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Re-examining the risk–return relationship in Europe: linear or non-linear trade-off?

Abstract

This paper analyzes the risk–return trade-off in Europe using recent data from 11 European stock markets. After relaxing linear assumptions in the risk-return relation by introducing a new approach which considers the current state of the market, we are able to obtain positive and significant evidence for a risk-return trade-off for low volatility states; however, this evidence turns out to be lower or even non-significant during periods of high volatility. Maintaining the linear assumption over the risk-return trade-off leads to non-significant estimations for all cases analyzed. These results are robust among countries despite the conditional volatility model used. This concludes that the controversial results in previous studies may be due to strong linear assumptions when modeling the risk–return trade-off. We argue that this previous evidence can only be viewed as partial evidence that fails to cover the global behavior of the relation between return and risk.

Keywords: non-linear risk-return tradeoff, pro-cyclical risk aversion, Regime-Switching GARCH, Regime-Switching MIDAS, risk premium

1. Introduction

One of the most discussed topics in financial economics is that of establishing a relationship between return and risk. Several attempts have tried to explain the dynamics and interactions between these two fundamental variables. From a theoretical framework, one of the most cited works analyzing this risk–return trade-off is the Merton's (1973) intertemporal capital asset pricing model (ICAPM). Merton (1973) demonstrates that there is a linear relationship between conditional excess market return and its conditional variance, and its covariance with investment opportunities:

$$\mu_M - r_f = A\sigma_M^2 + BX_{M,S} \tag{1}$$

where $\mu_M - r_f$ is the excess return of the market portfolio over the risk-free asset, σ_M^2 is the conditional variance of excess market returns (known as idiosyncratic portfolio risk), $X_{M,S}$ is the conditional covariance between excess market returns and the state variable that represents the investment opportunities (known as the hedge component), and A and B are the prices of these sources of risk. Assuming risk-averse investors, this model establishes a positive relation between expected return and market variance (risk).

However, despite the important role of this trade-off in the financial literature, there is no clear consensus about its empirical evidence. Campbell (1987), Glosten et. al (1993), Whitelaw (1994) and Brandt and Wang (2004) find a negative relation between these variables, while other authors such as Ghysels, et. al. (2005), Leon et. al. (2007), Guo and Whitelaw (2006), Ludvigson and Ng(2007) and Lundblad (2007) find a positive trade-off.

This paper analyzes the risk–return trade-off in 11 European countries (Germany, France, Spain, the United Kingdom, Switzerland, the Netherlands, Belgium, Denmark, Finland, Sweden and Greece) and tries to shed light on the controversial results about its sign and magnitude. We use different assumptions when modeling conditional volatilities (GARCH and MIDAS approaches) and relax the strong linear assumption (usually made in previous studies) by introducing a Markov Regime-Switching process. This non-linear methodology helps us condition our estimation upon the current state of the market obtaining different relationships between return and risk during periods of high and low volatility. To the best of our knowledge, this is one of the first attempts using non-linear models such as Regime-Switching MIDAS (RS-MIDAS) for analyzing the risk-return relation[1].

In the theoretical framework, all the parameters (the risk prices A and B in (1)) and the variables (the sources of risk σ_M^2 and $X_{M,S}$) are allowed to be time varying. However, to make the model empirically tractable one should make several assumptions; the most common is constant risk prices (Goyal and Santa-Clara, 2003; Bali et al., 2005). It is also necessary to assume specific dynamics for the conditional second moments representing the market risk. The most used are the GARCH models (Bollerslev, 1986). Finally, the empirical model is established in a discrete time economy instead of the continuous time economy used in the equilibrium model of the theoretical approach. Another common assumption is that we consider one set of investment opportunities constant over time, for example by retaining market risk as the only source of risk[2]

[1] The first attempt to use these models is very recent (Guérin and Marcellino (2010)) and it is a specification with potential applications to a large class of empirical studies in applied economics and finance yet to exploit.

[2] Few papers such as Scruggs (1998) and Scruggs and Glabadanidis (2003) show that the lack of empirical evidence of a risk-return trade-off is due to the omission of the hedge component. However,

(Glosten et al., 1993; Shin, 2005; Lundblad, 2007). In this paper, we follow these studies and analyze the effect of market returns given one risk factor defined by the conditional market volatility.

Given the assumptions mentioned above, many papers have introduced alternative empirical models to obtain favorable evidence following the theoretical intuition. The methodology most commonly used in the empirical analysis of the risk–return trade-off is the GARCH-M approach (Engle et al., 1987). This framework is simple to implement but the results obtained are controversial. Many studies fail to identify a statistically significant intertemporal relation between risk and return of the market portfolio (see Baillie and Di Gennaro, 1990; Campbell and Hendchen, 1992). A few studies do provide evidence supporting a positive risk–return relation (Bollerslev, 1986; Guo and Neely, 2008). Several studies even find that the intertemporal relation between risk and return is negative (examples include Nelson, 1991; Li et al., 2005). Therefore, alternative approaches to the simple GARCH-M methodology have been proposed when analyzing the risk–return trade-off. The most important frameworks developed as alternative to GARCH models essentially obtain different estimations for conditional volatility. Whitelaw (1994) uses an instrumental variable specification for the conditional second moments. Harrinson and Zhang (1999) use non-parametric techniques in their study in opposite to the parametric approaches used more often. Ghysels et al. (2005) propose the use of different data frequencies to estimate the mean (with lower data frequency) and the variance (with higher data frequency) equations. Despite the differences among all the models presented, they share a strong linear (monotonic) assumption in the definition of the relationship between return and risk. Recently, Muller et al. (2011) use the basic and asymmetric Cointegrated-GARCH (COGARCH) approach to test the Merton's hypothesis. They argue that the asymmetric COGARCH model is not supportive of Merton's hypothesis, while the symmetric version of COGARCH shows a significant positive covariance between the market risk-premia of both the CRSP value weighted and equal-weighted excess market returns and volatilities over the period 1953-2007.

However, Merton's model is not the only theoretical approach explaining the risk-return relationship. Whitelaw (2000) proposes a non-linear relationship between return and risk based on an equilibrium framework. This theoretical framework is quite different from Merton's (1973) approach because a complex, non-linear, and time-varying relationship between expected return and volatility is obtained. Similarly, Mayfield (2004) employs a methodology in which states of the market are essentially defined by volatility regimes and condition the risk-return trade-off upon these different states. Other authors also draw alternative frameworks where is not expected a monotonic risk-return-relationship (Veronesi, 2000) and even some of them (see Abel,1988; Backus and Gregory, 1992) develop theoretical models that support a negative risk-return relation.

The main result obtained in our paper is that a non-linear specification is necessary to reflect the positive and significant trade-off between return and risk. When several volatility states are considered, the risk–return relationship becomes significant, even ignoring possible changes in the set of investment opportunities. When linear patterns in the risk specification (GARCH and MIDAS) are considered, no significant relationship in any market is obtained. More

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they do not find clear evidence at all. Some alternative approaches use information not only about the market portfolio but also about additional risk factors such as other asset portfolios or macroeconomic indicators, thereby extending their empirical models to a multidimensional framework (see Ludvigson and Ng, 2007; Bali, 2008).

specifically, a positive and significant trade-off between return and risk is obtained for low volatility states when non-linear patterns are considered (RS-GARCH and RS-MIDAS models). However, for high volatility states the magnitude of this relationship becomes lower or non-significant. These results are robust for all the stock indexes analyzed and show that the lack of empirical evidence in previous studies may be due to the strong assumption of a linear risk–return relationship rather than a non-linear one revealing the perils of using linear frameworks to analyze empirically this trade-off. These results shed light on the controversial results obtained in previous studies using linear models about the sign and magnitude of this relationship. They also could explain why results from linear models appear not to be robust to the sample period used in the analysis. We argue that studies using linear models analyzing a sample period corresponding to a low volatility state are more likely to find a positive risk-return tradeoff, while studies that include episodes of crisis or high volatility are more likely to find a negative or insignificant trade-off. In both cases, the conclusions can only be viewed as partial evidence since the omission of non-linearities may misrepresent the evidence obtained.

Another interesting result in the paper is related to the magnitude of the market risk price in each regime. During low volatility periods the risk price is higher than during high volatility periods. Although this result may seem against the theoretical intuition claiming for higher returns under more volatile markets, there are other authors using different methodologies who reach a similar conclusion (see Bliss and Panigirtzoglou,2004; Kim and Lee, 2008; and Rossi and Timmerman, 2010).

The principal contributions of our paper are as follows. First, we study the risk-return relation for 11 European stock markets instead of US data which is more widely used in previous studies. Second, we develop an empirical framework with a non-linear risk return trade-off by using Markov-Switching processes for different specifications of the conditional variance (RS-GARCH and RS-MIDAS). Third, we show that a positive and significant risk–return trade-off is obtained for all European markets analyzed after considering non-linearities independently of the variance specification. Besides, we obtain a positive trade-off higher in magnitude during low volatility periods than during high volatility periods where the relationship is even non-significant or negative in some cases. Finally, we show the evolution of the risk premium in Europe during the recent years, including the recent period of the global financial crisis.

The remainder of this paper is structured as follows. Section 2 describes the data used in the study and develops the methodology. Section 3 reports and analyzes the main results obtained. Section 4 reports a battery of robustness studies confirming the main conclusions reached. Finally, section 5 summarizes.

2. Data and methodology

For the empirical analysis of the paper, we employ daily stock exchange indexes from 11 European countries[3] for the period August 1990 - May 2012. The sample includes data from DAX (Germany), CAC (France), IBEX35 (Spain), FTSE100 (United Kingdom), SMI (Switzerland), AEX-Index (The Netherlands), BEL20 (Belgium), OMXC20 (Denmark), OMXH25 (Finland), OMXS30 (Sweden) and Athex20 (Greece). As a robustness test, we also employ data from the US market (SP500 index). These data allow us to calculate daily and weekly returns for the same period. Although the main conclusions of the paper are reached using weekly data, we also need daily observations when estimating the conditional volatility of (RS / asymmetric) MIDAS models. All the index data is obtained from Thomson DataStream.

[3] Some countries such as Italy are not included in the analysis because the main stock index has been changed during the sample period leading to an irregular evolution of their quotations.

Only few authors (e.g., Theodossiou and Lee, 1995; Li et al., 2005; Guo and Neely, 2008) have investigated the risk-return relation in international stock markets, although a study considering a wider selection of countries could help resolve the puzzling results obtained from U.S. data. In this paper, we comprehensively analyze the patterns followed by this relation in the main European stock markets.

Because risk-free interest rate data are not available to all financial markets under consideration over the examined period, stock market volatility is measured based on stock returns instead of excess stock returns (which is equal to stock returns minus the risk-free interest rate). Many researchers (Baillie and DeGennarro, 1990; Nelson, 1991; Choudhry, 1996; Li et al., 2005) argue that such a practice produces little difference in estimation and inference in this line of research. All these authors state that there is virtually no difference in either the estimated parameters or the fitted variance. [4]

In the next subsections we develop the methodology proposed for all empirical models used to analyze the risk–return trade-off.

2.1. Standard GARCH

The first approach is the traditional GARCH-M model of Engle et al. (1987). This framework is the most used in the financial literature to study the risk–return trade-off despite the puzzled results from previous studies. In this approach the mean equation is defined as follows:

$$r_t = c + \lambda h_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, h_t) \qquad (2)$$

where r_t is the market return, h_t is the conditional variance, and ε_t represents the innovations, which are assumed to follow a normal distribution. The conditional volatility is obtained using a standard GARCH specification as in Bollerslev (1986):

$$\varepsilon_t = h_t z_t \qquad z_t \sim N(0,1) \qquad (3)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (4)$$

where ω, α and β are parameters to estimate and $\alpha + \beta < 1$ guarantees the stationarity of the process.

We estimate this first model using the quasi maximum likelihood (QML) function of Bollerslev and Wooldridge (1992), which allows us to obtain robust estimates of standard errors:

$$L(\theta) = \sum_{t=1}^{T} \ln\left[f\left(r_t, \Omega_t; \theta\right)\right] \qquad where \qquad f\left(r_t, \Omega_t; \theta\right) = \left(2\pi h_t\right)^{-\frac{1}{2}} e^{-\frac{(\varepsilon_t)^2}{2h_t}} \qquad (5)$$

However, this approach has not presented favorable evidence on the significance of a risk-return tradeoff in many previous studies, such as Baillie and De Gennaro (1990), Glosten et al. (1993), Shin (2005), and Leon et al. (2007). Some authors argue that the conditional volatility using this GARCH-M methodology has almost no explanatory power for realized returns and that could be the reason of the non-significant results (see Lundblad, 2007). Other authors claim that the controversial results are due to wrong modeling of conditional volatility (see Ghysels et. al, 2005; Leon et al., 2007).

2.2. MIDAS regression

Recently, a new methodology has been developed to capture a significant relationship between return and risk using data from different frequencies to obtain expected returns and variances, namely the MIDAS (mixed data sampling) regression (Ghysels et al., 2005). They find evidence of a significant positive trade-off between return and risk and state the advantages of this methodology regarding GARCH models. MIDAS models allow the estimation of smooth

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[4] Following the insightful suggestions from the referees, we also include a robustness test in section 4 considering the risk-free rate for a few representative countries.

expected return series using low frequency data and the estimations of more variable conditional variances using higher frequency data.

We use this specification with weekly returns (r_t) combined with *D=250* daily lag squared returns (R_t^2) to obtain the weekly variance.

The mean equation of this model is similar to Equation 2 with conditional variance as a explanatory variable for the expected returns:

$$r_t = c + \lambda VAR(r_t) + \varepsilon_t \qquad \varepsilon_t \sim N(0, VAR(r_t)) \qquad (6)$$

However, the MIDAS estimator of weekly conditional variance is not obtained through a GARCH parameterization but from a function of D lag squared daily returns (R_t^2):

$$VAR(r_t) = \sum_{d=0}^{D} \omega\left(k_1, k_2, d\right) R_{t-d}^2 \qquad (7)$$

$$\text{where} \quad \omega\left(k_1, k_2, d\right) = \frac{\exp\left(k_1 d + k_2 d^2\right)}{\sum_{i=0}^{D} \exp\left(k_1 i + k_2 i^2\right)} \qquad (8)$$

is the function which measure the impact of each lag daily return in the variance formation[5].

Assuming normality in returns $r_t \sim N\left(c + \lambda VAR(r_t), VAR(r_t)\right)$, we estimate this model by maximizing the Bollerslev–Wooldridge QML function, as in Equation 5.[6.]

2.3. Asymmetric case

The symmetric models presented above can easily be extended to the asymmetric case in which the variance responds more heavily after negative returns than it does after positive returns (leverage effect). For the GARCH specification, we add a new variable $\eta_t = \min\left(\varepsilon_t, 0\right)$ in the variance process using the asymmetric GJR model (Glosten et al., 1993). These models are estimated in a similar way to that presented above, substituting Equations 4 for 9.

$$h_t = \omega + \alpha \varepsilon_t^2 + \beta h_{t-1} + \delta \eta_{t-1}{}^2 \qquad (9)$$

We estimate the MIDAS model for the asymmetric case substituting Equation 7 for Equation 10:

$$Var\left(r_t\right) = \theta \sum_{d=0}^{D} \omega\left(k_1^-, k_2^-, d\right) r_{t-d}^2 \cdot 1_{t-d}^- + \left(2-\theta\right) \sum_{d=0}^{D} \omega\left(k_1^+, k_2^+, d\right) r_{t-d}^2 \cdot 1_{t-d}^+ \qquad (10)$$

where $\theta, k_1^-, k_2^-, k_1^+, k_2^+$ are the parameters to be estimated and $1_{t-d}^-, 1_{t-d}^+$ are the indicator functions for $\left\{r_{t-d} < 0\right\}$ and $\left\{r_{t-d} \geq 0\right\}$, respectively. We use Equation 5 again to estimate these models.

2.4. Non-linear models

Some authors claim that strong linear assumption for the risk-return relationship could lead to misleading results since imposing this condition may bias the evidence on this relationship. To overcome this limitation, some works develop alternative theoretical frameworks which assume a more flexible relationship between return and risk even proposing a non-monotonic relationship over time (Rossi and Timmerman, 2010).

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[5] Ghysels et al. (2007) develop several weight functions for the MIDAS estimator, but owing to its tractability, the Almon Lag specification is the most frequently used in the literature.

[6] Although some authors estimate this specification by using non-linear least squares, Ghysels et al. (2005) use the QML estimate in their original paper.

So, in the next subsections we develop the methodologies to analyze if there is a non-linear risk-return trade-off in the European markets. An explanation for the controversial results in previous studies may lie in the wrong specification for the relationship between risk and return which follows non-linear rather than linear patterns. Therefore, an insightful extension is to consider non-linearities in this trade-off against the linear framework usually implemented. In order to provide robustness to our results, we introduce non-linearites assuming two forms for the conditional volatilities. As a result, RS-GARCH and RS-MIDAS models are developed; their specifications are given below (for more details, see also Appendix A).

a) Regime Switching GARCH model

RS-GARCH specification is based on the model originally proposed by Hamilton (1989); it allows us to distinguish between different volatility states governed by a hidden state variable that follows a Markov process. In this model, the mean equation is not exactly as shown in Equation 2 because it is state-dependent:

$$r_{t,s_t} = c_{s_t} + \lambda_{s_t} h_{t,s_t} + \varepsilon_{t,s_t} \qquad \varepsilon_{t,s_t} \sim N(0, h_{t,s_t}) \qquad (11)$$

where r_{t,s_t}, h_{t,s_t}, and ε_{t,s_t} are the state-dependent returns, variances, and innovations respectively and $s_t = 1$ (state 1) or 2 (state 2).

The state-dependent innovations follow a normal distribution, with two possible variances depending on the state of the process. The state-dependent variances are modeled as in Equation 4 following a GARCH parameterization, but allowing different parameters depending on the state[7]. in this case.

$$\varepsilon_{t,s_t} = h_{t,s_t} z_t \qquad z_t \sim N(0,1) \qquad (12)$$

$$h_{t,s_t} = \omega + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} h_{t-1} \qquad (13$$

The shifts from one state to another are governed by a hidden state variable following a Markov process with a transition matrix:

$$P = \begin{pmatrix} \Pr(s_t = 1 | s_{t-1} = 1) = p & \Pr(s_t = 1 | s_{t-1} = 2) = (1-q) \\ \Pr(s_t = 2 | s_{t-1} = 1) = (1-p) & \Pr(s_t = 2 | s_{t-1} = 2) = q \end{pmatrix} \qquad (14)$$

Because of this state-dependence, the model is econometrically intractable[8]. We must, therefore, obtain state-independent estimates of variances and innovations. We use the recombinative method presented in Gray (1996) which assuming conditional normality in each regime, uses the definition of unconditional variance in returns maintaining the nature of the GARCH process:

$$h_t = E\left[r_t^2 | \Omega_{t-1}\right] - E\left[r_t | \Omega_{t-1}\right]^2 = \pi_{1,t}\left(\mu_{t,1}^2 + h_{t,1}\right) + \left(1-\pi_{1,t}\right)\left(\mu_{t,2}^2 + h_{t,2}\right) - \left(\pi_{1,t}\mu_{t,1} + \left(1-\pi_{1,t}\right)\mu_{t,2}\right)^2 \quad (15)$$

In order to obtain state-independent errors we use the definition of unconditional error:

$$\varepsilon_t = r_t - \pi_{1,t}\mu_{t,1} + \left(1-\pi_{1,t}\right)\mu_{t,2} \qquad (16)$$

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[7] Following Capiello and Fearnley (2000) to facilitate convergence, the constant variance term is not allowed to switch between regimes.

[8] See e.g. Gray (1996) and Dueker (1997). The main problem is derived from the fact that state-dependence increases exponentially the size of the likelihood function.

where h_t and ε_t are the state-independent variances and innovations, μ_{t,s_t} is the conditional mean equation $\mu_{t,s_t} = c_{s_t} + \lambda_{s_t} h_{t,s_t}$ for a given state s_t and:

$\pi_{1,t} = p \cdot P\left(s_{t-1} = 1 \middle| \Omega_{t-1};\theta\right) + (1-q)P\left(s_{t-1} = 2 \middle| \Omega_{t-1};\theta\right)$ (17) is the ex-ante probability

Where $\pi_{2,t} = 1 - \pi_{1,t}$ (18)

And the ex-post (filtered) probabilities are defined as:

$$P\left(s_t = k \middle| \Omega_t;\theta\right) = \frac{\pi_{s_t=k,t} f\left(r_t \middle| s_t = k, \Omega_t;\theta\right)}{\sum_{k=1}^{2} \pi_{s_t=k,t} f\left(r_t \middle| s_t = k, \Omega_t;\theta\right)} \quad (19) \quad \textit{for } k = 1, 2$$

We estimate this model by maximizing the QML function of Bollerslev–Wooldridge (1992) weighted by the filtered probability of being in each state:

$$L(\theta) = \sum_{t=1}^{T} \ln\left[\sum_{k=1}^{2} \pi_{s_t=k,t} f\left(r_t, \Omega_t;\theta\right)\right] \quad \textit{where} \quad f\left(r_t \middle| s_t, \Omega_t;\theta\right) = \left(2\pi h_{t,s_t}\right)^{-\frac{1}{2}} e^{-\frac{\left(\varepsilon_{t,s_t}\right)^2}{2h_{t,s_t}}} \quad (20)$$

b) Regime Switching MIDAS model

Further, the Markov Switching MIDAS incorporates regime-switching in the parameters of the mixed data sampling models (MIDAS) and allows for the use of mixed-frequency data in Markov-Switching models. The reason to introduce this model is to see the role of non-linearities in an alternative variance specification to GARCH modeling.

The modeling of a Regime-Switching MIDAS model for our purposes analyzing the risk-return trade-off is drawn as follows. We define the state-dependent mean equation using weekly returns ($r_{s_t,t}$) which are explained by a state-dependent constant and a time-varying state-dependent conditional variance using D daily lag squared returns (R_t^2); therefore, the mean equation of this model is:

$$r_{s_t,t} = c_{s_t} + \lambda_{s_t} VAR(r_{s_t,t}) + \varepsilon_{t,s_t} \qquad \varepsilon_{t,s_t} \sim N(0, VAR(r_{s_t,t})) \quad (21)$$

In this case, although the MIDAS estimator of weekly conditional variance is again a function of $D=250$ lag squared daily returns (R_t^2), we let the weight parameters to switch among states:

$$VAR(r_{t,s_t}) = \sum_{d=0}^{D} \omega\left(k_{1,s_t}, k_{2,s_t}, d\right) R_{t-d}^2 \quad (22)$$

where $\omega\left(k_{1,s_t}, k_{2,s_t}, d\right) = \frac{\exp\left(k_{1,s_t} d + k_{2,s_t} d^2\right)}{\sum_{i=0}^{D} \exp\left(k_{1,s_t} i + k_{2,s_t} i^2\right)}$ (23) is the state-dependent weight function for a given state $s_t = 1,2$.

To estimate this model we need the help of Bayesian inference in a similar way explained in the RS-GARCH model. Setting that the transition probability matrix, the ex-ante probabilities and the ex-post (filtered) probabilities are defined as in equation (17), (18) and (19) respectively, we can estimate this model by maximizing the following QML function.

$$L(\theta)=\sum_{t=1}^{T}\ln\left[\sum_{k=1}^{2}\pi_{s_t=k,t}\,f\left(r_t,\Omega_t;\theta\right)\right] \quad where \quad f\left(r_t\left|s_t,\Omega_t;\theta\right.\right)=\left(2\pi\cdot VAR(R_{t,s_t})\right)^{-\frac{1}{2}}e^{-\frac{\left(\varepsilon_{t,s_t}\right)^2}{2VAR(R_{t,s_t})}} \tag{24}$$

3. Empirical results

This section displays the estimations of the conditional mean and volatility of stock returns using the models from the previous section and it discusses the relationship between return and risk in Europe. First, we show the main results using our proposed linear models: GARCH and MIDAS. Second, we analyze if the introduction of an asymmetric effect on volatility has any impact when analyzing the risk-return trade-off. Third, we provide a discussion about the results obtained after relaxing the linear assumption on the risk–return trade-off through the use of Regime-Switching models. Finally, we study the evolution of the market risk premium in all the stock markets considered over the examined period (during the last twenty years).

3.1 Estimations for linear models

We initially discuss the results of the models presented in section 2.1 (GARCH) and 2.2 (MIDAS). Although these two models advocate for a linear relationship between return and risk, they are quite different in their construction and estimation methodologies for the conditional variance as it is explained in section 2. The main results for these models in all the stock markets considered are shown in Table 1.

[INSERT TABLE 1]

The results for the GARCH model (left side of table 1) are qualitatively similar to those presented in part of the literature (Glosten et al., 1993; Shin, 2005; Leon et al., 2007). The results indicate a non-significant relationship between return and risk suggesting there is no linear relation between market return and market risk. This confirms the puzzled results of previous studies which are incapable to provide clear evidence of this trade-off. Furthermore, the variance parameters present the typical patterns reported in the literature with a high persistence of the GARCH term (the persistence varies between 95% and 99.9% depending on the country). This fact has led some authors (Lameroux and Lastrapes, 1990; Marcucci, 2005) to consider this as a sign for the existence of different regimes for the variance process. They suggest that if these regime shifts are ignored, GARCH models tend to overestimate persistence in periods of financial instability and underestimate it in calm periods.

Further, the right side of Table 1 shows the results obtained using the MIDAS methodology. The main difference between this and previous models is the way we obtain conditional volatilities. We use different data frequencies to estimate expected returns (weekly data) and variances (daily data), as explained in the previous section. The risk price parameter is again non-significant for this kind of models. The results fail to provide a positive and significant relationship between return and risk as it would be expected. Our results are different from those of previous studies using this methodology which obtain favorable evidence using this methodology. These differences may be due to the use of mixed daily and weekly data, whereas most studies use mixed daily (variance) and monthly (returns) data, see Ghysels et al. (2005) and Leon et al. (2007). However, the consideration of the last financial crisis period (post-2008) in the empirical analysis could blur the evidence of a monotonic risk-return trade-off in a linear framework. The variance estimations using this specification also indicate a high degree of persistence because a great number of daily lags are needed to accurately estimate the variance. In almost all countries, the weights corresponding to lag returns superior to 30 days represent more than the 40% of the total volatility. This emphasizes the importance of considering more than a month of daily returns for measuring MIDAS conditional variance.

In conclusion, neither standard GARCH models nor standard MIDAS are able to show a significant trade-off between return and risk in Europe.

3.2 Estimations for asymmetric case

We now discuss the results of the models presented in section 2.3 (Asymmetric GARCH and MIDAS). There is evidence in the literature (Nelson, 1991; Glosten et al., 1993) of a different effect of shocks of different sign in the volatility formation. Negative shocks usually present a greater impact on volatility known as leverage effect. The inclusion of this effect on the conditional volatility estimation could have effects on the sign and significance of the risk-return trade-off observed in Europe. The estimations for the asymmetric models including the leverage effect for all the stock markets considered are shown in Table 2.

[INSERT TABLE 2]

The results for the asymmetric GARCH model (left side of table 2) are similar to those for the symmetric case. The results show again a non-significant relationship between return and risk. The only country with a significant trade-off is Greece which exhibits a negative relation between return and risk. The variance parameters present again a high level of persistence but it is slightly lower than the standard case (the persistence varies between 90% and 99.9% depending on the country).

The estimations for the asymmetric MIDAS also fail to show a significant risk-return trade-off for most of the countries. Using this model we find the abnormal case of Greece with a negative and significant risk-return trade-off. Regarding the variance persistence, this specification let us distinguish between the impact of positive and negative shock and how long they persist. It is very difficult to give a general interpretation of the patterns followed by positive or negative shocks for all countries since each market volatility seems to follow idiosyncratic patterns. However, in most of the countries negative shocks are less persistent than positive shocks. These findings could be in line with those of Marcucci (2005) since during periods of market jitters, there is an increase of the number of negative shocks; this increase in the number of innovation reduces their impact over time.

So, asymmetric GARCH and MIDAS models are not able to show a significant risk-return relationship for Europe during the sample period analyzed confirming the incapability of linear models and questioning the theoretical framework supporting them. Therefore, it seems important to go beyond this setup and relax the strong assumption of a linear risk-return trade-off.

3.3. Estimation for non-linear models

The results reported in the previous sections do not support the linear assumption of the risk-return trade-off. Even Merton (1980) remarks that this relationship does not have to be linear. For this reason, we introduce in the previous models a Regime-Switching process which relaxes the linear assumption taken when analyzing the risk-return trade-off by conditioning our results to states of high and low volatility. Next we show the results for our two volatility specifications in the case we introduce a non-linear risk-return trade-off; i.e. we discuss the results obtained from RS-GARCH and RS-MIDAS specifications.

a) Regime-Switching GARCH model

Table 3 presents the estimations for the non-linear model assuming a GARCH process in the volatility formation (RS-GARCH[9]). The results for this model let us shed light to the dynamics followed by the risk-return relation. In particular, we can associate state 1 with low volatility periods and state 2 with high volatility periods using the medians of the estimated volatility in each state[10]. For $s_t = 1$, corresponding to the low volatility state, there is a significant positive relationship between return and risk for almost all countries (at 1% for Germany, France, Spain, UK, Switzerland, Belgium, Denmark and Sweden; at 5% for Finland and at 10% for the Netherlands). The only country with no significant relationship between return and risk is Greece.

[INSERT TABLE 3]

However, when we look at the results for the state $s_t = 2$ we obtain less evidence for a positive and significant relationship between return and risk. Only for Germany, Spain and Sweden the relationship is significant at 5% and in Denmark, Belgium and France at 10%. In the rest of the countries the trade-off between these two variables is not significant during high volatility states. Besides, and even more interesting, the risk price coefficient during high volatility states ($\lambda_{s_t=2}$) is lower than it is for the low volatility regime. This finding is not consistent with the spirit of the theoretical linear models that suggest that higher volatility should be compensated with higher returns. However, some papers such as Lundblad (2007), Kim and Lee (2008), and Rossi and Timmerman (2010) report the same evidence. This fact indicates that in high volatility periods the investor's risk appetite is lower. One potential explanation for this result may be due to the existence of a different risk price depending on the volatility regime. An investment considered too risky in calm periods (low volatility) is less risky when there is a period of market instability with more uncertainty and any investment involving risk. This finding could also be explained by investors' characteristics in high volatility states. In these periods, more risk-averse investors leave the market, letting less risk-averse investors adjust the price of risk according to their less demanding preferences (Bliss and Panigirtzoglou, 2004). Authors such as Kim and Lee (2008) find a pro-cyclical behaviour in the investor risk appetite. During low volatility periods investors are more reluctant to take risk and during high volatility periods investors have more will to accept the same risk. However, a recent study developed by Rossi and Timmerman (2010) shows that the risk-return trade-off may follow non-monotonic patterns. These authors state that at low-medium levels of conditional volatility there is a positive risk-return trade-off but this relationship gets inverted at high levels of volatility. Our results seems to support these studies observing a strong evidence of a positive risk-return trade-off during periods of low volatility but the evidence is different depending on the country analysed during periods of high volatility.

The persistence of the GARCH term during low volatility states is higher than the observed for high volatility states. This fact confirms the evidence from the literature (Marcucci, 2005). He

9 Following the insightful suggestion from one anonymous referee we check the gains from adding regime switches in the constant parameter (c) compared to the case where the only parameter switching would be the one entering before the conditional variance (λ). The corresponding LR tests shows that the best model is the second one. Therefore, we show in table 3 the results of this specification. Results of this analysis are available from authors upon request.

10 For brevity, the table containing this information is not displayed in this version of the paper but is available upon request.

concludes that in high volatility periods there are a higher number of shocks affecting the variance formation and reducing their impact over time. Further, the persistence is overestimated in high volatility periods if regime-switching is ignored (Marcucci, 2005).

In addition, the expected duration[11] for the low volatility state is approximately 12 weeks, about four times higher than that obtained for the high volatility state. Figure 1 shows the smoothed probabilities[12] of being in state 1 for the sample period.

[INSERT FIGURE 1]

Interestingly, the smooth probabilities of being in low/high volatility states are very close with the economic cycles (boom / crisis) during the sample period and could be associated with them. For example, in figure 1 we can observe clearly the downturn in worldwide economic activity around 2001 and the effect of the last financial crisis in 2008 with the high volatility regime becoming the most important during these periods. Although there seems to be a clear link between market volatility states and business cycles this relationship does not always hold (Lustig and Verdelhan, 2012). Therefore, we should interpret our results as conditioned to the state of the market (more risk price during low volatility periods, less risk price during high volatility periods) rather than to the state of the economy (more risk price during boom periods, less risk price during crisis periods).

b) Regime-Switching MIDAS model

In the previous section we report a positive risk-return relationship during low volatility states under a non-linear specification with GARCH variances. Here, we provide robustness for the claim of a non-linear relation between return and risk by using an alternative variance model to GARCH.

Table 4 displays the estimations for the RS-MIDAS model[13] for all countries considered. The interpretation of regimes in the MIDAS specification is not as straightforward as in the RS-GARCH specification. In this specification the estimator of volatility does not explicitly model a switch in the level of volatility. So, we interpret the regime as “high” and “low” based on the probability charts of being in a given regime[14]. Supporting the results of the last section, during low volatility states the relation between return and risk is positive and significant for all countries considered. Also, the value for the risk price coefficient is higher than the obtained for high volatility periods. The results for high volatility periods are very different between countries although for the majority of markets the relationship gets inverted in periods of high volatility. For instance in the Netherlands, Finland and Sweden we obtain positive and

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[11] We obtain the expected duration of being in each state $S_t = 1,2$ as $\frac{1}{1-p}$ *and* $\frac{1}{1-q}$, respectively.

[12] The smoothed probability is defined as the probability of being in each state considering the entire information set $P\left(s_t = 1 \middle| \Omega_T;\theta\right) = P\left(s_t = 1 \middle| \Omega_t;\theta\right)\left[p\frac{P\left(s_{t+1} = 1 \middle| \Omega_T;\theta\right)}{P\left(s_{t+1} = 1 \middle| \Omega_t;\theta\right)}\right] + \left[(1-p)\frac{P\left(s_{t+1} = 2 \middle| \Omega_T;\theta\right)}{P\left(s_{t+1} = 2 \middle| \Omega_t;\theta\right)}\right]$

[13] Following the insightful suggestion from one anonymous referee we check the gains from adding regime switches in the weight function (k_1, k_2) compared to the case where the only parameter switching would be the one entering before the conditional variance (λ). The corresponding LR tests show that the best model is the second one. Therefore, we show in table 4 the results of this specification. Results of this analysis are available from authors upon request.

[14] We want to thank an anonymous referee for this comment. The probability charts for the RS-MIDAS models are not displayed in the paper since they follow very closely the ones for RS-GARCH models. However, they are available from authors upon request.

significant estimation for the risk-return trade-off in high volatility states (but of a lower magnitude than during low volatility states). For markets such as Switzerland the relationship is not significant. For the rest of the markets (Germany, France, Spain, the UK, Belgium, Denmark and Greece) the trade-off during high volatility periods is negative.

[INSERT TABLE 4]

The results for this family of models[15] seem to support again the interpretations about the existence of a pro-cyclical behavior in the investor risk appetite. The investors trading during high volatility periods are more willing to take risk than the investors trading during low volatility periods. They also support the existence of a non-monotonic (and non-linear) relationship between return and risk depending on the state of the market. During low volatility periods a positive and significant trade-off is observed, but this relationship turns to be different during high volatility periods.

3.4. Risk premium evolution in Europe

In this last section we analyze the evolution followed by the market risk premium during the last years in each European market. The risk premium demanded by the investors is given by the non-diversifiable risk existing in the market.

Figure 2 shows the risk premium evolution in Europe during the sample period for two representative countries (the rest can be found in the online appendix). The market risk premium is measured by the time-varying variable h_t in our models. For the Regime-Switching models, we obtain the independent estimation for the conditional variance at each period *t* through a weighted average using the filter probabilities $\left(h_t = \pi_{1,t} h_{t,1} + \left(1-\pi_{1,t}\right) h_{t,2}\right)$ where $\pi_{1,t}$ is the ex-ante probability of being in the state 1 and h_{t,s_t} $for\ s_t = 1,2$ are the state-dependent variances.

[INSERT FIGURE 2]

These figures represent the weekly market risk premiums (expressed in basis points) for all the sample period, the different methodologies and the countries considered. The figures show similar patterns for the risk premium evolution. It seems that risk exposure is similar for all methodologies with slight differences between them. However, the evolution is quite different depending on the country analyzed. Although all markets have been hit by a similar crisis, it seems that in some of them (Finland at the beginnings 2000s, Greece over last years) the effect was worse than in the rest. However, all the countries share a huge increase of the demanded risk premium in the recent years coinciding with the last financial crisis.

Table 5 shows the median[16] of the estimated weekly risk premiums series for all the European stock market indexes considered. Almost all the obtained risk premiums vary between 2%-4% depending on the country. Only in the cases of Greece and Finland the demanded premiums exhibits higher values (around 5.5% for Finland and 7% for Greece). The differences in the risk premiums among methodologies are slightly. Most of these premiums are similar than the 3% to 5% obtained in other studies for US data (Bali, 2008).

[INSERT TABLE 5]

[15] For all MIDAS specifications we repeated the estimations using a beta function instead of an exponential. The results lead to the same conclusion and are available from authors upon request.

[16] We use the median instead of the mean as a proxy for the average non-diversifiable risk in each period because it is less affected by outliers.

So, although the evolution of the market risk premium in Europe has followed similar patterns during the last years for most of the countries analyzed, there are certain differences among countries (due to idiosyncratic characteristics of each market) which lead to different levels in the demanded risk premium. Especially, countries such as Finland or Greece seem to departure from the 'standard' European risk premium.

4. Robustness

In this section we show several additional analyses for a selected group of representative countries[17] in order to check the robustness of the evidence obtained.

4.1. US data

Almost all the previous evidence and empirical studies about the risk-return tradeoff are obtained using US data. Although the aim of the paper is essentially the European market, it is always interesting comparing our results to this benchmark market[18]. Table 6 shows the empirical results for all the models presented in the paper using US data. In this case, the proxy used for the market returns is the S&P500 index collected from Datastream for the period August 1990 – May 2012.

[INSERT TABLE 6]

The results presented in Table 6 support the evidence obtained in the European markets. In other words, we cannot find favorable evidence for the symmetric or asymmetric GARCH or MIDAS models. However, when we relax the assumption of linear tradeoff between return and risk, we obtain positive and significant estimations in low volatility states. Again, the estimated coefficients during these periods are much higher than the ones in high volatility states. Also interestingly, the coefficient during high volatility states is negative when considering regime-switching models suggesting an inverted risk-return relation in the US market at high levels of volatility; this evidence is in line with Rossi and Timmerman (2011).

4.2. Excess market returns

The main theoretical model expressed in Equation (1) links excess market returns with risk. For the reasons stated thorough the paper, we have been forced to use simple market returns in our empirical study. In this subsection we see that if we account for the risk free rate in our returns series we do obtain almost the same results. Table 7 shows the estimation results for all the models presented in the paper considering three representative markets (Germany, UK and USA). Excess market returns are simply constructed by subtracting the market returns to the risk free rate. The choice of the proxy for the risk free rate is the local 3-month T-bill suitable compounded at the corresponding frequency.

[INSERT TABLE 7]

If we compare the results from Table 7 to the ones using simple market returns we can only observe slight differences in the estimated coefficients. The conclusions about the sign and significance of the relationships are clearly maintained. Given this evidence, , we are confident to claim that the no consideration of the risk-free rate when constructing the excess market

[17] The choice of the countries in these analyses is due to data limitations in some of the variables used and to the aim of maintaining brevity.

[18] We want to thank the comments from one anonymous referee which let us became aware of an independent and simultaneously written paper by Ghysels, Guérin and Marcellino (2013) which also analyse regime-switches in the risk-return tradeoffs for the US market.

returns series does not lead to different conclusions about the risk-return trade-off. This is in line with Baillie and DeGennarro (1990), Nelson (1991), Choudhry(1996) and Li et al. (2005).

4.3. Conditioning to macro variables

Another assumption taken in most of the previous empirical studies analyzing return and risk, considers one set of investment opportunities constant over time leaving the market risk as the only source of risk. A standard critique in the estimation of the risk-return relation is this lack of conditioning variables (Scruggs, 1998; Whitelaw, 2006) to control for some predictors. As a further robustness analysis to our results we run a series of models of the form:

$$r_t = c + \lambda_1 VAR(r_t) + \lambda_2 X_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, VAR(r_t))$$ (25) for linear models and

$$r_{t,s_t} = c_{s_t} + \lambda_{1,,s_t} VAR(r_{t,s_t}) + \lambda_{2,s_t} X_t + \varepsilon_{t,s_t} \qquad \varepsilon_{t,s_t} \sim N(0, VAR(r_{t,s_t}))$$ (26) for non-linear models

Where the variance specifications follow the symmetric, asymmetric and regime-switching GARCH and MIDAS dynamics presented in the paper for a selected group of countries (Germany, UK and USA). The control variables representing X_t in Equations 25 and 26 are the stock market dividend yield series, the local 3-month T-bill, the local 10-year Government Bond and the yield spread between the 10 year and the 3-month rates[19].

For the sake of brevity, we place the results of this analysis in an online appendix. As a brief overview, we argue that the results do not change significantly the conclusions reached so far. We obtain significant evidence for low volatility states when non-linear models are considered; however, this is not true when imposing a linear structure. We encourage the readers to visit the online appendix for further details.

4.4. Data frequency

Selecting the data frequency for both excess returns and market variance is an issue that previous studies do not give a clear answer. While some papers prefer low frequency observations free of short-term noise to detect this tradeoff (Guo and Whitelaw, 2006; Lundblad, 2007), other papers use weekly or even daily observations (Guo and Neely, 2008).

One of the advantages of the MIDAS specification presented in this paper is that it allows for using a mixture of different frequencies for the estimation of the mean and the variance equation. In the previous sections of this paper, we displayed a mixture between weekly and daily observations. In this final subsection we report the results obtained when a monthly frequency is considered for the market returns in the mean equations (Equation 6 and 21), while observations at a daily frequency are used for modeling the variance equation (Equations 7 and 22). We also estimate the remaining GARCH models using monthly observations. All these additional analyses can be found in the aforementioned online appendix. Again, the main results of the paper hold for all countries. [20]

5. Conclusion

This study proposes new evidence to the well-known controversy about the empirical relationship between return and risk. From the basis of the theoretical works explaining this trade-off, the interaction between these two variables is tested empirically using 11 European

[19] We enter these predictors in the risk-return regressions both sequentially and jointly (see online appendix for details).
[20] The results for the RS-GARCH specification are weaker since using monthly observations in a GARCH context leads to a sample of 267 observations which may present some problems related to small sample properties.

stock markets under two main different frameworks. The first framework considers a linear relation between return and risk, while the second one relaxes this assumption and allows for non-linear dynamics.

Linear empirical models show a non-significant evidence of this basic trade-off. However, when this strong linear assumption is relaxed, we are able to identify a significant relationship between expected return and risk. One of our claims is that the risk-return trade-off presents different patterns depending on the state of the market. The dynamics of this relation observed during low volatility states (which supports the theoretical intuition) are different from those observed during high volatility states. This fact leads to a non-monotonic relation over time which is totally against the linear assumption made in many previous studies. One of the other main results of our paper is that it provides a relationship between volatility regimes and attitudes towards risk. The risk price level in stock markets tends to be higher in low volatility states and lower in high volatility states. The investor profile in each context may have an influence on this lower risk appetite during high volatility periods. During low volatility periods investors are more reluctant to assume risk but during high volatility periods they have more will to accept the same levels of risk. The evidence obtained in the paper is also robust for US data, when conditioning the estimations to additional predictors and to different data frequencies.

Above all, these results highlight the perils of strong linear assumptions when analyzing the interactions between return and risk and suggest that previous studies using linear models were likely to fail on the attempt to capture the global behavior between these two variables.

APPENDIX A

All the models are estimated by maximum likelihood. The computations of the Regime-Switching models are carried out using the Optimization Library FMINCON of Matlab R2010b selecting the BFGS algorithm.

Although Regime-Switching GARCH models and Regime-Switching MIDAS models are different (as it is discussed in section 2.4 and 2.5), once the parameterization of the variance equation is defined in each case, the algorithm to implement is similar for both specifications.

Let Φ be the vector of parameters of the different models; $\pi_{s_t=k,t} = \Pr\left(s_t = k \middle| \Omega_{t-1}\right)$ the ex-ante probability of being in the state k (where Ω_{t-1} is the information set up to t-1); $P\left(s_t = k \middle| \Omega_t;\theta\right)$ the filtered probability of being in the state k; and $f\left(r_t \middle| s_t, \Omega_t;\theta\right) = \left(2\pi h_{t,s_t}\right)^{-\frac{1}{2}} e^{-\frac{\left(\varepsilon_{t,s_t}\right)^2}{2h_{t,s_t}}}$ the state- dependent likelihood vector (where the main difference between GARCH[21] and MIDAS specification is in the parameterization of the time-varying variance h_{t,s_t}).

The algorithm we used is described by the following steps:

1) Give initial values for the parameters of the model and the ex-ante probabilities:

$$\Phi^0, \ \pi_{s_t=k,t=1} = \Pr\left(s_{t=1} = k \middle| \Omega_{t=0}\right)$$

2) Implement Hamilton (1989) filtering procedure using this first observation.

$$P\left(s_{t=1} = k \middle| \Omega_{t=1};\Phi^0\right) = \frac{\pi_{s_t=k,t=1} f\left(r_{t=1} \middle| s_{t=1} = k, \Omega_{t=1};\Phi^0\right)}{\sum_{k=1}^{2} \pi_{s_t=k,t=1} f\left(r_{t=1} \middle| s_{t=1} = k, \Omega_{t=1};\Phi^0\right)} \qquad \textit{for } k = 1, 2$$

3) Compute the value of the log-likelihood function for t=1

$$\ln\left[\sum_{k=1}^{2} \pi_{s_t=k,t=1} f\left(r_{t=1}, \Omega_{t=1};\Phi^0\right)\right]$$

4) Repeat steps 2 and step 3 for all observations and compute the log-likelihood function until t=T

$$L\left(\Phi^0\right) = \sum_{t=1}^{T} \ln\left[\sum_{k=1}^{2} \pi_{s_t=k,t} f\left(r_t, \Omega_t;\Phi^0\right)\right]$$

5) Maximize the log-likelihood function to obtain an update version of the vector of parameters Φ^j:

$$L\left(\Phi^j\right) = \sum_{t=1}^{T} \ln\left[\sum_{k=1}^{2} \pi_{s_t=k,t} f\left(r_t, \Omega_t;\Phi^j\right)\right]$$

6) Iterate steps 2-5 with the updated parameters until achieving convergence.

Hamilton (1989) claims that this algorithm is a special case of the EM algorithm: the expectation (E) step corresponds to step 2 and the Maximization (M) step to step 3. During the Expectation step the algorithm is able to guess the values for the latent variable given the data and the updated parameters while the values of the parameters that maximize the log-likelihood function are driven in the Maximization step.

[21] Due to the recursive nature of the GARCH parameterization, we use a recombinative method to obtain independent variances and errors for each t. See section 2.4 for further details.

TABLE 1. Estimated parameters for GARCH and MIDAS models for all the European stock markets considered

	GARCH-M			***MIDAS***				
Parameter *(std. error)*	c	λ_1	Persistence	c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0027** *(0.0012)*	0.0098 *(0.0142)*	0.9534	0.0028** *(0.0012)*	-0.0466 *(0.0681)*	**15,60%**	**36,34%**	**48,06%**
France	0.0008 *(0.0015)*	0.0141 *(0.0185)*	0.9744	0.0012 *(0.0012)*	-0.0359 *(0.0716)*	**14.74%**	**38.14%**	**47.12%**
Spain	0.0019 *(0.0013)*	0.0075 *(0.0165)*	0.9884	0.0028** *(0.0012)*	-0.0993 *(0.0719)*	**14.64%**	**36.62%**	**48.74%**
UK	0.0011 *(0.0010)*	0.0214 *(0.0212)*	0.9727	0.0016* *(0.0009)*	-0.0599 *(0.0804)*	**14.58%**	**38.08%**	**47.34%**
Switzerland	0.0019** *(0.0009)*	0.0277 *(0.0173)*	0.9660	0.0019 *(0.0009)*	-0.0059 *(0.0875)*	**19.73%**	**40.38%**	**39.89%**
Netherlands	0.0023** *(0.0009)*	0.0060 *(0.0142)*	0.9957	0.0019** *(0.0009)*	-0.0606 *(0.0635)*	**16.34%**	**36.47%**	**47.19%**
Belgium	0.0015 *(0.0010)*	0.0017 *(0.0175)*	0.9509	0.0017* *(0.0009)*	-0.0923 *(0.0829)*	**15.79%**	**37.19%**	**47.01%**
Denmark	0.0026** *(0.0012)*	-0.0049 *(0.0205)*	0.9509	0.0028** *(0.0011)*	-0.1088 *(0.0929)*	**14.92%**	**35.46%**	**49.62%**
Finland	0.0025 *(0.0016)*	0.0402 *(0.1287)*	0.9847	0.0005 *(0.0014)*	0.0228 *(0.0547)*	**12.75%**	**35.93%**	**51.32%**
Sweden	0.0027* *(0.0014)*	0.0088 *(0.0157)*	0.9605	0.0025** *(0.0012)*	-0.0639 *(0.0745)*	**18.62%**	**41.97%**	**39.41%**
Greece	0.0029* *(0.0016)*	-0.0175 *(0.0166)*	0.9907	0.0031** *(0.0015)*	-0.1287** *(0.0610)*	**4.74%**	**22.06%**	**73.20%**

This table shows the estimated parameters for the standard GARCH and standard MIDAS models presented in the paper (robust standard errors in parentheses). ***, ** and * *represent significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE 2. Estimated parameters for asymmetric models

	Asymmetric -GARCH-M					Asymmetric-MIDAS				
	c	λ_1	Persist.			c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0021* *(0.0012)*	-0.0036 *(0.0145)*	0.9217	∅	I −	0.0023** *(0.0011)*	-0.0579 *(0.0667)*	**52.74%**	**46.89%**	**0.37%**
					I +			**4.20%**	**20.04%**	**75.76%**
France	0.0007 *(0.0013)*	-0.0015 *(0.0178)*	0.9542	∅	I −	0.0011 *(0.0012)*	-0.0355 *(0.0728)*	**43.95%**	**52.01%**	**4.04%**
					I +			**5.19%**	**24.08%**	**70.73%**
Spain	0.0026** *(0.0012)*	-0.0161 *(0.0162)*	0.9729	∅	I −	0.0027** *(0.0012)*	-0.1011 *(0.0743)*	**85.46%**	**15.54%**	**0.00%**
					I +			**11.87%**	**32.09%**	**56.04%**
UK	0.0013 *(0.0009)*	-0.0096 *(0.0193)*	0.9637	∅	I −	0.0016* *(0.0008)*	-0.0646 *(0.0830)*	**45.48%**	**53.64%**	**0.88%**
					I +			**3.62%**	**19.28%**	**77.10%**
Switzerl.	0.0020** *(0.0009)*	-0.0075 *(0.0172)*	0.9174	∅	I −	0.0023** (0.0010)	-0.0883 (0.0893)	**23.84%**	**48.40%**	**27.35%**
					I +			**0.01%**	**0.12%**	**99.87%**
Netherl.	0.0020** *(0.0009)*	-0.0097 *(0.0145)*	0.9777	∅	I −	0.0022*** *(0.0009)*	-0.0928 *(0.0662)*	**46.90%**	**48.39%**	**4.71%**
					I +			**3.54%**	**16.75%**	**79.71%**
Belgium	*0.0017** *(0.0010)*	-0.0128 (0.0181)	0.9256	∅	I −	0.0020** *(0.0009)*	-0.1109 *(0.0831)*	**18.69%**	**43.49%**	**37.81%**
					I +			**0.01%**	**0.01%**	**99.98%**
Denmark	0.0028** *(0.0013)*	-0.0165 (*0.0216)*	0.9581	∅	I −	0.0031*** *(0.0010)*	-0.1283 *(0.0895)*	**11.45%**	**32.94%**	**55.61%**
					I +			**33.24%**	**16.98%**	**49.79%**
Finland	0.0026* *(0.0016)*	-0.0060 *(0.0129)*	0.9447	∅	I −	0.0011 *(0.0014)*	0.0057 *(0.0519)*	**11.57%**	**32.45%**	**55.97%**
					I +			**5.97%**	**46.69%**	**47.33%**
Sweden	0.0028** *(0.0013)*	-0.0072 *(0.0147)*	0.9447	∅	I −	0.0029** *(0.0012)*	-0.0866 *(0.0790)*	**29.97%**	**58.08%**	**11.95%**
					I +			**6.05%**	**23.38%**	**70.57%**
Greece	0.0033** *(0.0016)*	-0.0246** *(0.0120)*	0.9907	∅	I −	0.0029* *(0.0015)*	-0.1235** *(0.0630)*	**4.98%**	**24.44%**	**70.58%**
					I +			**4.91%**	**21.06%**	**74.03%**

This table shows the estimated parameters for the asymmetric GARCH and asymmetric MIDAS models presented in the paper (robust standard errors in parentheses). ***, ** and * *represent significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE 3. Estimated parameters for RS-GARCH models

Parameter (std. error)	***RS-GARCH-M***					
	State k=1			***State k=2***		
	c	λ_1	Persist	c	λ_1	Persist.
Germany	-0.0124*** *(0.0041)*	0.6479*** (0.1493)	0.9016	-0.0124* *(0.0041)*	0.0520** *(0.0262)*	0.2109
France	-0.0102** *(0.0047)*	0.3451*** *(0.1177)*	0.8935	-0.0102** *(0.0047)*	0.0577* *(0.0307)*	0.2911
Spain	-0.0201*** *(0.0077)*	0.6378*** *(0.2002)*	0.8644	-0.0201*** *(0.0077)*	0.1027** *(0.0463)*	0.2032
UK	-0.0084** *(0.0033)*	0.5527*** *(0.1940)*	0.8640	-0.0084** *(0.0033)*	0.0760 *(0.0522)*	0.2663
Switzerland	-0.0124*** *(0.0042)*	0.7763*** *(0.1909)*	0.8912	-0.0124*** *(0.0042)*	0.0638 *(0.0389)*	0.2037
Netherlands	-0.0017 *(0.0026)*	0.2101* *(0.1454)*	0.6989	-0.0017 *(0.0026)*	0.0295 *(0.0175)*	0.4210
Belgium	-0.0081** *(0.0033)*	0.4995*** *(0.1354)*	0.8112	-0.0081** *(0.0033)*	0.0391* *(0.0213)*	0.2373
Denmark	-0.0063 *(0.0060)*	0.3222*** *(0.1074)*	0.8191	-0.0063 *(0.0060)*	0.0215* *(0.0118)*	0.3970
Finland	-0.0078 *(0.0062)*	0.1971** *(0.1058)*	0.8575	-0.0078 *(0.0062)*	0.0264 *(0.0240)*	0.2377
Sweden	-0.0265*** *(0.0092)*	0.7364*** *(0.2313)*	0.9191	-0.0265*** *(0.0092)*	0.1058** *(0.0532)*	0.1162
Greece	-0.0029 *(0.0049)*	0.0783 *(0.0782)*	0.6609	-0.0029 *(0.0049)*	0.0043 *(0.0189)*	0.1436

This table shows the estimated parameters for the RS-GARCH modes presented in the paper (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively.*

TABLE 4. Estimated parameters for RS-MIDAS

RS-MIDAS		c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	-0.0139*** (0.0002)	0.3324*** (0.0051)	**17.43%**	**46.82%**	**35.75%**
	St=2	-0.00432*** (0.0002)	-0.0415*** (0.0025)			
France	**St=1**	-0.0278*** (0.0001)	0.7302*** (0.0003)	**14.05%**	**40.16%**	**45.79%**
	St=2	-0.0278*** (0.0001)	-0.0228*** (0.0025)			
Spain	**St=1**	-0.0069*** (0.0010)	0.6586*** (0.0201)	**11.36%**	**44.92%**	**43.72%**
	St=2	0.0467*** (0.0006)	-0.0972*** (0.0093)			
UK	**St=1**	-0.0009 (0.0006)	0.8764*** (0.0125)	**10.90%**	**35.73%**	**53.37%**
	St=2	0.0467*** (0.0019)	-0.0930*** (0.0138)			
Switzerland	**St=1**	0.0053*** (0.0006)	0.3280*** (0.0901)	**49.52%**	**49.51%**	**0.97%**
	St=2	-0.0453*** (0.0007)	0.0125 (0.0119)			
Netherlands	**St=1**	0.0009 (0.0005)	0.6426*** (0.0196)	**59.18 %**	**30.87%**	**9.95%**
	St=2	-0.0486*** (0.0007)	0.0429*** (0.0037)			
Belgium	**St=1**	00018*** (0.0002)	0.2925*** (0.0067)	**32.81%**	**45.96%**	**21.22%**
	St=2	-0.0441*** (0.0008)	-0.0552*** (0.0067)			
Denmark	**St=1**	-0.0053*** (0.0000)	0.6532*** (0.0028)	**16.70%**	**35.02%**	**48.28%**
	St=2	0.0408*** (0.0004)	-0.0754*** (0.0060)			
Finland	**St=1**	0.0081*** (0.0005)	0.3302*** (0.0043)	**18.99%**	**44.95%**	**36.06%**
	St=2	-0.0552*** (0.0004)	0.0621*** (0.0027)			
Sweden	**St=1**	-0.0100*** (0.0022)	0.3864*** (0.0001)	**17.94%**	**52.49%**	**29.57%**
	St=2	-0.0561*** (0.0027)	0.1880*** (0.0062)			
Greece	**St=1**	-0.0029 (0.0028)	0.4421*** (0.0255)	**2.50%**	**12.55%**	**84.95%**
	St=2	0.0542*** (0.0039)	-0.0802*** (0.0102)			

This table shows the estimated parameters for the RS-MIDAS model in the restricted version of the paper (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance.*

TABLE 5. Annualized market risk premium for Europe

Average Risk premium						
	GARCH	*Asymmetric GARCH*	*RS-GARCH*	*MIDAS*	*Asymmetric MIDAS*	*RS-MIDAS*
Germany	3.882%	3.771%	3.684%	3.636%	3.692%	4.267%
France	3.812%	3.606%	3.552%	3.746%	3.823%	4.029%
Spain	3.981%	3.554%	3.246%	3.985%	3.993%	4.482%
UK	2.309%	2.057%	2.075%	2.277%	2.432%	2.424%
Switzerland	2.425%	2.130%	2.119%	2.307%	2.388%	2.219%
Netherlands	2.900%	2.627%	3.021%	2.891%	2.936%	2.577%
Belgium	2.422%	2.316%	2.067%	2.289%	2.243%	2.623%
Denmark	3.017%	2.838%	2.620%	2.619%	2.634%	2.600%
Finland	5.932%	5.816%	5.859%	4.877%	4.788%	4.830%
Sweden	4.132%	3.893%	3.463%	3.272%	3.486%	2.976%
Greece	6.881%	6.888%	8.054%	7.293%	7.315%	7.080%

This table shows the average risk premium (using the median of the series) for each country considered using the different models proposed.

TABLE 6. Estimated parameters for US market returns

Panel A.- Symmetric linear models								
	GARCH-M			***MIDAS***				
Parameter *(std. error)*	c	λ_1	Persistence	c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
USA	0.1499^{*} *(0.0829)*	0.0217 *(0.0175)*	0.9786	0.0018^{*} *(0.0007)*	-0.0367 *(0.0734)*	**11.60%**	**33.74%**	**54.66%**

Panel B.- Symmetric linear models										
	Asymmetric -GARCH-M					***Asymmetric-MIDAS***				
	c	λ_1	Persist.			c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
USA	0.1223^{*} *(0.0715)*	0.0029 *(0.0146)*	0.9625	∅	**I -**	0.0016^{**} (0.0007)	-0.0237 (0.0751)	**2.39%**	**11.67%**	**85.94%**
					I +			**27.96%**	**58.06%**	**13.98%**

Panel C.- RS-GARCH model						
Parameter *(std. error)*	***State k=1***			***State k=2***		
	c	λ_1	Persist	c	λ_1	Persist.
USA	-0.0049 *(0.0034)*	0.4004^{**} (0.1636)	**0.8980**	-0.0049 *(0.0034)*	-0.0589^{*} *(0.0332)*	**0.2569**

Panel D.- RS-MIDAS model						
RS-MIDAS		c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
USA	**St=1**	0.0158^{***} (0.0000)	0.5562^{***} (0.0271)	**11.56%**	**88.32%**	**0.12%**
	St=2	-0.0204^{***} (0.0034)	-0.0393^{***} (0.0020)			

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) when using US returns. ***, ** and * *represents significance at 1%, 5% and 10% respectively.*

TABLE 7. Estimated parameters for excess market returns

Panel A.- Symmetric linear models								
	GARCH-M			MIDAS				
Parameter *(std. error)*	c	λ_1	Persistence	c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.1681 *(0.1301)*	0.0122 *(0.0148)*	0.9534	0.0017 *(0.0011)*	-0.0431 *(0.0694)*	**16.54%**	**45.31%**	**38.15%**
UK	-0.0099 *(0.0977)*	0.0226 *(0.0178)*	0.9733	0.0007 *(0.0009)*	-0.0416 *(0.0832)*	**15.41%**	**44.19%**	**40.39%**
USA	0.0769 *(0.0831)*	0.0227 *(0.0175)*	0.9798	0.0012 *(0.0007)*	-0.0259 *(0.0734)*	**14.84%**	**43.25%**	**41.91%**

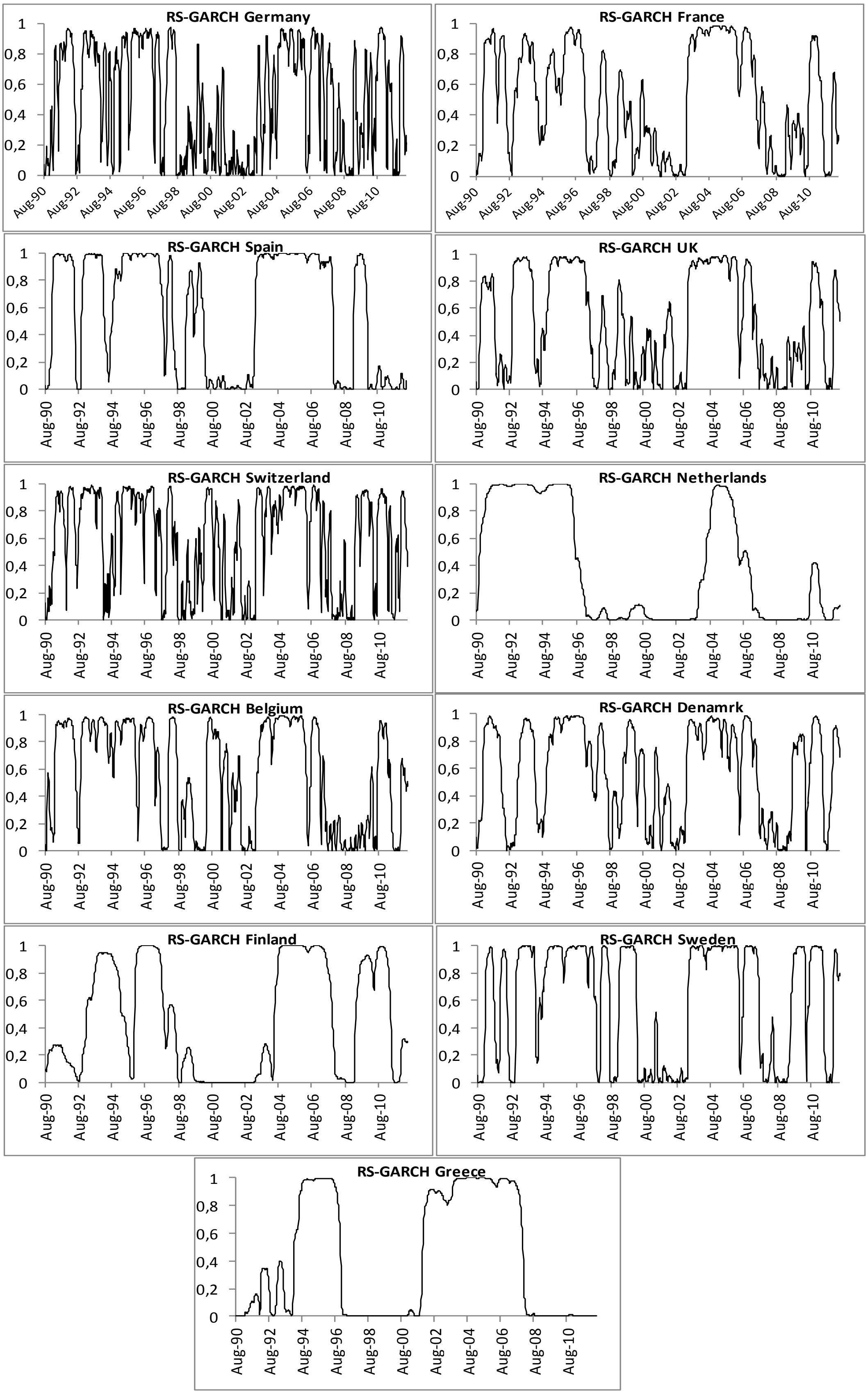
Panel B.- Symmetric linear models										
	Asymmetric -GARCH-M					Asymmetric-MIDAS				
	c	λ_1	Persist.			c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.1137 *(0.1052)*	-0.0016 *(0.0122)*	0.9191	∅	**I -**	0.0018 (0.0011)	-0.0448 (0.0691)	**42.99%**	**53.57%**	**3.44%**
					I +			**2.28%**	**11.22%**	**86.50%**
UK	0.0119 *(0.0825)*	-0.0091 *(0.0159)*	0.9640	∅	**I -**	0.0007 *(0.0009)*	-0.0425 *(0.0862)*	**36.04%**	**57.11%**	**6.85%**
					I +			**3.20%**	**15.01%**	**81.79%**
USA	0.0005 *(0.0007)*	0.3738 *(1.4630)*	0.9638	∅	**I -**	0.0011 (0.0007)	-0.0205 (0.0683)	**5.80%**	**24.60%**	**69.60%**
					I +			**25.35%**	**57.35%**	**17.30%**

Panel C.- RS-GARCH model						
Parameter *(std. error)*	State k=1			State k=2		
	c	λ	Persist	c	λ_1	Persist.
Germany	-0.0132*** *(0.0041)*	0.6363*** *(0.1469)*	**90.09%**	-0.0132*** *(0.0041)*	0.0520** *(0.0263)*	**21.24%**
UK	-0.0097*** *(0.0034)*	0.5621*** *(0.2026)*	**85.98%**	-0.0097*** *(0.0034)*	0.0798 *(0.0536)*	**26.30%**
USA	-0.0057 *(0.0035)*	0.4085** (0.1661)	**78.20%**	-0.0057 *(0.0035)*	-0.0613* *(0.0332)*	**38.15%**

Panel D.- RS-MIDAS model						
RS-MIDAS		c	λ	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	-0.0146 (0.0175)	0.3084*** (0.1011)	**19.16%**	**47.74%**	**33.10%**
	St=2	0.0426*** (00005)	-0.0400*** (0.0072)			
UK	**St=1**	-0.0048*** (0.0014)	0.5479*** (0.0509)	**14.02%**	**37.59%**	**48.39%**
	St=2	0.0461*** (0.0002)	-0.0296*** (0.0026)			
USA	**St=1**	0.0049*** (0.0002)	0.4821*** (0.0163)	**15.73%**	**84.16%**	**0.11%**
	St=2	-0.0343*** (0.0006)	-0.0120*** (0.0006)			

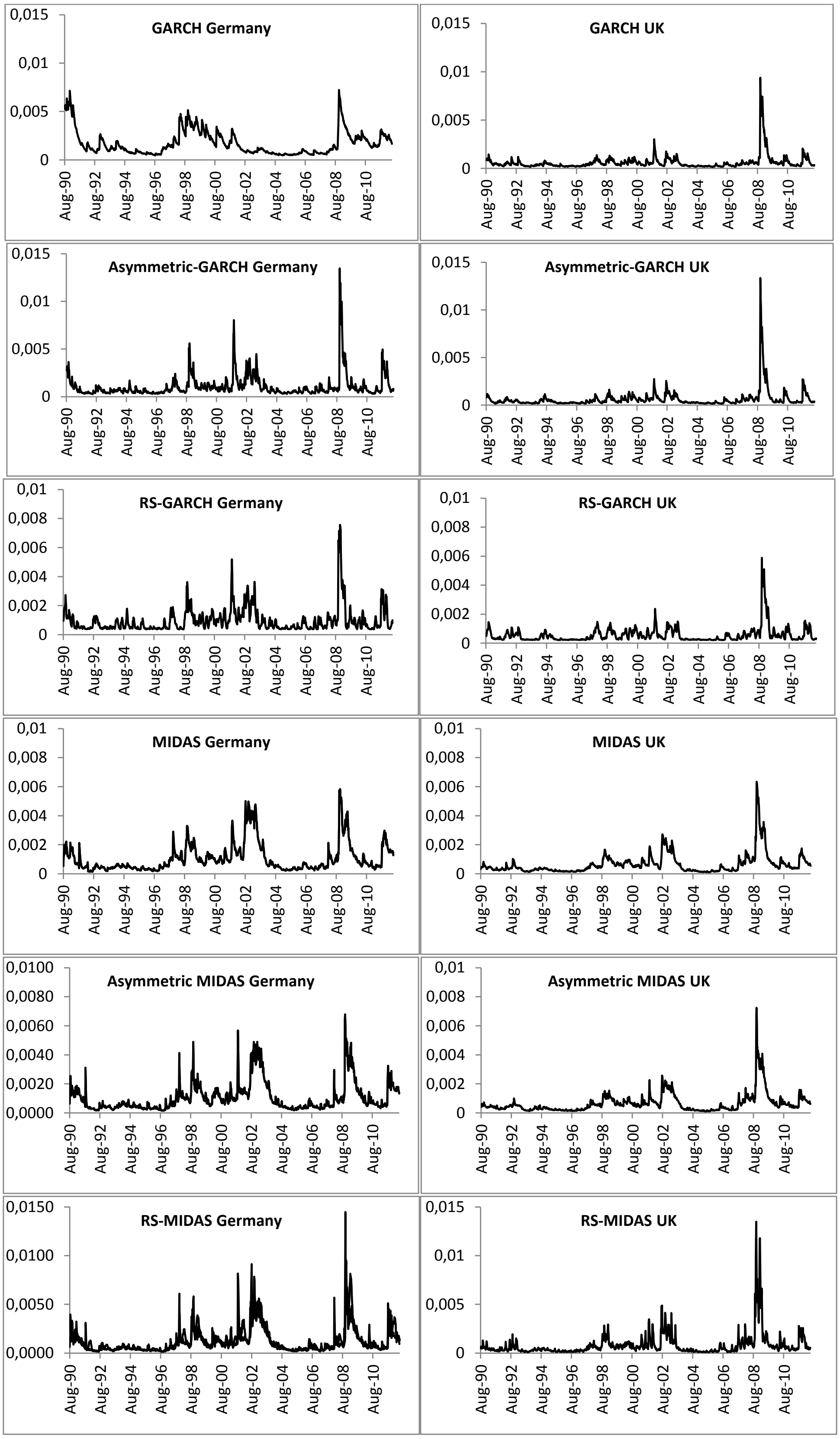
This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) for the excess market returns of a group of representative countries (Germany, UK and USA). ***, ** and * *represents significance at 1%, 5% and 10% respectively.*

FIGURE 1. Smoothed probability for low volatility state in Europe



This figure represents the probability of being in a low volatility state in each European country

FIGURE 2. Risk premium evolution in Europe (representative countries)



These figures show the risk premium evolution in European representative countries (Germany and UK) for all the specifications presented in the paper.

ONLINE APPENDIX

This online appendix provides further discussion of some results found in the paper "*Re-examining the risk–return relationship in Europe: linear or non-linear trade-off?*" submitted to the Journal of Empirical Finance.

OA. 1. Data frequency

This subsection shows the results discussed in section 4.3 *Data frequency* where the whole analysis performed in the paper at a weekly frequency is repeated using monthly data. The main results of the paper also hold for monthly observations but it is worth mentioning that the evidence obtained with the RS-GARCH is weaker. Using monthly observations in a GARCH context leads to a sample of 267 observations which may present some problems related to small samples properties (higher standard errors which tend to over-reject the parameter significance). This problem it is not observed in the MIDAS specification since the information set still considers daily observations (up to a total of 5834 observations).

TABLE OA.1. Estimated parameters for GARCH and MIDAS models for all the European stock markets considered

	GARCH-M			***MIDAS***				
Parameter *(std. error)*	c	λ_1	Persistence	c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0114 *(0.0075)*	-0.0088 *(0.0198)*	0.8775	0.0094* *(0.0050)*	-0.6895 *(1.2003)*	**25.85%**	**53.48%**	**20.67%**
France	0.0036 *(0.0075)*	0.0048 *(0.0249)*	0.8631	0.0028 *(0.0061)*	0.0093 *(1.4466)*	**74.71%**	**25.22%**	**0.07%**
Spain	-0.0559 *(0.0503)*	-0.0108 *(0.0087)*	0.9716	0.0118** *(0.0055)*	-1.6851 *(1.4217)*	**9.86%**	**34.89%**	**55.25%**
UK	0.0088** *(0.0036)*	-0.0169 *(0.0220)*	0.9495	0.0057 *(0.0037)*	-0.6489 *(1.4121)*	**23.60%**	**52.85%**	**23.55%**
Switzerland	0.0092 *(0.0060)*	-0.0204 *(0.0308)*	0.9177	0.0067* *(0.0039)*	-0.2477 *(1.3169)*	**21.40%**	**54.82%**	**23.78%**
Netherlands	0.0118** *(0.0046)*	-0.0162 *(0.0153)*	0.9077	0.0050 *(0.0037)*	-0.1591 *(1.0644)*	**24.58%**	**54.72%**	**20.70%**
Belgium	0.0115** *(0.0058)*	-0.0261 *(0.0237)*	0.8655	0.0088** *(0.0042)*	-1.8674 *(1.6114)*	**18.81%**	**48.18%**	**33.02%**
Denmark	-0.4702* *(0.2668)*	-0.0815* *(0.0459)*	0.4435	0.0115*** *(0.0051)*	-1.6117 *(1.9065)*	**16.65%**	**45.39%**	**37.96%**
Finland	0.0074 *(0.0076)*	0.0494 *(0.0123)*	0.9688	0.0098 *(0.0069)*	-0.3773 *(1.0520)*	**12.54%**	**40.56%**	**46.90%**
Sweden	0.0144** *(0.0066)*	-0.0094 *(0.0018)*	0.8788	0.0121** *(0.0062)*	-0.8467 *(1.4391)*	**5.25%**	**59.03%**	**35.72%**
Greece	0.0044 *(0.0092)*	-0.0012 *(0.0106)*	0.9446	0.0128* *(0.0071)*	-2.2477* *(1.3409)*	**2.86%**	**20.28%**	**76.86%**
USA	0.0059* (0.0033)	0.0076 (0.0175)	0.9848	0.0084*** *(0.0025)*	-0.8857 *(1.2288)*	**36.08%**	**57.39%**	**6.53%**

This table shows the estimated parameters for the standard GARCH and standard MIDAS models presented in the paper at a monthly frequency (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework*

TABLE OA.2. Estimated parameters for asymmetric models

	Asymmetric -GARCH-M					***Asymmetric-MIDAS***				
Parameter *(std. error)*	c	λ_1	Persist.			c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0145* *(0.0076)*	-0.0207 *(0.0198)*	0.7377	∅	**I -**	0.0086 (0.0080)	-0.5225 (1.7864)	**19.85%**	**25.65%**	**54.77%**
					I +			**70.78%**	**29.08%**	**0.14%**
France	0.0125 *(0.0080)*	-0.0320 *(0.0268)*	0.6961	∅	**I -**	0.0041 (0.0037)	-0.2720 (1.0655)	**23.56%**	**51.36%**	**25.08%**
					I +			**100%**	**0%**	**0%**
Spain	-0.0595 *(0.0414)*	-0.0113 *(0.0071)*	0.9671	∅	**I -**	0.0121*** (0.0055)	-1.7367 (1.4208)	**3.70%**	**16.98%**	**79.33%**
					I +			**65.50%**	**34.50%**	**0%**
UK	0.0084** *(0.0038)*	-0.0212 *(0.0232)*	0.9032	∅	**I -**	0.0040 (0.0036)	-0.0609 (1.4892)	**22.99%**	**49.38%**	**27.64%**
					I +			**75.15%**	**24.85%**	**0%**
Switzerl.	0.0089 *(0.0062)*	-0.0180 *(0.0309)*	0.9202	∅	**I -**	0.0092** (0.0044)	-1.0534 (1.5276)	**20.05%**	**79.63%**	**0.31%**
					I +			**4.53%**	**20.12%**	**75.35%**
Netherl.	0.0117** *(0.0047)*	-0.0234 *(0.0159)*	0.8526	∅	**I -**	0.0052 (0.0081)	-0.2203 (2.3535)	**19.54%**	**41.26%**	**39.20%**
					I +			**65.46%**	**29.46%**	**5.08%**
Belgium	0.0198** *(0.0079)*	-0.0710* *(0.0366)*	0.8203	∅	**I -**	0.0079 (0.0048)	-1.5707 (1.8499)	**14.36%**	**23.38%**	**62.25%**
					I +			**94.82%**	**5.18%**	**0%**
Denmark				∅	**I -**	0.0108 (0.0060)	-1.4192 (2.0942)	**100%**	**0%**	**0%**
					I +			**6.81%**	**27.88%**	**65.32%**
Finland	0.0093 *(0.0077)*	-0.0056 *(0.0129)*	0.9649	∅	**I -**	0.0111 (0.0073)	-0.5657 (1.1438)	**5.37%**	**65.91%**	**28.72%**
					I +			**3.62%**	**16.67%**	**79.71%**
Sweden	0.0147 *(0.0061)*	-0.0175 *(0.0164)*	0.8763	∅	**I -**	0.0111 (0.0043)	-0.6669 (1.0780)	**0.07%**	**55.60%**	**44.33%**
					I +			**0.04%**	**31.77%**	**68.19%**
Greece	0.0075 *(0.0094)*	-0.0064 *(0.0112)*	0.9501	∅	**I -**	0.0088 (0.0067)	-1.6289 (1.2971)	**0.47%**	**7.96%**	**91.57%**
					I +			**23.44%**	**68.93%**	**7.63%**
USA	0.0078 *(0.0033)*	-0.0107 *(0.0191)*	0.8473	∅	**I -**	0.0097 (0.0023)	-1.3015 (1.1650)	**12.44%**	**54.48%**	**33.08%**
					I +			**0.27%**	**7.96%**	**91.77%**

This table shows the estimated parameters for the asymmetric GARCH and asymmetric MIDAS models presented in the paper at a monthly frequency (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework*

TABLE OA.3. Estimated parameters for RS-GARCH models

Parameter (std. error)	RS-GARCH-M					
	State k=1			**State k=2**		
	c	λ_1	Persist	c	λ_1	Persist.
Germany	-0.0462 *(0.0322)*	0.3073* *(0.1545)*	0.9532	-0.0462 *(0.0322)*	-0.0713 *(0.0612)*	0.1654
France	-0.0664* *(0.0229)*	1.1896* *(0.5683)*	0.8195	-0.0664* *(0.0229)*	0.1850* *(0.0864)*	0.1403
Spain	-0.1562** *(0.0608)*	0.9818 *(0.6871)*	0.8403	-0.1562** *(0.0608)*	0.2370 *(0.1678)*	0.0615
UK	-0.0072 *(0.0213)*	0.3456 *(0.2368)*	0.9004	-0.0072 *(0.0213)*	-0.0117 (0.1187)	0.3130
Switzerland	-0.0536** *(0.0123)*	0.6197** *(0.1973)*	0.9845	-0.0536** *(0.0123)*	-0.0019 *(0.0336)*	0.0580
Netherlands	0.0158** *(0.0051)*	0.6045** *(0.2513)*	0.8845	0.0158** *(0.0051)*	-0.0103 *(0.0258)*	0.1733
Belgium	-0.0858 *(0.5956)*	0.7051 *(0.7125)*	0.8437	-0.0858 *(0.0956)*	0.0447 *(1.1079)*	0.1711
Denmark	0.0181 *(0.0165)*	0.1402 *(0.1156)*	0.9448	0.0181 *(0.0165)*	0.0112 *(0.0910)*	0.3250
Finland	-0.0334 *(0.1562)*	0.1649 *(0.4193)*	0.8950	-0.0334 *(0.1562)*	-0.0401 *(0.2625)*	0.4728
Sweden	-0.0293 *(0.0273)*	0.3087** *(0.1538)*	0.8237	-0.0293 *(0.0273)*	0.0111 (0.0327)	0.3132
Greece	-0.0271 *(0.0451)*	0.2716 *(0.1906)*	0.8248	-0.0029 *(0.5480)*	0.0104 *(0.0379)*	0.3250
USA	0.0033 *(0.0216)*	0.0448 *(0.0940)*	0.8904	-0.0029 *(0.5480)*	-0.0097 *(0.0170)*	0.2389

This table shows the estimated parameters for the RS-GARCH modes presented in the paper at a monthly frequency (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively.*

TABLE OA. 4. Estimated parameters for RS-MIDAS

RS-MIDAS		c	λ_1	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	0.0021*** *(0.0007)*	0.1180*** *(0.0107)*	**24.80%**	**51.20%**	**24.00%**
	St=2	-0.1396*** *(0.0066)*	0.0397*** *(0.0032)*			
France	**St=1**	-0.0372*** *(0.0022)*	0.3200*** *(0.0073)*	**39.23%**	**40.99%**	**19.78%**
	St=2	-0.1019*** *(0.0042)*	0.0594*** *(0.0027)*			
Spain	**St=1**	0.0018*** *(0.0003)*	0.1237*** *(0.0044)*	**10.52%**	**31.09%**	**58.40%**
	St=2	-0.1754*** *(0.0038)*	0.1142*** *(0.0046)*			
UK	**St=1**	0.0321*** *(0.0065)*	0.1529*** *(0.0348)*	**52.03%**	**26.19%**	**21.77%**
	St=2	-0.0504*** *(0.0018)*	-0.0133*** *(0.0037)*			
Switzerland	**St=1**	0.0172*** *(0.0002)*	0.1541*** *(0.0065)*	**31.05%**	**41.39%**	**27.56%**
	St=2	-0.0677*** *(0.0006)*	-0.0071*** *(0.0015)*			
Netherlands	**St=1**	-0.0071*** (0.0007)	0.1232*** (0.0028)	**23.10%**	**53.29%**	**23.61%**
	St=2	-0.1541*** (0.0043)	0.0223*** (0.0053)			
Belgium	**St=1**	0.0257*** (0.0007)	0.0317*** (0.0085)	**25.44%**	**45.97%**	**28.59%**
	St=2	-0.0719*** (0.0037)	-0.0527*** (0.0060)			
Denmark	**St=1**	-0.0389*** (0.0007)	0.4046*** (0.0038)	**6.38%**	**23.40%**	**70.22%**
	St=2	0.0565*** (0.0009)	-0.0208*** (0.0012)			
Finland	**St=1**	0.0937*** (0.0034)	0.0761*** (0.0019)	**20.35%**	**39.96%**	**39.69%**
	St=2	-0.0432*** (0.0027)	-0.0158*** (0.0011)			
Sweden	**St=1**	0.0704*** (0.0043)	0.0280*** (0.0027)	**21.63%**	**40.92%**	**37.44%**
	St=2	-0.0694*** (0.0055)	-0.0292*** (0.0037)			
Greece	**St=1**	0.0273*** (0.0094)	0.2038*** (0.0388)	**2.38%**	**16.80%**	**80.82%**
	St=2	-0.0716*** (0.0047)	0.0523*** (0.0061)			
USA	**St=1**	0.0091 (0.0179)	0.3099*** (0.0613)	**23.50%**	**43.72%**	**32.79%**
	St=2	-0.0151*** (0.0133)	-0.0430 (0.0342)			

This table shows the estimated parameters for the RS-MIDAS modes presented in the paper at a monthly (robust standard errors in parentheses). ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework*

OA.2. Conditioning to macro variables

The aim of this subsection is to extend the analysis of the paper when conditioning the relation between return and risk to other financial variables. Several papers (Scruggs, 1998, Guo and Whitelaw, 2006) develop and estimate empirical models (based on the spirit of Equation 1) which separately identify the two components of expected returns; the risk component and the component due to hedge changes in investment opportunities. They state that the omission of this component ($BX_{M,S}$ in Equation 1) may explain the contradictory results in the literature. In this subsection we repeat the analysis performed in the paper for a set of models which consider these changes in the investment opportunity set. In order to do this, we run a set of models of the form:

$$r_t = c + \lambda_1 VAR(r_t) + \lambda_2 X_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, VAR(r_t)) \qquad \textit{(OA.1)} \quad \text{for linear models}$$

where $VAR(r_t)$ is specified as a GARCH or MIDAS model and

$$r_{t,s_t} = c_{s_t} + \lambda_{1,s_t} VAR(r_{t,s_t}) + \lambda_{2,s_t} X_t + \varepsilon_{t,s_t} \qquad \varepsilon_{t,s_t} \sim N(0, VAR(r_{t,s_t})) \quad \textit{(OA.2)} \text{ for non-linear models}$$

where $VAR(r_{t,st})$ is specified as a RS-GARCH or RS-MIDAS model

To capture the changes in the investment opportunity set (X_t) we use similar variables to previous studies on US data (Scruggs, 1998, Scruggs and Glabadanidis, 2003). More specifically we use the local 3-month Treasury Bill, the local 10-year Government Bond, the yield spread between the 10-year and the 3-month rates and the dividend yield of the local stock market. We estimate the modified models for all the specifications presented in the above papers. Due to data limitations, this analysis is only performed for 3 representative countries, namely, Germany, UK and USA.

Tables OA.5 to OA.8 shows the estimation results of this analysis when each of the variables representing the changes in the investment opportunity set is introduced sequentially in the model. Table OA.9 shows the estimation results when the variables are considered jointly. In this last case the variable X_t and the parameters λ_2 and λ_{2,s_t} are vectors (Ghysels, 2005). In this last table we do not consider the yield spread since it is a linear transformation of the 3-month T-bill and the 10-year Government bond. So, its inclusion in the regressions may have caused multicolineallity problems in the estimation.
Generally, the main results in the paper hold when controlling for non-constant investment opportunity sets. We fail to identify a significant risk-return tradeoff when using linear models. However, when we distinguish among regimes, we are able to support a positive and significant relationship between return and risk.

TABLE OA.5 Estimated parameters for all models conditioning to 3-month T-Bill

Panel A.- Symmetric linear models										
	GARCH-M				*MIDAS*					
Parameter *(std. error)*	c	λ_1	X_t	Persist.	c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0044*** *(0.0017)*	1.0735 *(1.4710)*	-2.1405 *(1.3888)*	**0.9515**	0.0031** (0.0017)	-0.7612 (1.3223)	-1.2469 (1.5090)	**29.48%**	**54.59%**	**15.93%**
UK	0.0010 *(0.0016)*	2.2853 *(1.7782)*	-0.1083 *(1.1584)*	**0.9725**	0.0002 (0.0017)	-0.4120 (1.563)	0.9333 (1.4073)	**26.67%**	**54.59%**	**18.74%**
USA	0.0011 *(0.0016)*	2.2256 *(1.7803)*	0.5354 *(1.6298)*	**0.9793**	-0.0002 (0.0014)	-0.0625 (1.4444)	2.3688 (1.6132)	**25.06%**	**54.09%**	**20.85%**

Panel B.- Symmetric linear models											
	Asymmetric GARCH-M					*Asymmetric-MIDAS*					
	c	λ_1	X_t	Persist.		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
GER	*0.0039*** (0.0015)*	*-0.2771 (1.2232)*	*-2.3433* (1.2585)*	**0.9188**	**I -**	0.0042** (0.0017)	-1.2899 (1.2944)	-1.9944 (1.4433)	**94.70%**	**5.30%**	**0%**
					I +				**9.43%**	**31.30%**	**59.27%**
UK	0.0008 *(0.0014)*	-0.8943 *(1.5953)*	0.3183 *(1.0263)*	**0.9636**	**I -**	-0.0002 (0.0016)	-0.4316 (1.5467)	1.2098 (1.3921)	**6.16%**	**35.78%**	**58.06%**
					I +				**40.69%**	**53.73%**	**5.58%**
USA	0.0007 *(0.0012)*	0.3527 *(1.4791)*	0.7363 *(1.2593)*	**0.9635**	**I -**	-0.0008 (0.0015)	0.5069 (1.4670)	2.6958 (1.6710)	**5.67%**	**24.13%**	**70.20%**
					I +				**25.37%**	**59.01%**	**15.62%**

Panel C.- RS-GARCH model								
Parameter *(std. error)*	*State k=1*				*State k=2*			
	c	λ_1	X_t	Persist	c	λ_1	. X_t	Persist.
Germany	-0.0112*** (0.0042)	0.7301*** (0.2068)	-3.3732** (1.5189)	**0.9017**	-0.0112*** (0.0042)	0.0490* (0.0279)	-0.6876 (4.4369)	**0.2067**
UK	-0.0091*** (0.0008)	0.5677*** (0.0637)	0.1964 (0.0925)	**0.8589**	-0.0091*** (0.0008)	0.0795*** (0.0227)	0.3678 (1.4791)	**0.2741**
USA	-0.0057 (0.0035)	0.4355*** (0.1660)	1.8968 (2.3825)	**0.7806**	-0.0057 (0.0035)	0.0577* (0.0315)	0.1296 (1.8992)	**0.3762**

Panel D.- RS-MIDAS model							
RS-MIDAS		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	-0.0078*** (0.0017)	0.3209*** (0.0055)	0.0861*** (0.0251)	**28.67%**	**44.14%**	**27.19%**
	St=2	-0.0779*** (0.0012)	0.1070*** (0.0210)	0.1097*** (0.0033)			
UK	**St=1**	-0.0176*** (0.0009)	0.3934*** (0.0181)	0.3955*** (0.0165)	**22.55%**	**44.47%**	**32.98%**
	St=2	-0.0536*** (0.0005)	0.0043 (0.0055)	0.2878*** (0.0035)			
USA	**St=1**	-0.0077*** (0.0003)	0.0341*** (0.0031)	-4.0914*** (0.3218)	**18.26%**	**81.39%**	**0.35%**
	St=2	-0.0289*** (0.0002)	0.5856*** (0.0281)	14.7061*** (0.3550)			

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) conditioning the excess market returns to the 3-month bill. ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns in panels A, B and D represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE OA.6 Estimated parameters for all models conditioning to 10-year Government Bond

Panel A.- Symmetric linear models										
	GARCH-M			***MIDAS***						
Parameter *(std. error)*	c	λ_1	X_t	Persist.	c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0059** *(0.0027)*	0.9525 *(1.4774)*	-3.1494 *(2.0982)*	**0.9527**	0.0021 (0.0028)	-0.5850 (1.3348)	-0.1404 (2.3694)	**29.55%**	**54.61%**	**15.84%**
UK	0.0001 *(0.0021)*	2.3572 *(1.7943)*	0.7533 *(1.5001)*	**0.9730**	-0.0005 (0.0021)	-0.2774 (1.5818)	1.3943 (1.5811)	**26.50%**	**54.56%**	**18.94%**
USA	0.0012 *(0.0025)*	2.2081 *(1.8064)*	0.2583 *(2.0094)*	**0.9789**	-0.0012 (0.0025)	-0.0433 (1.4778)	2.5643 (2.0583)	**25.15%**	**54.17%**	**20.68%**

Panel B.- Symmetric linear models										
	Asymmetric GARCH-M					***Asymmetric-MIDAS***				
	c	λ_1	X_t	Persist.		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
GER	*0.0052*** *(0.0022)*	-0.3549 *(1.2318)*	-3.1471* *(1.7968)*	**0.9196**	**I −**	0.0029 (0.0026)	-0.7096 (1.2620)	-0.8515 (2.2044)	**7.79%**	**26.47%**	**54.74%**
					I +				**61.82%**	**37.81%**	**0.37%**
UK	0.0004 (0.0017)	-0.8227 (1.5923)	0.5954 (1.2662)	**0.9638**	**I −**	-0.0007 (0.0021)	0.1443 (1.5057)	1.3620 (1.5505)	**17.33%**	**82.67%**	**0%**
					I +				**20.03%**	**49.31%**	**30.66%**
USA	0.0012 *(0.0019)*	0.2873 *(1.4823)*	-0.0068 *(1.6300)*	**0.9625**	**I −**	-0.0018 (0.0023)	0.4607 (1.4545)	2.7558 (1.9992)	**6.59%**	**27.18%**	**66.23%**
					I +				**26.25%**	**59.01%**	**14.74%**

Panel C.- RS-GARCH model								
Parameter *(std. error)*	***State k=1***				***State k=2***			
	c	λ_1	X_t	Persist	c	λ_1	Persist.	Persist.
Germany	-0.0144** (0.0060)	0.9401*** (0.3480)	-5.0964** (2.1363)	**0.9036**	-0.0144** (0.0060)	0.0414 (0.0275)	4.1320 (5.3008)	**0.1964**
UK	-0.0113 (0.0069)	0.6627*** (0.2881)	0.2021 (1.9942)	**0.8644**	-0.0113 (0.0069)	0.0822 (0.0586)	1.8564 (3.9143)	**0.2511**
USA	-0.0063 (0.0043)	0.5435*** (0.2043)	-1.2665* (1.9216	**0.7650**	-0.0063 (0.0043)	0.0527* (0.0313)	2.6288 (3.1680)	**0.3485**

Panel D.- RS-MIDAS model							
RS-MIDAS		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	-0.0202*** (0.0017)	0.1388*** (0.0150)	0.6601*** (0.0201)	**31.12%**	**45.59%**	**23.29%**
	St=2	-0.1286*** (0.0028)	0.1253*** (0.0047)	0.2610*** (0.0123)			
UK	**St=1**	-0.0228*** (0.0016)	0.1130*** (0.0292)	0.2991*** (0.0444)	**32.43%**	**67.11%**	**0.46%**
	St=2	-0.1025*** (0.0249)	-0.1089*** (0.0242)	0.5391*** (0.1294)			
USA	**St=1**	-0.0149*** (0.0024)	0.5773*** (0.0424)	17.7210*** (3.1370)	**15.19%**	**84.50%**	**0.31%**
	St=2	-0.0364*** (0.0020)	0.0409*** (0.0022)	3.0658*** (0.6298)			

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) conditioning the excess market returns to the 10-year Government Bond. ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns in panels A, B and D represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE OA.7 Estimated parameters for all models conditioning for spread yield

Panel A.- Symmetric linear models										
	GARCH-M				***MIDAS***					
Parameter *(std. error)*	c	λ_1	X_t	Persist.	c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0021 *(0.0016)*	1.2281 *(1.5049)*	2.1661 *(3.3350)*	**0.9517**	0.0013 (0.0012)	-0.6366 (1.3125)	3.5212 (2.6937)	**29.47%**	**54.59%**	**15.94%**
UK	0.0005 *(0.0010)*	2.5015 *(1.7570)*	2.1720 *(1.9905)*	**0.9722**	0.0012 (0.0009)	-0.6123 (1.5356)	0.3431 (2.2783)	**26.80%**	**54.65%**	**18.55%**
USA	0.0018 *(0.0012)*	2.1331 *(1.7469)*	-0.8640 *(2.3810)*	**0.9790**	0.0021* (0.0012)	0.5680 (1.3972)	-1.3518 (2.3624)	**25.30%**	**54.19%**	**20.51%**

Panel B.- Symmetric linear models											
	Asymmetric GARCH-M					***Asymmetric-MIDAS***					
	c	λ_1	X_t	Persist.		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
GER	0.0013 *(0.0013)*	-0.1299 *(1.2346)*	3.1885 *(2.8642)*	**0.9191**	**I -**	0.0013 (0.0012)	-0.6544 (1.2844)	3.7651 (2.6830)	**8.78%**	**33.72%**	**57.50%**
					I +				**40.57%**	**27.91%**	**31.52%**
UK	0.0011 *(0.0009)*	-0.8789 *(1.5813)*	0.0307 *(1.7888)*	**0.9640**	**I -**	0.0013 (0.0009)	-0.6594 (1.5211)	0.1691 (2.2809)	**6.84%**	**36.61%**	**56.55%**
					I +				**41.35%**	**53.35%**	**5.30%**
USA	0.0020** *(0.0009)*	0.1745 *(1.4607)*	-2.0008 *(1.7559)*	**0.9638**	**I -**	0.0027 (0.0012)	-1.1979 (1.5235)	-1.9109 (2.3521)	**13.49%**	**39.62%**	**46.89%**
					I +				**100%**	**0%**	**0%**

Panel C.- RS-GARCH model								
Parameter *(std. error)*	***State k=1***				***State k=2***			
	c	λ_1	X_t	Persist	c	λ_1	. X_t	Persist.
Germany	-0.0181*** (0.0062)	0.8114*** (0.2463)	3.1278 (2.4766)	**0.9066**	-0.0181*** (0.0062)	0.0593** (0.0283)	22.3726 (14.7806)	**0.2071**
UK	-0.0087*** (0.0032)	0.5592*** (0.2032)	0.0181 (3.4324)	**0.8608**	-0.0087*** (0.0032)	0.0781 (0.0544)	1.3831 (4.0253)	**0.2757**
USA	-0.0039 (0.0027)	0.4149*** (0.1210)	-3.1647 (2.1252)	**0.7699**	-0.0039 (0.0027)	0.0502* (0.0303)	1.3757 (4.4365)	**0.3898**

Panel D.- RS-MIDAS model							
RS-MIDAS		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	0.0025 (0.0018)	0.2649** (0.1142)	-7.7374*** (0.0929)	**26.35%**	**43.02%**	**30.63%**
	St=2	-0.0698*** (0.0031)	0.1024*** (0.0358)	7.7251*** (1.2221)			
UK	**St=1**	-0.0222*** (0.0007)	0.8238*** (0.0286)	0.4553 (3.9051)	**13.07%**	**42.68%**	**44.25%**
	St=2	0.0174*** (0.0009)	-0.0209*** (0.0064)	6.5669** (2.7620)			
USA	**St=1**	0.0063*** (0.0002)	0.5537*** (0.0201)	7.3878*** (0.1330)	**18.02%**	**81.74%**	**0.24%**
	St=2	-0.0330*** (0.0015)	0.0263*** (0.0031)	6.4090*** (0.2673)			

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) conditioning the excess market returns to the spread yield between long and short-term Government fixed income assets. ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns in panels A, B and D represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE OA.8 Estimated parameters for all models conditioning for dividend yield

Panel A.- Symmetric linear models

	GARCH-M				MIDAS					
Parameter *(std. error)*	c	λ_1	X_t	Persist.	c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	0.0071** *(0.0034)*	1.6495 *(1.7227)*	-0.0021 *(0.0017)*	**0.9548**	0.0124*** (0.0032)	0.4515 (1.3344)	-0.0049 (0.0015)	**29.57%**	**54.61%**	**15.82%**
UK	0.0010 *(0.0032)*	2.2859 *(1.7788)*	-0.0002 *(0.0008)*	**0.9726**	0.0035 (0.0032)	-0.7431 (1.5493)	-0.0006 (0.0008)	**27.28%**	**54.76%**	**17.96%**
USA	0.0008 *(0.0023)*	2.2522 *(1.7679)*	0.0003 *(0.0009)*	**0.9788**	-0.0013 (0.0024)	-0.0249 (1.4547)	0.0012 (0.0009)	**25.57%**	**54.35%**	**20.08%**

Panel B.- Symmetric linear models

	Asymmetric GARCH-M					Asymmetric-MIDAS					
	c	λ_1	X_t	Persist.		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
GER	0.0062** *(0.0031)*	0.1511 *(1.3711)*	-0.0020 *(0.0014)*	**0.9208**	**I −**	0.0121*** (0.0031)	0.4185 (1.2616)	-0.0047*** (0.0013)	**7.62%**	**26.16%**	**66.22%**
					I +				**62.88%**	**36.67%**	**0.44%**
UK	0.0017 *(0.0026)*	-0.9126 *(1.5935)*	-0.0002 *(0.0007)*	**0.9633**	**I −**	0.0036 (0.0033)	-1.9523 (1.6793)	-0.0004 (0.0009)	**14.64%**	**42.05%**	**43.31%**
					I +				**98.97%**	**1.02%**	**0.01%**
USA	0.0033* *(0.0018)*	-0.0614 *(1.4781)*	-0.0009 *(0.0007)*	**0.9631**	**I −**	-0.0015 (0.0023)	0.3897 (1.4255)	0.0012 (0.0010)	**6.89%**	**28.14%**	**64.97%**
					I +				**26.65%**	**58.99%**	**14.36%**

Panel C.- RS-GARCH model

Parameter *(std. error)*	State k=1				State k=2			
	c	λ_1	X_t	Persist	c	λ_1	Persist.	Persist.
Germany	0.0023 (0.0024)	0.3769*** (0.0399)	-5.1525*** (0.0575)	**0.9256**	0.0023 (0.0024)	0.0372** (0.0125)	-0.0714 (0.1063)	**0.9167**
UK	-0.0126** (0.0050)	0.4644** (0.2219)	0.0016* (0.0007)	**0.8781**	-0.0126** (0.0050)	0.0731** (0.0301)	0.0012 (0.0014)	**0.3000**
USA	-0.0066** (0.0029)	0.5566*** (0.1711)	-0.0005 (0.0009)	**0.7455**	-0.0066** (0.0029)	0.0392 (0.0287)	0.0023 (0.0014)	**0.3477**

Panel D.- RS-MIDAS model

RS-MIDAS		c	λ_1	X_t	*% days 1–5*	*% days 10–30*	*% days >30*
Germany	**St=1**	0.0625*** (0.0161)	0.3163*** (0.0144)	-0.0285*** (0.0072)	**15.03%**	**39.25%**	**45.72%**
	St=2	0.0993*** (0.0025)	0.0043*** (0.0013)	-0.0179*** (0.0008)			
UK	**St=1**	0.0445*** (0.0017)	0.4607*** (0.0072)	-0.0163*** (0.0009)	**16.98%**	**36.90%**	**46.12%**
	St=2	0.0649*** (0.0011)	0.0196*** (0.0015)	-0.0097*** (0.0002)			
USA	**St=1**	-0.1380*** (0.0093)	0.2824*** (0.0422)	0.0019 (0.0037)	**34.28%**	**48.67%**	**17.05%**
	St=2	0.0055 (0.0079)	-0.0628 (0.0428)	0.0446*** (0.0057)			

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) conditioning the excess market returns to the dividend yield. ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three columns in panels A, B and D represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

TABLE OA.9. Estimated parameters for all models conditioning jointly to 3-month T-Bill, 10-year Government Bond and Dividend Yield.

Panel A.- Symmetric linear models						
	GARCH-M			***MIDAS***		
Parameter *(std. error)*	Germany	UK	USA.	Germany	UK	USA.
c	0.0147*** *(0.0051)*	0.0022 *(0.0032)*	2.1979 *(1.7839)*	0.0168*** *(0.0053)*	0.0051 *(0.0034)*	-0.0021 *(0.0027)*
λ_1	1.4200 *(1.6891)*	3.0380 *(1.9003)*	0.0012 *(0.0026)*	0.2129 *(1.3546)*	0.2001 *(1.5691)*	0.3901 *(1.4883)*
3*m Tbill*	1.6888 *(3.6729)*	-3.4354 *(2.1631)*	1.5099 *(2.6573)*	1.0800 *(3.1254)*	-2.0570 *(2.4371)*	3.3863 *(2.7445)*
10*y Gbond*	-6.6247 *(5.4083)*	6.5522* *(3.8089)*	-2.2723 *(4.3169)*	-3.8196 *(4.8085)*	7.6714** *(3.6666)*	-2.6042 *(4.3403)*
Divid yield	-0.0031* *(0.0017)*	-0.0016 *(0.0014)*	0.0008 *(0.0014)*	-0.0054*** *(0.0016)*	-0.0031** *(0.0014)*	0.0017 *(0.0014)*
Persistence	**0.9552**	**0.9729**	**0.9787**	-	-	-
% days 1–5	-	-	-	**29.46%**	**27.57%**	**25.42%**
% days 10–30	-	-	-	**54.59%**	**54.81%**	**54.24%**
% days >30	-	-	-	**15.95%**	**17.61%**	**20.34%**

Panel B.- Symmetric linear models							
		Asymmetric GARCH-M			***Asymmetric MIDAS***		
Parameter *(std.error)*		Germany	UK	USA.	Germany	UK	USA.
c		0.0139*** *(0.0040)*	0.0023 *(0.0026)*	-0.0838 *(1.5110)*	0.0169*** *(0.0051)*	0.0065* *(0.0034)*	-0.0029 *(0.0029)*
λ_1		-0.0370 *(1.3744)*	-0.6994 *(1.6387)*	0.0028 *(0.0020)*	0.1638 *(1.2684)*	-0.8453 *(1.7182)*	0.4293 *(1.7024)*
3*m Tbill*		1.0033 *(3.0606)*	-1.0868 *(1.9670)*	0.8300 *(1.8838)*	0.8293 *(2.9482)*	-2.1952 *(2.5681)*	4.4061 *(2.8841)*
10*y Gbond*		-6.1399 *(4.2195)*	3.4686 *(3.3858)*	1.2985 *(3.3213)*	-4.0686 *(4.5383)*	7.8180** *(3.9039)*	-2.5162 *(4.4500)*
Divid yield		-0.0029** *(0.0014)*	-0.0012 *(0.0012)*	-0.0015 *(0.0011)*	-0.0053*** *(0.0015)*	-0.0033** *(0.0014)*	0.0018 *(0.0015)*
Persistence		**0.9223**	**0.9661**	**0.9659**			
% days 1–5	**I -**				**7.65%**	**15.06%**	**13.13%**
	I +				**68.06%**	**100%**	**100%**
% days 10–30	**I -**				**26.59%**	**42.15%**	**38.40%**
	I +				**31.94%**	**0%**	**0%**
% days >30	**I -**				**65.76%**	**42.79%**	**48.47%**
	I +				**0%**	**0%**	**0%**

Panel C.- RS-GARCH model						
	State k=1			***State k=2***		
Parameter *(std. error)*	Germany	UK	USA.	Germany	UK	USA.
c	0.0014 *(0.0048)*	-0.0057 *(0.0049)*	-0.0055 *(0.0033)*	0.0014 *(0.0048)*	-0.0057 *(0.0049)*	-0.0055 *(0.0033)*
λ_1	0.3581*** *(0.1091)*	0.3177*** *(0.0712)*	0.5162** *(0.2012)*	0.0375 *(0.0931)*	0.0055 *(0.0950)*	0.0377 *(0.0280)*
3*m Tbill*	-4.7373 *(4.0419)*	-2.1486 *(3.4993)*	2.9233*** *(0.8981)*	-3.5606 *(12.9155)*	0.7683 *(5.8685)*	1.4335 *(4.5484)*
10*y Gbond*	3.3087 *(13.6628)*	3.2528*** *(0.8526)*	-4.1790 *(20.8603)*	3.7814*** *(0.1227)*	-5.1526 *(8.0680)*	-2.6770*** *(0.8465)*
Divid yield	-0.0523*** *(0.0105)*	-0.0187** *(0.0080)*	0.0004 *(0.0100)*	-0.0003 *(0.0012)*	0.0036** *(0.0016)*	0.0027 *(0.0023)*
Persistence	**0.9749**	**0.9901**	**0.8784**	**0.8691**	**0.8767**	**0.2313**

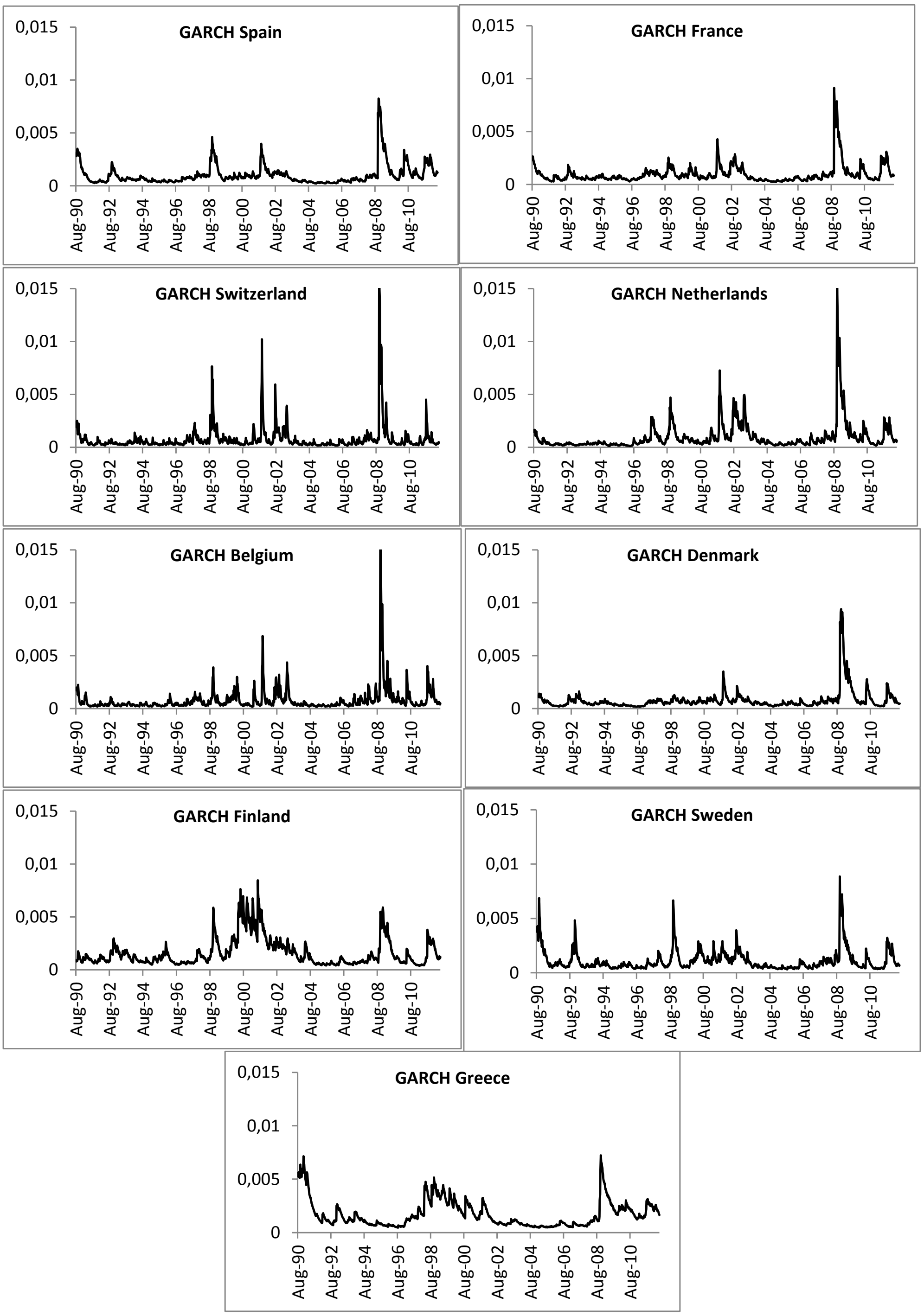
Panel D.- RS-MIDAS model						
	State k=1			***State k=2***		
Parameter *(std. error)*	Germany	UK	USA.	Germany	UK	USA.
c	0.0795*** *(0.0038)*	0.0531*** *(0.0015)*	-0.0159*** *(0.0029)*	0.0359*** *(0.0053)*	0.0082*** *(0.0027)*	-0.1097*** *(0.0027)*
λ_1	0.2712*** *(0.0212)*	0.2404*** *(0.0025)*	0.1520*** *(0.0087)*	0.0379*** *(0.0077)*	-0.0959*** *(0.0088)*	-0.0499*** *(0.0025)*
3*m Tbill*	-11.6982*** *(1.1808)*	18.0138*** *(1.2902)*	3.2204*** *(0.6478)*	-7.3537*** *(0.8774)*	5.2890*** *(2.2819)*	-1.8795*** *(0.2580)*
10*y Gbond*	3.0295*** *(0.9404)*	2.2846*** *(0.1627)*	2.7580*** *(0.7919)*	3.0320*** *(0.8841)*	2.2937*** *(0.0914)*	-1.5043*** (0.1132)
Divid yield	-0.0382*** *(0.0026)*	-0.0238*** *(0.0003)*	0.0080*** *(0.0015)*	-0.0469*** *(0.0008)*	-0.0213*** *(0.0001)*	0.0334*** *(0.0003)*
% days 1–5	**17.11%**	**18.75%**	**33.78%**	-	-	-
% days 10–30	**43.96%**	**39.41%**	**51.16%**	-	-	-
% days >30	**38.93%**	**41.84%**	**15.06%**	-	-	-

This table shows the estimated parameters for all the models presented in the paper (robust standard errors in parentheses) conditioning the excess market returns jointly to the 3-month T-Bill, the 10-year Government Bond and the dividend yield. ***, ** and * *represents significance at 1%, 5% and 10% respectively. The last three rows in panels A, B and D represent the percentage of the total weights assigned to the 1-5 first observations, 6-30 first observations and 31-250 observations respectively when estimating the conditional variance in a MIDAS framework.*

OA.3. Risk premium figures

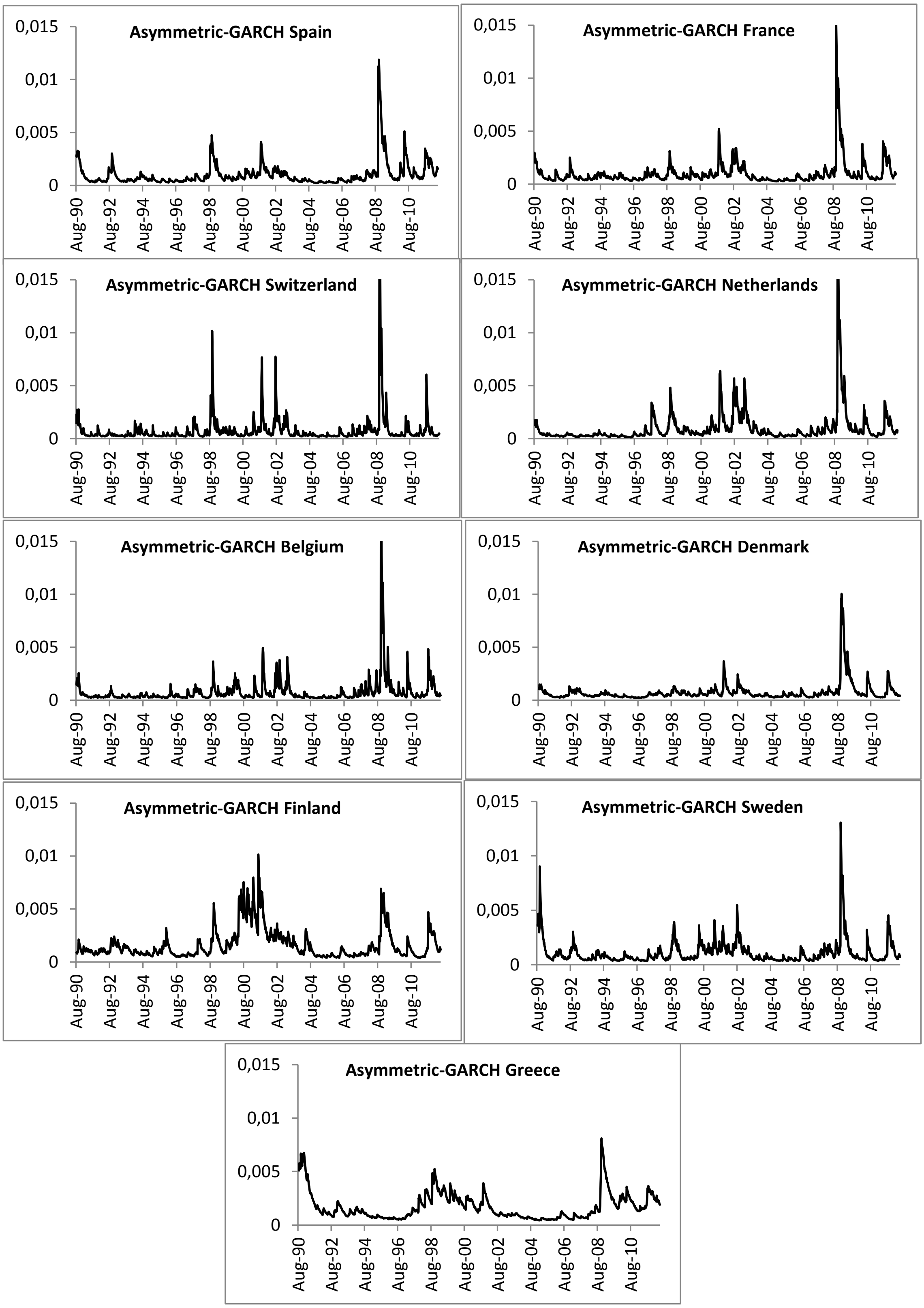
In order to keep a proper length of the paper we just show in the submitted version two representative countries in figure 2. The figures of the risk premium evolution for the rest of the countries are displayed below:

FIGURE OA1.A Risk premium evolution in Europe using the GARCH model



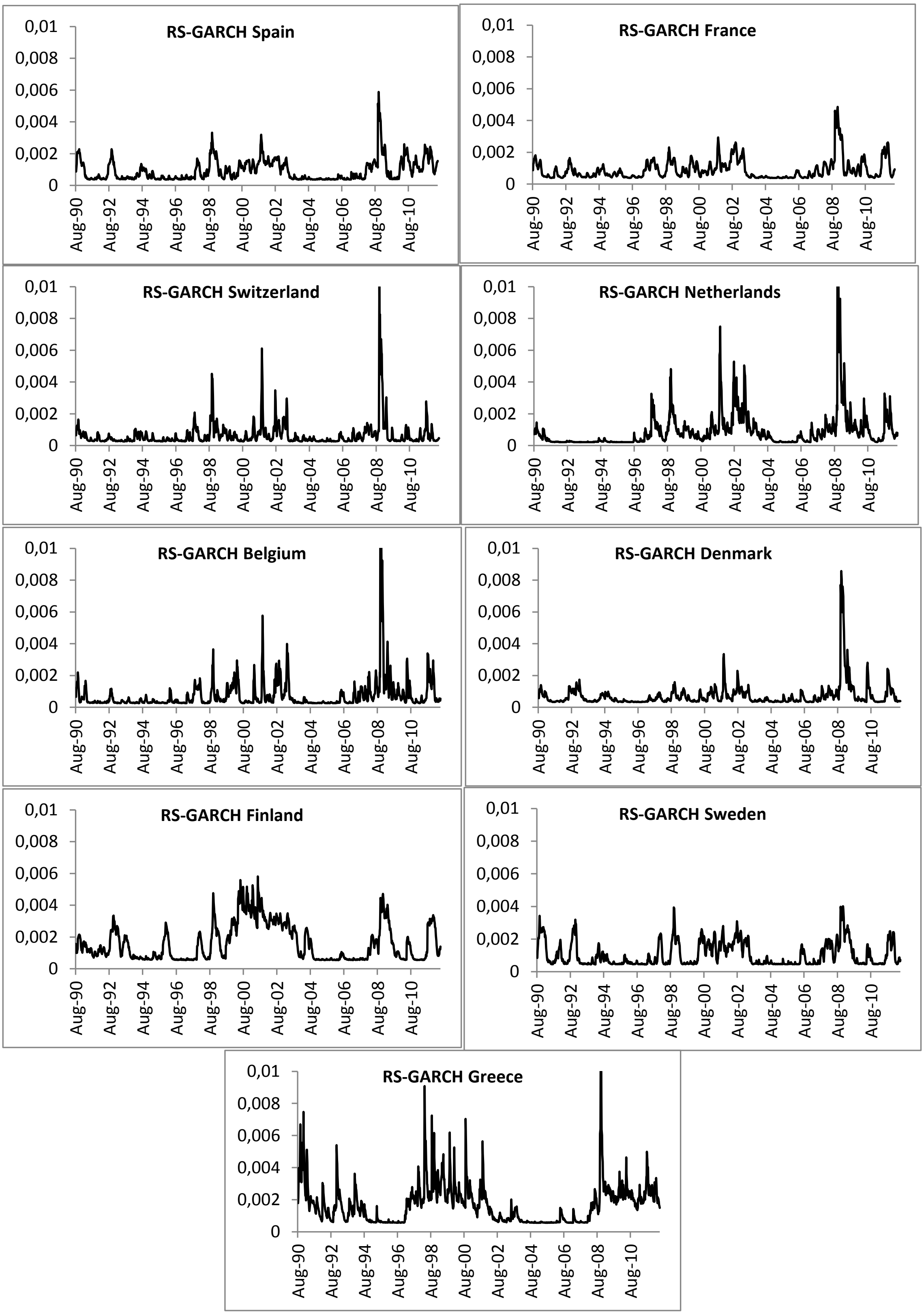
These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the GARCH specification

FIGURE OA1.B Risk premium evolution in Europe using the asymmetric GARCH model



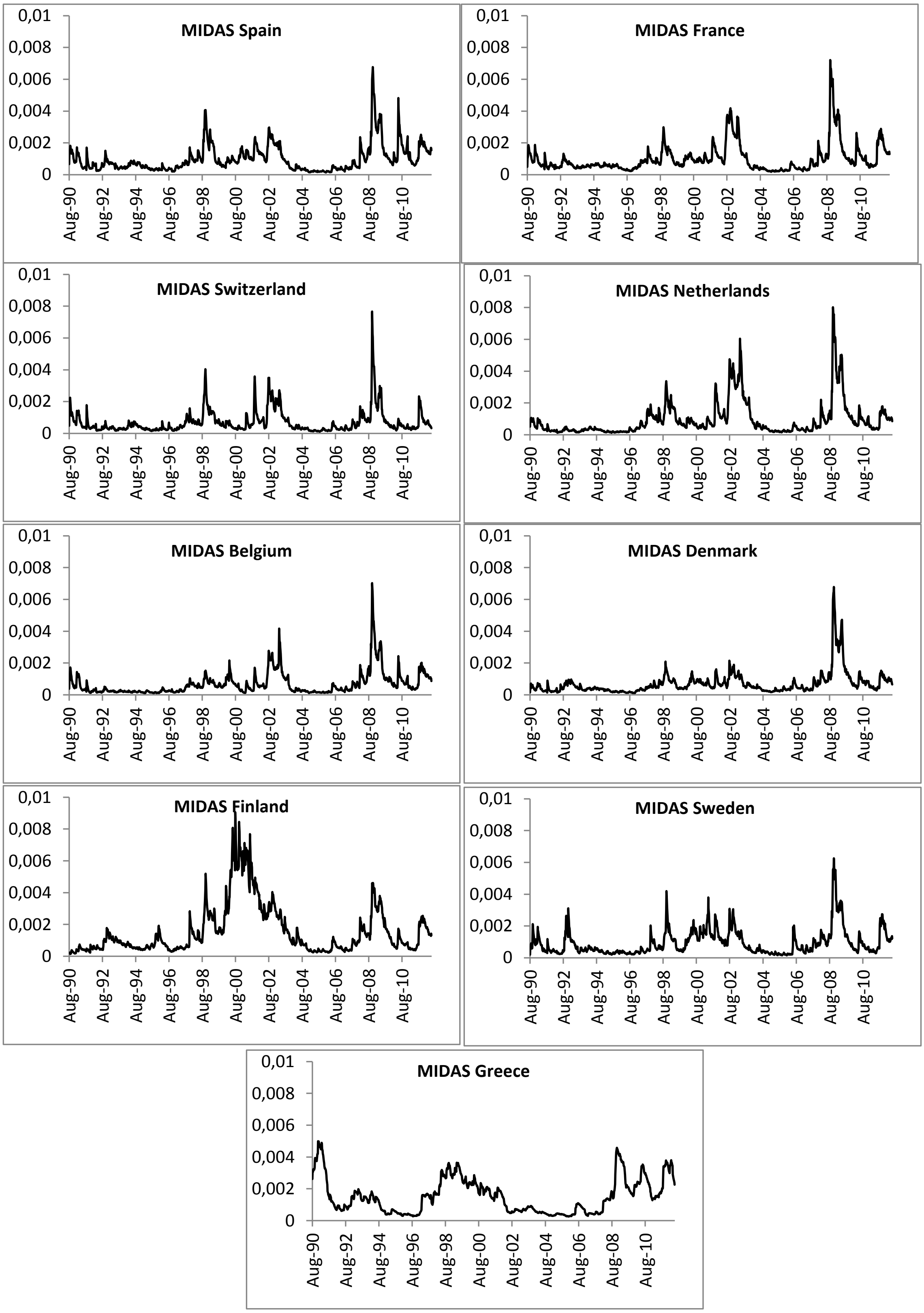
These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the asymmetric GARCH specification

FIGURE OA1.C Risk premium evolution in Europe using the RS- GARCH model



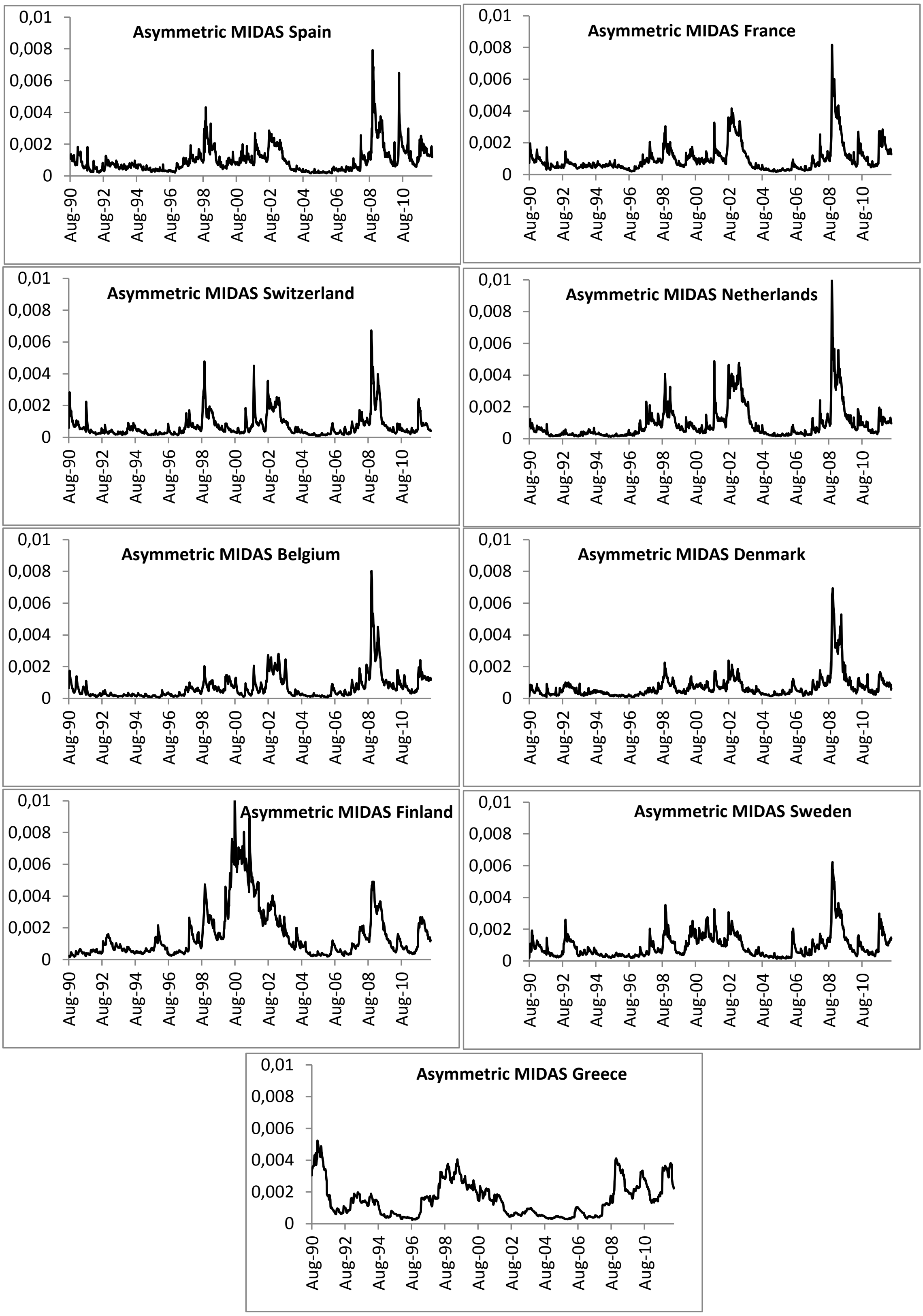
These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the RS-GARCH specification.

FIGURE OA1.D Risk premium evolution in Europe using the MIDAS model



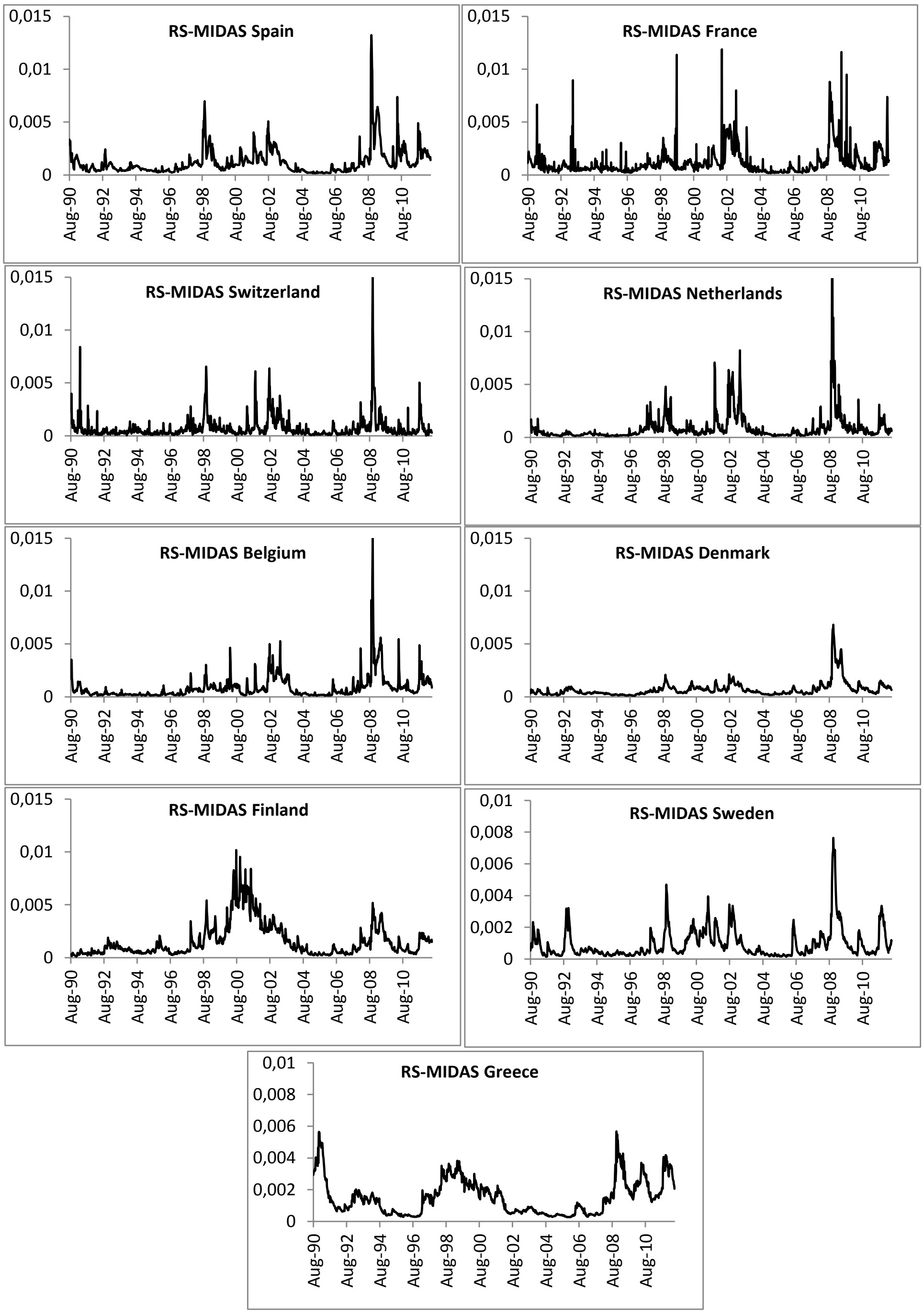
These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the MIDAS specification.

FIGURE OA1.E Risk premium evolution in Europe using the asymmetric MIDAS model



These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the asymmetric- MIDAS specification.

FIGURE OA1.F Risk premium evolution in Europe using the RS-MIDAS model



These figures show the risk premium evolution in all European countries not shown in the main text of the paper for the standard RS-MIDAS specification