lead of CDS over D2D is found for a subset of 10 with the differenced series and 9 banks with level series. These banks seem to be exclusively in Scandinavia, Great Britain, Germany, France, Austria and Italy.

It seems that the lead of distance-to-default or CDS spreads is not a general phenomenon due to these heterogeneous results, but perhaps the lead is only significant for banks with some similar characteristics or during some specific market conditions. We are going to test hypothesis 3 in the same VAR-framework as before with dummy variables for different bank characteristics and general market conditions. In tables 6, 7, 8, 9 and 10 are the results for the CDS equation of the VAR-model with interaction terms of D2D with the conditional dummy variables. The formal specification of the equation is

$$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1} \quad (6)$$

By introducing an interaction term into the VAR-model, we can separate the magnitude of the lead of D2D over CDS prices for different bank characteristics e.g. we can test whether the lead of D2D is statistically significantly stronger for banks in PIIGS countries or for more leveraged banks. We have used 11 different conditional dummies including proxies for general market conditions and for individual bank characteristics. The general market condition dummies represent proxies for crises times and are expected to have a positive coefficient β_3 in equation 6. In panel A almost all coefficients β_2 for the lagged D2D are negative as expected and statistically significant in four equation out of six. This just means that the decline of distance-to-default raises CDS prices in the next month.

The interaction coefficient for domicile in PIIGS, Euro Crisis and turmoil dummies are positive and highly statistically significant when introduced separately to the VAR-model. When included concurrently, the significance of the turmoil dummy disappears. The lead seems to be stronger at the time period after the European sovereign debt crises began and especially in banks that are in so called 'problem' countries. We also tested if a dummy for banks that have since been defaulted would also strengthen the lead or not. This variable of course overlaps the PIIGS dummy in a sense that many of the defaulted banks (except for three) are located in these countries. Not all banks in PIIGS countries defaulted which is why we want to test whether the lead is related to 'bad' banks or problem countries. By itself the default dummies interaction coefficient is positive and moderately significant. When the dummy is introduced to the model with all the other interactions, only the coefficient of Euro Crisis is statistically significant. Neither PIIGS or default coefficient are significant. It seems that the lead is statistically significantly stronger for a bank in a PIIGS country only if it has also defaulted since.

Hypothesis 3. *The lead of distance-to-default on credit default swap spreads is stronger*
i) for relatively small banks
ii) for more leveraged banks
iii) for banks in problem countries
iv) when there are sudden/large changes in credit risk
v) at crises times

The results for the bank specific characteristics can be found in panel B. Here we test if banks size and high leverage relative to other banks in this dataset affect the strength of the lead of distance-to-default. The coefficient of bank size interaction term is positive and moderately significant. The coefficient of high leverage dummy is negative, but not statistically significant. The results stay the same when the variables are introduced at the same time to the model. In panel C are the results for the final conditional dummies that also proxy bank specific financial turbulence. In all five equations β_2 is negative as expected and statistically significant in three equations. β_3 is positive for all four dummy interaction terms when introduced separately, but significant only for high CDS price and its difference. At the same time only the difference is significant. This could mean that when there happens a fast change in the credit risk of bank implied by the risen CDS spread, distance-to-default has signalled this rise earlier and CDS markets just adjust to that level rapidly later on.

In table 9, we have introduced different combinations of the most promising conditioning interaction terms. In all regressions β_2 is negative and highly significant as expected. The amplifying effect of a domcile in PIIGS countries becomes statistically insignificant when high CDS difference interaction is introduced, which itself stays positive and highly statistically significant in all model specifications. The results for the size variable are mixed as its coefficient is not significant and its sign changes when all other promising interactions are also included in the model. The surprising result of the insignificance of the PIIGS coefficient, makes us wonder if the significance is found when Italian banks are excluded, because we observed in the individual causality analysis for the differenced variables that Italian banks were mainly in the CDS lead sub sample. In table 10 PIIGS becomes PIGS as we exclude Italy and repeat the analysis in table 9. The results stay pretty much the same except that PIGS interaction coefficient becomes moderately significant and the coefficient for size interaction becomes even more negative indicating a stronger lead for relatively smaller banks.

Figure 4 visualizes part of these results as it displays the relation between bank size and the strength of distance-to-defaults lead for different banks[16]. It can be also seen in the figure that the lead seems to be stronger for banks in PIGS countries, but the interpretation of banks size effect on the relation might be slightly trivial. For none problem country banks the largest coefficients are in the lowest spectrum of bank size, so the slope of the regression line for that group of banks is close to vertical, but still negative. The same slope is evidently more gently sloping for banks in PIGS, so that the affect of banks size to the strength of distance-to-default lead is more clear: smaller banks have a stronger lead, atleast for banks in these countries. What probably makes this result not significant is the large dispersion of the observation and their small amount around the regression line.

Overall we can conclude with rather robust evidence that hypothesis 3 $iii) - v)$ hold outright. Now we know when the lead would be stronger, but we also conclude if the D2D or its interaction with the conditional dummy Granger cause CDS prices. From the results in table 11 we can state that D2D Granger caused CDS prices only after the Euro crisis began, because when the interaction term is introduced D2D by itself doesn't reject the null that D2D does not Granger cause CDS prices. Same thing can be said about the turmoil variable and moderately about bank size dummy. For the PIIGS domicile dummy both the D2D term and the interaction term Granger cause CDS prices, but for the interaction term the null is rejected with a smaller p-value.

4.3 Economic implications of the results

It seems that there is no general linear relationship between the two measures that would not change over time. The relationship seems to be more of a lead-lag relation, which varies between bank characteristics and general market conditions. The most robust results are that the lead of distance-to-default over CDS prices is significantly stronger during the European debt crisis and when there happens large upward changes in the CDS spreads. This could indicate that during the crises the amount of CDS contracts made would decline, because the evaluation of banks credit risk would be a harder task for

[16]One bank from each group was removed from the figure as an outlier as they had a very large market capitalization. After HSBC holdings and Eurobank Ergasis had been removed, the remaining dataset has 35 banks. Both of these removed banks had a distance-to-default coefficient of near zero.

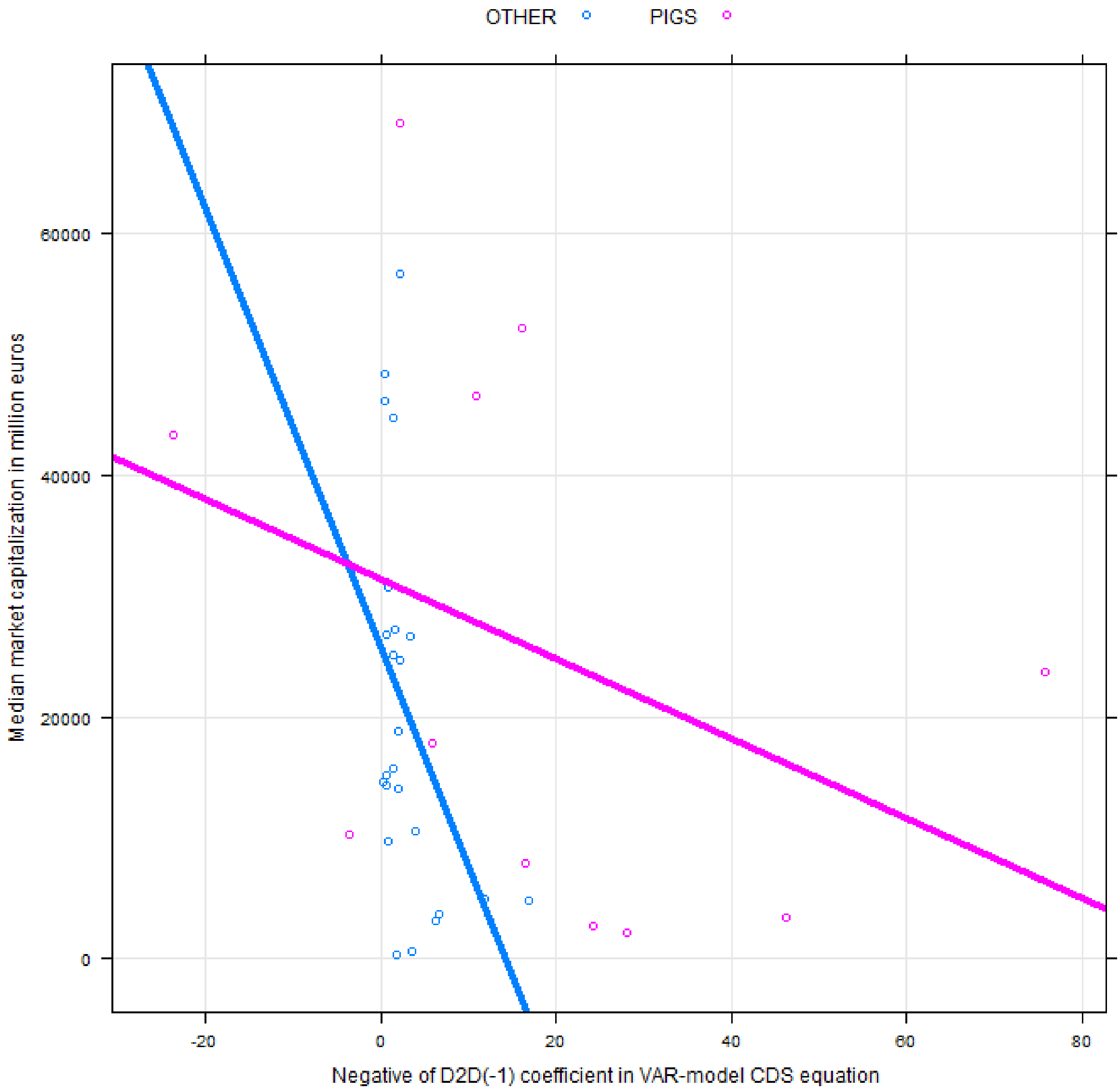


Figure 4: The relation between market capitalization and distance-to-default lead after the European debt crises began.

the seller and the buyer of the contract. This decline in transaction volume could affect the price discovery process and the markets would not be that efficient and informative, which would make the distance-to-default lead the CDS spreads more. Of course distance-to-default uses also market data, but this is from stock markets, that are probably far more liquid and thus more efficient[17]. The fact that CDSs are bilateral contracts traded over-the-counter mainly by large institutional investors supports this claim as the CDS markets would be rather 'thin' when compared with stock markets. Also the significance of the strengthening effect of a large positive CDS price change has on the lead of D2D implies similar phenomenon, but with bank specific turmoil conditions. Because the low D2D difference interaction coefficient was not significant and the coefficient for the

[17]Forte & Pena (2009) find that stocks lead bond and CDS markets more frequently than the other way around.

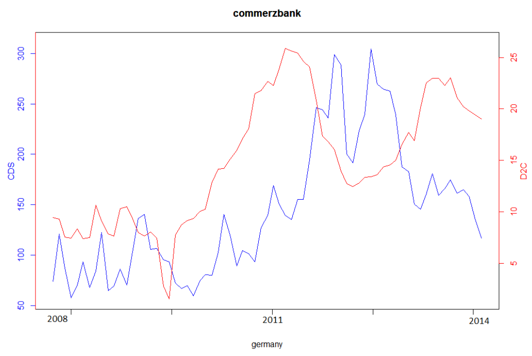
high difference of CDS spread was, this could also signal that D2D has included some amount of credit risk in its value for while that the CDS spread hasn't and then the CDS spread rapidly adjusts to that level at some point. These two findings entail that during financial turmoil the distance-to-default seems to be a better early warning indicator of banks declined state than CDS spreads.

There is also some weak indications[18] that the lead is stronger for smaller banks, which again is in line with the inefficiency explanation of the CDS markets. Smaller banks CDSs are probably traded seldom when compared to larger banks. This again may produce 'thin' CDS markets for some small bank, where the price discovery process is not as efficient as for larger banks and distance-to-default would lead the credit risk discovery process. Finally the so called 'PIIGS' countries, now became 'PIGS' as we found that after excluding Italy the lead of D2D was statistically significantly stronger for banks in this subgroup of countries. This result is again in line with the assumption that banks with lower credit quality are traded less frequently, which affects the efficiency of the CDS markets. The stock markets would also be affected, but perhaps CDS markets are influenced more as there might be more investors there that want to hedge from the banking crises of some country and less CDS contract sellers that are willing to bet that these banks will not default during such financial turmoil.

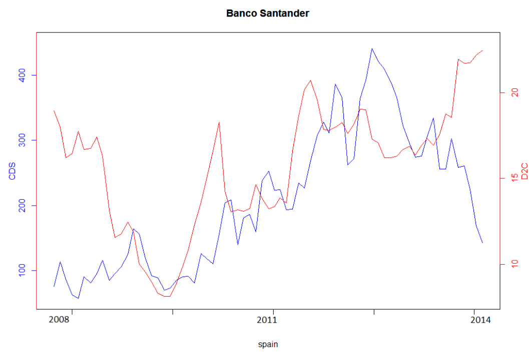
From many of the individual bank graphs - like figures 3a, 3b, 5b and 5c - comparing distance-to-default and CDS spreads it can be seen that the two measures seem to merge from opposite direction when the year gets closer to 2009. For many banks it seems that the credit risk is declining according D2D and rising according to the widening CDS spreads. After 2009 the negative of distance-to-default seems to move to the same direction, but ahead of CDS spreads by many months for numerous banks. This could suggest that a longer term lead might be possible. Again a longer lead would seem unrealistic with just the inefficiency hypothesis and would indicate miss-assessment of credit risk of the CDS markets in general. When testing the Granger causality for each bank individually, we allowed the maximum lag length to be six months when the lag length was chosen according to the information criteria. Schwarz criterion chose a longer lag length than one for only 3 banks[19], which doesn't favour general results of a longer lead. For many banks the indicated credit risk starts to move to separate directions during the final couple of years of the dataset. Distance-to-default seems to indicate risen credit risk for many banks where CDS spreads give the complete opposite signal. In the light of these results for some European banks, the declined credit risk implied by the declined CDS spread could correct itself dramatically if distance-to-default has indicated a risen credit risk, especially if the bank is small and is in a 'problem' country. The reasons why CDS spreads could differ from distance-to-default are e.g. the liquidity premium included in the CDS price, the downgrading effect of too-big-to-fail which could

[18]This result isn't statistically significant, so we can't accept hypothesis 3 i.

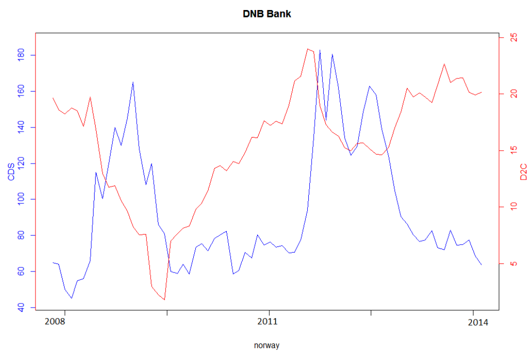
[19]Banco Bilbao Vizcaya Argentaria(2 months), Swedbank(3 months) and Unicredit(2 months).



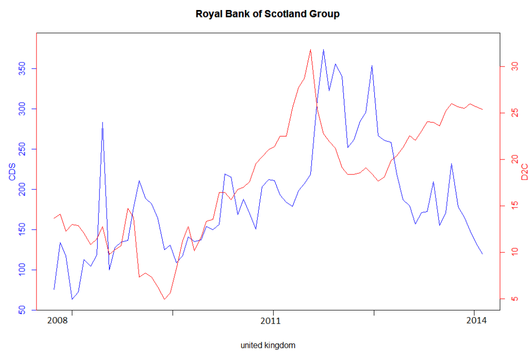
(a) Commerzbank



(b) Santander



(c) DNB bank



(d) Royal bank of Scotland

Figure 5: CDS spreads and negative of distance-to-default

potentially affect the CDS markets more because of the larger amount of speculators in the market, the cheapest-to-deliver option in CDS contracts in Europe.

5 Conclusions

This paper has studied the relationship between CDS spreads and distance-to-default for large European banks. In the light of our empirical results from panel VAR-analysis between the two credit risk measures, it seems with rather robust evidence that there is a lead-lag relationship of one month, the direction and magnitude of which vary with general market conditions, banks domicile country and bank specific characteristics. The individual bank results are very heterogeneous as there are both banks where CDS leads distance-to-default and banks where the Granger causality is the other way around. Clearly during the European debt crises that started in 2010, the lead of distance-to-default over CDS prices was significantly stronger. Now the so called 'PIIGS' countries became 'PIGS' as we found that the lead was even stronger, if the banks were from these problem countries excluding Italy. During large CDS differences distance-to-default also seemed to have a significantly stronger lead, when compared to times with smaller upward movements in CDS prices. Finally there was some indication - although not statistically significant - of a stronger lead for smaller banks. All of these results can be seen to relate to CDS market inefficiency in some way. During crises times and market turmoil, it is usually harder to assess the credit risk of corporations, especially financial institutions. This problem with credit risk assessment might decrease transaction volume in the already 'thinner' CDS markets, when compared to stock markets. Problem country banks usually have lower credit quality and smaller banks have smaller CDS markets than larger ones, which both affect the efficiency of the price discovery process. The other option for the occasional lead of distance-to-default might be related to its theoretical framework combined with market and balance sheet data. As the rise of credit risk by CDS spreads relies solely on market information, these results might imply that theoretical measures should be used beside market information and not just the latter. Further aspects to research in the subject could be the possible generalization of these results. Do these relations hold in general for banks everywhere or just in Europe and for this timespan? It would be interesting to replicate this analysis e.g. for banks in U.S. and Asia.

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A Tables and Figures

Table 3: **Panel regression results** (variables in levels, panel robust inference)

	Dependent variable: CDS spread			
	Pooled	fixed bank effects	fixed time effects	two-ways effects
D2C	16.029^{***}	-12.970^{***}	24.168^{***}	-3.841^{**}
	(3.436)	(1.178)	(1.341)	(1.533)
Constant	504.650^{***}			
	(67.7347)			
Observations	2374	2374	2374	2374
Adjusted R^2	0.155	0.704	0.676	0.795
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: **Short term panel VAR results** (variables in levels, panel robust inference)

	Dependent variable:							
	Pooled		Bank effects		Time effects		Twoways effects	
	CDS_t	$D2D_t$	CDS_t	$D2D_t$	CDS_t	$D2D_t$	CDS_t	$D2D_t$
$D2D_{t-1}$	-0.225^{*}	0.975^{***}	-1.615^{***}	0.767^{***}	0.977^{***}	0.891^{***}	-0.605	0.645^{***}
	(0.125)	(0.011)	(0.364)	(0.057)	(0.285)	(0.030)	(0.570)	(0.068)
CDS_{t-1}	0.983^{***}	-0.0002^{**}	0.933^{***}	-0.001^{**}	0.964^{***}	0.002^{***}	0.931^{***}	-0.001^{**}
	(0.011)	(0.0001)	(0.018)	(0.0005)	(0.015)	(0.0004)	(0.020)	(0.0005)
Observations	2373	2373	2373	2373	2373	2373	2373	2373
Adjusted R^2	0.970	0.955	0.971	0.960	0.979	0.962	0.979	0.968
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 5: **Short-term VAR results** (variables in differences, panel robust inference)

	Dependent variable:							
	CDS spread							
	Pooled		Bank effects		Time effects		Twoways effects	
	ΔCDS_t	$\Delta D2D_t$	ΔCDS_t	$\Delta D2D_t$	ΔCDS_t	$\Delta D2D_t$	ΔCDS_t	$\Delta D2D_t$
$\Delta D2D_{t-1}$	-1.985^{***}	-0.211	-1.928^{***}	-0.217	0.276	-0.293^{**}	0.321	-0.298^{*}
	(0.563)	(0.135)	(0.557)	(0.141)	(0.310)	(0.148)	(0.316)	(0.154)
ΔCDS_{t-1}	0.104^{*}	0.002^{***}	0.100^{*}	0.003^{***}	0.037	-0.003^{***}	0.032	-0.003^{***}
	(0.055)	(0.0004)	(0.055)	(0.0004)	(0.062)	(0.0006)	(0.062)	(0.0007)
Observations	2373	2373	2373	2373	2373	2373	2373	2373
Adjusted R^2	0.015	0.047	0.003	0.041	0.293	0.208	0.285	0.203

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: **Short-term panel VAR results with conditional dummies** (panel robust inference)

$$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$$

Panel A	CDS_t	CDS_t	CDS_t	CDS_t	CDS_t	CDS_t
$D2D_{t-1}$	-0.680^{**}	-0.052	0.133	-0.481^{*}	-1.286^{***}	-1.098^{***}
	(0.326)	(0.265)	(0.289)	(0.290)	(0.429)	(0.421)
$PIIGS_{t-1}$	1.361^{***}	-	-	-	0.887	1.442^{***}
	(0.527)				(0.701)	(0.507)
EURO $CRISIS_{t-1}$	-	2.344^{***}	-	-	2.281^{***}	2.292^{***}
		(0.626)			(0.666)	(0.667)
$TURMOIL_{t-1}$	-	-	1.662^{***}	-	0.798	0.797
			(0.527)		(0.582)	(0.580)
BANK $DEFAULTED_{t-1}$	-	-	-	1.014^{*}	0.467	-
				(0.520)	(0.703)	

Table 7: **Short-term panel VAR results with conditional dummies** (panel robust inference)
$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$

Panel B	CDS_t	CDS_t	CDS_t
D2D_{t-1}	-0.337	0.566^{*}	0.097
	(0.445)	(0.310)	(0.540)
BANK SIZE_{t-1}	0.973^{*}	-	1.077^{*}
	(0.587)		(0.568)
HIGH L/E_{t-1}	-	-0.596	-0.746
		(0.550)	(0.552)

Table 8: **Short-term VAR results with conditional dummies** (panel robust inference)
$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$

Panel C	CDS_t	CDS_t	CDS_t	CDS_t	CDS_t
D2D_{t-1}	-0.804^{**}	-0.307	-1.446^{***}	-0.105	-1.634^{***}
	(0.364)	(0.391)	(0.267)	(0.328)	(0.590)
HIGH CDS_{t-1}	1.387^{**}	-	-	-	0.303
	(0.561)				(0.726)
LOW D2D_{t-1}	-	0.195	-	-	-0.972^{*}
		(0.278)			(0.584)
$\text{HIGH } \Delta\text{CDS}_{t-1}$	-	-	3.377^{***}	-	3.452^{***}
			(0.568)		(0.524)
$\text{LOW } \Delta\text{D2D}_{t-1}$	-	-	-	0.731	-0.167
				(0.500)	(0.494)

Table 9: **Short-term VAR results with conditional dummies** (panel robust inference)
$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$

Panel D	CDS_t	CDS_t	CDS_t	CDS_t
D2D_{t-1}	-1.381^{***}	-1.863^{***}	-1.925^{***}	-1.488^{***}
	(0.517)	(0.497)	(0.441)	(0.472)
PIIGS_{t-1}	1.403^{**}	0.974	0.730	-
	(0.639)	(0.634)	(0.503)	
EURO CRISIS_{t-1}	2.442^{***}	1.624^{**}	1.629^{**}	1.578^{**}
	(0.633)	(0.700)	(0.706)	(0.687)
SIZE_{t-1}	0.560	-0.162	-	0.227
	(0.676)	(0.618)		(0.505)
$\text{HIGH } \Delta\text{CDS}_{t-1}$	-	3.171^{***}	3.135^{***}	3.255^{***}
		(0.598)	(0.614)	(0.592)

Table 10: **Short-term VAR results with conditional dummies** (panel robust inference)
$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$

Panel E	CDS_t	CDS_t	CDS_t	CDS_t
D2D_{t-1}	-1.394^{***}	-1.940^{***}	-2.072^{***}	-1.488^{***}
	(0.514)	(0.506)	(0.458)	(0.472)
PIGS_{t-1}	1.470^{**}	1.129^{*}	0.708	-
	(0.697)	(0.677)	(0.525)	
EURO CRISIS_{t-1}	2.526^{***}	1.703^{**}	1.716^{**}	1.578^{**}
	(0.633)	(0.704)	(0.710)	(0.687)
SIZE_{t-1}	0.339	-0.404	-	0.227
	(0.705)	(0.649)		(0.505)
$\text{HIGH } \Delta\text{CDS}_{t-1}$	-	3.165^{***}	3.106^{***}	3.255^{***}
		(0.593)	(0.608)	(0.592)

Table 11: **Granger causality tests with interactions** (panel robust inference)
$CDS_t = \alpha + \beta_1 CDS_{t-1} + \beta_2 D2D_{t-1} + \beta_3 D2D_{t-1} * DUMMY_{t-1} + \beta_4 DUMMY_{t-1}$

	H0: D2D does not cause CDS		*H0: Interaction term does not cause CDS*	
Interaction term	F-statistic	p-value	F-statistic	p-value
$D2D_{t-1} * PIIGS_{t-1}$	4.360	0.037	6.670	0.010
$D2D_{t-1} * EUROCRISIS_{t-1}$	0.038	0.845	14.021	0.000
$D2D_{t-1} * TURMOIL_{t-1}$	0.212	0.645	9.946	0.002
$D2D_{t-1} * BANKDEFAULTED_{t-1}$	2.744	0.098	3.803	0.051
$D2D_{t-1} * BANKSIZE_{t-1}$	0.576	0.448	2.748	0.098
$D2D_{t-1} * HIGHL/E_{t-1}$	3.329	0.068	1.174	0.279
$D2D_{t-1} * HIGHCDS_{t-1}$	4.886	0.027	6.113	0.014
$D2D_{t-1} * LOWD2D_{t-1}$	1.304	0.254	0.492	0.483
$D2D_{t-1} * HIGH\Delta CDS_{t-1}$	29.404	0.000	35.348	0.000
$D2D_{t-1} * LOW\Delta D2D_{t-1}$	0.103	0.748	2.137	0.144

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: **Granger causality results for individual banks for levels** (panel robust inference, 1 lag)

	H0: CDS does not cause D2D	*H0: D2D does not cause CDS*	
Bank	p-value	p-value	Causality
Danske Bank	0.188	0.114	No granger causality
BNP paribas	0.203	0.069	No granger causality
Societe generale	0.083	0.079	No granger causality
Credit agricole	0.342	0.058	No granger causality
Commerzbank	0.043	0.038	bidirectional Granger causality
Deutsche bank	0.008	0.271	CDS Spread Granger Causes D2D
IKB	0.050	0.081	No granger causality
UBI Banca	0.095	0.003	D2D Granger causes CDS spreads
Allied Irish Banks	0.496	0.242	No granger causality
Bank of Ireland	0.009	0.034	bidirectional Granger causality
Banca Popolare di Milano	0.580	0.064	No granger causality
Banco popolare societa cooperativa	0.104	0.016	D2D Granger causes CDS spreads
ING Groep	0.095	0.117	No granger causality
Banco Comercial Portugus	0.503	0.021	D2D Granger causes CDS spreads
Banco Bilbao Vizcaya argentaria	0.228	0.165	No granger causality
Bankinter	0.662	0.000	D2D Granger causes CDS spreads
Banco popular espanol	0.777	0.098	No granger causality
Banco de Sabadell	0.432	0.006	D2D Granger causes CDS spreads
Barclays	0.000	0.135	CDS Spread Granger Causes D2D
Royal Bank of Scotland Group	0.005	0.082	CDS Spread Granger Causes D2D
Svenska Handelsbanken	0.004	0.257	CDS Spread Granger Causes D2D
Swedbank	0.006	0.180	CDS Spread Granger Causes D2D
HSBC Holdings	0.054	0.410	No granger causality
DNB Bank	0.000	0.083	CDS Spread Granger Causes D2D
Alpha Bank	0.361	0.364	No granger causality
National bank of Greece	0.068	0.037	D2D Granger causes CDS spreads
Lloyds Banking Group	0.019	0.144	CDS Spread Granger Causes D2D
Mediobanca	0.054	0.000	D2D Granger causes CDS spreads
Dexia	0.083	0.011	D2D Granger causes CDS spreads
Banco BPI	0.997	0.056	No granger causality
Erste Group	0.000	0.050	CDS Spread Granger Causes D2D
Intesa Sanpaolo	0.962	0.192	No granger causality
UniCredit SpA	0.071	0.308	No granger causality
Banco Santander	0.685	0.117	No granger causality
Nordea	0.005	0.182	CDS Spread Granger Causes D2D
Eurobank Ergasis	0.455	0.826	No granger causality
Banca Monte dei Paschi di Siena S.p.A.	0.620	0.083	No granger causality

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: **Granger causality results for individual banks for differences** (panel robust inference, 1 lag)

	H0: CDS does not cause D2D	*H0: D2D does not cause CDS*	
Bank	p-value	p-value	Causality
Danske Bank	0.023	0.408	CDS Spread Granger Causes D2D
BNP paribas	0.123	0.013	D2D Granger causes CDS spreads
Societe generale	0.019	0.056	CDS Spread Granger Causes D2D
Credit agricole	0.063	0.001	D2D Granger causes CDS spreads
Commerzbank	0.015	0.085	CDS Spread Granger Causes D2D
Deutsche bank	0.007	0.277	CDS Spread Granger Causes D2D
IKB	0.704	0.650	No granger causality
UBI Banca	0.012	0.166	CDS Spread Granger Causes D2D
Allied Irish Banks	0.071	0.382	No granger causality
Bank of Ireland	0.568	0.027	D2D Granger causes CDS spreads
Banca Popolare di Milano	0.350	0.495	No granger causality
Banco popolare societa cooperativa	0.050	0.005	bidirectional Granger causality
ING Groep	0.019	0.213	CDS Spread Granger Causes D2D
Banco Comercial Portugus	0.228	0.562	No granger causality
Banco Bilbao Vizcaya argentaria	0.270	0.303	No granger causality
Bankinter	0.040	0.007	bidirectional Granger causality
Banco popular espanol	0.346	0.597	No granger causality
Banco de Sabadell	0.307	0.388	No granger causality
Barclays	0.000	0.249	CDS Spread Granger Causes D2D
Royal Bank of Scotland Group	0.005	0.427	CDS Spread Granger Causes D2D
Svenska Handelsbanken	0.011	0.338	CDS Spread Granger Causes D2D
Swedbank	0.079	0.057	No granger causality
HSBC Holdings	0.185	0.718	No granger causality
DNB Bank	0.103	0.082	No granger causality
Alpha Bank	0.339	0.001	D2D Granger causes CDS spreads
National bank of Greece	0.469	0.043	D2D Granger causes CDS spreads
Lloyds Banking Group	0.749	0.398	No granger causality
Mediobanca	0.032	0.000	bidirectional Granger causality
Dexia	0.075	0.970	No granger causality
Banco BPI	0.665	0.303	No granger causality
Erste Group	0.316	0.036	D2D Granger causes CDS spreads
Intesa Sanpaolo	0.061	0.475	No granger causality
UniCredit SpA	0.437	0.814	No granger causality
Banco Santander	0.180	0.005	D2D Granger causes CDS spreads
Nordea	0.008	0.111	CDS Spread Granger Causes D2D
Eurobank Ergasis	0.398	0.094	No granger causality
Banca Monte dei Paschi di Siena S.p.A.	0.068	0.007	D2D Granger causes CDS spreads

Note: *p<0.1; **p<0.05; ***p<0.01

The **Aboa Centre for Economics (ACE)** is a joint initiative of the economics departments of the Turku School of Economics at the University of Turku and the School of Business and Economics at Åbo Akademi University. ACE was founded in 1998. The aim of the Centre is to coordinate research and education related to economics.

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