Volatility prediction based on scheduled macroeconomic announcements

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SUMMARY

We investigate the impact of scheduled macroeconomic announcements to the volatility of exchange rates by introducing a flexible model with the following characteristics. For each macroeconomic index we estimate cutoff points in the surprise component of the announcement that specify the degree the volatility process is affected. This degree is quantified by a jump of unknown size that occurs before the announcement and a jump of unknown size that occurs at the time of the announcement and then dies out exponentially with unknown rate. We make inferences by using a population Markov chain Monte Carlo reversible jump algorithm and we illustrate our methodology by predicting the volatility of exchange rates using fifteen United States macroeconomic announcements. The empirical study includes extensions to multiple time series with many exchange rates and comparisons with competing existing models.

Keywords: Cholesky, dynamic conditional correlation, exchange rates, GARCH, population Markov chain Monte Carlo, Reversible jump, thresholds.

1. INTRODUCTION

Scheduled announcements of macroeconomic indices have been found to affect decisively the volatility of stocks and exchange rates in a wide range of studies. In this study we propose a rich model formulation that is capable of exploring how announcement surprises, defined as the absolute percentage differences of the realised minus the Bloomberg consensus reported values, affect the volatility process of daily exchange rates.

We propose a model formulation based on two ingredients. One is a GARCH-type process that captures the usual stylised facts such as heavy tails and volatility clustering. The second is nonparametric, threshold-based process that captures the impact of announcement surprises. Due to the predictive nature of the GARCH process and the fact that the announcements are scheduled, our model specification may serve as a volatility

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forecasting tool. Nevertheless, important financial insight is available by inspecting fitted summaries of interest for specific exchange rates and macroeconomic indices.

Our proposed non-linear structure that incorporates macroeconomic indices announcements is based on the following characteristics. First, we assume that for each index there is a different pre-announcement effect that is quantified by a jump of unknown size in the volatility process. Second, for each index the degree of announcement surprise has a different impact on the volatility process. To accommodate this, we define regions in the announcement surprise data that are specified by threshold points. Depending on both the index and the region of the announcement surprise, a volatility jump of unknown size which decays exponentially with unknown rate is added to the volatility process. The number of regions and their corresponding threshold points are unknown and different for each index.

The above model formulation can be readily embedded in any multivariate GARCH-type models. We illustrate how this can be achieved by enriching a dynamic conditional correlation (DCC) and a Cholesky-type multivariate GARCH model and by illustrating it with three exchange rate series.

Under such a flexible model framework, we need a powerful inference tool to explore a large number of models. We adopt Bayesian inference and construct a population reversible jump Markov chain Monte Carlo (MCMC) algorithm which has been proven to be an efficient way to sample from both the model and parameter space. The resulting samples of posterior summaries of interest can serve as forecasting tools through model averaging.

The methodology proposed here is illustrated in an empirical study in which we use data of three exchange rates of the US dollar and fifteen United States macroeconomic announcements. The results indicate that our proposed model formulation provides more accurate forecasts than typical conditional volatility models, and this is so even if we enrich the existing models appropriately so that macroeconomic announcements are incorporated. The announcements that mostly affect the exchange rates volatility were identified to be unemployment rate, trade balance and several early indicators of economic growth.

The rest of the paper proceeds as follows. In Section 2 there is a short review of studies investigating the effect of news announcements on volatility. In Section 3 we present a new class of threshold models for volatility under both a univariate and multivariate setup.

Section 4 describes the details of the MCMC implementation whereas Section 5 presents the data and the results. Finally, Section 6 concludes with a short discussion.

2. ANNOUNCEMENTS AND VOLATILITY

The impact of macroeconomic announcements on the asset and foreign exchange (Forex) markets has been the subject of extensive research in the past years. A large number of related studies is based on GARCH type models (Engle, 1982, Bollerslev, 1986), where additional explanatory variables are used to capture the effect of news announcements. A common formulation for these models is given as

$$y_t = \mu_t + \epsilon_t, \quad \epsilon_t \sim N(0, G_t E_t) \tag{1}$$

where y_t, $t = 1, \ldots, T$, denotes the exchange rate return, μ_t is the expected value of the mean process at time t, E_t is a function of some explanatory variables related to news announcements affecting the variance process and G_t is a GARCH-type process.

The main difference among these studies stands in the selection of explanatory variables affecting E_t. In fact, it is not unusual to differ not only on the type of announcements but also in the temporal effect on volatility, for example adopting formulations specifying before and after announcement effects. In this context, a large number of studies use indicator variables to account for macroeconomic announcements; see Jones *et al.* (1998), Bomfim (2000), Kim *et al.* (2004), Bauwens *et al.* (2005). In DeGennaro and Shrieves (1997) news announcements are captured by the number of headlines in each news category on the Reuters money news-alerts, while Hautsch and Hess (2002) use explanatory variables that capture surprises on headline figures.

A different collection of studies are those using Fourier flexible forms to capture the effect of news announcements. One of the most cited papers adopting this modelling route is that of Andersen and Bollerslev (1998b). They model the intraday deutsche mark-dollar exchange rate volatility by accounting for daily ARCH effects, calendar effects such as holidays and weekends and macroeconomic announcement effects. A related framework is used by Bollerslev *et al.* (2000) to examine the return volatility in US Treasury bond futures and

by Laakkonen (2004) who studies the impact of scheduled U.S. and European macroeconomic announcements on the volatility of the Euro-dollar exchange rate. Significant empirical results are also drawn from studies analysing the effect of news announcements directly on the absolute returns, see Ederington and Lee (1993), Mitchell and Mulherin (1994); or a financial index that measures the volatility, see Nikkinen and Sahlström (2001). An entirely different approach is followed by Andersen *et al.* (2007) who measure separately the continuous sample path variation and the discontinuous jump part of the quadratic variation process. By using high frequency data, they observe that significant jumps in the realized volatility process tend to coincide with the release of macroeconomic indices.

Although the empirical results from the above studies are in some cases contradicting, there are several points of agreement. First, all studies agree that news announcements are affecting decisively the volatility of exchange rates and stock markets, either when analysed on a daily or an intraday basis. Furthermore, all studies underline that the effect on the volatility is related to the type of announcement and the content of news, rather than the very act of releasing information. From all the types of news considered, most studies find that scheduled macroeconomic announcements are the most important, and their effect turns out to be stronger when compared to ARCH or calendar effects; see DeGennaro and Shrieves (1997), Andersen and Bollerslev (1998b), Bollerslev *et al.* (2000), Bauwens *et al.* (2005). The documented volatility autocorrelation and the day-of-the-week volatility patterns seem to depend strongly on the news generating process and the timing of major macroeconomic announcements; see Ederington and Lee (1993), Mitchell and Mulherin (1994), Jones *et al.* (1998). In addition, there is evidence that while the surprising factor plays a key role, even news that come out as expected seem to affect the volatility process; see Laakkonen (2004).

Studies seem to diverge with respect to the direction with which pre-announcement effects affect volatility. Nikkinen and Sahlström (2001), Hautsch and Hess (2002) and Bauwens *et al.* (2005) find that volatility increases before news announcements whereas DeGennaro and Shrieves (1997), Bomfim (2000) find that the volatility decreases.

3. THE PROPOSED MODELS

3.1 A Flexible Threshold-GARCH model based on indices releases

We propose the following variation of the general model (1). Assume that at time periods denoted by t^* there are announcements of macroeconomic indices. Then, ignoring the parameter μ_t which can be efficiently estimated independently of the volatility process, we propose the model

$$
\begin{aligned}
y_t &= \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2 G_t E_t) && (2)\\
G_t &= (1-\alpha_1-\alpha_2) + \alpha_1 \frac{\epsilon_{t-1}^2}{\sigma^2 E_{t-1}} + \alpha_2 G_{t-1} && (3)\\
E_t &= 1 + \sum_{i=1}^{K} \left(\sum_{j=1}^{J_i} I_{ij}(t^*)\gamma_{ij} \exp\left(-r_{ij}(t-t^*)\right) + s_i \mathbf{1}\left(t = t^*-1\right) \right) && (4)\\
I_{ij}(t^*) &= \mathbf{1}\left(c_{ij} \le Z_{it^*} < c_{i,j+1}\right). && (5)
\end{aligned}
$$

The positive scalar σ^2 is considered as the global static error variance whereas the GARCH process G_t has the form used in the Spline-GARCH model of Engle and Rangel (2008) with $E(G_t) = 1$ and positive parameters $0 < \alpha_1 + \alpha_2 < 1$. The threshold process E_t describes the way that announcements affect the volatility. In particular, there are K indices and for each of them there are J_i, $i = 1, \ldots, K$, regions. $I_{ij}(t^*)$ is a region-based indicator variable indicating that region j affects volatility through a jump of size $\gamma_{ij} > -1$ that occurred at time $t^* \le t$ and through an exponential decay with rate $r_{ij} > 0$. The announcement surprises of index i at time t are expressed through a variable Z_{it} and the degree of surprise is determined by threshold points c_{ij}, where $c_{i,J_i} := \infty$. Finally, our model specification is completed by allowing pre-announcement volatility jumps $s_i > -1$ occurring one time period before the announcements.

We call the above model formulation Flexible Threshold-GARCH model and we emphasize its rich flexibility: there are many models with varying number of parameters specified by the number of regions J_i and the number of indices that affect volatility. Call m such model, M the set of all models and use superscript m to denote the corresponding parameters within each model. Then, for each $m \in M$, the parameter vector is

$$\theta_m = \left(\sigma^m, \alpha_1^m, \alpha_2^m, K^m, J_i^m, \gamma_{ij}^m, s_i^m, r_{ij}^m, c_{ij}^m, \quad i = 1, \ldots, K^m, \quad j = 1, \ldots, J_i^m\right).$$

Therefore, our target under a Bayesian inference setup is to estimate the posterior probability of each model m and the posterior densities of θ_m within each model m.

The effect of the specification (4) in the volatility process is depicted in Figure 1. There are macroeconomic announcements at time points 3 and 10 of index 1, with different degrees of surprise, and at time 7 of index 2. Assume that pre-announcement jumps do not exist. The left panel depicts the three components that are added to produce the process E_t at the right panel.

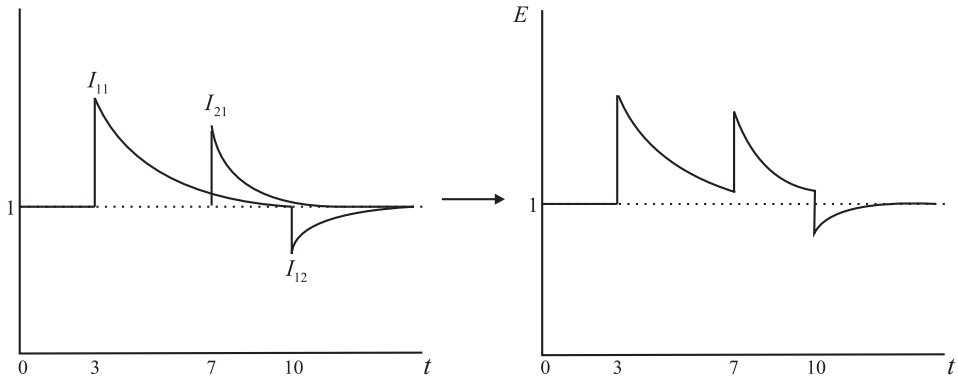

Figure 1: The effect of explanatory variables in the threshold process.

3.2 A Spline-GARCH model

Another way to capture, in a non-linear fashion, the volatility shifts caused by news announcements is to use a modification of the Spline-GARCH model of Engle and Rangel (2008). We propose an amendment of this model by applying the exponential spline function to the time instances in which announcements occur and not to equally spaced time intervals as in Engle and Rangel (2008). The number of spline knots, denoted by K, is assumed to be unknown. Hence, our proposed Spline-GARCH model is based on (2) and (3), but (4) and (5) are replaced by

$$E_t = \exp\left(w_0 t + \sum_{i=1}^{K}\left[w_i\left((t-t^*)_+\right)^2 + \gamma_i Z_{it^*} + s_i \mathbf{1}\left(t = t^* - 1\right)\right]\right), \tag{6}$$

where $(t-t^*)_+ = (t-t^*)$ if $t > t^*$ and zero otherwise. The parameter vector in this model, for each model $m \in M$, is

$$\theta_m = (\sigma^m, \alpha_1^m, \alpha_2^m, w_0^m, K^m, w_i^m, \gamma_i^m, s_i^m, \quad i = 1, \ldots, K^m).$$

As in Engle and Rangel (2008), the values of explanatory variables Z_{it} and the pre-announcement effect affect exponentially the variance process.

3.3 Multivariate Flexible Threshold-GARCH models

Assume that at time t we observe N zero-mean normally distributed exchange rates y_{lt}, $l = 1, \ldots, N$, $t = 1, \ldots, T$, stacked in vectors $Y_t = (y_{1t}, \ldots, y_{Nt})'$, with time-varying conditional covariance matrices Σ_t. Interest lies in investigating how announcements affect the matrices Σ_t. One way to expand the univariate model (2)-(5) in a multivariate setup, is to use the DCC model of Engle (2002). Under this framework, we can estimate the univariate variances using the Flexible Threshold-GARCH model, while the conditional correlation matrix is estimated ex post using the usual observation driven formula of DCC. We call this model DCC Flexible Threshold-GARCH.

An alternative adaptation of the Flexible Threshold-GARCH specification in a multivariate setup can be based on Dellaportas and Pourahmadi (2004) as follows. Consider an ordering of the exchange rates based on their unconditional variance, from the lowest to the highest. Then, assume that y_{1t} follows model (2)- (5) and regress each of the rest exchange rates on its predecessors such that (2) becomes, for exchange rates $l = 2, \ldots, N$,

$$y_{lt} = \sum_{k=1}^{l-1} (\phi_{lk} y_{kt}) + \epsilon_{lt}, \quad \epsilon_{lt} \sim N(0, \sigma_{lt}^2), \tag{7}$$

where $\sigma_{lt}^2 = \sigma^2 G_{lt} E_{lt}$ is estimated using (3)-(5) for every l. Then, by placing $-\phi_{lk}$ in the lk-th position of a unit lower triangular matrix T, it turns out that

$$\Sigma_t = T^{-1} H_t (T^{-1})', \tag{8}$$

with H_t being a diagonal matrix with entries $(\sigma_{1t}, \ldots, \sigma_{Nt})$, gives the desired conditional covariance matrix. Incorporation of the Flexible Threshold-GARCH model in the elements

of H_t provides estimates of Σ_t, the extra estimation burden being the $N(N-1)/2$ set of ϕ_{lk} parameters of matrix T.

4. INFERENCE

4.1 Priors

Our prior specification is non-informative, in the sense that vague proper priors are proposed, but special care is taken to avoid issues of Lindley's paradox (Bartlett, 1957) and model identifiability. To facilitate the discussion, we omit the superscript m.

First we note that proper prior densities are required to avoid Lindley's paradox and model identifiability issues. For example, as r_{ij} increases so that the exponent in (4) approaches zero, E_t as well as the likelihood function remain constant. Thus, the integrability of the posterior density conditional on any given model requires the use of proper priors. We performed the following (necessary) Bayesian data analysis exercise. For all models used in the empirical analysis, we increased the standard deviations of all prior densities by a factor of ten. We then examined the robustness of our results to the prior dispersion by inspecting posterior model probabilities and posterior summaries of interest such as volatility predictions. Although the posterior model probabilities do change slightly, the predictive densities of variances and covariance matrices based on model averaging remain identical. This certifies that our prior densities are vague enough not to affect the posterior summaries of interest. Additional details of these experiments can be found in Petralias (2010).

The prior probabilities of the discrete densities on the model space and on threshold points are set to be discrete uniforms over all possible models and distinct observed values of announcement surprises respectively. Within each model, prior densities for the parameters of the Flexible Threshold-GARCH model are chosen to be as follows. We first apply transformations to the real line, $g_{ij} = \log(\gamma_{ij}+1)$, $\varsigma_i = \log(s_i+1)$ and $\rho_{ij} = \log(r_{ij})$, $i = 1,\ldots,K$, $j = 1,\ldots,J_i$. We then place non-informative priors $\sigma^2 \sim IG(10^{-5}, 10^{-5})$, $\alpha_1, \alpha_2 \sim U(0,1)$ with $\alpha_1 + \alpha_2 < 1$, $g_{ij} \sim N(0, 0.4^2)$, $\varsigma_i \sim N(0, 0.4^2)$, $\rho_{ij} \sim N(0, 2^2)$. For

the Spline-GARCH model we use $w_i \sim N(0, 0.003^2)$, $\gamma_i \sim N(0, 3^2)$, $s_i \sim N(0, 0.5^2)$ and for the multivariate models $\beta_1, \beta_2 \sim U(0, 1)$ with $\beta_1 + \beta_2 < 1$, $\phi \sim N(0, 1)$.

4.2 The population reversible jump MCMC algorithm

In problems with complex multi-modal distributions standard vanilla MCMC samplers may fail to efficiently move around the support of the target distribution. One way to deal with these problems is to adopt Population-based MCMC methods; see Geyer (1991), Gilks *et al.* (1994), Liu *et al.* (2000), Liu (2001), Liang and Wong (2001), Jasra *et al.* (2007a). In summary, the basic idea is that MCMC operates by embedding the target density into a sequence of $\ell = 1, \ldots, L$ independent distributions obtained by simulating L parallel chains, whilst allowing the chains to interact via various moves. Recently, Jasra *et al.* (2007b) proposed an extension of these methods to transdimensional parameter spaces and we adopt ideas from this paper for our inference algorithm.

A population reversible jump algorithm includes the following basic moves. An exchange move is used to swap information between two adjacent (in terms of temperature) chains by exchanging all variables and associated parameters between them. In a crossover move only a fraction of the variables with their associated parameters is exchanged between two randomly chosen chains. A mutation move is used to update a chain according to a reversible jump step as suggested by Green (1995). We suggest the use of five parallel chains, four of them being tempered. The basic steps of the Flexible Threshold-GARCH reversible jump algorithm that obtains samples (θ_m, m), $m \in M$, on spaces of varying dimension follows. The specific details can be found in Appendix A.

The reversible jump Algorithm

- `Initialize the chain and sweep over the following:`

  1. `Randomly add, delete or replace an index variable.`
  2. `For all index variables, randomly propose to split or merge the current threshold points.`
  3. `Update all remaining parameters in the current model through a random walk Metropolis Hastings kernel.`

The above algorithm is enriched by applying a population algorithm. Denote by π be the reversible jump invariant distribution with states (m, θ_m). We construct four auxiliary distributions $\pi_\ell \propto \pi^{\zeta_\ell}$, $1 = \zeta_1 > \ldots > \zeta_5 > 0$, with ζ_ℓ denoting the inverse temperature parameter in chain ℓ.

The population Algorithm

- `Run` 5 `parallel Markov chains each one with target densities` π^{ζ_ℓ}.
- `Every` 10 `iterations choose randomly between`
  - `an exchange move which changes the states` (m, θ_m) `between two randomly chosen chains which are adjacent in terms of temperature.`
  - `a crossover move which changes a randomly chosen subset of variables included in` m `and its associated parameters` θ_m `between two randomly chosen chains.`
- `In the rest of the iterations perform a mutation move which updates the chains according to the reversible jump Algorithm.`

The temperature ladder is specified as $\zeta_\ell = z^{\ell-1}$, where the scalar z, $0 < z < 1$, is calibrated during the burn-in period of the algorithm as follows. We started from $z = 0.8$ and every 50 exchange move proposals we set $z' = z + \delta(0.5 - \alpha)$, where δ is a pre-specified sensitivity parameter and α is the acceptance rate of the exchange move during the latest 50 exchange move sweeps. The constant $\delta > 0$ is chosen to be $\delta = 0.1$ so that the exchange move is accepted about half of the time (Liu, 2001).

4.3 Prediction

We base all our predictions to Bayesian model averaging, see for example Raftery *et al.* (1997), Liu and Maheu (2009). The posterior distribution of a quantity Δ, which in our case corresponds to the model averaging variance and correlation forecasts, given the data

$\mathcal{D}$ and the models $m \in M$, is given as

$$f(\Delta \mid \mathcal{D}) = \sum_{m \in M} f(\Delta \mid m, \mathcal{D}) f(m \mid \mathcal{D}),$$

which is an average of the posterior predictive distribution under each model m,

$$f(\Delta \mid m, \mathcal{D}) = \int f(\Delta \mid \theta_m, m, \mathcal{D}) f(\theta_m \mid m, \mathcal{D}) d\theta_m$$

weighted by the posterior model probabilities $f(m \mid \mathcal{D})$. The algorithms run once using the in the sample observations and perform the out of sample forecasts on basis of these estimates.

To evaluate the predictive performance of each model we rely on measures adopted by, for example, Bollerslev *et al.* (1994), Andersen *et al.* (1999), Ledoit *et al.* (2003), that are based on the Mean Absolute Deviation (MAD) and the Root Mean Square Error (RMSE) of the covariance estimates compared with a true volatility proxy. Following, among others, Andersen and Bollerslev (1998a), Barndorff-Nielsen and Shephard (2002, 2004), we adopt as a reliable proxy of the true daily covariance matrix the realized covariance matrix with lk elements σ^*_{lk}, obtained by using 5-minutes high frequency data. The RMSE and MAD measures are given as

$$\begin{aligned} \text{RMSE}_{lk} &= \left[\frac{1}{T} \sum_{t=1}^{T} (\hat{\sigma}_{lk,t} - \sigma^*_{lk,t})^2 \right]^{1/2} \\ \text{MAD}_{lk} &= \frac{1}{T} \sum_{t=1}^{T} \left| \hat{\sigma}_{lk,t} - \sigma^*_{lk,t} \right|, \end{aligned}$$

where $\hat{\sigma}_{lk,t}$ denotes the estimated element of the covariance matrix. The TRMSE and TMAD for covariance matrices is obtained by summing over all $l, k = 1, \ldots, N$. The scope of our empirical study in the next Section is to consider how our model estimates $\hat{\sigma}_{lk,t}$ for both $t \leq T$ (in-the-sample) and for $t > T$ (out-of-sample).

5. EMPIRICAL STUDY

5.1 The data

Our data set consists of 849 daily observations from 1/1/2002 up to 1/4/2005 of the Euro-dollar (EURUSD) exchange rates returns calculated on basis of the Bid prices. The data were obtained from Bloomberg. From these observations we kept the first 784 in-the-sample data points that correspond to three year data for our inference and used the rest 65 points for the out-of-sample forecasting exercises. We excluded the weekends from Friday 21:00 GMT through Sunday 21:00 GMT since there is limited price action in Forex markets. For the multivariate models we also included the British pound-dollar (GBPUSD) and Dollar-Swiss franc (USDCHF) exchange rates for the same time periods. The exchange rates have sample correlations -0.94 (EURUSD and USDCHF), -0.71 (GBPUSD and USDCHF) and 0.73 (EURUSD and GBPUSD).

We used surprises of 15 monthly U.S. scheduled macroeconomic announcements, that we believed that they may affect the volatility process and/or have been found to explain volatility fluctuation by previous empirical studies. The surprises are defined as the absolute percentage difference of the realised minus the Bloomberg consensus reported values. The macroeconomic announcements used in this study, their number of distinct observations in-the-sample, as well as some basic statistics are presented in Table I.

Table I: List of the macroeconomic announcements and surprises descriptive statistics; minimum values are equal to zero.

Macroeconomic announcement		Group	Distinct values	Mean (×100)	St. dev. (×100)	Median (×100)	Maximum (×100)
1	GDP Annualized	OG	13	0.43	0.37	0.35	1.30
2	Industrial Production	OG	6	0.23	0.15	0.20	0.50
3	Durable Goods Orders	OG	26	1.70	1.54	1.15	7.20
4	Wholesale Inventories	OG	10	0.36	0.24	0.30	0.90
5	Advance Retail Sales	OG	12	0.38	0.38	0.30	1.50
6	Housing Starts	OG	36	4.77	2.97	4.27	12.38
7	ISM Manufacturing	CS	36	2.75	2.61	1.81	9.40
8	ISM Non-Manufacturing	CS	36	4.94	3.30	4.64	15.10
9	Leading Indicators	CS	4	0.10	0.10	0.10	0.40
10	Consumer Confidence	CS	36	4.49	4.36	2.85	16.88
11	Consumer Price Index	P	4	0.09	0.09	0.10	0.30
12	Producer Price Index	P	10	0.38	0.34	0.30	1.20
13	Trade Balance	BP	35	5.46	4.14	4.92	18.72
14	Unemployment rate	EW	4	0.11	0.10	0.10	0.30
15	Personal Income	EW	5	0.11	0.11	0.10	0.40

In an attempt to categorize these announcements we may define five general groups. The first group (OG) includes announcements associated with output and economic growth

and consists of the *Gross Domestic Product* (GDP Annualized) which is a gauge of the overall output (goods and services) of the economy and thus the most comprehensive overall measure of economic output, the *Industrial Production* which measures changes in the volume of output produced by the manufacturing, mining, and utility sectors, the *Durable Goods Orders* that depict the value of orders placed for relatively long lasting goods that have large sway over the actual production, the *Wholesale Inventories* that measures the stock of unsold goods held by wholesalers, the *Advance Retail Sales* which is a measurement of all goods sold by retailers based on a sampling of retail stores and the *Housing Starts* that gauges the change in the number of new houses built.

The second group (CS) includes confidence and sentiment reports evaluating the condition of the economy. This group is highly related to the first one, but is based on sample surveys that usually advance actual outcomes. This group includes the *ISM Manufacturing* that assesses the state of the industry by surveying executives on expectations for future production, new orders, inventories, employment and deliveries, the *ISM Non-Manufacturing* which assesses business conditions in non-manufacturing industries, the *Leading Indicators* which is a composite index designed to forecast trends in the overall economy and is based on the following ten key indicators: average manufacturing workweek, average weekly unemployment claims, manufacturer's new orders for consumer goods and materials, vendor performance, manufacturer's new orders for non-defense capital goods, housing permits, S&P 500 index, M2 money supply, interest rate spread and consumer expectations, and finally the *Consumer Confidence index* which assesses consumers regarding business conditions, employment and personal income.

The third group (P) is related to prices and thus includes the *Consumer Price Index* (CPI) and the *Producer Price Index* (PPI). CPI assesses changes in the cost of living by measuring changes consumer pay for a set of items and serves as the headline of inflation. PPI on the other hand, measures changes in the selling prices producers charge for goods and services. Because producers tend to pass on costs to consumers, the PPI is valuable as an early indicator of inflation. Inflation reflects a decline in the purchasing power of the domestic currency and thus affects exchange rates.

The fourth group (BP) is associated with balance of payments and includes the *Trade Balance* index that refers to the difference between exports and imports of goods and

services. Because foreign goods are usually purchased using foreign currency, trade deficits tend to weigh down the value of the currency, unless countered by comparable capital inflows.

The fifth group (EW) involves indices associated with employment and wages, namely *Unemployment rate* and *Personal Income*. Unemployment rate is the most widely used figure to assess the labor market conditions. A lower Unemployment rate translates into higher consumer spending, economic growth and potential inflationary pressures. Personal Income measures the pre-tax income households receive from employment, investments and transfer payments and thus is associated also with consumer spending and growth.

5.2 Univariate models

We investigate how well our models perform through a detailed comparison between the Flexible Threshold-GARCH, the Spline-GARCH, a Flexible Threshold model without GARCH effects and a typical GARCH(1,1) model. To avoid confusion, we call them 'model specifications' to distinguish them from models m within a model specification.

The four models with the highest estimated posterior probability within each specification are presented in Table II. Although most of the macroeconomic announcements are included in the four highest posterior density models of all specifications, we observe that Advance Retail Sales, Durable Goods Orders, GDP Annualized, ISM Non-Manufacturing, Trade Balance and Unemployment rate are found as the most important in the Flexible Threshold and Flexible Threshold-GARCH models, while Wholesale Inventories is additionally found important in the Spline-GARCH model.

Table II: The four models with the highest posterior probability and their estimated posterior probabilities under the Flexible Threshold, Flexible Threshold-GARCH and Spline-GARCH specifications.

	Flexible Threshold		Flexible Threshold-GARCH		Spline-GARCH	
Model	Variables	Prob. ($\times 10^{-3}$)	Variables	Prob. ($\times 10^{-3}$)	Variables	Prob. ($\times 10^{-3}$)
First	3,5,8,13,14	3.31	3,5,8,14	3.18	3,4	23.43
Second	1,3,5,8,13,14	3.20	1,3,5,8,14	3.15	3,4,14	22.07
Third	3,5,8,11,13,14	2.92	1,3,5,8,13,14	2.64	2,7	17.61
Fourth	3,5,8,9,13,14	2.81	3,5,8,13,14	2.50	2,3,4,14	11.55

An interesting feature present in Table II is that the Bayes factors based on any pairs of the first four models is in the range that the strength of evidence of one model against

another is 'barely worth mentioning'. This is a usual phenomenon in high dimensional model spaces, signaling that the focus and the comparative advantage in such model specifications is prediction rather than parameter inference based on a single model.

A quantity usually adopted to help identifying important regressors in high dimensional regression type problems is the marginal probability of inclusion of a variable (see Barbieri and Berger, 2004) which is calculated as the percentage of times this variable is observed in the transdimensional MCMC sample. Table III lists the macroeconomic announcements according to their marginal probability of inclusion in the three model specifications that we propose. There is generally a good agreement in threshold type specifications whereas Spline-GARCH presents some differences. An interesting observation is that volatility is affected by indices associated with output and growth, but perhaps curiously more by Advance Retail Sales and Durable Goods Orders and less by GDP Annualized and Industrial Production. Presumably this can be attributed to the fact that changes in actual growth have been mainly absorbed by results of indices that provide advance signs for the condition of the economy. This argument is further strengthened by the presence of ISM Non-Manufacturing in the list of the most important announcements. Finally, the Unemployment rate seems to be overall the most important index, something that is in agreement with various empirical studies; see Ederington and Lee (1993), Andersen and Bollerslev (1998b), Nikkinen and Sahlström (2001).

Table III: Marginal probability of inclusion of macroeconomic announcements that affect Euro-dollar volatility.

Macroeconomic announcement		Group	Flexible Threshold	Flexible Threshold-GARCH	Spline-GARCH
14	Unemployment rate	EW	0.9946	0.9956	0.3338
5	Advance Retail Sales	OG	0.7221	0.7746	0.2707
3	Durable Goods Orders	OG	0.7522	0.6211	0.4926
8	ISM Non-Manufacturing	CS	0.6538	0.6006	0.1940
13	Trade Balance	BP	0.8034	0.5358	0.1049
11	Consumer Price Index	P	0.4925	0.4681	0.1821
1	GDP Annualized	OG	0.3981	0.4464	0.1826
7	ISM Manufacturing	CS	0.4500	0.4380	0.2962
9	Leading Indicators	CS	0.4883	0.3877	0.1079
4	Wholesale Inventories	OG	0.3610	0.3421	0.5504
15	Personal Income	EW	0.3065	0.3027	0.2247
6	Housing Starts	OG	0.3051	0.2940	0.0613
2	Industrial Production	OG	0.3057	0.2761	0.3887
12	Producer Price Index	P	0.2892	0.2132	0.0460
10	Consumer Confidence	CS	0.2366	0.1772	0.0707

Table IV presents summary statistics for the posterior densities of pre-announcement

effects under the highest posterior probability model of each specification. There is a sign agreement in all specifications that represents drop or increase of volatility in different indices.

Table IV: Pre-announcement effect on the volatility based on models with the highest posterior probability; posterior standard deviations are in brackets.

Macroeconomic announcement		Flexible Threshold	Flexible Threshold-GARCH	Spline-GARCH
3	Durable Goods Orders	-0.27 [0.22]	-0.35 [0.21]	-0.64 [0.26]
4	Wholesale Inventories			0.10 [0.24]
5	Advance Retail Sales	-0.43 [0.22]	-0.40 [0.23]	
8	ISM Non-Manufacturing	0.22 [0.21]	0.21 [0.21]	
13	Trade Balance	-0.18 [0.21]		
14	Unemployment rate	-0.23 [0.22]	-0.20 [0.20]	

We were unable to identify such consistency in other model parameters. For example, there is no evidence under any specification that higher values of announcement surprises increase the volatility. This may be attributed to the fact that the effect of an announcement is dependent to past or anticipated announcements and cannot be isolated in a changing macro-economic environment; see Bollerslev *et al.* (2000), Hautsch and Hess (2002), Laakkonen (2004).

We now turn to forecasting aspects of our specifications. Figure 2 depicts in-the-sample variance estimates and out-of-sample variance predictions under each model specification. These can be visually compared with squared residuals and realized volatilities respectively. It is clear that specifications which use information from the macroeconomic announcements are more spiky than the usual smooth GARCH estimates, and in general they do a rather good job in predicting future volatility spikes. In particular, focusing on the out-of-sample predictions, Flexible Threshold models perform impressively well in predicting the second, third and fourth largest volatility spikes at days 849, 809 and 789 respectively. This is in line with the findings of various empirical studies (DeGennaro and Shrieves, 1997, Andersen and Bollerslev, 1998b, Bollerslev *et al.*, 2000, Bauwens *et al.*, 2005), in which the effects of news on the volatility are found to be stronger than that of GARCH effects.

In Table V we present the RMSE and MAD forecast errors for the Flexible Threshold, Flexible Threshold-GARCH, Spline-GARCH and GARCH specifications. These measures are calculated for both in-the-sample and out-of-sample observations. The Flexible Thresh-

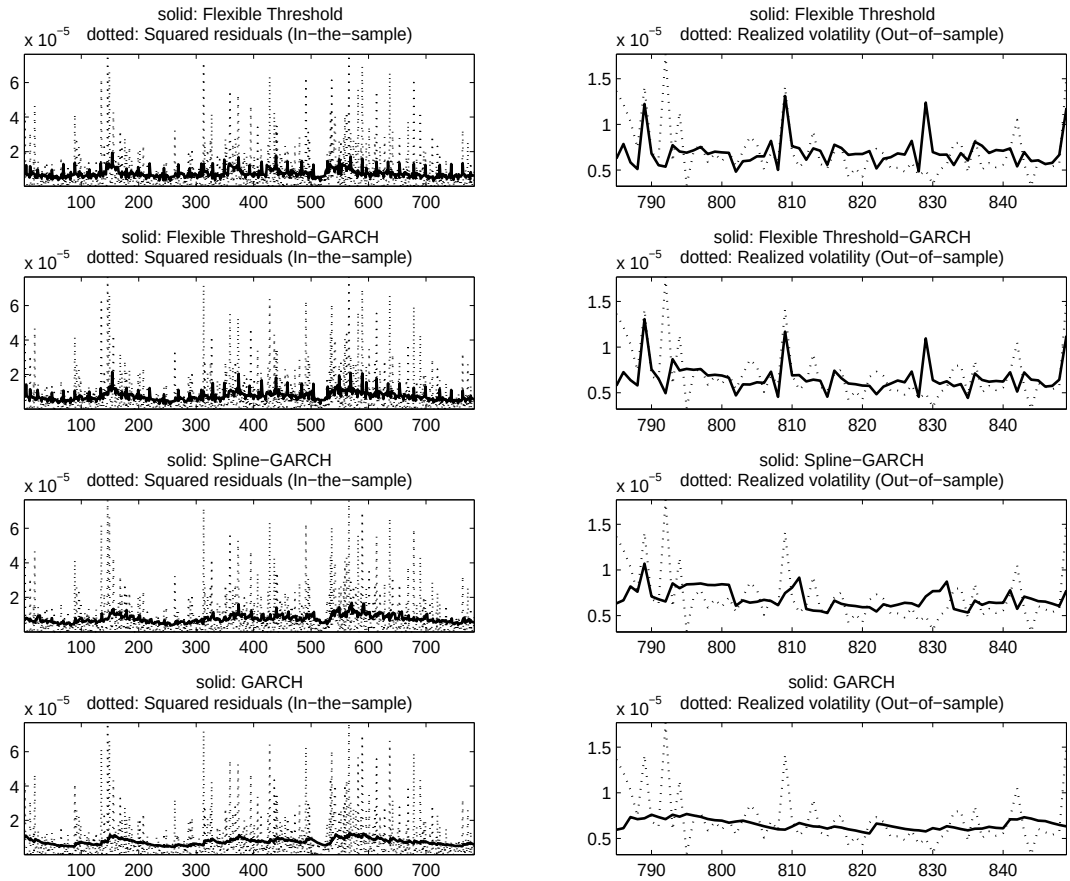

Figure 2: Estimated volatilities in-the-sample and out-of-sample.

old and Flexible Threshold-GARCH specifications seem to outperform the other models, with the Flexible Threshold-GARCH being the most promising specification for prediction purposes.

5.3 Multivariate models

We investigate how well the multivariate specifications described in Section 3.3 can be used to predict covariance matrices based on macroeconomic news announcements. In addition to the DCC Flexible Threshold-GARCH and the Cholesky Flexible Threshold-GARCH specifications we estimate for comparative purposes a DCC Spline-GARCH model and a typical DCC model, in which the univariate variances are modeled via a Spline-GARCH and a GARCH process respectively.

First, we present a comparative picture of the way the specifications based on the

Table V: Forecast errors ($\times 10^{-6}$). Bold denote smallest errors across rows.

Model	Flexible Threshold	Flexible Threshold-GARCH	Spline-GARCH	GARCH
In-the-sample errors based on squared residuals				
RMSE	**11.161**	11.288	11.690	11.809
MAD	**7.284**	7.384	7.734	7.770
Out-of-sample errors based on squared residuals				
RMSE	**8.388**	8.521	8.632	8.713
MAD	6.309	**6.301**	6.498	6.458
Out-of-sample errors based on realized volatility				
RMSE	2.755	**2.729**	2.899	2.913
MAD	1.855	**1.772**	2.038	1.884

Table VI: Marginal probability of inclusion of macroeconomic indices in Cholesky Flexible Threshold-GARCH and in DCC Flexible Threshold-GARCH specifications.

Macroeconomic announcement		Group	Cholesky Flexible Threshold-GARCH	DCC Flexible Threshold-GARCH		
				EURUSD	GBPUSD	USDCHF
7	ISM Manufacturing	CS	0.9994	0.4380	0.8159	0.3914
14	Unemployment rate	EW	0.9980	0.9956	0.2801	0.9896
5	Advance Retail Sales	OG	0.9980	0.7746	0.4198	0.6413
10	Consumer Confidence	CS	0.9685	0.1772	0.6919	0.3165
3	Durable Goods Orders	OG	0.9487	0.6211	0.4349	0.8031
13	Trade Balance	BP	0.9331	0.5358	0.3381	0.4522
11	Consumer Price Index	P	0.8624	0.4681	0.5174	0.7772
8	ISM Non-Manufacturing	CS	0.8484	0.6006	0.4270	0.7406
15	Personal Income	EW	0.8138	0.3027	0.2805	0.3023
12	Producer Price Index	P	0.8042	0.2132	0.5421	0.3008
4	Wholesale Inventories	OG	0.7989	0.3421	0.3011	0.4645
2	Industrial Production	OG	0.7845	0.2761	0.4722	0.3592
1	GDP Annualized	OG	0.7812	0.4464	0.3349	0.3731
6	Housing Starts	OG	0.7790	0.2940	0.2271	0.3992
9	Leading Indicators	CS	0.7214	0.3877	0.2784	0.3480

Flexible Threshold-GARCH model include macroeconomic index parameters in the trans-dimensional MCMC sample. Table VI presents the marginal probability of inclusion for the macroeconomic indices, under the Cholesky Flexible Threshold-GARCH and the DCC Flexible Threshold-GARCH specifications. It is interesting to observe that in the Cholesky Flexible Threshold-GARCH specification, there are representatives from all groups among the most important announcements affecting the covariance matrix. Furthermore in the univariate Flexible Threshold-GARCH specifications we observe that for EURUSD and USDCHF there are considerable similarities, while GBPUSD seems to be affected more by a different collection of macroeconomic announcements, that belong mainly to the groups of Confidence and Sentiment reports and Prices.

Figure 3 displays the out-of-sample forecasts of the volatilities and correlations of exchange rates based on the Cholesky Flexible Threshold-GARCH model, together with the realized variances and correlations obtained from 5-minute data. The announcements that

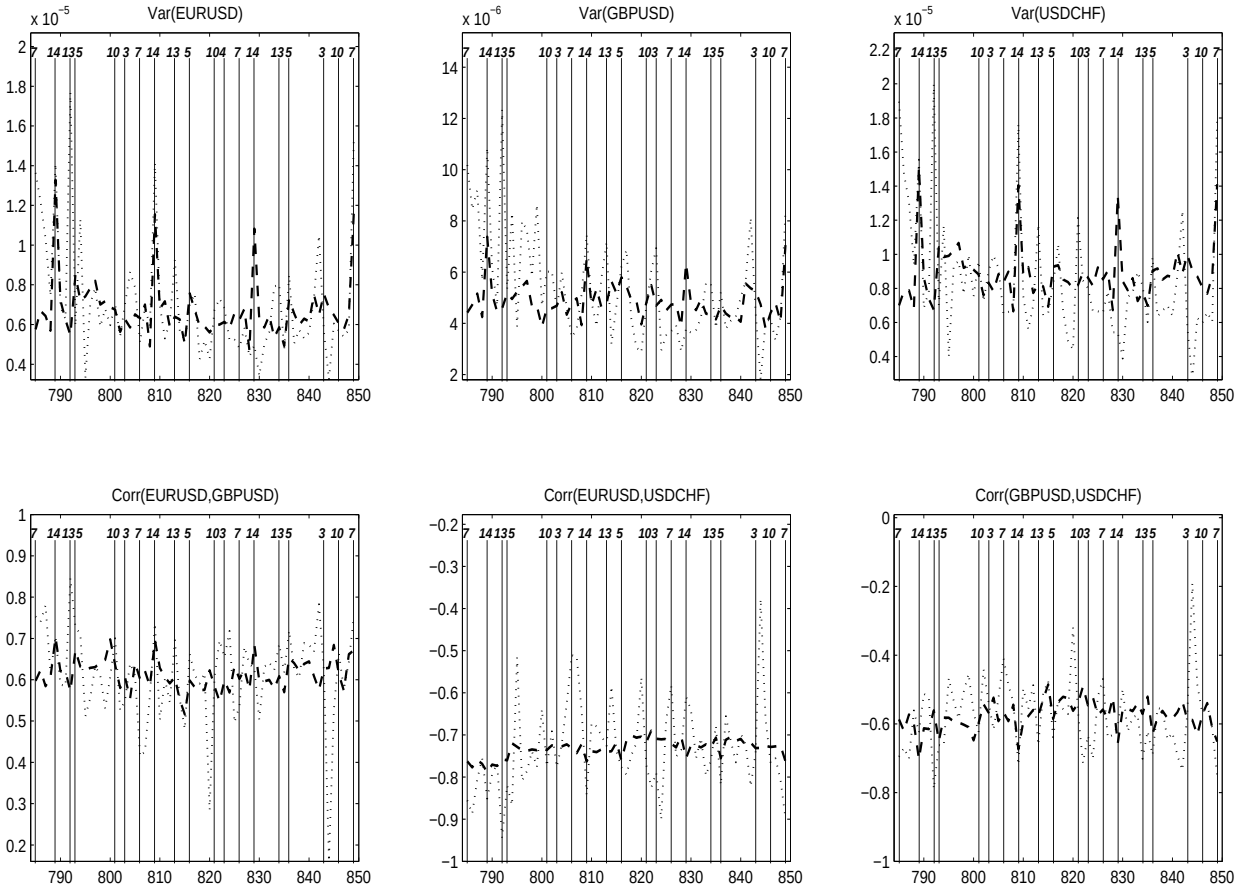

Figure 3: Out-of-sample forecasts of the Cholesky Flexible Threshold-GARCH model versus realized variances, correlations and news announcements; dotted: realized variances and correlations, dashed: Out-of-sample forecasts, solid: news announcements.

have posterior marginal probability of inclusion above 90% in Table VI are also depicted as vertical lines. A close inspection of this Figure reveals on the one hand that macroeconomic announcements affect simultaneously the volatilities of the three exchange rates, as well as their correlations; typical examples of this phenomenon are releases of Unemployment rate (14), Trade Balance (13) and Advance Retail Sales (5). Moreover, note that the release of a macroeconomic index may cause negative jumps in the volatility process, that is adequately captured by our model. Finally, an interesting observation is that the well-known strong correlation between the three exchange rates can be partially explained by the fact that the reaction to some announcement surprises is contemporaneous and towards the same direction.

Table VII: Forecast errors ($\times 10^{-6}$) for the multivariate models. Bold denote smallest errors across rows.

	Cholesky Flexible Threshold-GARCH	DCC Flexible Threshold-GARCH	DCC Spline-GARCH	DCC
RMSE	In-the-sample errors based on residual series			
Var(EURUSD)	**11.248**	11.288	11.690	11.819
Var(GBPUSD)	8.236	**8.154**	8.184	8.375
Var(USDCHF)	13.948	**13.847**	14.309	14.520
Cov(EURUSD,GBPUSD)	8.308	**8.278**	8.376	8.471
Cov(EURUSD,USDCHF)	**11.991**	12.004	12.405	12.575
Cov(GBPUSD,USDCHF)	9.153	**9.103**	9.201	9.326
TRMSE	10.446	**10.417**	10.676	10.824
MAD	In-the-sample errors based on residual series			
Var(EURUSD)	**7.381**	7.384	7.734	7.863
Var(GBPUSD)	5.205	**5.147**	5.244	5.348
Var(USDCHF)	9.280	**9.185**	9.668	9.803
Cov(EURUSD,GBPUSD)	**5.215**	5.232	5.343	5.412
Cov(EURUSD,USDCHF)	7.992	**7.970**	8.356	8.486
Cov(GBPUSD,USDCHF)	5.786	**5.770**	5.879	5.985
TMAD	6.650	**6.629**	6.867	6.975
RMSE	Out-of-sample errors based on of realized covariation			
Var(EURUSD)	**2.654**	2.729	2.899	2.884
Var(GBPUSD)	**2.003**	2.050	2.881	2.049
Var(USDCHF)	**3.507**	3.808	4.442	3.703
Cov(EURUSD,GBPUSD)	**1.970**	2.032	2.360	2.168
Cov(EURUSD,USDCHF)	**3.150**	3.447	3.928	3.625
Cov(GBPUSD,USDCHF)	**2.036**	2.341	2.967	2.346
TRMSE	**2.566**	2.772	3.267	2.846
MAD	Out-of-sample errors based on of realized covariation			
Var(EURUSD)	**1.703**	1.772	2.038	2.088
Var(GBPUSD)	**1.448**	1.478	2.398	1.531
Var(USDCHF)	**2.486**	2.803	3.536	2.839
Cov(EURUSD,GBPUSD)	**1.328**	1.531	1.943	1.715
Cov(EURUSD,USDCHF)	**2.406**	2.699	3.304	3.104
Cov(GBPUSD,USDCHF)	**1.441**	1.875	2.493	1.921
TMAD	**1.776**	2.029	2.606	2.215

In Table VII we present the forecast errors for the Cholesky Flexible Threshold-GARCH, DCC Flexible Threshold-GARCH, DCC Spline-GARCH and typical DCC models, both for in-the-sample and out-of-sample time periods. This Table conveys two important messages. First, the Flexible Threshold-GARCH specification can more adequately predict the elements of the covariance matrices when compared to the specifications based on DCC. Moreover, the Cholesky specification obtains the smallest out-of-sample errors for the variances.

6. CONCLUDING REMARKS

We presented a new class of flexible threshold models for predicting volatilities and correlations of exchange rates that incorporate information from scheduled news announce-

ments. For the dataset we used, we have found strong evidence that suggests the use of such extra information can enrich the usual GARCH structures commonly used.

The use of our proposed threshold models is intuitively appealing, although it may suffer from the usual problem of over-fitting. We have advocated the use of model averaging prediction that exploits modern MCMC strategies that sample in a transdimensional space and our detailed empirical analysis provided evidence that our models predict well when compared with other nonparametric formulations such as splines.

Our statistical framework is immediately applicable to extensions to other data sets such as stock returns and other types of news. Except than company results, it is not clear to us what kind of news may affect the volatility of a stock return and therefore we have limited our empirical study to exchange rates with macroeconomic announcements.

A. APPENDIX: THE POPULATION REVERSIBLE JUMP ALGORITHM

We provide some technical details for the implementation of the reversible jump MCMC algorithm. We propose, with equal probabilities, to select an *addition*, *deletion* or *replacement* moves with respect to the variables Z_{it}. When an *addition* move is chosen, we propose a new set of parameters $(c_{ij}, g_{ij}, \rho_{ij}, \varsigma_i)$ from their prior densities, while the rest of the parameters remain unchanged. In the *replacement* move we uniformly propose to replace one index present at the current model with another one. In the *split* move, we propose to increase the number of threshold points c_{ij} by one. A dependent proposal is needed when we propose to add the jth threshold point. We draw two random numbers u_1 and u_2 from the prior densities of g_{ij} and ρ_{ij} respectively and set

$$\begin{aligned} g'_{ij} &= g_{i,j-1} + u_1 \\ g'_{i,j-1} &= g_{i,j-1} - u_1 \\ \rho'_{ij} &= \rho_{i,j-1} + u_2 \\ \rho'_{i,j-1} &= \rho_{i,j-1} - u_2. \end{aligned}$$

The Jacobian term needed in the reversible jump acceptance probability ratio is then given

by

$$|J| = \left| \frac{\partial(g_{i,j-1}^{'}, g_{ij}^{'})}{\partial(g_{i,j-1}, u_1)} \right| = \begin{vmatrix} 1 & -1 \\ 1 & 1 \end{vmatrix} = 2.$$

Since the same Jacobian results for the ρ_{ij} parameters, in the final acceptance ratio the term $|J|^2$ is included. In the *merge* move we randomly select a threshold point to be deleted taking care so that the first threshold point ($j = 1$) is always included in c_i. Then we set the new parameters as

$$\begin{aligned} g_{i,j-1} &= (g_{ij}^{'} + g_{i,j-1}^{'})/2 \\ \rho_{i,j-1} &= (\rho_{ij}^{'} + \rho_{i,j-1}^{'})/2. \end{aligned}$$

The moves used to update the parameters $(\sigma^2, \alpha_1, \alpha_2, g_{ij}, \varsigma_i, \rho_{ij})$ are all random-walk Metropolis-Hastings kernels. Details including graphs and empirical statistics verifying that the chains mix well and in all empirical exercises presented here the parameters of interest have converged are available in Petralias (2010).

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