Computational Statistics and Data Analysis 76 (2014) 20–33

Contents lists available at ScienceDirect

Computational Statistics and Data Analysis

journal homepage: www.elsevier.com/locate/csda

Sovereign credit ratings, market volatility, and financial gains

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ARTICLE INFO

Article history:
Received 26 January 2013
Received in revised form 25 September 2013
Accepted 26 September 2013
Available online 5 October 2013

Keywords:
Sovereign ratings
Yields
Stock market returns
Volatility
EGARCH
Optimal portfolio
Financial gain
Risk management
Value-at-risk

ABSTRACT

The reaction of EU bond and equity market volatilities to sovereign rating announcements (Standard & Poor's, Moody's, and Fitch) is investigated using a panel of daily stock market and sovereign bond returns. The parametric volatilities are defined using EGARCH specifications. The estimation results show that upgrades do not have significant effects on volatility, but downgrades increase stock and bond market volatility. Contagion is present, and sovereign rating announcements create interdependence among European financial markets with upgrades (downgrades) in one country leading to a decrease (increase) in volatility in other countries. The empirical results show also a financial gain and risk (value-at-risk) reduction for portfolio returns when taking into account sovereign credit ratings' information for volatility modelling, with financial gains decreasing with higher risk aversion.

1. Introduction

In the last few years, we have seen the importance of credit rating agencies (Standard and Poor's, Moody's, and Fitch) and their crucial task in providing information on which investors base their decisions. These agencies often had a more important role than the one played by governments. After the 2008–2009 financial and economic crisis, volatility in financial markets has increased markedly in several European Union (EU) countries, notably in the euro area, both in the sovereign debt market and in the equity market segment. While policymakers have looked at rating agencies as a possible source contributing to the increase in financial markets volatility, so far the literature does not seem to have tackled the link with the second moments of those financial variables. Indeed, such volatility may exacerbate the level of financial instability and its unpredictability, since high volatility levels are associated with higher risk perception of market participants. Moreover, such increased volatility and perceived risk can have similar unwarranted effects regarding macroeconomic uncertainty by amplifying output volatility.

The purpose of the present paper is to study the volatility of stock market and sovereign bond market returns in EU countries, notably before and during the 2008–2009 economic and financial crisis. We focus on the role of sovereign credit rating announcements of upgrades and downgrades. Our daily dataset covers the period from January 1995 until October 2011.

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1 Tel.: +351 21 392 5985.
2 UECE is supported by FCT (Fundação para a Ciência e a Tecnologia, Portugal).

0167-9473/$ – see front matter
http://dx.doi.org/10.1016/j.csda.2013.09.028

Our contributions encompass the following aspects: (i) we analyse whether countries with higher credit ratings exhibit less volatility than lower rating countries; (ii) we look at differences in the effects of positive versus negative announcements; (iii) we assess whether volatility in some countries reacts to rating announcements of other countries (contagion), and whether there are asymmetries in the transmission of these spillover effects; and (iv) we evaluate the economic significance of the impact of rating announcements on volatility, by quantifying the financial gain and the risk reduction of a portfolio of stocks or bonds that consider this information.

Our analysis is complementary to several areas in finance, particularly on the effects of credit rating announcements on sovereign yields and CDS spreads, and bond and stock market volatility.

Several authors have analysed the effects of credit rating announcements. Kräussl (2005) uses daily sovereign ratings of long-term foreign currency debt from Standard and Poor's and Moody's. For the period between 1997 and 2000, he reports that sovereign rating changes and credit outlooks have a relevant effect on the size and volatility of lending in emerging markets, notably for the case of downgrades and negative outlooks. Also for emerging markets, Reisen and Maltzan (1999) find a significant effect on the government bond yield spread when a country is reviewed for a downgrade.

One of the recurrent conclusions of such studies is that only negative credit rating announcements have significant impacts on yields and CDS spreads; see Reisen and Maltzan (1999), Norden and Weber (2004), Hull et al. (2004), and Kräussl (2005). Micu et al. (2006) perform a similar analysis of the relationship between rating announcements and corporate CDS spreads.

Several other papers analyse contagion after announcements. Ismailescu and Kazemi (2010) assess the effect of sovereign rating announcements on sovereign CDS spreads and possible spillover effects. Using daily observations from 2001 to 2009 for 22 emerging markets, they find that positive events have a greater impact on CDS markets in the two-day period surrounding the event, being then more likely to spill over to other countries. Moreover, they report that a positive credit rating event is more relevant for emerging markets and that markets tend to anticipate negative events. Spillover effects were also reported in Gande and Parsley (2005), Arezki et al. (2011) and Afonso et al. (2012b).

The literature on the effects of rating announcements on volatility is relatively scarcer. Heinke (2006), for corporate bond spreads, and Reisen and Maltzan (1998), for sovereign bond yield spreads, have addressed the relevance of rating events for the historical spread volatility. Heinke (2006) reports that for German eurobonds from international issuers, credit ratings tend to rank the risk of each bond in accordance with the respective bond spread volatility. Moreover, spread volatility increases significantly with lower ratings. Reisen and Maltzan (1998) compute the historical volatility of sovereign bond yield spreads as an average over a window of 30 days. They report a significant change in the level of volatility for bond yield spreads and for real stock market returns when a rating event occurs, with volatility increasing (decreasing) with rating downgrades (upgrades).

Two other papers have analysed the effects of sovereign ratings on stock market volatility. Hooper et al. (2008) use data from 42 countries over the period 1995–2003 and find that upgrades reduce volatility and downgrades increase volatility, but to different extents. Ferreira and Gama (2007) analyse 29 countries over the period 1989–2003 and find similar results. Additionally, they report an asymmetric spillover effect of rating announcement on other countries.

Other studies have focused on the effect of macroeconomic news on bond yields and stock market volatilities. Jones et al. (1998) investigate the reaction of daily Treasury bond prices to the release of US macroeconomic news (employment and producer price index). They study whether the non-autocorrelated new announcements give rise to autocorrelated volatility. They find that announcement-day volatility does not persist, consistent with the immediate incorporation of information into prices. They also find a risk premium on these release dates.

Using a GARCH model, Christiansen (2007) reports a strong statistical evidence of volatility spillover from the US and aggregate European bond markets. For EMU countries, US volatility spillover effects are rather weak whereas for Europe the volatility spillover effects are strong. Gallo and Otranto (2008) identify the transmission mechanisms of volatility between markets within a Markov Switching bivariate model where the state of one variable feeds into the transition probability of the state of the other. They estimate the model on the weekly high–low range of five Asian markets. Their empirical results show plausible market characterisations over the long run with a spillover from Hong Kong to Korea and Thailand.

Billio and Caporin (2010) model the contemporaneous relationships among Asian and American stock markets using a simultaneous equation system with GARCH errors that captures variance spillovers. Using the fitted residuals, they analyse the correlation matrix over rolling windows, which allows a graphical analysis and the development of a statistical test of correlation movements. Their results show evidence of contagion between Asian and American stock markets, and they identified mean relations and variance spillovers. Finally, Engle et al. (2012) use a new class of asymmetric volatility multiplicative error models to study interrelations of equity market volatility in eight East Asian countries before, during, and after the Asian currency crisis. They report that the dynamic propagation of volatility shocks occurs through a network of interdependences, with Hong Kong having a major role as a net creator of volatility.

We add to this literature in two dimensions. First, we focus on the current Euro Area crisis, which provides a different set of countries with distinct characteristics from the previous studies. Understanding contagion effects during the current crisis is of foremost importance for policy makers and market participants. Second, we propose a novel methodology to quantify the economic significance of the rating information for volatility, rather than simply looking at the magnitude of regression coefficients or goodness-of-fit measures. We use the classical mean–variance portfolio choice approach to evaluate the financial gain and the risk reduction of an investor that uses the rating announcement information when making the forecast of time-varying volatility.

The paper is organised as follows. Section 2 presents the dataset and discusses the construction of the returns' volatility measures. Section 3 assesses the reaction of market volatility to rating announcements and tests for the presence of contagion in both stock and bond EU markets. Section 4 studies the relevance of rating information to portfolio diversification. Section 5 concludes.

2. Data and stylised facts

2.1. Sovereign ratings

A rating notation is an assessment of the issuer's ability to pay back in the future both capital and interests. The three main rating agencies use similar rating scales, with the best quality issuers receiving a triple-A notation.

Our data for the credit rating developments are from the three main credit rating agencies: Standard and Poor's (S&P), Moody's (M) and Fitch (F). We transform the sovereign credit rating information into a discrete variable that codifies the decision of the rating agencies. In practice, we can think of a linear scale to group the ratings in 11 categories, where the triple-A is attributed level 11, and where we could put together in the same bucket the observations in speculative grade (notations at and below BB+ and Ba1), which all receive a level of one in our scale.

On a given date t and country i, the dummy variables *up* and *down* assume the following values:

$$up_{it} = \begin{cases} 1, & \text{if an upgrade of any agency occurs} \\ 0, & \text{otherwise} \end{cases} \qquad down_{it} = \begin{cases} 1, & \text{if a downgrade of any agency occurs} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

We have constructed a similar set of discrete variables for each of the three agencies, S&P, Moody's, and Fitch, separately.

2.2. Data

We cover 21 EU countries: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Spain, Sweden, and United Kingdom. No data were available for Cyprus, Estonia and Luxembourg and the data for Malta, Slovakia and Slovenia had a very limited sample.

The daily dataset starts as early as 2 January 1995 for some countries and ends on 24 October 2011. This covers the period of the euro debt crisis, when some sovereign bond markets were not fully functioning, and when the ECB's Securities Market Programme was in place. The three rating agencies, S&P, Moody's and Fitch, provided the data for the sovereign rating announcements and rating outlook changes.

The data for the sovereign bond yields, which is for the 10-year government bond, end-of-day data, come from Reuters. We use 10-year data because that is the benchmark maturity in the market for government bond yields. Moreover, the average maturity for the outstanding government debt is usually also closer to that maturity length since it is a privileged source of capital markets financing. For the stock market, we use equity indexes for the local stock market, as reported in DataStream, which only start in 1 January 2002. More details can be found in the Appendix.

2.3. Rating announcements

In total, since 1995, there were 345 rating announcements from the three agencies. S&P and Fitch were the most active agencies with 141 and 119 announcements, respectively, whereas Moody's only had 87. Out of these announcements, most of them were upgrades (135) rather than downgrades (75), positive (71) and negative (54) outlooks. However, we cannot use the full set of rating announcements because data on sovereign yields start at a later period: for the 10-year yields the sample starts in 1995 and equity starts in 2002. Therefore, in our study we have 179 announcements overlapping with sovereign yield data and 214 overlapping with stock market returns. Although they are different, we always make a separate analysis of the two markets and the sample is homogeneous within each market. Finally, the sovereign yield data are not fully available or are less reliable for several eastern European countries, namely Romania, Lithuania, Latvia and Estonia.

2.4. Measuring stock and bond market volatilities

We first define stock market returns at time t and for each country i, say $r^s_{i,t}$, as the difference in log prices of the equity index at time t and $t-1$, while the bond market returns at time t and for each country i, say $r^b_{i,t}$, are defined as the difference in log yield at time $t-1$ and t:

$$r^s_{i,t} = \ln(\text{stock}_{i,t}) - \ln(\text{stock}_{i,t-1}), \tag{2a}$$

$$r^b_{i,t} = \ln(\text{yield}_{i,t-1}) - \ln(\text{yield}_{i,t}). \tag{2b}$$

As we cannot retrieve the conditional volatilities of all these stock and bond market returns, we have to filter them using parametric volatility models. We start our analysis of the impact of sovereign credit rating news on the financial market volatilities using the exponential generalized autoregressive conditional heteroskedasticity model (hereafter EGARCH model), developed by Nelson (1991). This model filters the conditional volatility processes from the specification of the conditional marginal distribution. Later on and for robustness check, we will also use the absolute value and the squared returns as proxies of volatilities.

The EGARCH models stipulate that negative and positive returns have different impacts on volatility, known as the asymmetric volatility phenomenon. For the EGARCH specification, we assume that the following model generates the equity and bond returns for each country *i*:

$$r_{i,t+1} = \mu_i + \varepsilon_{i,t+1}, \tag{3}$$

where $r_{i,t+1}$ is the continuously compounded return from time t to $t+1$ on the equity (bond) of the country *i*,

$$\varepsilon_{i,t+1} = \sigma_{i,t+1} z_{i,t+1} \tag{4}$$

and $z_{i,t+1}$ are i.i.d. t-distributed error terms with mean zero, scale one, and the degrees of freedom parameter υ will be estimated from the data. The t-distribution is used to adjust the fat tails that characterize the asset return distributions. Finally, we assume that the volatility of returns $r_{i,t+1}$, $\sigma_{i,t+1}$, is given by the following Nelson (1991) EGARCH (1, 1) model that can be rewritten in a simpler and intuitive manner as follows:

$$\ln(\sigma_{i,t+1}) = \omega_i + \beta_i \ln(\sigma_{i,t}) + \gamma_i z_{i,t} + \alpha_i(|z_{i,t}| - E|z_{i,t}|). \tag{5}$$

In Eq. (5), $z_{i,t} = \varepsilon_{i,t}/\sigma_{i,t}$ defines the standardised residuals and α_i is the coefficient that captures the asymmetric volatility phenomena meaning that negative returns have a higher effect on volatility compared to positive returns of the same magnitude. According to Asai and McAleer (2011)'s classification, the EGARCH (1, 1) in (5) falls into the case of models with *standard asymmetry*. In other words, in this model the response of volatility to positive and negative return shocks is asymmetric: for positive return shocks, the slope is equal to $\gamma_i + \alpha_i$, and for negative return shocks, it is equal to $\gamma_i - \alpha_i$. Further, if the coefficient α_i is positive and if the coefficient γ_i is negative (which is the case in our estimation results), then a negative shock has a higher impact on volatility than the positive one of the same magnitude, because $|\gamma_i - \alpha_i| \geq |\gamma_i + \alpha_i|$.

Notice that, at this stage, we do not use any additional information other than the stock and bond market returns, in particular, the information on credit rating announcements.

In Table 1 we report the estimation results of the EGARCH volatilities for equities and bonds across countries. From this, we see that, for most countries, the coefficients of the estimated EGARCH models are statistically significant. The high values of the estimates of β_i indicate that volatilities are persistent. Moreover, the estimated coefficient γ_i that captures the asymmetric effect of returns on volatility is also statistically significant for most of the countries, especially for equity returns.

Table 2 shows the average volatility in stock and bond markets for different rating categories. We can observe that although not completely straightforward, there is a ranking in terms of volatility. For the bond markets, there is no sharp difference in the top categories between AAA and AA−, but speculative grade countries experience between 3 and 4 times more volatility than AAA countries. For the stock market volatility, such pattern is weaker, with triple-A countries having similar volatilities as BBB countries and, while speculative grade rated countries have only about 50% more volatility.

3. Reaction of market volatilities to credit rating news

3.1. Reaction to upgrades and downgrades

In this section, we study the reaction of equity and bond market volatilities to sovereign rating upgrading and downgrading across the European countries. Therefore, we estimate the following country fixed effect panel regressions:

$$\log(\sigma_{i,t}) = \mu_i + \sum_{j=0}^{k} \lambda_j \, down_{i,t-j} + \sum_{j=0}^{k} \alpha_j \, up_{i,t-j} + \beta \log(\sigma_{i,t-1}) + \zeta^T X_{t-1} + \varepsilon_{i,t}, \tag{6}$$

where μ_i are country fixed effects and $up_{i,t-j}$ and $down_{i,t-j}$ are the dummies at time $t-j$ of the upgrading and downgrading (see Eq. (1)) that correspond to all rating agencies (S&P, Moody's, and Fitch) together, and X is a vector of other control variables such as dummy variables for the weekday, month and annual effects. In Eq. (6), we represent conditional volatility as an exponential function process to guarantee that it is positive. Finally, in the empirical application, $\sigma_{i,t}$ will be replaced by the conditional volatility filtered using the EGARCH (1, 1) model in (5).

Table 3 shows the estimation results for specification (6) using two lags. We have tested several lags, and generally, two lags are sufficient to capture the dynamics in stock and bond market volatilities. Looking at Table 3, we observe the existence of an asymmetry on the effects of sovereign rating developments on volatility. Upgrades do not have any significant effect on volatility. On the other hand, for the stock market sovereign downgrades increase volatility both contemporaneously and with one lag, whereas for bond markets downgrades raise volatility after two lags.

The R^2 of these regressions are high, above 0.95, which can be explained by the persistence in volatility (lagged volatility). We have run additional regressions without including the lag of volatility. The R^2 of these alternative regressions are also reported in Table 3, in square brackets, and are around 0.3.

In addition, Fig. 1 illustrates the impulse response functions of the impact of upgrade and downgrade announcements on both stock and bond market volatilities. We can see that the downgrade announcements have more impact on bond and equity market volatilities than the upgrade announcements. The effect of downgrade announcements is dominant, persistent, and robust to the number of lags considered in the models.

Table 1
Summary of EGARCH estimation results (Eq. (5)).

Country	Slope γ_i	Asymmetry α_i	Persistence β_i	D.F.	Obs.	Gaps
Stock market						
Austria	−0.074*** (0.000)	0.186*** (0.000)	0.981*** (0.000)	8.79	2564	0
Belgium	−0.118*** (0.000)	0.159*** (0.000)	0.979*** (0.000)	11.08	2564	0
Finland	−0.065*** (0.000)	0.105*** (0.000)	0.991*** (0.000)	6.41	2564	0
France	−0.153*** (0.000)	0.102*** (0.000)	0.982*** (0.000)	15.44	2564	0
Germany	−0.129*** (0.000)	0.113*** (0.000)	0.985*** (0.000)	11.41	2564	0
Greece	−0.053*** (0.000)	0.158*** (0.000)	0.985*** (0.000)	7.78	2564	0
Ireland	−0.072*** (0.000)	0.169*** (0.000)	0.986*** (0.000)	6.52	2564	0
Italy	−0.109*** (0.000)	0.105*** (0.000)	0.989*** (0.000)	8.95	2564	0
Netherlands	−0.131*** (0.000)	0.110*** (0.000)	0.987*** (0.000)	16.12	2564	0
Portugal	−0.073*** (0.000)	0.219*** (0.000)	0.978*** (0.000)	6.46	2564	0
Spain	−0.121*** (0.000)	0.127*** (0.000)	0.985*** (0.000)	8.05	2564	0
Bulgaria	−0.028 (0.204)	0.589*** (0.000)	0.933*** (0.000)	3.31	2564	0
Czech Republic	−0.061*** (0.000)	0.238*** (0.000)	0.969*** (0.000)	6.58	2564	0
Denmark	−0.069*** (0.000)	0.155*** (0.000)	0.981*** (0.000)	7.91	2564	0
Estonia	−0.020 (0.176)	0.331*** (0.000)	0.976*** (0.000)	3.37	2564	0
Hungary	−0.044*** (0.000)	0.167*** (0.000)	0.980*** (0.000)	8.62	2563	0
Latvia	−0.056** (0.043)	0.346*** (0.000)	0.950*** (0.000)	3.22	2564	0
Lithuania	−0.053** (0.022)	0.491*** (0.000)	0.877*** (0.000)	3.57	2563	0
Romania	−0.047* (0.051)	0.390*** (0.000)	0.952*** (0.000)	3.83	2564	0
Sweden	−0.118*** (0.000)	0.100*** (0.000)	0.986*** (0.000)	10.28	2564	0
United Kingdom	−0.135*** (0.000)	0.108*** (0.000)	0.987*** (0.000)	13.84	2563	0
Yield						
Austria	0.024*** (0.004)	0.134*** (0.000)	0.996*** (0.000)	7.27	4271	18
Belgium	0.021*** (0.010)	0.112*** (0.000)	0.995*** (0.000)	6.38	4034	1
Finland	0.026*** (0.009)	0.136*** (0.000)	0.994*** (0.000)	6.14	4372	8
France	0.032*** (0.000)	0.100*** (0.000)	0.997*** (0.000)	9.85	4020	2
Germany	0.031*** (0.000)	0.100*** (0.000)	0.998*** (0.000)	6.99	4380	4
Greece	−0.029** (0.042)	0.192*** (0.000)	0.977*** (0.000)	9.85	3384	3
Ireland	−0.006 (0.484)	0.117*** (0.000)	0.993*** (0.000)	5.69	4038	6
Italy	−0.012 (0.213)	0.120*** (0.000)	0.987*** (0.000)	7.31	4014	0
Netherlands	0.029*** (0.000)	0.095*** (0.000)	0.998*** (0.000)	7.78	4031	2
Portugal	−0.002 (0.818)	0.205*** (0.000)	0.988*** (0.000)	4.86	4312	25
Spain	−0.004 (0.728)	0.100*** (0.000)	0.990*** (0.000)	5.32	3992	3
Czech Republic	0.029* (0.092)	0.383*** (0.001)	0.994*** (0.000)	3.32	2989	10
Denmark	0.019** (0.035)	0.156*** (0.000)	0.994*** (0.000)	5.00	4305	33
Hungary	−0.082*** (0.004)	0.427*** (0.000)	0.943*** (0.000)	2.52	3160	25
Poland	−0.030 (0.101)	0.347*** (0.000)	0.962*** (0.000)	3.38	3172	11
Sweden	0.033*** (0.000)	0.113*** (0.000)	0.997*** (0.000)	8.81	3223	37
United Kingdom	0.027*** (0.000)	0.077*** (0.000)	0.998*** (0.000)	8.89	3928	4

Note: This table shows the results of the estimation of the EGARCH model in (5). The P-values for the statistical significance of the estimated coefficients are reported between parentheses. D.F. is to indicate the number of degrees of freedom of the t-distribution of the error term in (4). The gaps are missing observations.
* Represents statistical significance at 10%.
** Represents statistical significance at 5%.
*** Represents statistical significance at 1%.

3.2. *Robustness analysis*

As the main robustness exercise, we estimated three alternative volatility models to allow for different asymmetric volatility specification, different distribution for the error term in (5), and for time-varying expected returns: a GJR-GARCH model (Glosten et al., 1993), an EGARCH model with Gaussian distribution, and an EGARCH model with autocorrelated returns in the mean equation. As one would expect, the autoregressive coefficients are not statistically significant for most countries. We know from Ding et al. (1993) and others that the time series of returns exhibit little or no dynamic behaviour in the mean. For example, the first autoregressive coefficient is always very small (around 0.05) and statistically insignificant.

For each of the above models, we filter the corresponding volatilities and then estimate Eq. (6). Table 4 reports the estimation results of regression Eq. (6) for both stock and bond market volatilities, which are in line with the baseline estimations in Table 3. Using each of the three models, we find that the effect of upgrades is not statistically significant. However, the magnitude of the coefficients on downgrades is larger and statistically significant, particularly the first lag for stock markets and the second lag for the bond market.

We have also used, as an alternative to parametric volatility models, non-parametric measures of volatility: the absolute value and the squared returns as proxies of volatilities (see Jones et al., 1998, among others), and we have looked at the

Table 2
Average of stock and sovereign bond market volatilities for different rating categories.

Rating	Stock market volatility			Yield volatility		
	S&P	Moody's	Fitch	S&P	Moody's	Fitch
AAA	0.0037	0.0037	0.0037	0.0024	0.0022	0.0022
AA+	0.0033	0.0032	0.0040	0.0017	0.0017	0.0017
AA	0.0030	0.0029	0.0021	0.0016	0.0021	0.0017
AA−	0.0022	0.0025	0.0043	0.0017	0.0011	0.0019
A+	0.0038	0.0032	0.0046	0.0022	0.0059	0.0017
A	0.0035	0.0033	0.0027	0.0090	0.0025	0.0017
A−	0.0029	0.0043	0.0029	0.0030	0.0078	0.0029
BBB+	0.0040	0.0032	0.0037	0.0037	0.0037	0.0035
BBB	0.0035	0.0033	0.0043	0.0046	0.0019	0.0056
BBB−	0.0046	0.0051	0.0043	0.0065	0.0056	0.0092
<BB+	0.0051	0.0040	0.0048	0.0103	0.0070	0.0073

Note: This table reports the average values of stock and sovereign bond market volatilities for different rating categories (AAA, . . . , <BB+) and agencies (S&P, Moody's, Fitch). The volatilities are filtered using the EGARCH estimations in Table 1 and annualised.

Table 3
Estimation results of regressions of stock and bond market volatilities (Eq. (6)).

Events		*Stock market* (1)	*Bond market* (2)
Upgrade	t	0.019	0.029
		(0.81)	(0.18)
	$t-1$	0.033	−0.012
		(0.66)	(−0.63)
	$t-2$	−0.013	0.024
		(−0.54)	(0.83)
Downgrade	t	0.026**	0.025
		(2.30)	(0.13)
	$t-1$	0.072***	0.021*
		(4.02)	(1.97)
	$t-2$	0.008	0.112***
		(0.59)	(3.55)
Lagged volatility		0.963***	0.977***
		(156.87)	(300.61)
R^2		0.955 [0.324]	0.973 [0.360]
Observation		53 821	66 539
Countries		21	17
#Upgrades		74	65
#Downgrades		93	67
F-Test 3rd lag[a]		0.661	0.747
F-Test 5th lag[a]		0.003	0.539
F-Test 22nd lag[a]		0.334	0.414

Note: This table reports the estimation results that correspond to the regression equation in (6). The t-statistics for the statistical significance of the estimated coefficients are reported between parentheses. Control variables, X, in (6) include weekday, month and year dummies. In square brackets is the R-squared of the regression without the lagged dependent variable.
* Represents statistical significance at 10%.
** Represents statistical significance at 5%.
*** Represents statistical significance at 1%.
[a] P-values (F-tests) for joint statistical significance of the 3rd, 5th and 22nd lag are also reported in this table.

effects of positive and negative outlooks on volatilities. A recent paper that discusses the performance of these measures is Forsberg and Ghysels (2006). Also, these measures were used in several papers. For example, Bollerslev et al. (2006) have used these measures as the proxy of volatility to explain the asymmetric volatility phenomenon.

Furthermore, we re-estimated our specifications using different samples (Euro Area only, sample period 2008–2011 instead of 2002–2011) and control variables (week dummies instead of year dummies). Finally, we have also examined the effects of sovereign credit ratings' information on CDS market volatility, and we have run the estimations by agency. All these results are available upon request.

Our robustness analysis confirms that downgrades have a strong effect on both stock and bond market volatilities, while positive and negative outlooks do not have a statistical significant effect on those volatilities. Additionally, markets respond more to rating actions from S&P and Moody's by delivering higher stock and bond returns' volatility when sovereign downgrades take place. Finally, none of the estimated coefficients is significant for the case of Fitch.

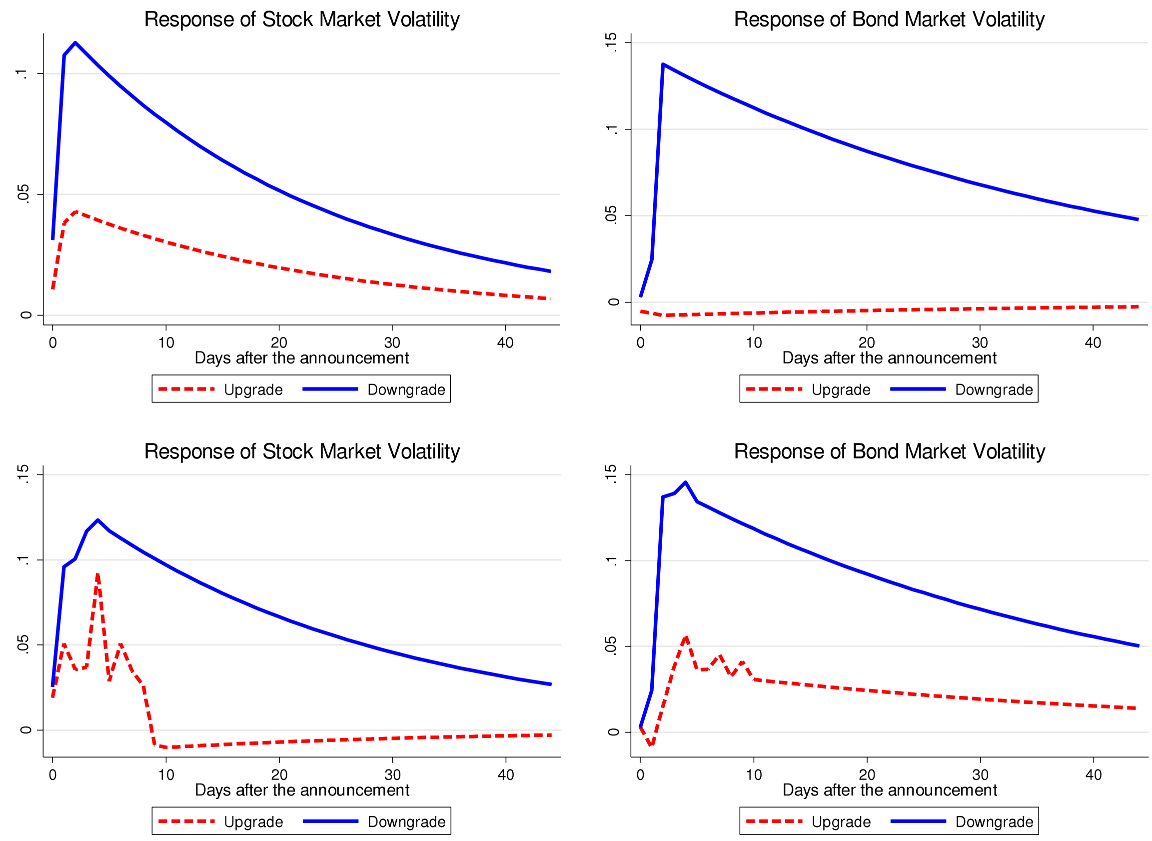

Fig. 1. Impulse responses of stock and bond market volatilities to upgrade and downgrade news, baseline estimations using 2 and 10 lags. *Notes*: This figure shows the impulse response functions of the impact of upgrade and downgrade announcements on both stock and bond market volatilities, using the specification in (6) with 2 (upper panel) and 10 (lower panel) lags. On the vertical axis, we have the effects of announcements on volatility.

3.3. Contagion

In this subsection, we examine the contagion due to the impact of upgrades and downgrades rating announcements from some countries on the volatility of another country. We restrict the analysis to Euro Area countries, but we also divide the latter into the *Core* (Austria, Finland, Germany, France, and Netherlands) and *Periphery* (Belgium, Ireland, Italy, Greece, Portugal and Spain) countries. This distinction is in line notably with the results reported by Afonso et al. (2012a) that split the euro area countries in a rather similar way, based on a principal component analysis. Therefore, we estimate the following country fixed effect panel regression:

$$\log(\sigma_{i,t}) = \mu_i + \sum_{j=0}^{k} \lambda_j \, down_{i,t-j} + \sum_{j=0}^{k} \alpha_j \, up_{i,t-j} + \sum_{j=1}^{k} \phi_j \, up_{i,t-j}^{-i} + \sum_{j=1}^{k} \delta_j \, down_{i,t-j}^{-i} + \beta \log(\sigma_{i,t-1}) + \zeta^T X_{t-1} + \varepsilon_{i,t}, \tag{7}$$

where μ_i are country fixed effects, $up_{i,t-j}$ and $down_{i,t-j}$ are the dummies at time $t-j$ of the upgrading and downgrading in a given country i, and $up_{i,t-j}^{-i}$ and $down_{i,t-j}^{-i}$ are the dummies at time $t-j$ of the upgrading and downgrading in any other country other than country i. The upgrades and downgrades are from all rating agencies (S&P, Moody's, and Fitch) together, and X is a vector of other control variables such as dummy variables for the weekday, month and annual effects. In Eq. (7) the contagion effects on the volatility in a given country i, due to the upgrading and downgrading in the other countries, are captured by the coefficients ϕ_j and δ_j, respectively. In the empirical application, $\sigma_{i,t}$ in Eq. (7) will be replaced by the conditional volatility, filtered using the EGARCH (1, 1) model in (5).

Table 5 reports the estimation results for stock and bond markets and using Euro Area, Core, and Periphery countries. In the latter, the estimation of the coefficients ϕ_j and δ_j are reported in the rows "Upgrade Others" and "Downgrade Others", respectively. We focus the analysis of the results on these two rows. Notice first that, in the covered period, there were no downgrades in the core set of countries. These are essentially countries that remained AAA throughout the crisis.

Table 4
Estimation results of regressions of stock and bond market volatilities (Eq. (6)), alternative volatility measures.

Events		*Stock market*			*Bond market*		
		GJR GARCH	EGARCH Gaussian distribution	EGARCH autocorrelated returns	GJR GARCH	EGARCH Gaussian distribution	EGARCH autocorrelated returns
Upgrade	t	0.021	0.016	0.027	−0.005	−0.001	−0.001
		(1.01)	(0.83)	(0.99)	(−0.29)	(−0.04)	(−0.09)
	$t-1$	0.044	0.028	0.029	−0.008	−0.015	−0.008
		(0.074)	(0.70)	(0.59)	(−0.72)	(−1.03)	(−0.46)
	$t-2$	−0.022	−0.011	−0.015	0.000	0.024	0.026
		(−0.77)	(−0.60)	(−0.68)	(0.01)	(0.98)	(0.86)
Downgrade	t	0.015	0.019**	0.025**	0.004	0.004	−0.009
		(1.01)	(2.33)	(2.26)	(0.23)	(0.21)	(−0.41)
	$t-1$	0.081***	0.064***	0.070***	0.019	0.027**	0.017
		(3.92)	(3.78)	(3.94)	(1.24)	(2.22)	(1.20)
	$t-2$	0.009	0.005	0.008	0.136***	0.117***	0.096**
		(0.59)	(0.34)	(0.54)	(3.24)	(4.23)	(2.66)
Lagged volatility		0.961***	0.977***	0.960***	0.972***	0.975***	0.977***
		(150.72)	(272.97)	(138.86)	(165.98)	(171.68)	(285.47)
R^2		0.947	0.959	0.948	0.969	0.971	0.971
Observation		53 821	48 695	46 132	63 529	66 539	62 155
Countries		21	19	18	16	17	16
#Upgrades		74	73	70	59	65	61
#Downgrades		93	93	93	67	67	55

Note: This table reports the estimation results that corresponds to the regression equation in (6) using volatilities that are filtered based on: (i) GJR-GARCH model (Glosten et al., 1993); (ii) EGARCH model with the Gaussian distribution; and (iii) EGARCH model with autoregressive terms in the mean equation. The t-statistics for the statistical significance of the estimated coefficients are reported between parentheses. Control variables, X, in (6) include weekday, month and year dummies.
** Represents statistical significance at 5%.
*** Represents statistical significance at 1%.

Based on the coefficient estimates and on the corresponding t-statistics, we find that the volatility of both stock and bond markets of a given country respond to announcements of agencies for other European countries. In particular, when a country has an upgrade, it is followed by a reduction of volatility in the rest of the Euro-area, which is more pronounced in the *Core* countries. As for downgrading movements, they increase the volatility of all other countries, particularly of periphery countries. The effect is also more relevant on the stock market rather than on the bond market.

To sum up, contrary to the main finding in the previous sections, we find that, for contagion, both upgrades and downgrades in one European country might explain the volatility in the rest of the European countries. Before, we find that upgrades in a given country play no role in explaining the volatility in the same country. However, it seems now that sovereign rating announcements create interdependence among European financial markets with upgrades (resp. downgrades) in one country leading to a decrease (resp. increase) in the volatility of the other countries. These new results might guide the European policy-makers to anticipate the negative financial shocks that can affect their financial markets due to negative shocks that happen in other countries and put in place the necessary mechanisms to absorb these negative shocks.

As robustness, we also ran the same regression including the lagged volatility of the returns in all European countries, to control for the natural contagion of markets independent of announcements. The coefficients of downgrades and upgrades remained statistically significant with the same magnitude.

4. Economic value of sovereign ratings' information

So far, we have shown that there is a statistical significant effect of rating announcements on stock and bond market volatilities, particularly of downgrades. However, it is hard to measure its economic significance. In this section, we propose a new methodology to quantify the economic significance of the impact of sovereign rating announcements on stock and bond market volatilities. This procedure follows the classical mean–variance portfolio choice approach. We first consider the problem of an investor that, to decide its portfolio of stocks and bonds, has to forecast the time-varying volatilities. We then measure the financial gain and the risk reduction of considering information on announcements on top of the other available information.

4.1. The investor's portfolio optimisation problem

In this section, we examine the economic implications of the impact of sovereign credit ratings' information on market volatilities for optimal portfolio diversification. We assume that the investors are risk averse with mean–variance type preferences.

Table 5
Estimation results of regressions of stock and bond market volatilities (Eq. (7)), contagion.

Events		*Stock market*			*Bond market*		
		Euro Area	*Core* countries	*Periphery* countries	Euro Area	*Core* countries	*Periphery* countries
Upgrade	t	−0.044*	−0.048***	−0.039	−0.005	−0.015***	−0.001
		(−2.21)	(−5.69)	(−1.75)	(−0.30)	(−47.15)	(−0.06)
	$t-1$	−0.038	−0.049***	−0.035	−0.004	0.045***	−0.017
		(−1.76)	(−5.50)	(−1.46)	(−0.28)	(102.85)	(−1.76)
	$t-2$	−0.049***	−0.015	−0.049**	−0.004	0.018***	−0.011
		(−4.01)	(−1.86)	(−3.83)	(−0.59)	(48.44)	(−2.08)
Downgrade	t	0.023**	–	0.020**	0.015	–	0.017
		(3.09)	–	(2.64)	(0.94)	–	(1.07)
	$t-1$	0.078***	–	0.075***	0.028***	–	0.030**
		(6.99)	–	(6.66)	(3.27)	–	(3.32)
	$t-2$	−0.013	–	−0.016	0.098**	–	0.100**
		(−1.59)	–	(−1.86)	(2.73)	–	(2.66)
Upgrade others	t	−0.010	−0.010**	−0.010	0.016***	0.020***	0.011*
		(−1.61)	(−3.36)	(0.74)	(4.75)	(7.10)	(2.17)
	$t-1$	−0.048***	−0.056*	−0.042	−0.016***	−0.015***	−0.017*
		(−3.40)	(−2.43)	(0.61)	(−5.08)	(−29.97)	(−2.62)
	$t-2$	−0.027**	−0.031**	−0.024	−0.018***	−0.011***	−0.024***
		(−2.20)	(−3.65)	(−0.52)	(−5.30)	(−6.38)	(−4.27)
Downgrade others	t	0.030***	0.029***	0.031**	0.011**	0.007***	0.014*
		(6.09)	(4.57)	(3.81)	(3.12)	(10.78)	(2.03)
	$t-1$	0.045***	0.042***	0.049***	0.003	0.003	0.003
		(6.94)	(5.05)	(4.69)	(0.76)	(1.32)	(0.36)
	$t-2$	−0.005	−0.010	−0.000	−0.004	−0.014	0.005
		(−1.45)	(−1.83)	(−0.04)	(−0.83)	(−20.04)	(0.72)
Lagged volatility		0.977***	0.978***	0.974***	0.980***	0.984***	0.975***
		(596.08)	(145.25)	(541.03)	(350.92)	(524.77)	(255.90)
R^2		0.976	0.975	0.977	0.984	0.989	0.979
Observation		28 193	12 815	15 378	45 434	21 227	24 207
Countries		11	5	6	11	5	6
#Upgrades		10	1	9	38	8	30
#Downgrades		56	0	56	57	0	57
#Upgrades (other)		100	49	51	349	175	174
#Downgrades (other)		533	265	268	558	273	275

Note: This table reports the estimation results that correspond to the regression equation in (7). The t-statistics for the statistical significance of the estimated coefficients are reported between parentheses. Columns "Euro Area", "Core", and "Periphery" contain the results of the estimation of the regression Eq. (7) using Euro Area, Core, and Periphery countries, respectively. Control variables, X, in (7) include weekday, month and year dummies. Euro Area (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain); Core (Austria, Finland, Germany, France, Netherlands); and Periphery (Belgium, Ireland, Italy, Greece, Portugal and Spain). "–" is to indicate that downgrades are not observed in Core countries.
* Represents statistical significance at 10%.
** Represents statistical significance at 5%.
*** Represents statistical significance at 1%.

We consider a standard mean–variance portfolio optimisation problem from which we can derive (in the closed form) the optimal portfolio weights in European bonds or equities. Thus, the investor with an initial wealth of $W_t = 1$ diversifies his or her portfolio between n European assets according to the following problem:

$$\begin{aligned} &\underset{\{\omega_t\}}{\mathrm{Max}} \left\{ \mu_p(\omega_t) - \frac{\eta}{2}\sigma_p^2(\omega_t) \right\} \\ &\text{s.t. } \omega_t' e = 1, \end{aligned} \tag{8}$$

where the "multiplier" η can be interpreted as a "risk aversion" coefficient, $\omega_t = (\omega_{1,t}, \dots, \omega_{n,t})'$ is the vector of portfolio weights, e is the $n \times 1$ vector of ones, and

$$\mu_p(w_t) = \mu' \omega_t \tag{9}$$

$$\sigma_p^2(\omega_t) = \omega_t' \Omega_t \omega_t \tag{10}$$

are the mean and variance of portfolio return, respectively, with μ and Ω being the mean and variance–covariance matrix of the vector of returns of the n European assets, respectively. The solution to the maximisation problem in (8) is given by the optimal vector of weights:

$$\omega_t = \frac{1}{\eta}\Omega_t^{-1}\left(\mu + \frac{1}{a}(e - be)\right), \tag{11}$$

where $a := e'\Omega_t^{-1}e$ and $b := e'\Omega_t^{-1}\mu$.

4.2. Financial gains from sovereign ratings' information

The vector of weights in (11) depends on the unobservable variance–covariance matrix of asset returns. To compute the optimal portfolio weights, investors need to forecast the diagonal elements (volatilities) of Ω, in addition to the covariance terms. Here we want to assess the financial gain of an investor who takes into account sovereign credit ratings information when forecasting the volatilities of European stock and bond returns. We base our analysis on the following expected utility function of the investor:

$$E(U(\omega_t)) = \mu_p(\omega_t) - \frac{\eta}{2}\sigma_p^2(\omega_t). \tag{12}$$

As in the previous subsection, the initial wealth is normalised to unity, i.e. $W_t = 1$. Following Amira et al. (2011), we define the financial gain g_t as the additional fraction of wealth necessary for an investor, who is not aware of the sovereign credit rating information, to match the same level of utility of an investor who is aware of this sovereign credit rating information. To get a simple analytical solution for g_t, we assume that the latter additional fraction of wealth (g_t) is not invested. Therefore, we want the solution of the following equation:

$$E(U(\omega_t^b) + g_t) = E(U(\omega_t^*)), \tag{13}$$

where ω_t^b is the optimal vector of weights invested in the European assets when the investor is not aware of the sovereign credit rating information, while ω_t^* is the optimal vector of weights when the investor considers that information. If instead we assume that this fraction g_t is invested, we will end up with a second order problem where the solution will depend on the values of the coefficients, and in some circumstances, the solution does not exist. Since g_t is not considered random, the mean–variance utility function implies that

$$g_t = E(U(\omega_t^*)) - E(U(\omega_t^b)). \tag{14}$$

To estimate the mean expected utility and the financial gain functions in (14) we proceed as follows. First, we measure the volatilities of the asset returns included in our dataset using the approach described in Section 2.4. Second, we estimate the panel regressions:

$$\log(\sigma_{i,t}) = \mu_i + \sum_{j=1}^{k} \lambda_j\, down_{i,t-j} + \sum_{j=1}^{k} \alpha_j\, down_{i,t-j}^{-i} + \beta \log(\sigma_{i,t-1}) + \zeta' X_{t-1} + \varepsilon_{i,t} \tag{15}$$

and

$$\log(\sigma_{i,t}) = \bar{\mu}_i + \bar{\beta}\log(\sigma_{i,t-1}) + \vartheta' X_{t-1} + \bar{\varepsilon}_{i,t}, \tag{16}$$

where μ_i ($\bar{\mu}_i$) are the country fixed effects, λ_j and α_j are the parameters of interest that capture the effect of downgrades on volatilities, β ($\bar{\beta}$) is the autoregressive coefficient of the log-volatility, ζ (ϑ) are the coefficients of the control variables X (including dummy variables for weekday and monthly effects), and $\varepsilon_{i,t}$ ($\bar{\varepsilon}_{i,t}$) are the error terms. In the empirical application, the number of lags k is equal to 10.

The specifications in (15) and (16) correspond to models of volatilities with and without taking into account the effect of sovereign credit ratings downgrade information, respectively. We abstract from the rating upgrades, because, as we saw in Section 4, they are not statistically significant. Moreover, following Section 4.3, we include the dummies of downgrades from other countries, $down_{i,t-j}^{-i}$. Finally, $\sigma_{i,t}$ in Eqs. (15) and (16) will be replaced by the conditional volatility filtered using the EGARCH (1, 1) model in (5).

Thereafter, we estimate the weights ω_t^* and ω_t^b using (11) in which the diagonal elements (variances) of Σ_t are replaced by the fitted-volatilities from the estimated regressions in (15) and (16), respectively. In order to focus on the effect of sovereign credit ratings information on volatilities, we use the unconditional estimate of the mean returns and of the correlation coefficients between the asset returns. In every period and following Bollerslev (1990), we update the covariance matrix to have a constant correlation equal to the unconditional correlation. Finally, we compute the average values of the estimated expected utility functions $E(U(\omega_t^b))$ and $E(U(\omega_t^*))$ and of the financial gain g_t due to the incorporation of the sovereign credit ratings' information.

To compute the optimal portfolio weights – with and without using sovereign credit ratings' information – we assumed constant unconditional expected returns and correlation structure. As our objective is to evaluate the effects of the rating information on volatility, we prefer to maintain this simple structure. However, we could develop the analysis by considering time-varying expected returns and correlations. For example, one can use autoregressive and distributed lag processes to model the conditional expected returns. Regarding the correlation structure, one evident generalisation would be considering the Engle (2002) dynamic conditional correlation model. Another alternative approach would be to follow Otranto (2010) who proposes a statistical procedure to detect the number of homogeneous groups of assets having similar correlation dynamics.

Another important issue is the estimation effect on the calculation of portfolio weights. It is well known (see for instance Scherer, 2007, or Jorion, 1986) that small perturbations of the unconditional expected asset returns may lead to completely different optimal portfolio weights. These perturbations may be due to a small sample estimation error. It is true that in our empirical analysis the sample size is quite large (2562 observations), but for small samples it is recommended to reduce the sensitivity of portfolio weights with respect to the estimation error in order to obtain robust and stable optimal portfolios.

Table 6
Financial gain in annualised basis points (bp) of credit rating downgrades information.

	Observations	$\eta = 3$	$\eta = 5$	$\eta = 7$
Relative to portfolio without rating information				
Stock Market				
In-sample prediction	*2562* (*554*)	9.8	6.1	4.6
Out-of-sample prediction	*518* (*289*)	5.4	3.3	2.4
Bond Market				
In-sample prediction	*2562* (*446*)	1.5	0.8	0.5
Out-of-sample prediction	*518* (*287*)	51.0	29.5	20.3
Relative to an equally weighted portfolio				
Stock Market				
In-sample prediction	*2562* (*554*)	8885	5897	4764
Out-of-sample prediction	*518* (*289*)	27 244	17 009	12 740
Bond Market				
In-sample prediction	*2562* (*446*)	1706	1237	1136
Out-of-sample prediction	*518* (*287*)	20 542	12 294	8830

Note: This table reports in-sample and out-of-sample predictions of the financial gain of credit rating downgrades information in (14). The second panel reports the financial gain relative to the equally weighted portfolio. The gain is in annualised basis points (bp). In this table "η" represents the risk aversion parameter. These financial gains are within two weeks of a downgrade. Between parentheses is the number of periods corresponding to two weeks after a downgrade.

Thus, one may use Bayesian shrinkage techniques to mitigate the negative effects of poor mean return estimation stability on the optimal portfolio weights. As outlined in Jorion (1986) the Bayes–Stein estimator offers an ideal trade-off between weighting a purely data-dependent estimator, such as the classical sample mean, and another estimator that relies less on the actual data but includes, for instance, expert views (analysts return expectations) or a measure derived from an equilibrium model.

To a lesser extent, but also important for the calculation of optimal portfolio weights, is the shrinkage of the variance–covariance matrix (see Ledoit and Wolf, 2004). Since the paper discusses financial gains from the information of sovereign ratings, this approach might be interesting to investigate, especially because the variance–covariance matrix in this case is based on the forecasts, which of course contain forecasting error.

4.3. Financial gains: empirical results

Our empirical results show the existence of a financial gain when we take into account the sovereign credit ratings downgrade information for volatility modelling. Table 6 reports the average financial gain in annualised basis points in the two weeks following the downgrade news. We report the results for different values of risk aversion: $\eta = 3$, 5, and 7, choosing these alternative values based on the empirical findings in the literature (see, for example, French and Poterba, 1991).

The in-sample prediction of the gains is for the sample period 2002–2011 and includes 2562 days of which around 500 days are within 2 weeks of downgrade announcements. The in-sample prediction analysis shows that the gains range between 5 and 10 annualised basis points (bp) for the stock market and around 1 bp for the bond market.

The financial gain is a decreasing function of the degree of risk aversion. We find that a less risk averse agent outperforms a more risk averse agent when both use the effect of credit ratings information on volatility to optimize their portfolios. The fact that higher risk aversion portfolios might tend to be more biased towards lower volatility countries can also explain this result. Indeed, such countries are in practice less prone to downgrades, as we have seen in our dataset.

We also did an out-of-sample exercise to evaluate the financial gains. To predict the financial gains we first predict the volatilities of all European assets that make up our portfolio with and without using the credit rating information. Again, as in our in-sample analysis, we only predict the volatilities, and thus we evaluate the mean returns and correlation coefficients between European equity and bond returns at their unconditional estimates. We consider one period (day) ahead static prediction during the last two years of the sample. This includes 518 days of which 287 days are within two weeks of downgrade announcements. For each additional day within the last two years of our sample, we re-estimate our volatility models using the data available until that day, we make one-day ahead prediction of these volatilities with and without using the Sovereign credit ratings information and compute the financial gains. Table 6 also reports the results of the out-of-sample prediction of the financial gains. These results show that the out-of-sample financial gains range between 2 and 6 bp for the stock market and between 20 and 50 bps for the bond market. The reason for the performance of the bond market is that its volatility responds more significantly to downgrade news after two days, while the stock market volatility responds contemporaneously and with one lag. However, because we assume that we can only restructure the portfolio one day after downgrades, we are not using all the information.

The second panel of Table 6 compares the financial gain of the portfolio with rating information with the equally weighted portfolio. We can see that the optimal portfolio has high financial gains relative to the equally weighted portfolio. In this period, there are many assets with average negative return. While the equally weighted portfolio puts a positive weight, the optimal portfolio puts a negative weight.

Table 7
Value-at-risk with and without credit rating downgrades information.

	$\eta = 3$	$\eta = 5$	$\eta = 7$
Stock market			
In-sample prediction			
Without rating information	−0.0824 (3.4%)	−0.0508 (3.4%)	−0.0376 (3.8%)
With rating information	−0.0820 (3.4%)	−0.0506 (3.4%)	−0.0375 (3.8%)
Percentage improvement	0.51%	0.49%	0.46%
Out-of-sample prediction			
Without rating information	−0.1450 (4.9%)	−0.0873 (4.5%)	−0.0627 (4.2%)
With rating information	−0.1439 (4.9%)	−0.0866 (4.5%)	−0.0622 (4.5%)
Percentage improvement	0.80%	0.80%	0.79%
Bond market			
In-sample prediction			
Without rating information	−0.0410 (3.4%)	−0.0271 (4.0%)	−0.0216 (3.7%)
With rating information	−0.0407 (3.4%)	−0.0269 (4.3%)	−0.0215 (3.7%)
Percentage improvement	0.74%	0.61%	0.49%
Out-of-sample prediction			
Without rating information	−0.1318 (3.8%)	−0.0799 (3.8%)	−0.0579 (4.7%)
With rating information	−0.1301 (3.8%)	−0.0789 (3.8%)	−0.0572 (4.7%)
Percentage improvement	1.27%	1.25%	1.22%

Note: This table reports in-sample and out-of-sample predictions of the value-at-risk with and without using credit rating downgrades information for estimating volatilities (Eqs. (15) and (16)). In this table "η" represents the risk aversion parameter. The value-at-risks are within two weeks of a downgrade. These value-at-risks correspond to each unit invested in the mean–variance portfolios. In brackets is the percentage of value-at-risk violations.

4.4. *Risk management: value-at-risk*

We also examine whether sovereign credit ratings' information can help protect investors against market risk. We compare the value-at-risk (VaR) of mean–variance portfolios with and without taking into account the effect of credit ratings information on stock and bond return volatilities.

Table 7 shows that for both in sample and out-of sample predictions, the value-at-risk of portfolios that consider the information of sovereign credit ratings are smaller than the ones of portfolios that do not take into account such information. The reduction of the value-at-risk is between 0.5% and 1.3% and is slightly higher for the bond market. The percentage of value-at-risk violations is, in most cases, identical. Furthermore, we found that the value-at-risk is decreasing in the coefficient of risk aversion. However, this observation cannot solely be attributed to financial gains due to the knowledge of firm-specific or country-specific ratings, but is also a direct consequence of the per se less risky portfolio strategies that more risk averse agents pursue.

5. Conclusion

We have considered a panel fixed-effect analysis of the daily EU stock market and sovereign bond market returns to study the impact of the three main rating agencies announcements (S&P, Moody's, Fitch) on financial markets volatility. Indeed, after the 2008–2009 financial and economic crises, the volatility in capital markets increased in most EU countries, both in sovereign debt and equity markets, challenging the euro area common currency.

In practical terms, we have first filtered the equity and bond returns volatilities via EGARCH models. Then, we have analysed the information content of sovereign upgrades and downgrades on these volatilities. Moreover, we assessed the potential financial gain for investors when considering such rating information on portfolio diversification decisions.

Our main results can be summarised as follows. We have shown empirically that sovereign rating changes have asymmetric effects on both equity and bond volatilities. Indeed, upgrades do not have any significant effect on volatility, but sovereign downgrades increase stock market volatility both contemporaneously and with one lag and rise bonds volatility after two lags. Interestingly, a rating upgrade in a given country reduces the volatility in the rest of the Euro-area, particularly in the core countries. On the other hand, a downgrade increases the volatility of all other countries, specifically in the periphery countries.

We have also shown the existence of a financial gain and risk reduction for portfolio returns when taking into account sovereign credit ratings information for volatility modelling. In addition, the financial gains are decreasing with the degree of risk aversion.

Finally, we find that the value-at-risk of portfolios that consider the information of sovereign credit ratings is smaller than the ones of portfolios that do not take such information into account, with the value-at-risk decreasing with risk aversion.

Acknowledgements

We thank Alexander Kockerbeck, Nicole Koehler, Moritz Kraemer, David Riley, Robert Shearman for providing us with the sovereign credit rating data. We are also grateful to Margarida Abreu, João Andrade e Sousa, four anonymous referees, an Associate Editor, and the Co-Editor Erricos John Kontoghiorghes for several useful comments. Earlier versions of this paper were presented at the International Conference on Computational and Financial Econometrics in Oviedo (2012), Time series workshop in Zaragoza (2013), and in seminars at ISEG/UTL Economics Department, Cardiff Business School, University of Minho, NIPE, Department of Economics, and School of Economics and Management. The opinions expressed herein are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. Pedro Gomes acknowledges financial support from the Bank of Spain's Programa de Investigacion de Excelencia. Abderrahim Taamouti acknowledges financial support from the Spanish Ministry of Science and Education through grants ECO2010-19357. UECE is supported by FCT (Fundação para a Ciência e a Tecnologia, Portugal), financed by ERDF and Portuguese funds.

Appendix. Data

Daily sovereign yield data come from Reuters. The respective tickers are:

BE10YT_RR, DE10YT_RR, IE10YT_RR, GR10YT_RR, ES10YT_RR, FR10YT_RR, IT10YT_RR, NL10YT_RR, AT10YT_RR, PT10YT_RR, FI10YT_RR, MT10YT_RR, SI10YT_RR, SK10YT_RR, DK10YT_RR, GB10YT_RR, BG10YT_RR, CZ10YT_RR, HU10YT_RR, LT10YT_RR, LV10YT_RR, PL10YT_RR, RO10YT_RR, SE10YT_RR.

Daily 5-year Credit default swaps spreads, historical close, are provided by DataStream.

Daily equity indexes are provided by DataStream:

Germany – Equity/index – DAX 30 Performance Index – Historical close – Euro
France – Equity/index – France CAC 40 Index – Historical close – Euro
Athens Stock Exchange ATHEX Composite Index – Historical close – Euro
Standard and Poors/MIB Index – historic close – Euro
Portugal PSI-20 Index – historic close – Euro
Amsterdam Exchange (AEX) Index – historic close – Euro
Spain IBEX 35 Index – historic close – Euro
Belgium BEL 20 Index – historic close – Euro
Ireland Stock Exchange Overall (ISEQ) Index – historic close – Euro
Nordic Exchange OMX Helsinki (OMXH) Index – historic close – Euro
Austrian Traded Index (ATX) – Percentage change in the latest trade price or value from the historic close -Euro
Slovenian Stock Exchange (SBI) Index – Percentage change in the latest trade price or value from the historic close – Euro
Cyprus Stock Exchange General Index – Historical close – Euro
Malta Stock Exchange Index – Percentage change in the latest trade price or value from the historic close – Maltese lira
Slovakia SAX 16 Index – Percentage change in the latest trade price or value from the historic close – Euro
Bulgaria Stock Exchange SOFIX Index – Historical close, end of period – Bulgarian lev, provided by Bloomberg
Prague PX 50 Index – Historical close, end of period – Czech koruna
Nordic Exchange OMX Copenhagen (OMXC) 20 Index – Historical close, end of period – Danish krone
Nordic Exchange OMX Tallinn (OMXT) Index – Historical close, end of period – Estonian kroon
Nordic Exchange OMX Riga (OMXR) Index – Historical close, end of period – Latvian lats
Nordic Exchange OMX Vilnius (OMXV) Index – Historical close, end of period – Lithuanian litas
Budapest Stock Exchange BUX Index – Historical close, end of period – Hungarian forint
Warsaw Stock Exchange General Index – Historical close, end of period – Polish zloty
Romania BET Composite Index (Local Currency) – Historical close, end of period – Romanian leu
Nordic Exchange OMX Stockholm 30 (OMXS30) Index – Historical close, end of period – Swedish krona
Financial Times Stock Exchange (FTSE) 100 Index – Historical close, end of period – UK pound sterling.

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