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Spillover effects from sovereign credit rating events to CDS market volatility: Evidence from Greece*

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Abstract: We study the potential spillover effects from Greece sovereign credit rating announcements to the volatility of sovereign credit default swaps (CDS) of economically similar European countries, namely Ireland, Italy, Portugal, and Spain. Dynamic logit and probit specifications are used to model Greece credit rating announcements and we posit EGARCH dynamics for the CDS volatilities. We then exploit the theory of copulas to model the dependence between the credit rating announcements and the volatilities in the sovereign CDS market. Finally, we assess the economic significance of incorporating Greece credit rating announcements when forecasting the out-of-sample CDS value-at-risk for each of the considered countries.

JEL classification: C51, E44, G15

Keywords: Sovereign ratings, CDS, Dynamic probit, EGARCH, Copula model

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1 Introduction

With the recent financial crisis, credit default swaps (CDS) and credit rating agencies have been written about extensively. Credit default swaps are now notoriously known due to their negative consequences with their critical role in the subprime mortgage crisis. Arentsen et al. (2015) shows empirically the adverse effect of CDS on subprime mortgage defaults. Using a multivariate probit model that captures the impact of CDS coverage on the probability of loan default, the authors test the prediction that CDS coverage had a positive effect on subprime mortgage defaults. They find a positive and significant relationship, which confirms that CDS were part of the chain of events that lead to the financial crisis. Credit rating agencies have also been criticized in the marketing of risky mortgage-backed securities due to the fact that they rated risky mortgage securities as high quality securities even though they were low quality securities. The financial crisis impacted many countries. Greece is one of them. The financial crisis notably lead to the Greek government-debt crisis, also known as the Greek Depression. See Ozturk and Sozdemir (2015) for a list of consequences of the global financial crisis on Greece. With the Greek government-debt crisis in mind and the critical role played by CDS in the financial crisis, would it be possible that Greece credit rating now conveys a great deal of credit information on the volatility of sovereign CDS? Would it also be possible that Greece credit rating information not only affects Greece, but also affects economically similar European countries? We aim to find answers to these two questions.

A few authors have written about how closely linked CDS spreads and ratings assigned by credit rating agencies are. For instance, Flannery et al. (2015) argue that CDS spreads could be viable substitutes for credit ratings. Focusing on CDS spreads based on obligations of fifteen large financial institutions that were involved in the financial crisis, the authors show that CDS spreads incorporate new credit information very quickly in the markets. The authors also suggest that CDS spreads would reflect information that is more accurate than the credit ratings themselves when it comes to the likelihood of default by the investment banks. Their results clearly depict that CDS spreads convey valuable credit information.

Several authors show the impact of credit rating events on returns of different financial instruments. Hull et al. (2004) study the impact of credit rating announcements produced by Moody's on the returns of corporate CDS spreads. They conclude that only the downgrade announcements have a significant impact. Their study suggests that a downgrade event is usually followed by a hike of 10 basis points in the CDS spreads on the following day of the announcement. They find no significant relationship as to the upgrade announcements. Micu, Remonola and Wooldridge (2006) study which type of rating announcement - outlooks, reviews, rating changes - both for positive and negative events is most likely to

impact corporate CDS spreads. Their sample spans the period from 2001 to 2005. They find evidence that all types of rating announcements have a significant impact on CDS spreads. Their findings also conclude that both positive and negative rating announcements are significant. Ismailescu and Kazemi (2010) produce a similar analysis with a focus on emerging markets. They study the effect of credit rating announcements on the returns of CDS spreads of sovereign debt for the period from 2001 to 2009 and their spillover effect. They find that upgrades have a significant impact in the two-day period surrounding the rating announcement and that upgrades are likely to spill over to other emerging countries. They also show that downgrades are anticipated by CDS markets. They use a logistic model for their study. Reisen and Maltzan (1999) also find a significant impact of credit rating announcements. They show that the impact is significant in the case of a downgrade event. Their study focuses on government bond yield spreads. Norden and Weber (2004) study the impact of credit rating announcements on both stock and CDS markets for the period from 2000 to 2002. They employ an event study methodology. The authors find that both downgrade events and reviews are anticipated by both stock and CDS markets. They claim that the anticipation starts approximately 60 to 90 days prior to the credit rating announcement. They also find insignificant market reactions around positive events. Gande and Parsley (2005) report the presence of contagion effect, that is a credit rating announcement from a specific country may influence the sovereign credit spreads of another country. They focus on 34 countries with publicly trader U.S. dollar denominated sovereign debt. They find that the effect is asymmetric, where positive events do not have a significant impact whereas negative events are associated with an increase in spreads. According to their findings, a downgrade of a sovereign bond is associated with a 12 basis point increase of sovereign bonds of another country.

Even though being scarcer, some part of the literature focuses on the effect of credit rating announcements on volatility instead of returns. Reisen and Maltzan (1998) address the relevance of credit rating announcements for sovereign bond yield spreads. They restrain their study on downgrades and find that negative outlooks lead to higher volatility for sovereign bond yield spreads. Their findings suggest that the impact is particularly strong in the case of emerging markets. Kräussl (2005) focuses on the impact of credit rating announcements in international financial markets and emerging market economies. With the use of an event study and a panel regression, he finds that credit rating agencies have substantial influence on the size and volatility of emerging markets lending. His results are significantly stronger in the case of negative events than positive events. Hooper et al. (2008) study the effect of downgrades and upgrades in the international financial markets as well. They cover 42 countries all around the globe for the period from 1995 to 2003. They use a panel regression. Their findings show that upgrades (downgrades) tend to increase (decrease)

stock market returns and decrease (increase) volatility. The responses are more pronounced in the case of downgrades than upgrades. Afonso et al. (2015) show that credit ratings affect European securities volatility. The authors study the reaction of bond and equity market volatility to sovereign rating announcements. Through the use of an EGARCH model and a panel regression, they find a significant and positive relationship between downgrade events and bonds and equity market volatility.

In view of Afonso et al. (2015) conclusion and due to the fact that Greece was highly impacted by the global financial crisis, we believe that Greece credit information conveys important information. We aim to study the impact of Greece downgrade events on sovereign CDS spreads volatility of economically similar European countries. We think that Greece credit rating announcements could incorporate spillover effect, also known as contagion effect, on the volatility of sovereign CDS of economically similar European countries. Since the majority of authors reject the idea that positive credit rating announcements significantly affect volatility, we focus on negative announcements only. We expect to obtain a significant and positive relationship between Greece downgrade events and sovereign CDS volatility of economically similar European countries. For our study, logit and probit models are estimated to predict Greece credit rating announcements. We employ an EGARCH model and the theory of copulas. We assess the economic value of incorporating Greece negative rating announcements in out-of-sample value-at-risk forecasting.

The rest of the paper is organized as follows. Section 2 provides a description of the countries, the rating events and the CDS data. Section 3 aims to model the probability of a downgrade event using either a logit or a probit model. Section 4 employs an EGARCH model to assess the effect of Greece negative ratings on volatility. Section 5 proposes a copula to model the dependence between Greece negative ratings and CDS volatility. Section 6 aims to assess the economic value of incorporating Greece negative ratings in out-of-sample VaR forecasting. Section 7 concludes the paper.

2 Data

2.1 Countries

We concentrate our analysis on the GIIPS countries - Greece, Ireland, Italy, Portugal, and Spain - five countries that were considered weaker economically following the financial crisis. The GIIPS have, among other things, been heavily impacted by sovereign credit ratings changes during the financial crisis, with ratings decreasing from high ratings (AAA, AA+, AA) prior to the crisis to low ratings (CCC-, CC, C) post-crisis. We define the set of countries $\Omega = \{\text{Greece, Ireland, Portugal, Spain, Italy}\}$.

2.2 Sovereign ratings

Sovereign credit ratings data are from the three main credit ratings agencies, namely Moody's (M), Standard and Poor's (S&P) and Fitch (F). Our data include sovereign credit ratings from 1988 to 2017, inclusively.

We define a credit rating change (also named a credit event) as three different events which can either be a change in the rating itself, an outlook or a credit watch. For the same agency, we consider outlooks and credit watches only when they occur on different dates than a change in the credit rating. In other words, an outlook or a credit watch followed a few months later by a change in the credit rating represent two events, whereas an outlook or a credit watch happening on the same day as a credit rating change represents only one event.

Outlooks and credit watches highlight the opinion of an agency regarding a potential direction of a short-term or long-term rating and assess economic conditions. According to S&P, in the case of an outlook, *consideration is given to any changes in economic and/or fundamental business conditions*, whereas in the case of a credit watch, the focus is given to *identifiable events and short-term trends that cause ratings to be placed under special surveillance*. Therefore, including outlooks and credit watches in our data allows us to work with a larger sample of credit events for our study and excluding them could lead to a loss of important information.

We apply a linear transformation to the credit ratings in order to standardize the three agencies ratings scale. Table 8 in Appendix A shows the linear transformation where the lowest ratings receive a value of 1 and the highest ratings receive a value of 17. We use the same scale as Afonso et al. (2015). In the case of outlooks and credit watches, they receive a value of 1 when positive and a value of -1 when negative. Table 9 in Appendix A shows the number of credit rating announcements since 1988 for each country by agency. Our data set includes a total of 55 upgrades, 90 downgrades, 34 positive outlooks/credit watches and 68 negative outlooks/credit watches.

Figure 6 in Appendix B shows the historical credit events for all five countries starting from 1988. Figure 7 in Appendix B shows binary downgrade events for each country - namely whether or not a downgrade event occurred at time t. Figure 7 illustrates that most downgrade events occurred during period from 2009 to 2013, which corresponds to the period of financial instability caused by the crisis of 2008.

Moody's and S&P historical ratings were respectively found on Moody's website `www.moodys.com` and S&P's website `www.standardandpoors.com`. Fitch historical ratings were found on Bloomberg.

Since we are solely interested in credit rating downgrades, we define the variable

$$\Delta rating_{i,t}^{agency} = rating_{i,t}^{agency} - rating_{i,t-1}^{agency} \tag{1}$$

where $rating_{i,t}^{agency}$ represents the rating for country $i \in \Omega = \{$Greece, Ireland, Portugal, Spain, Italy$\}$ at time t by a given agency $\in \{$S&P, Moody's, Fitch$\}$. Variable $\Delta rating_{i,t}^{agency}$ captures not only the conveyed information that a downgrade event occurred, but also the intensity of the downgrade event.

Finally, we define the union of downgrade events among all three agencies at time t as the sum

$$\Delta rating_{i,t} = \Delta rating_{i,t}^{S\&P} + \Delta rating_{i,t}^{Moody's} + \Delta rating_{i,t}^{Fitch} \tag{2}$$

which is simply the total of all downgrade events.

We also define the binary variable

$$y_{i,t} = \begin{cases} 1 & \text{if } \Delta rating_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

which captures whether or not country i was subject to a downgrade event at time t, not taking into account the intensity of the downgrade.

2.3 Credit default swaps spreads

We use daily 5-year CDS spreads historical close from October 26th 2005 to August 15th 2017. Our CDS contracts are denominated in US dollars. Our data set consists of 3080 observations. Data were extracted from Bloomberg. For a country $i \in \Omega$ at time t, we define the CDS spreads as $CDS_{i,t}$ and the log return is expressed as

$$R_{i,t} = \log CDS_{i,t} - \log CDS_{i,t-1} \tag{4}$$

2.3.1 Descriptive statistics

Historical CDS spreads are shown on Figure 8 in Appendix B. Historical CDS spreads log returns are shown on Figure 9 in Appendix B. Table 1 provides descriptive statistics for each country's CDS spreads log returns $R_{i,t}$.

We can see from Table 1 that the mean is close to zero for all five countries with little standard deviation ranging from 0.0180 to 0.0668. Two countries exhibit positive skewness, namely Greece and Italy, and three countries exhibit negative skewness, namely Ireland, Portugal and Spain. One important factor to notice is how extreme the kurtosis values are. The kurtosis values are ranging from 9.237 to 179.24, which are much higher than the kurtosis of a normal distribution which is 3. The extreme values for the minimum and

maximum returns as low as -1.004 and as high as 0.820 explain the extreme kurtosis values and depict the presence of heavy tails for our log returns series. The heavy tails are also evident from Figure 9.

The descriptive statistics therefore suggest that the daily spreads returns do not follow a normal distribution. The Jarque-Bera (JB) normality test agrees with values that are far beyond the critical value. JB values are shown in last column of Table 1. A distribution which encompasses heavy tails behavior might be well suited to capture the daily spreads log returns behavior, such as the student-t distribution.

Table 1: CDS spreads log returns descriptive statistics

The table summarizes descriptive statistics for our five countries CDS spreads log returns for the period from October 26th 2005 to August 15th 2017.

Country	Mean	Std	Skew	Kurt	Min	Max	JB
Greece	0.000827	0.0267	1.143	96.54	-0.469	0.550	1198500
Ireland	0.000340	0.0668	-0.273	84.28	-0.906	0.820	912970
Portugal	0.000455	0.0206	-0.290	11.24	-0.235	0.134	16307
Spain	0.000399	0.0418	-1.215	179.24	-1.004	0.812	4129600
Italy	0.000327	0.0180	0.298	9.237	-0.164	0.143	11016

2.3.2 Stationarity

In order to practice time series analysis, theory requires the series to be stationary. From Figures 8 and 9 in Appendix B, it is clear that the CDS spreads are not stationary, whereas the CDS spreads log returns appear to be stationary around 0. We perform the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test in order to study the stationarity of the daily spreads log returns series. Table 2 shows the results for both tests and their respective p-values. In all cases, the tests reject the null hypothesis that the series are not stationary. Consequently, time series theory will hold for our data.

Table 2: ADF and PP test results

Country	ADF	ADF p-values	PP	PP p-values
Greece	-13.43	0.01	-2936	0.01
Ireland	-19.06	0.01	-3385	0.01
Portugal	-14.30	0.01	-2844	0.01
Spain	-17.67	0.01	-2678	0.01
Italy	-14.55	0.01	-2401	0.01

3 Predicting the probability of a downgrade event for Greece

3.1 Objective

Since we are only interested in Greece in this section, we omit the subscript i to simplify the notation (for example, we write y_t instead of $y_{i,t}$). The objective of this section is to predict the probability of a downgrade in the rating of Greece at time t given the information set I_{t-1}. In other words, we desire a way to predict the values

$$P(Y_t = 1|I_{t-1}) \text{ and } P(Y_t = 0|I_{t-1}) = 1 - P(Y_t = 1|I_{t-1})$$

Therefore, we must think of a Bernoulli distribution, which is given by

$$\mathrm{B}(p; k) = \begin{cases} p & \text{if } k = 1 \\ 1 - p & \text{if } k = 0 \end{cases} \tag{5}$$

3.2 Prediction of downgrade events

At each time t, we quantify the value of a downgrade event x_t by

$$x_t = \Theta_0 + \Theta_1 \sum_{\tau=1}^{T} y_{t-\tau} + \Theta_2 x_{t-1} \tag{6}$$

where y_t is defined by (3). Note that x_t is most likely $\notin [0, 1]$. Logit and probit regressions will be used to restrict the possible values of x_t to the interval $[0, 1]$. We test for values of $T \in \{1, 2, 3\}$ to allow for persistent lagged effects. Also, note that we could start the sum as $\sum_{\tau=0}^{T}$ where τ starts at 0 instead of 1, which would lead to higher fitted conditional probabilities (as high as 1), but this would require the information set I_t and would not be a

predicted probability anymore, but rather an observed probability. Hence the lower bound $\tau = 1$.

3.3 Logit model

For the logit model, we first need to define the sigmoid function $S(x)$ which is given by

$$S(x) = \frac{e^x}{1 + e^x} \tag{7}$$

The sigmoid function maps any value $\in \mathbb{R}$ to the interval $[0, 1]$. In our case, the sigmoid function allows our model to treat the value x_t given by (6) as a probability value $\in [0, 1]$. Then, we define the random variable Y_t as $Y_t \sim \mathrm{B}(S(x_t))$, where $\mathrm{B}(p)$ is the Bernoulli distribution defined by (5), x_t the value of a downgrade event defined by (6) and $S(x)$ the sigmoid function defined by (7).

3.4 Probit model

For the probit model, we first need to define the normal cumulative density function $\Phi(x)$ which is given by

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-x^2}{2}} dx \tag{8}$$

Then, we define the random variable Y_t as $Y_t \sim \mathrm{B}(\Phi(x_t))$, where $\mathrm{B}(p)$ is the Bernoulli distribution defined by (5), x_t the value of a downgrade event defined by (6) and $\Phi(x)$ the normal cumulative density function defined by (8).

3.5 Maximum likelihood estimation (MLE)

We need to estimate the values of $\underline{\Theta} = (\Theta_0, \Theta_1, \Theta_2)$ that maximizes the log-likelihood function, namely we want to find $\hat{\underline{\Theta}}$ such that.

$$\hat{\underline{\Theta}} = \underset{\underline{\Theta}}{\operatorname{argmax}}\, \mathcal{L}(\underline{\Theta}) \tag{9}$$

3.5.1 Logit model MLE

The log-likelihood function for the logit model is given by

$$\begin{aligned}\mathcal{L}(\underline{\Theta}) &= \log \prod_{t=1}^{n} \mathrm{B}(S(x_t)|x_t, \underline{\Theta}) \\ &= \log \prod_{t=1}^{n} S(x_t)^{y_t}(1 - S(x_t))^{1-y_t} \\ &= \sum_{t=1}^{n} \log[S(x_t)^{y_t}(1 - S(x_t))^{1-y_t}] \\ &= \sum_{t=1}^{n} y_t \log(S(x_t)) + (1 - y_t)\log(1 - S(x_t))\end{aligned} \tag{10}$$

where $y_t \in \{0, 1\}$ is defined by (3), $S(x)$ is the sigmoid function defined by (7) and x_t is the quantified value of a downgrade event defined by (6).

3.5.2 Probit model MLE

Similarly, the log-likelihood function for the probit model is given by

$$\begin{aligned}\mathcal{L}(\underline{\Theta}) &= \log \prod_{t=1}^{n} \mathrm{B}(\Phi(x_t)|x_t, \underline{\Theta}) \\ &= \log \prod_{t=1}^{n} \Phi(x_t)^{y_t}(1 - \Phi(x_t))^{1-y_t} \\ &= \sum_{t=1}^{n} \log[\Phi(x_t)^{y_t}(1 - \Phi(x_t))^{1-y_t}] \\ &= \sum_{t=1}^{n} y_t \log(\Phi(x_t)) + (1 - y_t)\log(1 - \Phi(x_t))\end{aligned} \tag{11}$$

where $y_t \in \{0, 1\}$ is defined by (3), $\Phi(x)$ is the normal cumulative distribution function defined by (8) and x_t is the quantified value of a downgrade event defined by (6).

3.6 Numerical results

We estimate both logit and probit defined in sections 3.3 and 3.4 for Greece only. We use Greece downgrade events for the period starting on October 26th 2005 to August 15th 2017 - the same period as of our CDS spreads series. P-values were computed using likelihood-ratio tests.

Table 3 reports the estimated coefficients and their respective p-values along with AIC and BIC values. Coefficients Θ_1 and Θ_2 are both positive and significant at the level of 1%

both for logit and probit models and for all lag values $T \in \{1, 2, 3\}$. AIC and BIC values are slightly lower with a lag value of $T = 3$ and under a probit model. We conclude that both logit and probit models capture correctly the dynamics of Greece downgrade events prediction.

Table 3: Logit and probit estimated values

The table reports coefficient estimates both for logit and probit models. The sample consists of Greece downgrade events from October 26th 2005 to August 15th 2017.

Model	T	Θ_0	Θ_1	Θ_2	AIC	BIC
	1	-0.300	1.280	0.940	0.1180	0.1239
		(0.000)	(0.000)	(0.000)		
Logit	2	-0.311	0.654	0.937	0.1182	0.1241
		(0.000)	(0.000)	(0.000)		
	3	-0.364	0.483	0.926	0.1178	0.1236
		(0.000)	(0.000)	(0.001)		
	1	-0.165	0.599	0.933	0.1178	0.1236
		(0.000)	(0.000)	(0.000)		
Probit	2	-0.171	0.305	0.931	0.1180	0.1238
		(0.000)	(0.000)	(0.000)		
	3	-0.196	0.222	0.921	0.1175	0.1234
		(0.000)	(0.000)	(0.001)		

Figure 1 shows the conditional fitted probabilities. We can see that the predicted probability of a downgrade event for a given day t goes as high as 23% at the beginning of 2010. Most of the activity for the conditional probabilities occurs during the period from 2009 to 2013 and during the year 2015 as anticipated from Figure 7 in Appendix A. Most of the downgrade events happened during these years of the financial crisis.

Figure 2 shows the conditional fitted probabilities (in blue) plotted against the historical downgrade events to assess the fitted probabilities performance. The blue lines depict the conditional probabilities as estimated from the logit and probit models, and the black bars depict days during which downgrade events occurred. We can see that the conditional probabilities peaks match downgrade events. Our models therefore successfully predict downgrade events behavior for Greece.

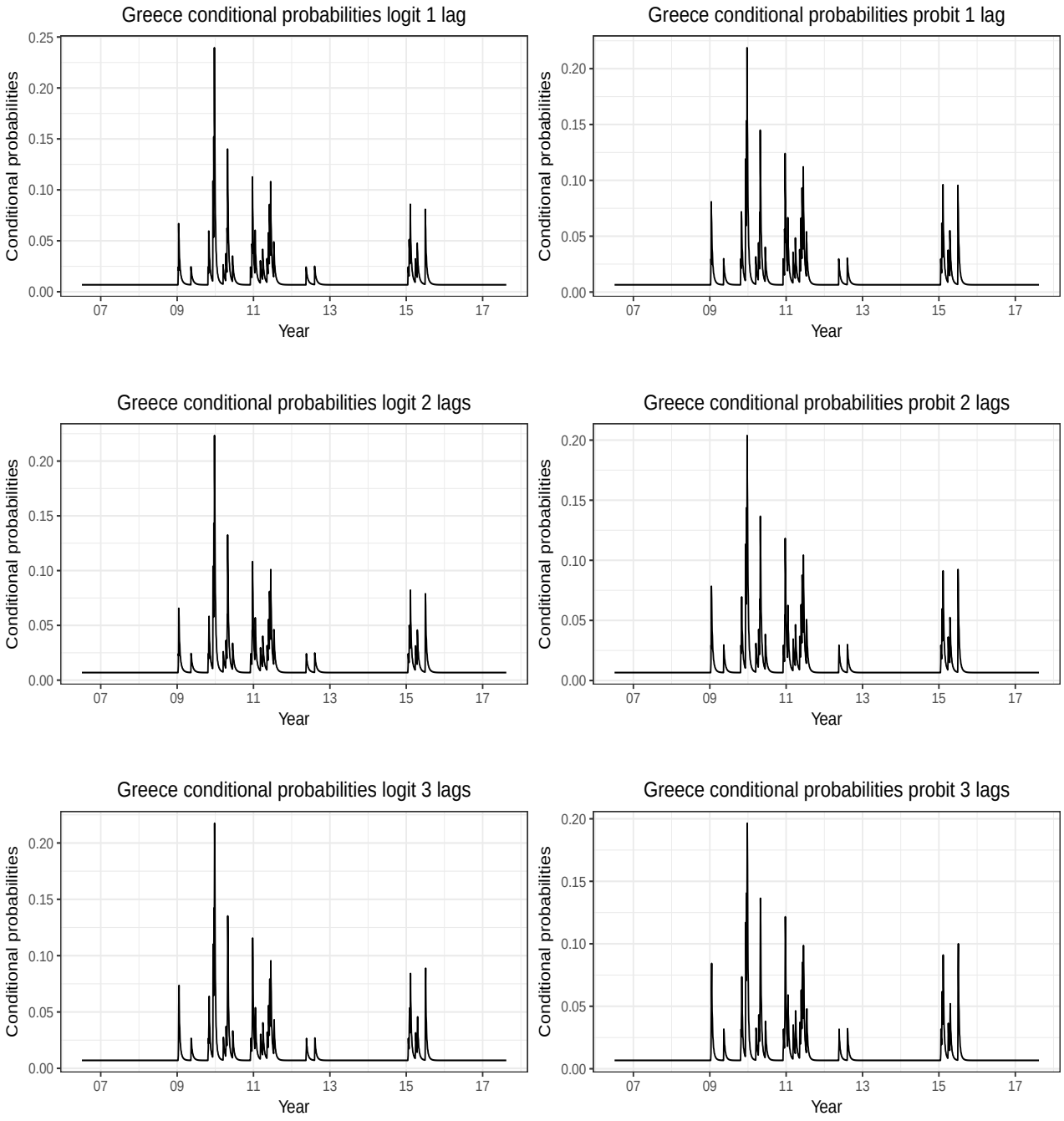

Figure 1: Logit and probit fitted conditional probabilities

Conditional probabilities estimated from both logit and probit models with lag values $T \in \{1, 2, 3\}$ for Greece downgrade events for the period from October 26th 2005 to August 15th 2017.

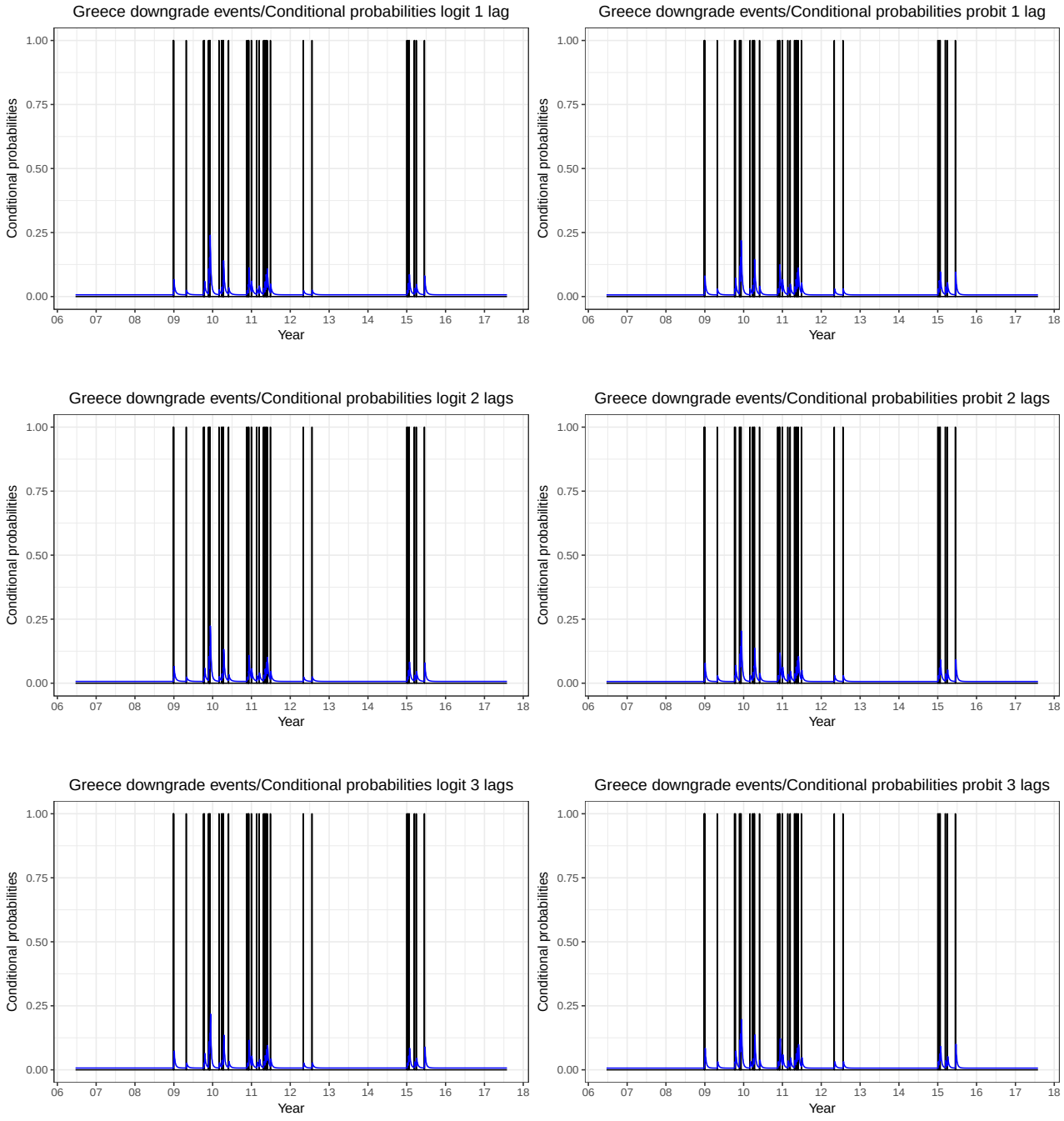

Figure 2: Logit and probit fitted conditional probabilities

In blue, conditional probabilities estimated from both logit and probit models with lag values $T \in \{1, 2, 3\}$ plotted against downgrade events, in black, for Greece for the period from October 26th 2005 to August 15th 2017.

4 Downgrade events on CDS spreads volatility

We aim to analyze the impact of downgrade events on CDS spreads volatility. In the light of Engle and K. NG (1993), many researchers have studied the asymmetric volatility models, in which good news and bad news have different predictability for future volatility. With credit rating events, where upgrades and downgrades respectively represent good news and bad news, it is reasonable to believe that the direction of credit rating events might impact CDS spreads asymmetrically. We therefore consider an Exponential-GARCH (EGARCH) model proposed by Nelson (1991) to analyze the impact of downgrade events on CDS spreads volatility.

4.1 EGARCHX

We first want to analyze the effect of downgrade events on their own country's CDS volatility as well as on other countries' CDS volatility. The first model therefore allows to examine the possibility of contagion - that is it allows to model the impact of downgrade events from some countries on the CDS volatility of another country. Consequently, for each country i at time t, we consider the following model

$$R_{i,t} = \mu_i + \epsilon_{i,t} \tag{12}$$

where μ_i is the expected return, $\epsilon_{i,t} = \sigma_{i,t} z_{i,t}$ follows a zero-mean white noise with $z_{i,t} \sim$ i.i.d. $t(\nu)$, and $\sigma_{i,t}$, the volatility of the log returns $R_{i,t}$, is given by

$$\begin{aligned} \log(\sigma_{i,t}^2) = \omega_i + \alpha_i z_{i,t-1} + \gamma_i(|z_{i,t-1}| - E|z_{i,t-1}|) + \beta_i \log(\sigma_{i,t-1}^2) + \\ \theta_{i,1} \sum_{\tau=1}^{T} \Delta rating_{Greece,t-\tau} + \theta_{i,2} \sum_{\tau=1}^{T} \Delta rating_{Ireland,t-\tau} + \\ \theta_{i,3} \sum_{\tau=1}^{T} \Delta rating_{Portugal,t-\tau} + \theta_{i,4} \sum_{\tau=1}^{T} \Delta rating_{Spain,t-\tau} + \\ \theta_{i,5} \sum_{\tau=1}^{T} \Delta rating_{Italy,t-\tau} \end{aligned} \tag{13}$$

Secondly, we want to analyze the effect of Greece downgrade events on all five countries separately. In order to do so, for each country i at time t, we now consider the following time series

$$R_{i,t} = \mu_i + \epsilon_{i,t} \tag{14}$$

where μ_i is the expected return, $\epsilon_{i,t} = \sigma_{i,t} z_{i,t}$ follows a zero-mean white noise with $z_{i,t} \sim$

i.i.d. $t(\nu)$, and $\sigma_{i,t}$, the volatility of the log returns $R_{i,t}$, is given by

$$\log(\sigma_{i,t}^2) = \omega_i + \alpha_i z_{i,t-1} + \gamma_i(|z_{i,t-1}| - E|z_{i,t-1}|) + \beta_i \log(\sigma_{i,t-1}^2) + \theta_i \sum_{\tau=1}^{T} \Delta rating_{Greece,t-\tau} \tag{15}$$

Variables $\Delta rating_{j,t}$ are defined by (1). Since for both models the innovations follow a student-t distribution with ν degrees of freedom, it is possible to calculate $E|z_t|$ from an analytical formula. We have

$$E|z_t| = \frac{2\Gamma[(1+\nu)/2]\sqrt{\nu-2}}{1+(\nu+1)\Gamma(\nu/2)\sqrt{\pi}} \tag{16}$$

For these two models, we use the variable $\Delta rating_{j,t}$ instead of variable $y_{j,t}$ since we believe that including the intensity of a downgrade event might convey more information than simply the binary downgrade event. The intensity variable $\Delta rating_{j,t}$ might produce a larger impact towards the volatility than just the binary downgrade events information given by variable $y_{j,t}$.

The only difference between the two models is the set of exogenous variables. For the first model shown in (13), we include all countries downgrade events as exogenous variables. This first model allows to analyze contagion effect for all countries. The purpose of the first model is to depict a broad view of how the downgrade events from all five countries interact altogether with regards to the volatility of all five countries. As we will see, Greece is the dominating country. For the second model, since the first model shows that Greece is the dominating country, we incorporate only Greece downgrade events in our exogenous variable. Equation (15) includes only Greece downgrade events. The purpose of the second model is to study the importance of Greece downgrade events on the volatility of all five GIIPS countries.

We estimate for different lag values of $T = \{1, 2, 3\}$ to allow persistent lagged effects. For both models, to ease the estimation process we first fix $\mu = 0$, which does not affect our results since all series mean are close to 0 as shown in Table 1. We also fix $\nu = 3$. Fixing ν at $\nu = 3$ significantly simplifies the estimation procedure. We choose a small value of $\nu = 3$ for the shape parameter due to the fact that our series encompass high kurtosis, as shown in Table 1. Since all our time series contain high kurtosis, the shape parameter ν tends to go below or equal to the value of 2 when optimizing the student-t distribution, which is harmful since the student-t distribution has an infinite variance for a shape parameter $\nu \leq 2$. Fixing $\nu = 3$ allows to avoid this possible problem. All p-values are computed using likelihood-ratio tests.

Table 4 reports coefficient estimates for the first EGARCHX model defined by (13) which includes downgrade events from all five countries as exogenous variables. This first

EGARCHX makes possible the presence of contagion effect from downgrade events on the volatility of all countries. The first result to notice from Table 4 is the fact that Greece downgrade events coefficient θ_1 is positive for all countries and significant at the level of 5% for all countries except Portugal. The fact that coefficient θ_1 emerges could mean that Greece downgrade events convey important economic information in such a way that economically similar countries are also affected by Greece's downgrade events. Another interesting result to notice is the fact that coefficient θ_2, Ireland downgrade events, are negative and significant at the level of 5% both for Ireland and Portugal. The negative signs indicate that downgrade events would lower the volatility. This result is in some way not expected and is against most of the literature which states that downgrade events lead to higher volatility, as concluded by Afonso et al. (2015). This unexpected result could be studied more deeply in future research.

Table 5 reports coefficient estimates for the second EGARCHX model defined by (15) which includes only Greece downgrade events as exogenous variable. The results obtained are consistent with those obtained from the first EGARCHX model reported in Table 4. Coefficient θ is positive for all countries and significant at the level of 5% for all countries except Portugal.

Results obtained from both EGARCHX models confirm that Greece downgrade events incur an increase in the volatility of sovereign CDS spreads. From the fact that Greece downgrade events affect not only Greece's CDS spreads, but also Ireland's, Spain's and Italy's, our analysis shows that there is a contagion effect from Greece's downgrade events. From Tables 4 and 5, we also notice that Greece's downgrade events really stand out from downgrade events across all countries - they are the downgrade events with the strongest impact on volatility for all five countries. The number of lags T does not unambiguously impact the level of significance of the results. In the case of Greece, AIC values and p-values are stronger for a lag value of $T = 1$, which might indicate that a downgrade event almost instantaneously impact Greece's CDS spreads log returns volatility. In the case of Italy, results show the contrary. Italy AIC values and p-values are the strongest for a lag value of $T = 3$, which could indicate that Greece's downgrade events take a few days before affecting Italy's CDS spreads log returns volatility.

4.2 Impulse responses of Greece downgrade events on CDS volatility for each country

In this subsection, we analyze the response of each country CDS volatility following the impact of Greece downgrade events. According to He, Teräsvirta and Malmsten (2002), the second unconditional moment of the CDS log returns given by (15) may be calculated with

Table 4: EGARCHX all countries numerical results

The table reports coefficient estimates for the EGARCHX model with all five countries as exogenous variables as defined by (13). The sample consists of all countries downgrade events from October 26th 2005 to August 15th 2017 as well as CDS spreads log returns for the same period.

Country	T	θ_1	θ_2	θ_3	θ_4	θ_5	AIC	BIC
	1	0.2701	-0.2296	-0.1143	0.4498	-0.5054	-5.4165	-5.3989
		(0.003)	(0.065)	(0.341)	(0.001)	(0.016)		
Greece	2	0.1282	-0.1150	-0.0785	0.2151	-0.2472	-5.4147	-5.3971
		(0.009)	(0.075)	(0.245)	(0.004)	(0.021)		
	3	0.0818	-0.0659	-0.0547	0.1298	-0.1996	-5.4139	-5.3963
		(0.018)	(0.123)	(0.238)	(0.019)	(0.009)		
	1	0.1397	-0.2337	0.2192	0.0628	-0.1136	-5.3209	-5.3033
		(0.019)	(0.004)	(0.002)	(0.499)	(0.345)		
Ireland	2	0.0743	-0.1195	0.1005	0.0397	-0.0518	-5.3205	-5.3029
		(0.014)	(0.004)	(0.007)	(0.391)	(0.396)		
	3	0.0494	-0.0814	0.0670	0.0254	-0.0269	-5.3203	-5.3026
		(0.016)	(0.005)	(0.007)	(0.412)	(0.515)		
	1	0.0827	-0.2550	0.0666	0.1754	-0.0729	-5.4300	-5.4124
		(0.339)	(0.020)	(0.523)	(0.142)	(0.651)		
Portugal	2	0.0399	-0.1383	0.0195	0.0895	-0.0706	-5.4300	-5.4124
		(0.374)	(0.016)	(0.725)	(0.135)	(0.395)		
	3	0.0282	-0.1009	0.0193	0.0555	-0.0619	-5.4302	-5.4125
		(0.356)	(0.013)	(0.590)	(0.175)	(0.282)		
	1	0.2242	-0.1452	0.1312	0.0578	-0.0229	-5.1005	-5.0829
		(0.001)	(0.152)	(0.119)	(0.562)	(0.871)		
Spain	2	0.1184	-0.0882	0.0621	0.0422	-0.0304	-5.1007	-5.0831
		(0.001)	(0.116)	(0.160)	(0.401)	(0.679)		
	3	0.0795	-0.0582	0.0428	0.0333	-0.0291	-5.1007	-5.0830
		(0.001)	(0.131)	(0.148)	(0.322)	(0.557)		
	1	0.1665	-0.0823	0.1650	0.0523	0.0147	-5.5568	-5.5392
		(0.074)	(0.475)	(0.109)	(0.670)	(0.929)		
Italy	2	0.0956	-0.0491	0.0864	0.0418	-0.0062	-5.5572	-5.5396
		(0.049)	(0.422)	(0.107)	(0.501)	(0.943)		
	3	0.0717	-0.0440	0.0673	0.0284	-0.0081	-5.5579	-5.5403
		(0.032)	(0.312)	(0.064)	(0.503)	(0.892)		

Table 5: EGARCHX only Greece downgrade events numerical results

The table reports coefficient estimates for the EGARCHX model with only Greece downgrade events as exogenous variable as defined by (15). The sample consists of Greece downgrade events from October 26th 2005 to August 15th 2017 as well as the five countries CDS spreads log returns for the same period.

Country	T	ω	α	β	γ	θ	AIC	BIC
	1	-0.2612	0.0703	0.9692	0.4416	0.2405	-5.4130	-5.4095
		(0.000)	(0.000)	(0.000)	(0.000)	(0.006)		
Greece	2	-0.2600	0.0707	0.9693	0.4414	0.1089	-5.4124	-5.4089
		(0.000)	(0.000)	(0.000)	(0.000)	(0.018)		
	3	-0.2595	0.0710	0.9693	0.4414	0.0684	-5.4121	-5.4086
		(0.000)	(0.000)	(0.000)	(0.000)	(0.033)		
	1	-0.2292	0.0031	0.9731	0.1655	0.1683	-5.3191	-5.3156
		(0.000)	(0.698)	(0.000)	(0.000)	(0.003)		
Ireland	2	-0.2293	0.0030	0.9731	0.1655	0.0858	-5.3191	-5.3156
		(0.000)	(0.707)	(0.000)	(0.000)	(0.003)		
	3	-0.2293	0.0030	0.9731	0.1655	0.0570	-5.3190	-5.3155
		(0.000)	(0.706)	(0.000)	(0.000)	(0.003)		
	1	-0.2821	0.0398	0.9635	0.3516	0.0754	-5.4302	-5.4267
		(0.000)	(0.029)	(0.000)	(0.000)	(0.362)		
Portugal	2	-0.2815	0.0401	0.9636	0.3515	0.0322	-5.4301	-5.4266
		(0.000)	(0.028)	(0.000)	(0.000)	(0.458)		
	3	-0.2815	0.0400	0.9636	0.3513	0.0234	-5.4302	-5.4266
		(0.000)	(0.028)	(0.000)	(0.000)	(0.430)		
	1	-0.3892	0.0062	0.9509	0.1883	0.2434	-5.1019	-5.0984
		(0.000)	(0.620)	(0.000)	(0.000)	(0.000)		
Spain	2	-0.3920	0.0061	0.9505	0.1889	0.1261	-5.1020	-5.0985
		(0.000)	(0.627)	(0.000)	(0.000)	(0.000)		
	3	-0.3911	0.0062	0.9507	0.1883	0.0854	-5.1019	-5.0983
		(0.000)	(0.622)	(0.000)	(0.000)	(0.000)		
	1	-0.5456	0.0361	0.9313	0.3509	0.1901	-5.5585	-5.5550
		(0.000)	(0.066)	(0.000)	(0.000)	(0.043)		
Italy	2	-0.5521	0.0360	0.9306	0.3506	0.1099	-5.5588	-5.5553
		(0.000)	(0.075)	(0.000)	(0.000)	(0.029)		
	3	-0.5603	0.0360	0.9296	0.3506	0.0837	-5.5592	-5.5557
		(0.000)	(0.070)	(0.000)	(0.000)	(0.013)		

a closed-form formula. The closed-form formula is given by (17).

$$E[R_t^2] = E[|z_t|^2]e^{\frac{\omega}{1-\beta}} \prod_{i=1}^{\infty} E[e^{\beta^{i-1} g(z_t)}] \tag{17}$$

with $g(z_t) = \alpha z_t + \gamma(|z_t| - E[z_t])$. In our case, we specifically have $z_t \sim t(\nu = 3)$.

We use (17) to calculate the unconditional volatility for each country CDS. The EGARCHX parameters are specified in Table 5. Figures 3, 4 and 5 illustrate the impulse response functions of the impact of Greece downgrade events on sovereign debt CDS for each country for lag values of $T \in \{1, 2, 3\}$. The red dashed line represents the long term volatility of the CDS.

For all five countries, it takes a maximum of 10 days for the CDS volatility to return to their long term volatility. In the cases of Greece and Italy, it takes less than 10 days. Greece and Italy volatility return to their long term value after more or less 8 days. We notice that for all countries, the impact of a Greece downgrade is significantly higher when employing a lag value $T = 1$ in our EGARCH model. Greece and Spain reach a volatility of more or less 0.30 on the day following the announcement under $T = 1$, whereas the volatility reaches much lower values in the case of $T = 2$ and $T = 3$ with values around 0.20. Ireland, Portugal and Italy volatility are also more impacted when employing a lag value $T = 1$ and less impacted with lag values $T = 2$ and $T = 3$.

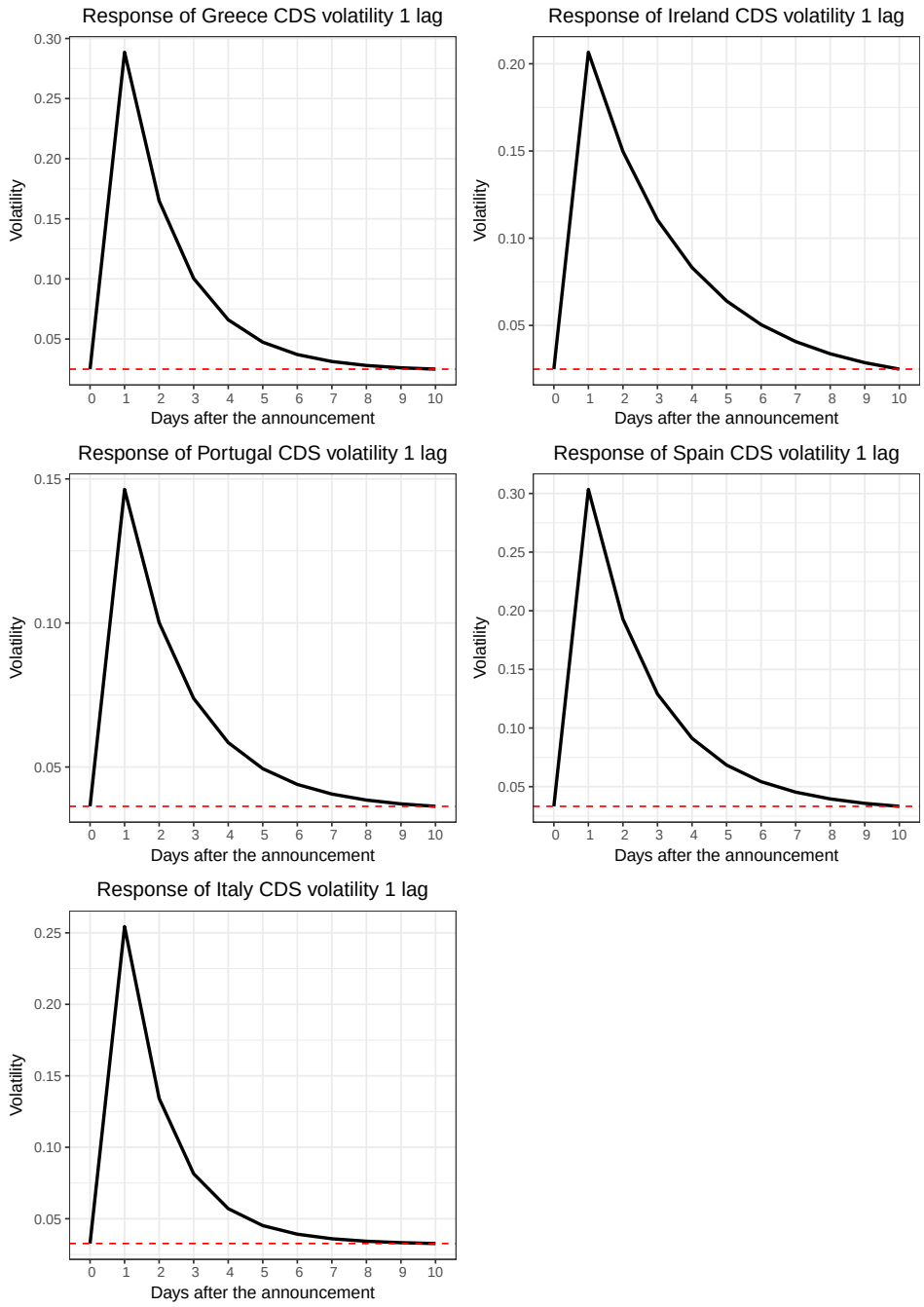

Figure 3: Impulse response functions with 1 lag

The figure shows the volatility of each country following a Greece downgrade event announcement when employing a lag value $T = 1$ for our EGARCH model defined by (15). The red dashed line represents the long term volatility of the CDS.

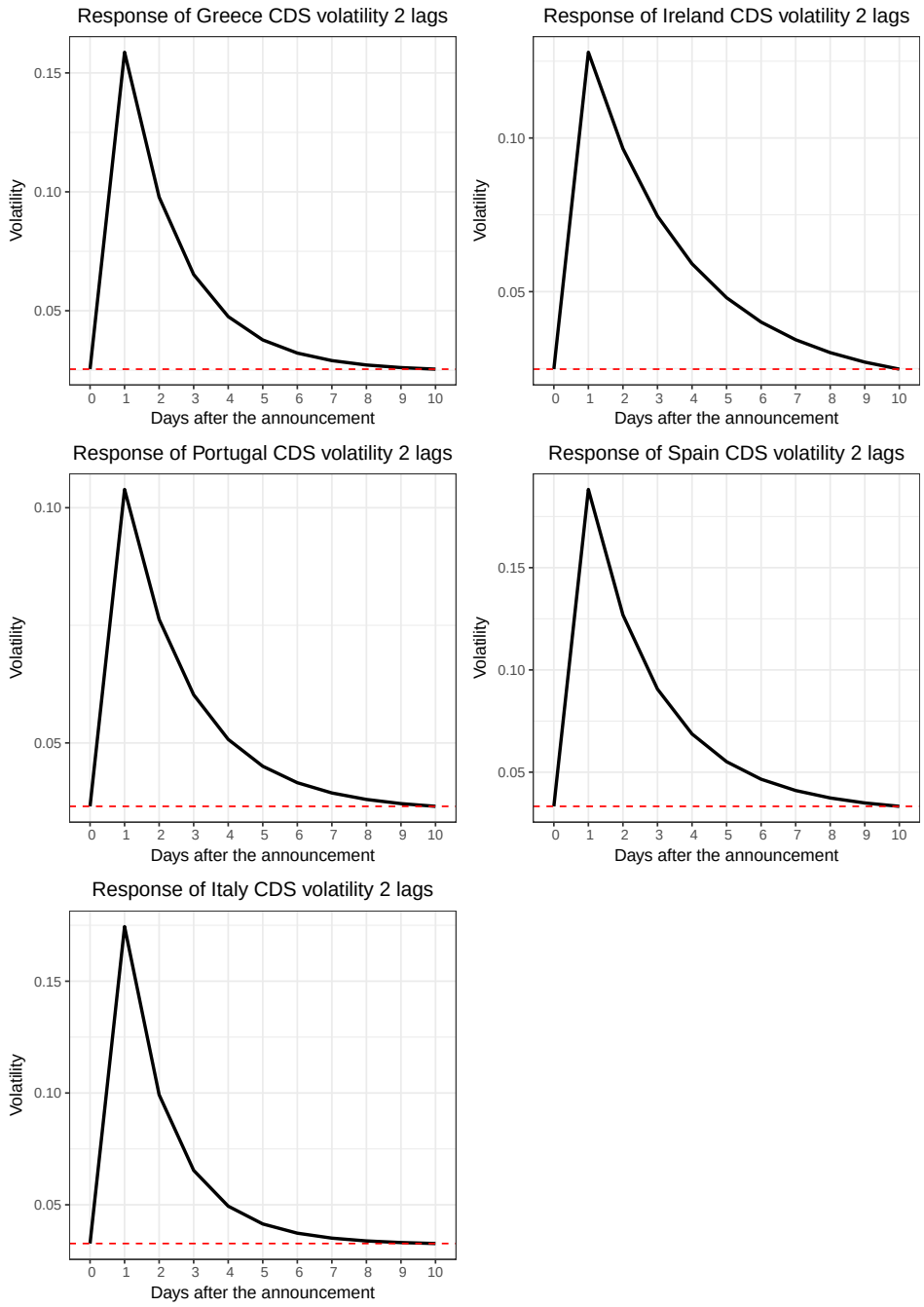

Figure 4: Impulse response functions with 2 lags

The figure shows the volatility of each country following a Greece downgrade event announcement when employing a lag value $T = 2$ for our EGARCH model defined by (15). The red dashed line represents the long term volatility of the CDS.

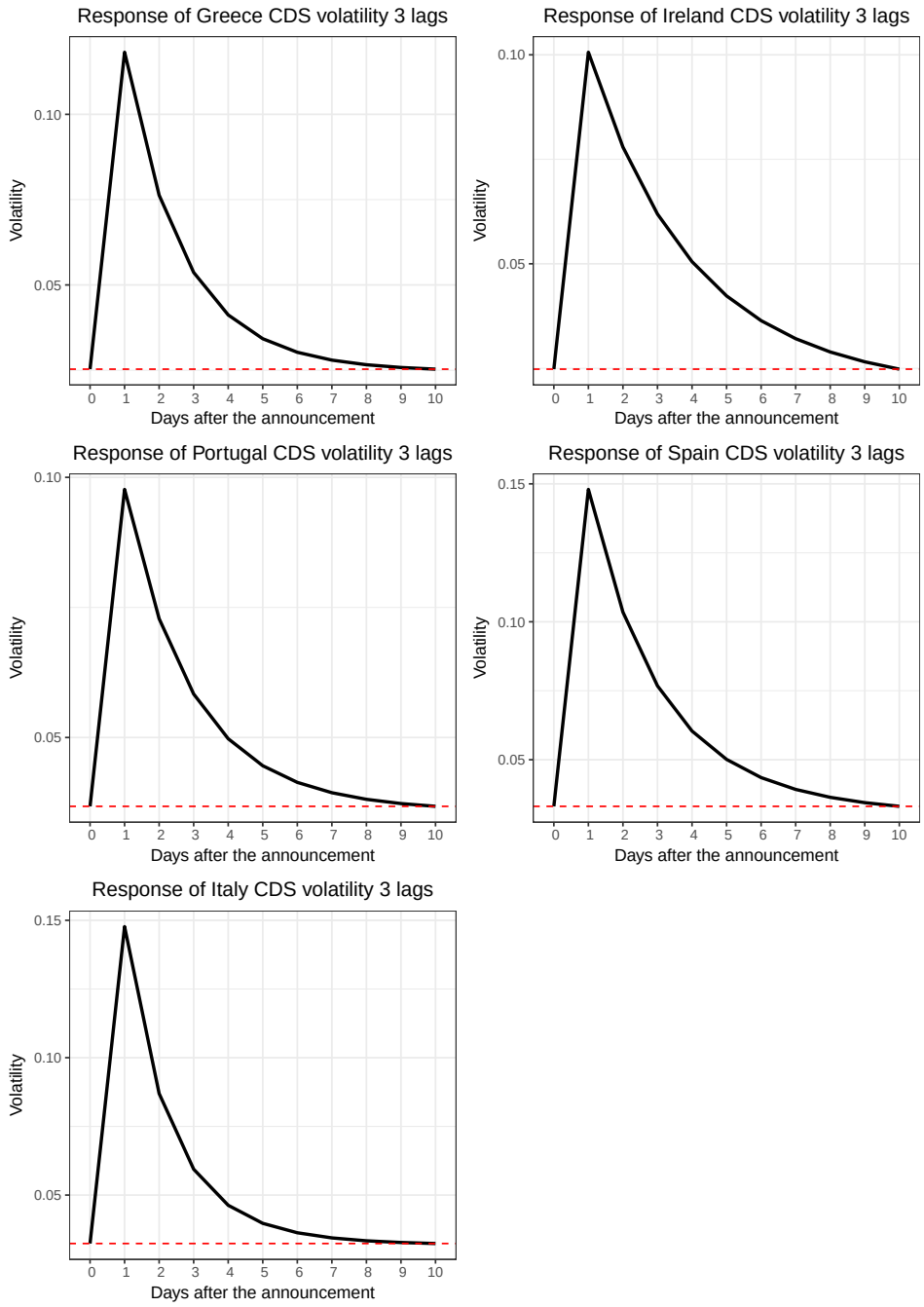

Figure 5: Impulse response functions with 3 lags

The figure shows the volatility of each country following a Greece downgrade event announcement when employing a lag value $T = 3$ for our EGARCH model defined by (15). The red dashed line represents the long term volatility of the CDS.

5 Dynamic interaction between Greece downgrade events and CDS spreads log returns volatility

We propose an approach to modeling the dynamic interaction between Greece downgrade events and CDS spreads log returns volatility. With the use of what we call *crossed copulas*, we aim to study the possible dependence between Greece downgrade events and all five countries CDS log returns volatility. The challenge here is to model the interaction between a discrete margin and a continuous margin. Following Anatolyev and Gospodinov (2010) and Liu and Luger (2015), the joint distribution of downgrade events and CDS spreads log returns is obtained by combining a dynamic binary choice model, an EGARCHX model and a copula to encapsulate their interaction. If Greece downgrade events exhibit dependence with the CDS spreads log returns volatility, we expect the dependence to be positive - that is a downgrade event should incur a rise in the CDS spreads volatility. Accordingly, we choose three copulas that make positive dependence possible.

5.1 Marginal distributions

The goal of the copula is to model the dynamic interaction between Greece downgrade events Y_t (Y_t instead of $Y_{i,t}$ to simplify the notation, we drop the subscript i here since we are only interested in Greece's downgrades) and CDS spreads log returns $R_{i,t}$. For the marginal distributions, we reuse the logit and probit models defined by (6), (7) and (8) and the second EGARCHX model defined by (14) and (15) which includes only Greece downgrade events. Therefore, we have $Y_t \sim \mathrm{B}(S(x_t))$ for the logit model and $Y_t \sim \mathrm{B}(\Phi(x_t))$ for the probit model. Next section describes how to employ copulas to model the joint behavior of marginals Y_t and $R_{i,t}$ given the information set I_{t-1}.

5.2 Joint distribution

We employ the theory of copulas to create the bivariate distribution $W_{i,t} = (R_{i,t}, Y_t)'$. From Sklar (1959), it is well known that a conditional distribution can be created as

$$F_{W_{i,t}}(u, v|I_{t-1}) = C(F_{R_{i,t}}(u|I_{t-1}), F_{Y_t}(v|I_{t-1})|I_{t-1})$$

where $F_{R_{i,t}}(u|I_{t-1})$ and $F_{Y_t}(v|I_{t-1})$ are the conditional distributions of $R_{i,t}$ and Y_t. $C(w_1, w_2|I_{t-1})$ is a conditional copula distribution function with parameter $\alpha_{i,t}$. From Anatolyev and Gospodinov (2010), the joint conditional density/mass function of $W_{i,t} = (R_{i,t}, Y_t)'$ is given by

$$f_{W_{i,t}}(u, v|I_{t-1}) = f_{R_{i,t}}(u|I_{t-1})\varrho_{i,t}(F_{R_{i,t}}(u|I_{t-1}))^v(1 - \varrho_{i,t}(F_{R_{i,t}}(u|I_{t-1})))^{1-v} \tag{18}$$

where

$$\varrho_{i,t} = 1 - \partial C(z, 1 - p_{i,t}|I_{t-1})/\partial w_1 \tag{19}$$

and the copula parameter $\alpha_{i,t}$ measures the dependence between $R_{i,t}$ and Y_t.

5.3 Copulas

We employ three different bivariate copulas to capture the dependence between Greece downgrade events and the CDS spreads log returns of all five countries.

Frank copula: The conditional Frank copula is given by

$$C(w_1, w_2|I_{t-1}) = \frac{-1}{\alpha_{i,t}} \log\left(1 + \frac{(e^{-\alpha_{i,t}w_1} - 1)(e^{-\alpha_{i,t}w_2} - 1)}{e^{-\alpha_{i,t}} - 1}\right)$$

where $\alpha_{i,t} < 0$ ($\alpha_{i,t} > 0$) implies negative (positive) dependence. As $\alpha_{i,t} \to 0$, the Frank copula approaches the independence copula $C(w_1, w_2) = w_1 w_2$. The function $\varrho_{i,t}(z)$ shown in (19) is defined as

$$\varrho_{i,t}(z) = \begin{cases} \left(1 - \frac{1-e^{-\alpha_{i,t}(1-p_{i,t})}}{e^{-\alpha_{i,t}p_{i,t}}} e^{\alpha_{i,t}(1-z)}\right)^{-1} & \text{for } \alpha_{i,t} \neq 0 \\ p_{i,t} & \text{for } \alpha_{i,t} = 0 \end{cases}$$

Farlie-Gumbel-Morgenstern copula: The conditional Farlie-Gumbel-Morgenstern (FGM) copula is given by

$$C(w_1, w_2|I_{t-1}) = w_1 w_2(1 + \alpha_{i,t}(1 - w_1)(1 - w_2))$$

where $\alpha_{i,t} \in [-1, 1]$ $\alpha_{i,t} < 0$ ($\alpha_{i,t} > 0$) implies negative (positive) dependence. The function $\varrho_{i,t}(z)$ shown in (19) is defined as

$$\varrho_{i,t}(z) = \begin{cases} 1 - (1 - p_{i,t})(1 + \alpha_{i,t}p_{i,t}(1 - 2z)) & \text{for } \alpha_{i,t} \neq 0 \\ p_{i,t} & \text{for } \alpha_{i,t} = 0 \end{cases}$$

To ensure $\alpha_{i,t} \in [-1, 1]$, we transform $\alpha_{i,t}$ as $\frac{e^{2\alpha_{i,t}}-1}{e^{2\alpha_{i,t}}+1}$ as proposed by Almedia and Czdao (2012).

Clayton copula: The conditional Clayton copula is given by

$$C(w_1, w_2|I_{t-1}) = (w_1^{-\alpha_{i,t}} + w_2^{-\alpha_{i,t}} - 1)^{-1/\alpha_{i,t}}$$

where $\alpha_{i,t} > 0$. As $\alpha_{i,t} \to 0$, the Clayton copula approaches the independence copula $C(w_1, w_2) = w_1 w_2$. The function $\varrho_{i,t}(z)$ shown in (19) is defined as

$$\varrho_{i,t}(z) = \begin{cases} 1 - \left(1 + \frac{(1-p_{i,t})^{-\alpha_{i,t}} - 1}{z^{-\alpha_{i,t}}}\right)^{-1/\alpha_{i,t}-1} & \text{for } \alpha_{i,t} \neq 0 \\ p_{i,t} & \text{for } \alpha_{i,t} = 0 \end{cases}$$

The Clayton copula is only specified for positive dependence $\alpha_{i,t} > 0$. To ensure $\alpha_{i,t} > 0$, we transform $\alpha_{i,t}$ as $e^{\alpha_{i,t}}$.

5.4 Estimation and log-likelihood function

We provide some details concerning the estimation procedure. We use the inference from margins (IFM) estimation approach. The likelihood function to maximize is given by

$$L(w_i|\underline{\Theta}) = f_{R_{i,t}}(R_{i,t}|I_{t-1})\varrho_{i,t}(F_{R_{i,t}}(R_{i,t}|I_{t-1}))^{y_t}(1-\varrho_{i,t}(F_{R_{i,t}}(R_{i,t}|I_{t-1})))^{1-y_t}$$

where $w_i = ((R_{i,1}, y_1), ..., (R_{i,T}, y_T))$ and the complete set of model parameters is given by $\underline{\Theta} = (\omega, \delta, \beta, \gamma, \theta, \Theta_0, \Theta_1, \Theta_2, \alpha)$.

Parameters $(\omega, \delta, \beta, \gamma, \theta)$ and $(\Theta_0, \Theta_1, \Theta_2)$ were first estimated separately from their respective models. Parameters $(\omega, \delta, \beta, \gamma, \theta)$ were estimated from the EGARCHX model defined by (14) and (15) and parameters $(\Theta_0, \Theta_1, \Theta_2)$ were estimated from either the logit or probit models defined by (6), (7) and (8). Therefore, the only remaining parameter to be estimated is the dependence parameter α. We redefine $\underline{\Theta}$ as $\underline{\Theta} = (\hat{\omega}, \hat{\delta}, \hat{\beta}, \hat{\gamma}, \hat{\theta}, \hat{\Theta}_0, \hat{\Theta}_1, \hat{\Theta}_2, \alpha)$ to make explicit the fact that the only free parameter is α and that the other parameters are fixed. Consequently, the log-likelihood function is defined as

$$\mathcal{L}(\underline{\Theta}) = \sum_{\tau=1}^{T} \log(f_{R_{i,t}}(R_{i,t})) + \sum_{\tau=1}^{T} \{y_t \cdot \log(\varrho_{i,t}(F_{R_{i,t}}(R_{i,t}))) + (1-y_t) \cdot \log(1-\varrho_{i,t}(F_{R_{i,t}}(R_{i,t})))$$

where $f_{R_{i,t}}$ and $F_{R_{i,t}}$ are respectively the student-t distribution function and the student-t cumulative distribution function, $\varrho_{i,t}$ is defined by (19) and y_t by (3) represents the binary downgrade events. P-values are computed using likelihood-ratio tests.

5.5 Numerical results

Table 6 reports the estimation results for our crossed copulas. Crossed copulas objective is to capture the dependence between Greece downgrade events and CDS spreads log returns volatility separately for each country after conditioning on information set I_{t-1}. We expect the dependence to be positive.

After conditioning on the information set I_{t-1}, the variables still exhibit dependence for some countries. For all countries, parameter α is positive which means that a downgrade event leads to an increase in the CDS volatility. Greece, Ireland and Portugal estimated parameter α is significant at the level of 5% under both Frank and FGM copulas. Clayton copula also seems to perform well and is significant at the level of 5% for Greece and also significant at the level of 10% both for Ireland and Portugal. For Spain and Italy, p-values are slightly higher, around 10% and 15%. The results also show that the highest dependence occurs with Greece itself as Greece exhibits the highest α estimates for all three copulas, which is expected. According to the AIC values, the Frank copula is the copula offering the best results among the three copulas. The number of lags T does not impact the level of

significance for the results, even though we notice that for a lag value of $T = 3$, the AIC values are a little lower, which indicates a higher maximum likelihood estimation.

The presence of a significant dependence after conditioning on the past is not much surprising. As our EGARCHX model defined by (15) depicted, Greece downgrade events significantly impact the CDS volatility of all countries but Portugal. However, one surprising result is the fact that in the case of Portugal, the copulas are significant whereas the EGARCHX model is not, as shown in Table 5. All in all, the results from our dynamic interaction model confirm the presence of dependence between Greece downgrade events and CDS spreads log returns volatility, mostly in the case of Greece, Ireland and Portugal.

Table 6: Crossed copulas numerical results

The table reports the dependence coefficient α estimates for the three crossed copula models. The sample consists of Greece downgrade events from October 26th 2005 to August 15th 2017 as well as the five countries CDS spreads log returns for the same period. P-values are reported in parentheses with AIC values below the p-values.

		Logit			Probit		
Country	T	Frank	FGM	Clayton	Frank	FGM	Clayton
	1	1.727	0.794	0.483	1.691	0.776	0.470
		(0.007)	(0.013)	(0.035)	(0.008)	(0.015)	(0.039)
		-5.3019	-5.3015	-5.3010	-5.3021	-5.3017	-5.3012
Greece	2	1.762	0.810	0.496	1.729	0.794	0.485
		(0.006)	(0.012)	(0.031)	(0.006)	(0.013)	(0.034)
		-5.3013	-5.3009	-5.3003	-5.3014	-5.3010	-5.3005
	3	1.794	0.820	0.505	1.765	0.808	0.496
		(0.005)	(0.011)	(0.029)	(0.006)	(0.012)	(0.031)
		-5.3015	-5.3010	-5.3005	-5.3016	-5.3012	-5.3006
	1	1.647	0.725	0.394	1.604	0.711	0.379
		(0.008)	(0.017)	(0.068)	(0.010)	(0.019)	(0.077)
		-5.2079	-5.2075	-5.2067	-5.2081	-5.2077	-5.2069
Ireland	2	1.685	0.735	0.399	1.647	0.722	0.387
		(0.007)	(0.015)	(0.065)	(0.008)	(0.017)	(0.072)
		-5.2079	-5.2074	-5.2066	-5.2080	-5.2076	-5.2068
	3	1.722	0.749	0.410	1.692	0.739	0.400
		(0.006)	(0.014)	(0.060)	(0.007)	(0.015)	(0.065)
		-5.2083	-5.2078	-5.2070	-5.2084	-5.2080	-5.2071
	1	1.270	0.610	0.380	1.236	0.595	0.369
		(0.036)	(0.048)	(0.081)	(0.041)	(0.053)	(0.088)
		-5.3182	-5.3180	-5.3177	-5.3184	-5.3182	-5.3180
Portugal	2	1.296	0.621	0.386	1.268	0.609	0.378
		(0.033)	(0.045)	(0.077)	(0.037)	(0.049)	(0.082)
		-5.3180	-5.3178	-5.3175	-5.3181	-5.3180	-5.3177
	3	1.327	0.633	0.394	1.304	0.624	0.388
		(0.030)	(0.042)	(0.073)	(0.032)	(0.044)	(0.076)
		-5.3185	-5.3183	-5.3180	-5.3186	-5.3185	-5.3182
	1	0.980	0.470	0.285	0.955	0.457	0.275
		(0.107)	(0.124)	(0.158)	(0.116)	(0.134)	(0.171)
		-4.9892	-4.9892	-4.9890	-4.9895	-4.9894	-4.9893
Spain	2	0.997	0.477	0.289	0.977	0.466	0.281
		(0.102)	(0.119)	(0.154)	(0.109)	(0.127)	(0.164)
		-4.9892	-4.9891	-4.9890	-4.9894	-4.9893	-4.9892
	3	1.005	0.482	0.293	0.990	0.474	0.287
		(0.100)	(0.116)	(0.152)	(0.105)	(0.122)	(0.158)
		-4.9895	-4.9895	-4.9893	-4.9897	-4.9896	-4.9895
	1	0.933	0.469	0.288	0.906	0.456	0.280
		(0.118)	(0.126)	(0.171)	(0.128)	(0.136)	(0.183)
		-5.4458	-5.4458	-5.4456	-5.4460	-5.4460	-5.4459
Italy	2	0.947	0.475	0.291	0.922	0.463	0.284
		(0.114)	(0.123)	(0.167)	(0.122)	(0.131)	(0.177)
		-5.4460	-5.4459	-5.4458	-5.4462	-5.4461	-5.4460
	3	0.968	0.485	0.298	0.946	0.475	0.291
		(0.108)	(0.117)	(0.160)	(0.115)	(0.124)	(0.168)
		-5.4468	-5.4468	-5.4466	-5.4470	-5.4469	-5.4468

6 Out-of-sample value-at-risk forecasting with Greece ratings

In this section we aim to assess whether or not including Greece downgrade events in our EGARCH volatility predictions improve value-at-risk (VaR) predictions. Given the country i, we define the one-day $VaR^p_{i,t}$ on a long position as

$$P(R_{i,t} \leq VaR^p_{i,t} | I_{t-1}) = p \tag{20}$$

The variable $VaR^p_{i,t}$ is therefore simply the $p \cdot 100\%$ conditional quantile of return $R_{i,t}$.

6.1 Value-at-risk forecasting

We compute the VaR predictions analytically using the formula

$$VaR^p_{i,t+1} = F(p) \cdot \hat{\sigma}_{i,t+1|I_t} \tag{21}$$

where F is the quantile distribution of a student-t and both for $p = 0.01$ and $p = 0.05$. The forecast $\hat{\sigma}_{i,t+1|I_t}$ is the forecast of conditional standard deviation at time t and it is defined as

$$\hat{\sigma}_{i,t+1|I_t} = \exp\left(\hat{\omega}_i + \hat{\alpha}_i z_{i,t} + \hat{\gamma}_i(|z_{i,t}| - E|z_{i,t}|) + \hat{\beta}_i \log(\hat{\sigma}^2_{i,t}) + \hat{\theta}_i \sum_{\tau=1}^{T} \Delta rating_{Greece,t-\tau}\right) \tag{22}$$

where $E|z_{i,t}|$ is defined by (16). We test four different models. In the first model, we force $\hat{\theta}_i = 0$ in (22) to compute VaR forecasts without the effect of Greece downgrade events. We then compute VaR forecasts by including Greece downgrade events in our EGARCH model ($\hat{\theta}_i \neq 0$). We allow for different lag values $T \in \{1, 2, 3\}$. For all forecasts, we test both for a rolling window of 1250 observations and 2500 observations. We generate one-day VaR forecasts both for 95% and 99% confidence levels ($p = 0.01$ and $p = 0.05$). This respectively gives a total of 1830 and 580 one-day VaR forecasts depending on the rolling window size. The parameters of the models are re-estimated every day taking into account information set I_t.

In order to compare our VaR models, we use the violation rate $\hat{p}$ criterion. The rate $\hat{p}$ is defined as the number of VaR exceedances (violations) divided by the evaluation sample size. The VaR forecasting performances are summarized by reporting the ratios $\hat{p}/p$. If the models perform well, the ratio should be close to one. If the ratio is less than 1 i.e. $\hat{p}/p < 1$, then loss estimates are too conservative. On the contrary, if the ratio is greater than one i.e. $\hat{p}/p > 1$, then actual losses are underestimated. We further assess the VaR forecasts with the unconditional coverage test by Kupiec (1995). Next section briefly describes Kupiec test. Table 7 in section 6.3 reports the numerical results. Figures 10 to 19 in Appendix C depict out-of-sample VaR forecasts for each country and their daily estimations and violations.

6.2 Unconditional coverage test (Kupiec 1995)

This section briefly describes the unconditional coverage test proposed by Kupiec (1995). First, we define the variable V_t

$$V_t = \begin{cases} 1 & \text{if } R_t < VaR_t \\ 0 & \text{if } R_t \geq VaR_t \end{cases} \tag{23}$$

We then define the variable N as $N = \sum_{t=1}^{T} V_t$, where N holds the number of observed VaR violations over a period of length T. It is intuitive that N follows a binomial distribution i.e. $N \sim \mathrm{B}(T, p)$. Kupiec (1995) shows that under the null hypothesis that the expected violation ratio $\frac{N}{T}$ equals the value p, i.e. $H_0 : \frac{N}{T} = p$, the likelihood ratio statistic is defined as

$$2\log\left[\left(1-\frac{N}{T}\right)^{(T-N)}\left(\frac{N}{T}\right)^{N}\right] - 2\log\left[(1-p)^{(T-N)}p^{N}\right] \tag{24}$$

Asymptotically, this test follows a χ^2 distribution with one degree of freedom. It is therefore possible to reject a model in the cases where we have too many or too little VaR violations.

6.3 Numerical results

Table 7 reports numerical results for our out-of-sample VaR forecasts. We compare violation ratios $\hat{p}/p$ in the cases where we first omit Greece ratings ($\theta_i = 0$) and where we include Greece ratings in our EGARCH model as defined by (22) ($\hat{\theta}_i \neq 0$). We allow for lag values of $T \in \{1, 2, 3\}$. We also perform Kupiec (1995) test to further assess our VaR forecasts. The p-values are reported in parentheses. Values in bold represent the cases for which including Greece downgrade events in our VaR forecasts improves the VaR violation ratio.

We find little evidence that Greece downgrade events improve one-day VaR forecasting of sovereign CDS. Greece downgrade events mostly improve the VaR violation ratio in the case of the 95% VaR ($p = 0.05$) both for lag values $T = 1$ and $T = 2$ when employing a rolling window of 1250 observations. Out of a total of 15 simulations for $N = 1250$ and $p = 0.05$, 11 violation ratios are closer to the desired value of 1 when including Greece downgrade events in our forecasting. The violation ratio is also closer to the desired value of 1 in the cases of Portugal and Spain for lag values $T = 2$ and $T = 3$ for the 99% VaR.

Although there is only very little improvement in the case of a rolling window of 2500 observations both for 95% VaR and 99% VaR, the cases of Portugal and Italy are interesting. In the case of Portugal, we obtain an impressive improvement in the violation ratio from 0.551 to 0.931 for the 95% VaR ($p = 0.05$) and a notable improvement from 0.344 to 0.517 for the 99% VaR ($p = 0.01$). In the case of Italy, we obtain little improvement for the 99% VaR for all lag values $T \in \{1, 2, 3\}$.

We conclude that Greece downgrade events add little value to one-day VaR forecasting of sovereign debt CDS for a few specific cases. The rolling window size of 1250 observations works better than the rolling window size of 2500 observations. The 95% VaR is more sensible to Greece downgrade events than the 99% VaR.

Figures 10 to 19 in Appendix C illustrate the out-of-sample one-day VaR forecasting violations for all countries, both for 95% and 99% VaR and for all lag values $T \in \{1, 2, 3\}$. On the figures, in grey we have the log returns, in black the daily value-at-risk and in red the value-at-risk violations.

Table 7: Value-at-risk violation ratios

The table reports the value-at-risk violation ratios $\hat{p}/p$ both for $p = 0.01$ and $p = 0.05$. In the first case we omit Greece ratings in our value-at-risk predictions (column No ratings). We then include Greece ratings. We test for different lag values $T \in \{1, 2, 3\}$. We simulated both for a rolling window size of 1250 observations and 2500 observations. P-values for the Kupiec unconditional coverage test are reported in parentheses.

	Size = 1250							
	$p = 0.01$				$p = 0.05$			
Country	No ratings	T = 1	T = 2	T = 3	No ratings	T = 1	T = 2	T = 3
Greece	1.693	1.748	1.857	1.803	1.409	**1.398**	**1.398**	1.409
	(0.007)	(0.004)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Ireland	0.983	0.983	0.983	1.202	0.961	**0.983**	**0.994**	**1.005**
	(0.944)	(0.944)	(0.944)	(0.400)	(0.706)	(0.872)	(0.957)	(0.957)
Portugal	0.382	0.382	**0.491**	**0.491**	0.808	**0.819**	**0.830**	0.786
	(0.002)	(0.002)	(0.015)	(0.015)	(0.053)	(0.087)	(0.053)	(0.053)
Spain	0.655	0.655	**0.710**	**0.710**	0.808	**0.830**	0.808	0.808
	(0.114)	(0.114)	(0.114)	(0.114)	(0.006)	(0.008)	(0.022)	(0.04)
Italy	0.437	**0.491**	0.437	0.437	0.786	**0.808**	**0.808**	**0.808**
	(0.006)	(0.015)	(0.006)	(0.006)	(0.006)	(0.053)	(0.053)	(0.053)

	Size = 2500							
	$p = 0.01$				$p = 0.05$			
Country	No ratings	T = 1	T = 2	T = 3	No ratings	T = 1	T = 2	T = 3
Greece	2.241	2.413	2.413	2.413	1.862	1.931	1.931	1.931
	(0.010)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Ireland	1.034	1.034	1.034	1.206	1.172	1.206	1.206	1.241
	(0.934)	(0.934)	(0.934)	(0.628)	(0.353)	(0.268)	(0.268)	(0.198)
Portugal	0.344	0.344	0.344	**0.517**	0.551	0.551	0.551	**0.931**
	(0.067)	(0.067)	(0.067)	(0.198)	(0.007)	(0.007)	(0.007)	(0.700)
Spain	0.689	0.689	0.689	0.517	0.551	0.551	0.551	0.517
	(0.426)	(0.426)	(0.426)	(0.198)	(0.007)	(0.007)	(0.007)	(0.003)
Italy	0.344	0.344	0.344	0.344	0.517	**0.551**	**0.586**	**0.551**
	(0.067)	(0.067)	(0.067)	(0.067)	(0.003)	(0.007)	(0.014)	(0.007)

7 Conclusion

We have proposed three different ways to assess how impactful Greece downgrade events are on European sovereign debt CDS contracts volatility. Our analysis focused on the GIIPS - Greece, Ireland, Italy, Portugal, and Spain - five countries that were considered weaker economically following the financial crisis. Our study covered the period from October 2005 to August 2017.

First, with the use of EGARCHX models, we showed that Greece downgrade events not only affect Greece's CDS spreads log returns volatility, but all five countries CDS volatility. Our EGARCHX models depicted a positive relationship between Greece downgrade events and the CDS volatility for all five countries. The relationship showed to be significant for all countries but Portugal.

Second, we used a dynamic model which allows us to study the dependence between Greece downgrade events and all five countries CDS spreads log returns separately. We employed a particular copula à la Anatolyev and Gospodinov (2010) that allows to model the dependence structure between a continuous margin and a discrete margin. We used logit and probit models for the discrete margins. The coefficient estimates from the copulas revealed that there exists a positive dependence between Greece downgrade events and each country CDS spreads log returns volatility separately. The estimates revealed to be stronger in the case of Greece, Ireland and Portugal.

Third, we analyzed the economic value of including Greece downgrade events in out-of-sample one-day 95% VaR and 99% VaR forecasting of European sovereign debt CDS. We tested both for a rolling window of 1250 observations and 2500 observations while allowing for different lag values of $T \in \{1, 2, 3\}$. We found little evidence that Greece downgrade events improve VaR forecasting. Most of the improvement occurs in the case of the 95% VaR with a rolling window of 1250 observations for which all five countries VaR forecasting become closer to the desired violation ratio value of 1.

In order to obtain better results for our analysis, one could consider improving our data set. As shown in Table 1, our time series include extreme kurtosis. Due to the extreme kurtosis, modifying the data set a little bit here and there showed to impact the results significantly (results not shown in the paper). A deeper analysis in which we would ignore some abnormal returns (chosen wisely) to reduce kurtosis could lead to better results.

A Additional tables

Table 8: Credit ratings linear transformation

Moody's	S&P	Fitch	Linear transformation
Aaa	AAA	AAA	17
Aa1	AA+	AA+	16
Aa2	AA	AA	15
Aa3	AA-	AA-	14
A1	A+	A+	13
A2	A	A	12
A3	A-	A-	11
Baa1	BBB+	BBB+	10
Baa2	BBB	BBB	9
Baa3	BBB-	BBB-	8
Ba1	BB+	BB+	7
Ba2	BB	BB	6
Ba3	BB-	BB-	5
B1	B+	B+	4
B2	B	B	3
B3	B-	B-	2
Caa1	CCC+	CCC+	1
Caa2	CCC	CCC	
Caa3	CCC-	CCC-	
Ca	CC	CC	
C	SD	C	
WR	D	RD	
	NR	D	
		DD	
		DDD	

Table 9: Credit rating announcements since 1988

Country	Upgrade	Downgrade	Positive outlook	Negative outlook	Positive credit watch	Negative credit watch
Greece	18(7,3,8)	25(10,6,9)	6(3,1,2)	7(4,0,3)	3(0,1,2)	13(4,6,3)
Ireland	16(7,6,3)	15(6,5,4)	6(4,1,1)	6(2,2,2)	3(0,3,0)	6(1,2,3)
Portugal	9(4,4,1)	16(6,5,5)	5(3,0,2)	7(3,2,2)	1(0,1,0)	7(4,3,0)
Spain	9(4,3,2)	15(6,5,4)	5(4,0,1)	2(1,0,1)	1(0,1,0)	7(2,4,1)
Italy	3(0,2,1)	19(7,6,6)	3(0,2,1)	8(5,2,1)	1(0,1,0)	5(1,2,2)

Notes: The announcements respectively include announcements by agency (S&P, Moody's, Fitch).

B Figures

B.1 Historical credit ratings

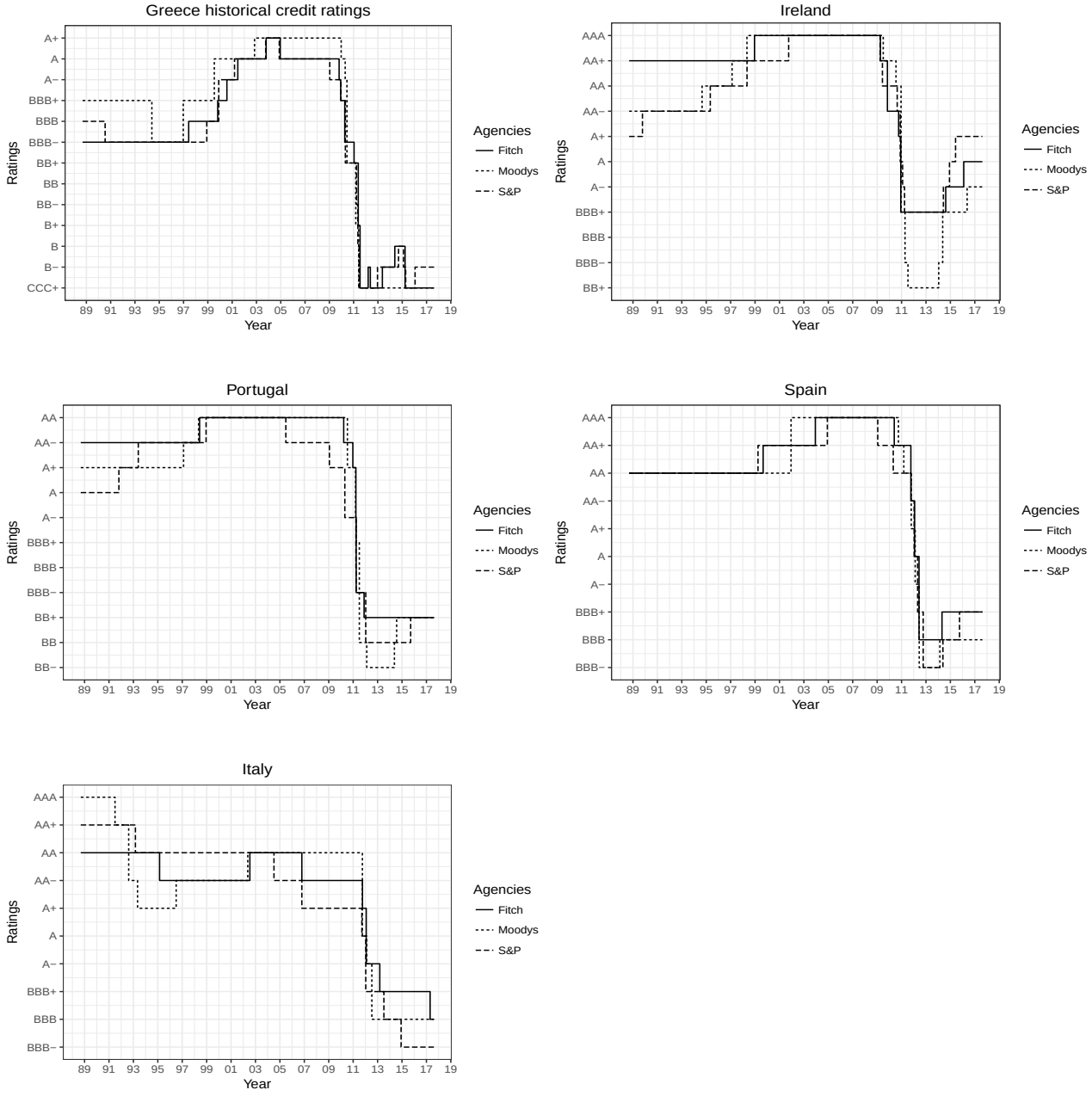

Figure 6: Historical credit ratings for each country

B.2 Historical binary downgrades

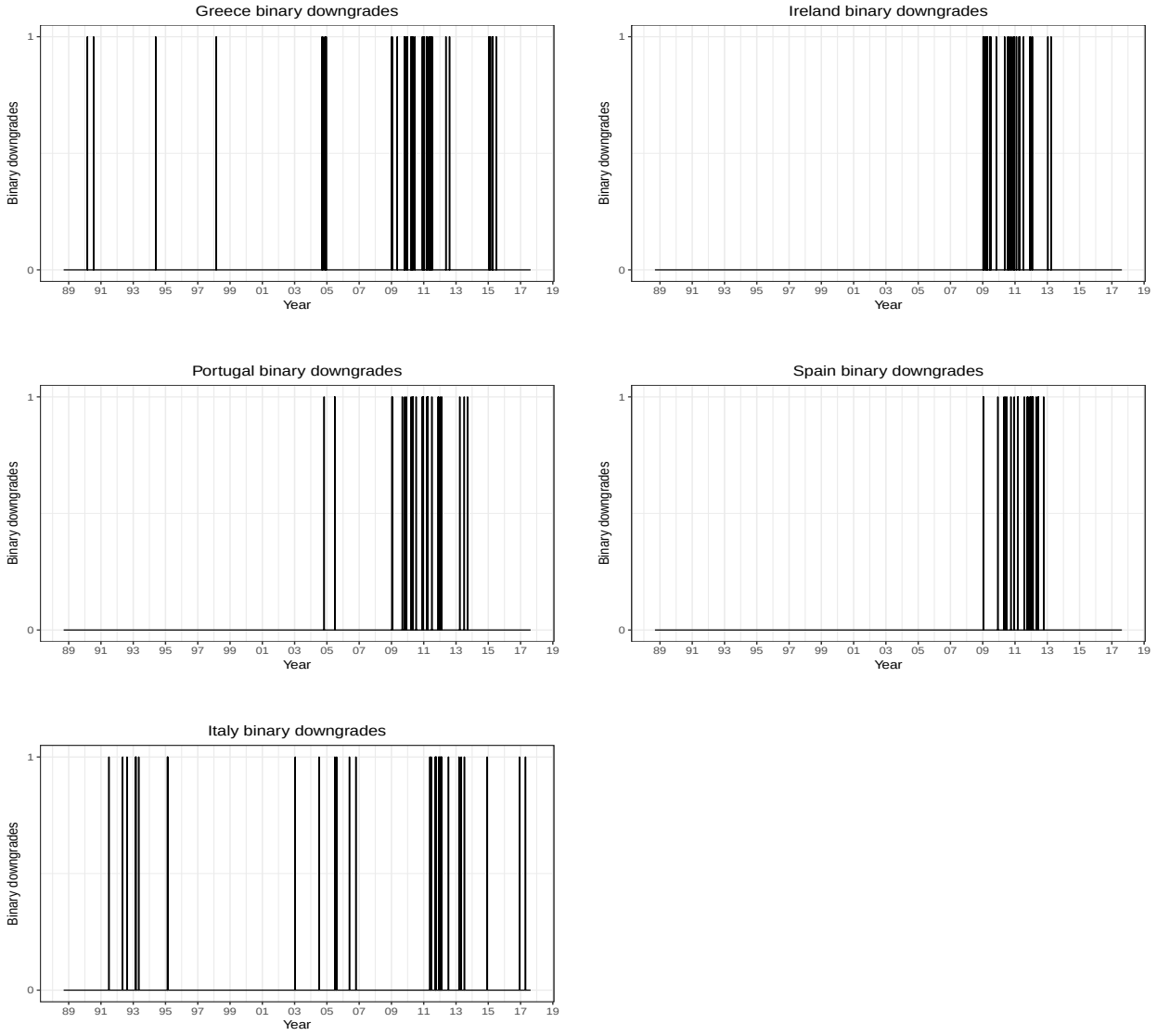

Figure 7: Binary downgrades - whether or not a downgrade event occurred at time t for each country

B.3 Historical CDS spreads

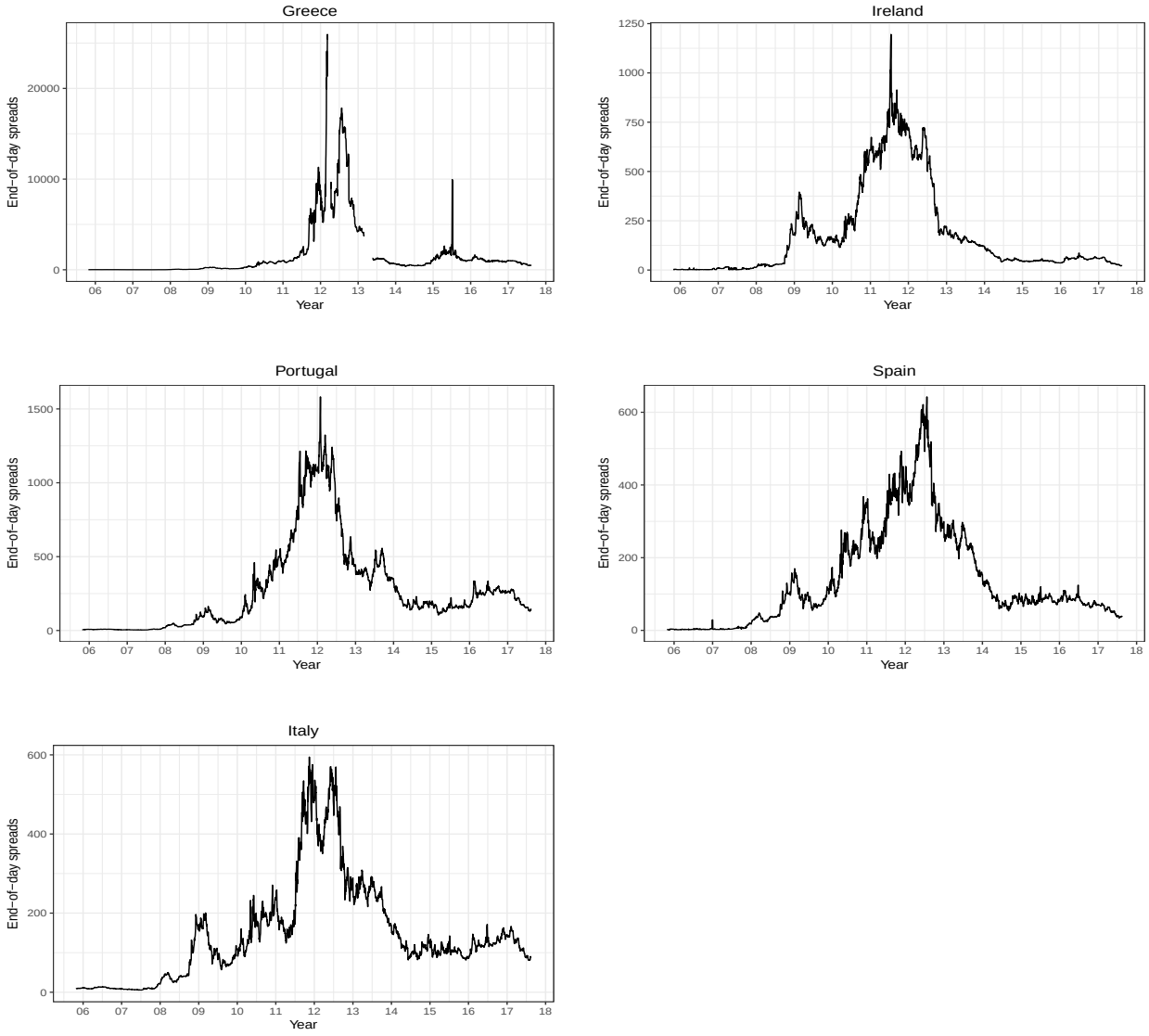

Figure 8: Historical CDS spreads for each country

B.4 Historical CDS spreads log returns

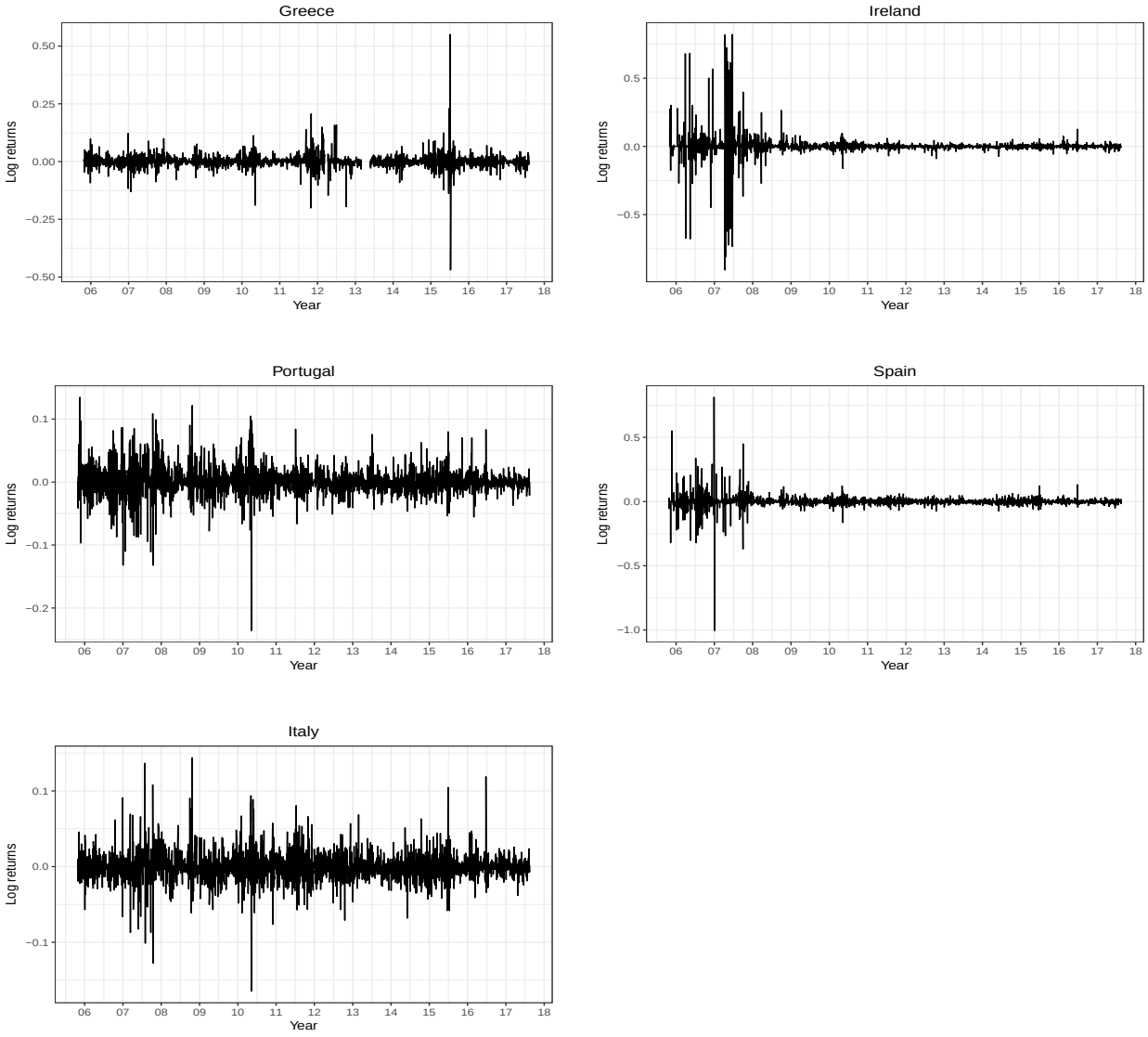

Figure 9: Historical CDS spreads log returns for each country

C Out-of-sample value-at-risk forecasting

C.1 Forecasting with rolling window of 1250 observations

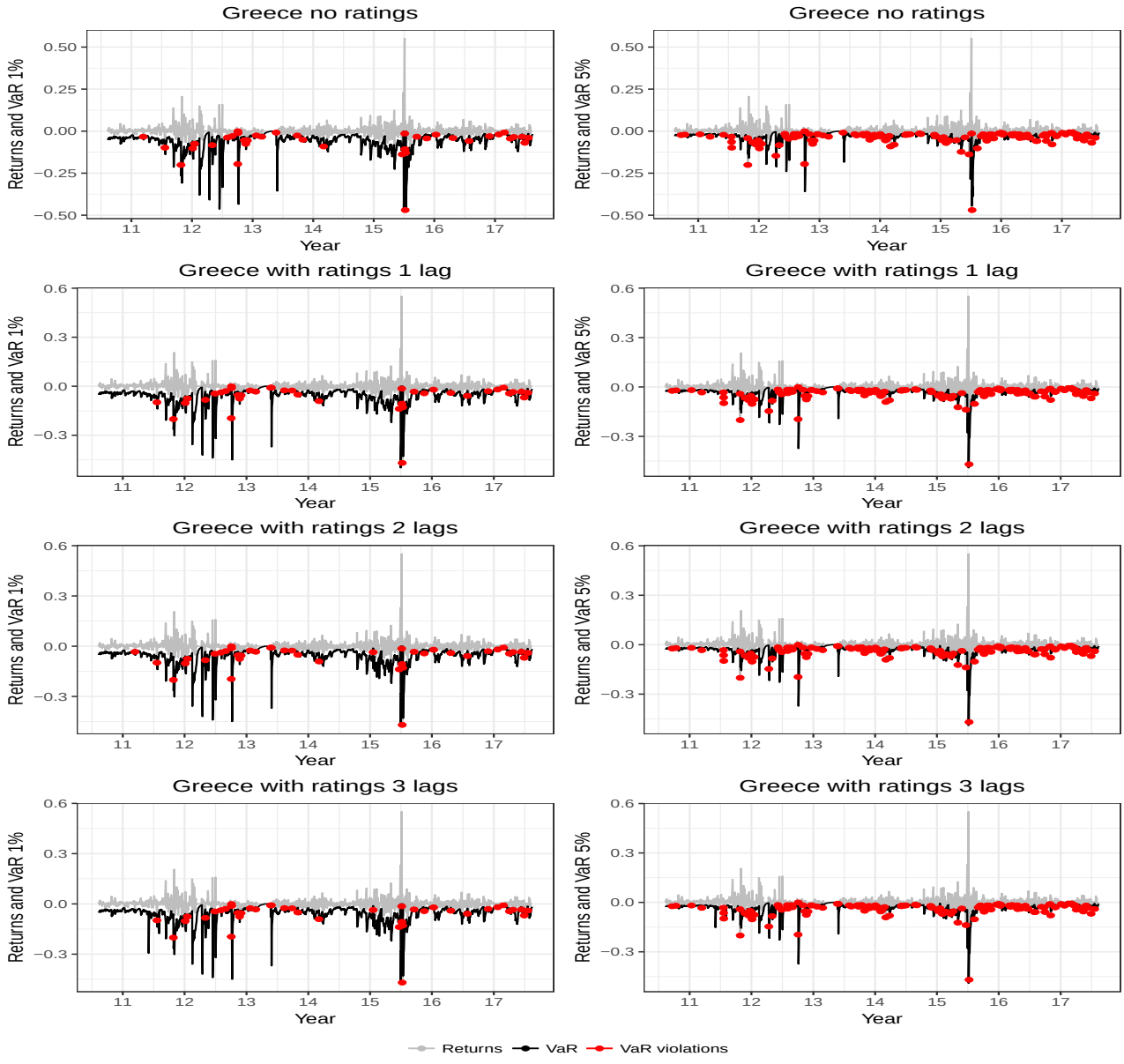

Figure 10: Greece out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Greece when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 1250.

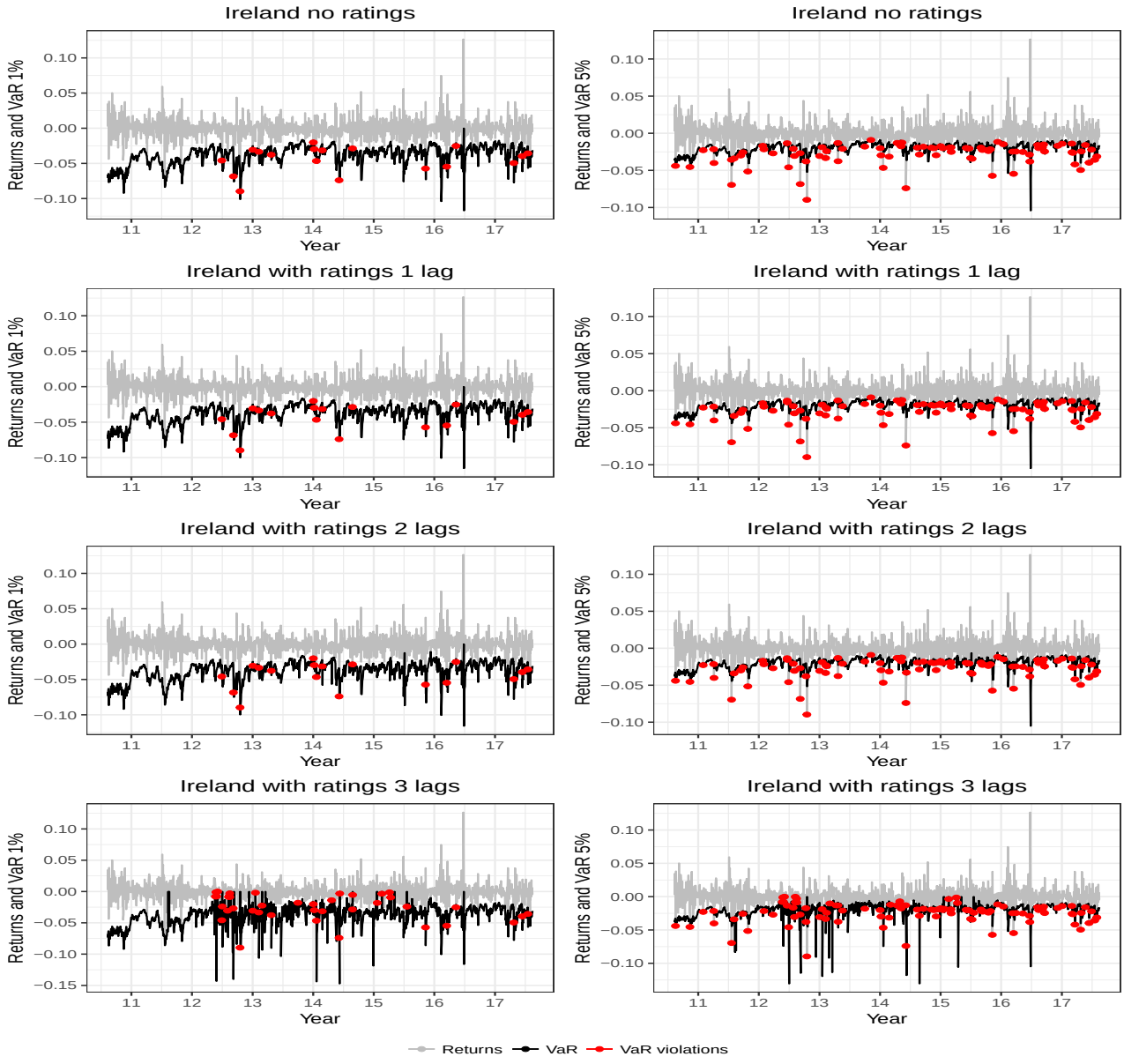

Figure 11: Ireland out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Ireland when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 1250.

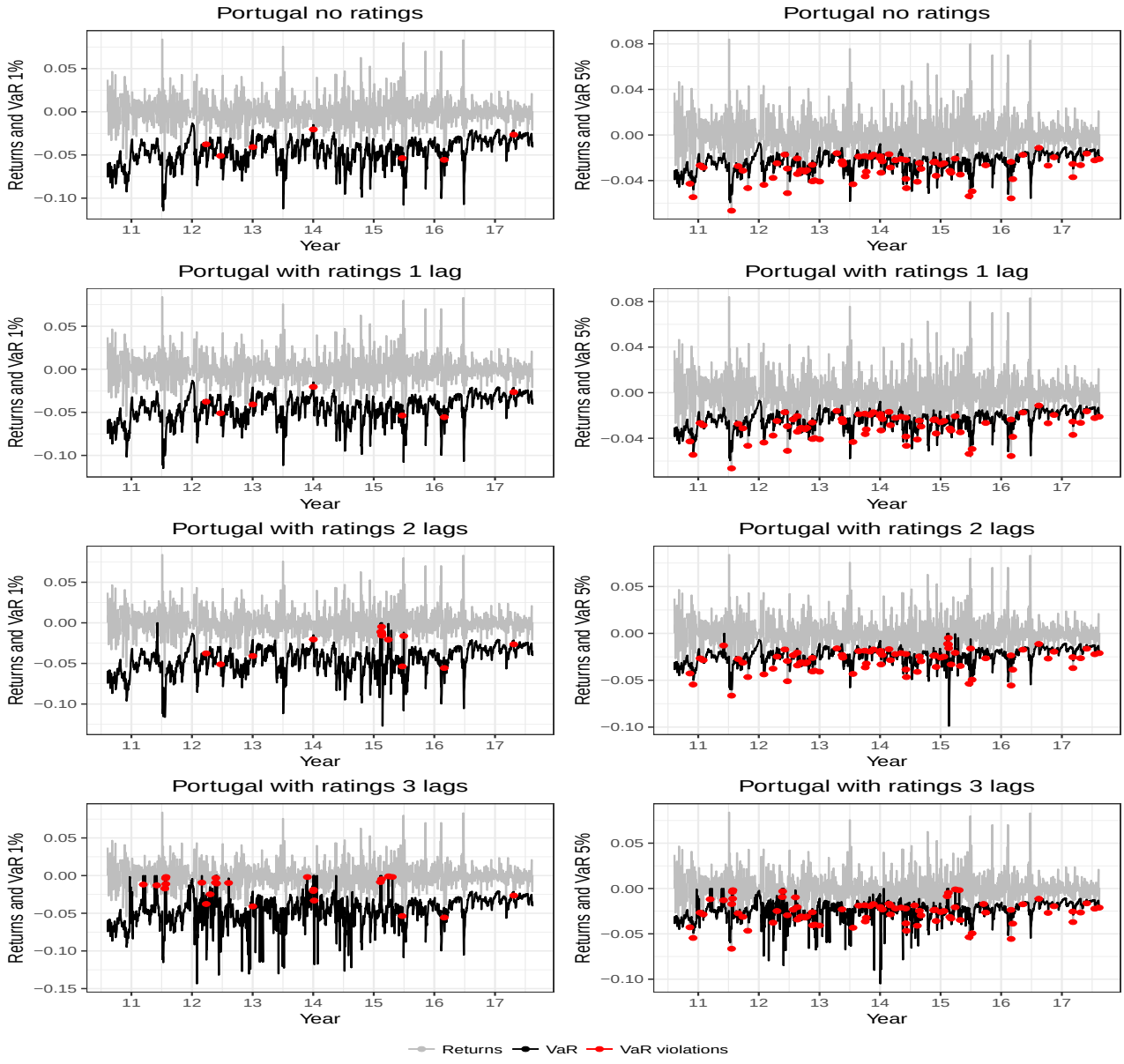

Figure 12: Portugal out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Portugal when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 1250.

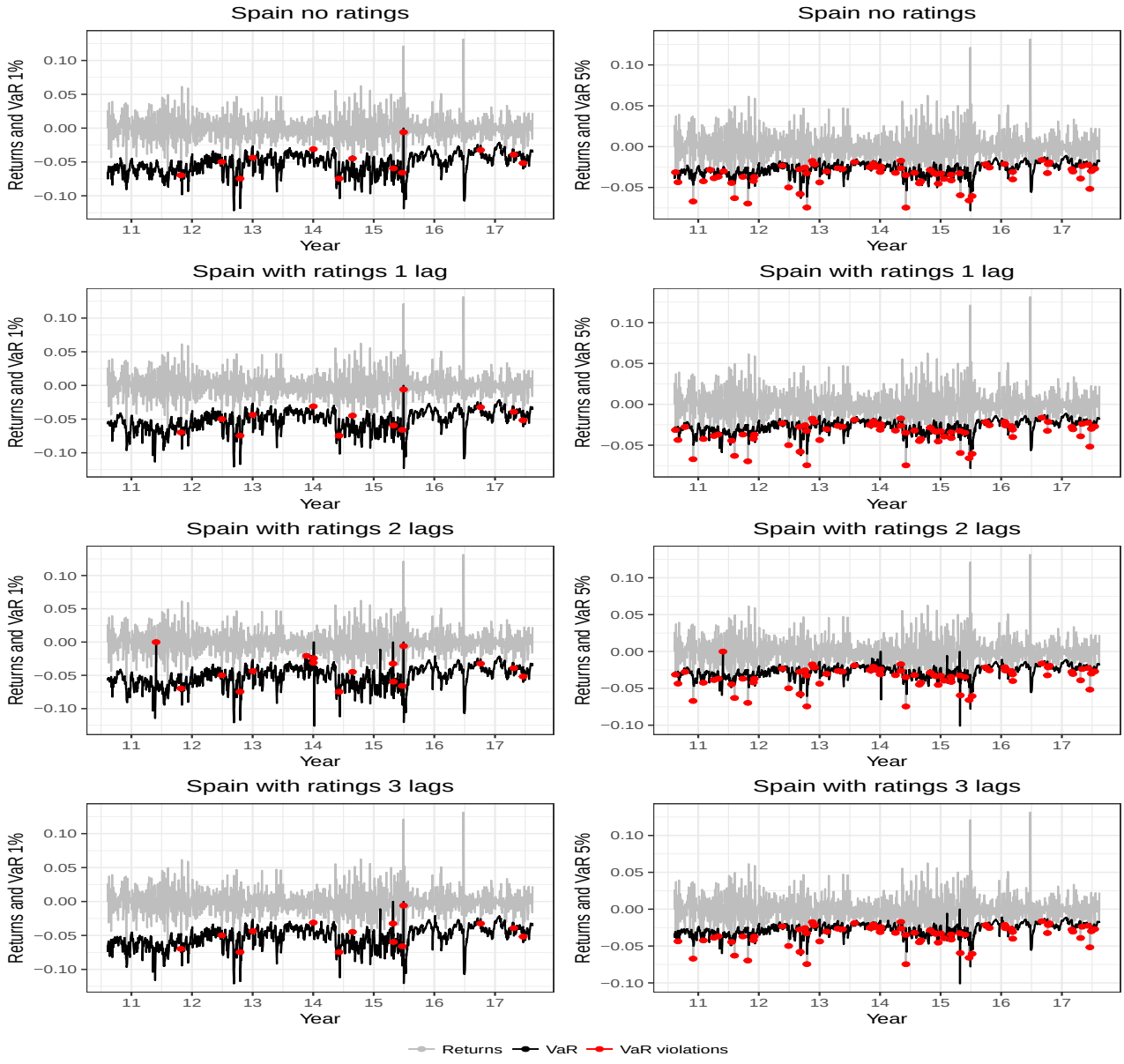

Figure 13: Spain out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Spain when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 1250.

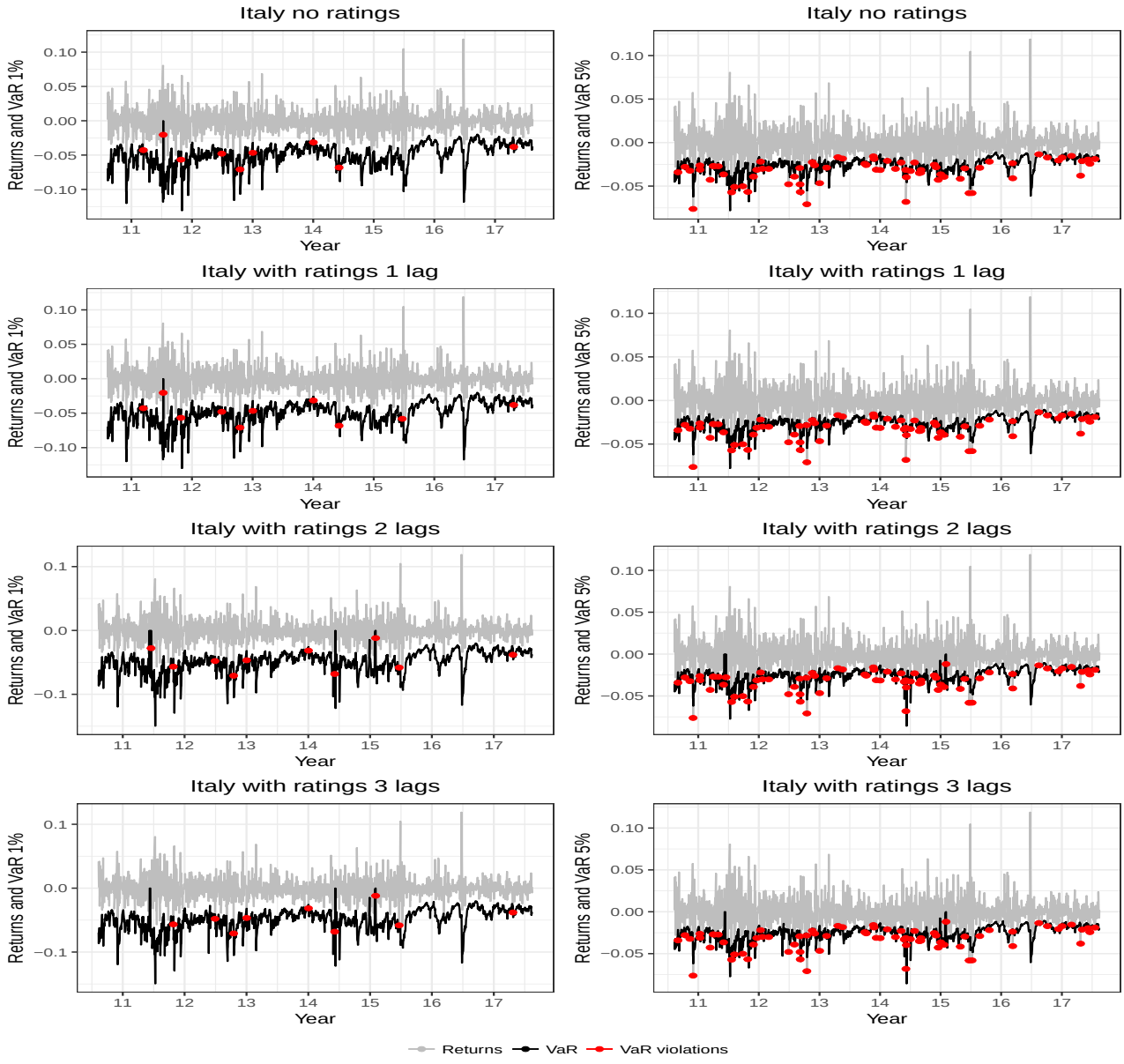

Figure 14: Italy out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Italy when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 1250.

C.2 Forecasting with rolling window of 2500 observations

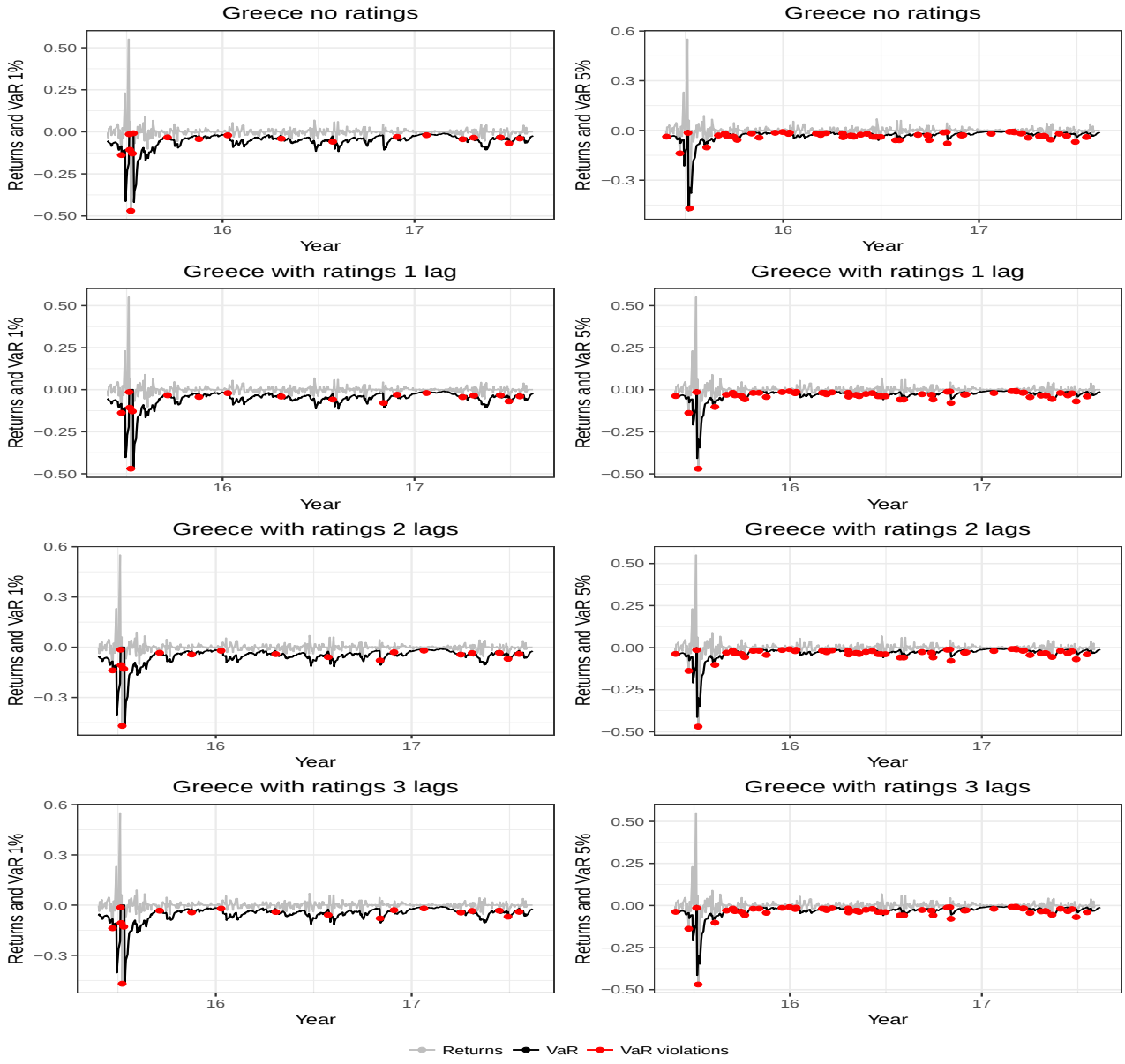

Figure 15: Greece out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Greece when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 2500.

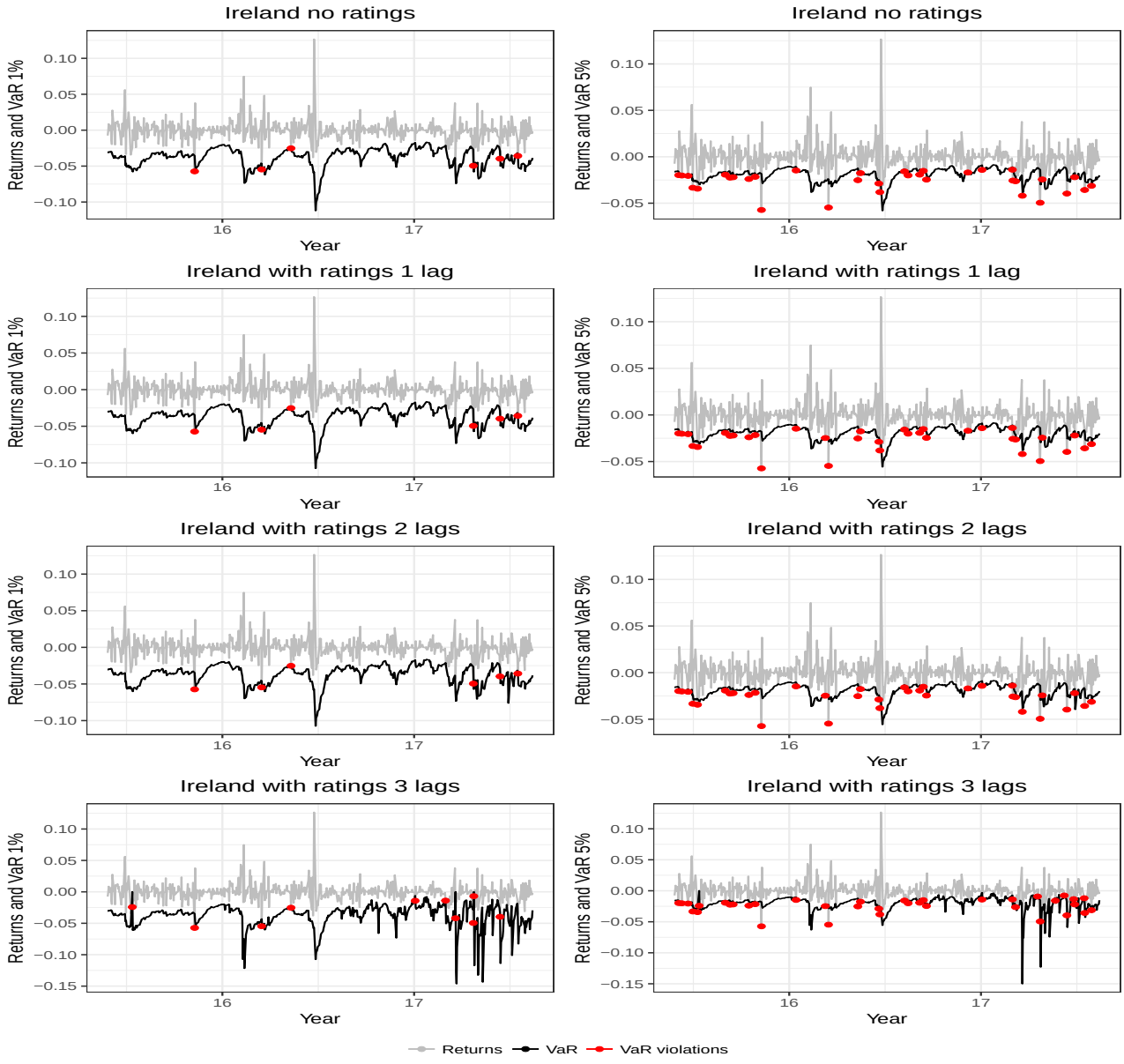

Figure 16: Ireland out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Ireland when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 2500.

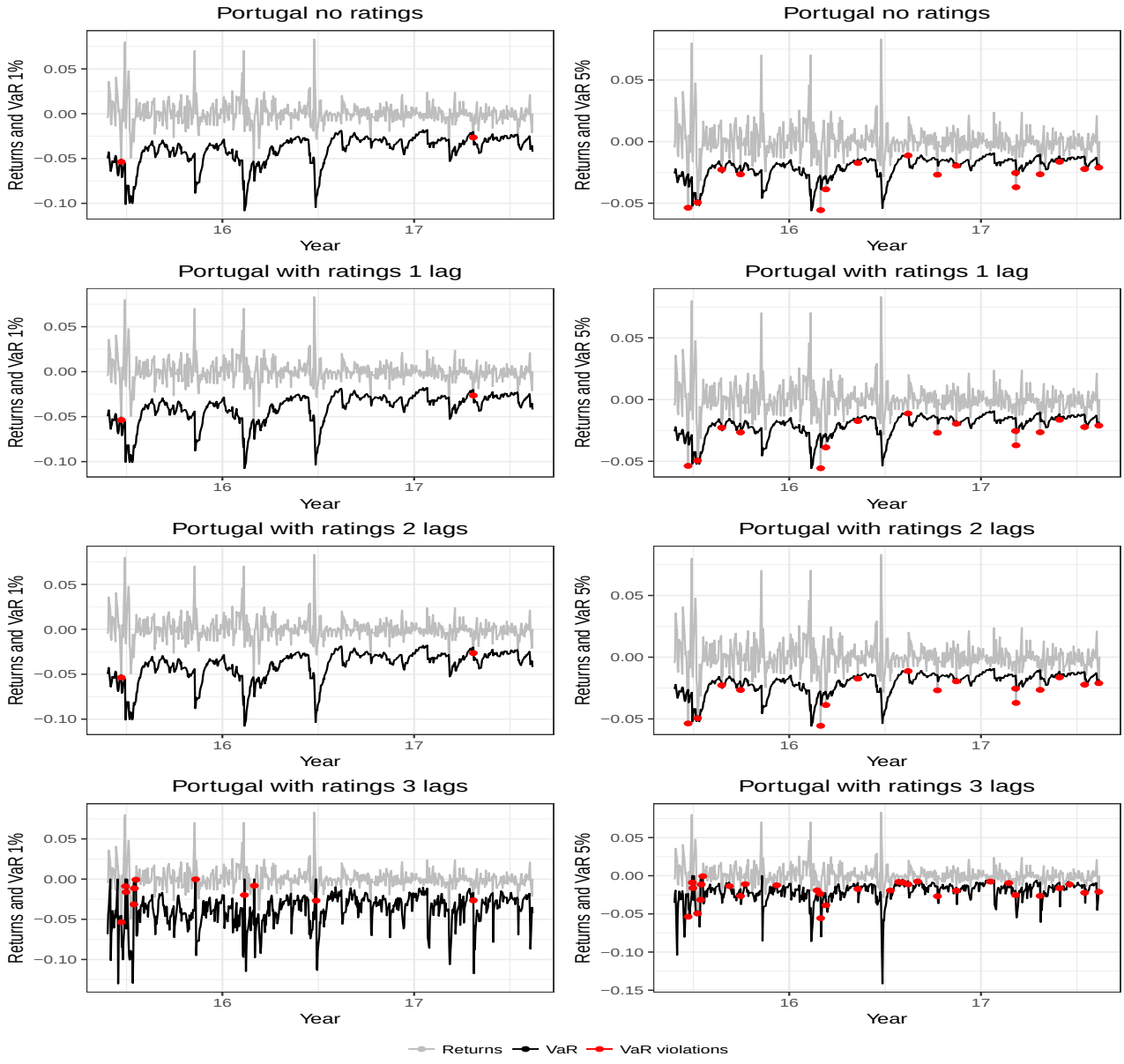

Figure 17: Portugal out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Portugal when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 2500.

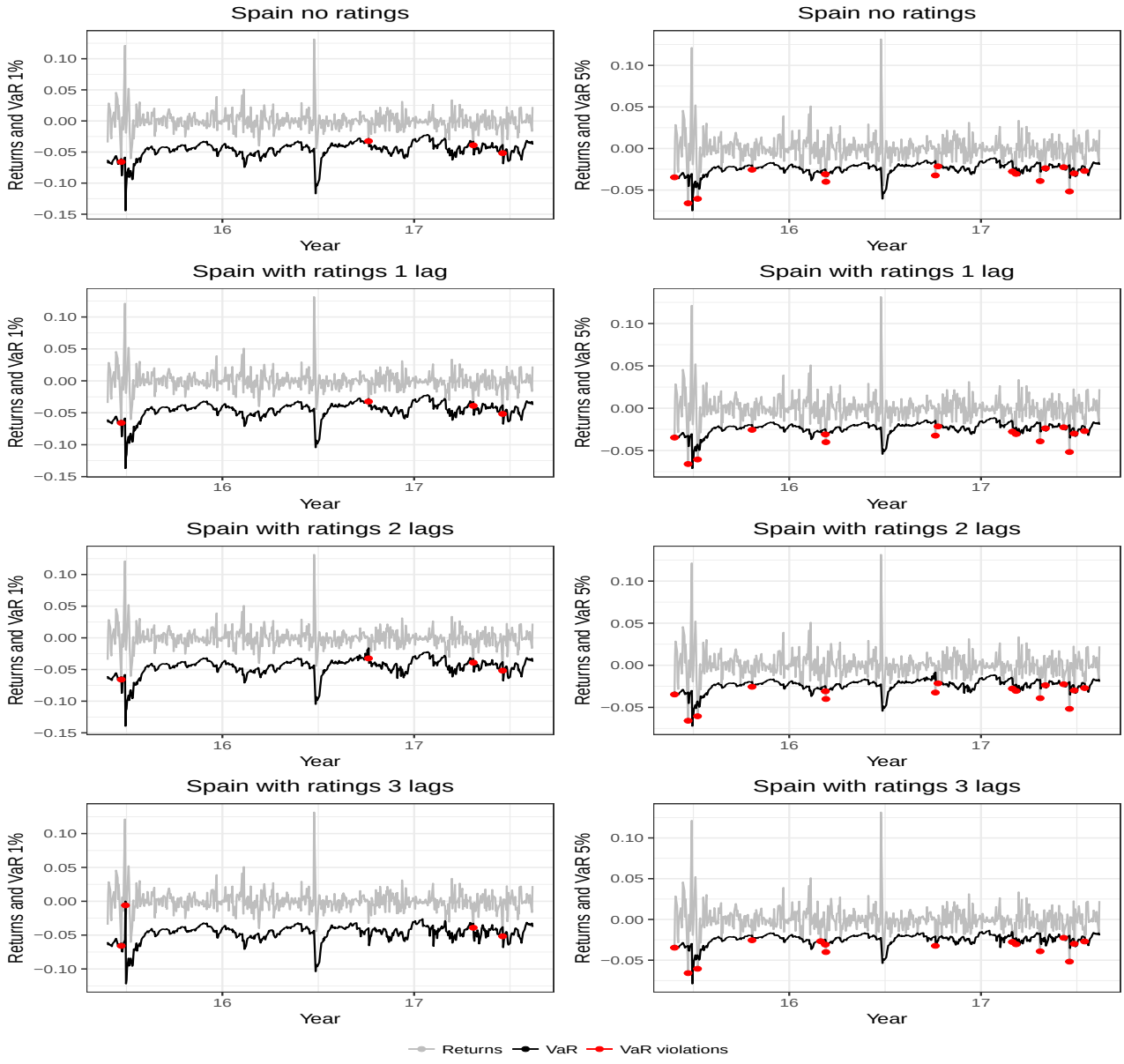

Figure 18: Spain out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Spain when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 2500.

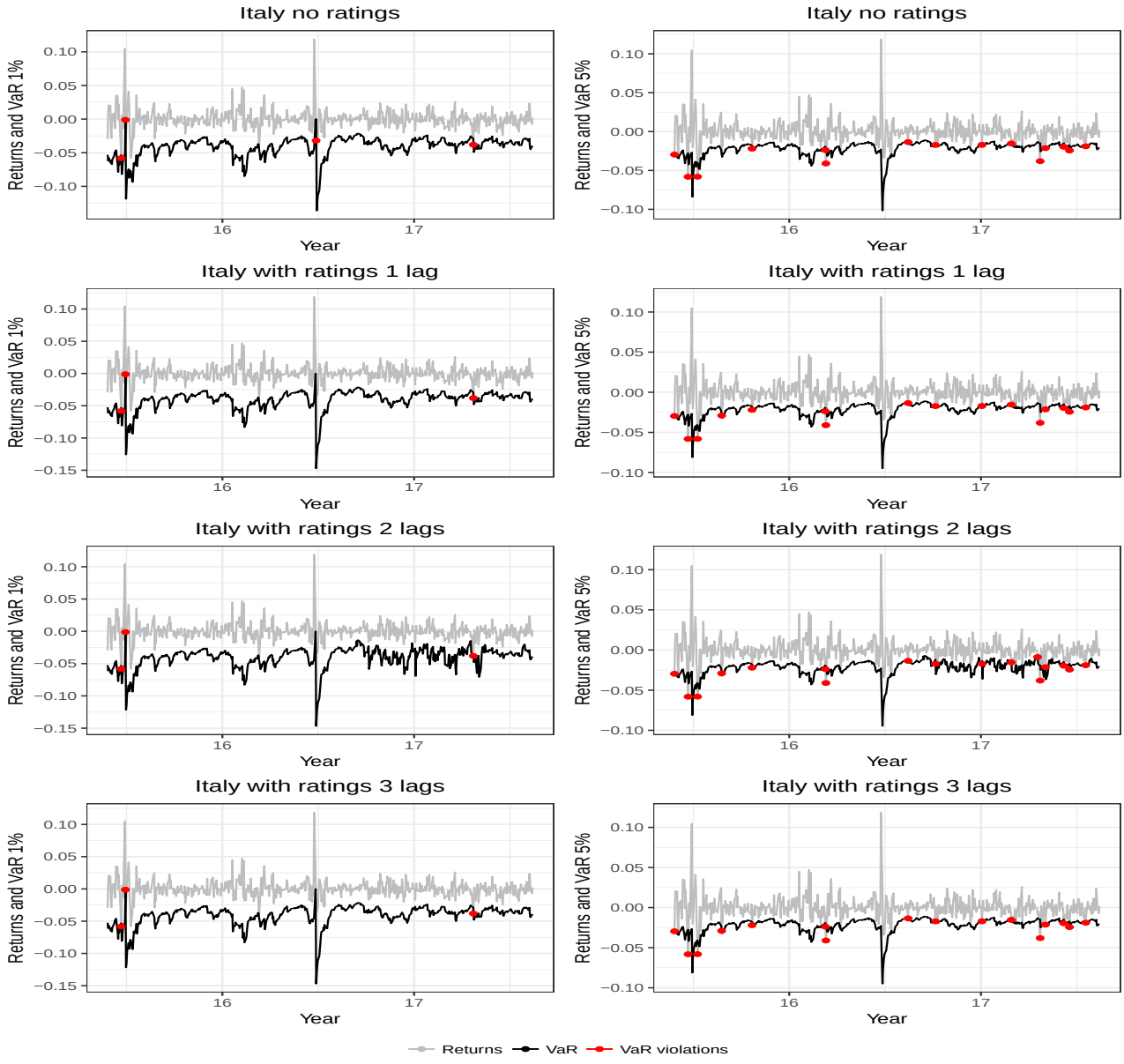

Figure 19: Italy out-of-sample VaR forecasting violations

Out-of-sample VaR forecasting violations for Italy when incorporating Greece downgrades in our VaR forecasting with a rolling window of size 2500.

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