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# Hedging Italian Equity Mutual Fund Returns during the Recent Financial Turmoil: A Duration-Dependent Markov-Switching Approach

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**Abstract**

We study optimal hedging design for returns on an Italian equity mutual fund index since 2008. Alternative hedging instruments include one-month futures contracts for FTSE-MIB, FTSE100 and Xetra DAX. We use bivariate models of our Italian equity mutual fund index and each hedging instrument to investigate the performance of optimal static hedges. Our main model is the Markov-switching vector autoregression with duration dependence for the conditional mean of returns proposed by Pegalatti [9]. The hedging performance is then compare with that of standard Dynamic Conditional Correlation models. Our results are twofold. First, DAX futures contracts are the best hedge for Italian equity mutual funds within our class of financial instruments. Second, the duration-dependent Markov-switching model improves on the hedging performance of the competing DCC models.

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# 1 Introduction

The stress in financial markets started in 2008 has waved through all the asset classes regardless of national boundaries. Since equity markets worldwide have been hit strongly by the turmoil, it is natural to investigate what financial instrument could provide a hedge against fluctuations in the value of equity mutual funds. This note focuses on the performance of equity mutual funds in Italy.

We consider the hedging properties of three alternative equity futures contracts with different characteristics. These include the FTSE-MIB index futures contract, which accounts for shocks idiosyncratic to the Italian equity market. We also use data for the FTSE100 and the Xetra DAX futures that are affected only indirectly by risk factors related to the Italian equity market.

Standard approaches to hedging modelling consider the role of time-varying conditional volatility and correlations. Alizadeh and Nomikos [1] use a markov-switching model to study optimal hedging strategies for stock indices. Brooks, Henry and Persand [3] investigates the effects of clustering in financial returns on the design of hedges.

We take a different perspective and employ bivariate models for the the conditional means of our Italian equity mutual fund index and each hedging instrument. In particular, our application uses a framework with time variation in the conditional mean and regime-switching. The regime change is driven a Markov Chain with transition probabilities that depend on the duration of the regime itself. This is the so-called duration-dependent Markov-Switching model of Pelagatti [9], which can capture the persistence in negative returns that has characterized the recent financial crisis. The idea of duration dependence has been used in the business-cycle literature to study asymmetry in U.S. macroeconomic time series (e.g., see Diebold and Rudebusch [4]). In a model comparison exercise, we consider standard versions of the Dynamic Conditional Correlation (DCC) model of Engle [5].

Our empirical results have clear implications for the measurement of hedging against fluctuations in returns on Italian equity mutual fund. First of all, we show that DAX futures provide the best hedging instruments within the our class of hedges. Although this type of result is typically model-dependent in the literature, we find that this is not the case for the purpose of our application setup. In our words, our findings suggest that the duration-dependent Markov-switching model delivers improved hedging performance across our model range. Since the type of duration persistence is different between regimes, the use of this type of Markov-switching model captures key features that would otherwise not be accounted for by alternative models, and explains the success of the model.

The outline for the paper is as follows. In section 2, we discuss the specification and estimation of the duration-dependent model, along with the competing frameworks. Section 3 deals with the construction of the dataset. In section 4, we discuss the results. Section 5 proposes some concluding remarks.

# 2 The DD-MSVAR model

## 2.1 Model specification

The process of the duration-dependend Markov-switching vector autoregression of order $p$ takes the form

$$y_t = \mu_0 + \mu_1 S_t + A_1 \left[y_{t-1} - \mu_0 - \mu_1 S_{t-1}\right] + \ldots A_p \left[y_{t-p} - \mu_0 - \mu_1 S_{t-p}\right] + \epsilon_t \quad (1)$$

where $y_t$ denotes the vector of observable variables. $S_t$ denotes an unobservable state variable evolves according to a Markov chain with time-varying transition probabilities. The error vector $\epsilon_t$ is a Gaussian white-noise with covariance matrix

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \quad (2)$$

To model dependence in regime duration, Pelagatti [9] builds a Markov chain for the pair $(S_t, D_t)$, where $D_t$ is defined as

$$D_t = \begin{cases} 1 & \text{if } S_t \neq S_{t-1} \\ D_{t-1} + 1 & \text{if } S_t = S_{t-1},\ D_{t-1} < \tau \\ D_{t-1} & \text{if } S_t = S_{t-1},\ D_{t-1} = \tau \end{cases} \quad (3)$$

where $\tau$ denotes the maximum duration. A parsimonious representation of the transition (finite-dimensional) probability matrix is obtained by specifying a Probit model for $Z_t$:

$$Z_t = [\beta_1 + \beta_2 D_{t-1}]\, S_{t-1} + [\beta_3 + \beta_4 D_{t-1}]\, (1 - S_{t-1}) + \xi_t \tag{4}$$

with $\xi_t \sim \mathrm{N}(0,1)$. This implies that

$$\begin{aligned} \mathrm{pr}(Z_t \geq 0 | S_{t-1}, D_{t-1}) &= \mathrm{pr}(S_t = 1 | S_{t-1}, D_{t-1}) \\ \mathrm{pr}(Z_t < 0 | S_{t-1}, D_{t-1}) &= \mathrm{pr}(S_t = 0 | S_{t-1}, D_{t-1}) \end{aligned} \tag{5}$$

## 2.2 MCMC estimation algorithm

The model can be estimated jointly using Bayesian Markov Chain Monte Carlo method through Gibbs sampling. Let us denote the parameter vectors as $\theta_1 = (\mu_0, \mu_1)$, $\theta_2 = (A_1, \dots A_p, \Sigma)$, $\theta_3 = (\beta_1, \dots \beta_4)$, $\theta_4 = \{S_t, D_t\}_{t=1}^{T}$, and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)$. Let $y^T = \{y_t\}_{t=1}^{T}$ denote the vector of observable variables. The conditional distribution of $\theta_i$ while running Gibbs sampling can be written as $f(\theta_i | y^T, \theta_{j \neq i})_{i=1,\dots 4}$.

Given the $i$-th realization of a parameter $\theta^{(i)}$, the Gibbs sampling algorithm for estimating the model consists of the following (e.g., see Kim [8]):

- Step 1: sampling from $f(\theta_1 | y^T, \theta_2^{i-1}, \theta_3^{i-1}, \theta_4^{i-1})$ to obtain $\theta_1^{(i)}$;
- Step 2: sampling from $f(\theta_2 | y^T, \theta_1^{i-1}, \theta_3^{i-1}, \theta_4^{i-1})$ to obtain $\theta_2^{(i)}$;
- Step 3: sampling from $f(\theta_3 | y^T, \theta_1^{i-1}, \theta_2^{i-1}, \theta_4^{i-1})$ to obtain $\theta_3^{(i)}$;
- Step 4: sampling from $f(\theta_4 | y^T, \theta_1^{i-1}, \theta_2^{i-1}, \theta_3^{i-1})$ to obtain $\theta_4^{(i)}$;
- Step 5: iterate steps 1-5 until convergence of parameter estimates and state-space estimation.

In our empirical application, we use the prior distributions proposed by Pelagatti [9].

## 2.3 Competing models

Given a multivariate model for the conditional mean,

$$\mathbf{Z}(L)y_t = \mathbf{c} + \varepsilon_t \tag{6}$$

with $\mathbf{Z}(L) = \mathbf{I}_N\xi(L)$ and $\mathbf{I}_N$ is a $N \times N$ identity matrix, and $\xi(L) = [1 - \xi_i L]_i$, we compare the performance of the DD-MSVAR model with the Dynamic Conditional Correlation (DCC) model of Engle [5]. Engle and Sheppard [6] demonstrate that the log-likelihood of the DCC model can be written as the sum of a mean and volatility part in addition to a correlation part. The conditional variance-covariance matrix $H_t$ for a DCC models is estimated as

$$H_t = D_t V_t D_t \tag{7}$$

$$D_t = \text{diag}(\sigma_{1,1,t}^{1/2}, \ldots \sigma_{N,N,t}^{1/2}) \tag{8}$$

$$V_t = \text{diag}(\theta_t)^{-1/2}\theta_t \text{diag}(\theta_t)^{-1/2} \tag{9}$$

$$\theta_t = (1 - \alpha - \beta)\bar{\theta} + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta\theta_{t-1} \tag{10}$$

where $\theta_t$ denotes the conditional variance-covariance matrix of residuals satisfying $\alpha + \beta < 1$, and $\bar{\theta}$ is the unconditional covariance matrix of $\epsilon_t$.

The DCC model can be estimated in two steps. In the first step, univariate models for the conditional mean and GARCH dynamics are estimated. The transformed residuals are then used to compute conditional correlation estimators, where the standard errors for the first-stage parameters are consistent.

We consider several univariate GARCH models underlying the DCC,. These can all be estimated using standard maximum likelihood methods. With the standard GARCH(1,1) model, the conditional variance takes the form

$$h_t = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \nu h_{t-1} \tag{11}$$

with $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\nu_1 \geq 0$ in order to ensure a positive conditional variance (see Bollerslev [2]). We call the resulting multivariate model a DCC-GARCH.

The presence of skewness in financial data has motivated the introduction of the Exponential GARCH (EGARCH) model:

$$\log(h_t) = \alpha_0 + \alpha_1 \left|\frac{\epsilon_{t-1}}{h_{t-1}}\right| + \gamma\frac{\epsilon_{t-1}}{h_{t-1}} + \nu\log(h_{t-1}) \tag{12}$$

The use of this specification gives rise to a DCC-EGARCH.

The GJR model deals with the asymmetric reaction of the conditional variance depending on the sign of the shock:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 \left[1 - \mathcal{I}_{\{\epsilon_{t-1}>0\}}\right] + \gamma \epsilon_{t-1}^2 \mathcal{I}_{\{\epsilon_{t-1}>0\}} + \nu h_{t-1} \tag{13}$$

In our multivariate application, this model generates a DCC-GJR.

Financial time series are typically characterized by high kurtosis. In order to model the fat tails of the empirical distribution of the returns, we assume that the error term $\epsilon_t$ follows either a Student's $t$ distribution with $v$ degrees of freedom or a Generalized Error Distribution. The probability density function of $\epsilon_t$ then takes the form

$$f(\epsilon_t) = \frac{\Gamma((v+1)/2)}{\sqrt{\pi}\Gamma(v/2)} (v-2)^{-1/2} (h_t)^{-1/2} \left[1 + \frac{\epsilon_t^2}{h_t(v-2)}\right]^{-\frac{v+1}{2}} \tag{14}$$

where $\Gamma(\cdot)$ indicates the Gamma function with the shape parameter $v > 2$. Under the Generalized Error Distribution (G), the model errors follow the pdf

$$f(\epsilon_t) = \frac{v \exp\left(1/2 \left|\frac{\epsilon_t}{\lambda h_t^{1/2}}\right|^v\right)}{h_t^{1/2} \lambda 2^{(2+1/v)} \Gamma(1/v)} \tag{15}$$

with $\lambda := \left[\left(2^{-2/v}\Gamma(1/v)\right)/\Gamma(3/v)\right]^{1/2}$. This formulation gives rise to the DCC-GED model.

# 3 Dataset

We use daily data for one-month futures contracts on FTSE MIB, FTSE 100 and the XETRA DAX indices for the period January 1 2008-December 31 2011.[2] Daily data are employed also for computing an average price index of Italian equity mutual funds. This index consists of a weighted average of daily share prices, or net asset values (NAV). The weights are equal to the share of assets under management within the class of Italian equity mutual funds.

Our data source consists in the newly-developed commercial dataset on mutual funds provided by Standard & Poor's. This includes fund-level information on daily-updated prices, monthtly-updated assets under management,

[2]This part of the dataset was obtained from Bloomberg.

as well as management and sales fees for over 1170 Italian mutual funds. We clean the dataset from a survivorship bias, and remove the funds that are not active over the entire sample period. As a result, we choose to include 227 mutual funds for the construction of our sector index.

There are two main issues with our data-handling strategy. The first problem we encounter in the construction of our average price index is that assets under management are available only at a monthly frequency. We disregard this issue and keep the monthly figure constant within the relevant four-week period. The second issue is related to the role of fund expenses in the determination of fund returns. Consistently with the daily figures for reported NAV, we use net returns. As explained by Grande and Panetta [7], the framework for fees and costs faced by Italian mutual funds is affected by the contractual agreement between the parties involved. In Italy, a contract is signed among an investor, the fund's management company, and a custodian bank. This suggests that our measure of returns disregard both the bank and management fees paid by the investment managers.

Given a price $p_t$, we estimate our models on the realized returns

$$y_t = \log(p_t/p_{t-1}) \tag{16}$$

Table 1 reports the descriptive statistics of our sample returns. We should stress that the empirical distributions of the data are both left-skewed and sizeably peaked. These features are consistent with the period of market stress that characterizes the sample.

# 4 Results

In the estimation of the DD-MSVAR mode, we set the order of the autoregression to one, and the maximum duration $D_t$ to 60. The Gibbs sampling algorithm is based on 500000 simulated observations, from which we disregard the first 50000. Table 2 reports the results for the estimation of the DD-MSVAR models, with selected moments and percentiles of the posterior distributions for each parameter. The Table includes three sections, with the bivariate model in each of them. For the purpose of parsimony, we do not include the parameter estimates of the competing DCC models.

The estimated coefficients $\beta = (\beta_1,\ \beta_2,\ \beta_3, \beta_4$ provide information on the duration dependence in state 0 and 1. Indeed, all these parameters have values higher than 1. This indeed suggests that there is strong dependence effects. We also find that, for all the bivariate models with different futures indices, there is a complex structure of duration persistence in the form of asymmetric dependence across states. In other words, the dependence structure in state 0 is different from that of state 1, as it is characterized by different signs on the estimated coefficient. For instance, in the model with FTSE-MIB futures and our mutual fund index returns, $\beta_1$ is estimated equal to 2.4707, and $\beta_3$ is given by -1.4755. This feature allows our model to capture the key aspect of the changing relation between equity mutual fund returns and the relevant futures contracts.

To study the hedging properties of the futures contracts, we start by computing the optimal hedging ratio consistent with a minimum-variance portfolio of two assets. This static hedge is equal to the ratio

$$\Phi = \frac{\mathrm{cov}(y_1, y_2)}{\mathrm{var}(y_2)} \tag{17}$$

In our empirical application, we have

$$\Phi = \frac{\sigma_{12}}{\sigma_{22}} \tag{18}$$

Our final aim is to compare the performance of alternative hedges across models. Hence, we construct the portfolios implied by each optimal static hedge ratios, and evaluate the variance of the portfolios. Given a series of returns $y_{1,t}$ and $y_{2,t}$, the hedge-implied variance is equal to

$$\text{var. of implied port.} = \mathrm{var}(y_{1,t} - \Phi y_{2,t}) \tag{19}$$

We denote as 'best' the hedge that delivers the smallest implied-portfolio variance.

The variance-minizing hedging ratios are reported in Table 3. Two main results emerge. The first one is that the DD-MSVAR model delivers the lowest hedging portfolio variance indipendently from the hedge considered. The second result is related to the choice of the hedging instrument for the Italian equity mutual fund index. The findings overwhelmingly suggest that DAX futures deliver the lowest variance for most of the models except for the DD-MSVAR.

What is the 'most effective' hedge? For each model, we compute the percentage reduction of hedging portfolio variance generated by a hedge as

$$\text{var reduction} = 100 \times \frac{\text{var(unhedged port)} - \text{var(hedged port)}}{\text{var(unhedged port)}} \tag{20}$$

Table 4 shows the change of hedging portfolio variance reduction delivered by the DD-MSVAR with respect to the other models we consider here. The DD-MSVAR generates a performance improvement across the entire range of competing models. The interesting point is that these improvements are contingent on the hedging instrument. In particular, the reduction of hedging portfolio variance is larger against competing models that deliver a higher variance level.

## 5 Conclusion

This note considers the dynamics of Italian equity mutual fund returns during the recent period of financial market turmoil since 2008. We investigate the issue of hedging through futures contracts, and compare the hedging performance of alternative equity index futures. We aggregate daily data from individual Italian equity funds to compute a capitalization-weighted index of prices. Relevant hedges we consider include the FTSE-MIB index futures contract, which focuses on the Italian equity market. We also include two index futures for foreign (non-Italian) markets, namely the FTSE100 and the Xetra DAX. Our empirical application models the joint dynamics of our Italian equity mutual fund index and futures contract through the duration-dependent Markov-Switching model of Pelagatti [9]. With this framework, we would like to capture the persistence in drawdowns that has characterized the recent crisis. We consider several standard DCC specifications as competing models, and compute unconditional measures of hedging performance. Our results indicate that the DAX futures provide the best hedging instruments within the class of contracts we consider. Moreover, we find that the duration-dependent model delivers a systematic improvement of hedging performance.

The analysis of this paper can be extended along several dimensions. We consider only the case of an optimal static hedge. It would thus be important to compare our models using optimally-dynamic hedges. That would require us to compute forecasts of moments of returns that can be used in the calculation of the hedges. When dealing with dynamic portfolio decisions, the re-allocation of portfolios can be designed to complement or substitute for hedging through futures contracts. This points to the observation that we have disregarded the role of transaction costs in the design of a hedging strategy.

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Table 1: Descriptive statistics

| | Mean | Std. dev. | Skewness | Kurtosis |
|---|---|---|---|---|
| Equity mut. fund index | 1.6526 | 0.1187 | -2.5272 | 4.0481 |
| FTSE-MIB futures | 1.6541 | 0.1281 | -2.8225 | 3.8066 |
| FTSE100 futures | 1.7122 | 0.0621 | -2.7683 | 3.9657 |
| DAX futures | 1.9848 | 0.0484 | -2.4011 | 3.7795 |

Table 2: Bayesian estimation of the DDMSVAR model for

| | Mean | Std. error | 0.05% | 50% | 99.5% |
|---|---|---|---|---|---|
| | FTSE-MIB futures/Equity mutual fund index | | | | |
| $\mu_0(y_1)$ | -0.10370 | 0.05717 | -0.92539 | -0.10211 | 0.03363 |
| $\mu_0(y_2)$ | 0.11003 | 0.06452 | -0.92652 | 0.11519 | 0.15022 |
| $\mu_1(y_1)$ | 0.19835 | 0.09473 | 0.00066 | 0.19920 | 0.47492 |
| $\mu_1(y_2)$ | -0.07155 | 0.11143 | -0.24767 | -0.04080 | 0.45026 |
| $\sigma_{11}$ | 1.2579 | 0.05007 | 1.1056 | 1.2566 | 1.3831 |
| $\sigma_{12}$ | 1.2506 | 0.04994 | 1.1021 | 1.2495 | 1.3814 |
| $\sigma_{22}$ | 1.2791 | 0.05065 | 1.1755 | 1.2780 | 1.4171 |
| $\beta_1$ | 2.4707 | 0.86514 | -0.60552 | 1.4481 | 3.9558 |
| $\beta_2$ | -2.1095 | 0.92546 | -5.3560 | -2.1142 | -0.30329 |
| $\beta_3$ | -1.4755 | 0.88748 | -4.5519 | -1.4047 | 0.71054 |
| $\beta_4$ | 2.5502 | 0.94066 | 0.18726 | 2.1038 | 4.7606 |
| | FTSE100 futures/Equity mutual fund index | | | | |
| $\mu_0(y_1)$ | -0.00720 | 0.035555 | -0.13365 | -0.00554 | 0.06604 |
| $\mu_0(y_2)$ | 0.19230 | 0.036149 | -0.00839 | 0.13600 | 0.21722 |
| $\mu_1(y_1)$ | 0.04992 | 0.041511 | -0.08442 | 0.03981 | 0.19783 |
| $\mu_1(y_2)$ | -0.24449 | 0.050488 | -0.39928 | -0.25225 | -0.07419 |
| $\sigma_{11}$ | 0.75844 | 0.029613 | 0.65425 | 0.75827 | 0.83939 |
| $\sigma_{12}$ | 0.78877 | 0.031586 | 0.54364 | 0.78800 | 0.87485 |
| $\sigma_{22}$ | 0.89814 | 0.035847 | 0.78963 | 0.89718 | 0.99668 |
| $\beta_1$ | 1.0205 | 0.89419 | -1.18480 | 0.93979 | 3.63810 |
| $\beta_2$ | -1.9381 | 0.88748 | -5.04720 | -1.87200 | -0.13000 |
| $\beta_3$ | -1.3558 | 1.10920 | -5.21720 | -1.14120 | 0.62538 |
| $\beta_4$ | 2.1560 | 1.10740 | 0.12995 | 2.00700 | 5.33220 |
| | DAX futures/Equity mutual fund index | | | | |
| $\mu_0(y_1)$ | -0.33241 | 0.092173 | -0.61243 | -0.33371 | -0.08894 |
| $\mu_0(y_2)$ | -0.15540 | 0.092427 | -0.41152 | -0.12474 | 0.11373 |
| $\mu_1(y_1)$ | 0.63740 | 0.15803 | 0.086541 | 0.63977 | 1.02431 |
| $\mu_1(y_2)$ | 0.21929 | 0.15861 | -0.31787 | 0.22100 | 0.65504 |
| $\sigma_{11}$ | 2.8596 | 0.12005 | 2.4911 | 2.8548 | 3.1884 |
| $\sigma_{12}$ | 2.7885 | 0.11560 | 2.4325 | 2.7841 | 3.1047 |
| $\sigma_{22}$ | 2.9224 | 0.15549 | 2.5732 | 2.9180 | 3.2452 |
| $\beta_1$ | 1.40422 | 0.94686 | -1.2253 | 0.92262 | 3.52450 |
| $\beta_2$ | -1.9662 | 0.95784 | -4.7720 | -1.8307 | -0.18548 |
| $\beta_3$ | -2.1043 | 1.09310 | -4.9417 | -0.8999 | 0.76027 |
| $\beta_4$ | 2.0496 | 1.09960 | -0.0511 | 1.8922 | 5.45050 |

Table 3: Hedging portfolio variances

| Hedge | DD-MSVAR | DCC-GARCH | DCC-EGARCH | DCC-GJR | DCC-GED |
|---|---|---|---|---|---|
| FTSE-MIB | 0.648114 | 1.868153 | 0.777610 | 0.662731 | 1.212540 |
| FTSE100 | 0.671115 | 1.754114 | 0.726324 | 0.717541 | 1.058531 |
| Xetra DAX | 0.558113 | 1.555960 | 0.771439 | 0.785556 | 0.698566 |

Table 4: Performance improvements of the DD-MSVAR over alternative models

| | Competing model | | | |
|---|---|---|---|---|
| | DCC-GARCH | DCC-EGARCH | DCC-GJR | DCC-GED |
| Hedge | | | | |
| FTSE-MIB | 87.43% | 41.29% | 35.09% | 73.79% |
| FTSE100 | 89.18% | 55.71% | 39.37% | 78.25% |
| Xetra DAX | 65.92% | 29.70% | 41.31% | 84.33% |