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Self-fulfilling dynamics: The interactions of sovereign spreads, sovereign ratings and bank ratings during the euro financial crisis*

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ABSTRACT

During the euro-area financial crisis, interactions among sovereign spreads, sovereign credit ratings, and bank credit ratings appeared to have been characterized by self-generating feedback loops. To investigate the existence of feedback loops, we consider a panel of five euro-area stressed countries within a three-equation simultaneous system in which sovereign spreads, sovereign ratings and bank ratings are endogenous. We estimate the system using two approaches. First we apply GMM estimation, which allows us to calculate persistence and multiplier effects. Second, we apply a new, system time-varying-parameter technique that provides bias-free estimates. Our results show that sovereign ratings, sovereign spreads, and bank ratings strongly interacted with each other during the euro crisis, confirming strong doom-loop effects.

Keywords: euro area financial crisis, sovereign spreads, rating agencies
JEL Classification: E63, G12

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1. Introduction

A large empirical literature has investigated the determinants of sovereign-bond spreads (and, in some cases, CDS spreads) in the euro-area stressed countries -- typically taken to include Greece, Ireland, Portugal and Spain, but sometimes also Cyprus and/or Italy -- in the years preceding and during the euro-area crisis. A key finding of the literature is the following: the various fundamental variables that have been used in attempts to explain spreads have not able to account for either the very low spreads (measured relative to German sovereigns) that prevailed in the years preceding the outbreak of the euro-area crisis in 2009 or the very sharp rise in spreads that took place following the onset of the crisis. The general finding that spreads overshot (relative to the fundamentals) in a downward direction before the crisis and in an upward direction after the crisis holds regardless of (a) the mix of fundamental variables used to explain spreads and (b) whether the fundamentals are supplemented with additional variables -- for example, measures of contagion (Grammatikos and Vermeulen, 2014), measures of credit risk (Annaert, De Ceuster, Van Roy and Vespro*,* 2013), and/or sovereign credit ratings (Gibson, Hall, and Tavlas, 2014; Aizenman, Binici and Hutchison 2013; Afonso, Furceri, and Gomes, 2012). Moreover, this finding is robust to the particular country sample and/or time period used, and the estimation procedure employed.[1]

A central feature of the euro-area crisis -- and one that potentially can explain the difficulty that researchers have had in accounting for the movements in spreads on the basis of the fundamental variables -- was the existence of doom loops -- that is, negative feedback loops -- among sovereign spreads, sovereign ratings, and bank ratings. To explain the intuition underlying these feedback loops, consider a world that includes two rating agencies, A and B. In assigning ratings to a particular sovereign assume that, initially, both agencies have access to essentially identical information sets comprised of the (present and projected) fundamentals, including spreads, competitiveness, real growth, inflation, fiscal and external positions, and, perhaps, non-economic variables

[1] For example, Gibson, Hall and Tavlas (2012, 2014) apply both ordinary least squares and the Kalman filter to Greek data, Arce, Mayordomo, and Peña (2013) apply a two-stage estimation procedure to a pooled sample of 32 euro-area banks, Maltritz (2012) applies Bayesian estimation on a pooled sample of ten euro-area countries, and Fabozzi, Giacometti, and Tsuchida (2016) utilize independent component analysis on a group of seven euro-are countries.

such as measures of political stability[2]. Suppose that, based on its assessment of the information set of a particular country, rating agency A moves to downgrade the sovereign debt of the country in question. The announcement of the downgrade will very likely trigger a rise in the sovereign's interest rate.[3] In addition, under the ECB's collateral framework, haircuts on sovereigns rise if ratings fall to a specified (triple-B) level and are non-eligible as collateral below the rating single-B minus. For these reasons, the action by rating agency A changes the information set available to rating agency B since that information set now includes both A's downgrade, the resulting higher interest rates, and possibly higher haircuts on collateral, lower projected growth (because of the rise in interest rates), and less-sustainable fiscal balances for the country in question. Consequently, rating agency B, which may have been content with the rating it had assigned to the sovereign in question prior to A's downgrade, may move to downgrade the sovereign's rating based on the changed information set. In this way, A's original action can precipitate a downgrade by B, triggering self-perpetuating feedback loops between sovereign ratings and spreads.

That, however, is not the end of the story. A salient feature of the euro-area crisis was the fact that (1) sovereign downgrades and rises of sovereign spreads led to downgrades of banks within the sovereign's jurisdiction, and (2) the bank downgrades contributed to both further sovereign downgrades and increases in spreads. This circumstance reflected the following factors. First, in the euro area, the governmental unit responsible for the health of the banks operating within its jurisdiction has been the individual nation state (in contrast to the situation in the United States, in which the federal government bears that responsibility). Second, the largest euro-area banks, which are roughly of the same size (in terms of total assets) as the largest U.S. banks, represent a much larger share of any individual *national* economy compared with the situation of U.S. banks. Hence, while the GDP of the euro-area economy as a whole is similar in magnitude to that of the United States, the governments of individual European countries have much smaller incomes that can be brought to bear in banking crises than

[2] None of the major rating agencies—Fitch, Moody's, and Standard and Poor's – makes the analytical models used to determine sovereign ratings and bank ratings available.
[3] Typically, market prices of sovereigns are tied to ratings.

does the government of the United States. Third, compared with U.S. banks, which typically hold small amounts of state and local-government debt in their portfolios, domestic euro-area banks typically hold relatively-large shares of debt issued by their respective national governments in their portfolios (O' Rourke and Taylor, 2013, pp. 181-182). An implication of these factors during the crisis was that downgrades of euro-area sovereigns weakened banks' balance sheets, which, in turn, increased the fiscal burdens of the sovereigns and led to doubts about the solvency of the sovereigns.

Thus, during the euro-area crisis a move by a single credit-rating agency to downgrade a sovereign's rating had the potential to set-off a chain reaction of multiple-feedback loops among sovereign ratings, sovereign spreads, and bank ratings.[4] A stylized representation of this process includes the following chain. Agency A downgrades a sovereign. This downgrade raises the sovereign's spreads, inducing agency B to downgrade. The rise in spreads lowers the country's growth prospects and increases the debt burden, making it more difficult to service the debt. Banks' balance sheets deteriorate. These developments trigger downgrades of the banks of the country in question and a reduction in credit creation (because of the strains on banks' balance sheets). Spreads rise further. The sovereign downgrades by both agencies and the ensuing bank downgrades lead to further sovereign downgrades. Spreads continue to rise; banks' balance sheets continue to deteriorate, and further sovereign and bank downgrades follow.[5]

The failure to account for such feedback loops in previous empirical studies may be a reason that these studies generally underpredicted the impact of changes in economic fundamentals on sovereign spreads during the crisis. In this paper, we account for these feedback loops by using a three-equation simultaneous-equation model that explains sovereign spreads, sovereign ratings, and bank ratings. To carry-out our investigation, we use a panel of five euro-area countries that were at the center of the euro crisis --

[4] In 2012, European leaders initiated a number of measures to create a Banking Union. The three pillars of the Banking Union are: the Single Supervisory Mechanism, the Single Resolution Mechanism and a common deposit guarantee system. An aim of the Banking Union is to help eliminate the negative feedback loops.

[5] The above representation is an accurate description of developments in Greece during the period end-2009 until mid-2012.

Greece, Italy, Ireland, Portugal, and Spain. The data are monthly and the estimation period is 1998m1 to 2013m3. For each country considered, we have constructed time series comprising the ratings of its sovereigns and its banks as determined by the three major rating agencies -- Fitch, Moody's, and Standard & Poor's (S&Ps). In addition to accounting for feedback loops, a further novelty of this paper is that we investigate this phenomenon in two distinct ways. First, we estimate the simultaneous equation system using panel GMM. GMM estimation of the system allows us to estimate persistence and multiplier effects of changes in fundamentals. However, GMM is subject to the potential criticisms that: (i) it may incorporate an incorrect functional form; (ii) it may not be stable, (iii) it may omit variables; and, (iv) there may be measurement errors in the variables. To deal with potential specification problems, we extend our analysis to a time-varying parameter framework under a system setting, and we develop a theory of identification for this model. This technique allows us to investigate the simultaneity issue in a completely different way than other approaches. The technique provides us with coefficients in which specification biases, such as those stemming from omitted variables, simultaneity, and measurement errors, have been removed.

Our results indicate that, controlling for economic fundamentals and political stability, during the euro-area crisis, sovereign ratings, bank ratings, and sovereign spreads strongly interacted with each other. Additionally, simulations suggest that changes in economic fundamentals and political stability can explain only a small proportion of the variation in spreads and ratings. A considerable part of the variation stems from previous movements in sovereign ratings, sovereign spreads and bank ratings, along with interactions among the three variables. These interactions tended to have long-lasting effects.

The remainder of this paper is structured as follows. Section 2 provides some context to our conjecture that spreads and ratings interact, using as an example the case of Greece, which experienced by-far more sovereign downgrades than any other euro-area country. Whereas Greece experienced 27 sovereign downgrades during the period examined, Portugal had 16, Spain, 15 and Italy, 11. Section 3 describes our data. Section 4 begins by describing our GMM simultaneous-equation set-up; the section then presents the GMM estimates, including the simulation results of the effects of changes in the fundamentals on spreads and ratings. Section 4 begins by describing our extension of the TVC methodology to a simultaneous-equation setting; the section then presents the results based on that technique. Section 6 compares the GMM and the TVC procedures and results. Section 7 contains our conclusions. An Annex provides a proof of the identification of the simultaneous time-varying-coefficient system.

2. Interactions between ratings and spreads

Sovereign ratings are important because they (1) directly influence the interest rate charged to the sovereign in the international capital markets, (2) affect size of the haircut applied to collateral (under the Eurosystem's collateral framework), and (3) impact on the ratings assigned to other borrowers, including banks, of the same national jurisdiction.

Table 2 lists the ratings' categories for long-term debt for each of the three major agencies. Fitch and S&P use identical symbols in assigning credit risk. The symbols used by Moody's differ from those of the other two agencies, but each Moody's symbol has a counterpart in the ratings of Fitch and S&P. Typically, the ratings assigned to sovereigns by the three agencies have shown close correspondence; when the ratings have not been in correspondence they have tended to differ by one notch.

The trigger for the euro-area crisis occurred in early-October 2009 following national elections in Greece on October 4, 2009. Several days later a newly-elected (socialist) government surprised the markets with the announcement that the fiscal deficit for 2009 was on a track that would bring it to more than double the outgoing (conservative) government's projection of a deficit of 6 per cent of GDP.[6] Prior to the elections, each of the rating agencies had maintained the ratings on 10-year Greek sovereigns unchanged since at least 2004, as follows: Fitch, A; Moody's, A1; S&P, A. In reaction to the news about Greece's fiscal position, the rating agencies moved quickly to downgrade Greek sovereigns. The following account focuses on Greece, but the ratings-downgrade scenario was replicated (though to a lesser extent) in other euro-area crisis countries.

[6] The final figure would be a deficit of 15.6 per cent of GDP.

On October 10, 2009, S&P downgraded the 10-year Greek sovereign from A to A-minus (Figure 1). On October 22, 2009, Fitch followed with an identical move. With the financial situation deteriorating,[7] spreads began to rise sharply (Figure 1). On December 8, 2009, Fitch moved again, cutting the sovereign rating from A-minus to triple-B-plus. On December 15, 2009, S&P followed with an identical move. Six days later, on December 22, 2009, Moody's cut its sovereign rating from A1 to A2. Sovereign downgrades were followed in rapid succession by downgrades of Greek banks. The processes of negative feedback loops between sovereign downgrades and spreads, and between sovereign downgrades and bank downgrades, were underway.

Over the next 27 months (*i.e.,* until March 2012), 18 additional downgrades of the sovereign took place; by the beginning of March 2012, Greek sovereigns were rated in the "selective default" category. During that 27-month period, the four major Greek banks (accounting for 85 per cent of the banking sector at the onset of the crisis) underwent a total of 77 separate downgrades[8]. At the end of the period, the banks were not able to use Greek sovereigns as collateral at the ECB.[9] The spread on the 10-year sovereign rose from 230 basis points at end-December 2009 to a peak of 3,800 basis points in February 2012.

To demonstrate the interactions among these variables, we performed Granger causality tests. The data are monthly and pooled for our sample of five countries over the period 1998M1 to 2013M3. The results are reported in Table 1.

As shown in the table, the null hypothesis that one of the three variables does not cause the others is rejected at a p-value of less than 0.0 per cent in all cases with the exception of the hypothesis that sovereign spreads do not cause bank ratings.

3. The data

[7] The rises in spreads made it increasingly difficult for the government to service the debt.
[8] The four major banks and the respective number of downgrades were as follows: National Bank of Greece: 18, Piraeus: 18, Alpha Bank: 20, Eurobank: 21.
[9] The banks had to satisfy their liquidity needs by obtaining Emergency Liquidity Assistance (ELA) from the Bank of Greece. The cost of borrowing ELA is higher than that under the Eurosystem's monetary-policy operations.

As mentioned, our focus is on five southern European countries that were at the center of the euro crisis -- Greece, Italy, Ireland, Portugal, and Spain. With the exception of Italy, each of these countries came under an ECB-EU-IMF adjustment programme. Italy almost had to resort to such a programme in 2011. In August 2011, however, the ECB began buying Italian government debt under the ECB's Securities Market Programme (SMP) which brought-down Italian spreads, easing the crisis in that country[10]. The data are monthly and the panel is unbalanced; most of the data are, however, available over the entire estimation period, 1998m1 to 2013m3 (see Annex 1 for sources and descriptive statistics). In those cases for which the original data are quarterly or annual, the data have been interpolated to a monthly frequency using quadratic interpolation. The three dependent variables are defined as follows:

Spreads. Spreads are the yield on each country's 10-year government bond relative to that of Germany.

Sovereign ratings. We constructed a series for sovereign ratings using the ratings of the three rating agencies. We date rating changes after identifying first-moves. Thus, to take a stylized example, assume a country is rated AAA by all three agencies in month 1. Then suppose that one agency downgrades the country to AA+ in month 2. This is counted as a downgrade and is registered in our series. If another agency downgrades the country to AA+ in month 3, this does not count in our series (the country is already considered to be at AA+). Similarly, if the country in question is downgraded within the same month by all three agencies, we can count only one of the downgrades; since our data are monthly, they cannot capture multiple downgrades within a month. To the extent that we can only capture first-moves, therefore, our series underestimates downgrades and the potential for doom-loops. Having constructed an ordinal series for ratings, we then transform the series into a cardinal series (as shown in Table 2). A rise in the rating indicates a downgrading of the sovereign.

Banking system ratings. Banking-system ratings are defined as the average rating of the largest (in terms of assets) two banks in each country (four banks in the case of Greece).

[10] Cyprus came under an adjustment programme in early 2012. We do not include Cyprus in our sample because of a lack of sufficient data.

The data on bank ratings for Italy, Ireland, Portugal, and Spain were provided to us by the ECB under the condition that the data be kept confidential. Once again, a rise in the series on the banking system rating implies a downgrading of the system's banks.

For the equations that explain spreads and sovereign ratings, we use five economic-fundamentals' variables and a variable that measures political stability. In the final specification, the variables are retained if they are significant at the 5 per cent level and if they have the expected sign. The explanatory variables are as follows.

Real GDP growth. A relatively high rate of economic growth suggests that a country's existing debt burden will become easier to service over time. Thus, an increase in the real growth rate should reduce spreads and produce a fall (*i.e.,* improvement) in sovereign ratings.

Relative prices. To help capture relative changes in competitiveness, we use each country's Harmonized Index of Consumer Prices (HICP, all items index) relative to that of Germany. A (substantial) rise in a country's relative prices signals a decline in competitiveness, which should raise the country's spreads, and worsen its sovereign ratings.

External balance. A large current-account deficit (relative to GDP) indicates that the public and private sectors together rely (heavily) on funds from abroad. Persistent current-account deficits result in growth of foreign indebtedness, which may become unsustainable over time. Thus, an increase in the current-account deficit (a negative change), should cause spreads to rise, so that the expected sign on the current-account variable is negative. Correspondingly, a rise in the deficit, if sustained, should lead to rating downgrades for a country's sovereign.

Government debt. A higher debt burden should correspond to a higher risk of default. We include the general government consolidated gross debt expressed as a percentage of GDP, interpolated from a quarterly to a monthly frequency. The expected sign of a rise in debt on spreads is positive; the expected sign on the sovereign ratings variable is also positive (i.e., a worsening of the sovereign's ratings raises spreads).

Fiscal news. In order to capture both a country's fiscal situation and the news (or surprise) element that has figured strongly in the euro-area experience, we construct real-time fiscal data. In particular, using the European Commission Spring and Autumn forecasts, we create a series of forecast revisions. For example, the revision in the Spring 2001 forecasts is the 2001 deficit/GDP ratio in the Spring compared to the forecast for 2001 made in the Autumn of 2000. This procedure allows us to generate a series of revisions, which, when cumulated over time, provides a cumulative fiscal news variable. A decrease in this variable indicates an unexpected move to a larger fiscal deficit, which should increase spreads. Thus, the expected sign on spreads is negative. Similarly, a decrease in the variable should lead to downgrades in the ratings of the sovereign. Again, the expected sign is negative.

Political stability. To measure the political climate, we use the IFO World Economic Survey Index of Political Stability. A rise in the index implies greater stability, which implies a negative relationship with spreads and the ratings of the sovereign.[11]

For the equation that has bank ratings as a dependent variable we use three banking-system-specific variables. As mentioned above, with the exception of Greece, we used the ratings on the largest two banks (in terms of total assets) in each of the countries considered as a measure of bank ratings. In the case of Greece, we had access to the ratings of the four largest commercial banks, and so we used the ratings of those four banks as the measure of banks ratings. The following variables were used to capture developments in a country's banking system, as represented by a country's five largest banks.[12]

Loan loss reserves/non-performing loans (NPLs). Rising NPLs are a problem for banks to the extent that banks cannot cover potential losses. The higher a bank's reserves, the

[11] Apart from the fiscal-news variable, the above variables are standard variables used in the empirical literature dealing with the determinants of spreads. The fiscal-news variable was introduced by Gibson, Hall, and Tavlas (2012). It has subsequently been incorporated in other studies.

[12] The use of five banks in constructing the explanatory variables for each county's banking system reflects the fact that we had access to such data, in contrast to the availability of data on bank downgrades.

stronger the bank's ability to service NPLs and, hence, the better the rating. Thus we anticipate a negative sign on the coefficient of this variable.

Pre-tax operating income/average total assets. This provides a measure of banking system profitability. Since profits can, if retained, generate internal capital, which covers unexpected losses, a rise in profitability would be expected to improve (decrease) credit ratings. A negative sign is thus expected.

Interbank ratio. This ratio indicates the net position of the banking system in the interbank market (with banks in other euro area and non-euro area countries). A value above 100 implies that the system is a net lender of funds in the interbank market. Thus a negative relationship between the interbank ratio and banking system ratings is anticipated.

As illustrated in Figure 1, the data with which we are dealing are almost certainly non-stationary.[13] The question which then arises is whether the data should be modelled in levels or differences. The decisive factor here is whether we have cointegration among the set of variables under consideration. To this end, we performed the Johansen-Fisher panel cointegration test which showed clear evidence of cointegration for the variables in each of our three equations. (For the spreads equation we found 4 cointegrating vectors; the p-value of the test of 3 against 4 cointegrating vectors was 0.009, and the p-value of 4 against 5 cointegrating vectors was 0.59. For the sovereign-ratings equation we found 3 cointegrating vectors; the p-value for 2 against 3 cointegrating vectors was 0.00, and the p-value of 3 against 4 cointegrating vectors was 0.05. For the commercial bank ratings we found 4 cointegrating vectors; the p-value for 3 against 4 cointegrating vectors was 0.001 and the p-value for 4 against 5 cointegrating vectors was 0.2.) All three sets of variables had a deficient rank, confirming the non-stationarity of the variables and, thus, that the modelling should be conducted in levels.

An issue arises with our treatment of ratings. We have turned the ratings series into a cardinal set of numbers that range from 1 to 20. There is no particular problem in treating the ratings as number but the assumption that the numbers are cardinal may be

[13] This circumstance was confirmed by standard augmented Dickey-Fuller tests.

unrealistic. Ideally, we would like to use an estimation strategy that would only make an ordinal assumption. This would require us to use a system-ordered-probit style technique, which would be very complex. However, an alternative approach is to allow for a non-linear effect from the ratings variable. This treatment may then capture the nonlinear effect coming from the possible non-cardinality of the data. We apply such a technique in the next section using TVC estimation. It is, of course, the case that ratings vary in some countries more than they vary in others. Sovereign ratings, for example vary between 7 and 20 for Greece but only between 1 and 5 for Spain, 1 and 8 for Ireland, 1 and 9 for Italy, and 1 and 12 for Portugal. It is purely an empirical matter as to whether this level of variation will allow us to uncover significant effects. It is certainly true, however, that the panel estimation will substantially increase our chances of finding reasonable results.

4. GMM estimation

4.1 GMM methodology

To shed light on the empirical relationships among sovereign ratings, sovereign spreads, and commercial bank ratings, we use a panel GMM estimator, which is robust to autocorrelation and heteroskedasticity (HAC). To explain our empirical set-up, consider a group of n countries, estimated over T periods. Our baseline model can be expressed as:

$$S_{it} = \alpha_0 + \alpha_1 SR_{it} + \alpha_2 BR_{it} + \sum_{k=1}^{K} \alpha_{2+k} X_{itk} + \varepsilon_{it} \tag{1}$$

$$SR_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 BR_{it} + \sum_{k=1}^{K} \beta_{2+k} X_{itk} + \omega_{it} \tag{2}$$

$$BR_{it} = \chi_0 + \chi_1 S_{it} + \chi_2 SR_{it} + \sum_{k=1}^{K} \chi_{2+k} X_{itk} + \upsilon_{it} \tag{3}$$

where i=1…N, t=1…T and K is the number of exogenous regressors. S_{it} is the interest rate spread between country i and Germany, SR_{it} is the sovereign rating for country i, BR_{it} is the rating for commercial banks in country i, and ε_{it} , ω_{it} and v_{it} are error terms. We assume there are suitable exclusion restrictions on the *α's, β's* and *χ's* to either exactly-identify or to over-identify the system.

GMM estimation requires the specification of a set of theoretical moment conditions that the parameters of interest φ should satisfy. Thus,

$$E(m(y,\varphi)) = 0 \tag{4}$$

where y is a vector of variables relevant for the specific moment conditions being specified , m is the moment function (e.g. mean, covariance, etc.), and the method of moments estimator is defined by replacing these population moments with their sample analogs.

$$\sum_t m(y_t,\varphi)/T = 0 \tag{5}$$

For the specific GMM estimator we are using, the moment conditions are specified in terms of orthogonality conditions between the residuals of each equation and a set of instruments (Z_t). That is, ε_{it} ω_{it} and υ_{it} are assumed to be orthogonal to the vector of instrumental variables Z.

If the number of parameters of interest is exactly equal to the number of moment conditions, then we can exactly satisfy these moment conditions and obtain the method of moment's estimator. However, if the number of moment conditions is greater than the number of parameters of interest, then we cannot meet all the moment conditions at the same time. In this case, we minimize the following function, which gives rise to the Generalised Method of Moments (GMM):

$$\sum_t m(y_t,\varphi)A(y_t,\varphi)m(y_t,\varphi) \tag{6}$$

where A is a weighting matrix. While any positive definite symmetric matrix will give rise to a consistent estimator, the optimal A is given by the inverse of the covariance matrix of the moment conditions.

The value of equation (6) at the estimated coefficient values is termed the J-statistic and it is reported in the estimation results in Table 3. The J-statistic is the minimized value of equation (6). It may be used to construct hypothesis tests between competing nested or non-nested models by constructing an equivalent to a likelihood ratio test using this statistic.

GMM may be applied in either a panel-data setting or in a non-panel setting. The traditional panel is one in which there is a large cross-section structure, but only a small time domain (e.g., the Arellano and Bond approach). In this paper we apply a version of GMM that has been developed to estimate panels with reasonably large T but small N. The technique does not use an increasing and complex instrument set; it has a much simpler instrument structure more akin to standard time series GMM but expanded to a small N panel -- see Hayashi (2000). Up to three lags on the variables were used as instruments. A potential problem that arises with regard to the control variables is that of endogeneity. We address this potential problem in the next section which deals with TVC estimation.

In interpreting the results presented below, the following issues merit comment. First, in practice it is not possible to achieve a perfect instrument set. Therefore, we need to be careful in providing a causal interpretation to the GMM results. Indeed, these results can be interpreted as associations rather than causal effects. Second, economic theory is not especially helpful in determining the identifying restrictions since theory essentially suggests that any of the fundamental variables could affect sovereign spreads, sovereign ratings, and bank ratings. Nevertheless, some restrictions are needed to identify the system in order to initiate the nesting-down procedure. We have, therefore, based these (minimal) restrictions on previous work (Gibson, Hall and Tavlas, 2016) which, among other things, found insignificant effects of the current account on sovereign ratings, and debt on sovereign spreads. Third, although it is not possible to assign causal effects to the GMM results that follow, this circumstance does *not* apply to the TVC results presented in Section 5. As explained in Swamy et al. (2016), TVCs have a clear causal interpretation.

The results of estimating this 3-equation system (using GMM) are presented in Table 3.[14] As expected, both the sovereign spreads equation and the sovereign ratings equations are directly impacted by the economic fundamentals. For sovereign spreads, the current account, fiscal news, relative prices, and real growth are significant. For sovereign ratings, government debt, fiscal news, and real growth are significant. In addition,

[14] The t-ratios are based on HAC standard errors. Notice that some of the variables in Table 3 have extremely high t-ratios (e.g., well-above 50). This result reflects the fact that the GMM minimand is extremely well-defined for our model. In other words, if the function is well-defined any movement away from the minimand causes the minimum to rise very sharply, indicating that the standard errors are very small.

political stability is significant in the spreads equation. In the bank-rating equation, the three banking-system-specific variables are each significant. Increases in loan-loss reserves to NPLs, profitability, and the net interbank position all lead to improvements in banking system ratings (a decline in the cardinal index). All three equations display strong persistence and simultaneity. Sovereign ratings help determine sovereign spreads. (Note that bank ratings do not directly impact on sovereign spreads.) Sovereign spreads and bank ratings help determine sovereign ratings. Finally, sovereign ratings and sovereign spreads help determine bank ratings.

These results provide evidence of the presence of negative feedback loops among spreads, sovereign ratings and bank ratings. Exogenous shocks to the economic, banking, and political fundamentals are propagated within the system through the interactions among the equations. To illustrate the propagation of exogenous shocks, we present the results of a simulation exercise, in which we show the impact of a permanent 1-notch downgrade to sovereign ratings, bank ratings and spreads.

The results are shown in Figures 2a to 2c. The long-run effect of the 1-notch downgrade of the sovereign rating on that same variable is a downgrade of about 2.9 notches (Figure 2a). This result reflects the impact of the initial rating downgrade on spreads, which, in turn, feeds back into sovereign ratings, and the impact of the lagged sovereign rating. The effect is nonlinear, with more than half of the total adjustment occurring in the first two years.

The propagation mechanisms present in the system imply that a shock to each fundamental determinant of spreads and/or ratings will have both impact effect (equal to $\beta_{2+k}\Delta X_{ik}$) and a long-term effect which takes the interactions into account. To assess the extent to which fundamentals affect spreads and ratings, we calculate plausible shocks to the fundamentals, based on developments during the euro-area crisis. For example, in one simulation we assume a 10 percentage points' rise in a country's debt-to-GDP ratio. By way of comparison, Greece's debt-to-GDP ratio rose by 20 percentage points in 2009, while Ireland's debt ratio rose by 12 percentage points in 2011 and again in 2012. The other shocks that we consider are: (i) a deterioration in the square of fiscal news of 10 percentage points -- that is, an unanticipated rise in the fiscal deficit of about

3 percentage points; (ii) a 2.5 percentage points widening of the current-account deficit relative to GDP; (iii) a 10 percent increase in prices relative to German prices; and (iv) a 1-percentage point reduction in real economic growth. All of the shocks are assumed to be sustained.

The results are reported in Table 4. Consider, first, the shock (of 10 percentage points) to the debt-to-GDP ratio. Initially, the shock results in a sovereign downgrade of only 0.13 of a notch. However, the effect builds over time and reaches 1.2 notches in 5 years, a considerable increase as a result of the interactions. The shock has no initial impact on spreads, but the interaction effects lead to a rise in spreads of 136 basis points after five years. The impact effect on bank ratings is also zero, but the total effect rises to almost 1 notch in the long run.

Both a deterioration in relative prices and a worsening of the current account (as a percentage of GDP) have small impact and long-run effects on both spreads and bank ratings (rises of 40 basis points and 90 basis points, respectively, for spreads, and downgrades of one-tenth of a notch in the long run for bank ratings). The impact of shocks to competitiveness on ratings is smaller than the debt-to-GDP increase. Negative fiscal news and a deterioration in growth (equivalent to an annual decline of 1 percentage point) also have small effects on spreads and ratings. In the case of growth, this suggests that most of the negative impact of a deterioration in growth comes through its effect on the debt-to-GDP ratio and the current-account-to-GDP ratio; there is no direct effect from growth. Since the figures in Table 3 examine the effect of a change in growth, holding the current-account-to-GDP ratio and the debt-to-GDP ratio constant, to calculate the full effect of growth on spreads and/or ratings, we would have to add together the direct growth effect plus the indirect effects through the growth-induced reduction in both the current-account-to-GDP ratio and the debt-to-GDP ratio.

The above effects of the exogenous macroeconomic shocks at first sight appear rather small relative to the large movement in spreads and ratings that have been observed since 2008 (see Figure 1). However, it is important to recall that euro-area countries experienced simultaneous shocks. In order to assess how much of the rise in spreads and the changes in both sovereign and credit ratings our model can explain, we undertake a second set of simulations: for each country, we examine the deterioration in the independent variables that, in fact, occurred. For competitiveness, we measure the deterioration in relative prices and the current account-to-GDP ratio over the period 2000 to 2008 (the year in which current-account deficits in most crisis countries peaked). In the case of Italy, relative prices continued to deteriorate until 2011 and so we use that year as our end-date. We employ a similar methodology for the political stability index and fiscal news. In the case of the debt-to-GDP ratio and growth, we focus on more recent developments. We use the cumulative deterioration in the debt-to-GDP ratio and growth from the beginning of 2008 until the beginning of a country's adjustment programme[15]. In the case of Italy, which was not under a programme, we focus on the period from the beginning of 2008 until the sharp rise in spreads in the summer of 2011.

This approach allows us to incorporate possible learning effects in the markets. Specifically, we do not expect rating agencies or markets to react immediately and fully to changes in economic fundamentals; therefore, we allow for lags. Such lags could result either from inertia or from the impact of nonlinearities, reflecting the idea that the deterioration in fundamentals has to cumulate significantly before rating agencies and markets will react.

The results of this exercise, along with the specific assumptions underlying the exercise are reported in Table 5. The main results are as follows.

Spreads. For Italy and Spain, the model overpredicts the rise in sovereign spreads. In the case of Italy, spreads peaked at around 500 basis points; the model predicts a long-run impact of 720 basis points. For Spain, the predicted rise in spreads is 1,450 basis points, whereas the actual peak in spreads was 550 basis points. In the cases of Ireland and Portugal, the model predictions are close to actual developments. For Ireland, spreads peaked at 1,000 basis points whereas our predicted value is 1,080 basis points. For Portugal, the corresponding figures are 1,230 basis points (actual) and 980 basis points (predicted). In the case of Greece, spreads peaked at 3,360 basis points, compared with a predicted rise of 2,190 basis points.

[15] Greece came under an adjustment programme in May 2010, Ireland in December 2010, Portugal in May 2011, and Spain in July 2012. Spain's programme applied to that country's banking sector.

Sovereign ratings. With the exception of Spain, for which the model predicts a downgrade of 8.9 notches, compared with an actual downgrade of 4 notches, the predictions of the model are close to actual developments. Here are the actual and predicted downgrades, respectively: Greece, 12.4 notches (actual) and 13 notches (predicted); Ireland, 8 notches (actual) and 7 notches (predicted); Italy, 4 notches (actual) and 4 notches (predicted); Portugal, 6.6 (actual) notches and 7 notches (predicted).

Bank ratings. With the exception of Portugal, for which the model predicts a downgrade of 4.8 notches, compared with an actual downgrade of 8 notches, the predictions of the model are again close to the actual downgrades. The predicted and actual downgrades, respectively, are as follows: Greece, 9.3 notches (actual) and 11.7 notches (predicted); Ireland 7 notches (actual) and 5.5 notches (predicted); Italy 3.1 notches (actual) and 4.3 notches (predicted); Spain, 5.5 notches (actual) and 6.8 notches (predicted).

Finally, Table 6 reports the contributions of the specific banking variables to bank ratings. We examine the impact on bank ratings of a 1 standard deviation deterioration in (i) the loan loss reserves ratio, (ii) profitability and (iii) net lending in the interbank market. Since there is considerable variation across countries, we provide results both by country and for all countries as a group. The results suggest that bank-specific fundamentals play only a small role in explaining movements in bank ratings. The largest effect comes from a decline in pre-tax operating income as a proportion of assets which in the long run is predicted to lead to a 2.5-notch downgrade on average for all countries and a 3-notch and 4-notch downgrades in the cases of Ireland and Greece, respectively.

5. Panel TVC system estimation

5.1 TVC methodology

Next, we explore the possibility of a simultaneous relationship among sovereign spreads, sovereign ratings and bank ratings within a time-varying-coefficient (TVC) framework.[16] Among the advantages of this framework compared with conventional, system approaches such as FIML or GMM, is that it eliminates the problem of some important

[16] For a textbook discussion of TVC estimation, see Asteriou and Hall (2016, Chapter 20).

variables being omitted from the system as well as dealing with the problem of a misspecified functional form and possible measurement errors. Again, our objective is to estimate a three equation simultaneous panel system for the sample of five countries (Greece, Italy, Spain, Portugal and Ireland). The application of TVC estimation to a simultaneous system is a new development as this technique has previously only been applied within the context of single-equations. While much of the technology to be used here is a straightforward extension of the single equation theory, the system setting does raise important issues of identification.

Here, we summarize the approach to TVC estimation that has been formalized in Swamy, Hall, Hondroyiannis and Tavlas (2010), and we extend it to a system context. We begin in a general way by outlining the system we are interested in analyzing. We assume that there are N endogenous variables in the system Y_i (i=1…N) and we also assume that the variables are generated by the following, true, nonlinear simultaneous system.

$$Y_i = f_i(Y, X, \vartheta, \Gamma) \tag{7}$$

where Y is the vector of N endogenous variables, X is the vector of K exogenous variables ϑ is an NxN matrix of coefficients on the simultaneous endogenous Y variables (with zeros along the main diagonal) and Γ is an KxN matrix of coefficients on the exogenous variables X, with suitable zero restrictions to ensure that the system is locally identified as discussed below.

TVC estimation proceeds from an important theorem that was first established by Swamy and Mehta (1975), and, which has subsequently been confirmed by Granger (2008). This theorem states that any nonlinear functional form can be exactly represented by a model that is linear in variables, but which has time-varying coefficients. The implication of this result is that, even if we do not know the correct functional form of a relationship, we can always represent this system as a set of TVC relationships and, thus, estimate it. Hence, any nonlinear system may be stated as;

$$y_{it} = \kappa_{i1t} y_{1t} + \kappa_{i2t} y_{2t} + \ldots + \kappa_{\mathrm{int}} y_{nt} + \gamma_{i0t} + \gamma_{i1t} x_{1t} + \ldots + \gamma_{iK-1t} x_{Kt} \tag{8}$$

Where, t=1…T, $\kappa_{iit} = 0$ and there are sufficient restrictions to either locally[17] exactly or over identify the system. Consequently, this theorem leads to the result that, if we have the complete set of relevant variables with no measurement error, then by estimating a TVC system subject to the identifying restrictions we will get consistent estimates of the true partial derivatives of each dependent variable with respect to each of the independent variables given the unknown, nonlinear functional form.

If we then allow for the fact that we do *not* know the full set of independent variables and that some, or perhaps all, of them may be measured with error, then the TVCs become biased (for the usual reasons). What we would like to have is some way to decompose the full set of biased TVCs into two parts -- the biased component and the remaining part; the latter would be a consistent estimate of the true parameter. While this is asking a great deal of an estimation technique, it is precisely what TVC estimation aims to provide (Swamy, Tavlas, Hall and Hondroyiannis, 2010). This technique builds from the Swamy and Mehta theorem, mentioned above, to produce such a decomposition[18].

Swamy, Tavlas Hall and Hondroyiannis (2010) show what happens to the TVCs as other forms of misspecification are added to the model. If we omit some relevant variables from the model, then the true TVCs get contaminated by a term that involves the relationship between the omitted and included variables. If we also allow for measurement error, then the TVCs get further contaminated by a term that allows for the relationship between the exogenous variables and the error terms. Thus, as one might expect, the estimated TVCs are no longer consistent estimates of the true partial derivatives of the nonlinear function. Instead, they are biased due to the effects of omitted variables and measurement errors. There are exact mathematical proofs provided for our statements up to this point.

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[17] We use the term 'locally' here as the issue of identification in nonlinear systems is quite complex. We will discuss this further below.

[18] Mathematically this model may appear to be a state space one. However, the interpretation of the coefficients is quite different from the standard state space representation. Omitted-variable biases, measurement-error biases and the correct functions of certain 'sufficient sets of excluded variables' are not considered parts of the coefficients of the observation equations of state-space models. This is the major difference between (1) and the observation equations of a standard state-space model.

To make TVC estimation fully operational, we need to make two key parametric assumptions; first, we assume that the time-varying coefficients themselves are determined by a set of stochastic linear equations which makes them a function of a set of variables we call driver (or coefficient-driver) variables. This is a relatively uncontroversial assumption. Second, we assume that some of these drivers are correlated with the misspecification in the model and some of them are correlated with the time-variation coming from the nonlinear (true) functional form. Having made this assumption, we can then remove the bias from the time-varying coefficients by removing the effect of the set of coefficient drivers, which are correlated with the misspecification. This procedure, then, yields a consistent set of estimates of the true partial derivatives of the unknown nonlinear function.

To formalize the idea of the coefficient drivers, we assume that each of the TVCs in (8) is generated in the following way.

Assumption 1 (Auxiliary information) *Each coefficient is linearly related to certain drivers plus a random error,*

$$\kappa_{\text{int}} = \pi_{in0} z_{it0} + \sum_{d=1}^{p-1} \pi_{ind} z_{dt} + \nu_{\text{int}} \quad (i = 1,..., N)(n = 1,..., N) \tag{9}$$

$$\gamma_{ijt} = \theta_{ij0} z_{it0} + \sum_{d=1}^{p-1} \theta_{ijd} z_{dt} + \varepsilon_{ijt} \quad (i = 1,...1N)(j = 0,1,..., K) \tag{10}$$

where the π's and θ's are fixed parameters, the z_{dt} are what we call the coefficient drivers and z_{ot} = 1; different coefficients of (9) and (10) can be functions of different sets of coefficient drivers.

The regressors and the coefficients of (9) and (10) are conditionally independent of each other given the coefficient drivers.[19] These coefficient drivers are a set of variables that, to a reasonable extent, jointly explain the movement in κ_{int} *and* γ_{ijt}.

Under our method, the coefficient drivers included in equation (9)and (10) have two uses. Insertion of equations (9) and (10) into equation (8) parameterizes the latter equation. This is the first use of the coefficient drivers. Here, the issue of identification of

[19] The distributional assumptions about the errors in (9) and (10) are given in Swamy, Tavlas, Hall and Hondroyiannis (2010).

the parameterized model (8) is important.[20] The other important use of the drivers allows us to separate the bias and bias-free components of the coefficients.

Assumption 2 *The set of coefficient drivers and the constant term in (9) and (10) divides into three different subsets* A_{1j} , A_{2j} . and A_{3j} such *that the first set is correlated with any variation in the true parameter that is due to the underlying relationship being nonlinear, the second set is correlated with bias in the parameter coming from any omitted variables, and the final set is correlated with bias coming from measurement error*

This assumption allows us to identify separately the bias-free, omitted-variables and measurement-error bias components of the coefficients of (7).

Assumption 2 is the key to making our procedure operational; it is the assumption that we can associate the various forms of specification biases with sets A_{2j} , and A_{3j} , which means that set A_{1j} simply explains the time-variation in the coefficients caused by the nonlinearity in the true functional form. If the true model is linear, then all that would be required for set A_{1j} would be to contain a constant. If the true model is nonlinear, then the bias-free components should be time-varying and the set of drivers belonging to A_{1j} will explain the time variation in these components.

It would, of course, be possible to substitute equations (9) and (10) into (8) and produce a highly non-linear set of equations with, what would look like a lot of interaction terms. In some ways this is exactly what is being done here, and one can think of the system as a translog approximation to the unknown nonlinear functional form. We could then estimate this system by FIML, GMM or nonlinear least squares (although estimation using such techniques would not deal with the simultaneity issue). However adopting this approach would not allow us to identify the bias free component, which is the ultimate aim of TVC estimation. It is only by using this structure of coefficient driver equations that we are able to identify the bias and bias free components within each coefficient.

[20] To handle this issue, we use Lehmann and Casella's (1998, pp. 24 and 57) concept of identification.

5.2 TVC estimates

The simultaneous TVC model is presented below in equations (11), (12) and (13). The model is comprised of three endogenous variables -- sovereign bond spreads, sovereign ratings, and bond ratings, with no exogenous explanatory variables. The system would, therefore, appear to be unidentified. However, we discuss the identification of this system in the Annex and we provide a proof that, in fact, it meets the sufficient condition for identification.[21]

$$S_{it} = \alpha_{0t} + \alpha_{1t} SR_{it} + \alpha_{2t} BR_{it} \tag{11}$$
$$SR_{it} = \beta_{0t} + \beta_{1t} S_{it} + \beta_{2t} BR_{it} \tag{12}$$
$$BR_{it} = \chi_{0t} + \chi_{1t} S_{it} + \chi_{2t} SR_{it} \tag{13}$$

In addition, by using different sets of drivers in each of the three sets of coefficient driver equations we generate additional over-identifying restrictions. The full, estimated coefficient driver equations are presented in Table 7. To obtain unbiased estimates of the time-varying coefficients of interest, we need to split these nine equations into two parts, one which is associated with the misspecification bias and one which gives the bias-free coefficients. The key coefficients we are interested in are the six coefficients linking the three endogenous variables to each other. We perform this split on the following basis: any terms which have been included in the driver equations in order to capture nonlinearity should be retained in the bias-free coefficients. The other terms, which capture omitted variables, should be removed. The main terms which capture nonlinearity are the lagged dependent variables; if these are significant and of the right sign, we retain these terms in the bias-free parameter specification.[22] All other terms are removed with the exception of the constant.

$$\alpha^*_{1t} = 0.06 + 0.05 S_{it-1}$$
$$\alpha^*_{2t} = 0.32$$

[21] As discussed in the Annex, this basic system will be identified as long as the information matrix is non-singular.

[22] There are several ways to achieve the split of drivers. See Hall, Swamy and Tavlas (2017, forthcoming).

$$\beta^{*}{}_{1t} = 0$$
$$\beta^{*}{}_{2t} = 0.5 + 0.2SR_{it-1}$$

$$\chi^{*}{}_{1t} = 0.3$$
$$\chi^{*}{}_{2t} = 0$$

Thus, the full system now looks as follows

$$S_{it} = \alpha^{*}{}_{1t}SR_{it} + \alpha^{*}{}_{2t}BR_{it}$$
$$SR_{it} = \beta^{*}{}_{2t}BR_{it}$$
$$BR_{it} = \chi^{*}{}_{1t}S_{it}$$

Consequently, if there is a shock to the sovereign ratings, it will lead to an increase in sovereign spreads which will, in turn, lead to an increase (*i.e.,* deterioration) in bank ratings. Bank ratings will then feed into sovereign ratings. Both of these effects will feed back into sovereign spreads, which will lead to further rises in ratings and so on. The size of these feedbacks will, of course, depend on the size of the parameters, and two of these parameters are time varying ($\alpha^{*}{}_{1t}$ *and* $\beta^{*}{}_{2t}$). In the estimation sample these parameters differ quite dramatically both over time and among countries. Figure 3[23] shows time varying coefficient $\alpha^{*}{}_{1t}$ (the effect of sovereign ratings on sovereign spreads) for each country, and Figure 4 shows the coefficient for $\beta^{*}{}_{2t}$ (the effects of bank ratings on sovereign ratings) for each country. As shown in these figures, the coefficients rose sharply over time.

We want to emphasize here exactly what we have estimated. We do not have a complete explanation of all of the determinants of our three variables and this system cannot be solved for the levels of the three variables. This observation follows because many things have been left out of the system. For example, sovereign ratings are determined by factors other than just bank ratings, so that the above equation for sovereign ratings does not provide a complete explanation of the determinants of sovereign ratings. What TVC *does* estimate is the bias-free partial derivatives which link the three variables together. That is, the coefficient, $\beta^{*}{}_{2t}$ on the bank-ratings variable in the above sovereign-ratings equation has been purged of specification errors, including

[23] It would be possible to calculate confidence intervals for these coefficients, but including the confidence intervals in these figures would make them unreadable. Given that all the estimated standard errors are very small, the confidence intervals would also be quite small.

those stemming from omitted variables, simultaneity and measurement errors. Thus, we can say something about how the system will change when it is shocked but we cannot use the system to solve or forecast the actual solution values for the three variables simply because we have estimated only a part of the unknown true system.

For any particular set of parameter values we can calculate the full multiplier effect which the system will apply to any shock. That is, if a shock of unity (*i.e.,* one-hundred basis points) hits the spread, what is the final impact to spreads once the simultaneous effects are worked through? Consider two extreme examples. First when α^*_{1t} *and* β^*_{2t} are at their minimum values, the multiplier effect is only 1.06. This was the case for the period before the 2008 global financial crises. During the euro-area crises (*i.e.,* beginning in 2010) the parameters increased substantially; a typical (although not the maximum) figure during the crises would have given a multiplier of around 5. Thus, if spreads increased by one percentage point, the final effect after the feedbacks would have been an increase of 5 percentage points for Greece, the most affected country. Figure 5 shows a time series of the TVC multiplier for each country.

Figure 5 shows the total multiplier effect of the system at each point in time and for each country. This effect varies over time and among countries because the two parameters, α_{1t}^* *and* β_{2t}^* are varying, and, in particular, they vary with the lagged spread and the lagged sovereign rating for each country. The effect in Greece is much larger than that for the other countries because the levels of both spreads and ratings are much higher in the case of Greece than for other countries. This result illustrates that, while this is still a panel estimation technique, we are not imposing the same time-varying parameters for each country, but rather that the parameters in the coefficient driver equations are the same, which allows the time-varying parameters to vary across countries.[24]

[24] In a conventional panel estimation, all of the coefficients are the same across the panel. In a TVC panel, what is common are the coefficients in the coefficient-driver equations (equations (9) and (10) above). However, because there are different variables for each country in the coefficient-driver equation, the time-varying coefficients themselves are different for each country.

6. Comparison of the GMM and TVC procedure and results

The two techniques we have employed allow us to have quite different views of the transmission process of shocks. Broadly, the advantages and disadvantages of each technique are as follows

GMM. The advantage of the GMM technique is that it allows a detailed analysis of the dynamic process of adjustment as well as providing a quantitative assessment of each different type of shock. Its disadvantages are that it may not use all the correct fundamental variables (potential omitted variables). Also, it assumes the effects are constant through time. We know that the model is not very stable if estimated over sub-periods. The choice of instruments is highly judgemental and will affect the results. Finally, GMM imposes the same coefficients on all the countries (the pooling assumption).

TVC: A major advantage of TVC is that it is robust to omitted variables, measurement errors and incorrect functional forms. As mentioned in the previous section, TVC estimation provides coefficients that have a causal interpretation (Swamy et al., 2016). It also gives us effects which vary both across countries and time. A TVC version of our detailed GMM model would involve a very large number of time-varying coefficients, and the estimation approach would become very difficult to manage.

By using both techniques, we gain important insights which are compatible. As shown in Figure 2 the broad multiplier effect of a shock caused by the interaction effects of the model is around six-fold. That is, an initial shock is expended by six times its initial value by the interaction. This of course is essentially an average effect for all periods and for all countries. Since GMM estimates the average effect over the sample, it does not allow for a possible “wake-up” effect at the start of the crisis. The TVC approach, in contrast, does allow for this effect; our TVC results indicate that there is both a “wake-up” effect and a strong simultaneous multiplier effect. In Figure 4 we get a much more sophisticated analysis from the TVC model than is possible from the GMM results; the effect of the total multiplier ranges from almost zero before the crises to a peak value of just under nine-fold at the height of the crises for Greece, the most affected country.

Thus, we can see from this analysis that the feedback effect has been very different both across countries and time periods. Before the onset of the financial crises the feedback effects were virtually zero for all countries. Once the crises began, the feedback effects rose sharply as the crises developed. The feedback effects also varied across countries. The GMM model suggests that the half-life of the full effect was around 2.5 years.

7. *Conclusions*

This paper has examined the interactions among sovereign spreads, sovereign ratings and bank ratings, while controlling for economic fundamentals and political stability which also influence spreads. Our aim was to examine whether there was any support for the widely-held view that the current euro area crisis has been characterised by interactions between sovereign spreads and credit ratings of the sovereign and banks which led to self-generating feedback loops.

To this end we have adopted two approaches; we estimated a simultaneous three-equation model and we adapted a TVC technique to investigate these interactions. Using a panel of 5 euro-area countries, those more likely to be affected by the feedback loops, we found that, controlling for the economic and political fundamentals, spreads and ratings strongly interacted with each other during the crisis. The effects produced go well-beyond those of the fundamentals and the dynamics demonstrate high levels of persistence.

Simulations suggest that the GMM system of equations can explain movements in spreads and ratings better than focusing purely on fundamentals. They also suggest that spreads in Spain and Italy rose by less than would have been predicted by the model, whereas those in Portugal, and especially in Greece, rose by more than predicted by the model. Similarly, downgrades were more prevalent in Greece and Portugal than would have been predicted by the model, whereas in Spain they were less so. The TVC results suggest that these effects have varied considerably both over time and among countries. Taken together, the results provide support for the view that interactions among sovereign spreads, sovereign ratings, and bank ratings in the case of Greece were exceptional, relative to other euro-area countries.

Annex 1: data sources

Spreads: yield on country's 10-year bond minus yield on 10-year Bunds (in percentage points). Source: ECB, Statistical Data Warehouse.

Ratings: sovereign ratings were sourced from Standard and Poor's, Fitch and Moody's. Bank ratings were provided by the ECB. See Table 2 for numerical representation of each rating.

Macroeconomic variables: Real GDP growth (proportion), HICPs (logarithm of HICP of country x minus logarithm of HICP in Germany), current account (proportion) and government debt (percentage) were taken from Thomson Reuters datastream. The data for fiscal news (percentage points) uses the European Commission Spring and Autumn forecasts published in *European Economy*.

Political stability (index 1-10): IFO World Economic Survey Index. Source: Thomson Reuters Datastream.

Individual bank data: the interbank ratio (percentage), the ratios of loan loss reserves to non-performing loans (percentage) and pre-tax operating income to average total assets (percentage) were taken from Bankscope.

Data: descriptive statistics						
		Spain	Greece	Ireland	Italy	Portugal
Sovereign spreads	Mean	0.92	4.05	1.06	0.96	1.81
	Standard deviation	1.35	7.03	2.50	1.20	2.98
Sovereign ratings	Mean	2.70	8.43	2.67	4.66	5.04
	Standard deviation	2.52	4.30	2.75	1.59	3.15
Bank ratings	Mean	4.24	9.49	6.17	5.05	6.61
	Standard deviation	1.61	3.71	2.36	1.16	2.60
Current account to GDP	Mean	-0.05	-0.08	-0.01	-0.01	-0.09
	Standard deviation	0.03	0.06	0.01	0.02	0.03
Cumulative fiscal news	Mean	31.27	-51.90	-117.64	94.05	-119.18
	Standard deviation	101.24	203.10	317.15	53.19	165.30
Debt to GDP	Mean	55.42	120.54	55.00	113.14	76.56
	Standard deviation	15.34	23.94	34.10	8.16	24.28
Relative prices	Mean	-0.01	-0.004	-0.04	-0.01	-0.02
	Standard deviation	0.05	0.07	0.05	0.03	0.04

GDP growth (monthly)	Mean	0.002	0.001	0.003	0.0003	0.001
	Standard deviation	0.002	0.006	0.009	0.003	0.004
Political stability	Mean	6.60	6.99	7.44	4.28	6.58
	Standard deviation	0.96	1.99	0.81	1.24	1.32
Loan loss reserves to NPLs	Mean	129.93	54.71	73.16	57.61	130.22
	Standard deviation	56.40	14.33	23.84	6.86	21.32
Profits to total assets	Mean	1.04	0.72	0.08	0.54	0.56
	Standard deviation	0.27	1.21	1.50	0.51	0.55
Interbank ratio	Mean	60.91	72.46	39.97	60.04	69.90
	Standard deviation	22.84	36.68	12.26	8.40	17.09
Data sources: see above						

Annex 2: Identification of the TVC Structure

Identification in the case of linear systems is well understood and stems from the seminal work of Koopmans, Rubin and Leipnik (1950), this work generated the well-known rank and order conditions for identification. Equations (7) however is a nonlinear system and there is quite a long, although sparse, literature on the identification issue in the case of nonlinear systems, this goes back to the pioneering work of Wald (1950) and Fisher (1959, 1961, 1965, 1966). However as Kelejian (1969) points out, Fishers work is both complex to implement and lacks an intuitive appeal. Kelejian (1969) then goes on to show how the nonlinear system discussed by Fisher can be cast into a particular linearized form which allows a standard rank and order condition to be applied to asses identification of the original structure in the usual way. Perhaps the most important contribution in this area is Rothenberg (1971) who gives precise definitions of observational equivalence (when a model is not identified) and identification when there is no other observationally equivalent model and thus the model is identified. Rothenberg then goes on to point out a number of problems with non-linear systems which makes it difficult to assess global identification. Nonlinear systems may not have a unique solution and even more importantly for certain values of the variable space derivatives may go to zero and hence identification may hold for some values of the variables but not others. He therefore defines the notion of locally identifiable as a point in the parameter space where there exists an open neighborhood around that point which does not contain any other point which is observationally equivalent. He then proves the following theorem (Rothenberg, 1971, p.579) where α is the set of parameters of interest and $R(\alpha)$ is the information matrix

α^0 is locally identifiable if and only if $R(\alpha^0)$ is non singular

This should not be surprising, the information matrix is essentially telling us how well determined the parameters of the model are, it is one of the standard measures of the covariance matrix of the parameters. If this matrix becomes singular then some of the parameters cannot be uniquely determined and so the model is not locally identified.

Rothenberg then goes on to discuss how local identification can be achieved in an analogous way to the standard case, by imposing a set of constraints on the general parameter space. This gives rise to a condition which is a generalization of the standard Rank condition. So intuitively we have a broadly similar case to the standard one. If a general model is not locally identified, identification may be achieved by imposing a suitable set of restrictions on the parameters of the model. This is a straightforward generalization of the exclusion restrictions usually used. Chesher (2003) subsequently showed that there was also an equivalent of the order condition for local identifiability for nonlinear systems.

We have assumed above that (7) is locally identified. (8) however is a linear representation of (7) with time varying parameters. Identification must hold in this system at each point in time and the information matrix must be non-singular.

However (8) is not the model we generally estimate as we do not generally know all the exogenous variables. Once we recognized that the estimated model will contain omitted variables it may no longer be possible to identify the structure simply through exclusion restrictions. To take an extreme case, suppose we estimate the following system.

$$y_{it\hbar} = \gamma_{it\hbar 0} + \sum_{\omega \neq \hbar} y_{it\omega}\gamma_{it\hbar\omega} \quad (\hbar = 1, \ldots, n) \tag{A1}$$

Within the TVC framework this structure can be identified through the coefficient drivers.

Inserting (10) into (A1) gives $(\mathrm{i}=1,\ldots\mathrm{N};\mathrm{t}=1,\ldots,\mathrm{T}), (\omega \neq \hbar = 1,\ldots,\mathrm{n})$

$$y_{it\hbar} = \theta_{\hbar 00}z_{it0} + \sum_{d=1}^{p-1}\theta_{\hbar 0d}z_{itd} + \varepsilon_{it\hbar 0} + \sum_{\omega \neq \hbar = 1}^{n}(\theta_{\hbar\omega 0}z_{it0} + \sum_{d=1}^{p-1}\theta_{\hbar\omega d}z_{itd} + \varepsilon_{it\hbar\omega})y_{it\omega}$$

$$= \boldsymbol{y}_{it}'\Theta_{\hbar}\boldsymbol{z}_{it} + \boldsymbol{y}_{it}'\boldsymbol{\varepsilon}_{it\hbar} \tag{A2}$$

where $\boldsymbol{y}_{it}' = (1, y_{it1}, \ldots, y_{it\hbar\,\hbar-1}, y_{it\hbar\,\hbar+1}, \ldots, y_{it\hbar\,n})$ is the $1 \times \mathrm{n}$ vector, $\Theta_{\hbar}$ is the $\mathrm{n} \times \mathrm{p}$ matrix having the θ's as its elements, $\boldsymbol{z}_{it} = (1, z_{it1}, \ldots, z_{it,p-1})'$ is the $\mathrm{p} \times 1$ vector, and $\boldsymbol{\varepsilon}_{it\hbar}$ =

$(\varepsilon_{it\hbar 0}, \varepsilon_{it\hbar 1}, \ldots, \varepsilon_{it\hbar,\hbar-1}, \varepsilon_{it\hbar,\hbar+1}, \ldots, \varepsilon_{it\hbar,n})'$ is the $n \times 1$ vector. It should be noted that the sources of these errors are not the y's but the $\gamma's$.

Assumption 2 For all *i,t* and $\hbar$, let g($\boldsymbol{y_{it}}$, $\boldsymbol{z_{it}}$) be a Borel function of $\boldsymbol{y_{it}}$ and $\boldsymbol{z_{it}}$ and E| $y_{it\hbar}$ | < ∞, E| $y_{it\hbar}$ g($\boldsymbol{y_{it}}$, $\boldsymbol{z_{it}}$)| < ∞.

Under Assumption 2, E($y_{it\hbar}$ | $\boldsymbol{y_{it}}$, $\boldsymbol{z_{it}}$) = $\boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}}$ (see Rao 1973, p. 97).

Assumption 3 For all $i = 1,\ldots,N$; $t = 1,\ldots,T$, $\hbar = 1,\ldots,n$, given $\boldsymbol{y_{it}}$ and $\boldsymbol{z_{it}}$, $y_{it\hbar}$ is conditionally, normally distributed with mean $\boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}}$ and variance $\sigma^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}$.

The log likelihood function for model (A2) is

$$\ln L = \sum_{i=1}^{N}\sum_{t=1}^{T}[-ln(\sigma_{\hbar\varepsilon}\sqrt{2\pi \boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}) - \frac{1}{2\sigma^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}(y_{it\hbar} - \boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}})^2] \tag{A3}$$

$$\frac{\partial \ln L}{\partial \boldsymbol{\theta}^{Long}} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{\boldsymbol{\sigma}^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\boldsymbol{\Delta}_{\hbar\varepsilon}\boldsymbol{y_{it}}}(y_{it\hbar} - \boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}})(\boldsymbol{z_{it}} \otimes \boldsymbol{y_{it}}) \tag{A4}$$

where $\boldsymbol{\theta}_\hbar^{Long}$ is the column stack of $\Theta_\hbar$ and $\otimes$ is a Kronecker product.

$$\frac{\partial^2 \ln L}{\partial \boldsymbol{\theta}^{Long}\partial(\boldsymbol{\theta}^{Long})'} = \sum_{i=1}^{N}\sum_{t=1}^{T} - \frac{1}{\sigma^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}(\boldsymbol{z_{it}}\boldsymbol{z_{it}'} \otimes \boldsymbol{y_{it}}\boldsymbol{y_{it}'}) \tag{A5}$$

$$-E\frac{\partial^2 \ln L}{\partial \boldsymbol{\theta}^{Long}\partial(\boldsymbol{\theta}^{Long})'} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{\sigma^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}(\boldsymbol{z_{it}}\boldsymbol{z_{it}'} \otimes \boldsymbol{y_{it}}\boldsymbol{y_{it}'}) \tag{A6}$$

$$\frac{\partial \ln L}{\partial \sigma^2_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[-\frac{1}{2\sigma^2_{\hbar\varepsilon}} + \frac{1}{2\sigma^4_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}(y_{it\hbar} - \boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}})^2] \tag{A7}$$

$$\frac{\partial^2 \ln L}{\partial \sigma^2_{\hbar\varepsilon}\partial \sigma^2_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{1}{2\sigma^4_{\hbar\varepsilon}} - \frac{1}{\sigma^6_{\hbar\varepsilon}\boldsymbol{y_{it}'}\boldsymbol{\Delta}_{\hbar\varepsilon}\boldsymbol{y_{it}}}(\mathbf{y}_{it\hbar} - \boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}})^2] \tag{A8}$$

$$-E\frac{\partial^2 \ln L}{\partial \sigma^2_{\hbar\varepsilon}\partial \sigma^2_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{2\sigma^4_{\hbar\varepsilon}} \tag{A9}$$

$$\ln L = \sum_{i=1}^{N}\sum_{t=1}^{T}[-ln(\sigma_{\hbar\varepsilon}\sqrt{2\pi \boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}) - \frac{1}{2\sigma^2_{\hbar\varepsilon}\boldsymbol{y_{it}'}\Delta_{\hbar\varepsilon}\boldsymbol{y_{it}}}(y_{it\hbar} - \boldsymbol{y_{it}'}\Theta_\hbar \boldsymbol{z_{it}})^2]$$

Let $\delta_{\hbar\varepsilon}$ be the column stack of $\Delta_{\hbar\varepsilon}$. To exploit the symmetry property of $\Delta_{\hbar\varepsilon}$, we add together the two elements of $(\boldsymbol{y_{it}'} \otimes \boldsymbol{y_{it}'})$ corresponding to the (*j*, j') and (j', *j*) elements of $\Delta_{\hbar\varepsilon}$ in $\delta_{\hbar\varepsilon}$ and eliminate the (j', *j*) element of $\Delta_{\hbar\varepsilon}$ from $\boldsymbol{\delta_\varepsilon}$ for *j* , j' = 0, 1, …, n. These operations change the $(1 \times n^2)$ vector $(\boldsymbol{y_{it}'} \otimes \boldsymbol{y_{it}'})$ to the (1 × n(n+1)/2) vector, denoted by ($\overline{y'_{it} \otimes y'_{it}}$), and change the $(n^2 \times 1)$ vector $\boldsymbol{\delta}_{\hbar\varepsilon}$ to the [n(n+1)/2] $\times 1$ vector, denoted by $\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}$. These new notations change the log likelihood function to

$$\ln L = \sum_{i=1}^{N}\sum_{t=1}^{T}[-ln(\sigma_{\hbar\varepsilon}\sqrt{2\pi(\overline{y'_{it} \otimes y'_{it}})\bar{\delta}_{\hbar\varepsilon}}) - \frac{1}{2\sigma^2_{\hbar\varepsilon}(\overline{y'_{it} \otimes y'_{it}})\bar{\delta}_{\hbar\varepsilon})}(y_{it\hbar} - y'_{it}\Theta_{\hbar}z_{it})^2]$$

$$\frac{\partial \ln L}{\partial \bar{\boldsymbol{\delta}}_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[-\frac{(\overline{y_{it} \otimes y_{it}})}{2(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}} + \frac{(\overline{y_{it} \otimes y_{it}})}{2\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}^2}(y_{it\hbar} - y'_{it}\Theta_{\hbar}z_{it})^2] \qquad \text{(A10)}$$

$$\frac{\partial^2 \ln L}{\partial \bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\partial \bar{\boldsymbol{\delta}}'_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{(\overline{y_{it} \otimes y_{it}})(\overline{y'_{it} \otimes y'_{it}})}{2\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}^2} - \frac{(\overline{y_{it} \otimes y_{it}})(\overline{y'_{it} \otimes y'_{it}})}{\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}^3}(y_{it\hbar} - y'_{it}\Theta_{\hbar}z_{it})^2] \qquad \text{(A11)}$$

$$-E\frac{\partial^2 \ln L}{\partial \bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\partial \bar{\boldsymbol{\delta}}'_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{(\overline{y_{it} \otimes y_{it}})(\overline{y'_{it} \otimes y'_{it}})}{2\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}^2} \qquad \text{(A12)}$$

$$-E\frac{\partial^2 \ln L}{\partial \boldsymbol{\theta}^{Long}\partial \boldsymbol{\sigma}^2_{\hbar\varepsilon}} = 0 \qquad \text{(A13)}$$

$$-E\frac{\partial^2 \ln L}{\partial \boldsymbol{\theta}^{Long}\partial \bar{\boldsymbol{\delta}}_{\hbar\varepsilon}} = 0 \qquad \text{(A14)}$$

$$-E\frac{\partial^2 \ln L}{\partial \boldsymbol{\sigma}^2_{\hbar\varepsilon}\partial \bar{\boldsymbol{\delta}}'_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{(\overline{y'_{it} \otimes y'_{it}})}{2\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}}] \qquad \text{(A15)}$$

$$-E\frac{\partial^2 \ln L}{\partial \bar{\boldsymbol{\delta}}\ \partial \boldsymbol{\sigma}^2_{\hbar\varepsilon}} = \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{(\overline{y_{it} \otimes y_{it}})}{2\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}}] \qquad \text{(A16)}$$

$$\text{Inf} = \begin{matrix} \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{\sigma^2_{\hbar\varepsilon}y'_{it}\Delta_{\hbar\varepsilon}y_{it}}(z_{it}z'_{it} \otimes y_{it}y'_{it}) & 0 & 0 \\ 0 & \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{2\sigma^4_{\hbar\varepsilon}} & \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{(\overline{y'_{it} \otimes y'_{it}})}{2\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}}] \\ 0 & \sum_{i=1}^{N}\sum_{t=1}^{T}[\frac{(\overline{y_{it} \otimes y_{it}})}{2\boldsymbol{\sigma}^2_{\hbar\varepsilon}\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}}] & \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{(\overline{y_{it} \otimes y_{it}})(\overline{y'_{it} \otimes y'_{it}})}{2\{(\overline{y'_{it} \otimes y'_{it}})\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}\}^2} \end{matrix} \qquad \text{(A17)}$$

A necessary condition for the identifiability of the parameter $\sigma^2_{\hbar\varepsilon}$ and the parameter vectors $\boldsymbol{\theta}^{Long}_{\hbar}$, and $\bar{\boldsymbol{\delta}}_{\hbar\varepsilon}$ is that the information (Inf) matrix in (A17) is positive definite. It can be seen that this matrix is symmetric and its diagonal elements are all in the form of the squares of variables. Therefore, the diagonal elements of (A17) are all positive and there are no visible dependencies in the columns of (A17). Given the data on $y_{it\hbar}$, $\boldsymbol{y}_{\boldsymbol{it}}$, and $\boldsymbol{z}_{it}$, the positive definiteness of (A17) can be numerically verified at the solutions of the likelihood equations based on (A4), (A7), and (A10). If these likelihood equations have multiple roots, then it is not easy to identify a consistent root (see Lehmann and Casella 1998, p. 453). In these cases, it is convenient to use an iteratively rescaled generalized least squares method to estimate the parameters of model (A9).

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Table 1: ***Granger causality among the dependent variables in the system***	
Hypothesis	*P-value*
Sovereign ratings do not cause sovereign spreads	0.000
Bank ratings do not cause sovereign spreads	0.000
Sovereign spreads do not cause sovereign ratings	0.000
Bank ratings do not cause sovereign ratings	0.003
Sovereign spreads do not cause bank ratings	0.200
Sovereign ratings do not cause bank ratings	0.000

Sample period: 1998M1 to 2013M3. The *p-values* indicate that the hypothesis can be rejected at the x per cent level (where x is the p-value).
Source: Own calculations. See text and annex 1 for data description.

Table 2: S&P, Moody's and Fitch ratings

Interpretation	Moody's	Fitch/Standard and Poor's	Numerical representation in the paper
INVESTMENT - GRADE RATINGS			
Highest credit quality – Lowest expectation of default – exceptionally strong capacity for payment	Aaa	AAA	1
Very high credit quality – Very low default risk – Very strong capacity to meet financial commitments	Aa1	AA+	2
	Aa2	AA	3
	Aa3	AA-	4
High credit quality – Low default risk -Strong payment capacity	A1	A+	5
	A2	A	6
	A3	A-	7
Good credit quality – Expectations of default risk are currently low - Adequate payment capacity but subject to business or economic conditions	Baa1	BBB+	8
	Baa2	BBB	9
	Baa3	BBB-	10
SPECULATIVE - GRADE RATINGS			
Speculative - Elevated vulnerability to default risk - Likely to fulfill obligations, ongoing uncertainty	Ba1	BB+	11
	Ba2	BB	12
	Ba3	BB-	13
Material default risk present, but a limited margin of safety remains – High-risk obligations	B1	B+	14
	B2	B	15
	B3	B-	16
Substantial Credit Risk – Default is a real possibility	Caa1	CCC+	17
	Caa2	CCC	18
	Caa3	CCC-	19
Very high levels of credit risk – Default appears probable	Ca	CC	20
Exceptionally high levels of credit risk – default is imminent or inevitable, or the issuer is at a standstill	C	C	21
Issuer has experienced an uncured payment default on any material financial obligation but is has not entered into bankruptcy filings, administration, liquidation or any other formal winding-up procedure		SD/RD	22
Default - Issuer has entered into bankruptcy filings, administration, liquidation or any other formal winding-up procedure		D	23

Table 3: System estimation: the determinants of sovereign spreads, sovereign ratings and banking system ratings.

GMM estimation
Observations: 1630 **Sample: 1998(11)-2013(3)**

		Coefficient	Std. Error	t-Statistic	Prob.
Constant – GR	SPREADS EQUATION	-0.85	0.01	-59.6	0.0
Current account to GDP		-0.02	0.0005	-42.0	0.0
Relative prices		0.24	0.05	4.9	0.0
Cumulative fiscal news		-0.003	9E-05	-34.8	0.0
Growth		-2.04	0.38	-5.3	0.0
Political stability		-0.003	0.001	-2.9	0.003
Spreads (t-1)		0.89	0.001	645.2	0.0
Sovereign rating		0.12	0.001	77.3	0.0
Constant – GR	SOVEREIGN RATING EQUATION	-0.52	0.01	-48.4	0.0
Debt to GDP		0.01	0.0001	79.3	0.0
Cumulative fiscal news		-0.001	3.5E-05	-33.6	0.0
Growth		-6.2	0.28	-21.5	0.0
Sovereign rating (t-1)		0.7	0.002	359.9	0.0
Spreads		0.064	0.0006	97.4	0.0
Banks rating		0.07	0.001	59.2	0.0
Constant – GR	BANKS RATING EQUATION	0.33	0.01	25.1	0.0
Spreads		0.004	0.0009	4.9	0.0
Sovereign rating		0.02	0.001	18.8	0.0
Loan-loss reserves/NPLs		-0.0004	2.2E-05	-19.5	0.0
Profits/total assets		-0.06	0.002	-26.0	0.0
Interbank position		-0.0008	5.7E-05	-14.4	0.0
Banks rating(t-1)		0.96	0.001	699.8	0.0
Constant – PT – spread eq.		-0.6	0.01	-57.8	0.0
Constant – PT – sovereign rating eq.		-0.34	0.006	-50.6	0.0
Constant – PT – banks rating eq.		0.3	0.01	25.3	0.0
Constant – SP – spread eq.		-0.3	0.009	-32.8	0.0
Constant – SP – sovereign rating eq.		-0.6	0.007	-82.4	0.0
Constant – SP – banks rating eq.		0.3	0.01	32.6	0.0
Constant – IT – spread eq.		-0.4	0.008	-59.1	0.0
Constant – IT – sovereign rating eq.		-0.8	0.01	-62.5	0.0
Constant – IT – banks rating eq.		0.2	0.008	24.2	0.0
Constant – IR – spread eq.		-0.2	0.004	-35.6	0.0
Constant – IR – sovereign rating eq.		-0.5	0.008	-66.5	0.0
Constant – IR – banks rating eq.		0.28	0.008	31.4	0.0
Determinant residual covariance			5.72E-19		
J-statistic			0.2		

Source: own calculations. See main text and Annex 1 for data description.

Table 4: The impact of changes in economic fundamentals: some simulation results

	Impact on sovereign ratings (notches)*		Impact on spreads (basis points)		Impact on banks ratings (notches)*	
Exogenous shock	Impact effect	Long-run effect	Impact effect	Long-run effect	Impact effect	Long-run effect
10pp increase in debt-to-GDP ratio	0.13	1.2	0	136	0	0.85
Deterioration in the square of cumulative fiscal news of 10 points	0.1	0.32	0.02	37	0	0.24
2.5pp deterioration in the current account to GDP ratio	0	0.34	5.7	90	0	0.28
10% increase in prices relative to Germany	0	0.14	2	38	0	0.12
1pp lower growth (per annum)	0.005	0.06	0.02	4	0	0.85

* a positive number implies a deterioration

Source: own calculations. See main text and Annex 1 for data description.

Table 5: Simulation results a simultaneous deterioration in the exogenous determinants of spreads and ratings

	Impact on sovereign ratings (notches)*			Impact on spreads (basis points)			Impact on banks ratings (notches)*		
	Impact effect	Long-run effect	Actual change	Impact effect	Long-run effect	Actual change	Impact effect	Long-run effect	Actual change
Greece	0.78	12.4	13	99	2190	3363	0.02	9.3	11.7
Ireland	0.7	8.0	7	30	1080	994	0.02	5.7	7
Italy	0.3	4.0	4	34	720	491	0.01	3.1	4.3
Portugal	0.57	6.6	7	33	973	1232	0.02	4.8	8
Spain	1.0	8.9	4	74	1450	555	0.03	6.8	5.5

Assumptions regarding the simultaneous exogenous shocks:	
(i) Greece	
Current account to GDP	10pp deterioration
Relative prices	17% deterioration
Debt to GDP	37pp deterioration
Cumulative fiscal news	11.3pp deterioration
Political stability	6 point deterioration
Growth	actual growth 2009-2010
(ii) Ireland	
Current account to GDP	6pp deterioration
Relative prices	14% deterioration
Debt to GDP	52pp deterioration
Cumulative fiscal news	11.3pp deterioration
Political stability	3 point deterioration
Growth	Actual growth 2008-2010
(iii) Italy	
Current account to GDP	6pp deterioration
Relative prices	7% deterioration
Debt to GDP	15pp deterioration
Cumulative fiscal news	4.5pp deterioration
Political stability	3 point deterioration
Growth	actual growth 2008-2010
(iv) Portugal	
Current account to GDP	2pp deterioration
Relative prices	8% deterioration
Debt to GDP	37pp deterioration
Cumulative fiscal news	5.7pp deterioration
Political stability	no change

Growth	actual growth 2009-2010
(v) Spain	
Current account to GDP	6.5pp deterioration
Relative prices	19.5% deterioration
Debt to GDP	39pp deterioration
Cumulative fiscal news	7.5pp deterioration
Political stability	2.5 point deterioration
Growth	actual growth 2009-2012
Source: own calculations. See main text and Annex 1 for data description.	

Table 6: The impact of a deterioration in banking fundamentals on bank ratings (notches)

		Spain	Portugal	Italy	Ireland	Greece	All countries
Loan loss reserves/NPLs	Impact	0.03	0.02	0.002	0.005	0.006	0.02
	Long-term	1.04	0.85	0.08	2.1	0.25	0.86
Pre-tax operating income/total assets	Impact	0.04	0.04	0.03	0.08	0.11	0.07
	Long-term	1.48	1.43	0.97	3.16	4.05	2.5
Interbank ratio	Impact	0.02	0.02	0.02	0.008	0.04	0.03
	Long-term	0.82	0.58	0.56	0.34	1.43	1.0

Source: own calculations. See main text and Annex 1 for data description.

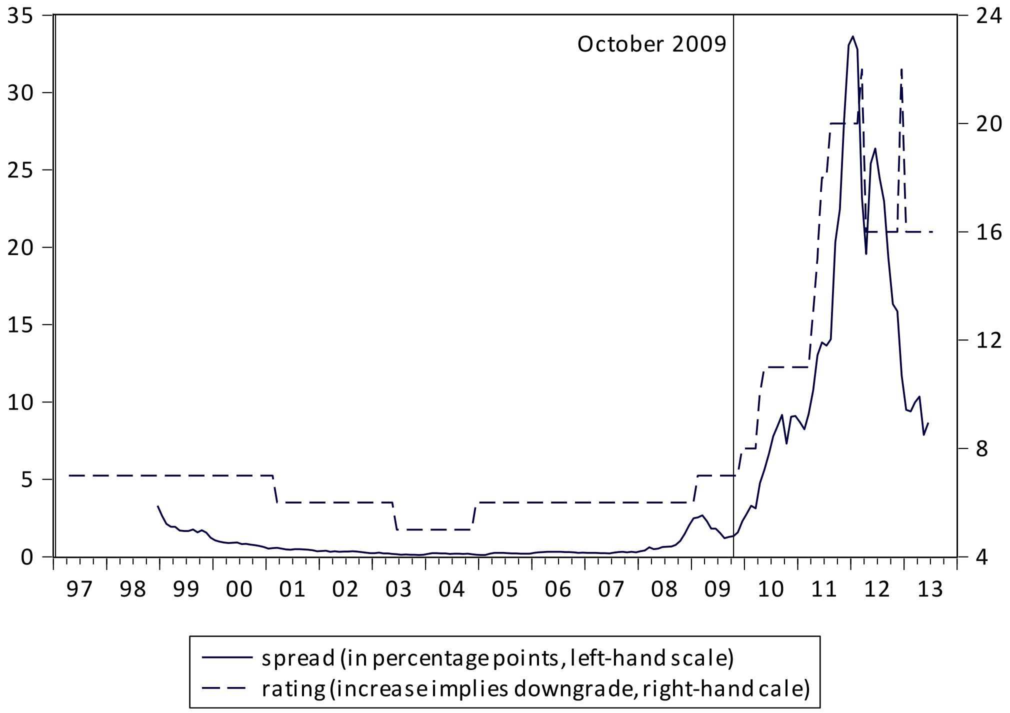
Table 7: TVC System Estimates: Coefficient Driver Equations

		Coefficients		
		α_{0t}	α_{1t}	α_{2t}
Constant	Spreads Equation	-1.5 (-6.8)	0.06 (2.0)	0.32 (6.9)
Current account to GDP		-0.08 (-3.2)	-0.002 (0.4)	0.08 (2.8)
Relative prices		-12.8 (-4.6)	0.21 (0.4)	2.3 (3.3)
Cumulative fiscal news		-0.02 (-9.1)	-0.0002 (-0.5)	0.002 (3.7)
Growth		-32.0 (-1.3)	-6.2 (-1.6)	5.50 (0.9)
Spreads (t-1)			0.05 (48.3)	
		β_{0t}	β_{1t}	β_{2t}
Constant	Sovereign Ratings Equation	-2.4 (12.5)	-0.004 (-0.07)	0.50 (11.8)
Debt to GDP		0.07 (34.6)	0.009 (11.6)	-0.02 (-30.8)
Cumulative fiscal news		0.08 (2.6)	-0.0002 (-1.8)	-0.0006 (-4.1)
Growth		1.40 (0.2)	-0.80 (-0.5)	-0.80 (-0.7)
Sovereign rating (t-1)			-0.14 (-31.0)	0.20 (94.8)
		x_{0t}	x_{1t}	x_{2t}
Constant	Bank Ratings Equation	0.05 (3.3)	0.30 (3.4)	-0.07 (-1.9)
Loan/loss reserves/NPLs		0.0002 (0.6)	-0.001 (-1.9)	0.000006 (0.4)
Profit/total assets		-0.08 (-2.2)	0.21 (0.4)	0.03 (2.5)
Intrabank position		-0.002 (-3.6)	-0.02 (-0.9)	0.0008 (4.0)
Bank ratings (t-1)		0.90 (40.0)	-0.008 (-0.8)	-0.003 (9.4)
Sovereign spreads				0.005 (1.1)
Sovereign ratings				0.003 (1.1)

t-statistics are in parentheses

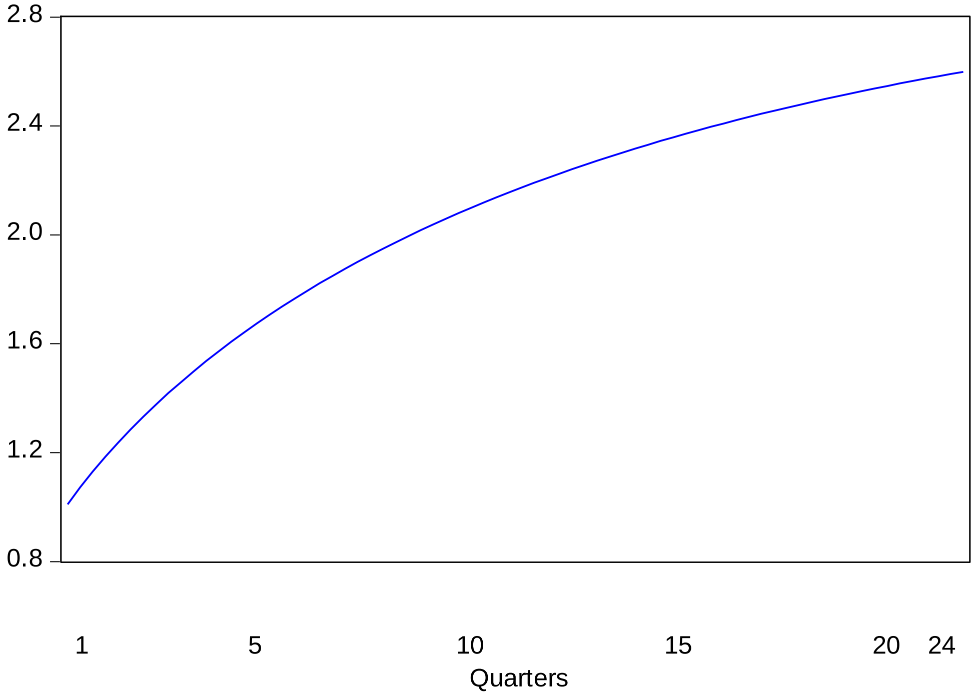
Source: own calculations. See main text and Annex 1 for data description.

Figure 1: Spreads and ratings in Greece



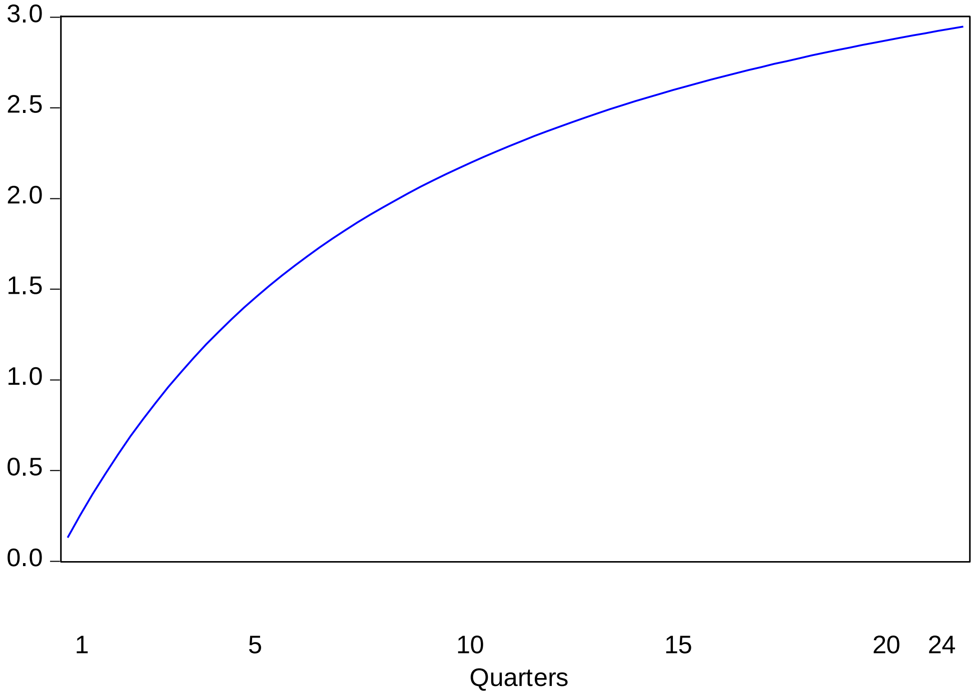
Note: Ratings have been transformed into a numerical series running from 1, equivalent to AAA, through to 22, which is selected default (see Table 2).
Source: ECB Statistical Data Warehouse

Figure 2a: The response of sovereign ratings to a 1-notch permanent downgrade of the sovereign (in notches)



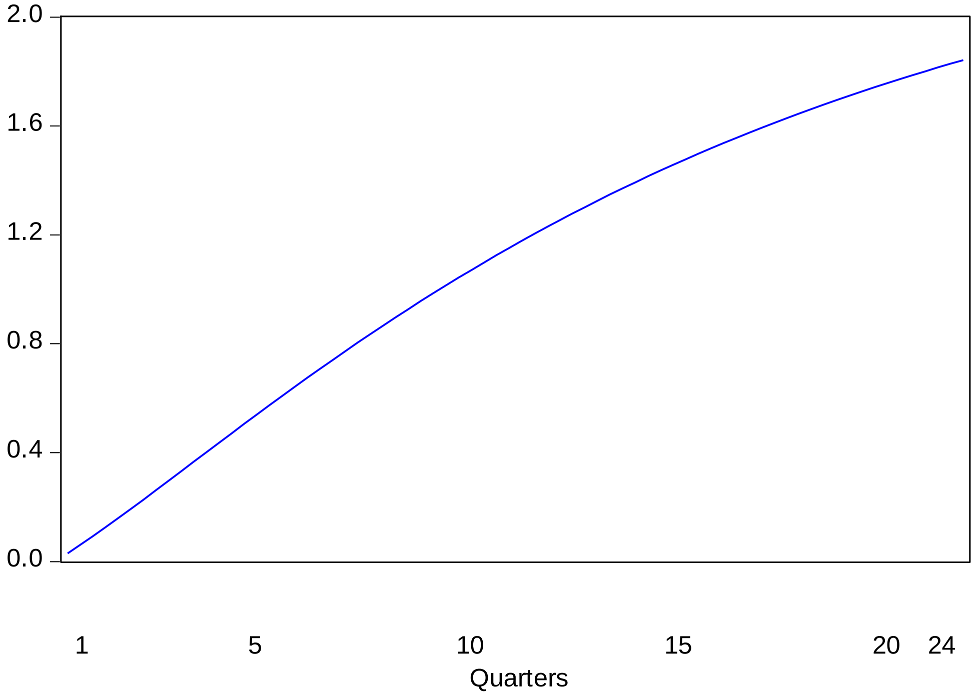
Source: own calculations from results in Table 3

Figure 2b: The response of spreads to a 1-notch permanent downgrade of the sovereign (in notches)



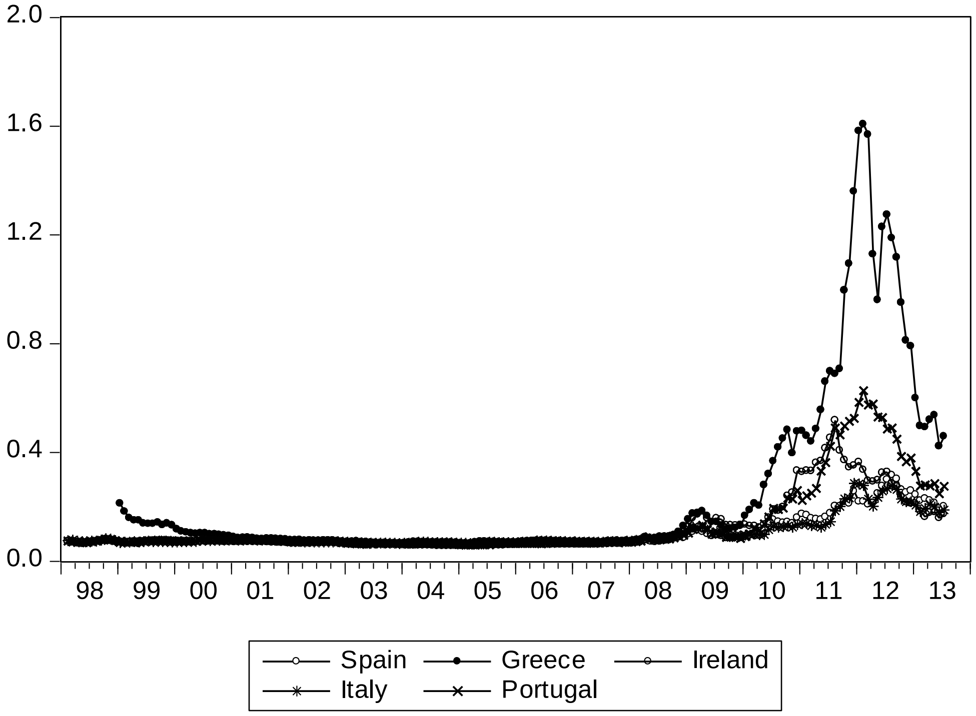
Source: own calculations from results in Table 3

Figure 2c: The response of banking system ratings to a 1-notch downgrade in sovereign ratings (in notches)



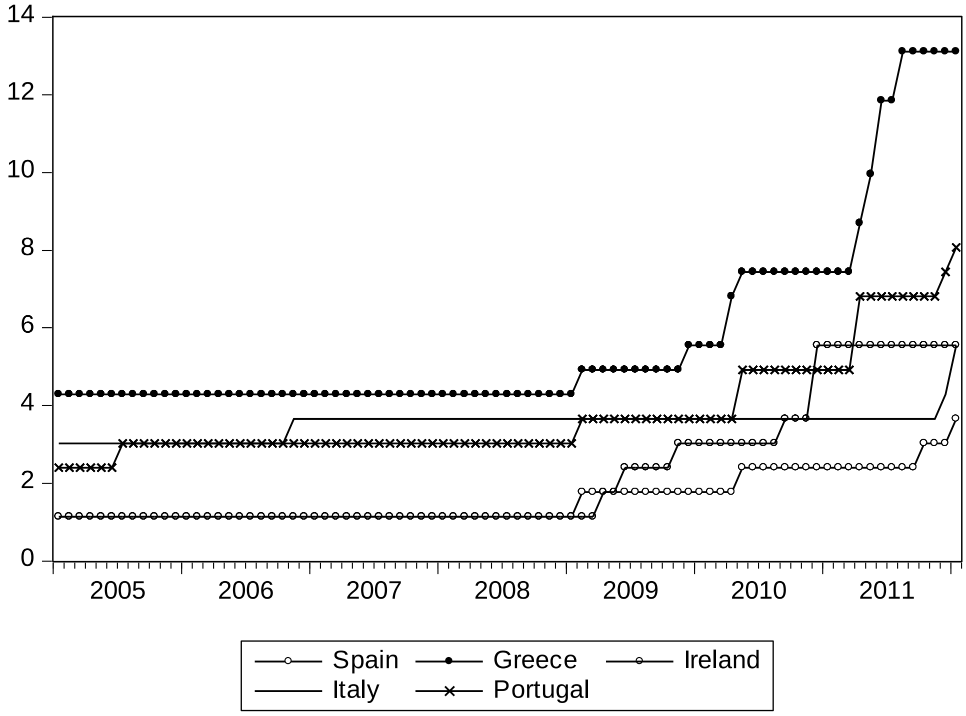
Source: own calculations from results in Table 3

Figure 3: TVC coefficient for sovereign ratings in the sovereign spreads equation



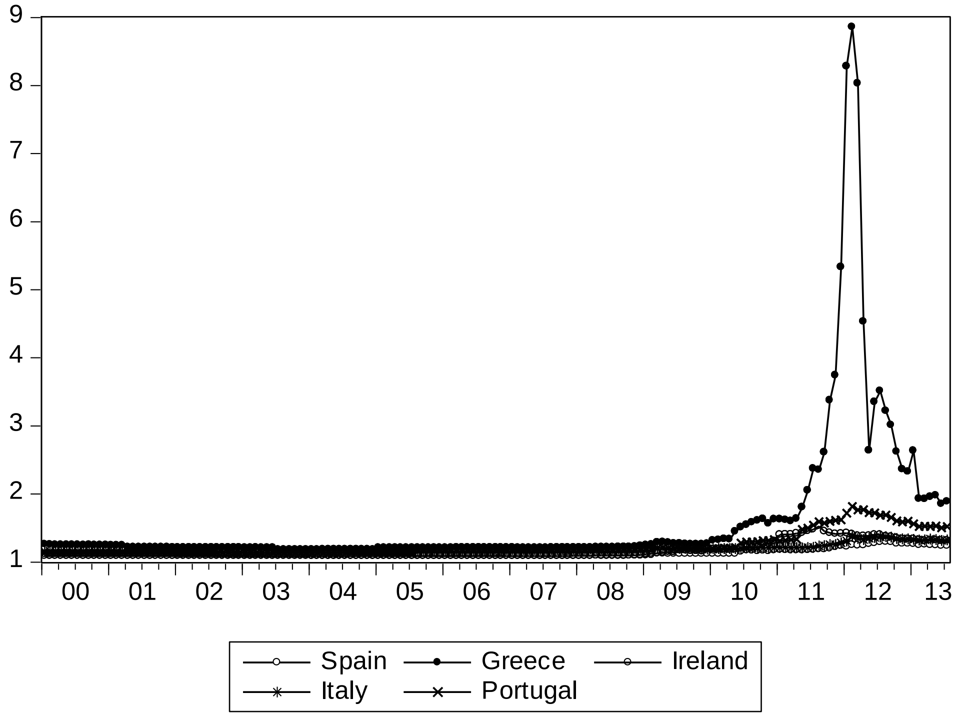
Source: Results in Table 7

Figure 4: Coefficient for bank ratings in the sovereign-ratings equation



Source: Results in Table 7

Figure 5: Full multiplier effect



Source: Results in Table 7