



**ON CLASSIFYING THE EFFECTS OF POLICY
ANNOUNCEMENTS ON VOLATILITY**

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On Classifying the Effects of Policy Announcements on Volatility

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Abstract

The financial turmoil surrounding the Great Recession called for unprecedented intervention by Central Banks: unconventional policies affected various areas in the economy, including stock market volatility. In order to evaluate such effects, by including Markov Switching dynamics within a recent Multiplicative Error Model, we propose a model-based classification of the dates of a Central Bank's announcements to distinguish the cases where the announcement implies an increase or a decrease in volatility, or no effect. In detail, we propose two naïve classification methods, obtained as a by-product of the model estimation, which provide very similar results to those coming from a classical k-means clustering procedure. The application on four Eurozone market volatility series shows a successful classification of 144 European Central Bank announcements.

Keywords: Markov switching model, Unconventional monetary policies, Stock market volatility, Multiplicative Error Model, Smoothed Probabilities, Model-based clustering.

Jel Classification: C32, C38, C58, E44, E52, E58.

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1 Introduction

Since the onset of the Great Recession, many Central Banks resorted to unconventional monetary policy in order to mitigate the consequences that the crisis had both on the real economy and financial markets. All the unconventional monetary policy measures are introduced by means of monetary policy announcements; recent literature focused on the consequences for the real economy (e.g. Kapetanios et al., 2012; Pesaran and Smith, 2016) and for the financial markets, in particular their volatility (Shogbuyi and Steeley, 2017; Kenourgios et al., 2015; Steeley and Matyushkin, 2015), modelling the effect of the announcements to be constant. In practice, however, the strength of an announcement ends up being a consequence of the conditions in which the measure is adopted, its wording, how it constitutes a surprise relative to the consensus, how divergent expectations are, and so on. The impact on asset prices, in particular on its volatility, is a consequence of an immediate diffusion of the new information and the formation of new equilibria after the announcement.

Within the class of Multiplicative Error Models (MEMs) Engle (2002), the recent work by Lacava et al. (2020) is a first attempt at measuring the unconventional policy effects as an unobservable component of volatility, distinguishing between implementation (as represented by a continuous proxy variable) and announcement (associating a dummy variable to it on that day) effects. In what follows, among their proposed models (cf. also the previous contribution by Brownlees et al. (2012)), we modify the Asymmetric Composite Model (ACM): we substitute the role of the dummy variable with two alternative nonobservable regimes, with the possibility to estimate different effects of the announcement in terms of changes in level and adopting a Markov Switching (MS) dynamics. A by-product of this model is the possibility to classify the announcements detecting if they provide a change in regime or the permanence in the same regime.

Despite its peculiarities in classification (not based on distance measures), our approach can be inserted in the traditional literature concerning model-based clustering (for a recent update on the state of the art, cf. Maharaj

et al. (2019)) ; convenient reviews of these methods are in Liao (2005) and Aghabozorgi et al. (2015). In particular, the latter paper differentiates among three different areas of analysis, namely, whole, subsequence and time-point analysis: in the last of these areas, in particular, one can address several issues of interest, such as discovering both expected and unusual patterns, recognizing dynamic changes in time series or prediction. Our approach falls within to this third area. By the same token, our proposal is clearly different from the model-based techniques aimed at developing clustering in volatility of financial markets, such as Caiado and Crato (2007), Otranto (2008), De Luca and Zuccolotto (2011), D’Urso et al. (2013), where the classification relates to the full time series and not to the individual observations. The same considerations can be made by comparing our approach with Otranto and Gargano (2015), where an ACM model similar to the one proposed in this paper is adopted, but, again, with the aim to classify the similarities between entire financial time series.

We apply our univariate approach to stock market realized volatility time series measured on four Eurozone stock indices (CAC40, DAX30, FTSEMIB and IBEX35), considering 144 announcements and classifying how such announcements had effects on the level of volatility: the groups we get are named *Plank* (a neutral effect), *Squat* (a decrease in volatility) and *Jump* (an increase in volatility). The classification techniques suggested, next to a formal statistical clustering approach, build on a simple processing of the smoothed probabilities of being on one of two regimes (low and high volatility), are simple to implement, and provide results very similar to the adopted k-means clustering approach.

The paper is structured as follows. We detail our MS approach to classification in Section 2, separating the presentation of the model in Subsection 2.1 from the proposed classification procedures in Subsection 2.2. The empirical application is contained in Section 3 where we discuss data features and the framework of events occurring in our sample period; estimation results are discussed in Subsection 3.1 and the corresponding classifications in Subsection 3.2. Finally, Section 4 contains some concluding remarks.

2 A Markov Switching Approach to Classification

2.1 A Policy Analysis-oriented Modelling Approach

Volatility modelling takes advantage of the availability of high frequency data, favouring a decoupling of measurement and modelling with respect to the more traditional approach based on GARCH models (Engle, 1982; Bollerslev, 1986). The so-called Realized Volatility (RV) is recognized to have better properties in measurement than the outcome of the estimated GARCH-based conditional variance of returns (Andersen et al., 2001). As per forecasting, several conditional models are available for RV; one of them is the MEM, proposed by Engle (2002), which takes volatility dynamics in terms of the product of two positive time-varying factors, one representing its conditional mean and the other a positive disturbance. After the seminal paper of Engle (2002), several proposals have improved the model to capture stylized facts and to accommodate specific cases; in particular the Engle and Gallo (2006) specification introduces the asymmetric and predetermined variable effects in modelling volatility within the MEM class. In what follows, with an eye to capturing policy effects, we propose a model that considers MS regimes within a MEM with dynamic components representing volatility dynamics and policy-induced effects, respectively:

$$\begin{aligned}
 RV_t &= \mu_{t,s_t} \epsilon_t, \quad \epsilon_t | \mathbf{I}_{t-1} \sim \text{Gamma}(\vartheta_{s_t}, \frac{1}{\vartheta_{s_t}}) \\
 \mu_{t,s_t} &= \varsigma_t + \xi_{t,s_t} \\
 \varsigma_t &= \omega + \alpha RV_{t-1} + \beta \varsigma_{t-1} + \gamma D_{t-1} RV_{t-1} \\
 \xi_{t,s_t} &= \varphi_0 + \varphi_1 s_t + \delta(E(x_t | \mathbf{I}_{t-1}) - \bar{x}) + \psi \xi_{t-1, s_{t-1}}
 \end{aligned} \tag{1}$$

As with any other MEM, the realized volatility at time t , RV_t , is seen as the product of a conditional (on the past information set \mathbf{I}_{t-1}) expectation term μ_t times a unit mean error term ϵ_t following a Gamma distribution. In our approach, in line with Lacava et al. (2020), the expected conditional volatility is decomposed as the sum of ς_t (a base volatility component), evolving as a

GARCH-like process (with asymmetric effects tied to the negative sign of past returns captured by a dummy variable, D_{t-1}), and a policy-specific and regime-dependent term ξ_{t,s_t} , which follows an AR(1) model. In the AR(1), the driving variable is x_t – an unconventional policy measures proxy entering the model as the deviation of its conditional expectation from a long term mean \bar{x} – which accounts for the Central Banks’ balance sheet composition and aims at capturing the unconventional policy effect.

What differs from the ACM model by Lacava et al. (2020)¹ is the consideration within the policy-specific component of a dichotomic discrete latent variable $s_t = 0, 1$, representing the regime at time t and following a first order Markov chain: thus ξ_t becomes ξ_{t,s_t} . When $s_t = 0$, the time series is in a low volatility regime with intercept φ_0 , increasing by $\varphi_1 \geq 0$ in the high volatility regime ($s_t = 1$). The regime is not observable, but its dynamics is driven by a Markov chain, so that:

$$Pr(s_t = j | s_{t-1} = i, s_{t-2} \dots) = Pr(s_t = j | s_{t-1} = i) = p_{ij}.$$

Positiveness ($\omega > 0, \alpha, \beta, \gamma \geq 0$) and stationarity ($\alpha + \beta + \frac{\gamma}{2} < 1$ and $|\psi| < 1$) conditions detected for the ACM are regime-independent and hence are valid for the MS-ACM as well.

The likelihood function of the MS-ACM is obtained by means of the so called Hamilton filter and smoother, as described in Hamilton (1994) (Ch. 22), adopting the approximated solution proposed by Kim (1994) to solve the path dependence problem, a computational problem due to the dependence of μ_t on all past values of s_t . In fact, at the end of the recursive Hamilton filter we have to keep track of all possible paths obtained by all the combinations of regimes from the first time until the last one, with 2^T possible different scenarios. To solve the path dependence problem, Kim (1994)

¹The ACM model is derived from the general framework in Brownlees et al. (2012), where the mean of the conditional volatility is the sum of two unobservable components: the particular ACM specification proposed by Otranto (2015) to model spillover effects in financial markets is adapted to representing the base volatility and the unconventional policy effect respectively. Formally, in their ACM model the last equation is:

$$\xi_t = \delta(E(x_t | \mathbf{I}_{t-1}) - \bar{x}) + \varphi(\Lambda_t - \bar{\Lambda}) + \psi \xi_{t-1}, \quad (2)$$

where, the Λ_t term is taken as deviation from its long-term mean, also here.

proposes to collapse the 4 possible values of μ_t at time t , obtained at the end of each step of the Hamilton filter, into 2 values, averaging and weighting them with the corresponding conditional probabilities $Pr[s_{t-1} = i, s_t = j | \mathbf{I}_t]$ (obtained in the same Hamilton filter step).

The Hamilton smoother will provide the so called smoothed probabilities $P[s_t | \mathbf{I}_T]$, used to make inference on the regime conditional on the full information available, \mathbf{I}_T ; a thumb rule consists in to assign the observation at time t to regime 1 if the smoothed probability that $s_t = 1$ is greater than 0.5, otherwise to regime 0. Moreover the smoothed probabilities are used to obtain an estimation of the intercept in (1), in terms of a weighted average of φ_0 and φ_1 ; calling $\hat{p}_t = P[s_t = 1 | \mathbf{I}_T]$:

$$\hat{\varphi}_t = \hat{\varphi}_0(1 - \hat{p}_t) + (\hat{\varphi}_0 + \hat{\varphi}_1)\hat{p}_t \quad (3)$$

where a hat indicates the QML estimate of the parameter. The coefficient $\hat{\varphi}_t$ is time-varying and represents the value of the intercept of ξ_{t,s_t} . The basic idea of MS-ACM is that, differently from (2), changes in the level of the series will be captured by a change in regime. In correspondence of the dates of the announcements, we can verify a possible change in the volatility level and its amplitude. In addition - by considering a switching constant in place of the announcement variable Λ_t in (2) - the effect of monetary policy announcements is no longer constant: in what follows, we propose three different methods to classify the considered announcements according to their specific effect on volatility.

2.2 Classification of announcements

Given the setup of our model, we can proceed to a natural classification of the announcements, based on the variations of the intercept value estimated on the day of an announcement relative to the day before. In formal terms, the N dates of announcements (i.e., when $\Lambda_t = 1$) are selected within the overall time series and, for those, the values $\hat{\varphi}_t - \hat{\varphi}_{t-1}$ are calculated. Notice

that, from (3):

$$\Delta\hat{\varphi}_\tau \equiv \hat{\varphi}_\tau - \hat{\varphi}_{\tau-1} = \hat{\varphi}_1(\hat{p}_\tau - \hat{p}_{\tau-1}) \equiv \hat{\varphi}_1\Delta\hat{p}_\tau \quad \forall \tau = t : \Lambda_t = 1, \quad (4)$$

that is, such announcement effects on the volatility level can be evaluated through the variations in the smoothed probabilities directly. Thus, a first form of classification of the N announcement is to apply a clustering algorithm to obtain groups with similar $\Delta\hat{p}_t$.

However, by the approach detailed in Eq.(4), one can notice that the announcement effect (a large movement in the intercept) will be estimated to be substantial, the larger the movement between the probability of being in regime 1 at time $t - 1$ and the corresponding one at time t . An alternative to a clustering-based method can therefore be suggested, exploiting the customary mapping of smoothed probabilities into a regime classification based on the threshold $\hat{p}_t = 0.5$.

A first naïve classification (dubbed *N-level*) can be obtained directly from the position of the probabilities \hat{p}_t , respectively, \hat{p}_{t-1} , relative to the threshold value 0.5. In this case we suggest 4 groups, with an immediate interpretation, in the following way:

1. *No effect and low volatility - (low) Plank*, if $\hat{p}_t \leq 0.5$ and $\hat{p}_{t-1} \leq 0.5$;
2. *No effect and high volatility - (high) Plank*, if $\hat{p}_t \geq 0.5$ and $\hat{p}_{t-1} \geq 0.5$;
3. *Decrease in volatility - Squat*, if $\hat{p}_t \leq 0.5$ and $\hat{p}_{t-1} \geq 0.5$;
4. *Increase in volatility - Jump*, if $\hat{p}_t \geq 0.5$ and $\hat{p}_{t-1} \leq 0.5$.

A second naïve classification (called *N-diff*, since it is based on $\Delta\hat{p}_t$) gives three groups as follows:

1. *No effect - Plank*, if $-0.5 \leq \Delta\hat{p}_t \leq 0.5$; this group will contain cases with a moderate effect, with or without regime change (i.e. irrespective of whether the threshold is crossed), since subsequent \hat{p}_t 's are close to one another;

2. *Decrease in volatility – Squat*, if $\Delta\hat{p}_t < -0.5$; in this case the volatility at time t is attributed to regime 0 whereas the volatility at time $t - 1$ to regime 1, with a sharper change in the value of the probability by more than 50%;
3. *Increase in volatility – Jump*, if $\Delta\hat{p}_t > 0.5$; in this case the volatility at time t is attributed to regime 1, whereas the volatility at time $t - 1$ to regime 0, and the change in the value of the probability is more than 50%.

The diff-groups here are different from the level-groups, even if they have the same label, since in this second approach we would classify as a Plank a change in regime between $t - 1$ and t , not accompanied by a relevant change in \hat{p}_t 's. By both classifications, however, Squats and Jumps come when the MS model produces a sharp mapping into regimes, and therefore should give similar results.

If well designed, the three classifications should provide similar results, and evidence will be provided below; although they are not based on a rigorous statistical procedure, both naïve classifications have the advantage of being immediately applicable each time an announcement is provided.

3 An Empirical Application

We consider the annualized realized kernel volatility of four Eurozone stock indices (CAC40, DAX30, FTSEMIB and IBEX35) as provided by the Oxford Man Institute² for the period from June 1, 2009 to December 31, 2019 (daily data, 2685 observations). Their profiles, shown in Figure 1, behave in a similar way, exhibiting peaks of market-related activity occurring in correspondence of some events of relevance: two remarkable peaks are recognized in the first part of the sample, coinciding with the flash crash on May 6, 2010 and August 8, 2011 (depicted as blue-dashed vertical lines in Figure 1). Similarly, some volatility spikes correspond to monetary policy announcements

²Data are available at <https://realized.oxford-man.ox.ac.uk/data/download>

(red-dashed line); this is the case, for example, of the so-called conventional monetary policy decisions concerning the interest rates (on August 2, 2012; November 7, 2013; December 4, 2014; December 3, 2015) and the *unconventional* policy decision on March 10, 2016, when the Corporate and Public Sector Purchases Programmes (CSPP and PSPP, respectively) were included in the Expanded Asset Purchases Programme (EAPP). In addition, in all the series the volatility clustering phenomenon emerges quite clearly, with a long period of low volatility starting in July 2012, whereas short-lived periods of high volatility are observed at the beginning of the sample, corresponding to the Greek sovereign debt crisis in May 2010 and in the mid of 2011 when the Eurozone crisis exploded affecting not only the Eurozone.

We proxy for the implementation effects, the term $E(x_t|\mathbf{I}_{t-1})$ in Eq.(1), via the ratio between the amount of securities held for unconventional policy purposes and the amount of securities employed for conventional policy measures³. The conditional expectation of x_t is estimated through the ARIMA(4,1,1) model according to a preliminary order identification procedure. Finally, the list of monetary policy announcements consists of $N = 144$ events, constructed starting from the ECB press releases⁴, each defining a $\Lambda_t = 1$.

³Data are obtained from the ECB website and Datastream.

⁴Available at <https://www.ecb.europa.eu/press/pr/activities/mopo/html/index.en.html>

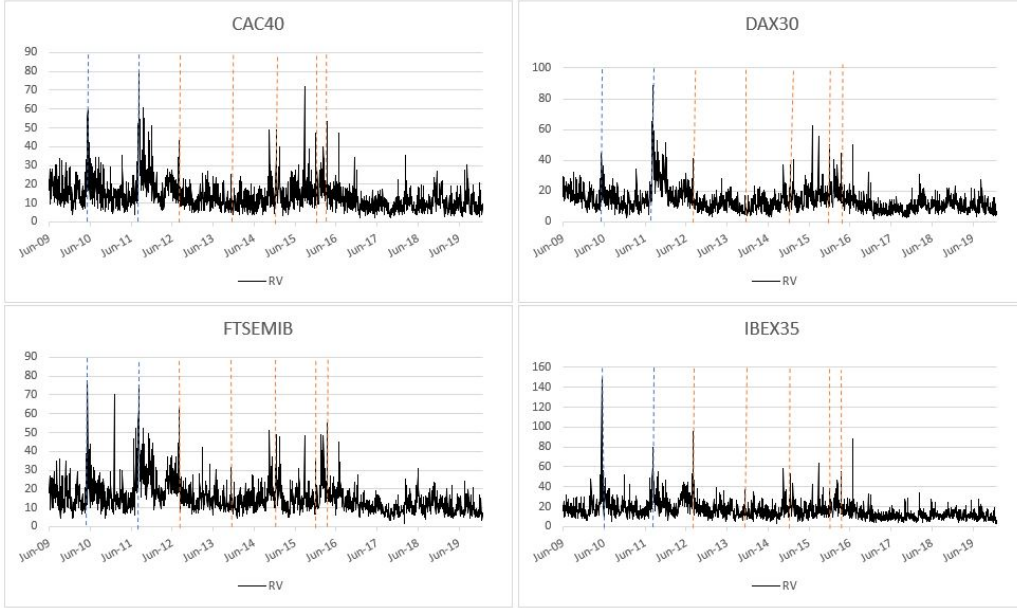


Figure 1: Realized Volatility series and relevant events (red and blue dashed-lines) for financial markets. Sample Period: June 1, 2009 to December 31, 2019

3.1 Estimation results

Estimation results of our MS-ACM are shown in Table 1 for the volatilities of each financial index. Recall that for our analysis we assume that the switching process applies to the ξ_{t,s_t} component in the form of a switching constant instead of inserting an announcement dummy variable (as considered by Lacava et al. (2020) – cf. Eq.(2)). Estimation results support this choice: the constant in the low volatility regime is equal to zero across indices (a regime without monetary policy announcements), whereas it increases remarkably in the high volatility regime; the unconventional policy proxy significantly enters the model with a negative sign, as it is expected to reduce the volatility level, with the strongest impact observed for the IBEX35 (-1.09) and the weakest occurring for the DAX30 (-0.44). As per the probability coefficients, the probability of remaining in the low regime is higher than that of the high volatility regime, leading to an average duration of 1 day (calculated as $\frac{1}{1-p_{ii}}, i = 0, 1$) in the high regime for all markets, while the duration in the low regime ranges between 14 days (FTSEMIB) and 53 days (DAX30).

Finally, none of the models shows a significant autoregressive coefficient (ψ), even if no substantial autocorrelation remains in the residuals.

In Figure 2, we compare the weighted average of the constant with the announcement variable. In brief, it seems that such an average jumps in correspondence of monetary policy announcements, more frequently so for the FTSEMIB and the IBEX35 than for the CAC40 and the DAX30. To provide a readable illustration, consider, in detail, three meaningful dates: August 4, 2011, when the ECB gave additional details on a Longer Term Refinancing Operation (LTRO); August 2, 2012, when the ECB communicated to the market that there would have been no changes of interest rates, and December 3, 2015, when, conversely, only the interest rate on deposit facility was decreased by 10bps. It is interesting to notice that these announcements affected returns in the sense of reducing them in all the cases, with the worst loss coinciding with the unconventional policy announcement (August 4, 2011), between 4.41% (DAX30) and 6.9% (FTSEMIB). More importantly, in the case of the two conventional policy announcements, the estimated probability to be in the high regime is near to 1, whereas the process appears to be in the low regime on the unconventional policy announcement day (August 4, 2011) supporting the idea that unconventional policies successfully were capable to reduce stock market volatility (this is in line with the negative sign of the δ coefficient in Table 1). Finally, we observe a reduction in the weighted average $\hat{\varphi}_t$ after the announcements, consistently with the average duration (1 day) of the high volatility regime.

Table 1: Estimation results (robust standard errors in parentheses) and p-values of Ljung-Box statistics for different lags of four MS-ACMs relative to different RV of European financial indices. Sample period: June 1, 2009 - December 31, 2019.

	CAC40	DAX30	FTSEMIB	IBEX35
ω	0.853 (0.083)	0.661 (0.095)	1.063 (0.18)	1.059 (0.029)
α	0.142 (0.016)	0.185 (0.016)	0.228 (0.02)	0.151 (0.015)
β	0.732 (0.02)	0.722 (0.021)	0.649 (0.032)	0.732 (0.017)
γ	0.112 (0.01)	0.082 (0.009)	0.08 (0.012)	0.086 (0.008)
δ	-0.775 (0.125)	-0.44 (0.105)	-0.741 (0.135)	-1.09 (0.125)
φ_0	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
φ_1	6.275 (1.743)	6.422 (1.941)	4.556 (1.324)	6.161 (2.379)
ψ	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
p_{00}	0.964 (0.024)	0.981 (0.014)	0.928 (0.028)	0.943 (0.032)
p_{11}	0.222 (0.1)	0.304 (0.119)	0.338 (0.118)	0.314 (0.082)
θ_0	8.852 (0.375)	11.249 (0.489)	15.033 (0.979)	11.99 (0.704)
θ_1	3.271 (0.71)	2.598 (0.735)	4.112 (0.836)	3.777 (0.682)
Ljung-Box 1 lag	0.711	0.161	0.403	0.22
Ljung-Box 5 lag	0.263	0.121	0.449	0.087
Ljung-Box 10 lag	0.364	0.276	0.639	0.34

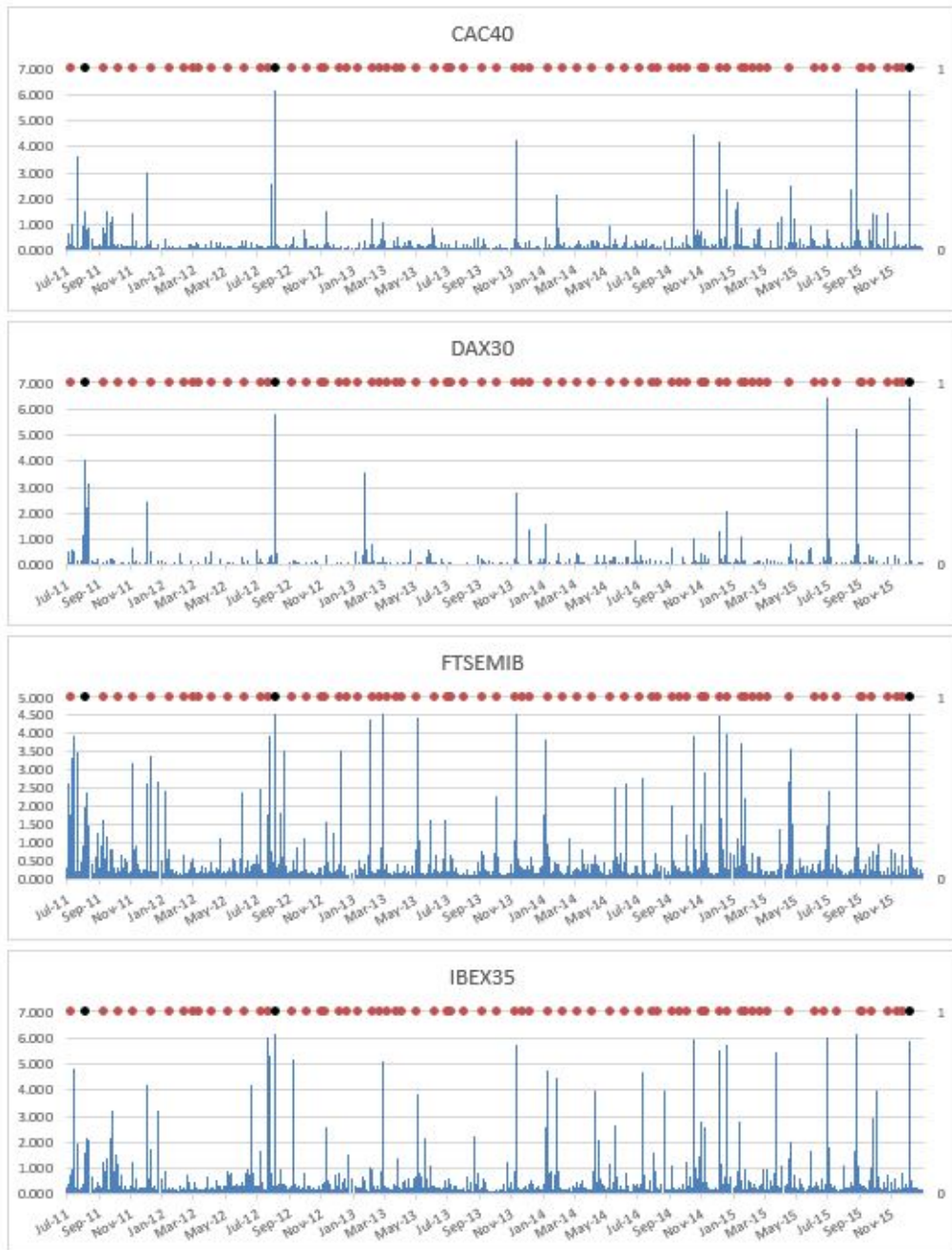


Figure 2: $\hat{\varphi}_t$ as a weighted average resulting from the MS-ACM (blue line) and monetary policy announcements (red dots). The period depicted spans July 1, 2011 to December 31, 2015. Black dots correspond to three meaningful announcements (details in the text): August 4, 2011, August 2, 2012, and December 3, 2015.

3.2 Classification Results

The estimated smoothed probabilities are used to classify the 144 dates of announcements into the three categories: *Plank*, *Squat*, and *Jump*. We calculated the variable $\Delta\hat{p}_t$ (see Eq.(3)) and apply a classical k-means algorithm, minimizing the sum of squares from points to the assigned cluster centers, to form three groups. In the first column of Table 2 we show the number of dates belonging to each group for each financial index. Most of the announcements do not cause a change in volatility (*Plank*); however, a remarkable percentage of the announcements cause a switching from the low to the high volatility for FTSEMIB and IBEX35, that is 15.3% and 8.3%, respectively, whereas it is less than 5% for CAC40 and DAX30. Some important announcements belonging to this category refer both to conventional policies (for example the decrease of interest rates established on December 3, 2015, when they became negative) and unconventional policies (e.g. the announcement on March 10, 2016 when the amount of securities purchased within the implementation of the EAPP passes from € 60 to € 80 billion per month; the announcement on September 12, 2019, when the ECB decided to run the EAPP as long as necessary).

Finally, a smaller percentage of the announcements caused a switching from the high to the low volatility regimes: some examples are represented by the details on the Covered Bond Purchases Program (CBPP) released on June 4, 2009 (for the CAC40), the Security Market Program (SMP) on May 10, 2010 (for the FTSEMIB) and the announcement on June 8, 2017 concerning details on the EAPP (for the IBEX35).

Our analysis confirms the results in Lacava et al. (2020) where the dummy representing the announcements has a positive sign and is more significant for the FTSEMIB and the IBEX35. The announcement effect seems to be more pronounced for the volatility of the Italian and Spanish markets than for the French and German ones, in line with the more stable performance of the latter during this turbulent period.

In the last two columns of Table 2 we show the clustering obtained with the two naïve approaches (we merged the two *Plank* cases in the N-level

classification, in order to make the results comparable with the other classifications). The outcome seems quite similar across methods, with a larger number of cases identified as *Plank* announcements relative to what the k-means clustering delivers. Also, considering the N-level approach, we can notice that almost all *Plank* cases are identified when the regime was one of low volatility at time $t - 1$.

The centers of each group are around 0 for the *Plank* group across classification methods. Some differences are present in the centers of the other two categories, in particular between the k-means method and the two naïve approaches; FTSEMIB seems the one market with less sharp classifications when derived from the three methods.

A formal evaluation of the differences in the classifications obtained with the three alternative methods can be conducted by means of the adjusted Rand index (Rand, 1971; Hubert and Arabie, 1985). Such a method is generally used to compare the groups obtained by a certain algorithm with respect to a benchmark clustering; in our case, we use it to verify the similarity of clustering methods by taking possible pairs in turn. The Rand index ranges in $[0, 1]$, and takes on value 1 when the two methods provide the same clustering, and value 0 in the case of maximum difference between them. In Table 3 we show the values of this index across volatility series; they are always larger than 0.9 (with the exception of the comparison between k-means and N-diff for the FTSEMIB, which is 0.85), with value 1 in the case of the two naïve methods for the CAC40 and the DAX30. Given that the three alternative methods provide very similar results, the naïve solutions receive a good support as an immediate by-product of the model estimation, not requiring statistical clustering algorithms.

Furthermore, to verify if the announcements are classified in a similar way, this time across the four volatility series, we calculate the Rand index for the same clustering method but for different markets (Table 4); once again we get a strong agreement in the classification results, with Rand indices always larger than 0.74, with a clear similarity between the CAC40 and the DAX30. Moreover, it seems that the N-diff method provides more similar patterns among markets relative to the other two methods. By comparisons, the

k-means provides lower values, but still high in terms of similarity.

We can conclude that the k-means statistical clustering provides a classification as a benchmark, but the naïve classifications confirm their good performance in providing reliable results also in view of their very practical derivation.

Table 2: Classification of announcements for the European volatility series using three alternative algorithms. The numbers in parentheses are the centers of the corresponding group. In the group "Plank" of the N-level classification, the number in square brackets represents the cases with high volatility both at t and $t - 1$ (High-Plank).

Group	k-means	N-level	N-diff	k-means	N-level	N-diff
	CAC40			DAX30		
Plank	132 (0.010)	136 [0] (0.004)	136 (0.004)	136 (0.007)	140 [1] (0.005)	140 (0.005)
Squat	5 (-0.261)	1 (-0.561)	1 (-0.561)	3 (-0.178)	0 -	0 -
Jump	7 (0.704)	7 (0.704)	7 (0.704)	5 (0.664)	4 (0.733)	4 (0.733)
	FTSEMIB			IBEX35		
Plank	118 (0.010)	125 [2] (0.018)	133 (0.035)	123 (0.020)	131 [3] (0.008)	132 (0.005)
Squat	4 (-0.460)	2 (-0.606)	1 (-0.726)	9 (-0.309)	2 (-0.498)	1 (-0.526)
Jump	22 (0.539)	17 (0.599)	10 (0.731)	12 (0.715)	11 (0.745)	11 (0.745)

Table 3: Adjusted Rand index between classification methods by volatility series.

	k-means/ N-level	k-means/ N-diff	N-level/ N-diff
CAC40	0.962	0.962	1
DAX30	0.962	0.962	1
FTSEMIB	0.925	0.851	0.919
IBEX35	0.922	0.913	0.990

Table 4: Adjusted Rand index between pairs of volatility series by classification method.

	k-means	N-level	N-diff
CAC40/DAX30	0.924	0.962	0.962
CAC40/FTSEMIB	0.792	0.875	0.951
CAC40/IBEX35	0.854	0.913	0.923
DAX30/FTSEMIB	0.812	0.859	0.933
DAX30/IBEX35	0.805	0.897	0.906
FTSEMIB/IBEX35	0.741	0.828	0.912

4 Concluding Remarks

In this paper we derive a novel Markov Switching Multiplicative Error Model to include a component related to monetary policy actions: such a model extends the recent MEM-class contribution by Lacava et al. (2020) which accommodates an additive component related to volatility dynamics induced by policy measures. As a relevant by-product, we advance a simple-to-obtain suggestion on how to map the information on estimated volatility regimes to classify announcements of a Central Bank in terms of their impact on volatility levels. Recent econometric literature is producing great efforts in evaluating these transmission mechanisms in real and financial economies, but generally they assume different announcements as producing the same effect.

In the model we propose within a more realistic scenario, the announcements are allowed to have different importance, and no prior classification is imposed. With MS features, our model has the merit of extracting from volatility an unobservable signal attributable the unconventional policy effects, with jumps in its intercept as a consequence of policy announcement: the estimated parameters allow us to derive a procedure to map the variations in the intercept in correspondence of the jumps into groups interpretable as policy effects on volatility.

We propose two naïve classifications, one based on the thumb rule of the classification based on the mode of the regime, and derived from the smoothed probabilities (*N-level* method), and another based on the differences of the same smoothed probabilities (we call it *N-diff*). The smoothed probabilities are a by-product of the Hamilton filter and smoother used to explicit the log-likelihood, so they are immediately available as the model is estimated, i.e. a classification of the announcement is automatic after the estimation step. The application on four European volatility indices in the empirical application shows how the naïve classifications provide a very similar clustering with respect to a statistical clustering algorithm (k-means).

In terms of directions of future research, given the time series framework, an important task would be to develop some tools to classify in real time the announcements, when new observations are available, and use the framework in a forecasting context. Given that the classification need to be reapplied to each new announcement, it remains to be seen how robust the previous classification is to the inclusion of new data or, for that matter, to outliers (see, for example, D’Urso et al. (2016)). Moreover, it could be interesting to verify whether such a classification method is robust with respect to alternative time-varying models, such as the smooth-transition MEM proposed in Gallo and Otranto (2015), and alternative clustering methods.

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