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(*) Contact authors: carmen.broto@bde.es; gabriel.perez@bde.es. We thank seminar participants at the Banco de España, the European Central Bank, the XIX Finance Forum in Granada, the II_t Workshop in Time Series Econometrics in Zaragoza, the VIII Workshop in Public Policy Design in Girona and the II Workshop on International Financial Markets in Ottawa. The opinions expressed in this document are solely the responsibility of the authors and do not represent the views of the Banco de España.

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Abstract

During the last crisis, developed economies' sovereign Credit Default Swap (hereafter CDS) premia have gained in importance as a tool for approximating credit risk. In this paper, we fit a dynamic factor model to decompose the sovereign CDS spreads of ten OECD economies into three components: a common factor, a second factor driven by European peripheral countries and an idiosyncratic component. We use this decomposition to propose a novel methodology based on the real-time estimates of the model to characterize contagion among the ten series. Our procedure allows the country that triggers contagion in each period, which can be any peripheral economy, to be disentangled. According to our findings, since the onset of the sovereign debt crisis, contagion has played a non-negligible role in the European peripheral countries, which confirms the existence of significant financial linkages between these economies.

Keywords: sovereign Credit Default Swaps, contagion, dynamic factor models, credit risk.

JEL classification: C32, G01, G15.

Resumen

Durante la última crisis, la relevancia de las primas de los *Credit Default Swaps* (en adelante, CDS) de las economías desarrolladas como herramienta para aproximar el riesgo de crédito ha ido en aumento. En este artículo se utiliza un modelo factorial dinámico para descomponer las primas de los CDS soberanos de diez economías de la OCDE en tres componentes: un factor común, un segundo factor ligado a la evolución de los diferenciales de las economías periféricas de la zona del euro y un componente idiosincrásico. Una vez modeladas las series, se propone una nueva metodología basada en las estimaciones en tiempo real del modelo utilizado para caracterizar el contagio entre los diez países. Este procedimiento permite esclarecer en cada período cuál es el país donde se origina el contagio, que puede ser cualquier economía periférica. Según los resultados obtenidos, desde el inicio de la crisis de deuda soberana europea el contagio ha desempeñado un papel indiscutible en los países periféricos, lo que confirma la presencia de importantes vínculos financieros entre estas economías.

Palabras clave: *Credit Default Swaps* soberanos, contagio, modelos factoriales dinámicos, riesgo de crédito.

Códigos JEL: C32, G01, G15.

1 Introduction

Understanding the dynamics of the recent increase of sovereign credit risk in the euro area is crucial given its financial stability implications and its major role in determining the financing costs of the public sector. Thus, higher perceived risk implies higher long-term domestic interest rates, which in turn increase debt costs and offset the stimulus measures adopted during the crisis. Besides, higher sovereign risk has adverse effects on bank funding conditions and financial markets (BIS, 2011).

Since the onset of the financial crisis in 2007, the sovereign credit default swap (hereafter, sovereign CDS) market in developed economies has become more liquid and trading volumes have strongly increased.[1] A CDS is an OTC (over-the-counter) derivative that functions as an insurance contract, where a protection buyer pays a fixed amount (the CDS premium) to the seller until maturity or until the occurrence of the credit event (Duffie 1999, Pan and Singleton, 2008).[2] For a sovereign CDS, the credit event is equivalent to the issuer country defaulting on its payment commitments. If this occurs before the CDS maturity, the protection seller pays a compensation to the buyer.[3] The premium paid by the buyer of a CDS can be decomposed into two basic components: the default risk and the sovereign risk premium component, which is the largest part of the spread (Remolona et al., 2007).

In principle, given the theoretical no-arbitrage condition (Duffie, 1999), sovereign risk can be approximated either through the interest rate spreads on public debt or through the risk premia from sovereign CDS.[4] We chose to analyze sovereign CDS spreads instead of bond spreads for two reasons. First, bond spread quantification involves choosing a risk-free rate, which means losing the spread of a relevant country in any empirical analysis.[5], [6] Second, in certain periods of financial stress there can be significant discrepancies between both measures. For example,

[1] According to the BIS (2010), the outstanding amount of sovereign CDS in the first half of 2010 was around 13% of all CDS, whereas at the beginning of the crisis (second half of 2007) this ratio was 6%.

[2] One key legal difference between a sovereign CDS and an insurance contract is that, contrary to an insurance contract, the CDS does not require the insured asset (that is, the sovereign bond) to be held.

[3] The International Swaps and Derivatives Association (ISDA) defines three possible credit events for a sovereign CDS, namely: failure to pay coupon or principal, restructuring and repudiation/moratorium.

[4] An abundant strand of this literature analyzes the deviations from this parity and price discovery between CDS and bond spreads. See Blanco et al. (2005), who study this link for corporate CDS spreads.

[5] In any case, recently the pool of government bonds considered as risk-free assets has narrowed so that their election would not be straightforward (Cooper and Scholtes, 2001).

[6] To overcome this problem, alternatively other authors use the swap rate as a risk-free rate to compute bond spreads (Fontana and Scheicher, 2010).

some bond yields could be driven by other effects, such as the "flight to quality" by investors. Nevertheless, during periods of turmoil, CDS spreads can also capture components attributable to counterparty risk (Arce et al., 2013)[7] or liquidity risk (see Das and Hanouna (2009) for corporate CDS).[8]

Despite the increasing relevance of sovereign CDS spreads, there are still few studies on their dynamics. Until the onset of the financial crisis, most research was focused on emerging markets, where these derivatives were already liquid from the beginning of the 2000s (see, among others, Pan and Singleton, 2008; Longstaff et al. 2011; Remolona et al., 2007).[9] By contrast, the literature on sovereign CDS for developed countries is still at an early stage amid strong doubts among market participants about its functioning.[10] However, as these time series become longer and this market deepens, these spreads are turning into an alternative measure of credit risk to government bonds in empirical applications. As a result, the recent literature that explicitly deals with sovereign CDS spreads in the euro area is increasing. Among other topics, these empirical works analyze CDS spread determinants or their link with bond spreads (price discovery).[11]

There are two empirical regularities in the literature on sovereign CDS spreads of relevance for our analysis. First, sovereign premia exhibit a strong commonality, meaning they are highly related to a common factor. For instance, Longstaff et al. (2011) analyze 26 sovereign CDS spreads (mostly from emerging countries) and conclude that the first principal component represents 64% of their total variation (see also Remolona et al., 2007). Second, sovereign credit risk seems to be mostly driven by global market factors rather than by country-specific fundamentals, as the changes in the common component of sovereign CDS premia are closely related to developments in aggregate worldwide risk aversion. Hence, Longstaff et al. (2011), in keeping with Pan and Singleton (2008), interpret that the main source of variation across credit spreads is linked to US stock market returns and volatility (as proxied by the VIX index).

[7] According to Arce et al. (2013), the presence of counterparty risk during global episodes of distress makes the use of bond spreads preferable.

[8] The lack of consensus among authors regarding the advisability of using CDS spreads or bond spreads to analyze crisis periods leads to some authors using both measures as a robustness check (Caporin et al., 2013).

[9] To date, the more developed strand of the literature on CDS is that on corporate CDS rather than sovereign CDS spreads. See Blanco et al. (2005), Longstaff et al. (2005), or Ericsson et al. (2009), among others.

[10] For instance, Duffie (2010) analyzes whether speculation drives up European sovereign CDS spreads.

[11] See Fontana and Scheicher, 2010; Arce et al., 2013; Carboni, 2011 or Palladini and Portes, 2011, for some recent papers on price discovery between sovereign CDS premia and bond yields. Alberola et al. (2012) analyze a broad sample of emerging and developed countries with a panel data model.

Given these regularities it seems sensible to use a dynamic factor model to analyze sovereign CDS spread dynamics. However, one of the peculiarities of the European sovereign debt crisis regarding multivariate credit risk modeling is that the classical factor decomposition into two factors—namely, common and idiosyncratic—has become obsolete given the emergence of a third element rooted in contagion from third countries. This new framework calls for rethinking as to how to model accurately the influence of individual countries, which will not be captured in the common component, taking into account that the country that drives contagion can change over time. For instance, Greece formally asked for a financial assistance programme in April 2010, which coincided with an increase of the CDS spreads of the remaining developed countries, especially the European peripheral economies. However, in an accurate time series exercise it would not be correct to consider Greece as the sole source of contagion in the subsequent time span. For instance, Ireland and Portugal could have also exerted an influence in the remaining countries when they asked for their assistance programmes in November 2010 and April 2011, respectively. Given the importance of financial contagion in the context of the sovereign debt crisis, this literature is growing rapidly, both for sovereign CDS and bond spreads (see, for instance, Amisano and Tristani, 2011; Fornari, 2012 or Caporin et al. 2013).[12]

The main objective of this paper is to analyze with a dynamic factor model the sovereign CDS spreads of ten OECD countries, namely, eight euro area countries, the United States and the United Kingdom.[13] Apart from the common and idiosyncratic component, we also fit a third component that is related to the impact of peripheral countries. As a novel contribution of the paper, once we decompose the ten series, we identify contagion using the estimates of the model in real-time by focusing on the dynamics of the elements of the Kalman filter. In a sense, our model approach is in line with that of Dungey and Martin (2007), as we also fit a dynamic factor model but, contrary to them, our contagion identification is not model-based but is disentangled through the real-time estimates of the model once it is identified. The main advantage of our procedure compared to previous models is that we do not impose the country source of contagion, which can vary across periods. That is to say, as our identification method is dynamic our approach is more flexible and realistic than those of prior empirical exercises.

[12] For further empirical works on financial contagion during the European sovereign debt crisis following diverse methodologies see, for instance, Andermatten and Brill, 2011; Zhang et al., 2011; Kalbaska and Gatkowski, 2012; Gündüz and Kaya, 2013 or Manasse and Zavalloni, 2013.

[13] As far as we know, to date Kocsis (2012) and Manasse and Zavalloni (2013) are the only papers that use a multivariate model to analyze sovereign credit risk in the euro area.

The remainder of this paper is organized as follows. After the introduction, Section 2 briefly reviews the literature on financial contagion and presents the specific definition of contagion that we use in this paper. In Section 3 we describe the data set and provide some intuition about how to aggregate CDS spreads data in a multivariate framework, which will be useful to enhance our dynamic factor model specification to decompose CDS spreads as stated in Section 4. In Section 5 we introduce our proposal to disentangle contagion based on the real-time estimates of the model and present the main empirical results for our sample. Finally, Section 6 concludes.

2 What is contagion? A literature overview

Currently, there is still no consensus on the definition of contagion, which has led to a broad empirical literature.[14] In this paper, we define contagion as a significant variation in the cross-country co-movement of CDS spreads, compared with that of non-crisis periods, triggered by a specific country or group of countries. Thus, according to our characterization of contagion, country-specific shocks become 'common'. Note that the transmission of the idiosyncratic shocks goes beyond what could be expected from the usual linkages between these CDS spreads in periods of calm (Constâncio, 2012), whereby the underlying interdependence between countries before the crisis is not contagion.[15]

Obviously, the quantification of contagion is highly dependent on its specific definition, so that there are practically as many modeling strategies as definitions. For the sake of simplicity, these methodologies can be classified in three broad categories. First, those authors that interpret contagion as an structural break in the transmission of shocks, such as Forbes and Rigobon (2002), Favero and Giavazzi (2002), Bae et al. (2003) or Corsetti et al. (2005), who identify contagion through increased bivariate correlations during stress periods. They correct these correlations for the hereroscedasticy bias of market returns during crises before testing.[16] Along these lines, other papers have introduced the non-linearities inherent to financial data using the increased correlations of extreme negative events through extreme value analysis (Longin and Solnik, 2001; Hartmann et al., 2004).

[14] See Claessens and Forbes (2001), Pericoli and Sbracia (2003) or Dungey et al. (2005) for a survey on financial contagion definitions and identification methodologies.

[15] Interdependence can be defined as a change in correlation that is consistent with the data generating process (Forbes and Rigobon, 2002).

[16] Corsetti et al. (2005) propose a single factor model with common and idiosyncratic components.

Second, other authors focus on the shock transmission beyond common fundamentals with respect to non-crisis periods. Those fundamentals could be interpreted as economic, which has led to empirical papers using VAR specifications (Bekaert et al. 1995), or could be related to pre-existing common factors. In this second case, these commonalities are analyzed by means of dynamic factor models that allow the study of the linkages between different asset classes and countries (Dungey and Martin, 2007).[17] In this line, some early papers study variations in the cointegration relations after one shock, as contagion was interpreted as changes in the long run links between markets (Longin and Solnik, 2001).

Finally, a third group of papers do not strictly study contagion but spillovers. An spillover is the lagged transmission of a shock, whereas contagion is simultaneous in nature. To this category belong those papers that study volatility spillovers by means of GARCH type models (Edwards, 1998) or those that identify contagion as a significant increase in the conditional probability of a crisis given a previous crisis in another country or market through probit or logit models (Eichengreen et al., 1996).

All in all, how does our definition and methodology fit into this vast literature? We strictly analyze contagion and not spillovers, as the real-time analysis allows to disentangle simultaneous effects in each iteration. Besides, as already mentioned, we analyze simultaneously 10 OECD countries, so that our interest is not in pairwise tests based on bivariate correlations as in Forbes and Rigobon (2002) or Corsetti et al. (2005) kind of tests. Thus, given our contagion definition, our methodology could be classified in the second group of empirical papers, as we condition contagion to the existence of common factors before the onset of the European debt crisis and the appearance of new dynamic factors in the post-crisis period. However, it is not directly comparable with previous papers of this category, as we use real-time estimates of the model to disentangle contagion for the first time in this field. In the next sections we describe in detail the dataset an the methodology.

3 The dataset

3.1 Data and descriptive statistics

We analyze the dynamics of the sovereign ten-year CDS premia of Belgium, France, Germany, Greece, Ireland, Italy, Portugal, Spain, United Kingdom and United States. We chose this

[17] See Cerra and Saxena (2002), Favero and Giavazzi (2002) or Dungey and Martin (2004) for a partial list of other approaches that also analyze empirically cross border transmissions from a single asset class.

sample of OECD economies to encompass eight countries of the euro area, both core and peripheral, and a control group of two additional developed economies, US and UK, that serve as further examples of "safe" countries—in opposition to the six European peripheral countries—. Although we could have included further developed economies in the sample, as the main contribution of the paper is methodological, an exhaustive country sample would not lead to significant additional information.[18] The maturity of the CDS premia was selected given that, contrary to corporate CDS, whose trading is more concentrated in 5-year contracts, sovereign CDS at maturities between 1 and 10 year are actively traded (Pan and Singleton, 2008). Besides, the ten year maturity is preferable for comparability reasons with the ten-year sovereign debt spreads. We use weekly data from 1/1/2007 to 12/3/2012, that is, $T = 272$.[19] Before 2007 market liquidity was still scarce, so that our analysis starts from that date. The end of the sample period has been chosen to coincide with the activation of the Greek CDS by the ISDA (International Swaps and Derivatives Association) once the Greek default was confirmed. All CDS premia are expressed in basis points (bp henceforth) and denominated in US dollars. Our data were obtained through Datastream.[20]

Figure 1 shows the evolution of the ten sovereign CDS spreads. Clearly, the highest increases correspond to the CDS premia of Greece, followed by those of Portugal and Ireland, which also received financial assistance by the IMF. The CDS spreads of other European peripheral countries, like Spain or Italy, whose credit ratings were also downgraded on different occasions, overcame 500 bp, whereas that of Belgium exceeded 300 bp at the end of the sample. The spreads of United States, France and Germany moved in a narrower range, although the French premium picked up in the last part of the sample.

Table 1 reports summary statistics of the CDS spreads for the whole sample period, as well as for the subsamples previous and posterior to the outbreak of the sovereign crisis in the euro area. We date this breakpoint in 12th October 2009 for two reasons. First, this is the moment when the Greek CDS spread overcame the other nine CDS and never came back. Besides, that week coincided with the starting rumors regarding solvency in Greece. Table 1 illustrates that the CDS spreads increased throughout the sample period and, as also shown

[18] For instance, Australia, Denmark, Japan, Norway, Sweden, Switzerland, and, in the euro area, Austria, Finland and the Netherlands also have a relatively liquid market of sovereign CDS.

[19] We use weekly data instead of daily data to avoid the need of a more complex model to capture the second order moments' dynamics of these series.

[20] Before 4/10/2010 the data source for the CDS spreads was CMA, whereas after that date the source is Thomson Reuters.

in Figure 1, those countries that were more affected by the European sovereign crisis—namely, Greece, Ireland, Portugal, Spain, Italy and even Belgium—, also exhibited the higher mean and standard deviation in the second subperiod, when all the CDS spread maxima are concentrated as well. However, as it can be inferred from Figure 1 and Table 1, these clear differences between peripheral and non-peripheral sovereigns did not occur prior to the European sovereign debt crisis. In the next subsection we exploit more formally this feature.

3.2 Aggregating the information of CDS spreads

Next, we provide some evidence about how do we aggregate the information of sovereign CDS spreads, which will be useful for the proposal of our dynamic factor model specification in the following section. Most of the previous literature that analyzes sovereign credit risk with CDS spreads use standard multivariate procedures to reduce the dimensionality problem—for instance, Pan and Singleton (1998) or Ang and Longstaff (2011) use principal components—. Along these lines, we also consider the CDS spreads decomposition based on principal components to make a preliminary characterization of the main properties of the series. The purpose of this subsection is to provide some evidence about the assumptions to be applied to identify the factors in our dynamic model.

In our sample all spreads are $I(1)$.[21] As a first step, we should identify the number of cointegration relations in the dataset. Thus, when all variables are $I(1)$, as in our case, Stock and Watson (1988) demonstrate that N variables with r linearly independent cointegration relations imply $N - r$ common factors. In Table 2 we report the cointegration tests, which are needed to identify r. The tests for the complete sample indicate that the ten spreads entail eight cointegration equations that imply the existence of two common factors, which we denote as f_1 and f_2.[22]

However, the identification of the number of common factors varies throughout the sample period. Precisely, one of the main characteristics of the dynamics of our CDS spreads is that they entail significantly different dynamics during the first subsample, that is, prior to the sovereign debt crisis. Table 2 also reports the cointegration tests for this subsample and confirms that there are clearly nine cointegration relations, so that only one factor is needed. Indeed, before the sovereign crisis the spreads exhibit a high degree of co-movement, as also

[21]Standard Dickey-Fuller tests for the null hypothesis of unit root are available upon request.

[22]The p-value of seven versus eight is 0.08 (significant at 10% level), so that we consider eight cointegration relations.

shown by the first principal component, which explains more than 96% of their total variation, in line with the empirical applications in Pan and Singleton (1998) or Ang and Longstaff (2011).

As already mentioned, our final purpose is to estimate a dynamic factor model for the CDS spreads that includes the two factors required by the long term relations of these variables. However, as it is well known, it is necessary to impose certain assumptions to identify a dynamic model with two distinct factors. Up to now, the unique available information about the second factor is that it only appears in the second subsample, although the main drivers of this second factor are still unknown. As a first approach, we calculate two common factors using principal components for the complete sample period. We call the estimated first and second factors $PC1$ and $PC2$, respectively. The weights of each series in the two principal components for the full sample estimation are shown in Table 3. They indicate that $PC1$ is basically driven by an equally weighted average of each series, whereas $PC2$ is fundamentally driven by a subset of the spreads related to the peripheral countries of the EMU. As shown in the cointegration analysis, $PC2$ explains, not only an important proportion of the variance, but also the long term movements of the series. The results are obviously different when estimating the two factors for the first subsample, as also reported in Table 3. In this period, the $PC1$ explains a significant proportion of the variance of the series. However, $PC2$ explains only 1% of the variance and its weights do not have any economic interpretation, implying, as already shown, that one factor would be enough to explain the comovements across all the economies in the first subsample.

It is also important to analyze the stability of the two principal components, $PC1$ and $PC2$, regardless the sample period. Figure 2 shows the evolution of $PC1$ and $PC2$ using, on the one hand, the whole sample and, on the other hand, the first subsample. Whereas the correlation between both $PC1$, the one calculated for the first subsample and for the complete sample, is 0.99, the correlation between both $PC2$ is only 0.17. That is, $PC2$ changes dramatically with the change in the sample. This evidence indicates that there is definitely something going on in the second subsample that alters dramatically the dynamics of the time series, which even has an effect on the long term properties of the spreads. Given the weights of $PC2$ for the entire sample, it is related to the behavior of the peripheral countries in the Euro zone.[23]

[23] An alternative method that could be more suited to estimate the long term factors that drive the long run behavior of our 10 series could be that of Gonzalo and Granger (1995). The main advantage of this latter approach is that the two estimated factors contain only long run dynamics. That is, they are not contaminated by short term movements. However, the estimated coefficients do not have any economic interpretation. Despite this drawback, we have also estimated the two factors using this second procedure. We find that the first and

Finally, as further evidence on the different dynamics of the ten series before and after the European debt crisis, Table 4 reports the correlation matrix with the subsample until October 2009. As expected, before the sovereign debt crisis there was a high degree of correlation between sovereigns. Indeed, the lower correlations between spreads during this period amounted to around 90%. However, this correlation dropped later, as confirmed by Table 5 that shows the difference of the correlation matrix of the second subsample, minus that of the first subsample. Almost all these differences are negative (they are zero for three pairs), which signals the differential dynamics of spreads in the aftermath of the crisis.

All in all, this evidence suggests the need of including the two common factors in a unique model specification, as shown in the next section. Besides, and more importantly, this analysis indicates an structural break in the series, as before the crisis only one common factor was identified, whereas after the outbreak of the crisis two factors were necessary. This fact will be crucial for our proposal for contagion identification.

4 Modeling strategy: A dynamic factor model

$I(1)$ variables such as our CDS spreads can be fitted by means of a dynamic factor model using the Kalman filter.[24] Peña and Poncela (2006) demonstrate that $I(1)$ variables do not prevent the use of multivariate models for dimension reduction, such as principal components or dynamic factor models, as non-stationary factors can be identified and their estimation can be carried out in state space form.

Therefore, let $y_t = (y_{1t}, ..., y_{10t})'$ be a (10×1) vector of sovereign CDS spreads where

$$y_{it} = A_i f_{1t} + B_i f_{2t} + u_{it} \qquad \forall i = 1, ..., 10 \tag{1}$$

and

$$f_{1t} = f_{1t-1} + \varepsilon_t^{f_1}, \quad \varepsilon_t^{f_1} \sim N(0,1) \tag{2}$$

$$f_{2t} = f_{2t-1} + \varepsilon_t^{f_2}, \quad \varepsilon_t^{f_2} \sim N(0,1) \tag{3}$$

$$u_{it} = \phi_i u_{it-1} + \nu_{it}, \quad \nu_{it} \sim N(0, \sigma_{\nu i}^2) \tag{4}$$

the second factor are highly correlated with those obtained by principal components. These results are available upon request.

[24] Although $I(1)$ variables do not prevent the use of multivariate models for dimension reduction, such as principal components, Gonzalo and Granger (1995) do provide the necessary algebra to calculate the $I(1)$ common factors and decompose the series in permanent and transitory components. However, as previously mentioned, given the lack of economic interpretation of the resulting decomposition we disregard this alternative approach.

and $E(u_{it}, u_{jt}) = 0 \quad \forall i \neq j$; $E(u_{it}, f_{1t}) = 0$ and $E(u_{it}, f_{2t}) = 0 \quad \forall i$, so that these components are mutually independent.

The first component, f_{1t}, is the factor that is related to the dynamics driven by shocks that are common to the ten countries, whereas the second component, f_{2t}, only reflects the contribution of the CDS spreads of the six countries that we consider as peripheral—namely, Greece, Ireland, Portugal, Spain, Italy and Belgium—in line with the outcomes of previous section. To enhance the model identification in the estimation process, we assume f_{2t} to be driven by this subsample of six economies, instead of using the ten spreads. If we had not constrained the second factor, we would have obtained similar estimates of f_{2t}.[25] Finally, u_{it} stands for the idiosyncratic component of each CDS spread, which is assumed to be stationary for simplicity. The disturbances of the common factors, $\varepsilon_t^{f_1}$ and $\varepsilon_t^{f_2}$, are Gaussian with unit variance.

Once we express the model from (1) to (4) in a convenient state space representation, the Kalman filter can be applied to compute the likelihood function to be maximized and obtain the estimates of the model. Specifically, the measurement equation follows this compact expression,

$$y_t = H\, h_t + w_t, \tag{5}$$

where $w_t \sim N(0, R)$, y_t denotes the (10×1) vector of CDS spreads and the (12×1) state vector, h_t, is given by

$$h_t = (f_{1t}\ f_{2t}\ u_{1t}, \ldots, u_{10t})' \tag{6}$$

The transition equation follows this expression,

$$h_t = F\, h_{t-1} + \xi_t, \tag{7}$$

where $\xi_t \sim N(0, Q)$. See Appendix A for a detailed description of all the elements of the measurement and transition equations in (5) and (7).

The estimates of the loading matrices for the whole sample are shown in Table 6. For the factor f_{1t} the loadings are similar for all countries while f_{2t} is linked to the peripheral countries. Figure 3 shows the evolution of the two factors for the sample period. The factor f_{1t} is linked to the comovements of the common drivers of CDS spreads, and captures aggregate risk, with a spike coinciding with Lehman Brothers' collapse, and a steady growth in the last part of the sample. On the contrary, f_{2t} only increases in the second part of the sample, and presents sharp movements associated to specific news in the sovereign CDS market.

[25] The estimates of f_{2t} computed for the full sample of ten countries are available upon request.

The factor model allows to decompose the CDS spreads as a function of the two common components, that for country i would be $A_i f_{1t} + B_i f_{2t}$, and an idiosyncratic shock,(u_{it}). Figure 4 shows the decomposition of the Spanish CDS spread according to our factor model. One possible interpretation of the figure—based on an standard factor analysis—is that the Spanish spread has been influenced by the evolution of the risk that is common to the ten countries (f_{1t}) and by the peripheral countries' risk (f_{2t}). Besides, it seems that Spain has tried to fight against this increase by means of an idiosyncratic behavior that is particularly negative when the CDS spread is higher.

However, this standard factor analysis does not allow to disentangle which is the contribution of the Spanish CDS spread to the factors as, if we use the standard weights decomposition, these weights only measure the relative importance of each variable in the factors for the average of the sample. However, as already shown, these weights change over time, and perhaps, they specially vary when an idiosyncratic shock is transmitted to the rest of the variables, and then, captured by the factor. These changing weights and their relation with the idiosyncratic shocks are precisely what we quantify in the next section by means of the real-time evolution of the common dynamics of these series.

Finally, from a methodological point of view, Figure 4 also suggests that fitting the second factor, f_{2t}, in (1) becomes necessary in the second subsample (that is, after the onset of the European debt crisis). Thus, if the sample period ended in September 2009, only one factor would be needed, in line with the evidence in Section 3. This example illustrates that in our approach f_{2t} will be a key element to identify contagion. In the next section, we analyze more formally the importance of f_{2t} to disentangle contagion by means a real-time analysis of these estimates.

5 Disentangling contagion: Real-time analysis

Our proposal is not the first contribution in the literature on contagion that is based on dynamic factor models. For instance, Dungey et al. (2000) use this approach to analyze yield spreads, whereas Dungey and Martin (2007) study contagion for currency and equity markets. However, and contrary to previous contributions, we do not identify contagion directly from the estimates of the model after imposing the effect of a single country that apparently triggers contagion in the measurement equation. Instead, we infer contagion using estimations in real-time, leaving the data speak with respect to which countries affect the others and when this contagion takes place. In this section, we first present our methodological proposal to disentangle contagion and then we present the main empirical results for our CDS spreads dataset.

5.1 Empirical methodology

According to our definition of contagion, which is an abnormal increase in the CDS spreads co-movement, compared with that of tranquil periods, triggered by a specific country or a group of countries, the evolution of the common factors, f_{1t} and f_{2t}, will play a crucial role. That is, if we follow this characterization, contagion could be identified precisely through the dynamics of f_{1t} and f_{2t} by means of real-time estimates throughout the sample period. We denote the breakpoint that divides the calm and turmoil subperiods as t^*. Thus, real-time estimates consist in the computation of the Kalman filter adding one observation to the sample on each iteration j after t^* which represents the first period for the out-of-sample analysis, so that the iterations run from 1 to $(T - t^*)$. In our particular exercise t^* is the week of 12th October 2009. Therefore, we start our real-time analysis just before the sovereign debt turmoil, so that the first observation that we analyze corresponds to the week ending on October 5th 2009. As in the previous sections, the last data corresponds to the week of March 12th 2012, when ISDA declared Greece to be in default on its debt, which implied the occurrence of a credit event and the activation of the Greek CDS payments.

As already seen in the previous section, when the sample period also includes the subsample from October 2009 it also requires a new integrated process to capture the long term dynamics of the CDS spreads series. This new integrated process, f_{2t}, is simply, as all the unobserved components obtained under a Kalman filter framework, no more than a weighted average of current and past data,[26] but this process precisely represents these abnormal comovements in the CDS market, never seen before, so that it entails crucial information to characterize contagion. What is more, this abnormal CDS premia comovement contains a unit root, which implies that this comovement is not only abnormal but also persistent throughout the sample period and determines the long term behavior of the series.

As a preliminary evidence of the outcomes that can be obtained with the real-time estimates, Figure 5 represents the common factors, f_{1t} and f_{2t}, of the model from (1) to (4) for the first

[26] We are considering only one-side-filters, because our purpose in the real-time exercise is to analyze the way in which surprises in one country trigger abnormal comovements in the rest of the series. Those surprises, which are linked to the prediction errors of the Kalman filter, imply forecast computation and forecasts do not need smoothing.

iteration, $j = 1$, and for iteration $(T - t^*)$. Whereas the real-time estimates of the first common factor, f_{1t}, for $j = 1$ and for $j = T - t^*$ nearly co-move, those of f_{2t} exhibit quite different dynamics. Thus, this distinct evolution of f_{2t} across iterations might entail the influence of idiosyncratic country shocks, as demonstrated by the own analytic specification of the Kalman filter throughout the estimation process in real-time. Therefore, we can exploit this feature to identify contagion through estimations in real-time by using certain elements of the Kalman filter. This methodology allows to disentangle which idiosyncratic shocks contribute to f_{2t}.

But, which elements of the Kalman filter are needed to analyze the shocks that contribute to f_{2t}? Once we have confirmed the importance of f_{2t} to identify contagion, we need to carefully analyze the meaning of "triggered by a specific country or a group of countries", as stated in the definition of contagion. The idea is the following. Suppose that we are in $(t^* - 2)$—September 29th 2009 to analyze the shocks in October 5th 2009, the last "tranquil" period—. As we know from previous section, at that moment there was no need to fit the second factor f_{2t}. Actually, at that time the second factor hardly explains any proportion of the variance of the data. However, we estimate a factor model with this additional factor, as we know in advance that it is the best model fit for the whole sample period, and we forecast the next observation for each of the ten countries in period $t^* - 1$.

As the realization in period $(t^* - 1)$ exactly coincides with the forecast estimated with the information until period $(t^* - 2)$, obviously the factor f_{2t} does not change its evolution and still behaves according to the dynamics calculated with the information until $(t^* - 2)$. However this is true for just $(t^* - 1)$ but it is false for all the following real-time iterations as the second factor, f_{2t}, starts being significant and, furthermore, it ends up being not only significant but also a key driver of the long term dynamics of the series because of its integrated behavior. Then, from t^* onwards there is a discrepancy between the forecasted CDS spread values and their realization in every time period. Therefore, it is clear that the forecasting errors feed the change in the dynamics of f_{2t} as they are the only source of discrepancy between the expected and the actual behavior of the series.

At this point and before following on with our analysis to identify contagion in real-time, we need to formulate the Kalman filter equations (see Appendix 1 for the particular details of our specification). Namely, let $h_{t|\tau}$ be the estimate of h_t based on the information up to period

τ and $P_{t-1|\tau}$ its covariance matrix, we can denote the prediction equations as

$$h_{t|t-1} = F\,h_{t-1|t-1} \tag{8}$$

$$P_{t|t-1} = F\,P_{t-1|t-1}F' + Q \tag{9}$$

whereas the prediction errors, $\eta_{t|t-1}$, and their corresponding covariance matrix, $\zeta_{t|t-1}$, are,

$$\eta_{t|t-1} = Y_t - Hh_{t|t-1} \tag{10}$$

$$\zeta_{t|t-1} = H\,P'_{t|t-1}H + R \tag{11}$$

Finally, the updating equations for $h_{t|t}$ and $P_{t|t}$ follow this expression,

$$h_{t|t} = h_{t|t-1} + K_t\eta_{t|t-1} \tag{12}$$

$$P_{t|t} = P_{t|t-1} - K_tHP_{t|t-1}, \tag{13}$$

where K_t, which denotes the Kalman gain, is defined as $K_t = P_{t|t-1}H(\zeta_{t|t-1})^{-1}$.

Specifically, to identify contagion we use the real-time estimates of $K_t\eta_{t|t-1}$ throughout the $(T-t^*)$ iterations. This expression is the Kalman gain, K_t, multiplied by the forecasting error, $\eta_{t|t-1}$, that, according to (12), can be interpreted as the updating element of the filter in each period of the new information available in period t. We do not need to analyze the complete column vector $K_t\eta_{t|t-1}$ of dimension (10×1), as we specifically focus on its second element, which is obtained by the partial product $K_{2t}\eta_{t|t-1}$, which is an scalar, where K_{2t} is the second row of K_t. In this manner, we only use those innovations that influence on f_{2t} and not those that update f_{1t}. The reason for this is twofold. First, we are worried about contagion among countries, which it is basically described only through f_{2t}, and second, the real-time estimates of the first component do not vary significatively after t^*. We use this notation,

$$K_{2t}\eta_{t|t-1} = \sum_{i=1}^{10} K_{it}\eta_{it|t-1} = \sum_{i=1}^{10} M_{it}, \tag{14}$$

where M_{it} represents the amount in which each CDS spread contributes to the updating of f_{2t} on each iteration from $j = 1$ to $j = (T - t^*)$ or, what is the same, from $t = t^*$ to $t = T$.[27]

[27] There is a technical issue that deserves some further comments. In this kind of models it is impossible to identify the values of the loading factors and the variance of the factors. Thus, we need to impose an identifying assumption (tipically variances of factors equal 1). Therefore, if we estimate the model in t and we make forecast for the variables in $t+1$ and the realizations are much volatile than the forecasts, we cannot include this increase in volatility in the variance of the factor which is identify to one in each iteration. To avoid this effect, we normalize in an slightly different way: we impose the factor to have the same variance than during the subsample previous to t^*.

5.2 Empirical results

Next, we represent graphically the elements of the Kalman filter that are relevant to understand contagion among sovereigns by means of the CDS spreads, namely the forecasting errors, $\eta_{it|t-1}$, and the contributions to the updating equation of f_{2t}, denoted as M_{it}. First, given the noisy dynamics of the ten series, in Figure 6 (upper plot) we represent an eight weeks (two months) moving average of the series of the forecasting errors, $\eta_{it|t-1}$. As shown in the plot, Greece presents the highest forecasting errors, but for some periods, Portugal is also a relevant source of shocks to the dynamics of f_{2t}, as well as Ireland, which is also is a big player, specially around September 2010.[28] On the other hand, countries such as Italy, Spain or Belgium have relatively low forecasting errors. Figure 6 (lower plot) represents the accumulated forecasting errors, from the first out-of-sample period to the last one. As shown the figure, Greece seems to have the highest size of forecasting errors followed by Portugal and Ireland.

However, the size of the errors, $\eta_{it|t-1}$, and the effect that they have over the contagion on other countries, M_{it}, are not the same concepts. Estimations of M_{it} are presented in Figure 7 in the form of the 8 weeks moving average (upper plot) and the accumulated sum from the beginning of the sample (lower plot). Remarkably, there are serious discrepancies between Figure 7, where we plot the shocks (that is, the forecasting errors $\eta_{it|t-1}$) times their weights in every period, and Figure 6, where we represent these shocks, although unweighted. Figure 7 indicates that, even though Portugal had smaller shocks than Greece—see Figure 6—, it had the highest influence on contagion among countries. This result leads to relevant results for the study of contagion in the sovereign debt crisis as, comparatively, shocks in Greece had significantly less influence on contagion to the remaining countries than those shocks of the same size in Portugal. In other words, a big shock generated by an individual country is not necessarily related to its capacity to trigger contagion to third countries. Other economy whose evolution of M_{it} could call the attention of the reader is that of Spain. Contrary to Greece, even though, as already shown, their shocks $\eta_{it|t-1}$ are very small, these minor forecasting errors for Spain are amplified once we multiply them by the Kalman gain to obtain the contributions to the updating equation of f_{2t}. Thus, it can be interpreted that Spain and Portugal have been in the eye of the hurricane during the sovereign debt crisis—and, therefore, they have

[28] By September 2010 the Irish government started negotiations with the ECB and the IMF given the problems of banks to raise finance that led to higher Irish sovereign bond yields.

generated contagion—in a way that is more than proportional to the size of the shocks that these economies have actually suffered.[29]

All in all, this procedure to identify contagion based on real-time estimates of M_{it} offers at least three advantages compared to previous contributions. First, it is based on a parsimonious model. Second, the model does not impose the triggering country of contagion, which can be any economy of the sample (op. Dungey and Martin, 2007). Besides, our contagion identification is dynamic, in that the contribution of each country to contagion may vary across iterations. From our point of view, this approach is more realistic than previous methodologies based on assigning a sole country as contagion source in a fixed amount throughout time. Finally, and also in contrast to the literature on sovereign contagion during the sovereign debt crisis, what we are identifying is *contagion*, in the sense that we are analyzing contemporaneous effects from the idiosyncratic shocks to the common factors, and not *spillovers*, which would be related to lagged effects of these innovations.

However, our method is not free from limitations. The main one is that its use is confined to those series where an additional common factor is identified after the breakpoint t^*. The sovereign CDS spreads of developed countries are a good example of these dynamics, but this method cannot be directly applied to all types of financial series. In this regard, a preliminary analysis of the emergence of new common factors during the sample period is required to implement our procedure.

6 Conclusions

Since the onset of the last crisis CDS spreads have become an alternative data source for the study of sovereign credit risk in developed countries given their increasing liquidity. In this paper we decompose the sovereign CDS premia of ten OECD countries, eight from the euro area plus the US and the UK, into three components by means of a rather parsimonious dynamic factor model: a factor common to all countries, a factor linked to the European peripheral countries and an idiosyncratic component that captures national factors affecting the market price of premia. Our study indicates that, although strictly national factors—approximated by the idiosyncratic component— have played a significant role in the behavior of sovereign spreads, phenomena such as contagion, which are more attributable to conditions in third countries, also seem to have operated, masking the effect of the policies of the authorities on the idiosyncratic factor.

[29] Note that, even though the core countries do not directly affect the evolution of f_{2t}, they contribute indirectly to it through the dynamics of f_{1t}. This result is a direct implication of the Kalman filter design.

That is to say, although the CDS premia contain very relevant information about sovereign credit risk, they should be previously corrected by the portion of the premium related to overall risk aversion and qualified by the contagion effects that may be present in the premia.

The main contribution of the paper is the proposal of a new procedure to characterize contagion based on the real-time estimates of the dynamic factor model. Our approach has the advantage of not imposing a sole country as the source of contagion. Indeed, the method does not need any a-priori regarding the contagion-driving country, which can be any of the ten economies. Moreover, this method allows the contribution of each country to the overall contagion to vary over time. This is relevant to reflect the fact that the country that transmits higher sovereign credit risk to third countries might vary throughout the sample period.

Regarding the interpretation of the empirical results, our analysis confirms that, in the context of the European sovereign debt crisis, the country source of contagion cannot be assigned to a sole economy, as it is sequential and varies over time. In other words, during the European sovereign debt crisis contagion has evolved as a "relay race": in the first stages of the crisis it was mostly triggered by Greece, but later it was also transmitted through other countries such as Portugal, Spain, Ireland or Italy. Further, our real-time analysis provides for the conclusion that the major shocks of the Greek CDS spreads are not necessarily related to the capacity of Greece to trigger contagion to third countries. On the contrary, we find that Portugal and, to a lesser extent, Spain have been more prone to generate contagion. Thus, these countries have affected other economies in a way that is more than proportional to the size of the shocks that these economies have actually undergone. We consider that this methodology based on real-time estimates involves a more realistic approach to the developments during the European debt crisis than most of the previous empirical contributions based on alternative analytical methods to identify contagion. Nevertheless, the mere existence of contagion might also indicate the presence of potential vulnerabilities at a national level which would have to be remedied in advance to reduce the sovereign risk premium.

Appendix A: State space representation of the model

In our model, assuming that the six peripheral countries run from country 1 to 6, the measurement equation $y_t = H\, h_t + w_t$, with $w_t \sim N(0, R)$ entails,

$$\begin{aligned} y_t &= (y_{1t}, \ldots, y_{10t})' & (15) \\ w_t &= 0_{10,1} & (16) \\ R &= 0_{10,10} & (17) \\ h_t &= (f_{1t} \quad f_{2t} \quad u_{1t}, \ldots, u_{10t})' & (18) \end{aligned}$$

where $0_{i,j}$ denotes a matrix of $(i \times j)$ zeroes and the matrix H follows this expression,

$$H = \begin{pmatrix} c & d & I_{10} \end{pmatrix} \tag{19}$$

where

$$\begin{aligned} c &= \begin{pmatrix} A_1 & A_2 & A_3 & A_4 & A_5 & A_6 & A_7 & A_8 & A_9 & A_{10} \end{pmatrix}' & (20) \\ d &= \begin{pmatrix} B_1 & B_2 & B_3 & B_4 & B_5 & B_6 & 0 & 0 & 0 & 0 \end{pmatrix}' & (21) \end{aligned}$$

and I_{10} is the identity matrix of order 10. The transition equation is $h_t = F\, h_{t-1} + \xi_t$, with $\xi_t \sim N(0, Q)$, where the matrix F is,

$$F = \begin{pmatrix} I_2 & 0_{2,10} \\ 0_{10,2} & E \end{pmatrix} \tag{22}$$

where I_2 is the identity matrix of order 2 and E is a (10×10) diagonal matrix with vector e in the main diagonal, where

$$e = (\phi_1, \ldots, \phi_{10})' \tag{23}$$

Finally, Q is a diagonal matrix where the elements of the main diagonal follow this vector,

$$q = (\sigma^2_{\nu_1}, \ldots, \sigma^2_{\nu_{10}})' \tag{24}$$

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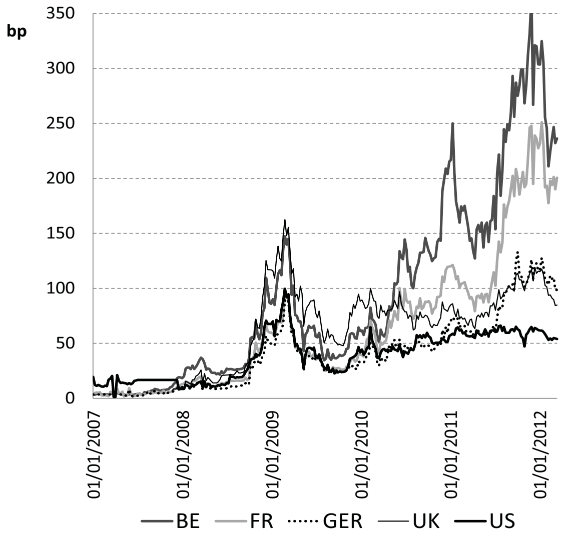
Figure 1: 10-year CDS spreads: Belgium (BE), France (FR), Germany (GE), United Kingdom (UK) and United States (US), (left), and Greece (GR), Ireland (IR), Italy (IT) and Portugal (PT) and Spain (SP) (right).



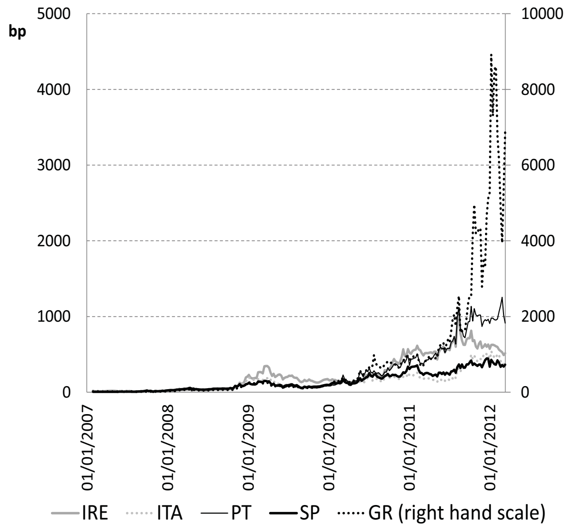
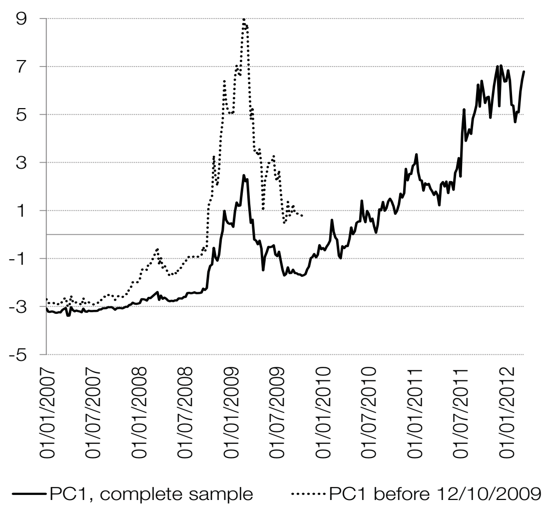


Figure 2: First and second principal components (denoted as PC1 and PC2, respectively) before the onset of the sovereign debt crisis and for the complete sample. Sovereign CDS spreads of ten OECD countries.



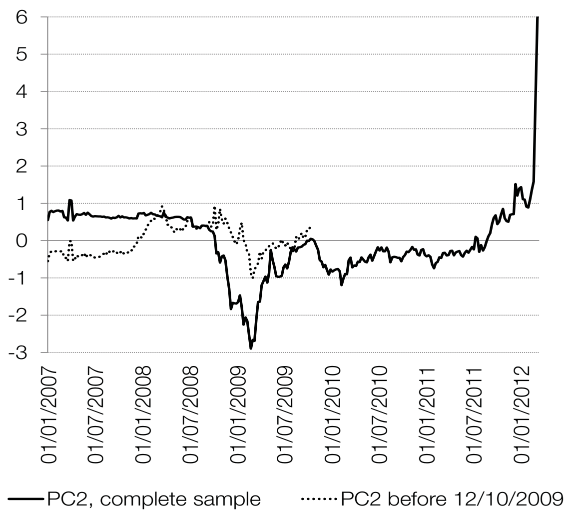


Figure 3: Estimates of f_{1t} and f_{2t} obtained with the dynamic factor model.

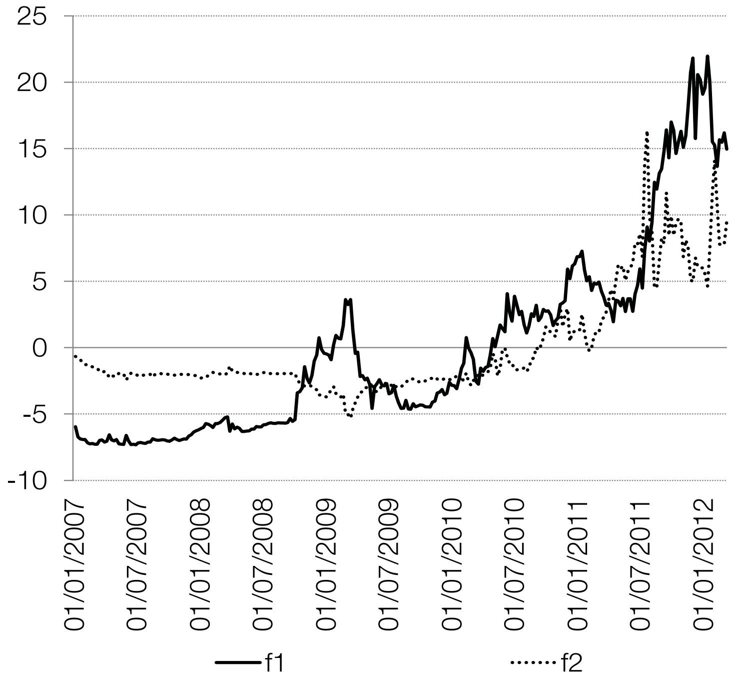


Figure 4: Decomposition of the Spanish 10-year CDS spread into a common factor (f1), a factor related to European peripheral countries (f2) and an idiosyncratic factor.

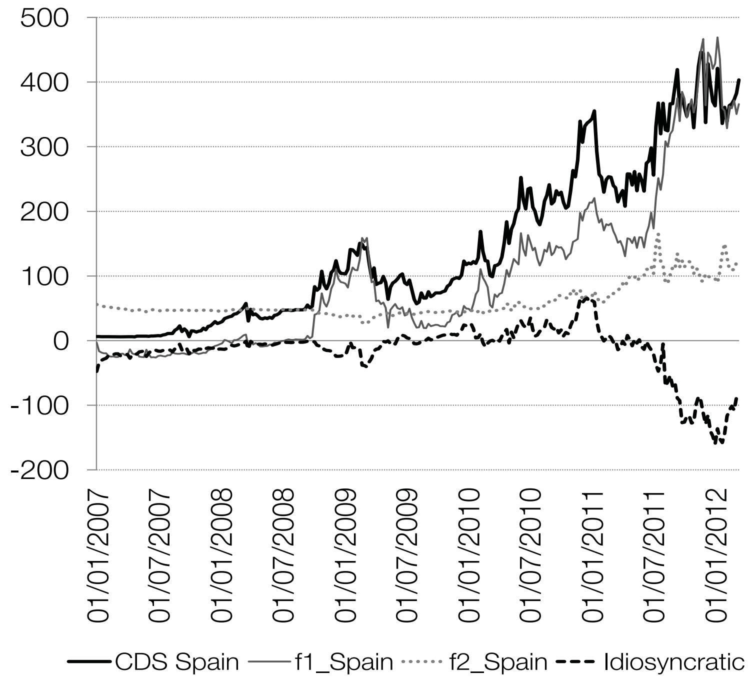
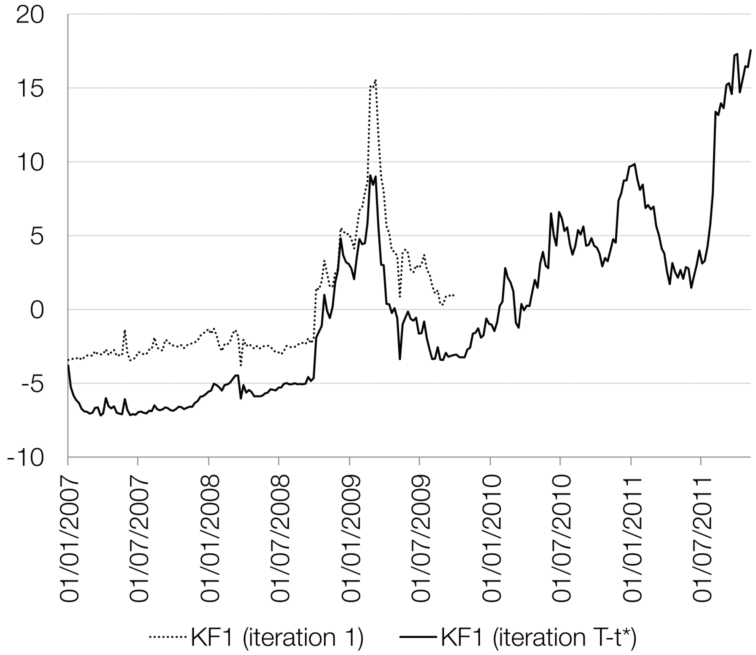


Figure 5: Real-time estimates of the first and the second common factor, KF1 and KF2—upper and lower plot, respectively—, of the dynamic factor model.



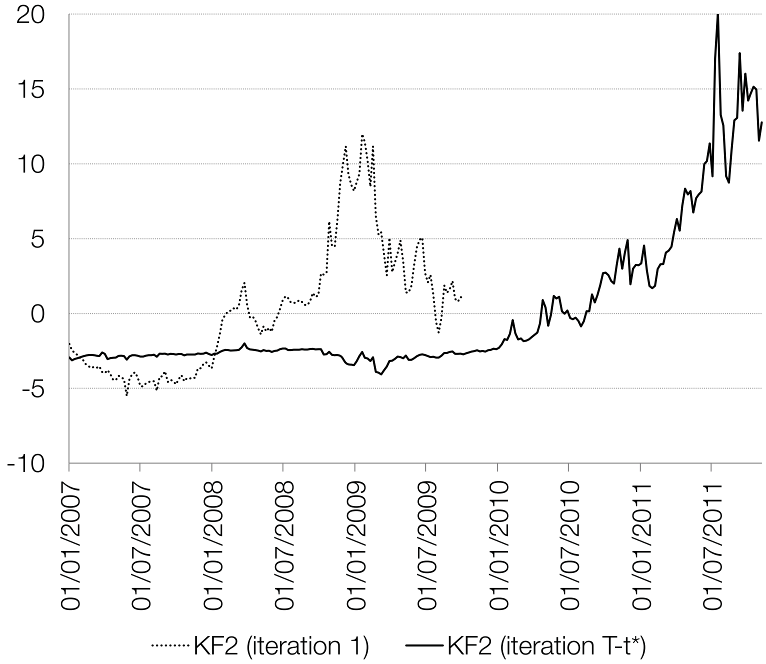
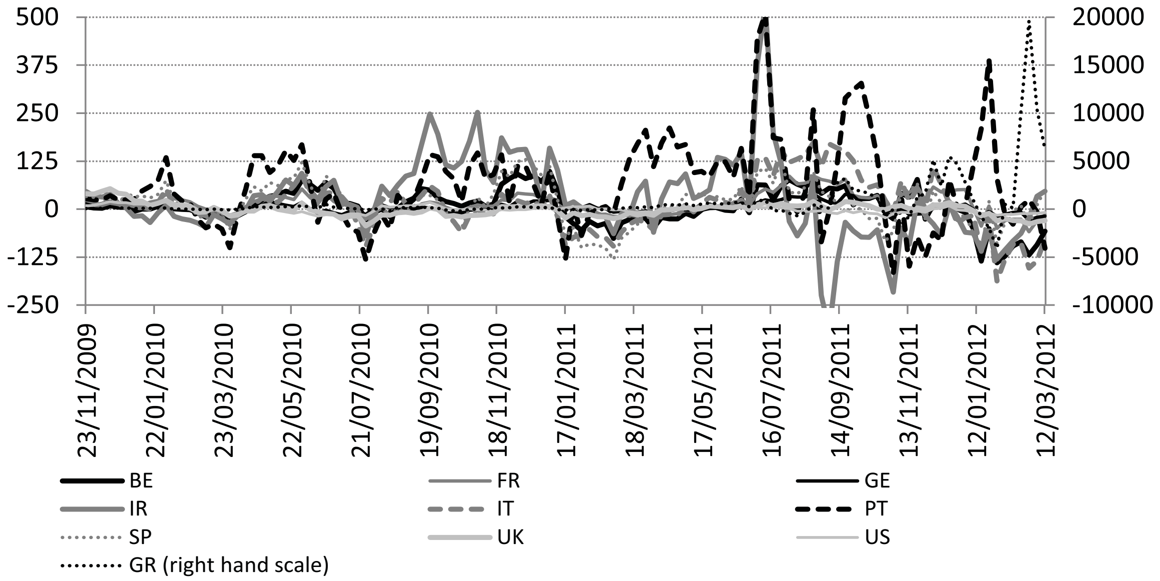
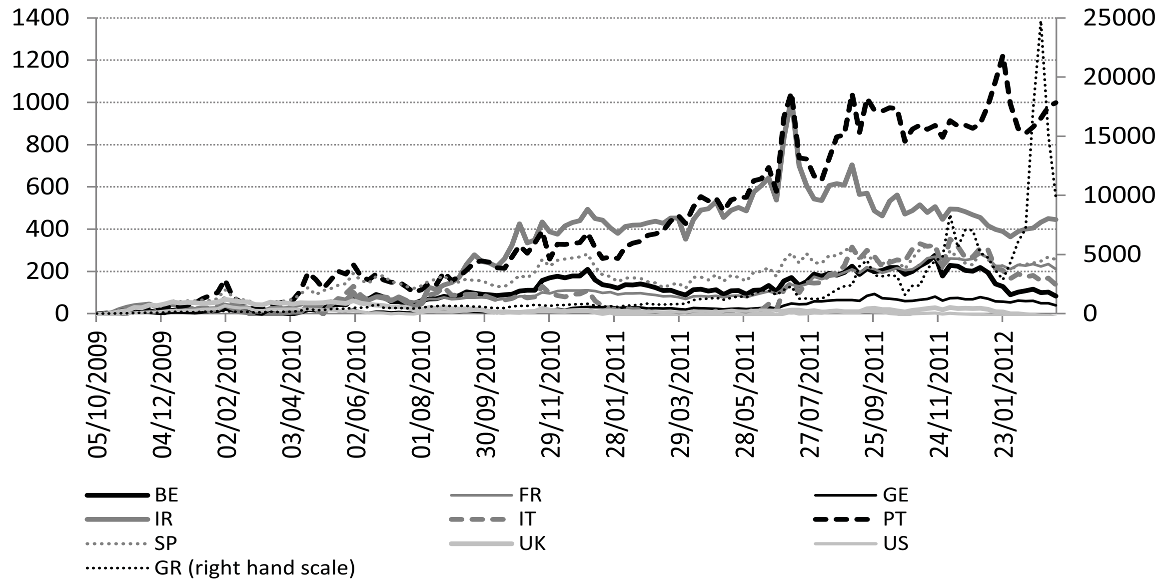


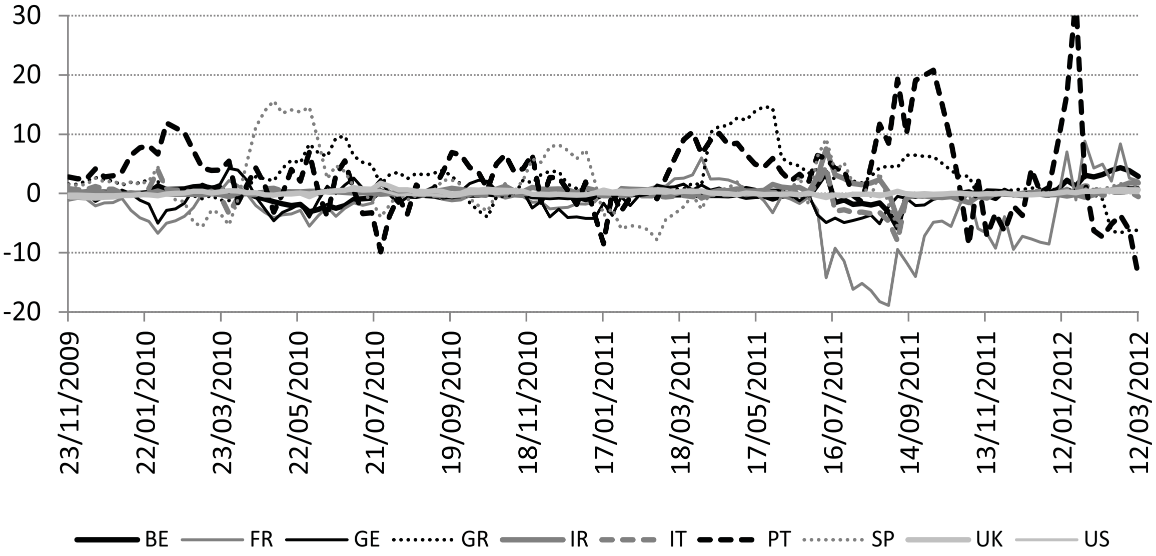
Figure 6: Real-time estimates. Surprises (forecasting errors $\eta_{t|t-1}$) smoothed by their two months rolling window sum (upper plot) and accumulated throughout iterations (lower plot).

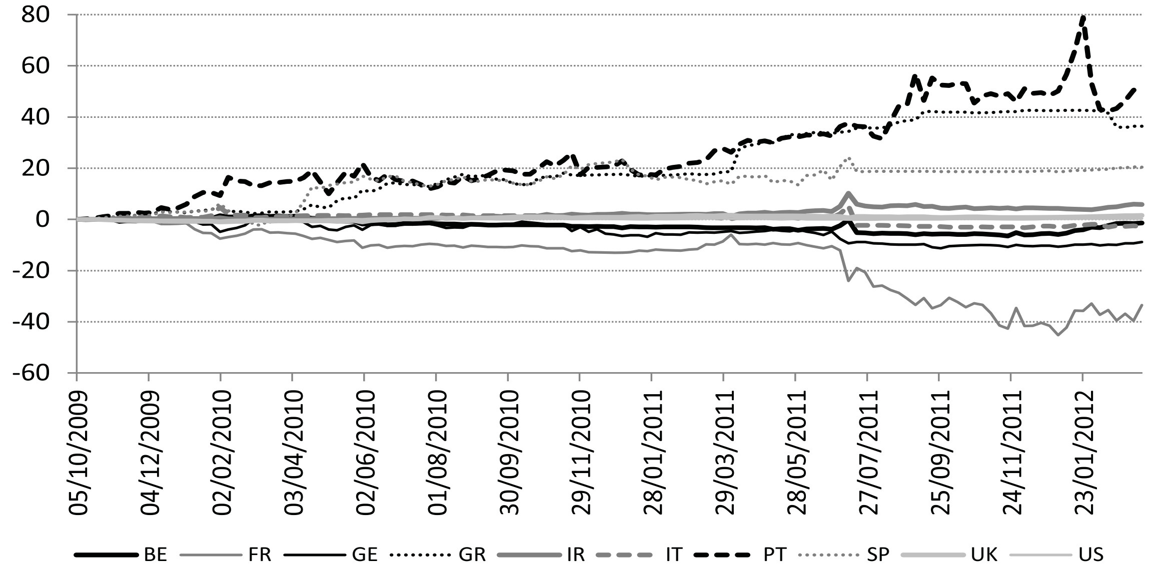




Notes: Units are basis points of an eight weeks rolling window sum throughout iterations (upper plot) and accumulated basis points (lower plot). Belgium (BE), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Portugal (PT), Spain (SP), United Kingdom (UK) and United States (US).

Figure 7: Real-time estimates. Contributions to the updating equation of f_{2t} (M_{it}, that is, Kalman gain, K_t, times the prediction errors $\eta_{t|t-1}$) smoothed by their two months rolling window sum (upper plot) and accumulated throughout iterations (lower plot).





Notes: Units are basis points of an eight weeks rolling window sum throughout iterations (upper plot) and accumulated basis points (lower plot). Belgium (BE), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Portugal (PT), Spain (SP), United Kingdom (UK) and United States (US).

Table 1: Summary statistics for the sovereign CDS spreads of ten sovereign CDS spreads.

		BE	FR	GE	GR	IR	IT	PT	SP	UK	US
Full sample	Mean	94.8	64.3	41.0	1092.7	244.6	142.4	259.0	143.9	72.0	39.0
	SD	87.8	62.3	33.5	3013.7	234.4	126.8	321.3	124.2	33.5	20.9
	Max	364.6	251.0	133.0	29082.7	1083.0	538.4	1253.1	446.3	162.3	99.6
	Min	3.0	1.4	1.8	11.0	2.5	11.4	7.2	5.5	6.7	1.2
Before 10/2009	Mean	36.3	23.3	20.0	84.7	84.3	63.5	48.6	50.9	56.6	27.3
	SD	34.7	21.9	20.1	74.1	92.3	51.6	35.4	40.1	43.0	21.0
	Max	147.4	94.5	89.2	272.8	346.0	197.5	143.4	150.5	162.3	99.6
	Min	3.0	1.4	1.8	11.0	2.5	11.4	7.2	5.5	6.7	1.2
After 10/2009	Mean	161.6	111.2	65.0	2243.6	427.6	232.5	499.2	250.2	84.1	52.4
	SD	82.3	60.4	29.4	4125.9	212.4	127.3	334.0	100.0	15.0	9.8
	Max	364.6	251.0	133.0	29082.7	1083.0	538.4	1253.1	446.3	119.0	66.2
	Min	38.6	25.2	23.1	129.7	117.0	74.4	57.5	73.8	47.9	24.0

Source: Datastream; The sample consists of weekly observations from January 1, 2007 to March 12, 2012; SD: Standard Deviation; Min: Minimum; Max: Maximun. BE: Belgium; FR: France; GE: Germany; GR: Greece; IR: Ireland; IT: Italy; PT: Portugal; SP: Spain; UK: United Kingdom; US: United States.

Table 2: Cointegration tests. Ten-year sovereign CDS spreads of ten OECD countries.

Complete sample (1/1/2007-12/3/2012)

$H_0 : r$	Eigenvalue	Trace test	Critical value	$p-$value
At most 6**	0.11	57.31	47.86	0.005
At most 7*	0.07	27.73	29.80	0.084
At most 8	0.03	9.36	15.49	0.332
At most 9	0.01	1.58	3.84	0.208

First subsample (1/1/2007-12/10/2009)

$H_0 : r$	Eigenvalue	Trace test	Critical value	$p-$value
At most 6**	0.21	79.90	47.86	0.000
At most 7**	0.16	47.21	29.79	0.000
At most 8**	0.15	22.56	15.49	0.003
At most 9	0.01	0.46	3.84	0.496

r denotes the number of possible cointegration relations; ** and * indicate rejection of the null hypothesis at 5% and 10%, respectively.

Table 3: Weights of the ten sovereign CDS spreads in a principal components analysis with two factors for the complete sample and for the first subsample.

	Complete sample		**First subsample**	
	$PC1$	$PC2$	$PC1$	$PC2$
BE	0.342	0.040	0.318	0.041
FR	0.342	0.114	0.320	−0.045
GE	0.343	−0.056	0.318	−0.247
GR	0.211	0.643	0.316	0.182
IR	0.325	−0.045	0.310	−0.317
IT	0.338	0.084	0.318	0.207
PT	0.325	0.251	0.314	0.502
SP	0.339	0.050	0.315	0.384
UK	0.279	−0.503	0.320	−0.142
US	0.289	−0.489	0.308	−0.580

Table 4: Correlation matrix, sample period previous to 12th October 2009. Ten OECD countries.

	BE	**FR**	**GE**	**GR**	**IR**	**IT**	**PT**	**SP**	**UK**	**US**
BE	1									
FR	0.99	1								
GE	0.98	0.99	1							
GR	0.96	0.97	0.95	1						
IR	0.94	0.94	0.96	0.95	1					
IT	0.98	0.98	0.96	0.99	0.93	1				
PT	0.97	0.97	0.94	0.97	0.90	0.98	1			
SP	0.96	0.97	0.95	0.97	0.94	0.97	0.99	1		
UK	0.97	0.98	0.98	0.97	0.97	0.97	0.93	0.94	1	
US	0.95	0.96	0.96	0.93	0.92	0.94	0.90	0.90	0.97	1

BE: Belgium; FR: France; GE: Germany; GR: Greece; IR: Ireland; IT: Italy; PT: Portugal; SP: Spain; UK: United Kingdom; US: United States.

Table 5: Difference of correlation matrices (after minus before 12th October 2009 subsamples). Ten OECD countries.

	BE	**FR**	**GE**	**GR**	**IR**	**IT**	**PT**	**SP**	**UK**	**US**
BE	0									
FR	−0.02	0								
GE	−0.03	−0.01	0							
GR	−0.45	−0.36	−0.38	0						
IR	−0.11	−0.20	−0.20	−0.60	0					
IT	−0.03	0.00	−0.01	−0.43	−0.22	0				
PT	−0.06	−0.03	0.00	−0.39	−0.05	−0.06	0			
SP	0.00	−0.03	−0.04	−0.44	−0.07	−0.06	−0.07	0		
UK	−0.24	−0.20	−0.19	−0.60	−0.52	−0.16	−0.25	−0.31	0	
US	−0.22	−0.29	−0.26	−0.66	−0.10	−0.32	−0.18	−0.13	−0.46	0

Correlation matrix of the subsample after October 2009 minus the correlation matrix of the subsample previous that date. BE: Belgium; FR: France; GE: Germany; GR: Greece; IR: Ireland; IT: Italy; PT: Portugal; SP: Spain; UK: United Kingdom; US: United States.

Table 6: Loading matrices estimation of the dynamic factor model for ten OECD countries.

	Matrix A	**SD**	**Matrix B**	**SD**
BE	0.144	0.008	0.027	0.006
GR	0.031	0.011	0.007	0.014
IR	0.092	0.010	0.118	0.009
IT	0.143	0.009	0.048	0.007
PT	0.073	0.009	0.120	0.008
SP	0.136	0.008	0.052	0.006
FR	0.136	0.007		
GE	0.126	0.007		
UK	0.123	0.010		
US	0.093	0.011		

BE: Belgium; FR: France; GE: Germany; GR: Greece; IR: Ireland; IT: Italy; PT: Portugal; SP: Spain; UK: United Kingdom; US: United States. SD: Standard Deviation.

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