

EMU equity markets' return variance and spill over effects from short-term interest rates

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Abstract

This paper examines the spillover effects from the short term interest rates market to equity markets within the Euro area. The empirical study is carried out by estimating an extended Markov Switching GJR in mean model with a Bayesian based Markov Chain Monte Carlo (MCMC) methodology. The result indicates that stock markets in the Euro area display a significant two regimes with distinct characteristics. Within a bear market regime, stock returns have a negative relationship with the volatility, and the volatility process responds asymmetrically to negative shocks of equity returns. The other regime appears to be a bull market regime, within which the returns have a positive relationship with the volatility, and the volatility is lower and more persistent. We find also that there is a significant impact of fluctuations in the short term interest rate on the conditional variance and conditional returns in the EMU countries. Such impact is asymmetrical, and it appears to be stronger in the bear market and when interest rate changes upward.

JEL classification : C10, C11, C13, G12, G19 .

MCMC, Markov Switching, GJR-M, EMU stock markets, Short term interest rates

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1 Introduction

The last decades have witnessed that policymakers use the stock market as the intermediate channel to stabilize inflation and output. However, much of the effects of monetary policy comes through the influence of short term interest rates on other asset prices including bond prices and stock prices which in turn importantly influence real economic activities. Since the Monetary Policy Committees in UK started to use short term interest rates as the tool for achieving its inflationary target in 1997, there is an increasing trend of using the short term interest rate rather than the money supply as intermediate targets for monetary policy in the world. Recently, the unexpected shocks from the money market, such as the Russian debt crisis in 1998 and the sub-prime mortgage crisis of 2007, have showed how the domino effect of short term interest rate shocks can affect the financial market globally. Henry (2009) argues that with huge fluctuations in the short term money market, firms seeking funding in the short term rate and lending in long term relatively illiquid securities, become insolvent simply because they can not access sufficient cash to finance their short term activities and not because they are unviable in the medium to long term. Therefore, it is important for policymakers and analysts to understand how short term interest rate changes affect stock prices and pay close attention to it in order to achieve their final objectives.

There are many researches examining the impact of interest rates on stock prices, but the finding about the relationship between the short term interest rate and the stock price is controversially conflicting. Earlier studies have employed the Treasury bill rates as a proxy for the expected inflation to examine the relationship between interest rates and stock returns (see, e.g., Nelson 1976, Fama & Schwert 1977, Fama 1981, Shanken 1990). These studies find a negative relationship between stock returns and the Treasury bill rates. Domain et al. (1996) mainly use yields on one-month Treasury bills to examine the relationship between stock returns and interest rate changes. The results from this study show a asymmetric relations, that is, drops in interest rates are followed by large positive stock returns while increases in interest rates have little effects. By present value models the negative relation between interest rates and stock prices is due to that an interest rate increase (decrease) causes an increase (decrease) in expected future discount rates which should cause stock prices to fall (rise) and long term interest rates to rise (fall). However, there have been certain empirical attempts that have provided evidence in favor of a positive relationship between interest rates and stock prices (see,

e.g., Asprem 1989, Shiller & Beltratti 1992, Barsky 1989). Barsky (1989) explains the positive relationship in terms of a changing risk premium. For instance, a drop in interest rates could be the result of increased risk and/or precautionary saving as investors substitute away from risky assets, e.g., stocks, into less risky assets, e.g., bonds. Shiller & Beltratti (1992) argue in favor of such a positive relationship on the grounds that changes in interest rates could carry information about certain changes in future fundamentals.

Meanwhile since the seminal paper by Bernanke & Blinder (1992), the impact of changes in different interest rate instruments, that have been used as the proxy for monetary policy on the stock market, has been examined in the financial literature.¹ In particular, using the three month Eurodollar rate as a proxy of monetary policy, Rigobon & Sack (2002) show that increases in the short term interest rate have a negative impact on stock prices, and a significant positive impact on market interest rates, with the largest effect on rates with shorter maturities.² Another important issue considered in the literature on the effect of interest rates on the stock market is that the effect of the interest rates is different in the bull and the bear market with the bull and the bear market defined in Maheu & McCurdy (2000) and in Perez-Quiros & Timmermann (2000), the bull market displays high returns coupled with low volatility (stable regime), and the bear market has a low return and high volatility (volatile regime). Some empirical studies have established that the effect of interest rates on conditional returns is larger in a volatile regime than that in a stable regime. For example, Chen (2007) investigates how the monetary policy measured by interest rate instruments affects on stock returns using a Markov-switching model, and concludes that such an impact is asymmetrically large in the bull periods. Henry (2009) uses a Markov Switching EGARCH model to examine the short term interest rate surprises impact on the volatility of returns in the U.K. stock market. Perez-Quiros & Timmermann (2000) study the relationship between changing credit market conditions including short term interest rate and stock market with a Markov switching model. They all find a similar asymmetry effect of the interest rate on stock returns in the bull market. Meanwhile an different conclusion is found in this Markov Switching framework, in contrast to the previous work suggesting interest rates significantly impact on the stock market, Ang & Bekaert (2002) confirm that even if the regime

¹See, e.g., Thorbecke (1997); Bomfim (2003); Rigobon & Sack (2002); Bernanke & Knutner (2005); Davig & Gerlach (2006); Basistha & Kurov (2008); Henry (2009).

²Ellingsen and Sderstrm (2001) have also used changes in the three month interest rate as a measure of policy innovations for estimating the response of the term structure. Favero, et al., (1999) examine the transmission of the monetary policy in Europe, three-month Euro rates is used as a proxy for the monetary policy.

switching characteristics is added in an empirical model, the evidence to support the effect of interest rate on returns does not exist.

This paper investigates the spill-over effect of interest rate impacts on stock returns and the volatility of returns in the Euro area in different regimes. We extend the current literatures in several aspects. First, departing from the most previous work primarily examining the effect of interest rates on stock prices and returns, we analyze the potential impact of changes in short term interest rate on both stock returns and the volatility of returns. Because the conditional variance is considered to be a proxy for risk in the financial and economic fields, it has important influence on monetary policy making, asset allocation decisions, and risk management. Merton (1980) suggests that one should use accurate variance estimates in accounting for the risk level when estimating expected returns. Optimal inference about the conditional mean of asset returns requires that the conditional variance be correctly specified. The investigation of the interest rate impact on both stock returns and the volatility of returns is of importance to financial market participants making effective portfolio selection and formulating risk management strategies.

Second, we contribute to the current literature by investigating the asymmetric effect of the increased interest rates on returns and the volatility of returns in the bull and the bear market in the EMU stock markets. Although there is substantial evidence of asymmetry effect of interest rates on stock returns in the bear and bull markets, the literature is not yet clear whether an increase and a drop in interest rates have the same effect in these two market regimes. Further, reviewing Sellin (2001)'s survey, you will find that most of the studies mainly focus on the effect of interest rate on US financial markets. In contrast, the impact of short term interest rate movements on stock markets in the EMU area has received surprisingly little attention in the recent literature. We examine the impact of the interest rates on the stock markets in the EMU countries.

Third, our empirical work updates the current literature by investigating the spillover effect of the money market on stock returns and the volatility of stock returns by extending the Markov switching GJR GARCH in mean model (MS GJR-M hereafter). We extend the MS GJR-M model by adding the interest rate movements to the variance process of the MS GJR-M model, and formulate the Extended Markov Switching GJR GARCH in mean model (EMS GJR-M hereafter). There are several advantages of the proposed model in this paper. First, a regime switching model can capture structural breaks in the volatility in terms of the bull

and bear markets.³ Second, given the wide spread evidence of the asymmetric effect of the negative news on stock volatility, (see, e.g., Glosten et al. 1993, Engle & Ng 1993) the MS GJR-M model has sufficient flexibility to characterize the persistence and the asymmetries response of the volatility to a shock. Third, via a GARCH in mean process from Engle et al. (1987), this model can explore the intertemporal relationship between risk and return which has long been an important topic in the modern financial theory. Finally, adding the interest rate movements and distinguishing the increase in the interest rates enable us to investigate two types of asymmetry effects in the variance process, i.e., the asymmetric effect of unexpected negative shocks in the stock market and from the interest rate market. We investigate these two different asymmetric effects by modifying the news impact curve as suggested by Engle & Ng (1993) to the News Impact Surface, in which the variance process depends on the shocks from the stock returns and from the interest rate changes. We estimate the MS GJR-M and EMS GJR-M models with the Markov Chain Monte Carlo (MCMC) method instead of the traditional maximum likelihood method. Because of the structure of the proposed model, the conditional variance depends on all past history of the state variables. The evaluation of the likelihood function for a sample path of length T and the k states requires the integration over all K^T possible paths, rendering the maximum likelihood estimation infeasible. To the best of author's knowledge, this is the first time that a MS GJR-M model has been estimated in the literature.

Our results suggest that two regimes exist in the EURO area stock markets, i.e., a high mean low variance (bull) market and a low mean high volatile (bear) market. Most of the Euro countries have the same regime switching status between the bull and bear markets. The correlation between the first two moments of returns is not stable over time but varies between the bull and the bear market. Our results suggest also that bad news from the unexpected stock returns (negative residuals from returns) has asymmetrically larger effect on the returns and the volatility than the good news. Such an impact is larger in the bear market than in the bull market. Surprisingly, implied in the News Impact Surface, we find that the change in short term interest rates only significantly affects the stock market volatility in the bear period in most of the EMU countries, in particular, the effect of an increase in interest rates is asymmetrically larger than a decrease in interest rates. The portfolio performance based on the out-of-sample forecast results of various models indicates that the EMS GJR-M model outperforms other models,

³Lamoreux & Lastrapes (1990), Hamilton & Susmel (1994) and Cai (1994) argue that ignoring these structural shifts in the volatility process causes GARCH models to overestimate the persistence of volatility.

i.e., MS GJR-M and a single switching GJR-M model. The models with regime switching yield better portfolio performance than the ones without the regime switching. This implies that the consideration of the interest rate impact and the regime specification when modeling the volatility are necessary. Any ignorance of such a state dependent asymmetric effects from short term interest rates on stock returns and the volatility of stock returns will lead to invalid inferences, biased forecasts and consequently inefficient portfolio selection and risk management due to the biased volatility estimates.

This paper proceeds as follows. Section 2 presents the extended Markov switching GJR GARCH in mean model. Section 3 demonstrates the model estimation algorithm. Section 4 describes the data used and reports the empirical results. Section 5 performs the asset allocation based on the out-of-sample forecasts result from various models.

2 The model

In this section, we present the model used and proposed in this paper.

2.1 The Markov switching GJR in mean model

There is a substantial literature describing the volatility of stock returns. Since Engle (1982) and Bollerslev (1986) introduced the original ARCH (Autoregressive Conditional Heteroskedasticity) model, and the standard GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, these types of volatility modeling techniques have been extended and applied extensively to characterize the volatility of stock returns. One extension of the GARCH model is the GARCH-M model,⁴ which allows the conditional volatility to enter into the conditional mean equation to explore the intertemporal relation between risk and return which has long been an important topic in asset valuation research. Another important extension of the standard GARCH model includes the EGARCH (Nelson 1991) and the GJR GARCH model (Glosten et al. 1993), which are the most used models to capture the asymmetry in the conditional variance, a phenomenon observed especially on equity markets and referred to as the leverage effect (Black, 1976). We choose to use the GJR model to capture the asymmetry in the volatility.

A standard GARCH model with asymmetric and the GARCH in mean effect, for which we

⁴The GARCH-M was primarily motivated by Merton (1973)'s Intertemporal Capital Asset Pricing Model (ICAPM)

refer to as the GJR-M (p,q) model, has the following specification,

$$\begin{aligned} r_t &= \beta\sqrt{h_t} + \epsilon_t, \quad \epsilon_t = \sqrt{h_t}z_t, \quad z_t \sim (0,1), \\ h_t &= \alpha_o + \sum_{i=1}^p (\alpha_i + \gamma_i d_i) \epsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2, \end{aligned} \quad (1)$$

where ϵ_t may be treated as a collective measure of news about equity prices arriving to the market over the last period, and $\alpha_o > 0, \alpha_i \geq 0, \beta_j \geq 0, \alpha_i + \beta_j + 0.5\gamma_i < 1$. d_i is an indicator for negative ϵ_{t-i} , that is,

$$d_i = \begin{cases} 1 & \text{if } \epsilon_{t-i} < 0 \\ 0 & \text{if } \epsilon_{t-i} \geq 0 \end{cases}$$

It can be seen from the model that a positive ϵ_{t-i} contributes $\alpha_i \epsilon_{t-i}^2$ to σ_i , whereas a negative ϵ_{t-i} has a larger impact $(\alpha_i + \gamma_i) \epsilon_{t-i}^2$. Therefore, if parameter γ_i is significantly positive, then negative innovations generate more volatility than positive innovations of equal magnitude.

While estimating financial and macroeconomic series, some economists find that both ARCH and GARCH models may encounter high persistence in volatility and lower accuracy in predicting performance. Diebold (1986) argues that the high persistence is caused by structural breaks in the volatility process during the estimation period. Lamoreux & Lastrapes (1990) point out that models with switched parameter values, like the Markov switching model of Hamilton (1989), may provide a more appropriate tool for modeling volatility. Hamilton & Susmel (1994) propose a model with sudden discrete changes in the process which governs volatility. They found that a Markov switching process provides a better statistical fit to the data than a GARCH model without switching.

This paper employs a two states Markov switching GJR in mean (MS GJR-M) model to capture the GARCH in mean effect in the conditional mean, the leverage effect and structure breaks in the conditional variance. The MS GJR-M (1,1) model is as follows:

$$\begin{aligned} r_t &= \beta_i \sqrt{h_{i,t}} + \epsilon_{i,t}, \quad \epsilon_{i,t} = \sqrt{h_{i,t}} z_t, \quad z_t \sim (0,1), \\ h_{i,t} &= \alpha_{io} + \alpha_{i1} h_{i,t-1}^2 + \alpha_{i2} \epsilon_{i,t-1}^2 + \alpha_{i3} d_i \epsilon_{i,t-1}^2, \end{aligned} \quad (2)$$

where $z_t \sim (0,1)$, and $i = 1, 2$ represents the state. $\alpha_{io} > 0, \alpha_{i1} \geq 0, (\alpha_{i2} + \alpha_{i3}) \geq 0, (\alpha_{io} + \alpha_{i2} + 0.5\alpha_{i3}) < 1$. Following Hamilton (1989) and Hamilton (1990), we assume that the state vector

S_t follows a first order Markov process with the following hidden transition probabilities matrix Π ,

$$\Pi = \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix}$$

where,

$$\begin{aligned} \pi_{11} &= P(S_t = 1 | S_{t-1} = 1) = 1 - e_1 \\ \pi_{12} &= P(S_t = 2 | S_{t-1} = 1) = e_1 \\ \pi_{21} &= P(S_t = 1 | S_{t-1} = 2) = e_2 \\ \pi_{22} &= P(S_t = 2 | S_{t-1} = 2) = 1 - e_2 \end{aligned} \quad (3)$$

where $0 < e_i < 1$, for $i = 1, 2$. A small e_i means that the return series has a tendency to stay in the i th state with expected duration.

For the model in 2 to be identifiable, we assume that $\beta_2 > \beta_1$ so that state 2 is associated with higher conditional returns. If $\alpha_{1j} = \alpha_{2j}$ for all j , the model becomes a simple GJR -M model. If $\beta_i \sqrt{h_t}$ is replaced by β_i then the models in (2) reduces to a Markov switching GJR model. The parameter β is the risk premium. A positive β indicates that the return is positively related to its volatility. Parameters in GARCH components satisfy conditions similar to those of GARCH models. If the parameters have significant differences between regimes, then there exists a bull market and a bear market in stock returns.

2.2 The Extended Markov switching GJR in mean model with the interest rate effect

Holding the transition probability matrix constant, we measure the impact of the interest rate differential on the stock market, by extending the MS GJR-M model to the EMS GJR-M model. This model is formulated by adding the interest rate changes to the variance process as follows,

$$\begin{aligned} r_t &= \beta_i \sqrt{h_{i,t}} + \epsilon_{i,t}, \quad \epsilon_{i,t} = \sqrt{h_{i,t}} z_t, \quad z_t \sim (0, 1), \\ h_{i,t} &= \alpha_{i0} + \alpha_{i1} h_{i,t-1}^2 + \alpha_{i2} \epsilon_{i,t-1}^2 + \alpha_{i3} d_i \epsilon_{i,t-1}^2 + \alpha_{i4} \chi_{i,t-1}^2 + \alpha_{i5} f_i \chi_{i,t-1}^2, \end{aligned} \quad (4)$$

where parameters in variance process satisfy conditions similar to those in the GJR-M model. The interest rate differential $\chi_t = \log(I_t/I_{t-1})$, captures changes in short term interest rates, where I_t is the interest rate level at time t . f_i is the indicator for positive values of changes in interest rates, namely, the increase in interest rates, which satisfies

$$f_i = \begin{cases} 1 & \text{if } \chi_{t-1} > 0 \\ 0 & \text{if } \chi_{t-1} \leq 0 \end{cases}$$

For this model to be well defined, we use the squared log difference of interest rates to examine the interest rates impact on the conditional variance. Alternatively, we can use the squared absolute value of the first difference in interest rates. However, as we are estimating the conditional variance, which is the squared conditional volatility in the GJR model, we use the squared differences of interest rates in order to keep the interest rate differentials and the estimated volatility at the same scale. In this specification, we can examine different asymmetrical effects on the volatility of stock returns. Besides the asymmetric effects from market news, we can also examine if the increase in interest rates asymmetrically affects the stock market in the bear and bull markets. Hence, a negative χ_{t-1} (drops in interest rates) contributes $\alpha_{i4} \chi_{t-1}^2$ to σ_i , whereas a positive χ_{t-1} (increases in interest rates) has a impact $(\alpha_{i4} + \alpha_{i5})\chi_{t-1}^2$ if α_{i5} is significantly different from zero. The coefficients α_{24} and α_{25} measure the effect of movements in the interest rate on the conditional variance in the bear market, while α_{14} and α_{15} measure the impact of interest rate fluctuations on the volatility in the bull market.

One alternative study of the interest rate impact can be done by allowing the transmission matrix to be time-varying. However, it is still an open question whether the specification of time-varying transition probability is suitable for all financial data. Some studies report that the regime switching model with the time-varying transition probability performs worse compared with the regime switching model with a fixed transition probability (see, e.g., Chang 2009, Perez-Quiros & Timmermann 2001).⁵ Therefore, we choose to analyze the MS GJR-M model and the EMS GJR-M model with a fixed transition probability.

⁵Perez-Quiros & Timmermann (2001) demonstrate that the regime switching model, with time-varying transition probability, is not applicable for large firms. Chang (2009) finds that the regime switching model with the time-varying transition probability performs worse in the out-of-sample forecasting than the one with fixed transition probability.

3 Model Estimation

In this section, we describe the estimation algorithm for a Monte Carlo Markov Chain method. This estimation algorithm will be tested by a Monte Carlo simulation.

3.1 Estimation method: MCMC

The evaluations of the likelihood function of models 2 and 4 are complicated as they are a mixture over all possible state configurations. This may lead to computational difficulties with the maximum likelihood estimation. We estimate the model with a Bayesian based Markov Chain Monte Carlo method (MCMC method). A Bayesian statistical model consists of a parametric statistical model, $f(x|\theta)$, and a prior distribution on the parameters $p(\theta)$. The optimal Bayes estimator under quadratic loss is simply the posterior mean: $\hat{\theta} = E[\theta|Y = y] = \int \theta p(\theta|y) d\theta$. Therefore we need to compute the posterior density of our model parameters. The posterior density is determined by the prior density and the likelihood.

$$\begin{aligned} p(\theta|y) &= \frac{f(y, \theta)}{f(y)} \\ &= \frac{f(y|\theta)p(\theta)}{\int f(y|\theta)p(\theta)d\theta} \end{aligned}$$

that is,

$$p(\theta|y) \propto f(y|\theta)p(\theta) \quad (5)$$

where $f(y|\theta)$ in equation 5 is the likelihood function and $p(\theta)$ is the prior distribution. The parameter vector of the model MS GJR-M (1,1), for $i = 1, 2$, specified in 2 is given by,

$$\begin{aligned} \Theta_i &= \{\beta_i, \theta_i, \pi_i, \mathbf{S}\}, \\ \theta_i &= (\alpha_{i0}, \alpha_{i1}, \alpha_{i2}, \alpha_{i3}), \\ \pi_i &= (\pi_{i1}, \pi_{i2}), \\ \mathbf{S} &= (S_1, S_2, \dots, S_T). \end{aligned} \quad (6)$$

To obtain the Bayesian estimators $\hat{\Theta}$, we compute the mean from the sample of the stationary distribution of the simulated Θ_i , and we need the following conditional posterior distributions: $f(\beta|\mathbf{R}, \mathbf{S}, \mathbf{H}, \theta_1, \theta_2)$, $f(\theta_i|\mathbf{R}, \mathbf{S}, \mathbf{H}, \theta_{j \neq i})$, $p(\mathbf{S}|\mathbf{H}, \mathbf{R}, \theta_1, \theta_2)$, $f(e_i|\mathbf{S})$, $i = 1, 2$, where \mathbf{R} is the

observed returns and \mathbf{H} is the conditional volatility vector and can be computed recursively. Following Tsay (2005), we use conjugate prior distributions for drawing β_i and e_i .⁶

3.1.1 Sampling β_i

Assume $\beta_i \sim \mathbb{N}(\beta_{i0}, \sigma_{io}^2)$, the posterior distribution of β_i only depends on the data in state i .

Define,

$$r_{it} = \begin{cases} \frac{r_t}{\sqrt{(h_t)}} & \text{if } s_t = i; \\ 0 & \text{otherwise.} \end{cases}$$

then we have,

$$r_{it} = \beta_i + \epsilon_i, \text{ for } s_t = i. \quad (7)$$

Let $\bar{r}_i = (\sum_{s_t=i} r_{it})/n_i$ where n_i is the total number of data points in state i , and $r_{it} \sim \mathbb{N}(\beta_i, \sigma^2)$.

Then the conditional posterior distribution of β_i is normal with mean β_i^* and variance σ_i^{2*} given

by,

$$\beta_i^* = \frac{\sigma^2 \beta_{i0} + n_i \sigma_{io}^2 \bar{r}_i}{\sigma^2 + n_i \sigma_{io}^2} \quad \text{and} \quad \sigma_i^{2*} = \frac{\sigma^2 \sigma_{io}}{\sigma^2 + n_i \sigma_{io}^2}. \quad (8)$$

3.1.2 Sampling e_i

The conditional posterior distribution of e_i only involves \mathbf{S} . Assume $e_i \sim \text{Beta}(\varphi_{i1}, \varphi_{i2})$ and let $\sum_{t=1}^n l_{1t}$ be the number of switches from state 1 to state 2, $\sum_{t=1}^n l_{2t}$ be the number of switches from state 2 to state 1, and let n_i be the number of the data observations in state i . l_{it} are Bernoulli distributed with parameter e_i , then the posterior distribution of e_i is beta as,

$$e_i \sim \text{Beta}(\varphi_{i1} + \sum_{t=1}^n l_{ti}, \varphi_{i2} + n_i - \sum_{t=1}^n l_{ti}). \quad (9)$$

3.1.3 Sampling α_{ij}

We draw α_{ij} with a modified Griddy Gibbs sampler. The Griddy Gibbs was first introduced by Tanner (1996). This method is widely applicable when the conditional posterior distribution is univariate. The main idea is to form a simple approximation to the inverse CDF based on the evaluation of the conditional posterior distribution on a grid of points. In our model the conditional posterior distribution function of α_{ij} does not correspond to a well known distribution,

⁶See DeGroot (1990) for a proof

however, as h_t contains α_{ij} , it can be evaluated easily as follow :

$$g(\alpha_{ij}|\cdot) \propto \sum_{t=1}^n \left\{ -\frac{1}{2} \left[\ln(h_t) + \frac{(r_t - \beta_i \sqrt{h_t})^2}{h_t} \right] \right\}, \quad \text{if } s_t = i,$$

$$f(\alpha_{ij}|\cdot) \propto \exp(g(\alpha_{ij})). \quad (10)$$

In order to avoid the problem of the fast convergence of the exponential distribution, we modify the Griddy Gibbs by adding a scale factor $u = \max(g(\alpha_{ij}))$ to the evaluated function as follow:

$$f(\alpha_{ij}|\cdot) \propto \exp(g(\alpha_{ij}) - u). \quad (11)$$

The Griddy Gibbs proceeds in the following steps:

1. Evaluate $f(\alpha_{ij}|\cdot)$ at a grid of points from a properly selected interval of α_{ij} , for example, $0 \leq \alpha_{i1} < 1 - \alpha_{i2} - \alpha_{i3}$, to obtain $\omega_k = f(\alpha_{ij}^k|\cdot)$ for $k = 1, \dots, m$. We choose $m = 200$.
2. Use $\{\omega_{k=1}^m\} = \omega_1, \omega_2, \dots, \omega_m$ to obtain an approximation to the inverse CDF (Cumulative Distribution Function) of $f(\alpha_{ij}|\cdot)$, which is a discrete distribution for $\{\alpha_{ij}^k\}_{k=1}^m$ with probability $p(\alpha_{ij}) = \omega_k / \sum_{v=1}^m \omega_v$.
3. Draw a uniform $(0, 1)$ random number and transform the observation via the approximate inverse CDF to obtain a random draw for α_{ij} .

3.1.4 Sampling S

Following Henneke et al. (2006), we draw the states S_t by the "Single Move" procedure. At each step, we sample from the full conditional posterior density of S_t given by,

$$P(S_t = i | R, \boldsymbol{\theta}_{-s}, S_{-t}), \quad (12)$$

where $\boldsymbol{\theta}_{-s}$ is the parameter vector in equation 6 excluding S and S_{-t} is the regime path excluding the regime at time t . In order to save space, we omit the notation of the explicitly condition on $\boldsymbol{\theta}$. Applying the rules of conditional probability to 12, we get,

$$P(S_{t=i} | R, S_{-t}) = \frac{P(S_i, R | S_{-t})}{P(R | S_{-t})} = \frac{P(R | S_{t=i}, S_{-t}) \cdot P(S_{t=i} | S_{-t})}{P(R | S_{-t})}. \quad (13)$$

The first term in the numerator, $P(R|S_{t=i}, S_{-t})$, is simply the models likelihood $L(S_t = i)$ evaluated at a given regime path, in which $S_t = i$, and,

$$L(S_t = i) = \prod_{t=j}^n f(\epsilon_t|H) \propto \exp(f_{ji}),$$

$$f_{ji} = \sum_{t=1}^n \left\{ -\frac{1}{2} \left[\ln(h_t) + \frac{(r_t - \beta_i \sqrt{h_t})^2}{h_t} \right] \right\} \quad \text{for } i = 1, 2, \text{ and } t \geq j. \quad (14)$$

Given $t \geq j$, one can compute h_t recursively. The denominator $P(R|S_{-t})$, is the sum of the two probability weighted conditional distributions,

$$P(R|S_{-t}) = \sum_{i=1}^{s=2} P(R|S_t = i, S_{-t}) \cdot P(S_{t=i}|S_{-t}), \quad (15)$$

due to the Markov property of the chain. $P(S_t = i|S_{-t})$ is only dependent on S_{t-1} and S_{t+1} ,

$$P(S_{t=i}|S_{-t}) = P(S_t = i|S_{t-1}, S_{t+1}) = \frac{\pi_{l,i} \cdot \pi_{i,k}}{\sum_{i=1}^{s=2} \pi_{l,i} \cdot \pi_{i,k}} \quad (16)$$

With $S_{t-1} = l$, $S_{t+1} = k$, and π_{ij} be the respective transition probabilities from the transition probability matrix. Finally, substitute equation 15 and equation 16 into equation 13, we compute the conditional posterior probability as,

$$P(S_{t=i}|R, S_{-t}) = \frac{L(S_t = i) \cdot \pi_{l,i} \pi_{i,k}}{\sum_{j=1}^{s=2} L(S_t = j) \cdot \pi_{l,j} \pi_{j,k}}. \quad (17)$$

The state S_t can be drawn using a uniform distribution in the interval $[0, 1]$.

3.2 Monte Carlo Simulation

In order to show that our algorithm works well, we perform a Monte Carlo simulation experiment. We simulate 10 data sets of 1000 points from model 2 with the same true parameters value for each data set. The total iterations are 5000, of which the first 400 of the sample are discarded as burn in. In table 1, we present the estimation results from the randomly chosen 1000 simulated data. We find that the mean of our estimated parameters are quite close to the true parameters and the square root of mean squared error are quite small. Figure 1 shows the plots of the true volatility and the estimated volatility process, as well as the plot of the true probability and the estimated probability of regime 1. The estimated probability of regime 1 is very close to the

true probability. Therefore, we can be confident that our algorithm performs very well and is reliable.

4 Data and Empirical Results

In this section, we present the data used in this paper and perform the empirical study and report the results.

4.1 Data

The data used in this study consist of the weekly stock index closing price of ten EMU countries that joined the Economic and Monetary Union's third stage on 1 January 1999.⁷ Specifically, they include Germany DAX, France CAC 40, Italy FTSEMIB, Spain IBEX35, Netherlands AEX, Ireland ISEQUIT, Finland HEX25, Austria ATX, Belgium BEL 20, and Portugal PSI 20. Furthermore, the 1-month Euro Interbank Offered Rate (EURIBOR) is the benchmark money market rate for the Euro area. While interest rates with shorter maturities are neglected because EURIBORS with maturities longer than one month may not be sensitive enough to representing the short term interest rates (see, e.g., Kleimeier & Sander 2006, Bohl et al. 1986).

The sample period is from 1 January 1999 to March 12, 2010, i.e., it begins when the European Central Bank (ECB) replaced the national central banks of EMU members and assumed responsibility for the conduct of unified monetary policy. The data is further divided into in-sample and out-of-sample periods. The in sample period starts on January 1, 1999 and ends on July 17, 2009. While the out-of-sample is from July 24, 2009 to March 12, 2010. The total sample size is 589. All the data are obtained from Thomson Financial Datastream.

We calculate the weekly returns as $\log(y_t/y_{t-1})$ and then annualize them by multiplying with a square root of 52. Table 2 presents the statistical description of returns of the EMU stock market indexes. It can be seen from this table that the mean of returns of the EMU countries are around zero. The standard deviations range from 0.1815% (Portugal) to 0.256% (Finland). The kurtosis statistics are far greater than 3 associated with the normal distribution. The negative skewness coefficients are also significantly less than the value of zero of the symmetric normal distribution. The P values of the Jarque Bera test show that the null hypothesis of normality is

⁷The Luxembourg stock market is the only EMU market which is not considered in this study due to a lack of the stock index price data.

clearly rejected for every series. However, the test statistics from the Augmented Dicky Fuller test are much less than the critical value, therefore, the null hypothesis of a unit root is rejected at the 5% significance level for all the return series. The p values of the Ljung-Box Q test at lags 10 indicate that there is no serial correlations in the series.

4.2 Empirical results

4.2.1 The validation of model estimations

Before the analysis, we examine the validity of the MS GJR-M model in different ways. First, the Ljung-Box Q- tests are carried out at Lags 20 to check the serial correlation in standardized residuals. The P-values of the tests are presented in the last column in Table 3, which suggest that the null hypothesis of no serial correlation cannot be rejected. Therefore, the MS GJR-M model fits the data properly.

We then benchmark the proposed MS GJR-M with a standard GARCH model, a GJR model, and a single switching GJR in mean model described in equation 2. Following Bhlman & McNeil (2002), we use $\sqrt{(r_t - \bar{r}_t)^2}$ as a proxy for true volatility, where \bar{r}_t is the mean of stock returns r_t . The Mean Squared Errors (MSE), the Mean Absolute Errors (MAE) and the Akaike's Information Criterion (AIC) are used as the model adequate selection criteria. The MSE, MAE, and AIC are calculated according to the following formulas:

$$\begin{aligned}
 MSE &= \frac{1}{N} \sum_{t=1}^N (\hat{\sigma}_t - \sigma_t)^2, \\
 MAE &= \frac{1}{N} \sum_{t=1}^N |\hat{\sigma}_t - \sigma_t|, \\
 AIC &= 2K + N \left[\log\left(\frac{2\pi \cdot RSS}{N}\right) + 1 \right].
 \end{aligned} \tag{18}$$

where $\hat{\sigma}_t$ is the estimated volatility, σ_t is the proxy of true volatility. $RSS = \sum_{t=1}^N (\hat{\sigma}_t - \sigma_t)^2$, N is the total sample size and K is the total number of parameters in the model.

The results of the model selection criteria are shown in the first four columns of Table 6, where we present the goodness-of-fit from various models. The results of the MSE, the MAE and the AIC all indicate that the MS GJR-M model performs the best compared with the GARCH model, the GJR model, and the single regime GJR-M model. We notice that allowing the conditional variance to enter into the conditional mean equation, a standard GJR-M model

improves the conditional variance in most of the EMU countries. For example, in Germany, the MSE is reduced from 0,028 (GARCH model) to 0,026 (GJR model), and is further reduced to 0,024 (GJR-M); the MAE declines from 0,125 to 0,117 from the GARCH model to the GJR-M model; the AIC is also reduced roughly by 3.2% from the GARCH model to the GJR-M model. In addition, allowing for a Markov switching effect, the MS GJR-M model further significantly improve the estimated volatility. This is particularly true in the medium and large countries. For example in the Italian market (FTSEMIB), both the MSE, MAE, and AIC from the MS GJR-M model are 8%, 3%, and 2% lower than the ones from the single regime GJR-M model. This confirms that the GARCH in mean and the Markov switching are all necessary for characterizing the return variance dynamics. Hence, the MS GJR-M model provides a better characterization of the EMU stock returns and the volatility compared with other GARCH family model, e.g. a GJR model or a single regime GJR-M model.

4.2.2 The time varying relationship between risk and returns

Table 3 presents the estimated parameters of all indices from the MS GJR-M model described in equation (2). The first two columns of Table 3 are the estimated parameters b_1 and b_2 , which are the GARCH in mean coefficients in the conditional mean in regime 1 and regime 2, respectively. The parameters b_1 in all countries are all negative and the parameters b_2 in all countries are all positive. A negative/positive beta shows that the mean of returns has a negative/positive correlation with the conditional variance. It is obvious that in regime 1, returns are negatively correlated with the volatility, while in regime 2, returns are positively correlated with the volatility. This means that in regime 1, a higher risk usually leads to a higher loss in the investment, but in regime 2, an increased volatility often leads to a higher profitability. Many empirical studies examine the relationship between the conditional mean and the conditional variance. However, the finding of the relationship between risk and return is controversially conflicting.⁸ We find a time varying relationship between risk and return which is in line with studies such as Harvey (1989, 2001), Kandel & Stambaugh (1990), and Whitelaw (1994). In particular, Harvey (2001) argues that the specification of the conditional variance influences the relation between the conditional mean and the conditional variance and provides

⁸Some papers report a positive relationship such as French et al. (1987), Campbell & Hentschel (1992), Li (2003), and Guo & Neely (2006). Some indicate a negative relationship such as Glosten et al. (1993), Pagan & Hong (1990), Li et al. (2005), and Guedhami & Sy (2005), while others do not find a significant relationship at all such as Bodurtha & Mark (1992), Baillie & DeGennaro (1990), and Shin (2005).

empirical evidence suggesting that there may be some time variation in the relationship between risk and return. Whitelaw (1994) reports also that the contemporaneous correlation between the first two movements of the return varies from large positive to large negative values. The negative relation between conditional mean and the conditional variance in the bear market is intuitive. In the bear market, investors are more risk averse. When investors are scared, they look for safety. They adjust their portfolios to include more safe assets and fewer risky assets. This kind of "flight to quality" leads investors to stay away from risky assets, e.g. stocks, which causes stock prices decline (Barsky 1989).

4.2.3 Bull markets and Bear markets in the EMU countries' stock market

By looking at α_{10} and α_{20} in Table 3, the intercept of the volatility equation in regime 1 and regime 2, respectively, we can see that the values of α_{20} are varied from 0.01 to 0.077, while the values of α_{10} are all almost zero. This implies that the annualized volatility will increase if the market switches from regime 2 to regime 1, and vice versa. These distinct characteristics of the two regimes are typical representations of the high-returns stable and the low returns volatile state in stock returns, which are conventionally labeled as bull markets and bear markets in Maheu & McCurdy (2000) and Perez-Quiros & Timmermann (2000). Obviously, the EMU stock markets have well identified bear markets (regime 1) and bull markets (regime 2). This is similar to the finding of Chen (2007) in the S&P 500 index, and Henry (2009) in the UK equity market.

The volatility persistence parameters α_{11} and α_{21} are quite significant in nearly all of the EMU stock markets. Interestingly, in most countries, $\alpha_{21} > \alpha_{11}$. This implies that the volatility is less persistent during the bear period. This result is similar to the report from Friedman and Libson (1989) and Daal et al. (2007). Friedman & Laibson (1989) apply a modified ARCH and GARCH model that allow for jumps and divide their sample into ordinary and unusual returns period. They find that the volatility of ordinary returns displays persistence but the volatility of the unusual price movements are less persistent. Daal et al. (2007) find the same pattern with a GARCH model allowing for jumps and asymmetry.

Furthermore, We notice that coefficients α_{12} are insignificant in all of the EMU countries, and α_{22} are insignificant at 5% significance level in majority of the EMU countries. However, this does not mean that the one week lagged error term has no effect on current volatility at

all. On the contrary, it influences volatility through the channel of leverage effect, as when bad news arrives (when residual is negative), the market displays a remarkably different response to news. Parameters α_{13} and α_{23} show this additional sharp response of volatility to bad news in most of the EMU countries. This is generally consistent with the well documented predicative asymmetrical effect in stock market (see, e.g., Campbell & Hentschel 1992, Engle & Ng 1993). Further, in all EMU countries, $\alpha_{13} > \alpha_{23}$, implying that the asymmetry of the volatility response to bad news during volatile periods is greater than during stable periods. For example, the volatility asymmetry coefficient of DAX is 0.3858 in the bear market, which is about 2.1 times that of the bull market. This can be explained that during the bear market, the confidence of investors is greatly damaged, market practitioners become more speculative oriented and more sensitive to any market news, especially to bad news.

In Figure 2, we present the smoothed probability of regime 1 (bear period) of all of the indices. We can see that nearly all of the countries entered into the bear period during 2000 and 2001, which was in the half burst of the dot-com bubble. Among them, the central European countries resisted to switch to the bear period, for example, Germany, Netherlands and Belgium started their bear period in the beginning of 2001. The Irish stock market behaved remarkably different and remained in the bull period until the late of 2001. This was due to its outstanding economic performance during that period. From year 1995 to 2000, the GDP growth of Irish was around 10% , while that of most other EMU countries were merely around 3%. A review from IMF in August 2000 attributed such performance to the roles played by "sound and consistent macroeconomic policies, a generally flexible labor market, a favorable tax regime and the long standing outward orientation of Ireland's trade and industrial policies", and regarded the Irish economy as "well placed to continue to perform strongly in the future". Therefore, the Irish stock market remained in the bull period until late in 2001, when its GDP growth rate dropped by half.

By the end of 2002 and the beginning of 2003, when key central banks desperately dropped their target rate to a historical low level with the ECB offering a deposit rate of merely 1.5%, all EMU stock markets started to see the light in the tunnel and entered into the bull period almost at the same time, though the economy of most countries was still sluggish. The exception here is the Austria market. Being the gate from the western Europe to the Eastern Europe, Austria enjoyed strong growth in export and inwards investment from 2000 to 2005, which made it being

the first EMU country leaving the bear period as early as in the beginning of 2002.

In most of the EMU countries, the bull period lasted for about 4 years, until the beginning of 2007, when the housing bubble burst and the sub-prime crisis sparked. The EMU countries then dived into the bear market at the same time again with the exception of Finland , Germany and Portugal , which delayed a couple of months. The reason could be that at the beginning of the sub-prime crisis, the market under-estimated its damage, and believed that some European countries which had better economic performance, better risk control and less speculation in the sub-prime mortgage market, could immunize from the crisis. Germany was a typical example.

Finally, the difference between all parameters in both regimes and their respective standard deviations are shown in Table 4. Besides the parameters representing the response of the market to market news, the differences between parameters are all statistically significant at a 1% significance level. This confirms that the bear and the bull market exist in the EMU stock markets. The estimated persistence for the regime i is $1/\epsilon_i$ for $i = 1, 2$. Regime 1 has a averaged persistence of 74,6 weeks, while Regime 2 has a averaged persistence of 117,6 weeks. This is consistent with findings from Napolitano (2006) and Chen (2007) which report that both bull markets and bear markets display persistent but the bear market is less persistent.

4.2.4 The impact of the short term interest rate on the EMU stock markets

We examine the impact of the short term interest rate by estimating the EMS GJR-M model as specified in equation (4). We are particularly interested in studying if the increase in interest rates have an additional effect on stock returns and the volatility and whether the effect varies in the bull and bear markets.

The full results of the interest rate impact on the EMU stock markets are presented in Table 5. The estimated parameters from the EMS GJR-M model are not quite different from the ones estimated from the MSGJR-M model, and the characteristics of both regimes are maintained. We find that the relationship between returns and the volatility remains largely unchanged in the EMU countries. The negative and significant parameter β_1 in most of the EMU stock markets implies that returns are negatively correlated with the volatility in regime 1, and the coefficient β_2 is positive and significant in majority of the EMU countries implying a positive relationship between returns and volatility in regime 2. The intercept of the volatility equation in regime 1 and regime 2 (α_{10} and α_{20}) indicates that the volatility is higher in regime 1 than in

regime 2. Therefore, the results provide strong evidence in favor of two states, a high mean low volatility state (bull market) and a low mean high volatility state (bear market) in the EMU stock markets. The coefficients α_{11} and α_{21} indicate that the volatility in the bull market is more persistent than in the bear market. However, the parameter of the innovations in both regimes (α_{12} and α_{22}) is insignificantly different from zero. This does not mean that market news has no effect on current volatility. If we look at the parameters α_{13} and α_{23} , we can find that market news influences the volatility through the leverage effect. The coefficient α_{23} is significant in most of the EMU countries (besides Finland, Spain, and Austria). The parameter α_{13} is significant in half of the EMU countries. Moreover, $\alpha_{13} > \alpha_{23}$ implies that the leverage effect of the bad news is much stronger in bear markets than in bull markets. For example, in Belgium, this additional effect is about 8 times larger in regime 1 than in regime 2.

Holding the transition probability constant, the interest rate fluctuations affect the equity returns via changes in the volatility. The parameters α_{i4} and α_{i5} , for $i=1,2$, indicate the interest rates impact on the EMU stock market volatility in bull markets and bear markets, respectively. If the parameters α_{i4} are significantly different from zero then changes in EURIBOR rates affect the conditional variance. Meanwhile, if the parameters α_{i5} are significantly different from zero, then an increase in interest rates causes an additional effect on the volatility by an amount of $\alpha_{i5}\chi_{t-1}^2$. It can be seen from Table 5 that the parameter α_{24} is in small value and is insignificant at the 5% level in most of the EMU countries. The parameter α_{14} is significant in most of the EMU countries (besides Belgium). This indicates that the change in interest rates has a much stronger effect on volatility in the bear market (low mean, high volatility state) than in bull market (high mean, low variance state). We find also that α_{15} is significant at the 5% level in all countries (in Germany, Italy, Spain, and Netherlands, it is even significant at the 1% level) and that α_{25} is only weakly significant in three countries (e.g., Finland, Belgium, and Portugal). This indicates that an increase in interest rates has an additional effect on current volatility and this effect is also much stronger in the bear market than in the bull market in most of the EMU stock markets. This result is in contrast to the finding from Domain et al. (1996) which report that drops in interest rates are followed by large positive stock returns while increases in interest rates have little effects. Our finding is generally consistent with the result from Perez-Quiros & Timmermann (2000, 2001), Basistha & Kurov (2008), Chen (2007), and Henry (2009). For example, Perez-Quiros & Timmermann (2000) find that the interest rate

can affect the conditional variance only in the low mean high volatility regime for large firms. Henry (2009) also reports that the relationship between short term interest rate changes and the equity volatility in the UK stock market is regime dependent, the effect of the interest rates in the bear market is higher than in the bull market. Basistha & Kurov (2008) show that the size of the response of stock returns to monetary shocks is more than twice as large in recessions and tight credit conditions as in good economic times. The reason of this phenomenon can be that during the bull period, the market confidence is high, and more investors believe in the market itself rather than the information, especially the information from other markets. This makes the market reluctant to response to the change in short term interest rates. While during the bear period, the market becomes nervous and more volatile, and the volatility becomes more sensitive towards to both information from the stock market and other markets, and therefore the stock market responses to the change in interest rates. Theoretically, according to recent models with agency costs of financial intermediation (finance constraint), people show that when there is information asymmetry in financial markets, agents may behave as if they are constrained financially. Moreover, the financial constraint is more likely to bind in bear markets (see, e.g., Gertler 1988, Bernanke & Gertler 1989, Kiyotaki & Moore 1997, Garcia & Schaller 2002). Therefore, a change in short term interest rates may have greater effect in bear markets than in bull markets.

Further, in an influential study, Gerlach & Smets (1995) conclude that the effects of monetary policy shocks are somewhat larger in Germany than in France or Italy. Clements et al. (2001) have also argued that output in Germany and France is more affected by monetary shocks than in either Spain or Italy. Contrary to results from these studies, the result from our study suggests that monetary policy is equally transmitted across the EMU stock markets, this may be the reason of the launching of Euro which makes the EMU stock markets more integrated than ever.

Finally, we check the goodness-of-fit of the EMS GJR-M model. It can be seen in the last column of Table 6, the goodness-of-fit indicators (MSE, MAE and AIC) suggest that obtaining the interest rates impact information, the EMS GJR-M model improves the performance and fundamental results of the MS GJR-M model in most EMU stock markets.

4.2.5 Asymmetric effects of bad news and increases in interest rates: the news impact surface

In this section we investigate the asymmetric news effects (returns residuals) and the asymmetric effect of the changes in short term interest rates on volatility by extending the News Impact Curve (NIC), introduced by Pagan & Schwert (1990) and christened by Engle & Ng (1993). This NIC shows the implied relationship between the lagged shock from returns and the volatility. We extend the news impact curve into the news impact surface, in which the conditional variance is evaluated at the level of unconditional variance of stock returns, the shock from conditional returns, and the change in interest rates. The news impact surface of the EMS GJR-M model illustrates the asymmetric effect of the stock market news and of the changes in interest rates on the volatility process. It has the following specification,

$$\begin{aligned}
 h_t &= A + \alpha_{i2}\epsilon_{t-1}^2 + \alpha_{i4}\chi_{t-1}^2, & \text{for } \epsilon_{t-1} > 0 \text{ and } \chi_{t-1} < 0, \\
 h_t &= A + (\alpha_{i2} + \alpha_{i3})\epsilon_{t-1}^2 + (\alpha_{i4} + \alpha_{i5})\chi_{t-1}^2, & \text{for } \epsilon_{t-1} < 0 \text{ and } \chi_{t-1} > 0, \\
 h_t &= A + \alpha_{i2}\epsilon_{t-1}^2 + (\alpha_{i4} + \alpha_{i5})\chi_{t-1}^2, & \text{for } \epsilon_{t-1} > 0 \text{ and } \chi_{t-1} > 0, \\
 h_t &= A + (\alpha_{i2} + \alpha_{i3})\epsilon_{t-1}^2 + \alpha_{i4}\chi_{t-1}^2, & \text{for } \epsilon_{t-1} < 0 \text{ and } \chi_{t-1} < 0.
 \end{aligned} \tag{19}$$

where $A = \alpha_{i0} + \alpha_{i1}\sigma^2$, σ^2 is the unconditional return variance, α_{ij} ($i = 1, 2, j = 1, 2, \dots, 5$) is the parameter from the estimated EMS GJR-M model, ϵ_{t-1} is the unpredictable return at time $t - 1$, and χ_{t-1} is the change in interest rates. The original news impact curve of the GJR model from Engle & Ng (1993) does not demonstrate shocks from interest rates and does not distinguish the shocks in the bull and the bear market.

Figure 3 plots the news impact surface of the Germany stock market. Values on X-axis indicate the change in interest rates, values on Y-axis indicate shocks from conditional returns, and values on Z-axis indicate the level of the volatility. The left plot is the news impact surface of Germany stock market in the bear market, and the right one plots the news impact surface of Germany stock market in the bull market. If we let the values on X-axis to be constant, then the change in values on Z-axis with respect to the change in values on Y-axis shows how the conditional volatility changes with respect to the change in market news. We find that the volatility is getting higher when the value on the Y-axis is changing towards the more negative values, and this is more obvious in the left plot than in the right one. This is consistent with

our result in the previous section that negative news has an asymmetric effect on the volatility in both bear markets and bull markets, however, this effect is higher in the bear market than in the bull market in the German stock market. If we let values on Y-axis to be constant, then the change in values on Z-axis with respect to the change in values on X-axis shows how the conditional volatility changes with respect to the change in interest rates. We find that the volatility is getting higher when the value on X-axis is changing towards the more positive values, and this situation can only be obviously found in the left plot (the bear market). This is consistent with our result that a rise in interest rates increases the volatility more than a fall in interest rates. The effect is much more stronger in the bear market than in the bull market in the German stock market.

We show the asymmetrical effect of shocks from unexpected returns and from the changes in the interest rates on all EMU stock return volatility in Figure 4, where we contour plot the news impact surface of each EMU stock market. Values on X-axis indicate the change in interest rates and values on Y-axis indicate shocks from conditional returns. The color indicates the level of the volatility, the higher the volatility, the brighter its color. The first and third columns plot the news impact curve contours in the bear market, while the second and fourth columns are contour plots of the news impact surface in the bull market. By looking at the Y-axis in the bear market in each EMU country, we find that the slope of the negative side (the left bottom corner) is much sharper and the color is much brighter than the one of the positive side (the left top corner). However, in the bull market, the slope of the negative side of the Y-axis (the left bottom corner) is only slightly sharper than the one of the positive side (the left top corner). This is consistent with our result that the bad news effect on the volatility is larger than good news in most of the EMU stock markets, and such an impact is also larger in the bear market than in the bull market. On the other hand, by looking at the X-axis in the bear market in each EMU stock market, we can see that the news impact surface captures the asymmetrical effect of the changes in interest rate on the volatility because it has a steeper slope and brighter color at the positive side (the right bottom corner where the interest rate moves upward) than the negative side (the left bottom corner where the interest rate follows downward market movements). However, we can only observe this situation in the bear market because in the bull market, the volatility is symmetrically centered at zero on the X-axis in nearly all of the EMU stock markets (besides Portugal). This again confirms our result that an increase in

short term interest rates has extremely larger impact on the stock volatility than a decrease in short term interest rates, and the impact is much stronger during bear periods than during the bull periods in most of the EMU markets.

4.2.6 Implications of the interest rates impacts on stock markets

To explain why the interest rate can affect the equity market, we resort to the Discounted Cash Flow (DCF) model, which is pioneered by Williams (1938). The DCF model views the intrinsic value of the common stock as the present value of its expected future cash flow. The expected future cash flow is often represented by the expected dividend, which is known as a DDM model (Dividend-Distribution Model). When interest rates change, first, the expected return need to be discounted with a different rate; second, the firms' future costs to conduct business are changed. These will ultimately affect the firms' expected profitability and adjust market expectations of the firms' abilities to pay a dividend. Furthermore, by changing the value of expected future cash flows, interest rates movements change the level of real activity in the economy in the medium and long term. Campbell & Ammer (1993) decompose the variance of unexpected excess returns implied by the dividend discount model into three factors, news about future dividends, news about future interest rates, and news about future excess returns, and predict that fluctuations to interest rates should cause equity prices to move and may also result in changes to the variance of equity returns. However, the result from Henry (2009) suggests that there is no direct influence of events in the money market on the conditional mean of returns in the UK stock market. Our results suggest that the influence of interest rate market on the conditional mean of stock returns is via the conditional variance because the conditional return and the volatility is negatively related in the bear market and positively related in the bull market. Therefore, the findings of the interest rates impacts from the proposed EMS GJR-M model in our paper support that the interest rate significantly affects stock returns and volatility and confirm the implication of the DCF model.

The empirical results from our paper have important implications for portfolio selection, asset pricing and risk management. For instance, as implied by the news impact surface, there are significant asymmetric effects of the news and the changes in interest rates on the EMU stock market, after a major impact from the money market, the predictable market volatilities given by the EMS GJR-M model and other models such as a standard GJR model or a GJR-M

model are very different, this may lead to a significant difference in current option price, portfolio selection, and dynamic hedging strategies.

To further demonstrate the importance of the interest rates impact when modeling the volatility dynamics, we apply various models to a portfolio choice problem under two scenarios, i.e., portfolio choices without and with the short selling constraints.⁹ We assume that an investor holds a portfolio consists of two stocks of German DAX and France CAC40 (risky assets) and that the investor tries to maximize the expected utility function within the mean-variance framework from Best & Grauer (1990),

$$\max \left\{ \lambda \mathbf{w}'\boldsymbol{\mu} - \frac{1}{2} \mathbf{w}'V\mathbf{w} \mid \mathbf{w}'I = 1 \right\}, \quad (20)$$

where \mathbf{w} is the vector of weights invested in risky assets, V is the variance-covariance matrix of the asset returns, $\boldsymbol{\mu}$ is the vector of the asset returns, λ is the risk aversion coefficient. The purpose is to find out the optimum weights of the assets in the portfolio which maximize the utility function. It has been confirmed that investment weights are very sensitive to the first two conditional movements of the risky asset returns (see, e.g., Best & Grauer 1990, 1991, Fleming et al. 2001). So the model that can better forecast the conditional mean and variance can provide better performance. Further, as the risk aversion coefficient also affects the weight of risky assets, we examine the portfolio performance with different risk aversion coefficients. The robustness of the empirical findings in the investment performance can be confirmed if similar results can be obtained under different risk aversion coefficients. Finally, we compute the optimum weights based on the out-of-sample forecasted conditional mean and variance of the German DAX and the France CAC40. The average returns of the portfolio and the Sharpe Ratio will be also calculated according to different risk aversion coefficients and are used to measure the forecasted portfolio performance.

The result of the portfolio performance are reported in Table 7. Panel 1 shows results from the unrestricted strategy, while panel 2 shows results from the restricted strategy. It is clear that among different models, the EMS GJR-M model provides the best investment performance in terms of the averages returns and sharp ratios. This is not surprising because the EMS GJR-M model yields a more accurate volatility forecast than other models in the out-of-sample forecast. This is evidenced in Figure 5 which plots the true volatility proxy and the out of

⁹In the case that the short selling strategy is not allowed, the investment weight is between 0 and 1

sample forecasted volatility of various models in the Germany DAX and the France CAC. The solid lines are the estimated volatility from various models, and the dashed lines are the true volatility which is proxied by the absolute values of the returns. We can observe that the volatility estimated from the EMS GJR-M model is more close to the true volatility proxy and can better describe the dynamics of the DAX and the CAC return variance compared with the MS GJR-M, the GJR-M, and the GJR models.

On the other hand, it is worth noting that the sharp ratio of the non-regime switching models declines in large amount compared to the regime switching models. Among the non-regime switching models, the GJR-M model dominates the GJR model in the unrestricted scenario. These results provide credible evidence that the short term interest rate effect, the regime switching, and the GARCH in mean effects play important role in modeling the dynamics of the EMU stock markets' returns and variance. Only models incorporate these effects can offer more accurate results of the conditional mean and conditional variance. We can observe that the portfolios volatility of the GJR-M and the GJR models are much less volatile due to the ignorance of the short term interest rates and regime switching, and consequently result in poor out-of-sample predictive portfolio performance. The poor forecasted portfolio performance from such models will definitely affect the investor's portfolio choice and risk management strategy.

5 Conclusion

The DCF (Discounted Cash Flow) model provides the theoretical background for the possible impact of interest rate changes on equity prices. With the increased use of short term interest rates rather than measures of money supply as intermediate targets for monetary policy, many studies have examined the impact of the interest rate market on the stock market. Unfortunately, most of the studies examine the interest rates impact on the US stock market and heavily consider the effect of changes in interest rates on stock prices and returns. This paper investigates the spillover effect of interest rate movements on stock markets in the Euro area, which has received surprisingly few attentions. Departing from the most previous works examining the effect of interest rates only on stock returns, we analyze the potential impact of short term interest rates surprises on both stock returns and the volatility of stock returns. We pay particularly more attention on the asymmetric effect of an increase in interest rates on the EMU stock markets in different market regimes, such as bull and bear markets. The empirical study is carried out by

estimating the EMS GJR-M and MS GJR-M model with a Monte Carlo Markov Chain method, which enjoys several advantages compared with the traditional Maximum likelihood method.

Empirical results suggest that two significant regimes exist in the EMU stock markets, i.e., a high mean low variance regime (bear market) and a low mean high variance regime (bull market). The relationship between the conditional mean and variance is time varying. They are positively correlated during bull periods, and negatively correlated during bear periods. Furthermore, the short term interest rates affect the stock returns and volatility in the EMU countries, this effect is extremely stronger in the bear market than in the bull market in most of the EMU countries, and the impact of an increase in interest rates has a larger effect on the EMU stock returns and the volatility than a drop in ones. It is also confirmed in the out-of-sample forecasted portfolio performance, that the EMS GJR-M model can better describe the volatility dynamics and provide more powerful portfolio performance prediction than the models without the interest rate impact and the regime switching. Our results are of importance not only to the policymaker anticipating the market response to the announced and implemented policies, but also to financial market participants making effective investment decisions and formulating appropriate risk management strategies.

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6 Tables

Table 1: Estimated Parameters from the Monte Carlo Simulation

	β_1	β_2	α_{10}	α_{20}	α_{11}	α_{21}	α_{12}	α_{22}	α_{13}	α_{23}	e_1	e_2
True	0.2000	0.6000	0.1000	0.2000	0.4000	0.5000	0.2000	0.2500	0.1000	0.1500	0.0200	0.0100
Mean	0.2106	0.5678	0.1103	0.1859	0.4104	0.5139	0.2124	0.2445	0.0941	0.1531	0.0149	0.0119
RMSE	0.0169	0.0173	0.0132	0.0122	0.0130	0.0302	0.0338	0.0115	0.0092	0.0030	0.0038	0.0047

Notes: the RMSE is the square root of the mean squared errors between the true and estimated parameters from all data sets

Table 2: Descriptive statistics on weekly returns in the EMU stock markets: from 1 January 1999 to 20 July 2009 (557 weekly observations)

	MEAN	STD	Skewness	Kurtosis	ADF test	JB test
DAX	-0.0044	0.2522	-0.6426	8.0147	-24.0798	0.0010
CAC40	-0.0035	0.2131	-0.8192	8.0416	-24.2817	0.0010
FTSEMIB	-0.0085	0.2310	-1.1698	12.9241	-23.5707	0.0010
IBEX35	-0.0003	0.2177	-1.1080	10.6583	-25.5623	0.0010
HEX25	0.0005	0.2556	-0.7829	6.3504	-23.2265	0.0010
ISEQ	-0.0086	0.2417	-1.9024	18.4048	-24.6172	0.0010
AEX	-0.0093	0.2432	-1.2709	12.6130	-23.4344	0.0010
ATX	0.0079	0.2394	-2.2525	24.8953	-23.5760	0.0010
BEL20	-0.0067	0.2163	-1.4305	13.9584	-23.0917	0.0010
PSI20	-0.0063	0.1815	-1.3557	12.2722	-22.6216	0.0010

Notes:

- 1.The ADF test is the augmented Dicky Fuller test and the test statistics are reported.
- 2.The JB test is the normality Jarqua Bera test and the p-values are reported.

Table 3: Estimated parameters from the MS GJR-M model

Index	Return Equation		Volatility Equation								Transition Prob.		LBTest Q(20)
	β_1	β_2	Intercept		Persistence		Response to News		Additional Response to Bad News		e_1	e_2	
DAX	-0.2746 (0.1289) **	0.0461 (0.0226) **	0.0769 (0.0153) ***	0.0042 (0.0018) **	0.2630 (0.1573) *	0.7150 (0.0645) ***	0.1260 (0.1287)	0.0686 (0.0384) *	0.3858 (0.0582) ***	0.1829 (0.0652) ***	0.0358 (0.0094) ***	0.0106 (0.0053) **	0.5613
CAC40	-0.0789 (0.0533)	0.2632 (0.0834) ***	0.0121 (0.0010) ***	0.0006 (0.0004) *	0.5676 (0.0364) ***	0.7838 (0.0641) ***	0.0326 (0.0317)	0.0832 (0.0569)	0.3409 (0.0581) ***	0.0917 (0.0571)	0.0122 (0.0056) **	0.0199 (0.0062) ***	0.9045
FTSEMIB	-0.1396 (0.0577) **	0.1193 (0.0616) *	0.0236 (0.0047) ***	0.0006 (0.0002) ***	0.1842 (0.0961) *	0.7984 (0.0390) ***	0.1064 (0.0804)	0.1221 (0.0369) ***	0.6018 (0.1313) ***	0.0612 (0.0326) *	0.0132 (0.0070) *	0.0110 (0.0063) *	0.6084
IBEX35	-0.1735 (0.0687) **	0.2439 (0.0781) ***	0.0133 (0.0035) ***	0.0005 (0.0002) ***	0.7177 (0.0653) ***	0.8429 (0.0538) ***	0.0265 (0.0238)	0.0470 (0.0377)	0.1413 (0.0613) **	0.0768 (0.0391) **	0.0432 (0.0199) **	0.0400 (0.0224) *	0.2582
HEX25	-0.2312 (0.0906) **	0.2089 (0.0672) ***	0.0536 (0.0232) **	0.0017 (0.0009) *	0.3843 (0.1771) **	0.7839 (0.0488) ***	0.0587 (0.0578)	0.1437 (0.0399) ***	0.3002 (0.1532) *	0.0265 (0.0240)	0.0442 (0.0181) **	0.0238 (0.0085) ***	0.3058
AEX	-0.1129 (0.0606) *	0.0648 (0.0644)	0.0078 (0.0033) **	0.0028 (0.0017) *	0.7060 (0.0900) ***	0.6847 (0.1056) ***	0.0350 (0.0347)	0.1042 (0.0834)	0.2231 (0.0833) ***	0.1938 (0.0931) **	0.0349 (0.0088) ***	0.0344 (0.0089) ***	0.7190
ISEQ	-0.2346 (0.0970) **	0.1328 (0.0575) **	0.0175 (0.0044) ***	0.0005 (0.0001) ***	0.4750 (0.0639) ***	0.8903 (0.0332) ***	0.0608 (0.0654)	0.0521 (0.0321)	0.3724 (0.1106) ***	0.0365 (0.0233)	0.0613 (0.0184) ***	0.0353 (0.0149) ***	0.7050
ATX	-0.1497 (0.0902) *	0.2552 (0.0767) ***	0.0101 (0.0047) **	0.0017 (0.0008) **	0.5150 (0.1137) ***	0.7361 (0.0710) ***	0.0739 (0.0616)	0.2151 (0.0838) **	0.3604 (0.1265) ***	0.0272 (0.0301)	0.0423 (0.0088) ***	0.0368 (0.0079) ***	0.8360
BEL20	-0.1777 (0.0652) ***	0.2108 (0.0701) ***	0.0151 (0.0070) **	0.0004 (0.0001) ***	0.4611 (0.1559) ***	0.8551 (0.0417) ***	0.0421 (0.0385)	0.0765 (0.0415) *	0.4434 (0.1335) ***	0.0343 (0.0277)	0.0345 (0.0086) ***	0.0333 (0.0087) ***	0.7282
PSI20	-0.3229 (0.0891) ***	0.2492 (0.0749) ***	0.0155 (0.0035) ***	0.0004 (0.0001) **	0.1858 (0.1326) ***	0.8522 (0.0316) ***	0.0929 (0.0853)	0.1132 (0.0322) ***	0.6177 (0.1516) ***	0.0151 (0.0144)	0.0372 (0.0085) ***	0.0310 (0.0093) ***	0.1463

Notes:

- 1.*** , ** , and * denote significance at 1% , 5% , and 10% levels respectively.
- 2.Values in parentheses under the estimates indicate standard errors.
- 3.The sample period is from 1 January 1999 to 20 July 2009 (557 weekly observations).
- 4.Q(20) is the Ljung-Box test statistic of the standard residuals of order 20 (p-value reported).

Table 4: Parameter differences between bull and bear markets

Index	Return	Intercept	Persistence	Response to News	Additional Response to Bad News
	β	α_0	α_1	α_2	α_3
DAX	-0.3208 (0.1374) **	0.0727 (0.0154) ***	-0.4520 (0.1700) ***	0.0575 (0.1343)	0.2029 (0.0874) **
CAC40	-0.3421 (0.0990) ***	0.0114 (0.0011) ***	-0.2162 (0.0737) ***	-0.0506 (0.0651)	0.2492 (0.0815) ***
FTSEMIB	-0.2588 (0.0844) ***	0.0230 (0.0047) ***	-0.6141 (0.1037) ***	-0.0157 (0.0885)	0.5405 (0.1353) ***
IBEX35	-0.4173 (0.1040) ***	0.0127 (0.0035) ***	-0.1253 (0.0846)	-0.0205 (0.0446)	0.0646 (0.0727)
HEX25	-0.4402 (0.1128) ***	0.0519 (0.0232) **	-0.3996 (0.1837) **	-0.0850 (0.0703)	0.2737 (0.1551) *
AEX	-0.1777 (0.0884) **	0.0050 (0.0037)	0.0213 (0.1387)	-0.0692 (0.0903)	0.0293 (0.1249)
ISEQ	-0.3675 (0.1127) ***	0.0170 (0.0044) ***	-0.4153 (0.0720) ***	0.0087 (0.0729)	0.3360 (0.1130) ***
ATX	0.4048 (0.1184) ***	0.0084 (0.0048) *	0.2210 (0.1340) *	0.1412 (0.1040)	0.3333 (0.1301) **
BEL20	0.3885 (0.0957) ***	0.0147 (0.0070) **	0.3940 (0.1614) **	0.0344 (0.0566)	0.4092 (0.1364) ***
PSI20	0.5721 (0.1164) ***	0.0151 (0.0035) ***	0.6664 (0.1364) ***	0.0203 (0.0912)	0.6026 (0.1523) ***

Notes:

1. ***, **, and * denote significant at the level of 1% , 5% , and 10%, respectively.
2. Values in parentheses under the estimates indicate standard errors.
3. All parameters are estimated from the MS GJR-M model.

Table 5: Estimated parameters from the MS GJR-M model with the interest rate impact

Index	Return equation		Volatility Equation												Transition Prob.	
	β_1	β_2	Intercept		Persistence		Response to News		Additional Response to bad news		Response to Interest Rates		Additional Response to Increased Interest Rates		e_1	e_2
DAX	-0.1573 (0.0793) **	0.0995 (0.0821)	0.0309 (0.0134) **	0.0041 (0.0021) *	0.3387 (0.1908) *	0.6449 (0.1076) ***	0.0710 (0.0757)	0.0540 (0.0486)	0.4021 (0.1860) **	0.2360 (0.0839) ***	0.1747 (0.0804) **	0.0331 (0.0224)	0.2085 (0.0698) ***	0.0346 (0.0258)	0.0379 (0.0082) ***	0.0288 (0.0091) ***
CAC40	-0.2080 (0.0751) ***	0.2254 (0.0775) ***	0.0247 (0.0076) ***	0.0007 (0.0005)	0.2288 (0.1658)	0.7398 (0.0625) ***	0.0425 (0.0413)	0.0706 (0.0566)	0.4727 (0.1678) ***	0.1450 (0.0686) **	0.1470 (0.0792) *	0.0290 (0.0216)	0.1854 (0.0825) **	0.0388 (0.0241)	0.0424 (0.0063) ***	0.0389 (0.0078) ***
FTSEMB	-0.1074 (0.0516) **	0.0746 (0.0489)	0.0246 (0.0088) ***	0.0005 (0.0004)	0.2463 (0.1591)	0.8343 (0.0524) ***	0.1145 (0.1115)	0.0569 (0.0394)	0.4565 (0.1896) **	0.0835 (0.0519)	0.1361 (0.0485) ***	0.0220 (0.0129) *	0.1387 (0.0484) ***	0.0183 (0.0128)	0.0623 (0.0184) ***	0.0312 (0.0111) ***
IBEX35	-0.2165 (0.0855) **	0.1838 (0.0621) ***	0.0207 (0.0090) **	0.0008 (0.0007)	0.4118 (0.1811) **	0.8059 (0.0690) ***	0.0623 (0.0592)	0.0522 (0.0357)	0.2186 (0.1378)	0.1125 (0.0704)	0.2082 (0.0684) ***	0.0174 (0.0146)	0.2297 (0.0605) ***	0.0279 (0.0224)	0.0419 (0.0064) ***	0.0317 (0.0089) ***
HEX25	-0.2642 (0.0956) ***	0.1589 (0.0597) ***	0.0580 (0.0377)	0.0026 (0.0014) *	0.4295 (0.2823)	0.7456 (0.0711) ***	0.0538 (0.0568)	0.1071 (0.0496) **	0.1472 (0.1388)	0.0700 (0.0520)	0.1758 (0.0826) **	0.0367 (0.0250)	0.1871 (0.0810) **	0.0501 (0.0280) *	0.0401 (0.0070) ***	0.0219 (0.0080) ***
AEX	-0.1149 (0.0613) *	0.1306 (0.0611) **	0.0154 (0.0079) *	0.0012 (0.0007)	0.5605 (0.1393) ***	0.7656 (0.0619) ***	0.0791 (0.0748)	0.0350 (0.0295)	0.2777 (0.1306) **	0.1556 (0.0624) **	0.1045 (0.0569) *	0.0221 (0.0125) *	0.1432 (0.0455) ***	0.0192 (0.0136)	0.0545 (0.0202) ***	0.0446 (0.0152) ***
ISEQ	-0.2543 (0.1039) **	0.1041 (0.0703)	0.0298 (0.0148) **	0.0015 (0.0012)	0.4203 (0.1584) ***	0.7666 (0.0733) ***	0.0794 (0.0740)	0.0418 (0.0352)	0.3359 (0.1515) **	0.1496 (0.0651) **	0.1750 (0.0810) **	0.0236 (0.0155) **	0.2208 (0.0660) ***	0.0201 (0.0172)	0.0413 (0.0068) ***	0.0289 (0.0092) ***
ATX	-0.1899 (0.1031) *	0.2072 (0.0660) ***	0.0247 (0.0194)	0.0061 (0.0030) **	0.3674 (0.1529) **	0.5517 (0.1569) ***	0.1792 (0.1377)	0.0695 (0.0592)	0.2909 (0.1935)	0.1832 (0.0954) *	0.1806 (0.0638) ***	0.0209 (0.0191)	0.1818 (0.0653) ***	0.0190 (0.0209)	0.0403 (0.0063) ***	0.0252 (0.0086) ***
BEL20	-0.1075 (0.0673)	0.1446 (0.0662) **	0.0209 (0.0091) **	0.0005 (0.0003)	0.3488 (0.2004) *	0.8220 (0.0528) ***	0.0486 (0.0514)	0.0651 (0.0418)	0.4825 (0.1870) ***	0.0571 (0.0427)	0.0810 (0.0574)	0.0203 (0.0131)	0.1108 (0.0560) **	0.0235 (0.0138) *	0.0675 (0.0174) ***	0.0447 (0.0135) ***
PSI20	-0.3200 (0.0942) ***	0.2053 (0.0609) ***	0.0161 (0.0033) ***	0.0003 (0.0000) ***	0.1629 (0.1034)	0.8978 (0.0287) ***	0.0765 (0.0672)	0.0347 (0.0316)	0.5371 (0.1722) ***	0.0148 (0.0138)	0.1712 (0.0863) **	0.0103 (0.0085)	0.1915 (0.0763) **	0.0516 (0.0207) **	0.0332 (0.0094) ***	0.0239 (0.0085) ***

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels respectively. Values in parentheses under the estimates indicate standard errors.

Table 6: The goodness-of-fit of various models

MSE					
Index	GARCH	GJR	GJR-M	MSGJR-M	MSGJR-M with interest impact
DAX	0.0279	0.0266	0.0247	0.0241	0.0237
CAC40	0.0240	0.02261	0.0226	0.0212	0.0207
FTSEMIB	0.0275	0.0261	0.0252	0.0232	0.0216
IBEX35	0.0228	0.0226	0.0216	0.0195	0.0191
HEX25	0.0310	0.0311	0.0307	0.0293	0.0277
AEX	0.0297	0.0320	0.0320	0.0263	0.0261
ISEQ	0.0319	0.0295	0.0274	0.0290	0.0295
ATX	0.0332	0.0300	0.0338	0.0315	0.0300
BEL20	0.0269	0.2671	0.0241	0.0224	0.0230
PSI20	0.0190	0.0187	0.0179	0.0160	0.0161

MAE					
Index	GARCH	GJR	GJR-M	MSGJR-M	MSGJR-M with interest impact
DAX	0.1248	0.1206	0.1171	0.1144	0.1157
CAC40	0.1177	0.1126	0.1128	0.1091	0.1077
FTSEMIB	0.1158	0.1134	0.1096	0.1060	0.1035
IBEX35	0.1126	0.1110	0.1097	0.1030	0.1032
HEX25	0.1328	0.1327	0.1298	0.1275	0.1268
AEX	0.1200	0.1229	0.1206	0.1101	0.1103
ISEQ	0.1240	0.1151	0.1112	0.1177	0.1184
ATX	0.1211	0.1194	0.1195	0.1143	0.1106
BEL20	0.1173	0.1141	0.1076	0.1060	0.1096
PSI20	0.0975	0.1016	0.0982	0.0933	0.0930

AIC					
Index	GARCH	GJR	GJR-M	MSGJR-M	MSGJR-M with interest impact
DAX	-1978.8	-2005.5	-2043.1	-2046.7	-2050.2
CAC40	-2062.5	-2095.1	-2092.5	-2119.0	-2124.8
FTSEMIB	-1986.7	-2016.03	-2033.0	-2068.5	-2101.5
IBEX35	-2091.0	-2095.1	-2119.5	-2166.3	-2171.5
HEX25	-1919.5	-1917.0	-1923.8	-1939.4	-1965.1
AEX	-1943.2	-1902.4	-1900.3	-1998.5	-2002.5
ISEQ	-1903.5	-1948.23	-1985.6	-1945.4	-1936.2
ATX	-1881.4	-1854.5	-1870.4	-1898.2	-1919.5
BEL20	-1997.7	-2002.49	-2056.8	-2088.1	-2067.7
PSI20	-2191.1	-2200.34	-2229.0	-2273.4	-2265.5

Table 7: Asset allocation performance results

	lambda=20	lambda=10	lambda=5	lambda=1
Panel 1: Unrestricted Strategy				
(A) Mean				
MS GJR-M with Interest	0.8652	0.4364	0.2220	0.0505
MS GJR-M	0.6825	0.3432	0.1736	0.0379
GJR-M	0.0004	-0.0003	-0.0012	-0.0029
GJR	0.0010	0.0006	0.0000	-0.0012
(B) Volatility				
MS GJR-M with Interest	3.5346	1.7748	0.8965	0.2092
MS GJR-M	3.0703	1.5263	0.7726	0.1635
GJR-M	0.5430	0.3782	0.1552	0.0613
GJR	0.2340	0.1553	0.0815	0.0635
(C) Sharp Ratio				
MS GJR-M with Interest	0.1817	0.1810	0.1782	0.1556
MS GJR-M	0.1450	0.1442	0.1421	0.1032
GJR-M	-0.0078	-0.0156	-0.0361	-0.1442
GJR	-0.0240	-0.0318	-0.0679	-0.1648
Panel 2: Restricted Strategy				
(A) Mean				
MS GJR-M with Interest	0.0093	0.0093	0.0093	0.0088
MS GJR-M	0.0031	0.0031	0.0031	0.0031
GJR-M	0.0008	0.0008	0.0008	0.0006
GJR	0.0013	0.0012	0.0012	0.0012
(B) Volatility				
MS GJR-M with Interest	0.1075	0.1055	0.1045	0.0968
MS GJR-M	0.0935	0.0935	0.0935	0.0935
GJR-M	0.1083	0.1082	0.1056	0.1021
GJR	0.1801	0.1778	0.1765	0.1756
(C) Sharp Ratio				
MS GJR-M with Interest	0.0456	0.0453	0.045	0.0410
MS GJR-M	-0.0127	-0.0127	-0.0127	-0.0127
GJR-M	-0.0396	-0.0396	-0.0410	-0.0431
GJR	-0.0184	-0.0191	-0.0198	-0.0198

7 figures

Figure 1: Estimate results for simulated Data

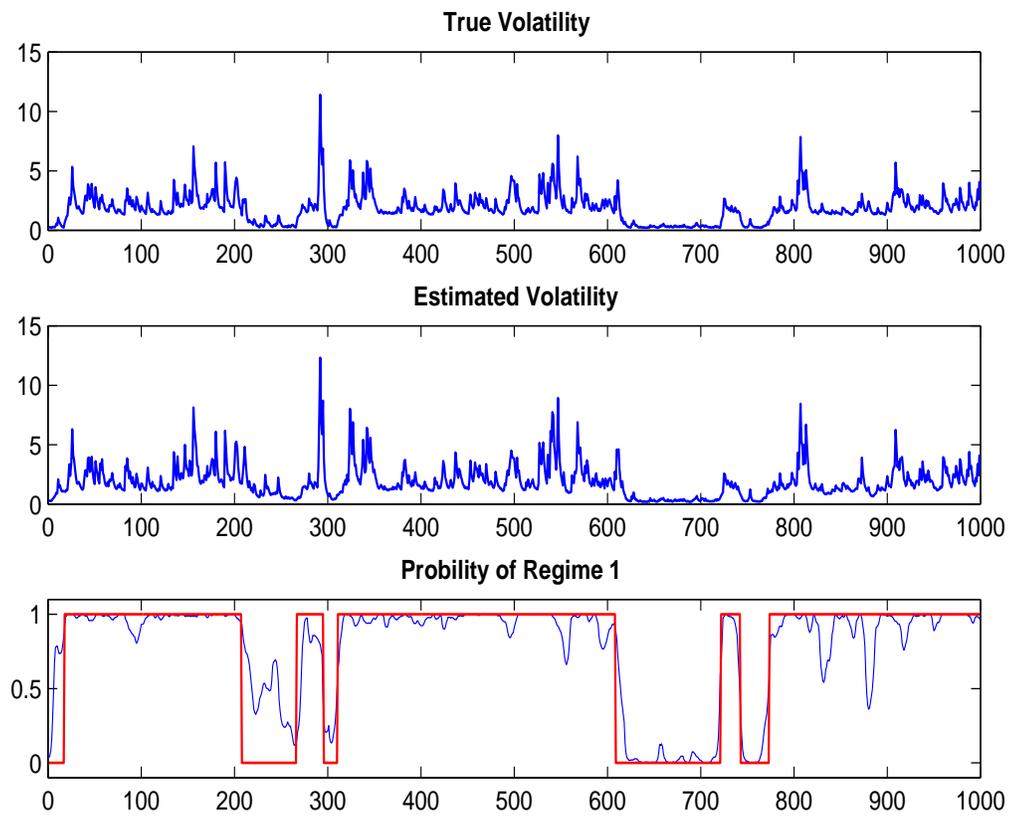
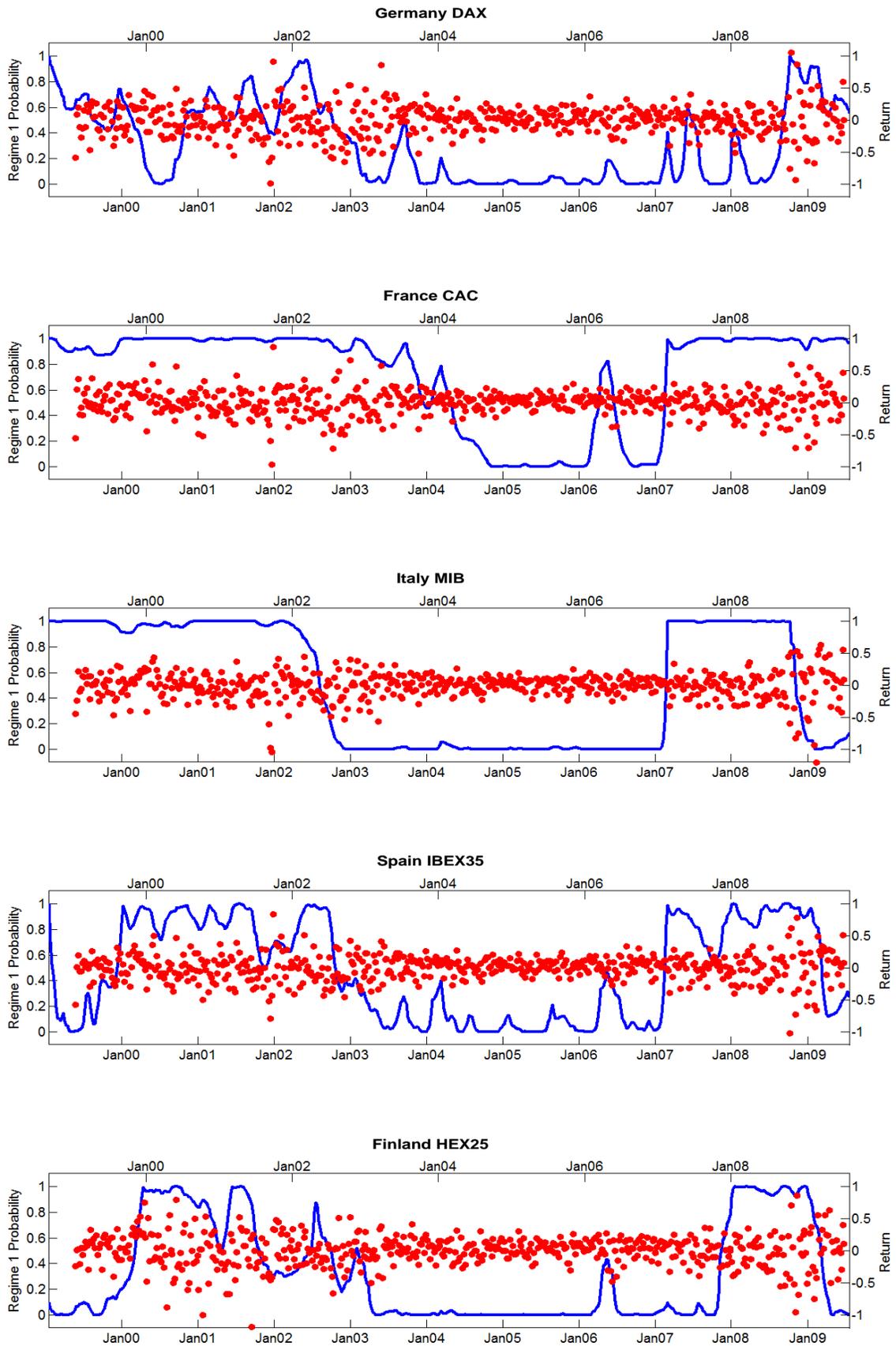


Figure 2: Bear regime probability



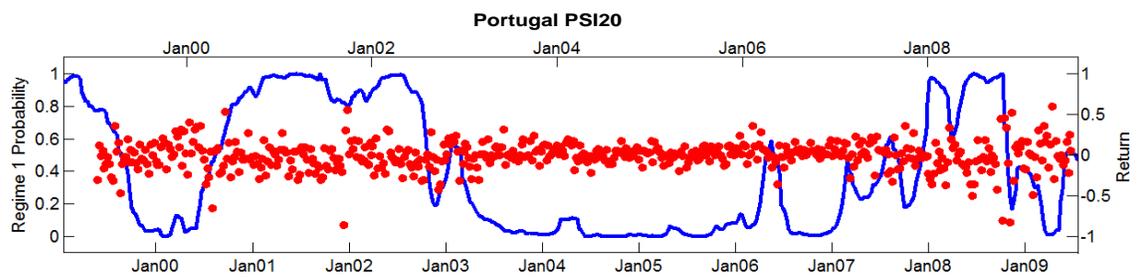
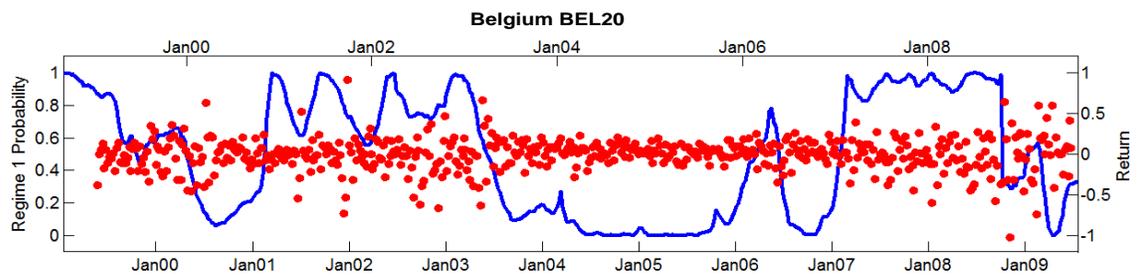
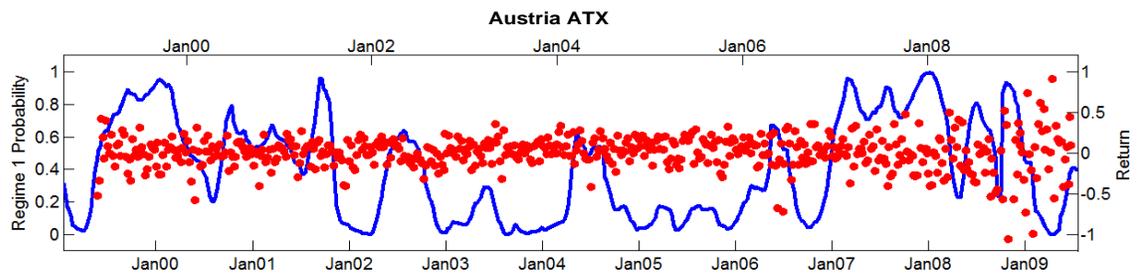
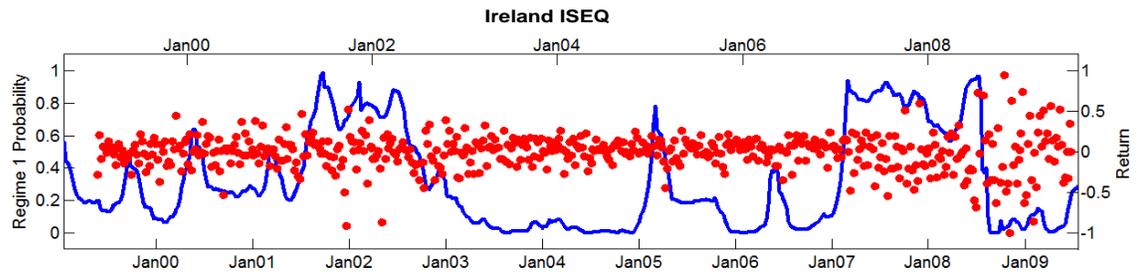
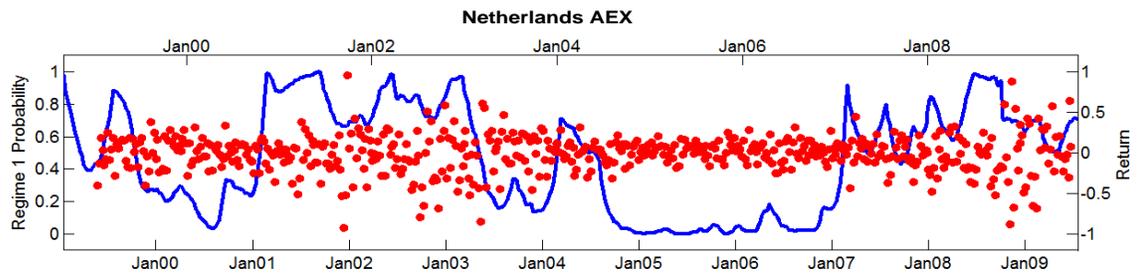
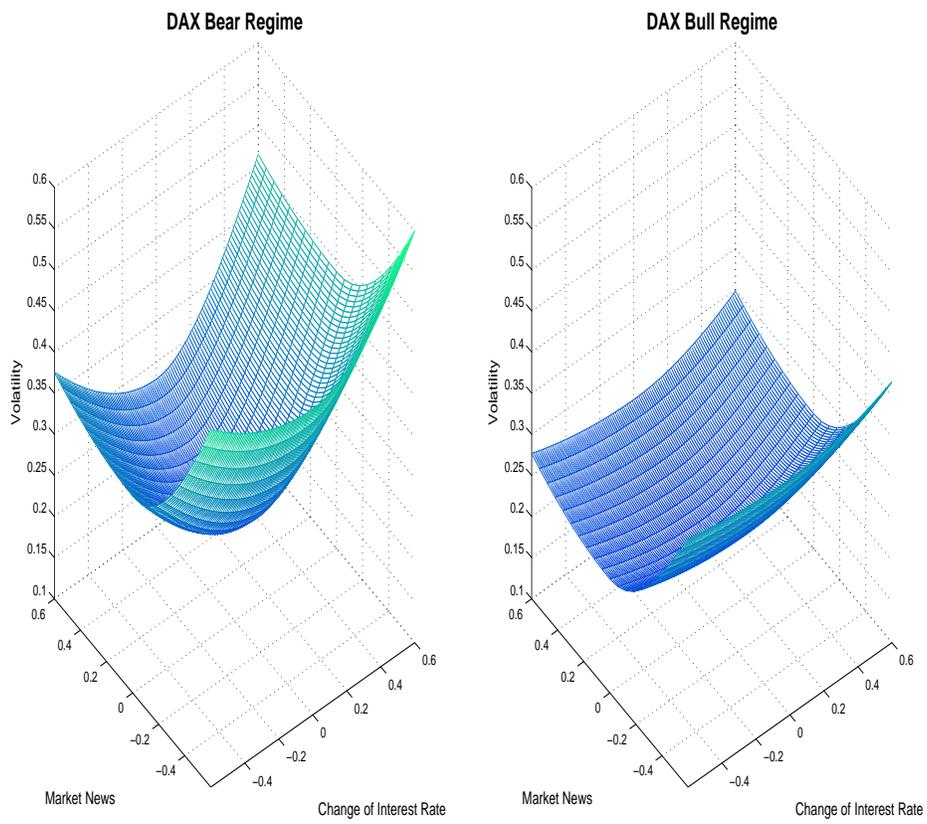
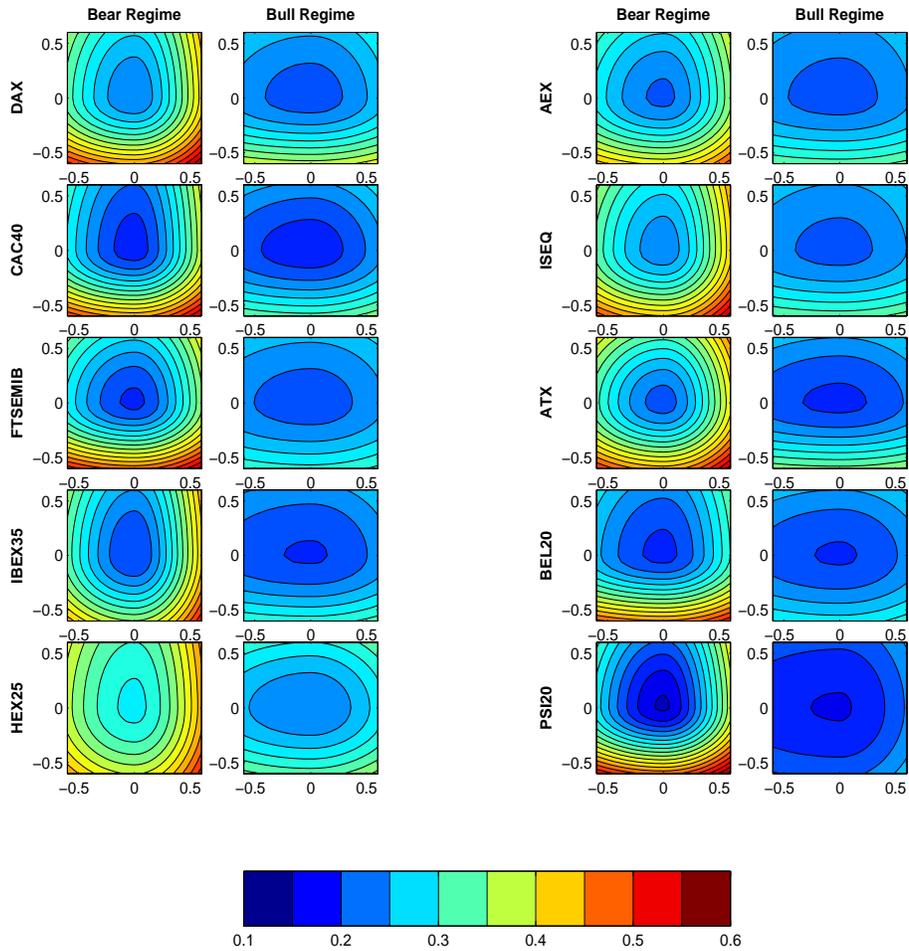


Figure 3: DAX news impact surface–3D Plot



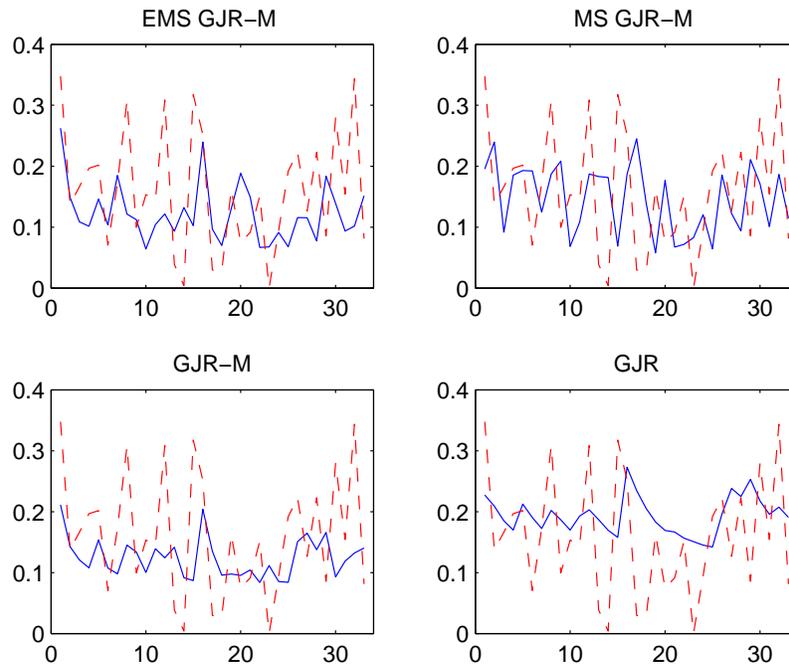
X-axis represents changes of interest rate, Y-axis represents market news

Figure 4: News impact surfaces

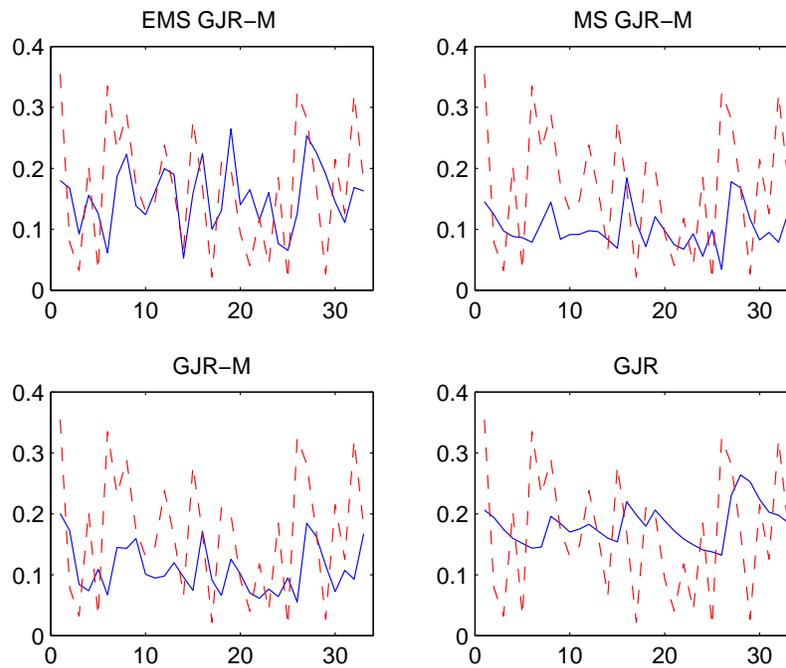


X-axis represents changes of interest rate, Y-axis represents market news

Figure 5: Plots of the out-of-sample forecasted Volatility and the true volatility



(a) Germany DAX



(b) France CAC40

The solid line represents the volatility estimate and the dashed line is the true volatility, which is proxied by the absolute value of the returns.