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Absence of speculation in the European sovereign debt markets[☆]

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ABSTRACT

European sovereign debt markets have been under scrutiny since the sovereign debt crisis of 2009. In this paper, we study to what extent the extreme dynamics were driven by fundamentals or speculation. We do so by decomposing bond and CDS spreads into fundamental and non-fundamental parts using a heterogeneous agent model. We find that bond markets are driven for 80% by liquidity trading, 13% by credit news, and only 5.4% by speculation. The CDS market is for 49% driven by credit news, 45% liquidity trading, and 5.5% speculation. The relative importance of the different types of agents varies over time, though.

1. Introduction

> *First, we must prevent speculative actions from causing so much uncertainty on the market that prices no longer provide accurate information [...].*

Sarkozy, Juncker, Merkel, and Papandreou in a letter to Barroso, March 10, 2010.[1]

The European sovereign debt crisis that erupted towards the end of 2009 has introduced unprecedented dynamics into European sovereign debt markets. Driven by fears that certain countries would not be able to repay their debts, the yields of the peripheral countries increased to record levels. At the same time, the yields of core countries reached all-time lows. As a consequence, there have been major changes in the correlation structures between sovereigns, changing from virtually identical movements across countries to opposite movements across core and peripheral countries. These changes illustrate the changes in perceived credibility of the 'no-bailout clause' of the European Union. The question arises, though, to what

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[1] See http://www.economist.com/blogs/buttonwood/2010/03/debt_politics_and_regulation

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extent these dynamics are driven by the underlying fundamental credit risk or non-fundamental factors, such as speculation as suggested by the European politicians in the quote above.

The main objective of this paper is to examine whether fundamentals or speculation drove the dynamics in credit spreads over the recent years. By doing so, we make the following contributions to the literature. First, to quantify the extent of speculation in debt markets, we exploit the fact that bond and CDS markets are theoretically driven by the same stochastic risk factor (Duffie, 1999), such that arbitrage forces should eliminate differences between them. We thus model both markets in a vector error correction model, which allows us to assess the strength of the arbitrage forces and whether there are any limits to arbitrage. Second, we simultaneously model the sovereign bond and CDS market using an empirical heterogeneous agent model. The advantage of this approach is that we do not have to make assumptions regarding exogenous variables proxying for sovereign credit risk and can introduce different types of agents in both markets. We therefore make an important contribution to the literature on heterogeneous agent models.

Empirically, we look at a set of 10 European sovereigns from 2008 until 2015.[2] The empirical results reveal that bond and CDS markets were driven by a combination of fundamental credit risk, liquidity-driven trading, speculation, and arbitrage. Interestingly, changes in CDS spreads are mainly driven by fundamental credit risk news (49%) and liquidity demand (45%). The bond market is less informative in the sense that it is driven for 13% by credit news and for 80% by liquidity trading. Both markets are only for approximately 5.5% driven by speculation. Arbitrage between the CDS and bond markets, finally, plays a negligible role. Interestingly, the importance of credit risk as a driver of bond and CDS markets is more important for peripheral countries than for core countries. We find the opposite for liquidity trading.

In a frictionless market, a bond and a CDS are equivalent because both are determined by the default probability of the underlying entity. However, several costs and risks prevent arbitrage strategies to be fully implementable.[3] These limits to arbitrage come in three forms, as suggested by Shleifer and Vishny (1997) and Barberis and Thaler (2003). First, implementation costs prevent complete arbitrage due to the costs incurred by arbitrageurs.[4] Second, fundamental risks are a risk to the arbitrage process because the market might move against the arbitrageur in the short run. Finally, noise trader risk refers to the possibility that noise traders drive prices further from fundamentals in the short run, going against the arbitrageur's position.

For our set of sovereigns, we find a significant implementation cost of the arbitrage which translates into a band around the long-run equilibrium relation of approximately 45 basis points preventing complete convergence. Given that the CDS and bond markets share the same fundamental, there is no fundamental risk. Noise trader risk can take different forms. In our model, noise trading is interpreted as liquidity trading and speculation (i.e., buying (selling) based on recent positive (negative) returns assuming these trends will continue). We find that liquidity trading is the main driver of variation in bond spreads (80%) whereas it is the second most important driver for the CDS market (45%).

Our empirical model is inspired by the literature on heterogeneous agent models (HAM) due to Brock and Hommes (1997, 1998).[5] In these models, agents are boundedly rational in their formation of expectations. The bounded rationality is captured by the fact that agents use heuristics in forming expectations. Typically, agents are assumed either to be of the 'fundamentalist' type expecting mean reversion towards a perceived fundamental value, or of the 'chartist' type expecting price trends to continue. Agents are assumed to be able to switch between the two types conditional on past performance. Our model builds on this reasoning and extends it in several ways. Instead of fundamentalists and chartists, we introduce arbitrageurs, speculators, and liquidity traders. Arbitrageurs expect the deviation between the bond and CDS spreads to decrease in the next period. The introduction of arbitrageurs is driven by the fact that we simultaneously study bond and CDS markets and these markets are driven by the same stochastic risk factor. The empirical advantage of this approach over having traditional fundamentalists in the model is that we do not have to make any assumptions regarding the fundamental value. Chiarella et al. (2015), for example, develop and estimate a HAM for the CDS market building on a fundamental value based on the reduced form model of Duffie (1999).

By simultaneously modeling the bond and CDS markets, we connect to the heterogeneous agent models on multiple asset markets.[6] Westerhoff and Dieci (2006) and Chiarella et al. (2005) both develop a HAM with two risky assets. Westerhoff and Dieci (2006) show that two fundamentally unrelated markets become related in the presence of common traders; Westerhoff (2004) and Chiarella et al. (2005) show that the presence of common investors can introduce excess co-movement in markets. De Jong et al. (2009) develop and estimate a HAM for multiple equity markets during the Asian crisis, in which agents partially form expectations based on the returns in foreign markets. Brock et al. (2009) simultaneously model a cash and derivative market in the presence of trader heterogeneity and show that introducing more

[2] Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain.

[3] A famous example of limits to arbitrage is given by Froot and Dabora (1999), who study the case of Royal Dutch Shell, which is listed on both the London and Amsterdam stock exchange. Despite that the stocks are a claim to the same underlying cashflows, the two market prices differ up to 35%.

[4] Think of transaction costs, information costs, etc.

[5] The HAM literature was initially fully theoretical, yielding insights from analytical and simulation exercises. The modeling approach has by now, though, also proven itself empirically; see Cheng et al. (2012) and Lux and Zwinkels (2018) for an overview. One of the first empirical results was found by Boswijk et al. (2007) for the S&P500. After that, authors have found empirical support in international equity markets (De Jong et al., 2009), foreign exchange markets (De Jong et al., 2010), commodity markets (Ter Ellen and Zwinkels, 2010), option markets (Frijns et al., 2010), and real estate markets (Kouwenberg and Zwinkels, 2014).Chiarella et al. (2015) propose and estimate a HAM for the sovereign CDS market. We extend their work by simultaneously analyzing the CDS and bond markets and find evidence of behavioral heterogeneity for all sovereigns in our study.

[6] The typical HAM only considers one risky asset.

derivatives might actually destabilize markets. To our best knowledge, we are the first to simultaneously model the bond and CDS markets and estimate the resulting empirical model.

Technically, our model reduces to a non-linear error correction model in state-space representation and is an extension of De Jong et al. (2009) who model a HAM with two asset markets using a nonlinear VAR. The non-linearity is introduced by the switching mechanism that allows agents to switch strategies over time. This allows us to study the time-varying importance of the different components. The error-correction model captures the arbitrage relation between the cointegrated bond and CDS spreads.[7] The state-space representation, finally, filters the common credit risk component out of the bond and CDS series when estimated simultaneously. This is related to the permanent-transitory decomposition of Gonzalo and Granger (1995).

A host of papers have studied the determinants of sovereign bond and CDS spreads; see Augustin (2014) for an overview. The main discussion revolves around the question to what extent spreads are driven by global risk factors due to the high comovement between sovereign spreads. Pan and Singleton (2008) find that the first principal component of daily sovereign CDS spreads explains up to 96% of spread variation; in our data this is 85%. The global factors that are found to be important are the US equity, volatility, and bond risk premia. Our state-space representation allows us to filter out the credit risk component from bond and CDS spreads. The first principal component explains 66% of the variation in the filtered credit news series. This is substantially less than the findings of Pan and Singleton (2008) and the first principal component of the raw CDS spread changes, implying that the non-fundamental factors have a more global character than fundamental factors do.

Our paper relates to the literature that studies the relation between bond and CDS markets. Blanco et al. (2005) study the relation between corporate bonds and CDS and find that the CDS market contributes more to price discovery than the bond market. Palladini and Portes (2011) study a set of six European countries and find the CDS market to lead the bond market. Our results are consistent with this finding. Arce et al. (2013) and Fontana and Scheicher (2016) document that there are sizeable deviations between CDS and bond spreads, which can be attributed to counterparty risk, equity volatility, illiquidity, funding costs, flight-to-quality, and ECB operations. We follow up on their results and show that there is strong time-variation in the importance of the explanatory factors, and add that the asymmetry in processing of fundamental information also plays a role. The time-variation is also documented by Calice et al. (2011), but using a VAR rather than a VECM. The VECM allows us to examine the fundamental information processing of the two markets.

The European sovereign debt crisis has also triggered renewed interest in the concept of contagion. Results in the literature tend to be conditional on the exact definition of the term contagion. Beirne and Fratzscher (2013) define fundamental contagion as an increased sensitivity of markets to fundamentals during crisis periods, and also find evidence for it. This is consistent with our results both in the time-series and the cross-section. Specifically, we find that for all countries the credit risk factor becomes more important in the 2009–2010 period. In addition, peripheral countries tend to be more strongly driven by credit risk than core countries. Ait-Sahalia et al. (2014) study the spread of shocks across European sovereign CDS markets. As in Bai and Wang (2006), we investigate the propagation of credit and liquidity shocks across countries. Based on a VAR analysis, we find that credit risk spreads positively from Germany to all other countries illustrating Germany's leading role in Europe, and from Spain to five other countries illustrating the fear of bankruptcy of a large country like Spain. Portuguese credit risk shocks spread negatively to core countries, suggesting a flight-to-quality mechanism (see Beber et al., 2009). We find much less evidence for the contagion of liquidity risk, especially for the bond market. These results are consistent with Bai and Wang (2006), who also finds a more important fundamental credit risk channel than liquidity channel.

The remainder of this paper is organized as follows. Section 2 presents our empirical strategy. Section 3 describes the data and Sections 4–6 the estimation results. Section 7 concludes.

2. Empirical Model

In this section, we develop our model for the dynamic interaction between the CDS and sovereign debt market in the presence of different types of traders: arbitrageurs, speculators, and liquidity traders.

Sovereign credit risk is traded in two markets: the sovereign bond market and the sovereign credit default swap (CDS) market. Under full market efficiency and refraining from liquidity risks and transaction costs, bond holders who hedge the credit risk of the bond issuer using a CDS written on the same reference entity should earn the risk free rate, see Duffie (1999); Lando (2004); Hull and White (2000). Hence, we would expect that the bond spread (BS_t), which is defined as the difference between the bond yield and the risk-free rate, is equal to the CDS spread (CDS_t). In this situation, both the CDS spread and the bond spread are fully driven by the underlying sovereign credit risk, ξ_t, and arbitrage immediately eliminates any dispersion between the two markets.

However, when there are limits to arbitrage in the sovereign credit market, the bond spread and CDS spread can diverge. Specifically, we assume that the divergence from the arbitrage spread can occur in both markets, K, where $K = \{BS, CDS\}$.

[7] For Greece, we do not find cointegration between the bond and CDS markets, forcing us to exclude Greece from the sample.

Then, x_t^K is the CDS - bond basis $(CDS_t - BS_t)$, such that:

$$\begin{pmatrix} BS_t \\ CDS_t \end{pmatrix} = \iota\xi_t + \begin{pmatrix} x_t^{BS} \\ x_t^{CDS} \end{pmatrix}, \tag{1}$$

in which ξ_t is the level of credit risk.

The equation presented above provides a common trend representation of the model for bond spreads and the CDS market. Following the Granger and Terasvirta representation theorem, such a common trend representation can be written as an error correction model. We continue by expressing the error correction representation, but provide an economic motivation for the dynamic behavior in this specification based on the heterogeneous agent literature; see Hommes (2006) for an overview.

We assume that the market for the bond spread and the CDS contains two types of traders driving x_t^K, which are active in both markets separately: Arbitrageurs and Speculators.[8] In addition, we assume that there is a third group of liquidity traders who trade randomly. Limits to arbitrage imply that the two markets will be in equilibrium in the long-run, but that there can be large and persistent deviations from the equilibrium relation in the short run. Therefore, x_t^{BS} and x_t^{CDS} are mean reverting processes. Arbitrageurs are assumed to trade on the expectation of mean reversion, i.e., that the difference between the bond spread and the CDS will converge to its long-run average. Hence their expectations of the future price movement in the CDS and bond spread are given as:

$$\begin{aligned} E_t^A \Delta CDS_{t+1} &= -\alpha^{CDS}(CDS_t - \lambda BS_t + c), \\ E_t^A \Delta BS_{t+1} &= \alpha^{BS}(CDS_t - \lambda BS_t + c), \end{aligned} \tag{2}$$

where $0 > \alpha^K > 1$ measures the expected speed of mean reversion and c is a constant that represents implementation costs. Given that $E(\Delta\xi_t) = 0$, and assuming rational trading and no arbitrage costs, we can equate $E_t \Delta CDS_{t+1} = E(x_t)$. In a perfect market, $\alpha = 1$, $\lambda = 1$, and $c = 0$.[9,10] This implies that mean reversion is immediate and complete. When there are limits to arbitrage, however, complete mean reversion takes longer than one period and might not be complete due to market frictions. Hence, arbitrageurs will not be active in the credit market when the difference between the two spreads is not large enough to cover costs, captured by c, and will not expect $\alpha^K = 1$.

Speculative traders do not trade on the basis of the price difference between *BS* and *CDS*, but trade on signals they extract from past price movements. This may cause the spread difference to persist. Specifically, Speculators trade on the lagged changes in *CDS* and *BS*, i.e.:

$$\begin{aligned} E_t^S \Delta CDS_{t+1} &= \beta_1^{CDS} \Delta CDS_t + \beta_2^{CDS} \Delta BS_t, \\ E_t^S \Delta BS_{t+1} &= \beta_1^{BS} \Delta CDS_t + \beta_2^{BS} \Delta BS_t, \end{aligned} \tag{3}$$

in which the $\boldsymbol{\beta}$'s measure the sensitivity to past changes in spreads.

Since both strategies are relatively simple to implement, agents can switch between strategies without any (significant) costs. We assume that switching occurs on the basis of the relative profitability of a certain strategy, i.e. if, say, an arbitrage strategy is more profitable (or making less losses) than any of the other strategies, then traders are inclined to switch to that strategy; see Brock and Hommes (1997, 1998) and DeLong et al. (1990) for a similar mechanism.[11] We measure profitability by considering the forecast error a trader would make by following a certain strategy. The forecast error, $\pi_t^{i,K}$ for strategy i in market K is given by:

$$\pi_t^{i,K} = \sum_{l=0}^{L^K} \left| E_{t-l-1}^i \Delta K_{t-l} - \Delta K_{t-l} \right|, \tag{4}$$

with $i \in A, S$ for arbitrageurs and speculators, respectively.[12] The optimal lag-length L^K is to be determined empirically.

Traders can change strategies based on the relative performance of each trading rule and are expected to switch when one rule is more profitable than the other. However, switching does not occur instantly as there may be some stickiness to past trading rules. Hence, we define a rule for switching between possible strategies based on Brock and Hommes (1998).

[8] This is motivated by the empirical model of Barberis et al. (1998) and experimentally shown by Bloomfield and Hales (2002) that (educated) individuals tend to have regime-shifting beliefs, in which the regimes are given by trend or mean reversion.

[9] The condition that $\lambda = 1$ builds on the fact that both the bond spread and the CDS have equal exposure to the underlying credit risk. While we would not expect λ to deviate from 1, we do test this in the subsequent section.

[10] We note that our model could be extended by making implementation costs, *c*, non-linear capturing, e.g., the fact that information costs may decrease as the spread increases. we thank the referee for highlighting this potential extension.

[11] An alternative way of interpreting this mechanism is given by Shleifer and Vishny (1997), who assume that arbitrageurs are intermediaries using other people's capital. As arbitrageurs generate negative returns, i.e., when spreads move against the parity relation, these people will tend to withdraw capital causing the market capital devoted to arbitrage to shrink.

[12] Note that various functional forms can be used to measure forecast error, including one based on squared errors. We employ absolute forecast errors, in line with recent empirical heterogeneous agent models (Kouwenberg and Zwinkels, 2014; Frijns et al., 2018). We also estimated our model based on squared forecast errors (see the Appendix) and obtain results similar to those reported in this paper. We do note that the likelihood values are lower for the squared error than for the absolute error.

We note that we have two sets of switching equations, one for the bond spread (*BS*) and one for the CDS market (*CDS*), i.e. $K = \{BS, CDS\}$. The switching functions are given as follows:

$$w_t^{A,K} = \left(1 + \exp\left[\gamma^K \frac{(\pi_{t-1}^{S,K} - \pi_{t-1}^{A,K})}{(\pi_{t-1}^{S,K} + \pi_{t-1}^{A,K})}\right]\right)^{-1},$$
$$w_t^{S,K} = (1 - w_t^{A,K}) = \left(1 + \exp\left[\gamma^K \frac{(\pi_{t-1}^{A,K} - \pi_{t-1}^{S,K})}{(\pi_{t-1}^{A,K} + \pi_{t-1}^{S,K})}\right]\right)^{-1}, \tag{5}$$

where γ^K ($K = \{BS, CDS\}$) is the so-called intensity of choice parameter and controls the intensity by which market participants switch between the different strategies. By construction, $w_t^{i,K} \in <0, 1>$ and $w_t^{A,K} + w_t^{S,K} = 1$. For instance, if $\gamma^K = 0$ traders do not consider the profitability of any of the strategies and thus $w_t^{i,K} = \frac{1}{2}\,\forall t$. On the other hand, when $\gamma^K \to \infty$ traders become infinitely sensitive to the relative performance of each strategy and completely switch to the strategy with the highest performance measure. A positive value for γ^K implies that market participants follow a positive feedback rule, by switching towards the strategy that performed relatively well in the recent past. A negative value for γ^K implies that market participants act in a contrarian way and follow a negative feedback rule by switching away from the strategy that performed relatively well in the recent past. Evidence of both positive and negative switching has been documented by e.g. Chiarella et al. (2015).[13]

The final model representing the changes in the CDS and bond spreads can now be given as a combination of trading of the different trader types. Specifically, we assume that the changes in the spreads are affected by the proportions of arbitrage and speculative traders, common shocks that represent the arrival of fundamental information to the market and idiosyncratic shocks that are due to liquidity demand in both markets:

$$\Delta CDS_t = w_t^{A,CDS}\left(-\alpha^{CDS}[CDS_{t-1} - \lambda BS_{t-1} + c]\right) + w_t^{S,CDS}\left(\beta_1^{CDS}\Delta CDS_{t-1} + \beta_2^{CDS}\Delta BS_{t-1}\right) + \eta_t + \varepsilon_t^{CDS},$$
$$\Delta BS_t = w_t^{A,BS}\left(\alpha^{BS}[CDS_{t-1} - \lambda BS_{t-1} + c]\right) + w_t^{S,BS}\left(\beta_1^{BS}\Delta CDS_{t-1} + \beta_2^{BS}\Delta BS_{t-1}\right) + \eta_t + \varepsilon_t^{BS}, \tag{6}$$

in which $\eta_t = \Delta\xi_t$ is the innovation to credit risk, and ε_t^{CDS} and ε_t^{BS} are liquidity shocks for the CDS and bond market, respectively. Eq. (6) shows that the model defined above takes the form of a vector error correction model (VECM) with time-varying parameters (see Granger and Terasvirta, 1993). This time-variation in the parameters is controlled by the intensity of choice parameter γ^K. If $\gamma^K = 0$, then there is no switching between strategies and the model reduces to a standard VECM with three stochastic processes, one shared and two specific to each market. The latter is related to the time-series issue of common trends in cointegrated systems from the econometrics literature (see Gonzalo and Granger, 1995; Stock and Watson, 1988). To quantify the limits to arbitrage and study the importance of sovereign credit risk news, we proceed to estimate the model given by Eq. (6) in the remainder of this paper. Estimation of this model is done using the Kalman filter, which we discuss in further detail in the next section.

3. Data and Methods

CDS data are collected from CMA through Bloomberg. Daily credit default swap spreads, CDS_t, on ten Eurozone sovereigns are collected from 01/01/2004 until 01/13/2015.[14] This equals over ten years of daily credit spreads adding up to 2638 daily CDS spreads per sovereign entity. Because there is no variation in the spreads prior to 2008, we restrict the sample in our analysis to the period 01/01/2008 until 01/13/2015, providing 1,836 daily observations. The ten European sovereigns include Austria, Belgium, France, Germany, Greece, Ireland, Italy, The Netherlands, Portugal and Spain. The 5-year USD-denominated CDS contracts are chosen since these are generally the most liquid. For each of these sovereign entities bond yields, BS_t, are collected from Thomson Reuters Datastream. These are zero-coupon bonds with a constant maturity of 5 years. Both bond and credit spreads are bid rates. Furthermore, we obtain interest rate swaps on EURIBOR with a 5-year maturity as our measure of the risk-free interest rate r_t^f. For estimation purposes, we transform all data to log-variables by taking $\ln(1 + CDS_t)$ and $\ln(1 + BS_t - r_t^f)$

The model in Eq. (6) is essentially a VECM, hence for being able to estimate it, the CDS and bond spread data need to be cointegrated. The top part of Table 1 presents the cointegration test results obtained using the Johansen (1995) cointegration test.

The cointegration test results indicate that the null-hypothesis of no cointegration is rejected for all countries, though marginally so for Ireland. The null-hypothesis of at least one cointegrating relation is not rejected for all countries. Hence, for all countries but Ireland the requirements for the estimation of the VECM are satisfied. The line labeled *UR* represents the result of a Dickey-Fuller unit root test on the CDS - bond basis $CDS_t - BS_t$, hence enforcing a cointegrating vector of $(-1, 1)$. This test is inspired by the theoretical restriction of $\lambda = 1$. The results show that the null of a unit root is rejected

[13] Note that a negative γ is against the standard interpretation of the heuristic switching model, due to the self-referential character of such models. Empirically, though, this need not be the case because the model fit is never perfect (i.e., there is a residual capturing the behavior of agents that are not part of the model). In this particular case, these are the credit risk innovations and the liquidity shocks.

[14] Due to limited data availability we are restricted to ten European sovereigns.

Table 1
Descriptive statistics.

	AU	BE	FR	GE	GR	IR	IT	NL	PO	SP
0 CE	0.000	0.002	0.001	0.000	0.033	0.109	0.074	0.001	0.007	0.036
$\leq$ 1 CE	0.440	0.633	0.503	0.283	0.436	0.834	0.366	0.290	0.566	0.495
UR	0.001	0.000	0.020	0.046	0.791	0.030	0.005	0.037	0.050	0.003
Descriptives ΔBS_t										
Mean	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.001	0.000
Max	0.313	0.419	0.344	0.549	0.264	0.280	0.217	0.426	0.264	0.285
Min	−0.278	−0.266	−0.333	−0.527	−0.633	−0.450	−0.296	−0.358	−0.443	−0.412
StDev	0.043	0.040	0.045	0.077	0.045	0.042	0.037	0.048	0.039	0.039
Skew	0.684	0.787	0.365	−0.099	−2.572	−0.695	−0.177	0.456	−0.479	−0.797
Kurt	11.39	16.09	10.35	12.92	45.88	18.79	9.00	15.84	19.26	15.63
Obs	1835	1835	1835	1835	1093	1835	1835	1835	1835	1835
Descriptives ΔCDS_t										
Mean	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000
Max	0.158	0.100	0.076	0.060	2.011	0.174	0.164	0.110	0.190	0.174
Min	−0.107	−0.147	−0.100	−0.067	−1.583	−0.248	−0.274	−0.070	−0.423	−0.277
StDev	0.018	0.020	0.016	0.011	0.086	0.025	0.026	0.014	0.030	0.026
Skew	0.615	−0.137	−0.008	−0.038	4.565	−0.102	−0.129	0.608	−0.976	−0.471
Kurt	13.33	9.15	7.62	8.22	298.48	15.16	13.42	10.23	28.02	13.22
Obs	1835	1833	1835	1833	1396	1830	1835	1830	1835	1833

This table shows the results of the cointegration test and the descriptive statistics of the changes in bond and CDS spreads, respectively. CE denotes cointegrating equations (p-values); UR denotes Unit Root (p-values). We report cointegration and descriptive statistics for Austria (AU); Belgium (BE); France (FR); Germany (GE); Greece (GR); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

for all countries but Greece. For further visual inspection, we plot the original time series in Fig. 1. Based on these findings, in the remainder of the paper we continue with a set of nine countries, excluding Greece, applying the restriction, $\lambda = 1$.

The lower part of Table 1 presents the descriptive statistics of changes in CDS and bond spreads.[15] All mean values are close to zero. The standard deviations and min-max spread, though, display substantial differences between countries. There is a clear divide between the core and peripheral European countries, with much higher volatilities, ranges, kurtosis, and negative skewness for the peripheral countries.

Table 2 presents the correlations between all bond and CDS spread changes. The top left quadrant displays the correlations between the bond spreads of the European countries. There is a substantial correlation between all countries, which is higher for countries that are located in the same region. The outlier is Germany, with a somewhat lower correlation to all other countries except for the Netherlands. The bottom right quadrant displays the correlations between the CDS spreads of the different countries. These are relatively large for all countries. The difference in the correlation structure between bonds and CDS market is a first indication that there is an important difference in the factors driving the spreads. The bottom left quadrant, finally, illustrates the correlations between the bond and CDS markets. Of particular interest are the values on the diagonal, representing the correlation between one country's bond and CDS spread. As expected, these values are typically high, except for Germany with a slightly negative correlation of -19%.

As in Section 2, the model is effectively a non-linear error correction model. The fundamental news about the sovereign credit risk, η_t, however, is an unobserved variable. To distinguish between the liquidity process, ε_t, and the fundamental credit risk news, η_t, we put the model in a state-space representation and estimate it using the Kalman Filter and multivariate Quasi-Maximum Likelihood in which ΔCDS_t and ΔBS_t are observed signals and η_t is an unobserved state variable. Here we assume that news on sovereign credit risk is a random variable with $\eta_t \sim N(0, \sigma_\eta^2)$, such that the only additional free parameter to be estimated is the variance term, σ_η^2. Because the fundamental credit risk process is equal across the two markets, whereas the liquidity process, ε_t^K, is specific to each market, we can identify the underlying fundamental credit risk. Hence, the major advantage of simultaneously modelling the bond and CDS market is that it allows us to filter out the underlying fundamental credit risk process, η_t, without making any assumptions regarding (exogenous) factors that presumably drive sovereign credit risk. The demand for liquidity, ε_t^K, is then obtained as the residual of the two-market estimation. In contrast, if we would only have one market under investigation, we would not be able to distinguish between the fundamental credit risk and the liquidity factor. Even with a state space model one market would not suffice because it remains unclear what the filtered state variable would represent, news or liquidity. Our VECM with a common news component is essentially equal to a Permanent-Transitory decomposition; the common component, ξ_t, is a shared $I(1)$ process whereas the x_t^K terms are transitory $I(0)$ processes. Gonzalo and Granger (1995) propose a similar method to extract the common component from cointegrated series in an error correction model.

The model is estimated for both markets simultaneously by multivariate quasi-maximum likelihood. To determine the optimal lag length L^K for each market, we estimate the model for all 100 combinations of L^K, $K \in \{BS, CDS\}$ between one and ten, and use the Schwarz/Basian Information Criterion to select the optimal model. Given the non-linearity of the switching

[15] Note that these represent percentage changes in the spreads because we are working with logarithmic values.

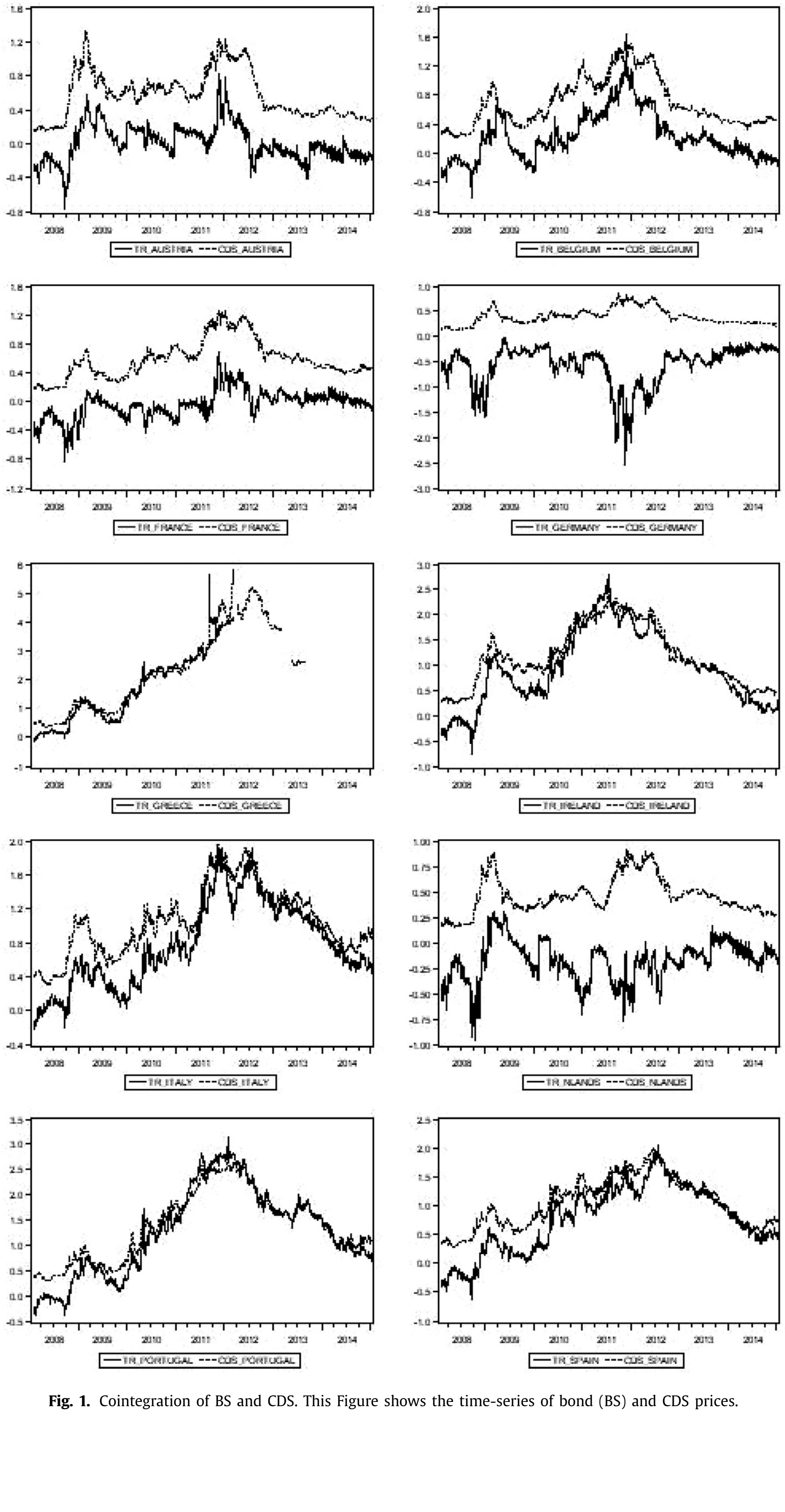

Fig. 1. Cointegration of BS and CDS. This Figure shows the time-series of bond (BS) and CDS prices.

Table 2
Correlations.

		ΔBS_t									ΔCDS_t							
		AU	BE	FR	GE	IR	IT	NL	PO	SP	AU	BE	FR	GE	IR	IT	NL	PO
ΔBS_t	BE	0.59																
	FR	0.60	0.60															
	GE	0.36	0.22	0.34														
	IR	0.32	0.40	0.30	0.13													
	IT	0.32	0.49	0.41	0.00	0.48												
	NL	0.54	0.51	0.68	0.47	0.30	0.34											
	PO	0.24	0.32	0.17	0.05	0.52	0.45	0.18										
	SP	0.37	0.52	0.46	0.10	0.54	0.75	0.41	0.47									
ΔCDS_t	AU	0.15	0.27	0.18	−0.18	0.22	0.37	0.07	0.21	0.34								
	BE	0.13	0.31	0.13	−0.23	0.23	0.42	0.04	0.23	0.38	0.71							
	FR	0.14	0.28	0.20	−0.24	0.21	0.38	0.02	0.20	0.33	0.74	0.75						
	GE	0.13	0.26	0.15	−0.19	0.21	0.35	0.05	0.22	0.31	0.70	0.68	0.76					
	IR	0.04	0.22	0.06	−0.18	0.38	0.39	−0.03	0.34	0.38	0.61	0.64	0.59	0.57				
	IT	0.10	0.29	0.11	−0.21	0.31	0.54	0.00	0.31	0.49	0.64	0.72	0.69	0.62	0.69			
	NL	0.12	0.26	0.16	−0.17	0.17	0.33	0.10	0.19	0.30	0.71	0.67	0.69	0.69	0.56	0.57		
	PO	0.04	0.20	0.02	−0.16	0.34	0.38	−0.04	0.42	0.36	0.52	0.59	0.54	0.51	0.71	0.72	0.46	
	SP	0.08	0.28	0.09	−0.22	0.31	0.50	−0.01	0.32	0.49	0.64	0.70	0.69	0.61	0.74	0.87	0.59	0.73

This table shows the correlations between bond and credit spread changes. We report correlations for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

function given by Equation (5), the estimation procedure could be sensitive to starting values of the coefficients. Therefore, we first estimate the model without switching, i.e., by setting $\gamma^K = 0$, and use the estimated coefficients of the static model as starting values for estimation of the switching model. We set $\gamma^{BS} = \gamma^{CDS} = 0$ as starting value for the switching parameters. Experiments indicate that the estimation results are insensitive to the latter choice.

4. Estimation results

In this section, we present the estimation results of the model presented in Section 2. We start by estimating the linear model, which sets all weights to 0.5, i.e. by setting $\gamma^{CDS} = \gamma^{BS} = 0$.[16] Next, we estimate the nonlinear model by first introducing switching in one market, then switching in the other, and finally allowing for switching in both markets. By comparing the likelihoods of the different model configurations, we are able to determine to what extent switching in either market adds to the explanatory power of the model.

4.1. Static model

Table 3 presents the estimation results for the non-switching model with $\gamma^K = 0,\ K = \{BS, CDS\}$.

Overall, the estimation results for the static model are consistent with the theoretical framework consisting of arbitrageurs and speculators. For all countries, we find significant evidence for both arbitrage forces and speculative forces.

First, we consider the arbitrage dynamics in the bond and CDS markets. The estimates for c are negative and significant for all countries but Portugal, indicating that the CDS spread is higher than the bond spread in equilibrium. On average, c is equal to −0.45 meaning that there is an approximately 45 basis point implementation cost for arbitrageurs that prevent the two spreads from complete convergence. The mean reversion parameter for the arbitrageurs in the bond market, α^{BS}, is positive and significant for all countries. Hence, arbitrage forces are of importance in describing the bond market dynamics. On average, α^{BS} is equal to 0.038 implying that arbitrageurs in the bond market expect the spread difference between the bond and CDS to decrease by almost 4% per day. From the perspective of the CDS market, the evidence for arbitrage forces is substantially smaller. The estimated values for α^{CDS} are only significant for Ireland at the 10% level. In terms of price leadership or price discovery, the parameter estimates imply that the CDS market is leading the bond market as it is the bond market that reacts to the cointegrating relationship. Specifically, the Gonzalo and Granger (1995) component share, defined as the contribution of a specific market to the common component for the CDS (bond) market is 89% (11%), a finding that is broadly in line with Blanco et al. (2005). These results imply that informed traders trade based on their information primarily in the CDS market. This informational trade can cause an imbalance in the price of the CDS and the BS. When this gap occurs, our results show that indeed arbitrageurs trade in the bond market as this is the price that is stale of information and needs to be adjusted to the CDS price.

[16] We note that in fact there are infinitely many combinations of weights possible under $\gamma^k = 0$. These combinations are all observationally equal and produce the same log-likelihood, except for the degenerate cases where the weight on one type of trader is zero. In those degenerate cases, the log-likelihoods will be lower than those presented below, as our shows that the coefficients on the speculative and arbitrage strategies are both statistically significant.

Table 3
Results static model.

	AU	BE	FR	GE	IR	IT	NL	PO	SP
c	−0.568***	−0.468***	−0.621***	−0.941***	−0.210**	−0.273***	−0.633***	−0.076	−0.257***
	(−14.632)	(−16.403)	(−9.995)	(−4.767)	(−2.928)	(−6.190)	(−7.433)	(−1.062)	(−3.695)
α^{BS}	0.055***	0.067***	0.038***	0.023***	0.030***	0.038***	0.031***	0.026***	0.030***
	(5.354)	(5.880)	(3.895)	(4.656)	(4.465)	(3.998)	(4.040)	(3.866)	(4.157)
β_1^{BS}	0.464***	0.618***	0.274**	−0.729***	0.736***	0.386***	0.340***	0.819***	0.682***
	(5.693)	(7.338)	(2.199)	(−2.895)	(11.080)	(6.329)	(2.803)	(23.280)	(11.330)
β_2^{BS}	−0.233***	−0.089**	−0.337***	−0.353***	−0.180***	−0.043	−0.330***	−0.044	−0.233***
	(−7.280)	(−2.362)	(−9.987)	(−15.26)	(−6.662)	(−1.019)	(−12.67)	(−1.447)	(−6.958)
α^{CDS}	−0.001	0.004	0.002	0.001	0.008*	0.005	0.003	0.005	0.010
	(−0.312)	(0.696)	(0.553)	(0.694)	(1.791)	(0.740)	(1.454)	(0.835)	(1.633)
β_1^{CDS}	0.418***	0.272***	0.333***	0.355***	0.341***	0.267***	0.150***	0.301***	0.314***
	(14.30)	(8.010)	(9.259)	(11.074)	(9.691)	(6.570)	(4.711)	(8.421)	(9.147)
β_2^{CDS}	−0.006	0.042**	0.005	0.006	0.074***	0.110***	0.003	0.065***	0.007
	(−0.299)	(2.634)	(0.310)	(1.143)	(2.949)	(3.186)	(0.292)	(2.700)	(0.246)
LL	7902.76	7949.26	8090.26	7691.00	7525.76	7778.74	8154.80	7341.68	7610.96

This table shows the estimation results of the static model given by Eq. (6). *, **, *** represent significance at the 10, 5, and 1% level, respectively. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Table 4
Results switching.

	Austria			Belgium			France		
γ^{CDS}	7.399***		−8.042***	4.502**		−7.881***	−15.601**		−8.342***
	(4.396)		(-553.61)	(2.018)		(-446.67)	(-1.969)		(-444.85)
γ^{BS}		645.582	649.99		1.292*	1.382		7.178***	7.466***
		(0.481)	(0.474)		(1.652)	(1.615)		(3.075)	(3.119)
L	2	4	2, 4	2	1	2, 1	5	1	5, 1
LR_1	14.74***	14.19***	29.12***	3.79*	6.33**	9.52***	6.53**	19.52***	26.96***
LR_2	−14.38***	−14.93***		−5.73**	−3.19*		−20.43***	−7.44***	
	Germany			Ireland			Italy		
γ^{CDS}	−12.045***		−8.968***	3.836*		−7.451***	8.592***		−7.305***
	(-2.352)		(-502.59)	(1.878)		(-509.17)	(2.727)		(-473.61)
γ^{BS}		143946	159796		−3.619*	−3.389		2.426	2.652*
		(0.002)	(0.000)		(-1.657)	(-1.586)		(1.648)	(1.672)
L	9	10	2, 10	6	7	6, 7	10	1	10, 1
LR_1	4.77***	41.17***	44.10	1.34	3.78*	4.79**	5.55**	4.70**	10.28***
LR_2	−39.33***	−2.93*		−3.44*	−1.01		−4.73**	−5.58**	
	Netherlands			Portugal			Spain		
γ^{CDS}	−101181		−8.578***	12.172***		−7.027***	11.796***		−7.307***
	(-0.003)		(-541.0)	(4.101)		(-657.7)	(3.132)		(-435.8)
γ^{BS}		1.506**	1.563**		−5.936***	−5.038***		−6.697**	−7.854**
		(2.438)	(2.443)		(-4.721)	(-4.812)		(-2.550)	(-2.520)
L	10	1	10, 1	3	7	3, 10	1	7	1, 9
LR_1	14.15***	3.21*	16.75***	20.95***	44.13***	61.16***	16.70***	12.55***	28.26***
LR_2	−2.60	−13.54***		−40.21***	−17.03***		−11.56***	−15.71***	

This table shows the estimated switching parameters γ^{CDS} and γ^{BS}, as well as the results of the likelihood ratio tests of the switching model versus the static model (LR_1) and the model with switching in one market versus switching in both markets (LR_2). *, **, *** represent significance at the 10, 5, and 1% level, respectively.

The estimated β coefficients allow us to draw inferences on the existence of speculative forces in the two credit markets. First, we observe that β_1 is positive for both the bond and CDS market. Hence, lagged movements in the CDS market positively affect both the bond and the CDS markets. This is an indication of speculative forces as positive autocorrelation is inconsistent with market efficiency. On average, the bond market reacts stronger to lagged changes in the CDS market than does the CDS market; $\beta_1^{BS} > \beta_1^{CDS}$. Looking at the reaction of the markets to lagged changes in the bond market, captured by β_2, we observe that only the bond market reacts to its own lags; the CDS market is hardly affected by lagged changes in the bond spread. For all countries, β_2^{BS} is negative implying that an increase in the bond spread is followed by a decrease. The absolute magnitude of β_2^{BS}, though, is smaller than β_1^{BS}.

4.2. Allowing for switching between strategies

Having established that arbitrage and speculative forces are relevant in explaining the spreads, we now address the question whether the relative importance of the two is constant over time. To examine this, we first allow for switching only in the CDS market; switching only in the bond market; and switching in both markets.

Table 5
Forecasting results.

	AU	BE	FR	GE	IR	IT	NL	PO	SP	AVG
	CDS									
1	0.997	0.984	0.959	0.962	0.911	0.951	0.990	0.961	0.951	0.963
2	0.974	0.969	0.965	0.969	0.917	0.978	1.011	0.954	0.983	0.969
3	0.998	0.992	0.983	0.988	0.923	0.980	1.033	0.957	0.984	0.982
4	0.995	0.998	0.990	0.991	0.922	0.991	1.046	0.971	0.990	0.988
6	1.013	1.010	0.994	1.008	0.929	1.003	1.062	0.976	0.999	0.999
8	1.022	1.014	0.992	1.015	0.932	1.003	1.100	0.979	1.003	1.007
10	1.027	1.024	0.993	1.023	0.934	1.004	1.108	0.981	1.003	1.011
AVG	1.007	1.002	0.986	0.999	0.926	0.992	1.060	0.971	0.991	0.993
	BS									
1	0.942	0.954	0.922	0.926	0.919	0.965	0.938	0.911	0.957	0.937
2	0.921	0.928	0.926	0.914	0.880	0.926	0.936	0.859	0.934	0.914
3	0.933	0.923	0.935	0.955	0.872	0.921	0.935	0.878	0.949	0.922
4	0.933	0.919	0.947	0.968	0.856	0.918	0.927	0.899	0.962	0.925
6	0.936	0.898	0.943	0.997	0.837	0.892	0.900	0.906	0.955	0.918
8	0.923	0.882	0.943	1.021	0.823	0.851	0.870	0.906	0.941	0.907
10	0.932	0.870	0.946	1.023	0.805	0.804	0.834	0.894	0.914	0.891
AVG	0.932	0.905	0.938	0.981	0.848	0.890	0.899	0.896	0.945	0.915

This table shows the forecasting results comparing the RMSE of the model to that of a random walk forecast. A number < 1 represents outperformance of the model. AVG denotes average. We report forecasts for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Table 4 presents the estimated values of γ^{CDS} and γ^{BS} as well as the result of the likelihood ratio test comparing the switching model to the static model (LR_1) and comparing switching in both markets to switching in one market only (LR_2).[17] We present the results for the optimal lag L. For the setup with switching in both markets, we have considered all 10×10 possible combinations of L^{BS} and L^{CDS}.

First and foremost, the estimation results indicate that the model with switching is optimal for all countries. The LR_1 statistics all reject the null hypothesis that model (3) is equal to the static case. For Belgium and Ireland, we only find significant switching in the bond market whereas for the Netherlands we only find significant switching for the CDS market. Hence, the impact of arbitrage and speculation is typically stable in neither the bond market nor the CDS market.

Recall that a positive (negative) γ implies that if either arbitrage or noise is more profitable in period t, traders will increase (decrease) their weight on that strategy in period $t+1$. For both the bond and the CDS market, we observe that γ is positive for six out of nine countries, implying that positive feedback trading (i.e. positive past profitability of the strategy lead to an increase in the weight put on that strategy) is the dominant strategy for traders in both markets. For seven out of nine countries, switching is more aggressive in the CDS market than in the bond market, i.e., $|\gamma^{CDS}| > |\gamma^{BS}|$. Certain estimated γ's are clearly rather large, such as γ^{BS} for Germany and γ^{CDS} for Netherlands. This implies very aggressive switching between trading rules when there are differences past profitability of the trading strategies.[18]

The optimal lag lengths, L^{BS} and L^{CDS}, vary across countries and markets, but are consistent whether we allow for switching in a single market or in both simultaneously.

4.3. Forecasting

As an additional test of the switching model, we evaluate its forecasting power. Specifically, we run rolling regressions with an expanding window and form 10 dynamic out-of-sample forecasts for each country and market at each step. The first in-sample period runs from January 1, 2008 to December 12, 2011 (1000 daily observations), resulting in 804 out-of-sample forecasts for each horizon.

Table 5 presents the root-mean-squared-error (RMSE) of the model over the RMSE of a random walk forecast. A number less than one implies a better forecasting performance for our model. For both markets, our model outperforms the random walk forecast. This suggests that for both markets the Efficient Market Hypothesis is violated, and thus that there is predictability in both these markets. For the CDS market, we observe that the model outperforms the random walk forecast by, on average, 0.7%. There is, however, quite some variation across countries and over the forecast horizon. Specifically, the model tends to perform better on the shorter forecast horizons (3.7% outperformance on average) than the longer horizons (1.1% underperformance). Furthermore, the model performs better for the peripheral countries Ireland, Italy, Portugal, and Spain (3% outperformance) than the core countries (1.68% underperformance).

Our model shows stronger forecasting power for the bond market than for the CDS market. On average, the outperformance in the bond market is 8.5%. Interestingly, whereas the performance decreases with the forecast horizon for the CDS

[17] The other coefficient estimates are reported in the appendix to this paper.

[18] This is the reason why the coefficient itself is not significant whereas the likelihood ratio test indicates that allowing for switching is. The non-linear structure of the logit function induces this paradoxical result. The significance of the likelihood ratio test, however, is conclusive; see Granger and Terasvirta (1997).

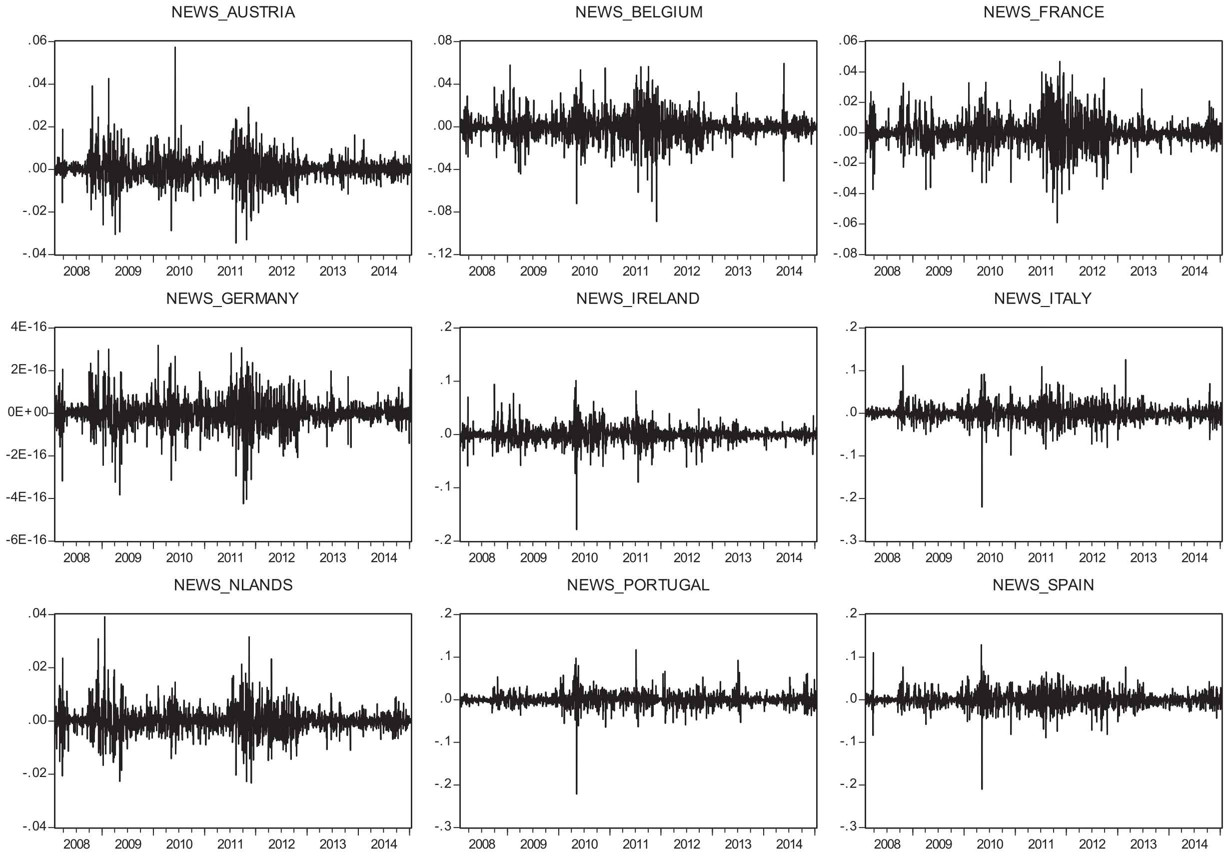

Fig. 2. News. This Figure shows the filtered credit risk news series.

Table 6
Credit risk news.

	AU	BE	FR	GE	IR	IT	NL	PO	SP
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.057	0.060	0.047	0.000	0.101	0.125	0.039	0.117	0.129
Minimum	−0.035	−0.089	−0.059	0.000	−0.179	−0.220	−0.023	−0.221	−0.210
Std. Dev.	0.006	0.012	0.009	0.000	0.015	0.020	0.005	0.016	0.019
Skewness	0.545	−0.163	0.053	−0.234	−0.377	−0.341	0.657	−0.820	−0.497
Kurtosis	12.395	8.594	7.446	7.877	18.487	15.224	10.473	28.332	15.134
Observations	1814	1814	1814	1814	1814	1814	1814	1814	1814

This table shows the descriptive statistics of the filtered credit risk news series η_t. We report descriptives for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

market, it increases with the forecast horizon for the bond market. As for the CDS market, though, the performance of the model is better for the peripheral countries (8.03% outperformance) than for the core countries (6.9% outperformance).

Overall, the better forecasting performance of our model in the bond market is in line with the findings observed in Table 3, which revealed that the CDS market was dominant in terms of price discovery and did not adjust to price discrepancies between the CDS and the bond market. This suggests that the CDS market is driven much more by fundamental forces, which are captured well by the random walk assumption used as a benchmark in this forecasting exercise.

5. Which factors drive credit spreads?

Now that we have settled on the optimal model, we subsequently study how and to what extent the different elements (fundamental news, arbitrage, speculative trading, and liquidity demand) affect the credit spreads in the two markets. To this end, we first study the filtered news processes, followed by the processes for arbitrage and speculative trading. Finally, we perform a variance decomposition to see how important each element is in describing the credit spreads in the bond and CDS markets.

Table 7
Noise trader risk.

	AU		BE		FR		GE		IR	
	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$
Mean	0.564	0.479	0.529	0.501	0.490	0.506	0.514	0.514	0.518	0.482
Med	0.605	0.061	0.536	0.500	0.485	0.511	0.527	1.000	0.522	0.491
Max	0.999	1.000	0.988	0.799	1.000	0.999	0.970	1.000	0.813	0.855
Min	0.001	0.000	0.010	0.201	0.002	0.001	0.016	0.000	0.233	0.101
Stde	0.271	0.492	0.179	0.125	0.258	0.335	0.170	0.500	0.084	0.099
Skew	−0.375	0.082	−0.110	−0.067	0.103	−0.032	−0.321	−0.057	−0.219	−0.390
Kurt	2.091	1.026	3.067	3.003	1.883	1.662	3.300	1.004	3.683	3.817
Obs	1813	1813	1813	1813	1813	1813	1813	1813	1813	1813

	IT		NL		PO		SP	
	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$	$W^{S,CDS}$	$W^{S,BS}$
Mean	0.527	0.500	0.374	0.500	0.539	0.427	0.528	0.468
Med	0.533	0.500	0.000	0.499	0.552	0.428	0.543	0.466
Max	0.972	0.934	1.000	0.826	1.000	0.880	1.000	0.917
Min	0.101	0.066	0.000	0.173	0.001	0.045	0.000	0.059
Stdv	0.155	0.178	0.484	0.134	0.259	0.148	0.356	0.162
Skew	−0.002	−0.042	0.521	0.033	−0.200	0.079	−0.107	0.097
Kurt	2.783	3.126	1.271	3.071	2.019	2.688	1.580	2.760
Obs	1813	1813	1813	1813	1813	1813	1813	1813

This table shows the descriptive statistics of the proportion of speculative traders in the bond and CDS markets, $W^{S,BS}$ and $W^{S,CDS}$. We report statistics for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

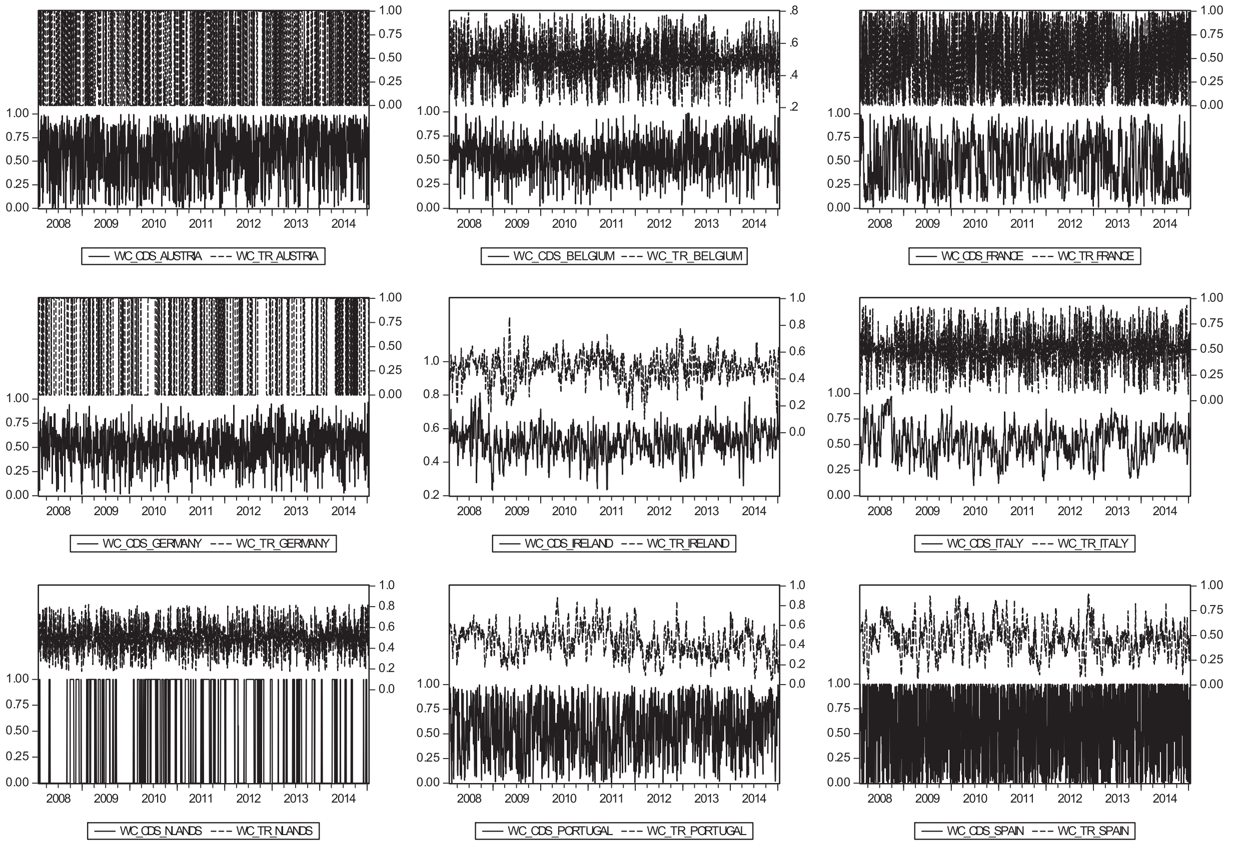

Fig. 3. Noise Trader Risk. This Figure shows the estimated proportion of speculative trader in the CDS and bond markets, $W^{N,TR}$ and $W^{N,CDS}$.

Table 8
Variance decomposition.

	NEWS		LIQUIDITY		ARBITRAGE		SPECULATION	
	BS	CDS	BS	CDS	BS	CDS	BS	CDS
AU	2.3%	18.7%	93.5%	72.5%	2.2%	0.0%	2.1%	8.7%
BE	10.2%	67.6%	84.5%	27.7%	1.9%	0.1%	3.4%	4.7%
FR	4.5%	65.3%	91.3%	29.3%	0.3%	0.1%	3.8%	5.3%
GE	0.0%	0.0%	93.0%	97.0%	0.0%	0.1%	7.0%	2.9%
IR	15.4%	65.8%	78.5%	26.8%	0.8%	0.2%	5.3%	7.1%
IT	34.3%	81.9%	62.8%	12.8%	0.8%	0.0%	2.0%	5.4%
NL	1.0%	21.4%	95.5%	75.5%	0.7%	0.0%	2.8%	3.1%
PO	21.2%	44.7%	61.7%	48.5%	0.7%	0.0%	16.4%	6.8%
SP	26.8%	78.2%	66.7%	16.7%	0.4%	0.0%	6.1%	5.1%
AVG	12.9%	49.3%	80.8%	45.2%	0.9%	0.1%	5.4%	5.5%

This table shows the resutls for the Variance Decomposition. *, **, *** represent significance at the 10, 5, and 1% level, respectively. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

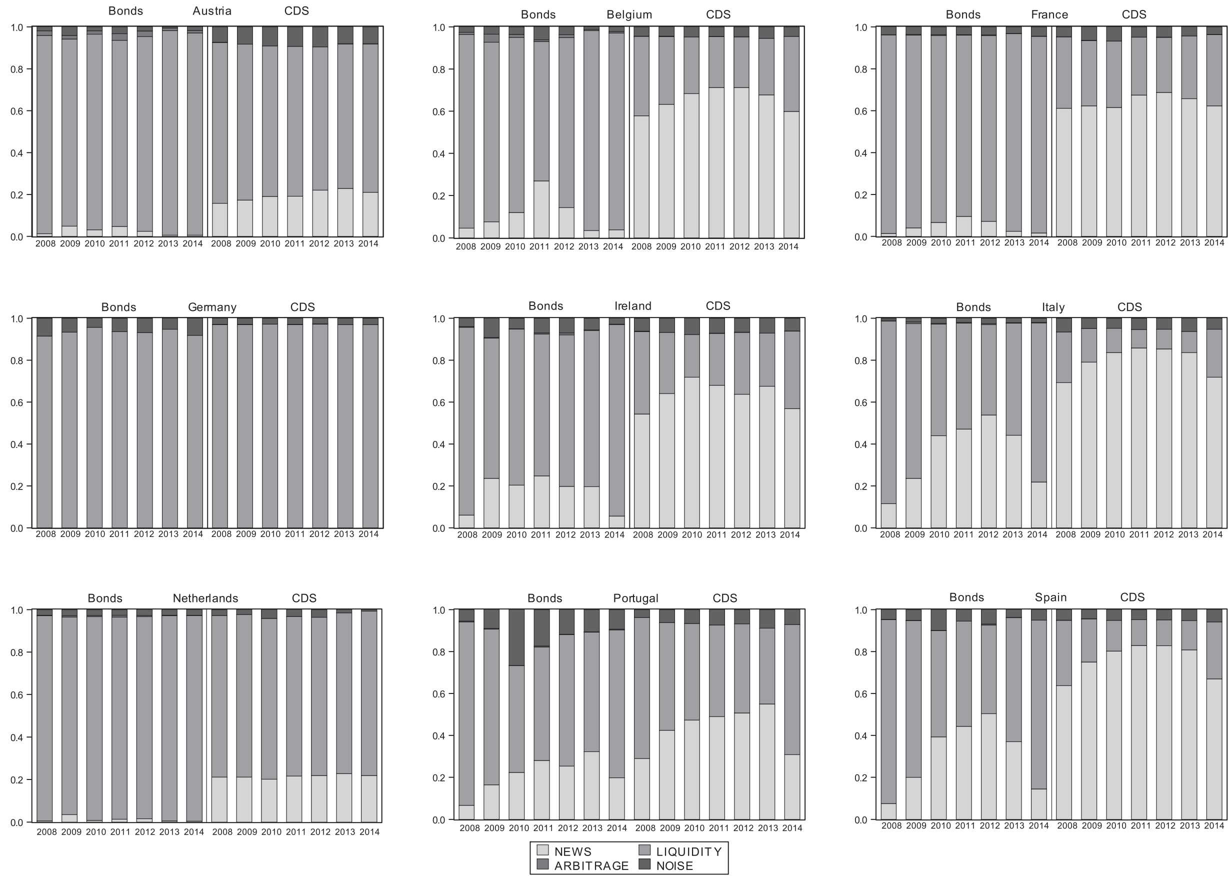

Fig. 4. Variance decomposition. This Figure shows the variance decomposition results for each of the years in the sample.

5.1. Fundamental news about sovereign credit risk

The fundamental news component, η_t, as described above, is obtained by means of a Kalman Filter approach. Because we are simultaneously analyzing both the bond and the CDS market, we are able to filter out the fundamental value without making any assumptions regarding the functional form or exogenous variables. Fig. 2 presents the filtered news processes for all nine countries and Table 6 presents the corresponding descriptive statistics.

Fig. 2 and Table 6 show that there is ample variation in the fundamental credit risk, η_t, for the European countries. The difference in variation between countries, however, is rather large. For Germany, the variation is minimal whereas for Italy the estimated daily standard variation is 2%. The difference is again clear between peripheral countries with a standard deviation close to 2% and core countries with a standard deviation below 1%.

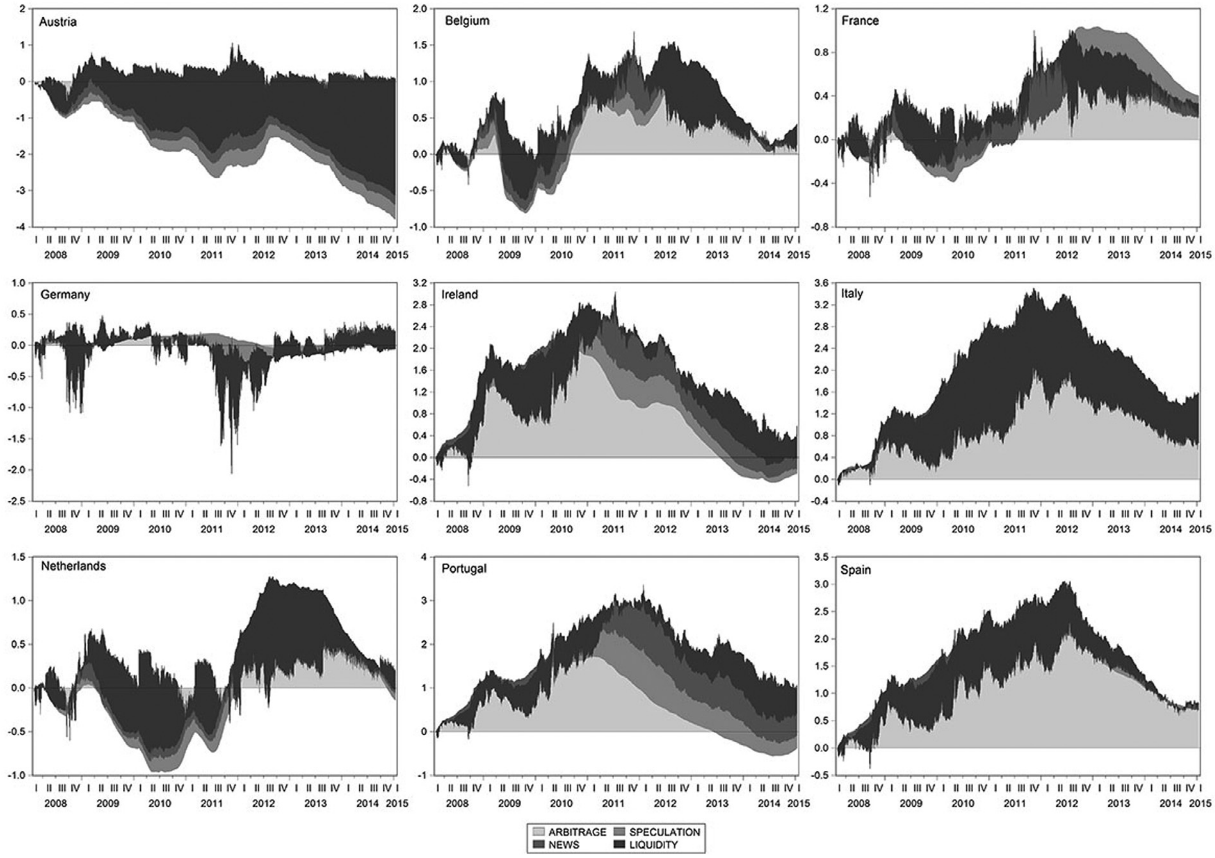

Fig. 5. Bond Spread Decomposition. This Figure shows the decomposed credit spreads for the bond market.

Fig. 2 illustrates that there is also a substantial portion of comovement among the sovereign credit risk measures. For all countries, the negative spike on May 10 2010 is clearly recognizable, illustrating the positive reaction to the announcement of the creation of the European Financial Stability Facility (EFSF) by the EMU countries and the IMF and the installment of the Securities Markets Programme by the ECB.

5.2. Arbitrage and speculative trading

The time variation in speculative trading is captured by the weights $w_t^{i,K}$. As illustrated in Section 4, the credit markets are better described by allowing for time variation in the proportion of arbitrageurs versus speculative traders. Therefore, we present the properties of this time variation. Table 7 and Fig. 3 give the speculative trading weights in both markets, $w_t^{S,CDS}$ and $w_t^{S,BS}$ (note that arbitrage weights are given by $1 - w_t^{S,K}$).

For all countries, we observe ample variation in the proportion of noise traders active in the credit markets. The variability is directly related to the absolute value of the estimated γ's as this regulates the sensitivity of agents to differences in performance. The Austrian, German, and Dutch bond markets stand out, as weights continuously jump from zero to one. For five countries, the average proportion of speculative traders is higher in the CDS market; this is especially so for core countries.

The model poses that there are two types of traders that are active in both markets; we do not, however, specifically model traders being active in both markets simultaneously. To examine whether traders are indeed active in both markets at the same time, we compute the correlation between the weights on the arbitrage strategy in both markets. We observe that the correlation between the weights on arbitrageurs ($w^{A,\ BS}$ and $w^{A,\ CDS}$) is quite high, ranging between 63 and 69% for the different countries (results not shown in the paper). Hence, without being explicit about simultaneous trading, the results do point in that direction.

5.3. Relative importance of factors

To examine the contribution of each of the elements defined in the model to the total variation in credit markets, we perform a variance decomposition. Specifically, we calculate the ratio of the variance of each of the elements

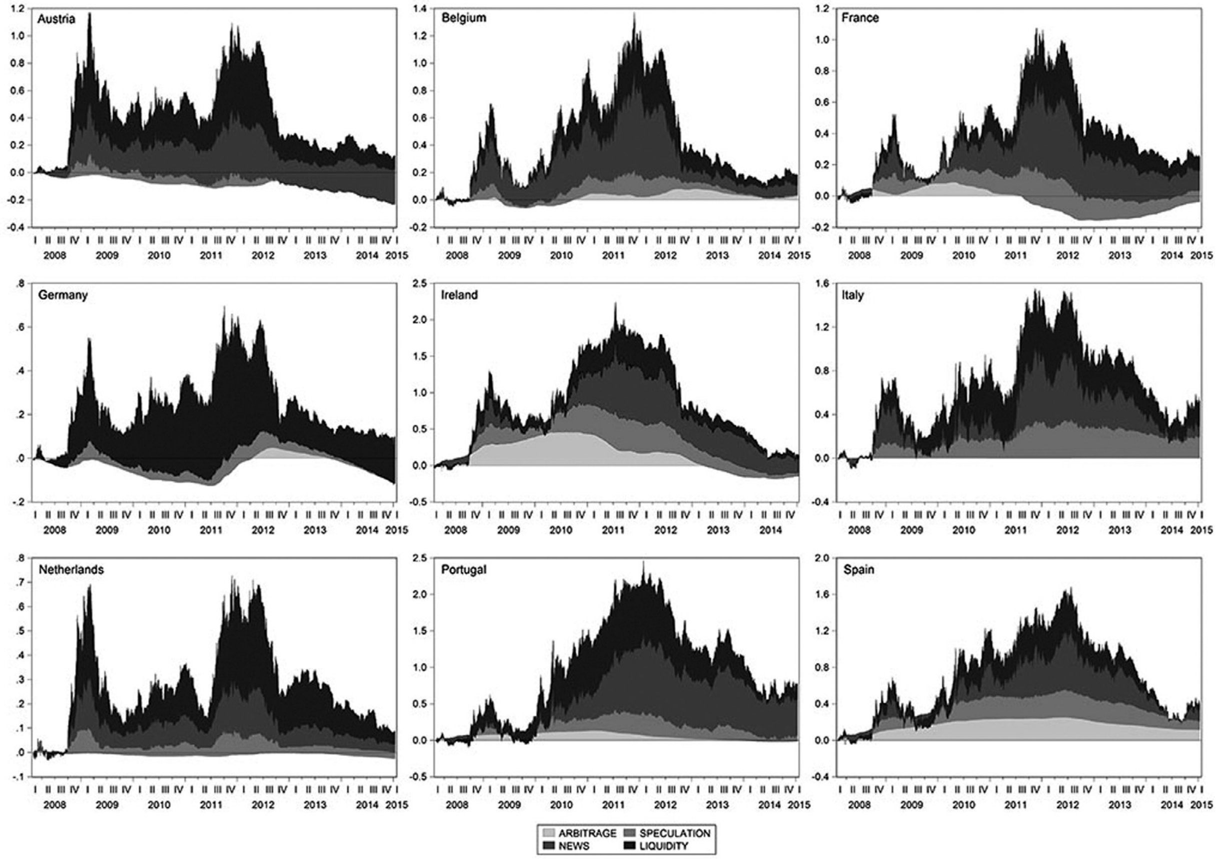

Fig. 6. CDS Spread Decomposition. This Figure shows the decomposed credit spreads for the CDS market.

relative to the variance of the bond and CDS spread changes ΔBS_t and ΔCDS_t, respectively.[19] We define news by η_t, arbitrage by $w_t^{A,K}\left(\alpha^K[CDS_{t-1} - BS_{t-1} + c]\right)$, speculative trading by $w_t^{S,K}\left(\beta_1^K \Delta CDS_{t-1} + \beta_2^K \Delta BS_{t-1}\right)$, and liquidity trading by ε_t^K. Table 8 presents the percentages of credit spread variation explained by each of the four elements over the full sample period.

Table 8 shows that the news and liquidity elements are generally the most influential drivers of spread changes, followed by speculation and arbitrage, respectively. For core countries, the liquidity element is the main driver whereas for peripheral countries news on their credit risk is the main driver of changes in credit spreads. For all countries, the CDS market is more affected by news than the bond market. This is explained by the fact that the higher liquidity plus the possible leverage in the CDS market attracts sophisticated investors to CDS market rather than the bond market. This is consistent with the information share estimates in the previous section showing that the CDS market leads the bond market in price discovery. The bond market, on the other hand, is more affected by arbitrage, noise, and liquidity trading than the CDS market.

The influence of speculative traders is, on average, limited to 5.5% for the CDS market and 5.4% for the bond market. Only for Portugal we find substantial evidence for speculation of up to 16.4% in the bond market.

Fig. 4 presents the variance decomposition analysis broken down by year. For all peripheral countries, we observe that the impact of news is increasing over the years, especially in the CDS markets, until 2014 when it tapers off again. Hence, there appears to be an increased focus on market fundamentals during the European sovereign debt crisis, which decreases again as the crisis weakens. This growth mainly goes at the expense of liquidity trading; arbitrage and noise are quite stable over time. The exception to the latter is Portugal, for which we observe a strong increase in speculative trading in the bond market from 5 to 27% in 2010.

Whereas Fig. 4 represents the decomposition of the variation in the credit spreads, Figs. 5 and 6 present the decomposition in the level of the credit spread. Because the model is estimated in first differences, we need to make an assumption about the starting level of the bond and CDS spreads in 2008 to be able to visualize the level decomposition. We normalize the levels of both the bond and CDS spread at 1/1/2008 at zero.

[19] This method does not take the covariances between elements into account. The sum of variances of the elements, however, is always within 95% of the variance of the spread changes. The covariances are therefore small.

Table 9
Fundamental contagion.

	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU(-1)	−0.151***	−0.024	0.024	0.000	−0.164*	−0.163	0.051*	−0.288***	−0.126
	(-3.977)	(-0.316)	(0.415)	(0.181)	(-1.707)	(-1.329)	(1.746)	(-2.941)	(-1.079)
BE(-1)	0.045**	−0.217***	0.074**	0.000*	0.065	−0.041	0.051***	−0.104**	0.053
	(2.242)	(-5.429)	(2.420)	(1.657)	(1.277)	(-0.620)	(3.261)	(-2.003)	(0.852)
FR(-1)	−0.046*	0.011	−0.206***	0.000	0.042	−0.090	−0.006	0.038	−0.098
	(-1.666)	(0.204)	(-4.950)	(-0.159)	(0.601)	(-0.018)	(-0.307)	(0.543)	(-1.157)
GE(-1)	1.1E+13***	2.1E+13***	1.2E+13**	−0.104***	6.4E+12	2.9E+13***	6.1E+12**	1.1E+13	1.9E+13*
	(3.370)	(3.334)	(2.452)	(-2.818)	(0.783)	(2.772)	(2.418)	(1.345)	(1.922)
IR(-1)	0.013	0.017	−0.006	0.000	−0.075**	0.044	0.013	0.121***	0.019
	(0.876)	(0.567)	(-0.281)	(0.781)	(-2.000)	(0.919)	(1.138)	(3.140)	(0.411)
IT(-1)	0.017	0.026	0.035	0.000	0.005	−0.093*	0.011	−0.037	0.055
	(1.092)	(0.850)	(1.455)	(-0.237)	(0.114)	(-1.831)	(0.893)	(-0.905)	(1.127)
NL(-1)	−0.032	0.073	0.007	0.000	−0.051	−0.020	−0.228***	−0.012	−0.060
	(-0.700)	(0.818)	(0.099)	(0.902)	(-0.444)	(-0.134)	(-6.557)	(-0.105)	(-0.429)
PO(-1)	−0.044***	−0.086***	−0.050**	0.000	0.011	−0.061	−0.023**	−0.170***	−0.032
	(-3.327)	(-3.279)	(-2.465)	(-1.298)	(0.319)	(-1.425)	(-2.283)	(-4.976)	(-0.781)
SP(-1)	0.035**	0.126***	0.056**	0.000	0.048	0.167***	0.019	0.194***	−0.042
	(2.059)	(3.784)	(2.172)	(1.645)	(1.115)	(3.059)	(1.446)	(4.450)	(-0.803)
Wald Test (p-value)	0.023**	0.000***	0.637	0.000***	0.086*	0.538	0.964	0.000***	0.000***

This table shows the estimation results of the VAR on the filtered credit risk news series. We report the coefficient estimates and their associated t-statistics in parentheses. The last row of the table reports the p-values for the test on the joint significance of all contagion coefficients (Wald test). *, **, *** represent significance at the 10, 5, and 1% level, respectively. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Table 10
Liquidity Contagion CDS.

	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU(-1)	−0.144***	0.032	0.025	0.037	0.025	0.039	0.073***	−0.037	0.011
	(-3.787)	(1.323)	(1.274)	(1.046)	(0.797)	(1.576)	(2.629)	(-0.715)	(0.389)
BE(-1)	0.063	−0.211***	0.027	0.058	0.078*	−0.055	0.116***	−0.123	0.020
	(1.082)	(-5.678)	(0.909)	(1.077)	(1.661)	(-1.472)	(2.727)	(-1.550)	(0.476)
FR(-1)	−0.128	0.014	−0.189***	0.022	0.053	−0.025	0.046	0.124	−0.043
	(-1.582)	(0.261)	(-4.511)	(0.285)	(0.808)	(-0.467)	(0.780)	(1.124)	(-0.742)
GE(-1)	0.106**	0.067**	0.050***	−0.127***	−0.039	0.027	0.071***	0.061	0.037
	(2.646)	(2.602)	(2.421)	(-3.387)	(-1.195)	(1.031)	(2.409)	(1.119)	(1.265)
IR(-1)	0.060	−0.006	−0.021	−0.001	−0.103***	−0.030	−0.025	0.015	−0.060*
	(1.387)	(-0.202)	(-0.922)	(-0.028)	(-2.924)	(-1.055)	(-0.792)	(0.261)	(-1.943)
IT(-1)	0.098	0.029	0.021	−0.014	0.022	−0.051	0.015	0.075	0.013
	(1.634)	(0.751)	(0.673)	(-0.244)	(0.447)	(-1.306)	(0.345)	(0.909)	(0.301)
NL(-1)	−0.026	0.017	−0.009	0.062	−0.007	0.003	−0.250***	−0.033	−0.007
	(-0.553)	(0.541)	(-0.381)	(1.384)	(-0.172)	(0.084)	(-7.099)	(-0.507)	(-0.194)
PO(-1)	−0.026	−0.011	0.012	0.009	0.011	0.008	0.006	−0.144***	0.053***
	(-1.047)	(-0.677)	(0.916)	(0.383)	(0.558)	(0.470)	(0.332)	(-4.283)	(2.962)
SP(-1)	0.135***	0.138***	0.076***	0.080	0.054	0.063*	0.067	0.320***	−0.054
	(2.357)	(3.759)	(2.569)	(1.495)	(1.163)	(1.705)	(1.596)	(4.080)	(-1.308)
Wald Test (p-value)	0.055*	0.020**	0.653	0.000***	0.399	0.746	0.935	0.153	0.000***

This table shows the estimation results of the VAR on the estimated liquidity factor in the CDS market. We report the coefficient estimates and their associated t-statistics in parentheses. The last row of the table reports the p-values for the test on the joint significance of all contagion coefficients (Wald test). *, **, *** represent significance at the 10, 5, and 1% level, respectively. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

As shown before, the figures confirm that the spreads mainly consist of fundamental credit risk and liquidity demand. The influence of speculation, as feared by policy makers, is only limited. The figures do illustrate that the effect of arbitrage is larger than expected from the variance decomposition results, especially for the bond market.

6. Contagion

Based on the decomposed fundamental credit risk and liquidity series, we can further study the propagation of shocks through the European sovereign debt markets. Specifically, we estimate a VAR for the filtered fundamental credit news series as well as for the estimated liquidity factors for both the bond and CDS market. This allows us to separate fundamental contagion (i.e., the spread of credit risk shocks) from non-fundamental contagion (i.e., the spread of liquidity shocks).[20]

[20] We restrict ourselves to these two elements because of the limited explanatory power of arbitrage and speculation.

Table 11
Liquidity contagion bonds.

	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU(-1)	−0.092***	−0.019	0.029	0.067	−0.056**	−0.003	0.048	−0.051***	−0.004
	(-2.890)	(-0.685)	(0.859)	(1.108)	(-2.009)	(-0.139)	(1.269)	(-2.342)	(-0.164)
BE(-1)	−0.011	0.065**	0.099***	−0.107	−0.022	0.048**	0.038	0.030	0.029
	(-0.295)	(2.039)	(2.568)	(-1.556)	(-0.688)	(1.967)	(0.896)	(1.227)	(1.087)
FR(-1)	0.051	−0.025	−0.033	0.079	0.032	−0.077***	−0.014	−0.008	−0.049*
	(1.487)	(-0.823)	(-0.922)	(1.229)	(1.065)	(-3.379)	(-0.350)	(-0.348)	(-1.939)
GE(-1)	−0.045***	−0.030**	−0.015	−0.001	−0.001	0.003	−0.024	0.020**	0.011
	(-3.084)	(-2.330)	(-0.956)	(-0.039)	(-0.051)	(0.302)	(-1.398)	(2.068)	(0.981)
IR(-1)	0.000	0.005	−0.036	0.034	−0.038	−0.002	−0.040	0.037*	−0.023
	(-0.013)	(0.160)	(-1.045)	(0.556)	(-1.365)	(-0.070)	(-1.040)	(1.670)	(-0.967)
IT(-1)	0.066	0.127***	−0.025	−0.254***	0.209***	0.084***	−0.041	0.151***	0.078***
	(1.404)	(3.052)	(-0.492)	(-2.858)	(5.109)	(2.667)	(-0.747)	(4.737)	(2.231)
NL(-1)	0.041	−0.005	−0.034	−0.086	−0.021	−0.014	−0.008	−0.015	−0.040*
	(1.365)	(-0.201)	(-1.049)	(-1.495)	(-0.813)	(-0.676)	(-0.227)	(-0.734)	(-1.763)
PO(-1)	−0.005	−0.028	−0.020	0.064	−0.023	−0.026	−0.011	−0.102***	0.002
	(-0.117)	(-0.790)	(-0.461)	(0.854)	(-0.676)	(-0.987)	(-0.238)	(-3.769)	(0.054)
SP(-1)	0.030	−0.033	0.006	0.267***	0.001	−0.057*	−0.005	0.015	0.001
	(0.657)	(-0.825)	(0.119)	(3.113)	(0.014)	(-1.872)	(-0.088)	(0.486)	(0.040)
Wald Test (p-value)	0.090*	0.031**	0.007***	0.002***	0.617	0.000***	0.264	0.929	0.064*

This table shows the estimation results of the VAR on the estimated liquidity factor in the bond market. We report the coefficient estimates and their associated t-statistics in parentheses. The last row of the table reports the p-values for the test on the joint significance of all contagion coefficients (Wald test). *, **, *** represent significance at the 10, 5, and 1% level, respectively. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Table 9 presents the VAR estimation results for the fundamental contagion. We observe that the German credit risk shocks positively and significantly affect the credit risk of all countries in the sample. Spanish credit risk shocks are also positively related to the majority of countries, illustrating the fear of a bankruptcy in a major European sovereign. Conversely, Portuguese credit risk shocks are negatively related to the credit risk of the core countries. This result illustrates that traders did not directly fear the consequences of a bankruptcy of Portugal, and a flight-to-quality instead. We also note that the coefficients on the diagonal are all negative and significant, suggesting that our credit news series have a mean-reverting component.[21] Finally, we note that the joint contagion effect coming from other markets is significant in most cases; i.e. Wald tests on the joint significance of the contagion parameters are significant for all countries, except for Italy.

Regarding the non-fundamental contagion, Table 10 and Table 11, which is based on liquidity shocks, shows that we find much less contagion across countries (although Wald tests for joint significance are still mostly significant). Again, the German and Spanish shocks appear to have some effect, but much less so than for the fundamental shocks. This is especially the case for the CDS market. In the bond market, there are a few more relationships but it is hard to draw consistent conclusions.

7. Conclusions

In this paper, we develop a model for arbitrage and speculative trading in the European sovereign bond and CDS markets. We propose an empirical model based on the heterogeneous agent literature, where traders can either follow an arbitrage strategy (focusing on long-run mean-reversion) or a speculative strategy (by extrapolating past price patterns). Empirically, we find evidence of the presence of both types of traders in the markets, with a stronger presence of arbitrage traders in the bond market than in the CDS market. In addition, we observe that traders apply feedback rules and switch between trading strategies based on their past performance. A variance decomposition exercise illustrates that the effect of speculation on credit spreads, as feared by policymakers, was limited, and that it was mainly fundamental news that drove both markets during the European Debt Crisis.

Most empirical papers on heterogeneous agent models only consider a single asset. Given that we consider multiple assets in this paper, the question arises what determines the behavior of agents in the cross-section of assets. The number of assets in our sample does not allow for a full-fledged empirical analysis of the cross-sectional determinants of switching behavior. As a first step in this direction, we looked into the holdings data of European sovereign debt.[22] There does not appear to be a clear relation between the estimated intensity of choice parameter and the holdings of non-bank residents.

[21] We note that in our Kalman Filter estimation, we assume that the credit news process is an i.i.d process, while the VAR analysis suggests that the credit news process may be autocorrelated. We have re-estimated the Kalman Filter based on the assumption that the credit news is an AR(1) process and find that for all countries, except Portugal, the AR(1) term is insignificant. We have also verified the time series properties of the original credit news series and also find that these series are uncorrelated. Hence, the autocorrelations reported in Table 9 (and Tables 9 and 11) seem to be induced by the cross-autocorrelations coming from the other markets. We have further estimated the VAR without controlling for the AR effect and find that results for the cross-effects are very similar to those reported in Tables 9 to 11. The estimation results are in the Appendix.

[22] Specifically, the Bruegel database of sovereign bond holdings developed in Merler and Pisani-Ferry (2012)

This might be explained by the fact that there are many other differences between the countries in our sample that might cause the switching behaviour to differ, such as the credit quality, liquidity, etc. Some other papers do look into this question. Frijns et al. (2018) show that foreign investors have a higher tendency to switch between strategies. Furthermore, Hommes et al. (2018) show that switching is more prevalent in financial assets than in macro-assets. All in all, this is an important direction for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

	Full Results Switching Model								
	Austria			Belgium			France		
c	−0.569***	−0.655***	−0.655***	−0.468***	−0.457***	−0.453***	−0.625***	−0.580***	−0.700***
	(-14.72)	(-31.57)	(-31.88)	(-16.66)	(-20.50)	(-29.02)	(-10.59)	(-5.51)	(-13.03)
α^{BS}	0.055***	0.041***	0.041***	0.068***	0.065***	0.073***	0.036***	0.021***	0.020***
	(5.40)	(10.63)	(10.59)	(6.01)	(6.80)	(8.56)	(3.84)	(2.66)	(2.74)
β_1^{BS}	0.467***	0.384***	0.384***	0.626***	0.687***	0.671***	0.268**	0.207**	0.186**
	(5.71)	(8.13)	(8.02)	(7.45)	(8.34)	(8.39)	(2.14)	(2.35)	(2.22)
β_2^{BS}	−0.232***	−0.156***	−0.156***	−0.089**	−0.153***	−0.152***	−0.342***	−0.380***	−0.379***
	(-7.20)	(-6.70)	(-6.64)	(-2.39)	(-3.66)	(-3.74)	(-10.36)	(-10.20)	(-10.21)
α^{CDS}	0.002	−0.001	0.002	0.004	0.004	0.005	−0.003	0.000	−0.004
	(0.76)	(-0.20)	(0.81)	(1.02)	(0.75)	(1.34)	(-1.12)	(0.02)	(-1.32)
β_1^{CDS}	0.461***	0.412***	0.455***	0.299***	0.284***	0.301***	0.299***	0.328***	0.293***
	(16.96)	(14.28)	(16.89)	(9.12)	(8.33)	(9.19)	(7.18)	(9.15)	(7.01)
β_2^{CDS}	−0.002	0.000	0.002	0.041**	0.029*	0.032*	−0.007	0.004	−0.007
	(-0.12)	(-0.01)	(0.18)	(2.51)	(1.78)	(1.91)	(-0.52)	(0.23)	(-0.54)
γ^{CDS}	7.399***		−8.042***	4.502**		−7.881***	−15.601**		−8.342***
	(4.40)		(-553.61)	(2.02)		(-446.67)	(-1.97)		(-444.85)
γ^{BS}		645.58	649.99		1.292	1.328		7.718	7.466
		(0.48)	(0.47)		(1.65)	(1.62)		(3.075)	(3.119)
	Germany			Ireland			Italy		
c	−0.942***	−1.046**	−1.124***	−0.223***	−0.239***	−0.248***	−0.273***	−0.252***	−0.251***
	(-4.65)	(-2.23)	(-3.52)	(-3.15)	(-3.11)	(-3.35)	(-6.04)	(-6.75)	(-6.44)
α^{BS}	0.023***	−0.002	−0.001	0.030***	0.027***	0.028***	0.035***	0.035***	0.035***
	(4.68)	(-0.82)	(-0.46)	(4.51)	(3.74)	(3.88)	(3.87)	(5.19)	(5.24)
β_1^{BS}	−0.723***	−0.190**	−0.214**	0.739***	0.800***	0.796***	0.409***	0.395***	0.402***
	(-2.87)	(-2.22)	(-2.06)	(10.57)	(10.05)	(9.82)	(6.97)	(7.44)	(7.89)
β_2^{BS}	−0.348***	−0.366***	−0.373***	−0.187***	−0.197***	−0.201***	−0.055	−0.066*	−0.067*
	(-15.46)	(-33.96)	(-25.13)	(-5.97)	(-7.65)	(-6.90)	(-1.37)	(-1.65)	(-1.74)
α^{CDS}	0.000	0.001	0.001**	0.007**	0.007	0.007*	0.000	0.000	0.000
	(0.18)	(1.32)	(2.02)	(1.96)	(1.63)	(1.85)	(0.00)	(0.00)	(0.00)
β_1^{CDS}	0.334***	0.340***	0.354***	0.358***	0.351***	0.364***	0.312***	0.272***	0.307***
	(9.03)	(10.63)	(11.05)	(10.25)	(9.97)	(10.29)	(8.84)	(6.93)	(8.99)
β_2^{CDS}	0.002	0.007	0.002	0.058**	0.072***	0.059**	0.091***	0.094***	0.085***
	(0.41)	(1.35)	(0.41)	(2.47)	(2.91)	(2.48)	(3.63)	(2.85)	(3.56)
γ^{CDS}	−12.045**		−8.968***	3.836*		−7.451***	8.592***		−7.305***
	(-2.35)		(-502.59)	(1.88)		(-509.17)	(2.73)		(-473.61)
γ^{BS}		143946	159796		−3.619*	−3.389		2.426*	2.652*
		(0.00)	(0.00)		(-1.66)	(-1.59)		(1.65)	(1.67)
	Netherlands			Portugal			Spain		
c	−0.634***	−0.637***	−0.657***	−0.083	−0.075	−0.119*	−0.286***	−0.204**	−0.245**
	(-7.19)	(-7.28)	(-7.89)	(-1.10)	(-1.29)	(-1.67)	(-3.98)	(-2.10)	(-2.42)
α^{BS}	0.030***	0.029***	0.029***	0.024***	0.026***	0.020***	0.028***	0.021***	0.018***
	(3.91)	(4.25)	(4.38)	(3.84)	(4.84)	(3.64)	(4.07)	(2.91)	(2.71)
β_1^{BS}	0.350***	0.342***	0.245**	0.839***	0.874***	0.929***	0.675***	0.743***	0.734***
	(2.88)	(2.88)	(2.07)	(25.56)	(18.77)	(19.70)	(11.32)	(11.16)	(10.58)
β_2^{BS}	−0.337***	−0.325***	−0.325***	−0.053*	−0.062**	−0.106***	−0.235***	−0.235***	−0.268***
	(-12.95)	(-11.23)	(-11.29)	(-1.79)	(-2.40)	(-3.92)	(-8.32)	(-8.48)	(-9.08)

(continued on next page)

α^{CDS}	0.000	0.003	0.000	0.002	0.006	0.002	0.005	0.007	0.002
	(-0.02)	(1.39)	(-0.03)	(0.48)	(0.93)	(0.42)	(1.60)	(1.26)	(0.82)
β_1^{CDS}	0.176***	0.151***	0.177***	0.373***	0.311***	0.377***	0.354***	0.335***	0.377***
	(63.28)	(4.68)	(8.40)	(12.17)	(8.89)	(11.86)	(10.53)	(9.84)	(11.26)
β_2^{CDS}	−0.022***	0.004	−0.022**	0.060***	0.077***	0.062***	0.015	0.008	−0.013
	(-3.83)	(0.30)	(-2.12)	(2.96)	(3.20)	(2.97)	(0.92)	(0.29)	(-0.68)
γ^{CDS}	−101181		−8.578***	12.172***		−7.027***	11.769***		7.307***
	(0.00)		(-541.00)	(4.10)		(657.70)	(3.13)		(-435.80)
γ^{BS}		1.506**	1.563**		−5.936***	−5.038***		−6.697**	−7.854**
		(2.44)	(2.44)		(-4.72)	(-4.81)		(-2.26)	(-2.52)

Fundamental Contagion without Self									
	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU		−0.095	−0.040	0.000	−0.173	−0.168	0.002	−0.301	−0.130
		(-0.852)	(-0.464)	(-0.214)	(-1.033)	(-0.887)	(0.054)	(-2.025)	(-0.772)
BE	0.031		0.040	0.000	0.059	−0.064	0.035	−0.118	0.051
	(1.065)		(0.929)	(0.954)	(0.759)	(-0.707)	(1.468)	(-1.539)	(0.502)
FR	−0.070	−0.056		0.000	0.041	−0.106	−0.028	0.062	−0.104
	(-2.349)	(-0.813)		(-0.765)	(0.381)	(-0.894)	(-0.916)	(0.615)	(-0.803)
GE	3.8E+8	8.5E+8	2.0E+8		2.5E+8	1.3E+9	1.2E+8	4.2E+8	8.5E+8
	(2.001)	(2.548)	(0.775)		(0.457)	(2.085)	(0.804)	(0.846)	(1.461)
IR	0.011	0.010	−0.004	0.000		0.044	0.012	0.054	0.012
	(0.576)	(0.352)	(-0.171)	(0.596)		(0.838)	(0.926)	(1.458)	(0.198)
IT	0.016	−0.006	0.024	0.000	0.002		0.015	−0.070	0.030
	(0.736)	(-0.156)	(0.742)	(-0.220)	(0.029)		(0.761)	(-1.118)	(0.572)
NL	−0.072	0.000	−0.039	0.000	−0.048	−0.002		0.026	−0.063
	(-1.336)	(-0.001)	(-0.422)	(0.326)	(-0.365)	(-0.014)		(0.220)	(-0.387)
PO	−0.046	−0.094	−0.043	0.000	−0.018	−0.075	−0.020		−0.037
	(-3.248)	(-3.422)	(-1.826)	(-1.318)	(-0.544)	(-1.655)	(-1.807)		(-0.798)
SP	0.033	0.119	0.045	0.000	0.027	0.106	0.013	0.167	
	(1.365)	(2.705)	(1.575)	(1.081)	(0.408)	(1.992)	(0.694)	(2.479)	

This table shows the estimation results of the VAR on the filtered credit risk news series excluding the country itself. We report the coefficient estimates and their associated t-statistics in parentheses. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Liquidity Contagion CDS without Self									
	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU		0.012	0.009	0.011	0.015	0.039	0.020	−0.051	0.010
		(0.274)	(0.277)	(0.203)	(0.272)	(1.121)	(0.465)	(-0.608)	(0.251)
BE	0.030		−0.008	0.049	0.061	−0.062	0.078	−0.151	0.018
	(0.364)		(-0.216)	(0.724)	(0.917)	(-1.438)	(1.296)	(-1.561)	(0.329)
FR	−0.181	−0.062		−0.064	0.051	−0.029	−0.019	0.118	−0.055
	(-1.921)	(-0.984)		(-0.687)	(0.619)	(-0.463)	(-0.252)	(0.746)	(-0.755)
GE	0.074	0.059	0.019		−0.044	0.025	0.023	0.054	0.037
	(1.485)	(2.175)	(0.840)		(-1.096)	(0.923)	(0.597)	(0.969)	(1.115)
IR	0.041	−0.025	−0.020	−0.006		−0.031	−0.043	−0.049	−0.071
	(0.722)	(-0.919)	(-0.804)	(-0.131)		(-0.806)	(-1.091)	(-0.626)	(-1.603)
IT	0.098	−0.001	0.013	−0.020	0.018		0.025	−0.004	−0.013
	(1.125)	(-0.019)	(0.305)	(-0.276)	(0.224)		(0.414)	(-0.028)	(-0.272)
NL	−0.070	−0.004	−0.023	0.030	−0.012	0.005		−0.011	−0.007
	(-1.240)	(-0.093)	(-0.731)	(0.557)	(-0.261)	(0.154)		(-0.169)	(-0.166)
PO	−0.031	−0.018	0.011	0.007	−0.003	0.003	0.013		0.049
	(-1.157)	(-1.100)	(0.811)	(0.286)	(-0.128)	(0.176)	(0.733)		(2.526)
SP	0.131	0.132	0.055	0.086	0.022	0.040	0.047	0.266	
	(1.575)	(2.504)	(1.463)	(1.097)	(0.305)	(0.936)	(0.751)	(1.951)	

This table shows the estimation results of the VAR on the estimated liquidity factor in CDS, excluding the country itself. We report the coefficient estimates and their associated t-statistics in parentheses. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Liquidity Contagion Bonds without Self									
	AU	BE	FR	GE	IR	IT	NL	PO	SP
AU		−0.002	0.021	0.067	−0.059	−0.002	0.048	−0.058	−0.004
		(-0.056)	(0.559)	(0.809)	(-1.918)	(-0.077)	(1.068)	(-2.205)	(-0.131)
BE	−0.038		0.091	−0.108	−0.028	0.054	0.038	0.026	0.029
	(-0.957)		(1.879)	(-1.439)	(-0.760)	(2.206)	(0.886)	(0.954)	(1.145)
FR	0.026	−0.011		0.080	0.036	−0.074	−0.016	−0.002	−0.049
	(0.654)	(-0.324)		(1.012)	(1.068)	(-2.819)	(-0.417)	(-0.094)	(-1.591)
GE	−0.050	−0.031	−0.016		−0.002	0.000	−0.027	0.019	0.011
	(-3.057)	(-2.663)	(-0.930)		(-0.142)	(-0.035)	(-1.315)	(1.818)	(0.937)
IR	−0.008	0.006	−0.032	0.041		−0.001	−0.038	0.012	−0.024
	(-0.230)	(0.202)	(-0.679)	(0.510)		(-0.038)	(-0.784)	(0.395)	(-0.636)
IT	0.069	0.136	−0.027	−0.254	0.199		−0.042	0.134	0.078
	(1.242)	(2.826)	(-0.445)	(-2.402)	(3.697)		(-0.538)	(3.160)	(2.129)
NL	0.030	0.000	−0.045	−0.088	−0.020	−0.010		−0.012	−0.040
	(0.852)	(0.008)	(-1.191)	(-1.090)	(-0.544)	(-0.429)		(-0.468)	(-1.247)
PO	−0.015	−0.023	−0.018	0.062	−0.042	−0.014	−0.012		0.002
	(-0.372)	(-0.655)	(-0.399)	(0.883)	(-1.243)	(-0.551)	(-0.244)		(0.044)
SP	0.032	−0.028	−0.001	0.264	−0.012	−0.020	−0.007	0.001	
	(0.616)	(-0.572)	(-0.017)	(2.755)	(-0.161)	(-0.510)	(-0.093)	(0.018)	

This table shows the estimation results of the VAR on the estimated liquidity factor in bonds, excluding the country itself. We report the coefficient estimates and their associated t-statistics in parentheses. We report results for Austria (AU); Belgium (BE); France (FR); Germany (GE); Ireland (IR); Italy (IT); the Netherlands (NL); Portugal (PO); and Spain (SP).

Results Switching with Squared Loss									
	Austria			Belgium			France		
γ^{CDS}	5.449		−8.041	2.456		−7.879	−3.495		−8.338
	(4.495)		(-553.2)	(1.816)		(-442.084)	(-1.298)		(-4443.0)
γ^{BS}		1.606	1.633		1.098	1.120		4.874	4.835
		(1.110)	(1.132)		(2.025)	(2.050)		(3.325)	(3.347)
L	2	4	2, 4	2	1	2, 1	5	1	5, 1
LR_1	14.56	0.78	15.38	2.34	5.18	7.79	1.00	29.26	30.16
LR_2	−0.82	−14.61		−5.46	−2.62		−29.16	−0.90	
	Germany			Ireland			Italy		
γ^{CDS}	−4.510		−8.967	1.630		−7.451	3.893		−7.303
	(-1.663)		(-499.1)	(1.606)		(-503.0)	(2.623)		(-469.4)
γ^{BS}		10.167	0.000		−2.071	−1.976		1.611	1.855
		(4.671)	(0.000)		(-1.576)	(-1.541)		(1.855)	(1.926)
L	9	10	2, 10	6	7	6, 7	10	1	10, 1
LR_1	1.92	8.97	−0.21	0.58	3.53	3.95	2.87	5.06	8.40
LR_2	2.13	9.18		−3.37	−0.42		−5.53	−3.34	
	Netherlands			Portugal			Spain		
γ^{CDS}	1.762		−8.571	5.822		−7.030	5.874		−7.305
	(0.182)		(-516.6)	(4.118)		(-650.0)	(3.232)		(-429.5)
γ^{BS}		0.938	0.844		−3.259	−3.043		−4.544	−5.338
		(2.500)	(2.335)		(-4.367)	(-4.403)		(-2.488)	(-2.383)
L	10	1	10, 1	3	7	3, 10	1	7	1, 9
LR_1	0.02	1.58	1.55	16.08	32.47	45.59	15.90	12.59	27.31
LR_2	−1.53	0.04		−29.51	−13.13		−11.41	−14.72	

This table shows the estimated switching parameters γ^{CDS} and γ^{BS} of the model with squared loss functions instead of absolute, as well as the results of the likelihood ratio tests of the switching model versus the static model (LR_1) and the model with switching in one market versus switching in both markets (LR_2).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2019.11.017.

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