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Unconventional policies effects on stock market volatility: The MAP approach

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Abstract

Taking the European Central Bank unconventional policies as a reference, we suggest a class of multiplicative error models (MEMs) tailored to analyse the impact such policies have on stock market volatility. The new set of models, called MEM with asymmetry and policy effects, keeps the base volatility dynamics separate from a component reproducing policy effects, with an increase in volatility on announcement days and a decrease unfolding implementation effects. When applied to four Eurozone markets, a model confidence set approach finds a significant improvement of the forecasting power of the proxy after the expanded asset purchase programme implementation. A multi-step ahead forecasting exercise estimates the duration of the effect; by shocking the policy variable, we are able to quantify the reduction in volatility which is more marked for debt-troubled countries.

KEYWORDS

financial markets, impulse response function, model confidence set, multiplicative error model, realized volatility

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1 | INTRODUCTION

During the Great Recession, with policy interest rates reaching the zero lower bound, many Central Banks, the Federal Reserve (FED), the European Central Bank (ECB) and the Bank of England (BoE) in particular, adopted unconventional actions in order to stimulate the real economy. Among such monetary policies, a relevant place is held by the central bank balance sheet expansion—generally through asset purchase programmes (APP)—which affects the real economy by reducing long-term yields and the credit spread, and by modifying inflation rate expectations during periods in which the liquidity trap makes the conventional policy no longer effective. Since 2009, the ECB resorted to this so-called quantitative easing (QE) in order to inject liquidity into the financial system. Geared towards preventing a systemic collapse not only due to the deterioration of credit ratings, but also to an adverse market attitude towards debt-ridden economies, these policies have been credited with successfully reducing market uncertainty and increasing Eurozone stability. Part of the merit goes to a well-organized communication by Central Banks in which the goal of anchoring expectations of market participants about an orderly evolution and consistency of policies, following the Great Financial Crisis turmoil.[1]

For the bond markets, the effects of monetary policy actions are studied in two directions: an increase in prices due to increased direct demand (and hence a reduction in yields) and a lower volatility (because of the increased stability brought to the system). Among the empirical analyses we cite Eser and Schwaab (2016); De Santis (2020) and Ghysels et al. (2017) use intradaily high-frequency data to document an asymmetric effect due to the presence of Security Market Programme (SMP) purchases in a GARCH(1,1). They find that unconventional monetary policies by ECB had a highly statistically significant dampening impact on yield volatility for most countries and maturities.[2]

For the exchange rate markets, Kenourgios et al. (2015b) insert some dummy variables for QE announcements within an APARCH(1,1) model for the conditional mean and variance of returns. Kenourgios et al. (2015a) extend the model to analyse the effects of QE announcements by the ECB, BoE and BoJ on the intraday volatility transmissions among their currencies. They consider volatility transmission from one currency to another, finding that there is a positive volatility transmission from EUR and JPY to the other currencies, while the volatility of GBP affects negatively the volatility of the other two currencies. Fassas et al. (2021) resort to implied volatility-derived indices on major currencies exchange rates relative to the USD to examine whether the changes in volatility are affected by QE announcements, supporting the existence of a risk-taking channel of monetary policy in the currency market.

As per the stock market, the directional effect is less pronounced: event studies pinpoint to single positive effects on stock prices (Haitsma et al., 2016); the transmission of monetary policy to the stock market can be traced to the portfolio-rebalancing channel (Georgiadis & Gräb, 2016) in redetermining asset allocations as an indirect result of bond price movements; inflation expectations have been less of a concern for at least the past 15 years, while the confidence channel mitigates general uncertainty with what we consider a price direction-neutral effect.

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[1]See, for example the analysis by Kenourgios et al. (2020) about how Consensus forecasts of macrovariables are affected by a Central Bank's announcements.

[2]Rather than lengthening the citations of this rich literature in the bond markets, as they address issues and transmission channels which are not the main focus of this paper, we prefer to summarize some of them in a table in the supplemental material.

The focus of this paper is the impact of the unconventional policies and the evolving communication strategy by a Central Bank (the ECB in our case) on the volatility of stock markets: our contribution departs from other papers that use GARCH-type models (Bollerslev, 1986; Engle, 1982) in which some policy-related variables (usually one or more dummies) are inserted in the equation for the conditional variance of returns. In what follows, we exploit the established merits of working with a daily realized measure of volatility (Andersen et al., 2006), directly modelling its expectation, conditional on an information set which includes relevant policy variables. The daily framework is suitable to exploit persistence in the data, and to allow the expected volatility to react adequately to new information: in our contribution, using daily data allows us to pinpoint the contribution of policy actions on the dynamics of volatility for forecasting purposes. To achieve this goal, we favour the framework of the multiplicative error model (MEM) (Engle, 2002; Engle & Gallo, 2006): being a positive-valued process, volatility is modelled as the product of a time-varying factor (following an autoregressive-type process) and a positive random variable. Under mild conditions on the parameters, positiveness of the forecasts is ensured and the model offers the advantage of not needing to resort to logarithmic transformations. Relative to the heterogeneous autoregressive (HAR Corsi, 2009) model (and relative to linear models of volatility in general), MEMs offer robustness against heteroskedastic measurement errors in realized measures (Cipollini et al., 2021).

Within the MEM class, Brownlees et al. (2012) propose a model - the Composite AMEM (ACM)—in which the conditional expected volatility is the sum of a short-run component and a long-run component. This model suggests a new way to separate two volatility components, one representing the usual autoregressive dynamics of volatility and the other where we gather both the announcement and the implementation effects of unconventional policies. As a by-product of estimating the latent factors, we can calculate the share of the policy-related component on total expected volatility, a novel feature that provides a quick tool to evaluate (even graphically) the impact of policy actions on the dynamics of volatility. To extend this model, labelled MEM with asymmetry and policy effects (MAP), we consider the case in which the two latent factors, rather than combining additively, are modified to be a product of each other (with two specifications suggested).

The empirical application analyses the impact of unconventional monetary policies adopted by the ECB on stock market volatility, taking the four largest Eurozone countries as our leading case: France, Germany are more stable economies, while Italy and Spain are representative of how debt-burdened markets are more sensitive to market reactions to news. We proxy for unconventional policies by using the ratio between the securities purchased by the ECB for unconventional policy purposes and the ECB total asset (similarly to D'Amico et al., 2012). Our main results show that announcements cause an immediate peak in volatility, whereas the implementation of unconventional policies has a mitigating effect along time; moreover, including these variables in the model, improves the out-of-sample forecasting, in particular after the expanded asset purchase programme (EAPP) announcements.

The paper is organized as follows. Section 2 describes data as well as the stylized facts on volatility with respect to the unconventional policies implementation. Section 3 introduces the novel MEM-based models employed in our empirical analysis, in Section 4. We discuss model estimation and inference in Section 4.1, model comparisons including an analysis of which models enter model confidence set in various subsamples (in Section 4.2) and a multi-step forecasting exercise to determine the estimated duration of the effects and the volatility response to a shock to the policy variable (in Section 4.3). Finally, Section 5 concludes with some remarks.

2 | PROXIES FOR UNCONVENTIONAL MONETARY POLICIES

In investigating the impact of unconventional monetary policies by ECB, we consider two different variables, which refer to announcement and implementation effects on volatility, respectively. The former is measured by means of a dummy variable taking value of 1 on days in which ECB releases communications regarding a monetary policy decision[3]. To proxy for the implementation effect, we use the amount of securities held by ECB as a fraction of total asset[4] (cf. D'Amico et al., 2012).

Our analysis is based on a data set consisting of 2686 daily observations of annualized realized kernel volatility[5] (RV hereafter) which is a robust estimator of the volatility, in particular with respect to microstructure noise (Barndorff-Nielsen et al., 2008). The analysis relates to four Eurozone market indices (CAC40 for France, DAX30 for Germany, FTSE MIB for Italy and IBEX35 for Spain—referred to by country in what follows) for the period between 1 June 2009 and 31 December 2019. The choice of the sample is to provide a wide reference period for the evolution of the ECB monetary policy, in the aftermath of the Great Financial Crisis with its apex in September 2008 with the collapse of Lehman Brothers. The ECB acted a few years later than the Fed in adopting both unconventional policies and in inserting statements of so-called *Forward Guidance* in its press releases.

We analyse this data set by a simple visual inspection of the graphs, highlighting the main announcements in the time span considered, and by analysing some stylized facts that justify the model proposed in Section 3.

2.1 | Graphical Analysis of Announcements

Figure 1 shows the evolution of our series. All series seem to follow a similar pattern, with a period of low volatility in the first year of the sample. The RV series seem not be affected by some actions established by the ECB around the beginning of our sample, namely the 12-month longer term refinancing operations programme—the LTRO (May 2009)–and the covered bond purchase programme—the CBPP (July 2009)–which were the first attempts aimed at containing the liquidity crisis and the consequent credit crunch for the Eurozone. To establish a useful timeframe, in Figure 1, we report as vertical lines some major policy actions corresponding to an increase in volatility in all four markets:

1. the SMP (Security Market Programme) announcement on 10 May 2010. By means of purchases of government bond in the secondary market, the ECB aimed to control the increase in the credit spread and to restore the proper functioning of monetary policy transmission channels. While the RV jumped on the day when the SMP was announced, the subsequent implementation of this program had a dampening effect on volatility.
2. the 'Whatever it takes' declaration by Mario Draghi on 26 July 2012, which served to reassure investors regarding the emerging denomination risk. Through this declaration, the ECB

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[3]https://www.ecb.europa.eu/press/pr/activities/mopo/html/index.en.html

[4]Data are taken from the ECB website and Datastream.

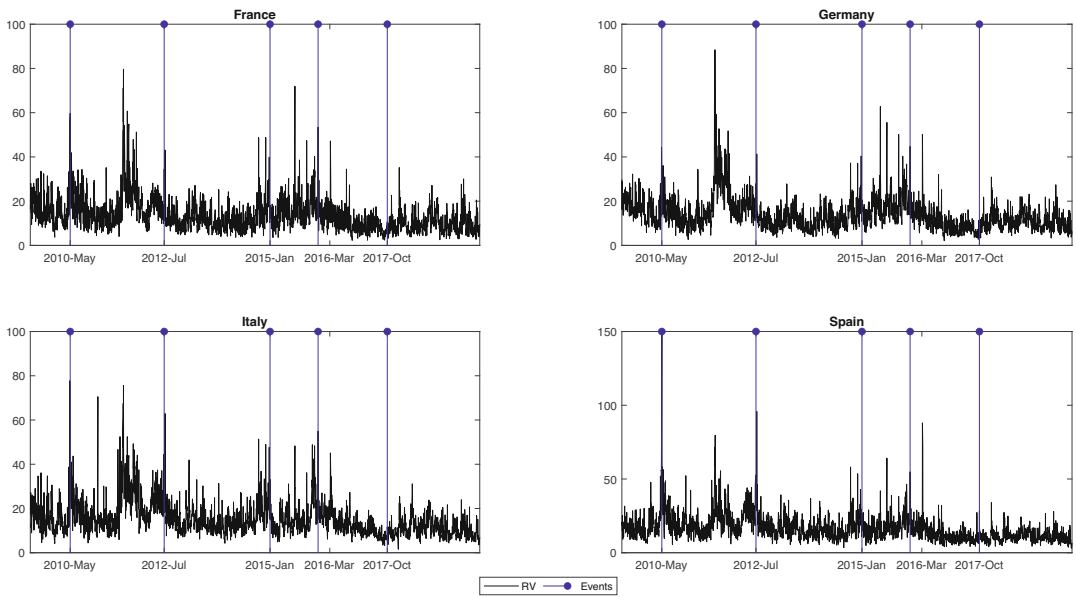[5]Data from https://realized.oxford-man.ox.ac.uk/data/download

FIGURE 1 France, Germany, Italy and Spain RV. Sample period: 1 June 2009 to 31 December 2019. Number of observations:2686. The vertical lines represent relevant events for policy actions (see text).

announced the outright monetary transaction (OMT), which replaced the SMP successfully, depressing volatility until the end of 2014.

3. the EAPP announcement on 22 January 2015. It was established mainly to improve monetary policy transmission mechanisms as well as to adjust the inflation rate toward the target level of 2%. It refers to a series of unconventional measures such as the assed backed securities purchase programme (ABSPP), the CBPPs and the corporate and public sector purchase programme (CSPP and PSPP, respectively), through which ECB conducted monthly securities purchases.

4. 10 March 2016. The amount of securities purchased within the EAPP passed from the initial level of € 60 billion to € 80 billion per month, causing a downward trend in the RV series.

5. 26 October 2017. Volatility increases after the announcement through which ECB communicated the cut in the monthly purchases, which were reduced to € 15 billion. In contrast to the previous announcement, it caused an increasing trend in all the markets considered.

A simple visual inspection shows the decrease in volatility in correspondence of these events; moreover, we notice also an effect caused by the amount purchased by ECB. We aim to quantify this effect and its weight on the level of volatility.

2.2 | Stylized facts

In order to analyse the effects of unconventional monetary policy on volatility, one would have to build a structural model detailing the channels of transmission onto financial markets, isolating the nature of the innovations. What is preferred in empirical investigations is a reduced-form approach in which the net effect of certain variables is examined without resorting to a structural

TABLE 1 Percentage variation of the average of volatility (5 days before and after the announcement date) with respect to the volatility of the announcement day for four volatility time series

	France	**Germany**	**Italy**	**Spain**
Before	−4,40	−5,92	−9,79	−8,56
After	−5,52	−5,39	−7,39	−5,02

explanation, also not to enter in the subjective choice about which theory to adopt (Ghysels et al., 2017). We adhere to this strategy, starting from some stylized facts which may serve as the basis for making time series modelling choices later in the paper. We will not delve on the well-known persistence features of realized volatility and its asymmetric behaviour relative to upward and downward movements in a market. We rather suggest a few results about the relationship between volatility and policy variables.

The first stylized fact is about higher volatility on the days of announcements. Not being able to repeat a visual inspection of our set of 144 ECB announcements in the time span considered (as we did in Figure 1), we suggest to see whether there is a pattern in terms of volatility behavior before and after an announcement, by calculating the average realized volatility 5 days before and 5 days after the announcements;[6] Table 1 shows how these averages compare to the volatility on the day of the announcement in relative percentage terms. As all the variations are negative, the announcement days mark, on average, a peak of volatility, with a subsequent reduction after the announcement.

A second empirical regularity is about the direction of the causal relationship (in a Granger's sense) between the realized volatility and the unconventional policy proxy (allowing also for a dummy on announcement days). The non-causality tests[7] seem to support the idea that the unconventional policy affects the realized volatility, but not for the reverse.

A third issue is whether there is a systematic difference between average returns on announcement and non-announcement days, simply assessed by regressing returns standardized by the realized volatility on the dummy for announcement days. Since the corresponding coefficient is never significant, we proceed with the empirical regularity that there is no systematic impact of the announcements on returns.

3 | POLICY-RELATED VOLATILITY COMPONENTS

The availability of high-frequency data has given rise to a stream of literature on realized variance measures (Andersen et al., 2006) with models based on the features of volatility traditionally investigated in the GARCH framework (Bollerslev, 1986; Engle, 1982). Among these, a prominent place is taken by MEMs as defined by Engle (2002) and successively revised by Engle and Gallo (2006) to allow for asymmetric effects (AMEM).

The model we propose is an extension of the composite AMEM (ACM) (Brownlees et al., 2012, to which we refer for details) in which the conditional expected volatility is the sum of a short-run

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[6]The only exception relates to first announcement occurred at $t = 4$, so that the average in that case involves only 3 terms before and after.

[7]In view of the stationarity of the realized volatility and of the non-stationarity of the policy variable, we adopted the procedure suggested by Toda and Yamamoto (1995) which envisages a VAR(6) in levels with five lags on either side to be cross-tested and an extra one (not to be tested).

component and a long-run component.[8] In this ACM, we insert the effect of unconventional policies as a latent factor, explicitly affecting the dynamics of the volatility. More precisely, our model is based on the decomposition of the volatility level in the sum of two components, representing the base volatility component (ς) and what can be related to the unconventional policies (ξ), respectively, allowing us to quantify its relative effect on the overall level of volatility.

Thus, our composite MEM with MAP consists of four equations:

$$RV_t = \mu_t \epsilon_t, \quad \epsilon_t | \Psi_{t-1} \sim Gamma(\vartheta, \frac{1}{\vartheta})$$

$$\mu_t = \varsigma_t + \xi_t$$
$$\varsigma_t = \omega + \alpha RV_{t-1} + \beta \varsigma_{t-1} + \gamma D_{t-1} RV_{t-1}$$
$$\xi_t = \delta(E(x_t | \Psi_{t-1}) - x^\star) + \varphi(\Delta_t - \Delta^\star) + \psi \xi_{t-1} \tag{1}$$

where Ψ_t is the information set available at time t. Following Engle and Gallo (2006), we consider the error term ϵ_t as Gamma distributed, in view of its flexible dependence on just one parameter, ϑ, and of its good empirical performance. From these assumptions, we get not only a time-varying conditional mean $E(RV_t | \Psi_{t-1}) = \mu_t$, but also a time-varying conditional variance (volatility of volatility) $\text{Var}(RV_t | \Psi_{t-1}) = \mu_t^2 / \vartheta$; as ς_t follows a GARCH-type dynamics, the model is suitable to capture possible clustering in volatility. In our model (1), D_{t-1} represents a dummy variable taking value of 1 if the return of the asset (index) at time $t-1$ is negative, 0 otherwise.

The additional component ξ_t is an AR(1) involving x_t and Δ_t as predetermined variables (in view of the stylized facts), representing, respectively, the implementation and announcement effect; finally, $x^\star$ is a constant, for example the unconditional mean or an initial value (to accommodate a random walk process). Similar remarks apply to $\Delta^\star$ and Δ_t; this structure, under the hypothesis of stationarity, ensures a zero unconditional mean for ξ_t. As for the timing of these predetermined variables, since the days of monetary policy announcements are put on the calendar well in advance, we can consider the announcement variable, Δ_t, at its contemporaneous time. By contrast, the proxy representing the implementation effect has to enter in expected terms: for simplicity, given its behaviour assessed as a random walk, we adopt the lagged value as an expectation. Thus, by also replacing $x^\star$ and $\Delta^\star$ with the respective sample means $\bar{x}$ and $\overline{\Delta}$, the last equation in model (1) for operational purposes will become: $\xi_t = \delta(x_{t-1} - \bar{x}) + \varphi(\Delta_t - \overline{\Delta}) + \psi \xi_{t-1}$.

Note that in Equation (1), when we set $\psi = \beta$, we get the X-MAP specification for μ_t (which corresponds to an AMEM with an exogenous regressor):

$$\mu_t = \omega + \alpha RV_{t-1} + \beta \mu_{t-1} + \gamma D_{t-1} RV_{t-1} + \delta(E(x_t | \Psi_{t-1}) - x^\star) + \varphi(\Delta_t - \Delta^\star), \tag{2}$$

which, in turn, nests the classical AMEM upon imposing $\delta = \varphi = 0$.

For stationarity in the MAP, it is required that both components are stationary in covariance, that is $(\alpha + \beta + \frac{\gamma}{2}) < 1$ and $\psi < 1$; positiveness, instead, requires that $(\varsigma_t + \xi_t > 0)$ for each t, which could be ensured even though δ is negative, as we expect.

Finally, as argued by Engle and Lee (1999), the coefficient ψ in ξ_t process is required to be less than β to ensure the identification of the model. Since one of the main ECB aims by

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[8]Another model treating volatility components additively is the spillover AMEM (SAMEM) by Otranto (2015), which captures volatility spillovers among markets in a univariate framework.

means of unconventional policies is to stabilize financial markets in the short run, we expect an immediate effect of this kind of policy in reducing stock market volatility. In other words, in our model, the part of volatility depending directly on unconventional policies represents the short run component of realized volatility as well as the proper volatility dynamics represents the long-run component. From this assumption, we expect the long-run component to have a higher persistence than the short one, that is $0 < \psi < \beta < 1$, as an identification condition.

It is important to underline that ξ_t is an unobservable signal, with its own dynamics, which can be jointly estimated so as to quantify and plot the separate effect of the unconventional ECB actions on the volatility RV_t. As a by-product, we can also derive the share of this component relative to the overall level of volatility, that is $1 - \frac{\varsigma_t}{\mu_t} = \frac{\xi_t}{\mu_t}$.

As shown by Engle (2002) for the MEM case, quasi-maximum likelihood maximization implies that the estimators of the unknown coefficients in model (1) are consistent and asymptotically normal, under an assumption of correct specification of the conditional mean equation, irrespective of the distributional assumption, as discussed by Engle and Gallo (2006). When the scale parameter ϑ is unknown, robust standard errors will shield against the actual shape of the Gamma distribution.

Whether the policy impact on the general level of volatility should enter in an additive way, as in model (1), or multiplicatively is always open to question.[9] In what follows, we discuss two different specifications of the multiplicative version of MAP which ensure the compliance with the constraint that the unconditional mean of ξ_t is equal to one so that the model is identified.

In the first specification, we allow ξ_t to impact on RV_t through a logistic function—and by means of the delta method. The model, called logistic-MAP (L-MAP), is specified as in model (3)

$$RV_t = \mu_t \epsilon_t, \quad \epsilon_t | \Psi_{t-1} \sim Gamma(\vartheta, \frac{1}{\vartheta})$$

$$\mu_t = 2\varsigma_t \left(\frac{\exp(\xi_t)}{1 + \exp(\xi_t)} \right)$$

$$\varsigma_t = \omega + \alpha RV_{t-1} + \beta \varsigma_{t-1} + \gamma D_{t-1} RV_{t-1}$$

$$\xi_t = \delta(E(x_t | \Psi_{t-1}) - x^\star) + \varphi(\Delta_t - \Delta^\star) + \psi \xi_{t-1} \tag{3}$$

Alternatively, we can add a constant term in the ξ_t equation, providing a plain-MAP (P-MAP) specification, namely:

$$RV_t = \mu_t \epsilon_t, \quad \epsilon_t | \Psi_{t-1} \sim Gamma(\vartheta, \frac{1}{\vartheta})$$

$$\mu_t = \varsigma_t \xi_t$$

$$\varsigma_t = \omega + \alpha RV_{t-1} + \beta \varsigma_{t-1} + \gamma D_{t-1} RV_{t-1}$$

$$\xi_t = (1 - \psi) + \delta(E(x_t | \Psi_{t-1}) - x^\star) + \varphi(\Delta_t - \Delta^\star) + \psi \xi_{t-1} \tag{4}$$

A way to characterize how the suggested models differ in terms of how the policy proxy impacts expected volatility is by calculating the marginal effects of a change in x_{t-1} (respectively, Δ_t) on $\mu_{t+\tau}$ (τ-steps ahead), as done in Table 2.[10]

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[9]Within the MEM class, a multiplicative component MEM is suggested by Brownlees et al. (2011), adapting a GARCH approach by Engle and Sokalska (2012).

[10]The derivation of the formulas is available as supplemental material.

TABLE 2 Marginal effects of policy variables x_{t-1} and Δ_t on $\mu_{t+\tau}$, $\tau \geq 0$

Model	Marginal effect on $\mu_{t+\tau}$
MAP	$\kappa \psi^\tau$
X-MAP	$\kappa \beta^\tau$
L-MAP	$2\varsigma_{t+\tau} \kappa \psi^\tau \frac{\exp(\xi_{t+\tau})}{(1+\exp(\xi_{t+\tau}))^2}$
P-MAP	$\kappa \psi^\tau \varsigma_{t+\tau}$

Note: $\kappa = \delta$ for the marginal effects of the implementation variable x_{t-1}; $\kappa = \varphi$ for the marginal effects of the announcement variable Δ_t.

4 | EMPIRICAL APPLICATION

4.1 | Estimation results

The goal of this section is to show how different models for the realized volatility series of the four indices take the policy variables into consideration and how the effects are exerted on the level of volatility in different specifications.

Parameter estimation of the different models are shown in Tables 3 and 4. Coefficients are highly significant in all cases with a volatility persistence $(\alpha + \beta + \frac{\gamma}{2})$ which decreases by about 2% passing from the AMEM to our more complex MAP. Moreover, the impact of the more recent observed values, measured by the α and γ coefficients, is generally higher in the AMEM. This indicates a lower influence of current shocks on volatility projections, in line with the expected calming effect that the unconventional monetary policies have on market volatility.

Diagnostics on the standardized residuals is given by the Ljung–Box statistics for lags 1, 5 and 10 (at the bottom of the table): we see how the AMEM is able to capture the persistence in the volatilities (we fail to reject the null of no serial correlation at 1% significance level, with the exception of Germany at the highest lag, as well as Spain at lag 5). However, our additive model (the MAP) seems to have a better statistical performance in this respect, especially in the case of Spain, where we never reject the null of no autocorrelation at 1% level.

Model performance in terms of estimation results can be compared in Table 5, where we report the information criteria (AIC and BIC) and two loss functions (mean square error—MSE—and quasi-likelihood—QLike, consistent in the sense of Patton, 2011) to evaluate the fitting capabilities of the models. For all countries, the best performing model (the one in bold) is the L-MAP. The only exception is Spain, where the L-MAP has better performance in terms of the information criteria, even if the P-MAP is marginally better in terms of MSE.

For what concerns the unconventional policy proxies, coefficients are significant at 1% level and they enter the model with the expected sign. According to other results in this stream of research (see, e,g, Bomfim, 2003; Chan & Gray, 2018; Shogbuyi & Steeley, 2017), the coefficient φ of the dummy variable is positive, meaning that there is an immediate reaction in the market on announcement days, in line with our stylized facts. Conversely, δ is negative; therefore, the unconventional policies implementation successfully reduces stock market volatility, as expected.

This implementation effect can also be seen in Figure 2, which plots the evolution of the two volatility components (the blue line for the base component, left axis, and the red dotted-line, for the policy component, right axis). This effect is more evident starting from October 2014—when the ECB implicitly communicated to the market that it would purchase corporate (next to government) bonds—coming in the form of a change in the slope of ξ equation, lasting for the

entire period of the programme. This is one of the most interesting results, as it implies that the effectiveness of these policies rests on the total amount of securities held for monetary policy purposes, relative to ECB total asset. Moreover, an increase in this volatility component is observed in April 2017, which coincides with the reduction in the amount of securities purchased by ECB, set to € 60 billion per month from the previous level of € 80 billion.

Results remain by and large the same, when we consider the Multiplicative MAP specifications. Once again, the proxies enter the models with the expected sign and with the highest level of significance. In both cases, coefficients are fairly lower, in view of the multiplicative way components combine: in other words, while in the MAP we generally have a negative ξ_t, within the multiplicative versions the effect by unconventional policies of dampening volatility is had when the ξ_t process is less than 1 (by construction it is always positive): this requires lower proxies' coefficients, and this is achieved without imposing any kind of constraints.

Some questions could arise as of whether the policy message should be better characterized by several suitable dummy variables, rather than a single one, simply labelled as an *announcement*.

TABLE 3 Models estimation results (France and Germany). Sample: 1 June 2009–31 December 2019

	France					Germany				
	AMEM	X-MAP	MAP	L-MAP	P-MAP	AMEM	X-MAP	MAP	L-MAP	P-MAP
Coefficient estimates (robust s.e. in parentheses)										
ω	0.857	1.136	1.056	1.011	1.025	0.957	1.081	1.034	1.026	1.034
	(0.046)	(0.121)	(0.065)	(0.007)	(0.053)	(0.017)	(0.052)	(0.016)	(0.059)	(0.519)
α	0.171	0.165	0.154	0.151	0.153	0.193	0.191	0.183	0.182	0.183
	(0.017)	(0.020)	(0.015)	(0.015)	(0.017)	(0.010)	(0.011)	(0.014)	(0.012)	(0.055)
β	0.708	0.689	0.707	0.712	0.709	0.692	0.684	0.696	0.696	0.694
	(0.019)	(0.029)	(0.015)	(0.014)	(0.018)	(0.011)	(0.016)	(0.013)	(0.014)	(0.094)
γ	0.113	0.120	0.117	0.119	0.119	0.087	0.090	0.089	0.090	0.090
	(0.008)	(0.009)	(0.011)	(0.010)	(0.012)	(0.006)	(0.011)	(0.008)	(0.008)	(0.008)
δ		−0.636	−1.836	−0.297	−0.161		−0.454	−1.328	−0.219	−0.115
		(0.075)	(0.326)	(0.057)	(0.029)		(0.035)	(0.283)	(0.052)	(0.057)
Φ		1.297	2.817	0.464	0.231		1.067	2.317	0.378	0.188
		(0.381)	(0.539)	(0.093)	(0.045)		(0.311)	(0.470)	(0.073)	(0.073)
ψ			0.111	0.194	0.134			0.098	0.175	0.138
			(0.060)	(0.081)	(0.083)			(0.077)	(0.097)	(0.204)
θ	7.559	7.728	7.817	7.827	7.820	9.460	9.610	9.700	9.719	9.714
	(0.222)	(0.228)	(0.231)	(0.230)	(0.231)	(0.290)	(0.298)	(0.301)	(0.301)	(0.301)
Loglik	−7825.1	−7793.9	−7778.1	−7776.2	−7777.4	−7592.5	−7570.6	−7557.8	−7555.0	−7555.7
p-values for Ljung-Box statistics										
lag 1	0.155	0.258	0.132	0.108	0.125	0.171	0.262	0.184	0.173	0.194
lag 5	0.111	0.167	0.215	0.192	0.207	0.028	0.063	0.056	0.051	0.054
lag 10	0.115	0.137	0.210	0.201	0.201	0.002	0.004	0.003	0.003	0.003

TABLE 4 Models estimation results (Italy and Spain). Sample: 1 June 2009–31 December 2019

	Italy					Spain				
	AMEM	X-MAP	MAP	L-MAP	P-MAP	AMEM	X-MAP	MAP	L-MAP	P-MAP
Coefficient estimates (robust s.e. in parentheses)										
ω	1.198	1.708	1.533	1.480	1.490	1.055	1.533	1.438	1.410	1.426
	(0.073)	(0.221)	(0.260)	(0.239)	(0.146)	(0.075)	(0.110)	(0.135)	(0.621)	(0.132)
α	0.268	0.274	0.249	0.248	0.250	0.224	0.205	0.197	0.193	0.195
	(0.018)	(0.032)	(0.033)	(0.042)	(0.022)	(0.013)	(0.014)	(0.024)	(0.060)	(0.023)
β	0.608	0.568	0.604	0.605	0.603	0.671	0.656	0.671	0.674	0.671
	(0.023)	(0.043)	(0.043)	(0.049)	(0.030)	(0.007)	(0.020)	(0.027)	(0.091)	(0.028)
γ	0.084	0.086	0.086	0.089	0.088	0.078	0.087	0.085	0.086	0.086
	(0.005)	(0.011)	(0.019)	(0.022)	(0.008)	(0.022)	(0.007)	(0.015)	(0.017)	(0.009)
δ		−1.074	−2.354	−0.343	−0.178		−1.025	−2.823	−0.389	−0.207
		(0.161)	(0.519)	(0.048)	(0.031)		(0.086)	(0.528)	(0.133)	(0.037)
φ		2.059	3.448	0.518	0.254		1.964	3.428	0.501	0.247
		(0.471)	(0.569)	(0.084)	(0.038)		(0.361)	(0.671)	(0.087)	(0.042)
ψ			0.051	0.089	0.058			0.058	0.123	0.072
			(0.083)	(0.055)	(0.073)			(0.090)	(0.298)	(0.112)
θ	10.593	11.030	11.183	11.185	11.181	9.149	9.487	9.580	9.626	9.623
	(0.423)	(0.427)	(0.436)	(0.437)	(0.436)	(0.317)	(0.338)	(0.349)	(0.355)	(0.352)
Loglik	−7721.3	−7665.3	−7646.3	−7646.1	−7646.5	−8117.0	−8066.5	−8052.9	−8046.3	−8046.7
p-values for Ljung-Box statistics										
lag 1	0.299	0.691	0.300	0.287	0.324	0.010	0.025	0.011	0.006	0.008
lag 5	0.497	0.721	0.800	0.805	0.824	0.009	0.015	0.019	0.012	0.015
lag 10	0.336	0.472	0.647	0.625	0.624	0.047	0.086	0.119	0.089	0.100

In particular, as shown by Hattori et al. (2016), in any relatively recent policy announcement there is an element tied to the QE-related actions and another, distinct, element related to the *Forward Guidance* (FG). The latter are statements that anticipate future behaviour, in a major contribution to forming and anchoring market participants' expectations. In the case of the ECB, it is not easy to distinguish between the two, as done in the case of the FOMC by, for example, Hattori et al. (2016) who cover a period including the crisis with a detailed taxonomy of days of announcements (not just of the scheduled meetings), according to the prevailing message in that day. The ECB explicitly adopted a stance about FG as of July 2013, but only after 21 July 2016 does it consistently provide FG elements in the press releases. As a robustness check, we thus re-estimated our models by splitting the dummy variable for the announcements into two separate ones, attributing the meaning of plain announcement to one set (a total of 64) and the meaning of FG to the other (a total of 80). The estimation results show that there is little, if any, impact on the models.[11] The

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[11]The complete tables with estimation details are reported in the supplemental material.

TABLE 5 Model comparisons via Information Criteria (AIC and BIC) and forecasting capability (MSE and MAE)–Sample period: 1 June 2009–31 December 2019. Best model in bold

	AMEM	X-MAP	MAP	L-MAP	P-MAP
France					
AIC	5.830	5.809	5.797	**5.796**	5.797
BIC	5.841	5.824	5.815	**5.814**	5.815
MSE	29.531	29.117	28.844	**28.627**	28.639
QLike	0.068	0.066	**0.065**	**0.065**	**0.065**
Germany					
AIC	5.657	5.642	5.633	**5.631**	5.632
BIC	5.668	5.658	5.651	**5.649**	**5.649**
MSE	23.551	23.269	23.096	**22.930**	22.939
QLike	0.054	0.053	**0.052**	**0.052**	**0.052**
Italy					
AIC	5.753	5.713	**5.699**	**5.699**	**5.699**
BIC	5.764	5.728	**5.717**	**5.717**	**5.717**
MSE	28.171	27.634	27.209	**27.191**	27.203
QLike	0.048	0.046	**0.045**	**0.045**	**0.045**
Spain					
AIC	6.048	6.011	6.002	**5.997**	**5.997**
BIC	6.059	6.027	6.02	**6.015**	**6.015**
MSE	42.048	40.918	40.462	39.461	**39.439**
QLike	0.056	0.054	**0.053**	**0.053**	**0.053**

coefficients of the dynamics maintain the same values, and a Wald t-test statistic for the equality of the coefficients of the two dummies fails to reject all cases but three (X-MAP for France and Spain and MAP for Spain). These models accommodating the FG do not change the outcome in terms of the best model reported in Table 5.

A similar concern arises for the actual *surprise* content of the announcement, which, at least in principle, should be entail a change in volatility. To that end, an interesting methodology was suggested by Swanson (2021) who built a database of intradaily data for a number of assets. He combined the 30-min returns straddling the time of the press release into factors with an eye to classifying market movements on the days of the FOMC announcements according to their federal funds rate, forward guidance and large-scale asset purchase (LSAP) content. From that approach, we retain the need to check, as a second robustness analysis, whether classifying announcement days according to their surprise content could be of help in sharpening the models' performance and in enhancing the interpretability of volatility dynamics. In our context, we resort to volatility jumps (Andersen et al., 2007) as a way to identify whether on the day of the announcement, there was some different feature in the evolution of realized volatility. We rely on the definition of a volatility jump provided by Barndorff-Nielsen and Shephard (2004) as the positive value of the difference between the plain
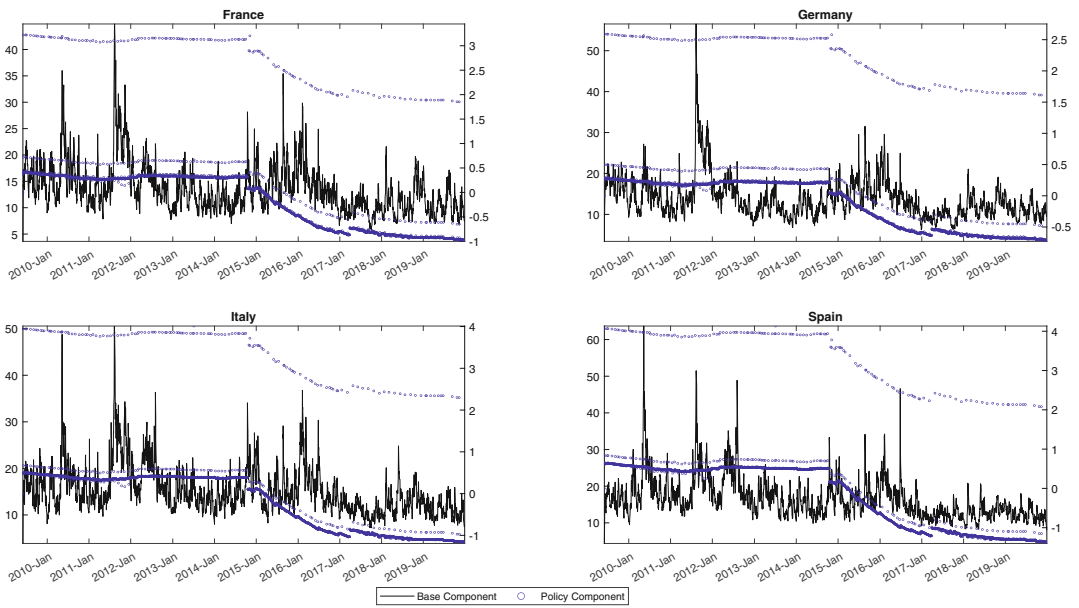
FIGURE 2 France, Germany, Italy and Spain Base (left axis) and Policy (right axis) component of volatility from the MAP. Sample period: 1 June 2009 to 31 December 2019. For the ξ series, we recognize three different patterns of interest: the highest values correspond to the announcement days in which the dynamics is directly affected by the presence of φ; the intermediate values correspond to the days after an announcement with an inertial effect connected to $\psi\varphi$ (recall that the estimated ψ is between 0.05 and 0.1); the lowest corresponds to the remaining days in which the inertial effect vanishes constant $+ \delta E(x_t|\Psi_{t-1}) + \psi\xi_{t-1}$.

vanilla realized volatility and the bipower realized volatility, a measure robust to the presence of jumps. Accordingly, we label the day of an announcement as a surprise day when such jumps are present in all four markets considered. In this case, splitting the original announcement dummy variable into two complementary dummies (surprise—60 days; no surprise—84 days) does not entail any significant changes in the estimated models with the null hypothesis of no difference between the two coefficients failing to be rejected for all four markets and all models.[12]

In order to compare economic effects across models, it is instructive to compute the corresponding marginal effects of the policy variables (x_{t-1} and Δ_t) on μ_t: while in the additive specification they are constant and equal to the estimated coefficients, in the multiplicative specifications marginal effects are time varying. Looking at the average values[13] (Table 6), the higher marginal effect of the implementation proxy is associated to the P-MAP. More specifically, a marginal increase in the proxy leads to a range of reductions in realized volatility comprised between −1.577 (Germany) and −3.382 (Spain); conversely, on announcement days volatility marginally increases, on average, by 2.603 and 4.146 points, in Germany and Spain, respectively. Overall, while unconventional policies had a higher impact on debt-troubled countries, the effect is present also for the others.

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[12]Also here, the complete tables with estimation details are reported in the supplemental material.

[13]For what concerns Δ_t, the marginal effects are considered only with respect to announcement days, and, as such, the average relates just to such days.

TABLE 6 Average marginal effects of policy variables on μ_t—Sample period: 1 June 2009–31 December 2019 (parameter estimates by country as in Tables 3 and 4)

	Marginal effect of x_{t-1} on μ_t			Marginal effect of Δ_t on μ_t		
	MAP	**L-MAP**	**P-MAP**	**MAP**	**L-MAP**	**P-MAP**
France	−1.836	−1.571	−2.172	2.817	2.236	3.177
Germany	−1.328	−1.158	−1.577	2.317	1.821	2.603
Italy	−2.354	−2.033	−2.693	3.448	2.785	3.953
Spain	−2.823	−2.489	−3.382	3.428	2.912	4.146

Note: the average marginal effect of Δ_t refers to the announcement days (see text).
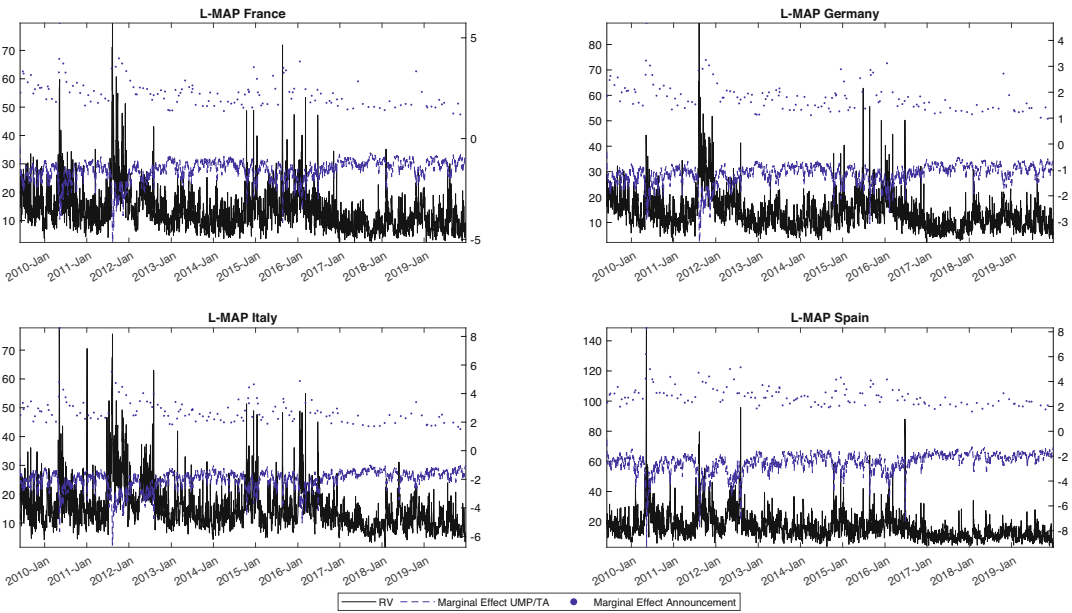
FIGURE 3 France, Germany, Italy and Spain: marginal effects from the L-MAP. Sample period: 1 June 2009 to 31 December 2019.

The evolution of the marginal effects associated to the two multiplicative component specifications is shown in Figures 3 and 4: for both models and for all the markets, marginal effects have a specular behaviour, to a certain extent mirroring the behaviour of the realized volatility measure. In order to facilitate the interpretation of the results in terms of the major ECB decisions described in Section 1, we have superimposed some red asterisks at the horizontal axis in correspondence to the dates reported above. In particular, the marginal effects of Δ_t have peaks in correspondence of volatility spikes, whereas the period of lower marginal effects of the proxy corresponds to periods of low volatility in the market. This result validates the dynamics in our models with the policy variables we adopted.

In the case of the MAP, the impact of unconventional policies on stock market volatility can also be measured as the ratio of the policy-related component ξ_t to the general level of volatility μ_t. The average of such a ratio signals a reduction in volatility associated with the ECB
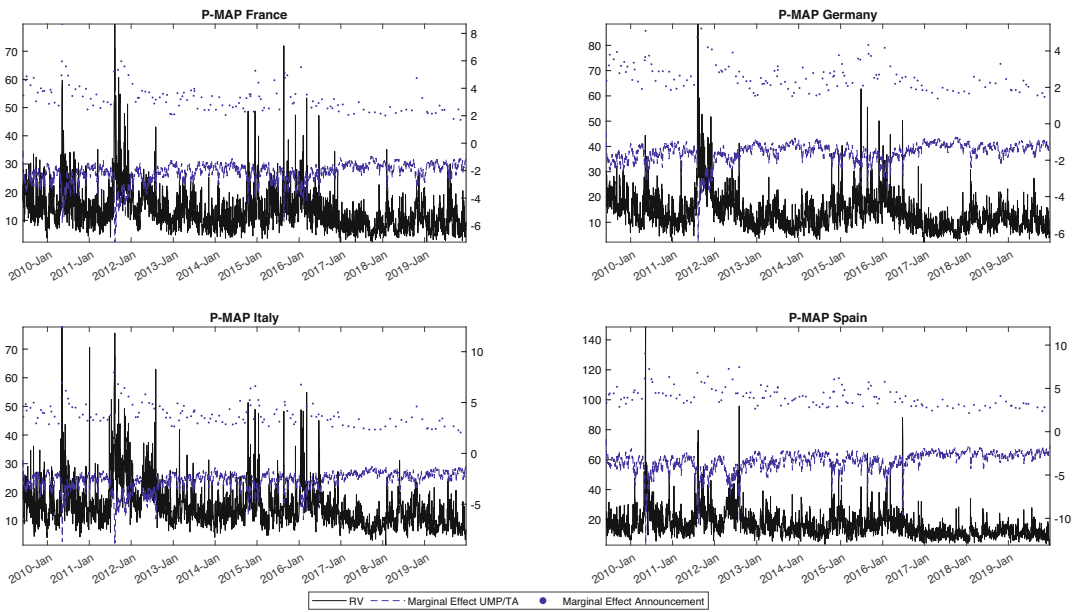
FIGURE 4   France, Germany, Italy and Spain: marginal effects from the P-MAP. Sample period: 1 June 2009 to 31 December 2019.

unconventional policies between −0.6% and −1.1%, when measured for Germany and France, which becomes more marked for Italy (−1.24%) and Spain (−1.38%).

As far as the dynamics of the ξ_t component is concerned, the persistence effects, driven by the coefficient ψ, are fairly weak: such a coefficient is significant at 5% only for France across models and only marginally so for Germany for the L-MAP model. As a result, the data show that the policy-related volatility component follows the evolution of the policy proxy (with parameter δ) and the changes occurring on announcement days (with parameter φ).

4.2 | Out-of-sample performance

In order to compare the one-step-ahead out-of-sample forecasting performance across the estimated models, we compute the model confidence set (MCS, Hansen et al., 2011) using the MSE and the QLike loss functions at the 10% significance level.

For this purpose, we split the sample at the end of a year and we compute the one-step-ahead out-of-sample forecasts for the following year. The choice of the splitting dates is driven by the need to exclude the most important QE programme, the EAPP, so that the first subsample considered stops at the end of 2014. We then consider each additional year in turn until 2018, in order to consider the full period of the EAPP.

As shown in Table 7, both loss functions provide similar results, confirming that the proxy-augmented models capture the features of the EAPP in delivering an improved forecasting performance. This outcome is more apparent when considering the subsamples individually. Before the EAPP announcement, the MCS results in the 2015 column of Table 7 show, for example, that all the models enter the best set of models (according to QLike, represented by the

TABLE 7 The model confidence set results. *p*-value 10%

	2015	2016	2017	2018	2019
France					
AMEM	□ ●	■ ●			
X-MAP	□	□ ○	■ ●		□ ○
MAP		□ ○	○		□ □
L-MAP	■ ○	□ ○			□
P-MAP	□ ○	□ ○	○	■ ●	■ ●
Germany					
AMEM	■ ●	■ ●		○	
X-MAP	□ ○				
MAP	□ ○				
L-MAP	□ ○				□ ○
P-MAP	□ ○	□ □	■ ●	■ ●	■ ●
Italy					
AMEM	□ ○	■ ●			
X-MAP	□ ○	□ ○	■ ●	■	□ ●
MAP	■ ●	□ ○	○		□ ○
L-MAP	□ ○	□ ○			□ ○
P-MAP	□ ○	□ ○		□ ●	■ ○
Spain					
AMEM	●	□ ○			
X-MAP	○	■ ●	■ ○	○	
MAP		○	○	○	
L-MAP	○	○	○		□
P-MAP	■ ○	□ ○	□ ●	■ ●	■ ●

Note: □(○) indicates models belonging to the best set according to the MSE(QLike) loss function; ■(●) represents the best model.

symbol ○) in three out of four cases, and even that the AMEM is the best model (●) in France, Germany and Spain and it belongs to the best set in Italy, for which the best model is the MAP (results are more mixed for the MSE).

These benchmark results are confirmed in the forecasting period ending in 2016. For both loss functions, this time, the AMEM is the best model in three out of four cases, whereas in Spain such a role goes to the X-MAP: no component model is present in the best set in Germany, where the AMEM is the only model belonging to the best set (together with the P-MAP if we consider the MSE).

When we move to the forecasting period ending in 2017, characterized by a remarkable change in the ECB balance sheet composition, this good performance of the base AMEM is

seriously challenged by our models: during this period the ECB purchased assets at a pace of € 80 billion per month until March 2017 and € 60 billion per month until the end of the year. This time the policy-augmented models have a better forecasting performance and the AMEM is always excluded from the best set of models. Importantly, focusing on the QLike, the MAP enters the best set in three out of four cases, whereas the P-MAP is the best model for Germany and Spain.

This latter model becomes the best across all cases considering the forecasting periods ending in 2018 and 2019, respectively. The difference in the results of these two sub-samples is in the best set of models, which is larger in the last year, possibly due to the fact that no APP was implemented until November 2019, when the ECB purchased new assets at a level of € 20 billion per month. Overall, however, unconventional policies seem to have played a crucial role in reducing stock market volatility.

4.3 | Volatility responses to policy actions

In order to further analyse the dynamic effects of the policy actions on volatility, we graphically appraise the multi-step forecasts by model, as well as the profile of the impulse responses to a one standard deviation shock to the policy variable. For either case, we can evaluate the persistence of the effects and the time taken by different models in converging to the unconditional level of volatility. This puts us in the position to address two substantive questions: (a) for how long do QE policies affect stock market volatility? (b) what would be the volatility response to a higher QE shock?
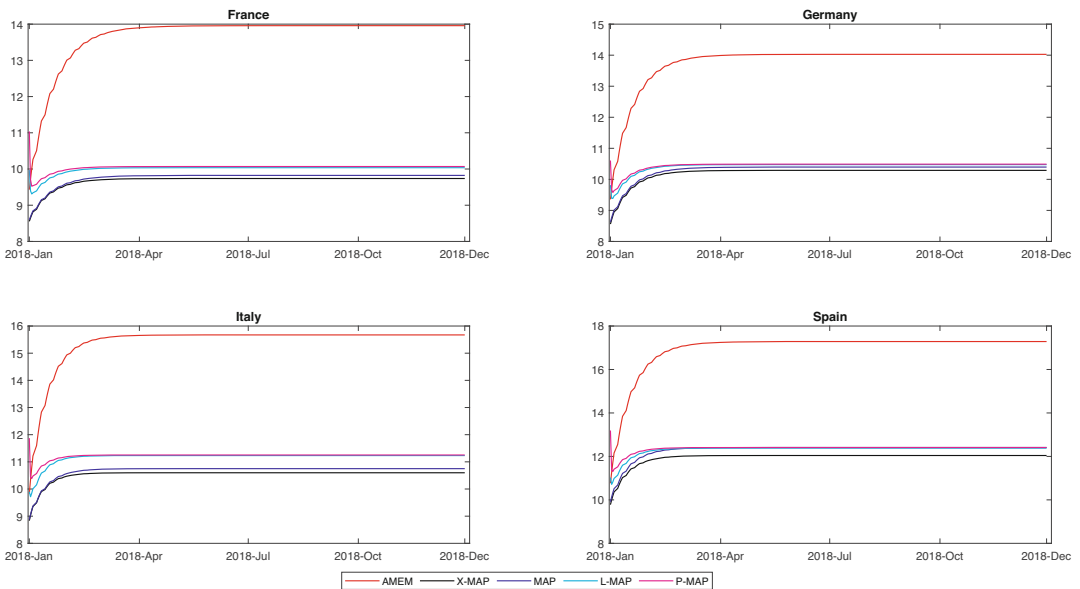

F I G U R E 5 Multi-step forecast. Sample period: 1 June 2009 to 31 December 2017. Forecast Period: 1 January 2018–31 December 2018.
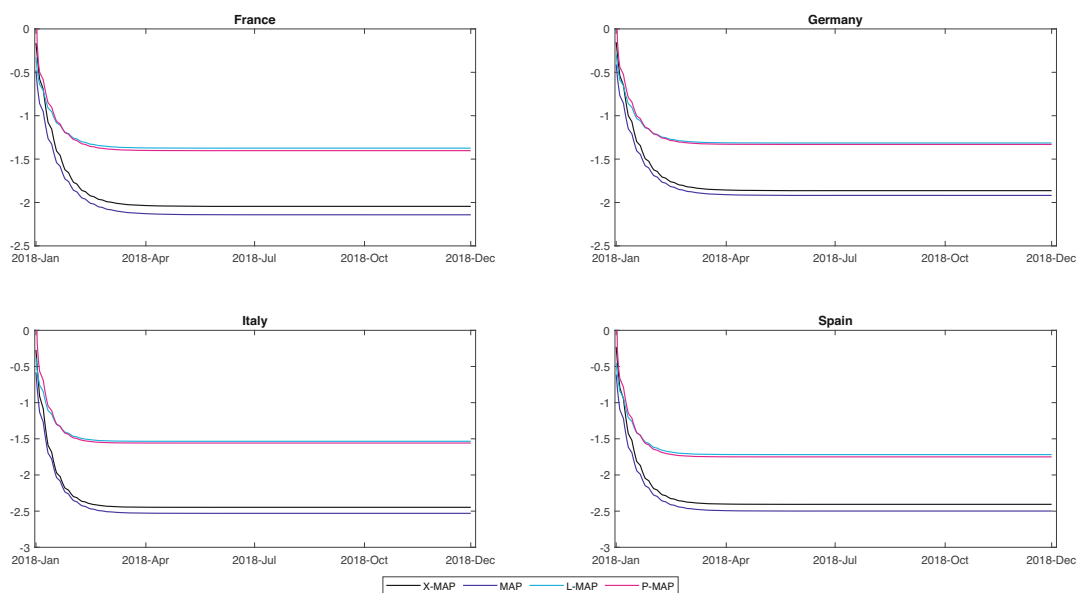
FIGURE 6 Impulse Response Function: the effect on volatility of a 1 standard deviation unconventional policy shock. Sample period: 1 June 2009 to 31 December 2017. Forecast Period: 1 January 2018–31 December 2018.

We focus on the subsample for the estimation period ending in 2017, with the following year used as the out-of-sample period and apply multi-step ahead forecasting,[14] obtaining the results shown in Figure 5. As expected, the duration of the effect—measured as the number of days the volatility needs to reach the unconditional level, that is the unconditional mean[15]—depends on the country: we get an average duration between 41 business days (estimated in Italy via P-MAP) and 96 business days (from the MAP in Germany). Furthermore, regardless of the duration, once the unconventional policy effect is completely absorbed by the market, volatility converges to its unconditional level, which does not depend on the different model specifications; however, due to the different way they account for the policy effect, a slight difference between models presents itself, more marked for the AMEM, which neglects those effects altogether. As expected, in all the cases the convergence path is upward sloping, with volatility reaching a higher level when the downward impact of unconventional policies ceases. Such an upward profile is shared by the AMEM as well, given that volatility is lower than its unconditional level at the beginning of the forecasting period.

Finally, we analyse how volatility would have responded to a higher QE shock. For this purpose, we have increased the QE proxies by one standard deviation (0.26). Taking the previous multi-step forecasting values as a baseline scenario, in Figure 6 we represent the results as the difference between the two scenarios. The role played by unconventional policies in reducing stock market volatility is clear: a higher unconventional policy shock would have had a stronger downward effect, with volatility that would have been lower down to 2.5 points in debt-troubled countries (2 points in France and Germany) relative to the baseline scenario.

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[14]The derivation of the formulas is available in the supplemental material.

[15]For practical purposes, convergence is considered achieved when subsequent forecasts do not differ by more than 1 basis point of volatility.

5 | CONCLUDING REMARKS

In this paper, we suggested a new class of models to analyse how unconventional monetary policies affect realized volatility. In detail, we suggested variants of MEM with two components, one representing what depends directly on QE policies, the other reproducing base volatility dynamics: such components may combine additively or multiplicatively. As shown by our results on ECB policies for four important Eurozone markets, what matters for the effectiveness of these policies is the balance sheet composition (as argued by Curdia & Woodford, 2011). Indeed, an increase in securities held by ECB for monetary policy purposes relative to total asset reduces volatility in both debt-troubled countries (Italy and Spain, in our analysis) and in benchmark countries (France and Germany), with more benefits for the former, in general. Admittedly, our policy proxies do not allow us to go deeper into the specific impact of each implemented policy, so that we cannot identify which of these extraordinary measures is more effective. This, of course, is an issue worth pursuing in future analysis, as well as the possibility to control also for spillovers among countries in a multivariate context, which could also highlight the presence of a common response across markets.

The presence of our proxy in the models entering the MCS when evaluating the out-of-sample forecasting performance underlines the importance of the EAPP. This is also confirmed by the multi-step forecast procedure, given that, on the one hand, unconventional policies have lasting effects in lowering volatility for at most 90 business days, and, on the other, when shocking unconventional policies by one standard deviation stock market volatility decreases by up to 2.72 points.

Exploiting the component structure of our models, we can extract a separate and distinctive signal related to the policy effects on volatility: between the additive and multiplicative way of combining the components, the results show a preference for the latter in estimation and out-of-sample, especially in 2018 and 2019. In economic terms, such results document that the unconventional monetary policy has a mitigating effect on market volatility at times of distress, when the interest rates are close to the zero lower bound, as a further tool available to central banks in order to restore the proper functioning of the economy.

Distinguishing between announcement days as of whether they contain Forward Guidance or not, or whether they entail a surprise or not led to a lack of discrimination between the two types of dummies for our models in all markets. A possible interpretation about these results is only tentative: as far as the FG is concerned, it is possible that one should extend the type of textual analysis of policy communication by the ECB (not just the announcements), in order to be able to discern more defined messages of forward guidance beyond the template that is being offered with the press statement. In this respect, the FOMC has a more varied modulation of release of information (cf. e.g. the availability of minutes of the FOMC meetings). The impressive work[16] done by Cantú et al. (2021) for several Central Banks actions during the pandemic crisis gives an example of the complex task in such a classification and an effort for previous periods (similar to what was done in Hattori et al., 2016, combining various sources) is not available yet.

As far as the surprises are concerned, our choice of proxying them by volatility jumps may be a weak approximation to the actual examination of market movements around the time of the

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[16]Cf. the dashboard at https://www.bis.org/publ/work934.htm.

announcement, but as noted before, the task of reconstructing a data set similar to what was used by Swanson (2021) is prohibitive at this stage.

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