Do Sovereign CDS and Bond Markets Share the Same Information to Price Credit Risk? An Empirical Application to the European Monetary Union Case

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Abstract

We analyze the extent to which the sovereign Credit Default Swap (CDS) and bond markets reflect the same information on their prices in the context of the European Monetary Union. The empirical analysis is based on the theoretical equivalence relation that should exist between the CDS and bond spreads in a frictionless environment. We first test and find evidence in favour of the existence of persistent deviations between both spreads during the crisis but not before. Such deviations are found to be related to some market frictions, like counterparty risk and market-illiquidity. Finally, we find evidence suggesting that the price discovery process is state-dependent. Specifically, the levels of counterparty and global risk, funding costs, market liquidity and the volume of debt purchases by the European Central Bank in the secondary market are all found to be significant factors in determining which market leads price discovery.

Keywords: Sovereign Credit Default Swaps, Sovereign Bonds, Credit Spreads, Price Discovery.

JEL Codes: G10, G14, G15.

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1. Introduction

In the last years many studies have analyzed the relationship between CDS and bond spreads for corporate as well as for emerging sovereign reference entities. However, the relation between sovereign CDS and bonds markets in developed countries has not attracted much interest until very recently, mainly for two reasons. First, sovereign CDS and bonds spreads in developed countries have been typically very low and stable given the perceived high credit quality of most issuers (see Table 1). Second, trading activity in this segment of the CDS market was scarce.

However, the global financial crisis that followed the collapse of Lehman Brothers in September 2008 triggered an unprecedented deterioration in public finances of the world's major advanced economies in a peacetime period. Since 2010, some countries in the euro area, including Greece, Ireland and Portugal, and to a lesser extent Spain and Italy, have faced some episodes of heightened turbulences in their sovereign debt markets. Against this context, the levels of perceived credit risk and the volume of trading activity in the sovereign CDS markets in many advanced economies have increased considerably.

The previous literature have paid much attention to investigate the relationship between the corporate bond market and the corporate CDS markets, but as far as we know, only a few papers have studied whether the empirical regularities identified in the corporate markets, including those related to price discovery, are also found in the case of sovereign reference entities. The aim of this paper is to fill this gap by providing empirical evidence focusing on sovereign bonds and CDS markets of several countries in the context of the recent episodes of sovereign-debt crises witnessed recently in the European Monetary Union (EMU).

Specifically, this paper analyses the theoretical equivalence relation between the sovereign bond yield and CDS spreads. More specifically, we focus on the bond spreads over the risk free rate and the CDS spreads.[1] For a given reference entity, both spreads can be thought as prices for the same underlying credit risk. Abstracting from market frictions and other contractual clauses both spreads should use basically the same

[1] The results are obtained following the standard market practice in terms of the risk-free rate definition, namely, the German bond yield

information on the credit risk of a given reference entity and therefore should yield identical results. Moreover, they should reveal the credit risk information in a similar way. The current European sovereign debt crisis poses a new scenario that allows us to test for the previous hypothesis. In particular, we analyze the bond-CDS equivalence relation from three different perspectives.

First, we test the "no-arbitrage" theoretical frictionless relation that should exist between the bond and the CDS spreads because they are supposed to be the prices for the same credit risk. We nevertheless find persistent deviations from the theoretical parity relation between both spreads. Interestingly, we find that the deviations begin with the outset of the subprime crisis with no evidence of such deviations before then.

Second, based on the previous finding about the breakdown of the theoretical frictionless relation between the CDS and bond spreads during the crisis period, we study the possible causes of the deviations between them. Specifically, we analyse the determinants of the basis, defined as the difference between the CDS spread and the corresponding bond spread. As the determinants of the basis we consider different types of risk and market frictions. In particular, we find that the counterparty risk indicator has a negative and significant effect on the basis, especially during the most recent period. Both funding costs and a low liquidity in the bond market relative to the CDS market also have a negative effect on the basis. In periods in which shocks originated in the bond market are transmitted into the CDS market, which we label as *spillovers*, we find an overreaction-effect in this last market. Finally, we show that the speed of reversion of the basis is asymmetric, with positive bases typically requiring a longer time to diminish.

Third, based also on the previous evidence of some persistent divergences between the two prices, we address the point of what market leads the price discovery process. To this aim, we follow a dynamic price discovery approach, based on Gonzalo and Granger (1995). In particular, we find evidence suggesting that the price discovery process is state-dependent. Specifically, the levels of counterparty and global risk, funding costs, market liquidity and the volume of debt purchases by the European Central Bank in the secondary market are all found to be significant factors in determining which market leads price discovery.

The remainder of the paper is organized as follows: Section 2 discusses the related literature. Section 3 describes the data. Section 4 summarizes the methodology and the results based on the analysis of persistent deviations between CDS and bond spreads. Section 5 describes the results obtained from the analysis of the determinants of the basis. Section 6 presents the results of the dynamic price discovery test. Section 7 contains some final remarks.

2. Related literature

There is a growing literature analyzing the link between corporate and sovereign CDS and bond market from different perspectives. In this section we focus on papers related to the three approaches we employ in our paper: persistent deviations between bond and CDS spreads, determinants of the difference between such spreads, and the price discovery process in the bond and CDS markets.

The analysis of persistent deviations between CDS and bond markets has only been applied to the corporates in Mayordomo, Peña and Romo (2011a). They analyse the existence of persistent deviations between CDS and asset swap spreads of European corporations using pre-crisis and crisis periods. Their results show that there are persistent deviations both in the pre-crisis and the crisis periods.

There is an extensive literature addressing the determinants of corporate bond and CDS spreads.[2] Although this type of analyses is less frequent for the case of sovereign bond and CDS spreads, this topic has been attracting more attention since the formation of the EMU being the studies of the bonds' yield spreads the more frequent.[3] Our aim is not to study the determinants of the CDS or bond spreads but the determinants of the basis to test whether both market reflect different information. Although the analysis of the determinants of the basis is less frequent than the analysis of the individual credit

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[2] Elton, Gruber, and Agrawal (2001), Collin-Dufresne, Goldstein and Martin (2001), Chen, Lesmond and Wei (2007), among others study the determinants of the corporate bond spread. The studies analyzing the determinants of the corporate CDS spreads include Longstaff, Mithal and Neis (2005), and Ericsson, Jacobs and Oviedo-Helfenberger (2009), among others.

[3] See Codogno, Favero and Misale (2003), Geyer, Kossmeier and Pichler (2004), Bernoth, von Hagen and Schuknecht (2006), Favero, Pagano and Von Thadden (2009), Beber, Brandt and Kavajecz (2009), or Mayordomo, Peña, and Schwartz (2011) among others.

spreads, some examples appear in the sovereign credit markets.[4] For instance, Fontana and Scheicher (2010) employ weekly data to analyse the determinants of the basis which is obtained using as the bond spread the difference between the bond yield and the interest rate swap (IRS) for the same maturity.[5] They find that the sovereign bases are significantly linked to the cost of short-selling bonds and to country specific and global risk factors. In his analysis of the CDS-bond parity, Levy (2009) finds that this parity does not hold for emerging markets sovereign debt but manages to restore much of the theoretical predictions of a zero basis spread once he accounts for liquidity effects. Küçük (2010) relates the CDS-bond basis for 21 emerging market countries between 2004 and 2008 to bond liquidity, speculation in CDS market, CDS liquidity, equity market performance, and world macroeconomic factors. Foley-Fisher (2010) studies the relation between bond and CDS spreads for ten EMU countries on the basis of a theoretical model. He shows that the basis is consistent with a relatively small dispersion in the beliefs of investors on the probability that certain European countries would default.

Finally, the most frequent analysis of the CDS-bond relation in corporate and sovereign credit markets is based on the concept of price discovery. Most of the recent papers study price discovery on the basis of either Hasbrouck's (1995) or Gonzalo and Granger's (1995) methodologies. Both methodologies are supported by an empirical test based on a VAR with an Error Correction Term model. For the period before the subprime crisis the repeated empirical finding is that the CDS market reflects the information more accurately and quickly than the bond market in the corporate sector (see Norden and Weber (2004), Blanco, Brennan, and Marsh (2005), Zhu (2006), or Forte and Peña (2009) among others). Most of the analyses of price discovery in sovereign markets have been applied to emerging markets. For instance, Ammer and Cai (2007) find that bond spreads lead CDS premiums more often than had been found for investment-grade corporate credits. Chan-Lau and Kim (2004) find that it is difficult to conclude that one particular market dominates the price discovery process. Using bond and CDS data from eight emerging market countries for the period January 2003 - September 2006, Bowe, Klimaviciene, and Taylor (2009) find that the CDS market does

[4] Analyses of the basis in the corporate credit market include: Trapp (2009), Nashikkar, Subrahmanyam, and Mahanti (2008), and Bai and Collin-Dufresne (2009) among others.
[5] The IRS is not a fair proxy for the risk-free rate because it includes systemic risk coming from the financial institutions.

not dominate price discovery, which appears to be country-dependent. The recent crisis has increased the interest on the price discovery process in the European sovereign debt markets. Thus, Fontana and Scheicher (2010) find that since the start of the crisis, the bond market has a predominant role in price discovery in Germany, France, the Netherlands, Austria, and Belgium while the CDS market is playing a major role in Italy, Ireland, Spain, Greece and Portugal. Delatte, Gex, and Lopez-Villavicencio (2010) find that the bond market leads the price discovery process in the core European countries in low tension periods while in tension periods, the CDS market becomes the leader. In the high-yield European countries, the CDS spread reflect credit risk more adequately than the bond spreads in tension and low tension periods but the leadership of the CDS spread is exacerbated by financial turmoil. All these analyses have been carried out on a static basis that is, they obtain a measure for the whole period analysed. However, as Longstaff (2010) states, the nature of the price-discovery process in financial markets could be state dependent. Thus, Delis and Mylonidis (2010) study by the first time the dynamic interrelation between bond and CDS spreads on the basis of a Granger causality test. They find feedback causality during periods of financial distress. As we will show later, Gonzalo and Granger (1995) test is more useful to determine who the leader is and who the follower is.

3. Data

The data consists of daily 5-year sovereign bond yields and CDS spreads for eleven EMU countries (Austria, Belgium, Finland, France, German, Greece, Ireland, Italy, The Netherlands, Portugal, and Spain) from January 2004 to September 2010. Bond yields are obtained from Reuters and CDS spreads from Credit Market Analysis (CMA), which reports data (bid, ask and mid) sourced from 30 buy-side firms, including major global investment banks, hedge funds, and asset managers.[6]

Table 1 reports the main properties of the data on bond and CDS spreads employed in our analysis. As becomes evident from this table, average CDS rates vary substantially across countries and periods. For the period 2004-2008, the lowest average CDS spread was 5 basis points (bp) for Germany and the highest one was 23 bp points for Greece.

[6] Mayordomo, Peña and Schwartz (2011) compare the quality of the data on CDS from different providers and find that CMA produces, on average, the most reliable data.

For the same period, the lowest average bond spread is 4 bp for both France and The Netherlands,[7] and the highest average is 25 bp for Greece. We note that CDS spreads are on average higher than bond spreads in most of the countries, i.e. the basis, defined as the difference between the CDS and bond spreads, is positive. For the second period (Panel B), the lowest average CDS spread during that year was 36 bp for Germany and the highest average was 190 bp for Ireland. The lowest average bond spread was 23 bp for France and the highest was 166 bp for Greece. In this more recent period, the CDS spreads are, again, on average, higher than the bond spreads in most of the countries. Finally, during 2010 Greece showed the maximum average credit spreads (593 bp, being the maximum daily CDS spread at 1,126 bp) and the lowest average at 31 bp for Finland. The maximum average CDS spread as well as the maximum daily CDS spread corresponds to Greece (664 and 1,293 basis points, respectively). As in the other two periods, the CDS spread is on average higher than the bond spread. These data also show that, in general, the average credit spreads and their volatility in the peripheral countries both increased over time.

< Insert Table 1 here>

As for the rest of the data used in the subsequent estimations, the country-stock indexes and global risk, which is proxied by means of the implied volatility index (VIX), are obtained from Reuters. To capture funding costs we use the difference between the 90-day US AA-rated commercial paper interest rates for financial companies and the 90-day US T-bill, both from Datastream. We employ liquidity measures for the sovereign CDS and bonds which are obtained from the bond and CDS bid-ask spreads. Bond bid-ask prices are obtained from Reuters while CDS bid-ask spreads come from CMA. To proxy the counterparty risk on the side of CDS dealers, we employ the CDS spreads of the 14 banks most active as dealers in the CDS market. These CDS spreads are obtained from CMA.

Data on CDS volume (gross notional amount outstanding) come from the Depositary Trust and Clearing Corporation (DTCC). Data on the amount of debt issued by each

[7] Recall that the bond spreads are obtained using the German bond yield as the risk free rate. This standard has been used by Balli (2008), Bernoth, von Hagen, and Schuknecht (2006), Delis and Mylonidis (2010), Favero, Pagano, and Von Thadden (2009), Foley-Fisher (2010), Geyer, Kossmeier, and Pichler (2004), among others

country are obtained from Dealogic. The information regarding the European Central Bank (ECB) bond purchases which took place after May 2010 was obtained from the ECB webpage.

4. Are there persistent deviations between CDS and bond spreads?

Suppose that an investor buys a bond at its par value with a maturity equal to T years and a yield to maturity equal to *ytm*. Also, assume that at the same time the investor buys protection on such reference entity for T years in the CDS market and the premium of such contract is s. The investor has eliminated the default risk associated to the underlying bond and the investor's net annual return is equal to $ytm - s$. Absent any friction, arbitrage forces would imply that the net return should be equal to the T-year risk-free rate, which we denote by r. Alternatively, if $ytm - s < r$, then by means of a short position in the bond, writing protection in the CDS market and buying the risk-free bond the investor could have obtained a positive profit without any risk. If, on the contrary, $ytm - s > r$, the investor could obtain a certain profit by buying the risky bond, buying protection in the CDS market and taking a short position in the risk-free bond. Hence, in equilibrium, $ytm - r = s$.

In order to investigate the existence and persistency of deviations between CDS and bond spreads, that violate the previous equilibrium relation, we apply the statistical arbitrage test employed by Mayordomo, Peña and Romo (2011a). This test is based on a notion of arbitrage introduced by Hogan, Jarrow, Teo and Warachka (2004) according to which, absent market frictions, an arbitrage opportunity (in an statistical sense) represents a zero-cost, self-financing trading opportunity that has positive expected cumulative trading profits with a declining time-averaged variance and a probability of loss that converges to zero as time passes. Bearing in mind that, within the logic of this methodology, the existence of arbitrage opportunities is conditioned to the absence of market frictions, in our application of this test, we interpret the results in a rather agnostic way, avoiding identifying persistent deviations between both spreads with unexploited arbitrage opportunities. Indeed, when such deviations are found, we relate them, in a statistical sense, to several potential market frictions (see Section 5).

To test for the existence of persistent deviations from the zero-basis, we first compute the increase in the "discounted trading profits", which would obtain under the assumption of no trading or funding costs, as follows. The "profits" from a given investment strategy are defined as the basis times the contract notional value. We compute such profits quarterly and the payment on a given date t is added to the trading profits accumulated from the first investing date to the day before, t-1. The accumulated profits constructed in this way are assumed to have been invested or borrowed at the risk-free rate in the interim, from t-1 to t. The cumulative trading profits are then discounted up to the initial date. The increase in the discounted cumulative trading profits at a given date t is denoted by Δv_t and is assumed to evolve according to the following process:

$$\Delta v_t = \mu t^{\theta} + \sigma t^{\lambda} z_t \qquad (4)$$

for $t = 0, 1, 2, \ldots, n$, with n denoting the last investment date and where z_t are innovations. We assume the following initial conditions: $z_0=0$ and $v_0 = 0$ (i.e. the strategy is self-financed). Parameters θ and λ determine whether the expected trading profits and the volatility, respectively, are decreasing or increasing over time and their intensity. Under the assumption that z_t is an *i.i.d. N(0,1)* variable, the expectation and variance of the discounted incremental trading profits in equation (4) are $E[\Delta v_t] = \mu t^{\theta}$ *and* $Var[\Delta v_t] = \sigma^2 t^{2\lambda}$, respectively.

Then, the discounted cumulative trading profits generated by a given strategy satisfy:

$$v_n = \sum_{t=0}^{n} \Delta v_t \sim N\left(\mu \sum_{t=0}^{n} t^{\theta}, \sigma^2 \sum_{t=0}^{n} t^{2\lambda} \right) \qquad (5)$$

We then define the log-likelihood function for the increments in equation (5) and estimate the parameters of interest $(\mu, \theta, \sigma, \lambda)$ by maximizing that function using a non-linear optimization method based on a Quasi-Newton-type algorithm. Then, we implement formally the notion of statistical arbitrage test outlined before through the specification and testing of the following three simultaneous hypotheses:

$$H1: \lim_{t\to\infty} E^{`P}[v(t)] > 0 \quad \Rightarrow \qquad \mu > 0, \ \ and$$
$$H2: \lim_{t\to\infty} P(v(t) < 0) = 0 \quad \Rightarrow \qquad \lambda < 0 \ \ or \ \ \theta > \lambda, \ \ and$$
$$H3: \lim_{t\to\infty} Var[\Delta v(t) \mid \Delta v(t) < 0] = 0 \quad \Rightarrow \theta > \max\left\{ \lambda - \frac{1}{2}, -1 \right\}.$$

Statistical arbitrage requires that the expected cumulative discounted profits, $v(t)$, are positive (*H1*), the probability of loss converges to zero (*H2*), and the variance of the incremental trading profits $v(t)$ also converges to zero (*H3*).[8]

Hence, these three conditions must be simultaneously satisfied to have support for the existence of persistent non-zero basis. In practice, this implies an intersection of several sub-hypotheses. To maximize the power of the test, instead of testing whether the previous hypotheses are simultaneously satisfied, we redefine the null hypothesis as the absence of persistent non-zero basis and so, our test is based on the following union of sub-hypotheses which are given by the complementary of the previous hypotheses (see Jarrow, Teo, Tse, and Warachka, 2007):

$$\begin{aligned}
&H1^C : \mu \leq 0, \quad or \\
&H2^C : \lambda \geq 0 \quad and \quad \theta - \lambda \leq 0, \quad or \\
&H3_1^C : \theta - \lambda + \frac{1}{2} \leq 0, \quad or \\
&H3_2^C : \theta + 1 \leq 0,
\end{aligned}$$

where $H1^C$ and $H2^C$ are the complementary of hypotheses *H1* and *H2* while $H3_1^C$ and $H3_2^C$ come from the complementary of hypothesis *H3*. If one of the last four hypotheses above is satisfied, we conclude that no persistent deviations exist.

To test these hypotheses we need to estimate the *p-values* for the previous restrictions. To this aim, we follow the methodology developed by Politis, Romano, and Wolf (1997 and 1999). This technique provides an asymptotically valid test under weak assumptions.

Specifically, our analysis leads to two one-tail tests:

a) H_0: no persistent deviations and H_A: negative deviations (the bond spread is significantly higher than the CDS spread);

b) H_0: no persistent deviations and H_A: positive deviations (the CDS spread is significantly higher than the bond spread).

[8] Implicit in hypothesis *H3* is the idea that investors are only concerned about the variance of a potential decrease in wealth. Whenever the incremental trading profits are nonnegative, their variability is not penalized.

The results of these tests are summarized in Table 2. Panels A and B report the results for the period ranging from January 2004 to September 2008 for negative and positive bases, respectively. Panels C and D report the corresponding results for the period September 2008 - September 2010. As shown in Panels A and B, we cannot reject the null hypothesis (no persistent deviations) at any standard significance level. This result holds irrespectively of whether we consider either positive or negative bases. However, after the collapse of Lehman Brothers, the CDS spread is persistently higher than the bond spread in six cases (see Panel D) while none of the countries analysed presents a persistent negative basis, as shown in Panel C.

< Insert Table 2 here >

As a conclusion, the above results reveal that the zero-basis hypothesis cannot be rejected when we consider the pre-crisis period although temporary non-zero basis are not rare during that episode. This last result must be interpreted with caution since, as argued before; a non-zero basis can not be understood mechanically as an opportunity for arbitrage. For instance, Schonbucher (2003) and Mengle (2007) emphasize that shorting a bond with a required maturity, even years, is not always a feasible option. Moreover, the fact that non-zero basis seem to appear during the crisis period may be symptomatic of the presence of other restrictions and frictions that prevent a perfect timeless alignment between the CDS and the bond spreads and whose relevance may have been exacerbated by the crisis itself. This could be the case, for instance, of funding costs, differences in liquidity across markets and counter-party risk in the CDS market. In the following section we test for the significance of these (and other) factors, as potential explanatory variables for the cases of non-zero basis detected during the crisis.

5. The determinants of the basis

In this section we test whether the differences between the CDS and bond spreads are purely random or, alternatively, whether they are related to any market-specific or global factors. Specifically, we consider the following potential explanatory factors:

a. Counterparty Risk. In principle, the higher the counterparty risk of the seller of protection via CDS is, the lower should be the CDS spread charged as a result of the lower quality of the protection. We test for this effect by using the first principal component obtained from the CDS spreads of the main 14 banks which act as dealers in that market.[9] The first principal component series should reflect the common default probability and, hence, it is akin to an aggregate measure of counterparty risk.[10] Actually, the first PC for the series of CDS spreads of this set of dealers explains 87.5% of the total variance of the observed variables.

b. Liquidity. In theory, one would expect that higher liquidity in the bond market relative to the CDS market would go hand in hand with a higher basis, since a more liquid bond implies a higher price and, hence, a lower bond spread. To test for this relative liquidity effects, we construct a ratio of relative liquidity between the bond and the CDS. Specifically, the degree of liquidity in the CDS market is proxied by the relative bid-ask spread which is obtained as the ratio between the bid-ask spread of the CDS premium and the mid-premium, i.e. (Ask-Bid)/((Ask+Bid)/2). The higher this ratio is, the lower is the degree of liquidity in the CDS market. A similar measure of liquidity is computed for the bond market and the ratio between both is taken as indicative of the relative liquidity in the bond market vis-à-vis the CDS market. As this ratio rises, liquidity in the bond market relative to the CDS market falls and so does the basis.

c. Financing Costs: One would expect that higher financing costs would lower the demand for bonds, as buying them require funding, and could lead to a decrease in prices, and hence, to higher bond spreads. The effect of funding costs on CDS spreads should be lower given that in this case the required amount of funding to get the same (gross) risk position is lower (i.e. risk-leverage is higher in the case of the CDS investment). For this reason, an increase in financing costs would have a negative effect on the basis. Due to the difficulty in obtaining data on institution-level funding constraints, we use the spread between financial commercial paper and T-bill rates as a

[9] The 14 main dealers are: Bank of America, Barclays, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan, Morgan Stanley, Royal Bank of Scotland, Societé Generale, UBS, and Wachovia/Wells Fargo. These dealers are the most active global derivatives dealers and are known as the G14 (see for instance ISDA Research Notes (2010) on the Concentration of OTC Derivatives among Major Dealers).

[10] The use of the dealers' CDS spreads as a proxy of counterparty risk is based on the Arora, Ghandi, and Longstaff (2009) study which analyses the existence of counterparty risk in the corporate CDS market.

common proxy for the funding constraints faced by financial intermediaries, as in Acharya, Schaefer and Zhang (2006). Specifically, we use the spread between the 90-day US AA-rated commercial paper interest rates for the financial companies and the 90-day US T-bill.

d. Domestic and global risk premiums: As additional potential explanatory variables for the basis, we consider a measure of the country and global risk premium. If both the CDS and bond spreads are prices for the same credit risk, the effect of the country-specific and global risk premiums on the basis should be non-significantly different from zero. However, in order to control for the fact that this idiosyncratic and global volatility could be priced differently in the two markets, we use the previous risk factors as additional explanatory variables. The country-specific risk premium is proxied by means of the stock market volatility. The global risk premium or global risk is proxied by means of the VIX Index. The correlation between the VIX Index and the counterparty risk variable is around 0.8. Thus, in order to avoid any multicollinearity problem, we modify the counterparty-risk variable and define it as the residual of the regression of the first principal component CDS spreads corresponding to the main CDS dealers onto the VIX Index such that counterparty risk and VIX are now orthogonal variables and the counterparty risk is not related to changes in the perception of global risk.

e. Bond-CDS Spillovers: We here use the notion of spillovers between the CDS and the bond markets as the variation in the CDS (bond) spread that is not attributable to its past values but to contemporary shocks to the bond (CDS) spread. To measure such spillovers or contagion-effects, we use a procedure based on Diebold and Yilmaz's (2010) methodology and described in Appendix A.1. The Bond-CDS spillovers variable is obtained after dividing the spillovers from the changes in bond spread to the changes in CDS spread relative to spillovers from the CDS to the bond spread changes. This variable reflects the increase in a given spread due to a direct effect of the other market. We work in relative terms because the dependent variable is the difference between both credit spreads. A positive (negative) sign implies that when the ratio increases, that is, the shock transmission from the bond market to the CDS market is stronger (weaker) than in the opposite direction, then the basis widens (narrows) , or in other words, the CDS spread increases (decreases) with respect to the bond spread.

f. Lagged basis: The lag of the basis should absorb any lagged information transmitted into the current observation. It also permits us to test the speed of adjustment of a positive and negative basis. Due to the existence of persistent deviations between CDS and bond spreads documented in Section 4, we expect a positive sign.

We estimate the coefficients for the above variables of interest using a fixed-effects estimation procedure that is robust to heteroskedasticity. We use the bootstrap methodology to correct for any potential bias in the standard errors due to the use of generated regressors. We report the results for different time periods in Table 3. Columns 1, 2, and 3 refer to the period which spans from Jan-2004 to Sep-2010, Jan-2007 to Sep-2010, and Jan-2008 to Sep-2010, respectively.

Interestingly, we observe that the relevance of the counterparty risk indicator increases in the last part of the sample. In particular, when we restrict the sampling period to January 2008 – September 2010, the counterparty risk proxy has a negative, as expected, and significant effect. Although non-significant at 5% level, the relative liquidity has a negative effect, as expected. Funding costs have a negative effect, as expected, in the three sub-samples, although non-significant. The global risk variable is not significant in any of the three scenarios which may suggest that both markets reflect global risk to a similar extent. Similarly, the country risk premium, proxied by the squared of the stock index returns, seems not to be priced differently in both markets. We also find that the shock-spillovers ratio has a positive and significant effect. That is, when the shock transmission from the bond to the CDS market dominates the shock transmission in the opposite direction, then the basis widens. One economic implication of this empirical finding is that in periods in which the ratio of spillovers from the bond market to the CDS market increases we observe *ceteris paribus* a CDS's market relative overreaction and thus, the CDS spread will signal a stronger default probability for a given reference name than the bond spread. In line with the results of the previous section, we find a high level of persistency in the basis. That is, there is a relatively low speed of adjustment towards the long-run bond-CDS equivalence relation. Finally, the constant term reflects whether the basis differs, on average, from zero and the magnitude of such deviation. The results show that for the first two sub-periods the basis does not significantly differs from zero, that is, the bond-CDS equivalence relation holds when we take into account the market frictions described above and the costs that are needed to trade the basis. Although in the third time-period the basis is on average significantly positive, its magnitude is low relative to the average basis during that period (1.4 basis points relative to 7.7 basis points). The relatively high R-square of this regression is mainly due to the effect of the lagged basis and the fixed effects. However, it should be noted that the explanatory variables retain a relatively high explanatory power even when we ignore the lagged basis and the fixed effects, in which case the R-square is around 0.3. Actually, this is of a similar magnitude of the one reported by Trapp (2009) on a daily basis for corporates using firm fixed-effects but ignoring the effect of the lagged basis.

< Insert Table 3 here >

We next study whether there is any asymmetry between positive and negative bases. For this purpose, we repeat the previous regression but we now distinguish between positive and negative lagged bases. In particular, we allow for two separate variables: *Positive basis = max(Basis,0)* and *Negative basis= min(Basis,0).* The results corresponding to the new estimation are reported in Table 4. The difference between the coefficient referred to a positive basis and the one referred to a negative basis is significantly higher than zero for the three time periods considered in Table 4. As the theory suggests, apparently, it is more difficult to close a positive basis than the opposite. The reason is that to close the former deviation an investor would need to take short positions in CDS (sell protection) and bonds, respectively. Similar results are obtained for the three sampling periods considered (January 2004 – September 2010 in Column (1); January 2007 – September 2010 in Column (2); and January 2008 – September 2010 in Column (3)).

< Insert Table 4 here >

6. Price-discovery analysis

An efficient price discovery process is characterized by a quick adjustment of market prices from the old to the new equilibrium as new information arrives (see e.g. Yan and Zivot, 2007). The previous literature that has tried to measure this form of market-efficiency has focused on static price-discovery analyses. In contrast, we here show that the price discovery process in the markets for sovereign credit risk in the EU does not show a time-invariant pattern (Section 6.1). Given this finding, we then try to identify the effect of several potential explanatory variables of the price-discovery metrics obtained in the previous step (Section 6.2).

6.1. A dynamic price-discovery metric

To estimate a time-variant price discovery metric we extend the Gonzalo and Granger (1995) price-discovery analysis using rolling windows. The Gonzalo and Granger's model of price-discovery is based on the following vector error correction model (VECM) specification:

$$\begin{pmatrix} \Delta BSpr_t \\ \Delta CDSSpr_t \end{pmatrix} = \alpha(BSpr_{t-1} - \beta_2 - \beta_3 CDSSpr_{t-1}) + \begin{pmatrix} \sum_{i=1}^{p} \lambda_{1,i} \Delta BSpr_{t-i} \\ \sum_{i=1}^{p} \lambda_{2,i} \Delta BSSpr_{t-i} \end{pmatrix} + \begin{pmatrix} \sum_{i=1}^{p} \delta_{1,i} \Delta CDSpr_{t-i} \\ \sum_{i=1}^{p} \delta_{2,i} \Delta CDSSpr_{t-i} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} \quad (6)$$

The above empirical model is a vector autoregressive (VAR) system formed by two equations defined from the vector which includes the bond and CDS spreads of the same underlying country, denoted by $BSpr_t$ and $CDSSpr_t$, respectively, and an error correction term (ECT) which is defined by the expression $\alpha(BSpr_{t-1} - \beta_2 - \beta_3 CDSSpr_{t-1})$, where β_2 and β_3 are estimated in an auxiliary cointegration regression and the parameter vector α' = (α_1, α_2) contains the error-correction coefficients measuring each price's expected speed of adjustment. The estimation of the VECM specification is restricted to the existence of a cointegration relation between the bond and CDS spreads. This cointegration relation appears in the ECT as $(BSpr_{t-1} - \beta_2 - \beta_3 CDSSpr_{t-1})$. The parameters $\lambda_{1,i}$, $\lambda_{2,i}$, $\delta_{1,i}$, and $\delta_{2,i}$ for $i= 1,..p$, with p indicating the total number of lags, contain the coefficients of the VAR system that measure the effect of the lagged first difference in the CDS and bond spreads on the first difference of such spreads at time t.[11] Finally, u_t denotes a white noise vector.

The price discovery metric for the bond and CDS markets, denoted by GG_{bond} and GG_{CDS}, respectively, can then be constructed from the elements of the vector α', which contains the coefficients that determine each market's contribution to price discovery:

[11]The optimal number of lags is determined by means of the Schwarz information criteria.

$$GG_{Bond} = \frac{\alpha_2}{-\alpha_1 + \alpha_2}; \qquad GG_{CDS} = \frac{-\alpha_1}{-\alpha_1 + \alpha_2}$$

Given that $GG_{Bond} + GG_{CDS} = 1$, we would conclude that the bond (CDS) market leads the price discovery process whenever GG_{Bond} is higher (lower) than 0.5. The intuition for this is the following. The larger the speed in eliminating the price difference from the long-term equilibrium attributable to a given market, the higher the corresponding α according to (6), and the higher is the price discovery metric.

In order to apply the methodology outline above to provide a dynamic metric of price-discovery leadership in the two markets at stake, we estimate the system in equation (6) using rolling windows with different lengths: 500, 750, and 1,000 days. To do so, we first need to check for the order of integration of the CDS and bond spreads and then for the existence of a cointegration relation. Using rolling windows with a length of 500 observations (henceforth, we use this as our baseline window-length), we find that the bond spread is integrated of order one (non-stationary) in all the countries and dates, except for Greece in 42 dates, or equivalently, in 3.5% of the windows the bond spread of Greece is stationary at a 5% confidence level. Regarding the CDS spread, it is integrated of order one in all the dynamic sub-samples considered and for all the countries at a significance level of 5%.[12]

We next apply the cointegration test to a total of 1,203 500-day windows for each of the ten countries and find cointegration between both spreads in 7,284 cases (61% of the total). In particular, the country with the lowest (highest) percentage of cointegration relations is France (The Netherlands) with cointegration in 38% (82%) of the windows. As we increase the window length, we find a higher number of cointegration relations. For instance, for a window length of 750 (1,000) cointegration exists in 67% (76%) of the cases.

Figure 1 shows the average price discovery metrics obtained for the three different window-lengths. In particular, we report a 30-day moving average of the mean price-discovery metrics which is obtained as an equally weighted mean across the ten euro

[12] The number of lags employed in the Granger causality test is chosen according to the Schwarz information criterion.

area countries. A first interesting feature is that the estimated metrics do not seem to be very sensitive to the window length. Based on this, in the remaining of the paper we focus on 500-day windows.

An important message steaming from Figure 1 is that the price discovery metrics are not static but rather evolve over time, with the relative leadership of the CDS market in the process of price-discovery being more pronounced around some specific dates. Specifically, before the summer of 2007 the CDS market clearly leads sovereign risk price discovery. This finding is consistent with the results reported by, e.g., Blanco, Brennan and Marsh (2005), Zhu (2006), or Norden and Weber (2009) in the context of the corporate debt markets. The first noticeable rise in the relative leadership of the bond market took place around February 2008, around the collapse of Bear Stearns. Afterwards, in September 2008, coinciding with the fall of Lehman Brothers and AIG the bond price discovery metric again jumps to reach its highest value at the end of 2008. This pattern suggests that during these two specific episodes, Bear Stearns and Lehman-AIG, the bond spread led, although by a small margin, the price discovery process. Next, we observe another rebound in the price-discovery indicator in Figure 1 around April 2010, coinciding with the worst moments of the Greek sovereign debt crisis. However, right after the approval of a rescue package for Greece by the European Union and the International Monetary Fund, the CDS market started to regain its leadership role.[13]

< Insert Figure 1 here >

Figure 2 shows the estimated price-discovery metric for two groups of countries in the sample, peripheral and central countries.[14] Except for some gaps between the two country-groups price-discovery metrics witnessed before the crisis (around 2006 and the first half of 2007) the pattern followed by the metrics corresponding to the two groups of countries has been remarkably similar for most part of the period under study. However, in the final part of the sample period (from around the spring of 2010 onwards) the empirical model detects some decoupling between the price-discovery

[13] In line with Mayordomo, Peña, and Romo (2011b) these results confirm the role of the bond markets during this period as a fair measure of credit risk.

[14] The peripheral group includes Ireland, Italy, Greece, Portugal and Spain. The core group includes Austria, Belgium, Finland, France and The Netherlands. The window length in all cases is 500 days.

measure for the core and the peripheral countries. Specifically, from May 2010 on, the CDS spread clearly leads the price-discovery process in the peripheral group with a much higher intensity than observed in the core countries. Furthermore, whereas the CDS market continues gaining relative efficiency in the peripheral economies during the last months of the sample, the opposite obtains for the core economies, where the bonds market seems to improve their relative efficiency.

The last result may be reflecting the ECB policy of buying sovereign debt from the peripheral countries. Another potential explanation is the use of the core countries sovereign debt as a reserve asset during periods of heightened aggregate uncertainty during which investors' perception of risks change dramatically in a way that may not be easily reconciled with risk attitudes observed in normal times.[15]

All in all, the above results show that the CDS market usually leads the price discovery process with a few exceptions. When the bond market leads its weight is always lower than 0.6. However, the role of the bond spread as a credit risk information provider has increased during the crisis and, especially, at times of heightened global uncertainty, like in aftermath of the collapse of Lehman Brothers.

< Insert Figure 2 here >

In Figure 3 we show the price discovery metrics for individual countries. Like Figure 2, it is constructed using the 30-day moving average of the price discovery metrics. This figure confirms the idea that, for the majority of countries, the CDS market reflects information more efficiently before the crisis. In some specific periods and for some countries this pattern changes and the bond market has correspondingly improved its informational role. For instance, in the period January 2008 – April 2008 (around the Bear Stearns collapse) the bond clearly leads the CDS in Belgium, France, Finland, Greece, Italy, The Netherlands, and Portugal, reaching the maximum value of 1 in France and The Netherlands. The last results could be reflecting the use of the French and Dutch sovereign debt as a reserve asset, in the sense described earlier. A similar

[15] Caballero and Krishnamurthy (2008) provide a theoretical framework that exploits the notion of Knightian uncertainty to rationalize, among other phenomena, the intense accumulation of high-quality assets during episodes of macroeconomic instability and Caballero and Kurlat (2009) illustrate that idea within the context of the Great Recession.

pattern is observed in the period September 2008 – January 2009 (around the Lehman Brothers episode), when the bond clearly leads the CDS in Austria, Belgium, France, Ireland, The Netherlands, and Spain reaching maximum values in at the end of 2008 and the beginning of 2009, coinciding with the collapse of Lehman and the global uncertainty that followed. Now, focusing on the peripheral countries in the first stage of the Greek debt crisis, during the first half of 2010, the bond spread reflects credit risk more efficiently than the CDS spread in Italy and Spain whereas the opposite holds for Greece and Ireland.

< Insert Figure 3 here >

The Granger-causality test has also been commonly employed in some previous price-discovery analyses. This methodology requires the credit spreads to be integrated of order one and for this reason can be applied to a larger number of days than the Gonzalo and Granger (1995) test due to the absence of the cointegration requirements in the former method. Hence, we repeat the analysis using a rolling windows Granger causality test in which the optimal lag length of the VAR is obtained by means of the Schwarz information criteria. In general, we find that before the end of 2007 none of the credit spreads causes the other. Afterwards we find a bidirectional causation relation in the peripheral countries. Thus, attending to the Granger causality test we cannot clearly differentiate whether the bond or CDS leads the process of price discovery in the peripheral countries. In the core countries we observe that the CDS causes the bond spread while there is no causation effect from the bond spread from the beginning of 2008 to the end of the sample.

The Granger causality test is the approach followed by Delis and Mylonidis (2010) to estimate the dynamic price discovery process and results are consistent with the ones they found for the countries they study (Greece, Italy, Portugal, and Spain). However, these results confirm that Granger causality test is not so informative to determine which market leads the price discovery process, as it is the case in the peripheral countries, while Gonzalo and Granger's methodology enables us to conclude which market leads at every date.

6.2. An analysis of the determinants of the market leadership in price-discovery

In this section we aim at providing a (partial) explanation of the dynamic pattern of the price-discovery metrics estimated before, by regressing them on some potential explanatory factors.

Specifically, for each country, we construct a dummy variable that takes a value of 1 when the bond market reflects information more efficiently than the CDS market and 0 otherwise. This dummy is constructed on the basis of a rolling window estimation using 1,000 observations,[16] and then it is used as the dependent variable in a Logit regression that includes as regressors the same used in the regression contained in Table 2 with the exception of the lagged basis and the relative spillovers measure. The last measure is not included due to potential endogeneity problems. We consider these regressors because they have been found to have a significant effect on the deviations from a zero-basis. Hence, as this reflects that the effect of such regressors is not reflected in the same way in the two markets, it seems natural to consider that one market could capture better than the other the effect of each determinant of the basis. Additionally, as mentioned informally before, the role of the two markets providing efficient information on credit risk could have been affected by the interventions of the ECB after May 2010 buying sovereign debt. For this reason we also use as an explanatory variable the amount of sovereign debt purchased by the ECB. Additionally, we distinguish the effect of such potential determinants of the price discovery metrics on peripheral and core countries.

The results are reported in Table 5. Column 1 contains the results for the period December 2007 – September 2010.[17]. Column 2 shows the results for the period spanning from September 2008 – September 2010. Columns 3 and 4 show the results

[16] When faced with missing values (due to a lack of cointegration relation between the CDS and the bond spreads), the value of the dummy is imputed according to the Granger-causality analysis performed earlier. For the remaining missing values, the value of the dummy is imputed whenever there is another observed value within the next month which coincides with the previous price discovery value observed and persists at least in the next ten observations. If after a given date there are not cointegration relations up to the end of the sample we do not impute any value. For sake of the robustness of this procedure, we use the 1,000-observation estimation. We do not employ the price discovery metric directly, which is a concrete value comprised between 0 and 1, but instead assign a value one or zero to such metrics, thus softening such strong assumption. We impute a total of 885 observations (i.e. 14% of the observations), out of which 197 of the observations are imputed by means of the Granger-causality test and 688 by the alternative method.

[17] Notice that in choosing the length of the first period we are restricted by the (conservative) choice of a 1000-day window.

obtained for the subgroups of core and peripheral countries, respectively, for the period December 2007 – September 2010.

One might expect that the higher the counterparty risk the lower should be the ability of the CDS market to reflect adequately the credit risk. The sign is the expected (positive) and significant in Columns (1) and (2) referred to the whole group of countries. In line with the results obtained in Table 3, as we use a period closer to the collapse of Lehman Brothers and the European sovereign debt crisis the coefficient increases and becomes more significant. We also observe remarkable differences across the core (Column 3) and peripheral (Column 4) countries. The effect of counterparty risk is positive for both groups of countries but is only significant for the group of peripheral countries. Thus, counterparty risk significantly lowers the ability of the CDS spreads to reflect adequately credit risk in the peripheral countries but not in the core countries.

We find that a low degree of liquidity in the bond market relative to the CDS market affects negatively to the price discovery metric. The effect is higher in Column (2) than in Column (1), possibly due to the higher influence of low liquidity in CDS markets around the Lehman Brothers collapse and the rescue of Greece. Surprisingly, for the group of core countries (Column 3) the effect of the liquidity ratio is positive, being negative and significant for the group of peripheral countries (Column 4), as the theory would suggest.

Funding costs affect negatively to the bond buyers contrary to the CDS market which allows for higher-leveraged positions. For this reason the funding costs affect negatively to the ability of the bonds market for anticipating the credit risk relative to the CDS market. The effect of this variable dilutes as the sample period comprises the European sovereign debt crisis. The magnitude of the coefficient for the funding cost variable is similar for the two groups of countries. This result suggests that funding costs affect similarly to the capacity of price discovery of credit spread for the different countries.

In line with the results obtained by Mayordomo, Peña and Romo (2011b) the bond spreads tend to reflect credit risk more efficiently than CDS spreads during periods of high global risk (high values of the VIX Index). This result is consistent for the four regression specifications. The country specific risk premium proxied by means of the squared returns of the national stock index is not significant at 5% significance level but the related coefficient has different signs for the core (positive sign) and peripheral (negative sign) countries.

If the ECB is buying debt independently of the price, information derived from such market could become less revealing of the fundamental value of the traded security. This hypothesis is confirmed by the significant and negative sign of the variable representing the amount of sovereign debt purchased by the ECB which is obtained in the four columns. Interestingly, the magnitude for such coefficient differs between the core and peripheral countries being the latter magnitude significantly higher than the former. This result may be reflecting the ECB policy of buying sovereign debt from the peripheral countries

< Insert Table 5 here >

7. Conclusions

This paper analyzes the extent to which the sovereign Credit Default Swap (CDS) and bond markets reflect the same information on their prices in the context of the European Monetary Union. The main results can be summarized as follows.

We first test the "no-arbitrage" theoretical relation that should exist between the bond and the CDS spreads in a frictionless environment since both spreads are supposed to be the prices for the same credit risk. Our results show that after the subprime crisis there are persistent deviations from that theoretical parity relation that were absent before. In particular, we find evidence in favour of a persistent positive basis for the crisis period in a number of countries.

Based on the previous finding, we analyse the role of some potential determinants of the basis, including several different types of risks (counterparty, country-idiosyncratic and global) and market frictions. In particular, we find that the counterparty risk indicator has a negative and significant effect on the basis, especially during the most recent period. Both funding costs and a low liquidity in the bond market relative to the CDS market also have a negative effect on the basis. In periods in which shocks originated in the bond market are transmitted into the CDS market, which we interpret as spillovers or contagion-effects, we find an overreaction-effect in this last market. Finally, we show that the speed of reversion of the basis is asymmetric, with positive bases typically requiring a longer time to diminish.

Finally, we conduct a dynamic analysis of market leadership in the price discovery process. An important result here is that the price discovery process is state-dependent. Specifically, the levels of counterparty and global risk, funding costs, market liquidity and the volume of debt purchases by the European Central Bank in the secondary market following the rescue of the Greek economy in May 2010 are all found to be significant factors in determining which market leads price discovery.

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Appendix A.1

Estimation of the spillovers between the CDS and bonds markets

We use a notion of spillover effects according to which such effects are defined from a variance decomposition associated with an N-variable vector auto regression following the methodology employed by Diebold and Yilmaz (2009) and later improved in Diebold and Yilmaz (2010) by measuring directional spillovers in a generalized VAR framework that eliminates the possible dependencies of results on ordering. The spillovers between the CDS and bond spreads here estimated can be interpreted as the degree of variation in the changes of the CDS (bond) spreads that is not attributable to their historical information but to contemporary shocks (innovations) in the changes of the bond (CDS) spreads. This indicator of contagion takes higher values as the intensity of the contagion effect which is caused by the specific shocks of the bond (CDS) market increases. In the extreme case in which there is no contagion from the bond to the CDS market the indicator series is equal to zero.

In particular, we first consider a covariance stationary *N-variable VAR (p)*:

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t \qquad (1)$$

where X_t denotes a vector of stationary changes in the CDS and bond spreads of a given country and $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances such that the moving average representation is $X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$, where the *NxN* coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ... + \Phi_p A_{i-p}$, with A_0 being an *NxN* identity matrix and $A_i=0$ for $i<0$. Thus, the error from the forecast of X_t at the *H-step-ahead* horizon, conditional on information available at *t-1*, can be expressed as $\xi_{t,H} = \sum_{h=0}^{H} A_h \varepsilon_{t+H-h}$, and the variance covariance matrix of the total forecasting error is computed as $Cov(\xi_{t,H}) = \sum_{h=0}^{H} A_h \Sigma A_h'$, where Σ is the variance-covariance matrix of the error term in equation (1), ε_t.

The moving average coefficients are the key to understanding the dynamics of the system. We rely on variance decompositions, which allow us to parse the forecast error variances of each variable into parts attributable to the various system shocks. By means of this variance decomposition we can obtain the proportion of the *H-step-ahead* error variance in forecasting X_i that is due to shocks to $X_j, \forall j \neq i$, for each i.

We first compute the variance shares which are defined as the fractions of the *H-step-ahead* error variances in forecasting X_i due to shocks to X_i, for $i= 1, 2,\ldots, N$. we then derive the cross variance shares, or spillovers, defined as the fractions of the *H-step-ahead* error variances in forecasting X_i due to shocks to X_j, for $i, j = 1, 2, \ldots, N$ such that $i \neq j$. The *H-step-ahead* forecast error variance decompositions are denoted by $\theta_{ij}^{g}(H)$, for $H = 1, 2, \ldots$, i.e.:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_h' e_i\right)} \qquad (2)$$

where Σ is the variance matrix for the error vector ε, σ_{ii} is the standard deviation of the error term for the *i-th* equation, and e_i is the selection vector with one as the *ith* element and zeros otherwise. The sum of the elements of each row of the variance decomposition table is not equal to 1, i.e. $\sum_{j=1}^{N}\theta_{ij}^{g}(H) \neq 1$. Each entry of the variance decomposition matrix can be normalized such that the elements of each row sum 1 as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \qquad (3)$$

We compute the spillovers from shocks in the first differences in CDS and bond spreads. That is, we estimate spillovers between the bond and CDS spreads for a given country. We use first differences instead of percentage changes to minimize the effect of the outliers which are obtained when we use in the denominator the bond spread which is very close to zero, and even negative, in some countries at some points in time in which the bond yield does not differ materially from the German bond yield.[18]

[18] Spillovers can be computed from either shocks in the mean or the volatility. Diebold and Yilmaz (2010) estimate spillovers in volatility using as a measure for such volatility daily high and low prices. We have end-of-day CDS and bond spreads and for this reason, the only possibility to compute volatility is as the square of the measure employed to compute the mean spillovers (changes in credit spreads). We find that the variable refereed to shock spillovers in the mean is highly correlated with the equivalent measure for the variance.

Table 1: CDS and Bond Spreads Descriptive Statistics

Table 1 reports the CDS and bond spreads main descriptive statistics (mean, standard deviation, maximum, and minimum) for different time periods (2004 - 2008, 2009, and 2010). The bond spreads are obtained as the difference between the country A's yield and the German yield.

			Bond	CDS
Austria	2004-2008	Mean	7	8
		Std.Dev.	12	21
		Max.	80	158
		Min.	-1	1
	2009	Mean	52	104
		Std.Dev.	25	49
		Max.	120	259
		Min.	20	52
	2010	Mean	41	77
		Std.Dev.	11	14
		Max.	88	110
		Min.	25	49
Belgium	2004-2008	Mean	9	8
		Std.Dev.	17	14
		Max.	96	94
		Min.	-4	2
	2009	Mean	49	63
		Std.Dev.	29	33
		Max.	124	149
		Min.	14	30
	2010	Mean	46	89
		Std.Dev.	21	29
		Max.	119	151
		Min.	17	46
Finland	2004-2008	Mean	5	6
		Std.Dev.	12	9
		Max.	74	71
		Min.	-5	1
	2009	Mean	34	37
		Std.Dev.	21	19
		Max.	89	91
		Min.	8	16
	2010	Mean	-1	31
		Std.Dev.	12	4
		Max.	24	38
		Min.	-16	24
France	2004-2008	Mean	4	6
		Std.Dev.	9	9
		Max.	44	61
		Min.	-7	1
	2009	Mean	23	40
		Std.Dev.	12	20
		Max.	53	95
		Min.	4	16
	2010	Mean	22	64
		Std.Dev.	9	17
		Max.	44	100
		Min.	9	29
Germany	2004-2008	Mean		5
		Std.Dev.		7
		Max.		50
		Min.		1
	2009	Mean		36
		Std.Dev.		18
		Max.		89
		Min.		19
	2010	Mean		39
		Std.Dev.		7
		Max.		60
		Min.		25

Table 1 (Cont.): CDS and Bond Spreads Descriptive Statistics

Greece	2004-2008	Mean	25	23
		Std.Dev.	36	36
		Max.	255	240
		Min.	6	5
	2009	Mean	166	165
		Std.Dev.	78	54
		Max.	329	284
		Min.	63	95
	2010	Mean	664	593
		Std.Dev.	279	241
		Max.	1293	1126
		Min.	212	245
The Netherlands	2004-2008	Mean	4	6
		Std.Dev.	8	12
		Max.	59	91
		Min.	-7	1
	2009	Mean	30	53
		Std.Dev.	18	30
		Max.	85	124
		Min.	7	24
	2010	Mean	21	42
		Std.Dev.	6	7
		Max.	47	56
		Min.	9	30
Ireland	2004-2008	Mean	9	13
		Std.Dev.	20	31
		Max.	127	219
		Min.	-8	2
	2009	Mean	151	190
		Std.Dev.	56	62
		Max.	276	368
		Min.	85	111
	2010	Mean	167	204
		Std.Dev.	68	60
		Max.	327	352
		Min.	62	115
Italy	2004-2008	Mean	19	19
		Std.Dev.	25	27
		Max.	147	187
		Min.	2	5
	2009	Mean	74	103
		Std.Dev.	32	39
		Max.	153	191
		Min.	35	54
	2010	Mean	93	150
		Std.Dev.	37	41
		Max.	185	245
		Min.	38	90
Portugal	2004-2008	Mean	13	14
		Std.Dev.	20	19
		Max.	117	114
		Min.	0	4
	2009	Mean	71	76
		Std.Dev.	37	27
		Max.	170	152
		Min.	25	42
	2010	Mean	195	232
		Std.Dev.	88	84
		Max.	443	461
		Min.	58	83
Spain	2004-2008	Mean	8	12
		Std.Dev.	15	20
		Max.	93	123
		Min.	-4	2
	2009	Mean	54	89
		Std.Dev.	30	26
		Max.	129	163
		Min.	13	51
	2010	Mean	124	177
		Std.Dev.	65	54
		Max.	249	275
		Min.	42	92

Table 2: Statistical Arbitrage Test for the Existence of Persistent Mispricings

This table reports the p-value obtained from the statistical arbitrage methodology of Mayordomo, Peña, and Romo (2011a). A p-value lower than 0.05 indicates that a significance level of 5% there are persistent mispricings between the 5-year CDS and bond spreads. The bond spread is obtained as the difference between the country A's bond yield and the risk-free rate which is equal to the German bond yield. Panels A and B report the results for the period ranging from January 2004 to September 2008 for CDS-bond negative and positive bases, respectively. Panels C and D report the results for the period which spans from the collapse of Lehman Brothers (September 2008) to September 20010 for CDS-bond negative and positive bases, respectively. *** (** and *) indicates the existence of persistent mispricings at a significance level of 1% (5% and 10%, respectively).

Panel A: Persistent Negative Basis Before Lehman Brothers Collapse

	P-value	Persistent Mispricing
Austria	1.000	No
Belgium	0.961	No
Finland	1.000	No
France	1.000	No
Greece	0.999	No
The Netherlands	0.988	No
Ireland	1.000	No
Italy	0.678	No
Portugal	1.000	No
Spain	0.988	No

Panel B: Persistent Positive Basis Before Lehman Brothers Collapse

	P-value	Persistent Mispricing
Austria	1.000	No
Belgium	0.957	No
Finland	1.000	No
France	1.000	No
Greece	1.000	No
The Netherlands	0.987	No
Ireland	0.706	No
Italy	0.378	No
Portugal	1.000	No
Spain	0.988	No

Table 2 (Cont.): Statistical Arbitrage Test for the Existence of Persistent Mispricings

Panel C: Persistent Negative Basis After Lehman Brothers Collapse

	P-value	Persistent Mispricing
Austria	1.000	No
Belgium	1.000	No
Finland	0.871	No
France	0.655	No
Greece	0.723	No
Ireland	1.000	No
Italy	0.658	No
The Netherlands	0.942	No
Portugal	0.932	No
Spain	0.789	No

Panel D: Persistent Positive Basis After Lehman Brothers Collapse

	P-value	Persistent Mispricing
Austria	0.003	Yes***
Belgium	0.466	No
Finland	0.129	No
France	0.012	Yes**
Greece	0.387	No
Ireland	0.003	Yes***
Italy	0.060	Yes*
The Netherlands	0.003	Yes***
Portugal	0.392	No
Spain	0.043**	Yes**

Table 3: Determinants of the basis

This table reports the effect of the potential determinants of the basis based on a fixed effects regression robust to heteroskedasticity. We test the effect of such determinants for three different periods. Column (1) reports the results for the period which spans from January 2004 – September 2010. Column (2) presents the results for the period January 2007 – September 2010. Finally, Column (3) shows the results for the period January 2008 – September 2010. The table contains the explanatory variables' coefficients and the *t-statistic* between brackets. *** (** and *) indicates whether the coefficients are significant at a significance level of 1% (5% and 10%). The bootstrap methodology is employed to correct any potential bias in the standard errors due to the use of generated regressors.

	(1)	(2)	(3)
Counterparty risk net of global risk	-0.017	-0.044	-0.157***
	(-0.31)	(-0.86)	(-3.19)
Ratio bond/CDS liquidity	-0.082**	-0.083*	-0.086*
	(-1.98)	(-1.88)	(-1.83)
Financing costs	-0.592	-0.676	-0.877
	(-1.38)	(-1.48)	(-1.62)
Global risk (VIX)	0.008	0.004	-0.011
	(0.71)	(0.37)	(-0.89)
Squared of country stock index returns	637.908	659.727*	690.787*
	(1.63)	(1.68)	(1.66)
Shock spillovers from bond to CDS spreads	0.735**	0.720**	0.642**
relative to spillovers from CDS to bond spreads	(2.25)	(2.18)	(2.13)
Lagged basis	0.946***	0.944***	0.941***
	(34.71)	(33.48)	(33.99)
Constant	0.212	0.494*	1.430***
	(1.19)	(1.68)	(2.66)
Number of observations	11089	8207	6478
F statistic	65116.88	55045.15	41138.17
Prob>F	0.00	0.00	0.00
Adjusted R-squared	0.93	0.93	0.92

Table 4: Determinants of the basis. Asymmetries in the Basis

This table reports the effect of the potential determinants of the basis based on a fixed effects regression robust to heteroskedasticity focusing on the speed of adjustment of positive and negative bases to test if there is any asymmetry between positive and negative bases. The explanatory variables are the same employed in Table 3 but the lagged basis variables is divided in two variables to control by the positive or negative bases. These variables are: *Positive basis≡ max(Basis,0)* and *Negative basis≡ min(Basis,0).* We test the effect of such determinants for two different periods. Column (1) reports the results for the period which spans from January 2004 – September 2010. Column (2) presents the results for the period January 2007 – September 2010. Finally, Column (3) shows the results for the period January 2008 – September 2010. The table contains the explanatory variables' coefficients and the *t-statistic* between brackets. *** (** and *) indicates whether the coefficients are significant at a significance level of 1% (5% and 10%). The bootstrap methodology is employed to correct any potential bias in the standard errors due to the use of generated regressors.

	(1)	(2)	(3)
Positive lagged basis	0.975***	0.974***	0.970***
	(57.84)	(56.58)	(58.83)
Negative lagged basis	0.907***	0.903***	0.900***
	(11.16)	(10.84)	(10.94)
Counterparty risk net of global risk	-0.070	-0.091**	-0.200***
	(-1.57)	(-1.96)	(-3.15)
Ratio bond/CDS liquidity	-0.132	-0.132	-0.134
	(-1.27)	(-1.25)	(-1.29)
Financing costs	-0.444*	-0.518**	-0.681**
	(-1.92)	(-2.24)	(-2.40)
Global risk (VIX)	-0.006	-0.009	-0.024
	(-0.37)	(-0.53)	(-1.23)
Squared of country stock index returns	599.536*	617.781**	642.989**
	(1.85)	(1.96)	(2.01)
Shock spillovers from bond to CDS spreads relative to spillovers from CDS to bond spreads	0.487***	0.457***	0.387**
	(3.19)	(2.77)	(2.10)
Constant	0.239	0.472*	1.367***
	(1.18)	(1.78)	(3.19)
Number of observations	11089	8207	6478
F statistic	72833.95	64022.48	47471.40
Prob>F	0	0.00	0.00
Adjusted R-squared	0.93	0.93	0.92

Table 5: Determinants of the Price Discovery Metrics

This table reports the effect of the potential determinants of the price discovery metrics using a panel fixed effects Logistic regression robust to heteroskedasticity. The price discovery metrics are obtained from the Gonzalo and Granger's (1995) methodology using rolling windows of 1,000 observations. The dependent variable takes value 1 when the bond spread reflects the information more efficiently than the CDS spread while a value equal to 0 indicates that the CDS spread leads the price discovery process. The bond spread is defined as the difference between the country A's yield and the German yield. Column (1) reports the results for the period which spans from December 2007 – September 2010. This sample length is due to the use of the first 1,000 observations to estimate the price discovery metric. Column (2) shows the results for the period which spans from the Lehman Brothers collapse to September 2010. Columns (3) and (4) report the results obtained using the subgroups of core and peripheral countries, respectively, for the same period as in Column. The table contains the explanatory variables' coefficients and the *t-statistic* between brackets. *** (** and *) indicates whether the coefficients are significant at a significance level of 1% (5% and 10%).

	(1)	(2)	(3)	(4)
Financing costs	-2.265***	-1.029***	-2.253***	-2.086***
	(-17.24)	(-5.14)	(-14.5)	(-9.26)
Counterparty risk net of global risk	0.071***	0.147***	0.027	0.121***
	(2.57)	(3.93)	(0.70)	(3.58)
Global risk (VIX)	0.089***	0.035***	0.099***	0.074***
	(17.44)	(4.72)	(11.43)	(10.73)
Ratio bond/CDS liquidity	-0.014	-0.041**	0.278***	-0.037**
	(-1.59)	(-2.13)	(6.94)	(-2.52)
Squared of country stock index returns	25.117	-106.141	137.010*	-152.585
	(0.39)	(-1.44)	(1.76)	(-1.42)
Bonds purchased by ECB	-0.207***	-0.284***	-0.204***	-0.243***
	(-9.29)	(-7.47)	(-6.89)	(-3.25)
Constant	-1.484***	-2.826***	-5.183***	-0.549**
	(-8.03)	(-8.47)	(-11.98)	(-2.47)
Number of observations	5843	4101	2715	3128
Wald chi2	1114.04	962.28	614.20	466.44
Prob > chi2	0.00	0.00	0.00	0.00
Log pseudolikelihood	-1907.93	-1202.17	-901.4	-962.54
Pseudo R2	0.463	0.5627	0.5101	0.3792

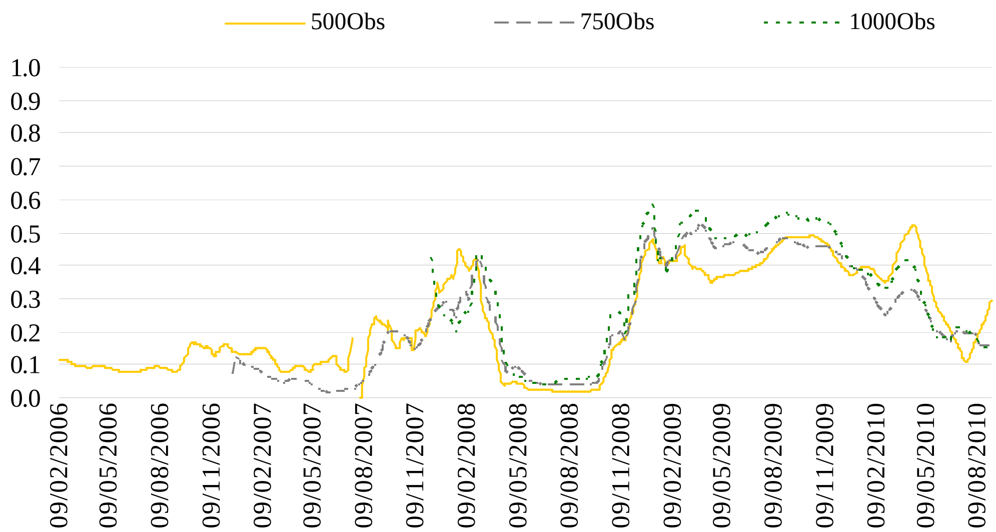

Figure 1: EMU Price Discovery Metrics: This figure shows the 30-days moving average of the EMU countries price discovery metrics. These metrics are obtained as the weighted average of the country specific price discovery metrics. The figure reports different lines depending on the number of days used in the rolling window estimation (500, 750, and 1000 days).

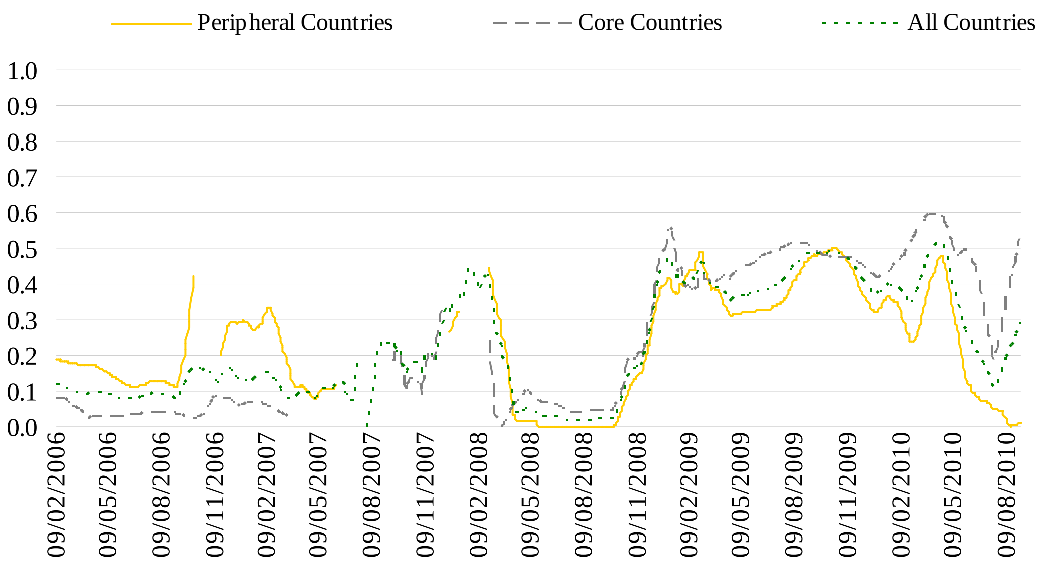

Figure 2: Price Discovery Metrics for Groups of EMU Countries. This figure shows the 30-days moving average of the price discovery metrics for the peripheral, core, and all the EMU countries. These metrics are obtained as the equally weighted average of the country specific price discovery metrics.

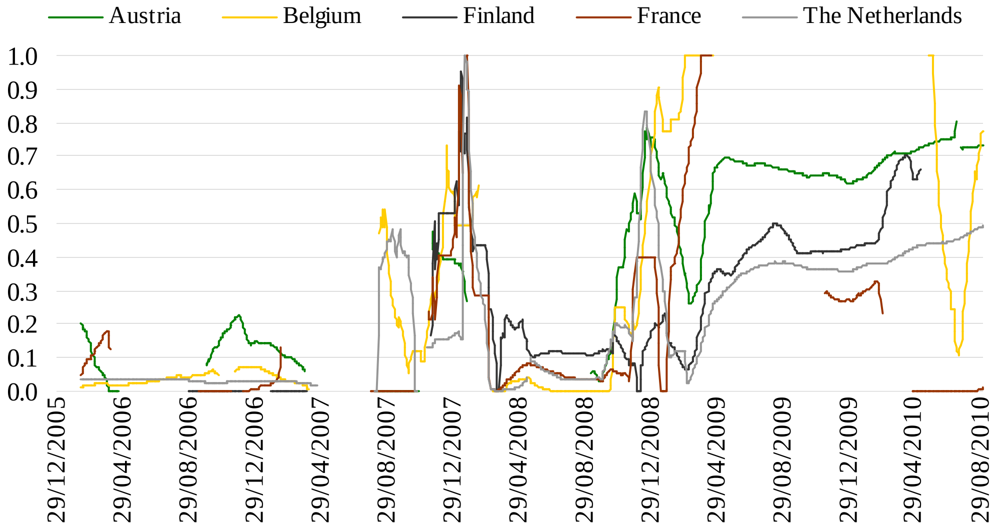

Figure 3.A: Price Discovery Metrics for Individual EMU Countries. This figure shows the 30-days moving average of the price discovery metrics for Austria, Belgium, Finland, France, and The Netherlands.

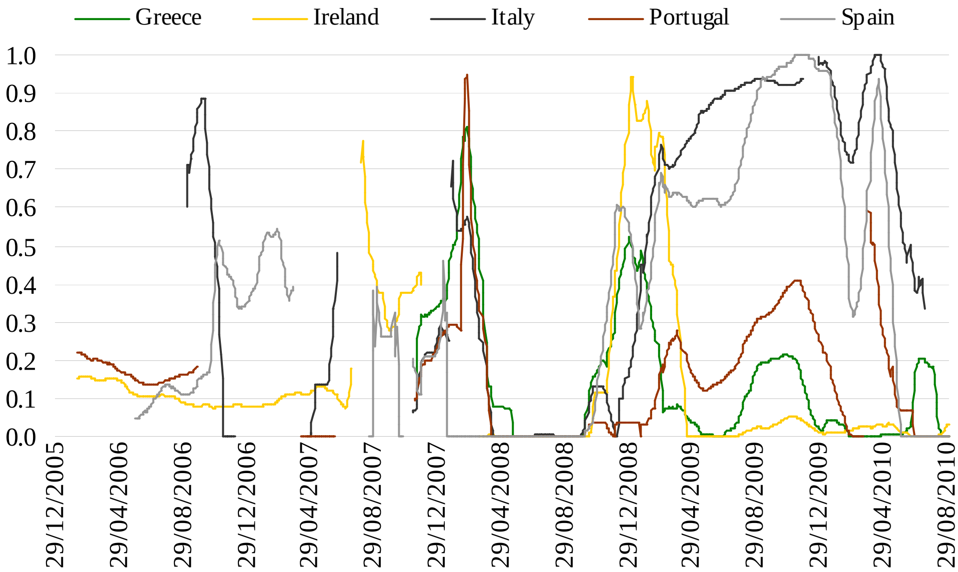

Figure 3.B: Price Discovery Metrics for Individual EMU Countries. This figure shows the 30-days moving average of the price discovery metrics for Greece, Ireland, Italy, Portugal, and Spain.