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Abstract

We study optimal asset allocation for a portfolio of European fixed-income mutual funds during the recent financial turmoil. We use a sample of daily returns for country indices of French, German and Italian funds to investigate the quest for international diversification. Our analysis focuses on the specific role of Italian funds. We compute optimal portfolio allocations from a modified mean-variance framework that takes as input the out-of-sample forecasts for the conditional mean, volatility and correlation of the funds returns. VaR forecast comparisons between alternative models provide support for a fractionally-integrated GARCH for the conditional variance. The interaction between the funds is modelled as the Dynamic Conditional Correlation of Engle (2002). Our results are twofold. First, the optimal portfolio allocates more than 50% of assets to German funds, while assigning equal shares of approximately 20% to both French and Italian funds. This strategy generates portfolio returns that are more stable than those of our competing models. It is also characterized by a worsening of the risk-return tradeoff throughout the evaluation period. The second result is that overweighing Italian funds with respect to the optimal strategy causes the portfolio to hold additional volatility of returns without generating compensation for risk.
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1 Introduction

Holdings of mutual funds represent a sizeable share of portfolios of both institutional investors and households around the world. Since the shares of any fund are available to virtually any investor regardless of her geographical location, investors face the choice of how to diversify their mutual fund holdings across countries. This choice has evidently become more difficult since the outbreak of the global financial turmoil in 2007.

In this paper, we focus on the international diversification across the European mutual fund industry during the recent phase of market disruption. In particular, we investigate the relative performance of funds managed in France, Germany and Italy. Despite the fact that a large block of European countries is tied together by a common currency, local financial markets still face idiosyncratic regulations, different tax regimes and, most of all, a different phases of development.

Our study also deals with the specific role of Italian funds. Most of the literature on Italian funds has concentrated on the measurement of management fees (e.g., see Anolli and Del Giudice, 2008) and performance (e.g., see Cesari and Panetta, 2002). To our knowledge, no existing contribution has considered the role of Italian mutual funds in international asset allocation.

Regardless of the specific national factors at play, the turmoil in financial markets that erupted in August 2007 has pushed central banks around the world to keep a loose monetary policy stance for the last five years. This has obviously contributed to a fall of interest rates both on the short and on the long end of the yield curves of most advanced economies. For this reason, our analysis concentrates on mutual funds investing in fixed-income assets. In this asset class, we include both bonds and money-market instruments.

To provide insight on the scope for international diversification, we build on the standard mean-variance framework of Markowitz (1952) to construct forecast-based optimal plans for asset allocation with a constraint on Value-at-Risk (VaR). As a starting point, we estimate joint models and generate forecasts for the conditional mean, volatility and correlation of funds returns in the three economies. These forecasts are then used to compute the optimal allocations. Our dataset consists of aggregate indices for daily excess returns of French, German and Italian funds starting in September 2007.

The conditional correlation is modelled through the Dynamic Conditional Correlation framework of Engle (2002). Since our dataset covers a period of persistent turbulence and volatility in the financial markets, we start by considering a a fractionally-integrated Generalized Autoregressive Conditional Heteroskedasticity (GARCH) specification for the underlying conditional variance (e.g., see Baillie, 1996). The results from out-of-sample VaR forecast comparisons with alternative GARCH specifications point in favour of our model with fractional integration.[1]

[1]Several papers have already used a fractionally-integrated GARCH to deal with datasets characterized by persistence in volatility. For example, the reader may refer to Ding, Granger, and Engle (1993) for an

The empirical results produced by the forecasts of the DCC model with fractionally-integrated GARCH suggest that an optimal portfolio should include a large share of German funds. Both Italian and French funds should be allocated portfolio shares of 20% each. In other words, Italian mutual funds play a marginal role in international asset allocation. The strategy prescribed by our model generates portfolio returns that are relatively stable than those of alternative models, despite the fact that they are generated over a period of turbulence for financial markets. The second result concerns the specific role of Italian mutual funds. Assigning a higher weight to Italian funds with respect to the optimal strategy causes the portfolio to face sizeable volatility of returns without adding compensation for this source of risk. Overall, we can take these results as face value for the underperformance of Italian mutual funds.

This paper is organized as follows. Section 2 outlines the models for the conditional variance and correlation, as well as the framework for studying optimal asset allocation. Section 3 deals with the dataset. Section 4 discusses the estimation results for the fractionally-integrated GARCH models. It also compares the predictive ability for out-of-sample VaR of competing models, and outlines the implications for optimal portfolio diversification of fixed-income mutual funds. In section 5 we present some concluding remarks.

2 Modelling approach

In this paper, we model daily excess returns of assets. Given a price p_t and a risk-free interest rate r_t, we define the realized excess return in period t as:

$$r_t = 100 \times \log(p_t/p_{t-1}) - r_t \tag{1}$$

2.1 Univariate fractionally-integrated model

We start by considering a univariate model for excess returns:

$$\begin{aligned} (1-\xi L)r_t &= c + \epsilon_t \\ \epsilon_t &= e_t\sqrt{h_t} \end{aligned} \tag{2}$$

with $c \in (0,\infty)$, $|\xi| < 1$, $\{e_t\}_{t=1}^{\infty}$ are independently and identically-distributed randon variables. The term h_t denotes the conditional variance. We start by modeling h_t as the FIGARCH(1,d,1) of Baillie, Bollerslev, and Mikkelsen (1996):

$$(1-\beta L)(h_t - \omega) = [(1-\beta L) - (1-\phi L)(1-L)^d]\epsilon_t^2 \tag{3}$$

where $\omega = h_0$ and $|\phi| \leq 1$. The coefficient d denotes the fractional-integration parameter.

application to the hedging of stock prices.

2.2 Multivariate extension

Let us define the N-dimensional vector of returns $\mathbf{r}_t$ and the corresponding vector $\mathbf{e}_t$. The conditional mean of the model can be written as

$$\mathbf{Z}(L)\mathbf{r}_t = \mathbf{c} + \mathbf{e}_t \tag{4}$$

with $\mathbf{Z}(L) = \mathbf{I}_N \xi(L)$ and $\mathbf{I}_N$ is a $N \times N$ identity matrix, and $\xi(L) = [1 - \xi_i L]_i$.

To model the conditional correlation, we use the Dynamic Conditional Correlation (DCC) model of Engle (2002). Following Engle and Sheppard (2001), we can estimate the model in two steps. First, the univariate model 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. The conditional variance-covariance matrix H_t is estimated as

$$\begin{aligned} H_t &= D_t V_t D_t \\ D_t &= \mathrm{diag}(\sigma_{1,1,t}^{1/2}, \ldots \sigma_{N,N,t}^{1/2}) \\ V_t &= \mathrm{diag}(\theta_t)^{-1/2} \theta_t \mathrm{diag}(\theta_t)^{-1/2} \\ \theta_t &= (1 - \alpha - \beta)\bar{\theta} + \alpha \mathbf{e}_{t-1}\mathbf{e}'_{t-1} + \beta \theta_{t-1} \end{aligned} \tag{5}$$

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

2.3 Competing univariate GARCH models

In our empirical application, we compare the asset allocation performance of the multivariate FIGARCH models with that of alternative specifications. We use the standard GARCH(1,1) based on the Normal distribution (denoted as NGARCH)

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \nu h_{t-1} \tag{6}$$

with $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\nu_1 \geq 0$ in order to ensure a positive conditional variance. The presence of skewness in financial data has motivated the introduction of the Exponential GARCH (EGARCH) model (see Bollerslev, Chou, and Kroner, 1992):

$$\log(h_t) = \alpha_0 + \alpha_1 \left| \frac{\epsilon_{t-1}}{h_{t-1}} \right| + \gamma \frac{\epsilon_{t-1}}{h_{t-1}} + \nu \log(h_{t-1}) \tag{7}$$

The GJR model generates an asymmetric reaction of the conditional variance depending on the sign of the shock:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 \left[1 - \mathcal{I}_{\{\epsilon_{t-1} > 0\}}\right] + \gamma \epsilon_{t-1}^2 \mathcal{I}_{\{\epsilon_{t-1} > 0\}} + \nu h_{t-1} \tag{8}$$

2.4 Framework for optimal asset allocation

In this paper we consider a dynamic approach to portfolio allocation. We use one-month ahead forecasts for the conditional mean and covariance of returns generated by each model. The out-of-sample forecasts for each period are then fit into a mean-variance framework to compute the optimized portfolio composition.

We modify the standard mean-variance model along the lines of Lejeune (2012) by introducing constraints that are economically-relevant, and that provide stability to the solution of the optimal allocation problem. We assume that the representative investor maximizes one-period ahead expected returns of the portfolio

$$\max_{\mathbf{w}_t} \mathrm{E}\mathbf{r}_{p,t+1} = \max_{\mathbf{w}_t} \mathbf{w}_t' \mathrm{E}\mathbf{r}_{t+1} \tag{9}$$

subject to the standard constraint

$$\sum_i w_i = 1 \tag{10}$$

We impose a diversification constraint with both an upper limit for the holdings of each asset j in each period. Given the lower bound $w_{\max}$ on portfolio shares, we introduce a binary variable $\delta_j \in \{0,1\}$ for each asset $j = 1, \ldots n$ such that

$$w_{j,t} \leq w_{\max}\delta_j \tag{11}$$

We also include so-called buy-in thresholds that prevent the portfolio from having small positions in a mutual fund

$$w_{\min}\delta_j \leq w_{j,t} \tag{12}$$

where $w_{\min}$ is the lower limit on the positions.

To limit the risk of the optimized portfolio, we introduce a bound on the one-period ahead forecast for portfolio variance

$$\mathbf{w}_t' H_{t+1} \mathbf{w}_t \leq s \tag{13}$$

where H_{t+1} denotes the covariance matrix forecast. Finally, our framework includes a VaR-forecast constraint

$$\mathbf{w}_t' \mathrm{E}_t \mathbf{r}_{t+1} + F_{\mathbf{w}}^{-1}(0.05)\sqrt{\mathbf{w}_t' H_{t+1} \mathbf{w}_t} \geq -\beta \tag{14}$$

In the empirical application, we set $w_{\max}$ to 90%, $w_{\min}$ to 1% for all the assets, and β to 5% in order to achieve a 95% VaR. The numerical optimization problem is solved using the mixed-integer non-linear programming (MINLP) solver.[2]

3 Dataset

We construct daily indices for prices of fixed-income mutual funds sold to investors in France, Germany and Italy. We select the funds that manage assets in the form of corporate and goverment bonds, as well as money-market instruments. We aggregate the data across funds sold in a given country by computing weighted averages. The weights are equal to the share of assets under management (AUM) by both national and foreigner managers registered in each country. Since our analysis intends to focus on the recent turmoil period, our sample period goes from September 1 2007 until December 31 2011. We measure the risk-free rate by the yield on 3-month German government bonds. This is consistent with anecdotal evidence on flight-to-safety episodes during the turmoil.

Data on daily fund prices are obtained from a commercial dataset provided by Standard & Poor's. This includes fund-level information on daily-updated prices, monthtly-updated assets under management, as well as management and sales fees for a large sample of European mutual funds. In this paper we control for the effect of survivorship bias by disregarding the funds that are not active over the entire sample period. This narrows down the number of funds that are included to a major extent. In particular, our national indices are computed on 85 French, 79 German and 62 Italian funds. Regardless, the French funds included in the dataset account for 71%, the German funds for 64%, and the Italian funds for 70% of national assets under management within the fixed-income funds class.

Table 1 reports the descriptive statistics of our index returns. The impact of the turmoil on the mutual fund industry is reflected by large skewness and kurtosis coefficients. In particular, the empirical distributions are left-skewed. The Jarque-Bera test statistics rejects the null of normality very significantly. Table 1 includes also the statistics for the normality test of Anderson and Darling (1952). This is a modification of the Kolmogorov-Smirnov test that gives weight to the tails of the empirical distribution of the data. Also this test points towards a strong rejection of the null of normality. As an additional step, we test for nonlinear dependence using the BDS test of Brooks, Dechert, and Scheinkman (1996). These tests reject the null of independence and identical distribution for the returns. The last panel of Table 1 reports the unconditional correlations between the excess returns. While the returns on Italian fixed-income funds are strongly correlated, the German funds are somewhat decoupled from both the French and the Italian funs. Finally, we check for the presence of ARCH effects in every series. For this purpose, we use the Lagrange Multiplier test of Engle (1982). The results are reported in Table 2, which documents large rejections of the null of no ARCH.

[2]The open-source code for optimization is available at https://projects.coin-or.org/Bonmin.

4 Empirical results

After proper statistical testing, we choose to estimate a VAR of order 1 for the conditional mean. For the purpose of parsimony, in this section, we discuss the empirical estimates for the alternative DCC models.[3] We start by presenting the parameter estimates for the univariate fractionally-integrated GARCH models. We then compare the out-of-sample predictive ability for Value-at-Risk of the alternative GARCH models. Finally, we turn to the multivariate models for conditional correlation, and present evidence in favor of time-varying correlations against constant the alternative of constant correlations.

We carry out the estimation in the following way. We reserve the last 150 observations of the dataset for out-of-sample forecast evaluation. The models are estimated in-sample on the preceding part of the dataset. At the beginning of the evaluation subsample, we start estimating the models on a recursive sampling scheme, whereby a new observation is used for estimation after is has been forecast.

4.1 Evidence of fractional integration in conditional variance

Table 3 shows the estimated parameters for the univariate GARCH models. These are estimates obtained by maximizing standard likelihood function

$$\mathcal{L} = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\log h_t^2 + \frac{\epsilon_t^2}{h_t^2}\right] \tag{15}$$

The first panel of Table 3 indicates that the estimated coefficients of fractional integration are all statistically significant. The average value for $\hat{d}$ is equal to 0.8. This could be interpreted as preliminary statistical evidence in favor of the fractionally-integrated model for conditional volatility. The estimated parameters provide the sufficient conditions to guaranteee the non-negativity of the variance estimates. The second panel of Table 3 reports the Ljung-Box test statistics for serial correlation in the standardized and squared standardized residuals, denoted as Q_{12} and Q^2_{12} respectively. The tests indicate that the univariate FIGARCH models suffer from no significant source of misspecification.

We test for persistence in conditional variance by Wald tests against the null hypothesis for $d = 0$ and $d = 1$. Table 4 reports the tests statistics and the associated p values. Both null hypothesis are strongly rejected, thus supporting the proposition of fractional integration in the conditional variance process.

4.2 Out-of-sample VaR comparison

Our asset-allocation model includes a constraint based on VaR prediction. Hence, comparing the predictive ability of the competing univariate GARCH models using VaR criteria can

[3]The draft does not report the parameter estimates for the competing GARCH models either. These estimated parameters can be obtained from the author upon request.

provide insights into the optimal diversification of fixed-income funds.[4] Given a VaR forecast, several statistical tests are available to assess the predictive ability of the GARCH models.

The time until first failure ($TUFF$) is computed from the number of exceptions of the VaR for model k, denoted as $\mathcal{I}_{r_t<\mathrm{VaR}_t^k}$. A model can then be judged as appropriate when the proportion of failures (PF) is close to the nominal value. Under the assumption that the number of failures is i.i.d. and distributed as a binomial, a test for proportion of failures is formulated with the null hypothesis

$$\mathcal{H}_0: \ \mathrm{E}(\mathcal{I}_{r_t<\mathrm{VaR}_t^k}) = \gamma \tag{16}$$

Christoffersen (1998) proposes a test of independence failures that accounts for the role of volatility clustering. The null of independent failure rates (IND) is tested against a first-order Markov failure process with the test statistics. Finally, we consider a conditional test of correct coverage (CC) where the null of independent failures with a probability γ is tested against first-order Markov failure.

Table 5 presents the test results based on one-step ahead VaR forecasts at the 95%. Figures in bold identify the minima for each evaluation criterion. The theoretical TUFF at the 5% is 15. First of all, most of the models have time until first failure that exceed the theoretical value. The fractionally-integrated models deliver the lowest percentage of failure probabilities for all the countries. The test results indicate that the FIGARCH models also generate both unconditional and conditional coverage that are consistent with the theoretical levels. The lowest number of test rejections is produced by the FIGARCH, whereas the largest share of rejections is obtained by the GJRGARCH.

4.3 Evidence for time-varying conditional correlation

In order to test the specification of the DCC with FIGARCH models, we test for constancy of the conditional correlations. In the testing framework of Engle and Sheppard (2001), the null and alternative hypotheses are, respectively

$$\begin{aligned} &\mathcal{H}_0: \ V_t = V \\ &\mathcal{H}_1: \ \mathrm{vec}(V_t) = \mathrm{vec}(V) + \phi_1 \mathrm{vec}(V_{t-1}) + \ldots \phi_m \mathrm{vec}(V_{t-m}) \end{aligned} \tag{17}$$

This procedure requires to define the auxiliary model

$$\begin{aligned} &\hat{\mathbf{w}}_t = \omega_0 + \omega_1 \hat{\mathbf{w}}_{t-1} + \ldots \omega_m \hat{\mathbf{w}}_{t-m} \\ &\hat{\mathbf{w}}_t = \mathrm{vec}(\hat{\mathbf{l}}_t \hat{\mathbf{l}}_t^T - \mathbf{I}_n) \end{aligned} \tag{18}$$

where $\hat{\mathbf{l}}_t$ is a vector of standardized residuals $\hat{\mathbf{l}}_t = \hat{V}^{-1/2}\hat{D}_t^{-1}\hat{\mathbf{e}}_t$. The null hypothesis implies that the coefficients ω_ι of equation 18 are jointly equal to zero, with a test statistically

[4] From a statistical point of view, loss functions based on VaR are a natural alternative to the standard statistical loss functions, like the root mean squared error (see Brooks and Persand, 2003).

that is asymptotically distributed as a $\chi^2(m-1)$. Table 6 reports the tests statistics with the respective p values. The results provide strong support for a time-varying correlation structure.

4.4 Results for optimal forecast-based asset allocation

We plug the one-step ahead forecasts for both the conditional mean and the covariance matrix into the portfolio allocation framework. We then solve the resulting maximization problem to compute the optimal fund allocation plan.

Table 7 reports some selected moments for the distribution of optimizing portfolio weights for each competing model. The first panel includes the average weights obtained over the forecasting period. Regardless of the modelling framework, the evidence suggests that a wealth-optimizing investor holds the largest share of German fixed-income funds. This asset may absorb up to more than 70% of a portfolio as measured by the maximum weight. If we focus on the model with the best statistical record - i.e., the DCC-FIGARCH -, we notice that the optimal share of German funds is twice as large as that of French funds. On the other hand, optimized portfolios assign only a share of 18% on average to Italian funds. Competing models provide very different allocation strategies. For instance, the DCC-GJRGARCH delivers a portfolio of almost equally-weighted funds. For the DCC-FIGARCH model, our optimal portfolios prescribe asset weights that vary widely through time. In fact, there are sizeable differences between the maximum and the minimum weights that characterize optimal portfolios. For the DCC-FIGARCH, the maximum weight on German funds is three times the minimum portfolio share. The weight on Italian funds drops to as low as 3% for the same model.

In the following step of our analysis, we consider the performance of the optimal portfolios of funds. Figure 2 plots the means of the distributions of optimal frontiers for each forecasting model. These curves are constructed as simple averages of the optimizing mean-variance combinations over the evaluation period for out-of-sample forecasts. The reader should notice that the frontiers are not as well-shaped as in the standard portfolio optimization approach of Markowitz (1952). The reason lies in the additional constraint that we use to achieve stability in our dynamic asset allocation plans. Figure 2 shows that, on average, a given increase in portfolio standard deviation for the DCC-FIGARCH generates an increase in expected return higher than for the competing models. Moreover, for a given level of portfolio return volatility, the DCC-FIGARCH achieves higher excess return than the other DCC specifications.

How do the mean-variance frontiers change during the turmoil period? Figure 1 provides insight into the movements of the curve once a year, from June 30 2008 until June 30 2011. This figure depicts the progressive worsening of the trade-off between volatility and expected portfolio returns that has taken place during the recent period of market turmoil. In particular, the frontier for June 15 2011 becomes almost flat, which indicates that the reward for taking additional risk in the fixed-income fund sector is marginal.

To gain understanding on the distribution of expected returns from alternative portfolio allocations, Table 8 reports some selected statistics. The first relevant observation is that the excess returns from the DCC-FIGARCH are stable, as they vary over a range smaller than that of the competing models. This pattern of stability of portfolio returns emerges is reflected also by the second panel of Table 8, which reports the standard deviation of excess returns. Overall, these figures suggest that the DCC-FIGARCH allows to construct portfolios with higher returns while, at the same time, producing the lowest standard deviation of returns. The DCC-GJRGARCH, which assigns the smallest mean weight of German funds, generates portfolio returns with the highest variability. This supports the previous finding about the desirability of putting a large weight on German funds and a small weight on Italian funds in our setup of international portfolios.

What is the performance impact of deviating from the optimal allocation of Italian funds? How important are mistakes from overweighting Italian funds in the design of optimal portfolios? We study this issue by fixing the weight on the Italian mutual index, and by computing the optimizing portfolio shares for French and German funds that solve the planning problem. Figure 3 plots the resulting average frontiers of optimal expected returns and standard deviations for three values of w_{ITA} - $w_{ITA} = 0.3$, $w_{ITA} = 0.4$ and $w_{ITA} = 0.5$ - with the DCC-FIGARCH as the forecasting model. The curve moves towards a region with higher standard deviations for each level of portfolio return as w_{ITA} increases. In other words, deviating from the optimal share of Italian funds generate a clear cost in the terms of additional variability of returns. By how much do the optimal combinations of risk and return change, on average, as we deviate from the optimal w_{ITA}? In Table 9, we report the percentage rate of increase of both expected returns and standard deviations of returns from the figures generated by the portfolio with optimal weights for all the three assets. Choosing a share of Italian funds in excess of the optimizing weight leads to an increase in portfolio return variability that outpaces largely the increase in expected returns. For instance, raising w_{ITA} to 0.5 produces an ancrease of expected return equal to 9.2%, while the standard deviation rises by almost 53%.

5 Conclusion

This paper considers the optimal allocation problem in a a portfolio of European fixed-income mutual funds during the recent period of financial turmoil. We consider daily price indices for French, German and Italian funds to study the benefits from international diversification since September 2007. In particular, our analysis focuses on the role of Italian mutual funds. We model the conditional correlations of the funds returns using the DCC model of Engle (2002). The conditional variance is modelled as a fractionally-integrated process. Out-of-sample VaR forecast comparisons with alternative GARCH specifications indicate that the fractionally-integrate model bears desirable empirical properties. We compute a dynamic optimal asset allocation plan that take as input out-of-sample forecasts for the conditional mean, volatility and correlation of the funds returns. Given one-step ahead forecasts for these moments, we solve a mean-variance allocation problem for each day of the forecast-evaluation period. The structure of this portfolio optimization problem includes several constraints, such as a bound on out-of-sample VaR.

The results obtained from the forecasts of the DCC-FIGARCH are twofold. First of all, a wealth-optimizing investor should hold a large fraction of German fixed-income funds for approximately 60%, while assigning a share of approximately 20% to both French and Italian funds. These optimal allocations vary widely on a daily basis. However, they generate portfolio returns more stable than those of alternative models, and are characterized by a worsening of the risk-return tradeoff across the forecast evaluation period. The second result concerns the role of Italian mutual funds. Overweighing Italian funds with respect to the optimal strategy causes the portfolio to hold additional volatility of returns without generating compensation for risk. We can interpret this result as a reflection of the underperformance of the Italian mutual fund industry.

The analysis presented here can be extended in several ways. From a modelling point of view, we could introduce a fully multivariate model where fractionally-integrated processes for both the conditional variance and correlation are jointly estimated (e.g., see Conrad, Karanasos, and Zeng, 2011). The optimal asset allocations could be computed using the approach of Black and Litteman (1992), rather than relying on arbitrary types of boundaries to generate stable portfolio plans. Most important, we should consider the role of transaction costs and management fees for measuring mutual fund performance. Hence, we should compare optimal allocations based on gross returns with those for net returns.

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Table 1: Descriptive statistics for excess returns on fixed-income funds

	French index	German index	Italian index
Minimum	-2.04	-1.57	-2.09
Maximum	2.23	2.43	1.99
Mean	1.053	1.141	1.016
Std. dev.	2.30	3.61	2.38
Skewness	-15.52	-35.64	-9.70
Kurtosis	29.85	13.65	27.40
Jarque-Bera	170.09	144.16	17.905
	[0.0]	[0.0]	[0.0]
Anderson-Darling	45.93	31.99	47.72
	[0.0]	[0.0]	[0.0]
BDS(2)	9.70	12.44	19.10
	[0]	[0]	[0]

	Correlations		
	French index	German index	Italian index
French index	1	0.19	0.66
German index	0.19	1	0.38
Italian index	0.66	0.38	1

Legend: Brackets denote p-values. The BDS test was computed by setting the largest dimension to 2, and the length of the correlation integral to one times the standard deviation of the series. These values are chosen so that the first-order correlation integral estimate lies around 0.7.

Table 2: Lagrange-multiplier tests of ARCH effects

Lag	Engle (1982)		
	French index	German index	Italian index
1	37.79 [0.0]	12.20 [0.0]	7.54 [0.0]
2	54.20 [0.0]	19.79 [0.0]	15.46 [0.0]
3	162.23 [0.0]	98.04 [0.0]	56.79 [0.0]
4	164.56 [0.0]	125.59 [0.0]	56.74 [0.0]
5	164.72 [0.0]	131.20 [0.0]	56.97 [0.0]

Legend: p-values are in brackets.

Table 3: Parameter estimates of FIGARCH univariate model

	German index	French index	Italian index
β	0.55 (7.13)	0.68 (8.03)	0.16 (8.13)
ϕ	0.25 (5.99)	0.37 (8.93)	0.49 (7.55)
d	0.80 (10.38)	0.89 (9.26)	0.90 (12.04)
Q_{12}	14.90 [0.53]	10.37 [0.61]	14.08 [0.50]
Q^2_{12}	14.60 [0.28]	9.17 [0.31]	11.52 [0.47]

Legend: Round brackets denote t statistics. Square brackets refer to p values.

Table 4: Wald tests for restrictions on fractional differencing parameter

	$\mathcal{H}_0: \; d = 0$	$\mathcal{H}_0: \; d = 1$
German index	15.71 [0.01]	29.40 [0.00]
French index	19.52 [0.00]	41.85 [0.00]
Italian index	11.95 [0.03]	13.33 [0.01]

Legend: Square brackets denote p values.

Table 5: One-step ahead VaR farecasting evaluation

Model	TUFF	PF(%)	LF_{PF}	LF_{IND}	LF_{CC}
FR - FIGARCH	24	4.100	**0.213**	2.648	5.331*
DE - FIGARCH	13	**2.390**	0.722	2.796	13.927*
IT - FIGARCH	25	3.599	0.263	3.690	**3.953**
FR - NGARCH	11	11.735	0.299	4.959*	4.999
DE - NGARCH	23	5.097	14.131*	**2.450**	13.490*
IT - NGARCH	37	4.159	0.472	4.959*	5.442*
FR - EGARCH	19	5.405*	0.250	4.648*	4.898
DE - EGARCH	28	2.541	14.131*	2.796	13.927*
IT - EGARCH	14	4.880	0.116	4.851*	4.967
FR - GJRGARCH	27	5.541*	0.440	8.241*	8.411*
DE - GJRGARCH	27	2.973	7.443*	4.357*	14.800*
IT - GJRGARCH	19	4.595	0.263	3.69	4.930

Legend: * indicates significance at the 5% level.

Table 6: Tests for constant conditional correlations

Lag	Test statistics
1	28.53 [0.0]
2	33.96 [0.0]
3	45.49 [0.0]
4	45.52 [0.0]
5	52.70 [0.0]

Legend: p-values are in brackets.

Table 7: Composition of optimal portfolios

	French index	German index	Italian index
		Mean weight	
DCC-FIGARCH	23%	59%	18%
DCC-NGARCH	35%	51%	14%
DCC-EGARCH	21%	47%	32%
DCC-GJRGARCH	31%	39%	30%
		Maximum weight	
DCC-FIGARCH	40%	79%	41%
DCC-NGARCH	45%	72%	38%
DCC-EGARCH	37%	65%	50%
DCC-GJRGARCH	57%	59%	44%
		Minimum weight	
DCC-FIGARCH	9%	26%	3%
DCC-NGARCH	8%	11%	5%
DCC-EGARCH	5%	14%	10%
DCC-GJRGARCH	9%	22%	5%

Table 8: Statistics on performance distribution of optimal portfolios

	Mean	Maximum	Minimum
	Portfolio excess return		
DCC-FIGARCH	1.53	1.75	1.19
DCC-NGARCH	1.43	2.05	0.38
DCC-EGARCH	1.27	1.98	0.26
DCC-GJRGARCH	1.41	1.97	0.35
	Standard deviation		
DCC-FIGARCH	15.97	19.90	10.19
DCC-NGARCH	21.15	23.95	14.42
DCC-EGARCH	19.70	24.10	16.99
DCC-GJRGARCH	29.82	24.05	17.20

Table 9: Percentage change in portfolio performance arising from deviations of w_{ITA}

	% change in $\mathrm{E}_t \mathbf{r}_{p,t+1}$	% change in $\sigma(\mathbf{r}_{p,t})$
$w_{ITA} = 0.3$	1.99%	3.71%
$w_{ITA} = 0.4$	4.77%	28.33%
$w_{ITA} = 0.5$	9.20%	52.94%

Legend: This plot is obtained by fixing the weight on Italian funds fixed to w_{ITA}, and by computing asset-allocation plans by optimizing the weights for French and German fund indices. The underlying forecasting model is the DCC-FIGARCH. The term $\mathrm{E}_t \mathbf{r}_{p,t+1}$ denotes the expected portfolio return, and $\sigma(\mathbf{r}_{p,t})$ is the standard deviation of the portfolio returns over the forecasting period.

Figure 1: Mean of distribution of optimal frontiers for each forecasting model

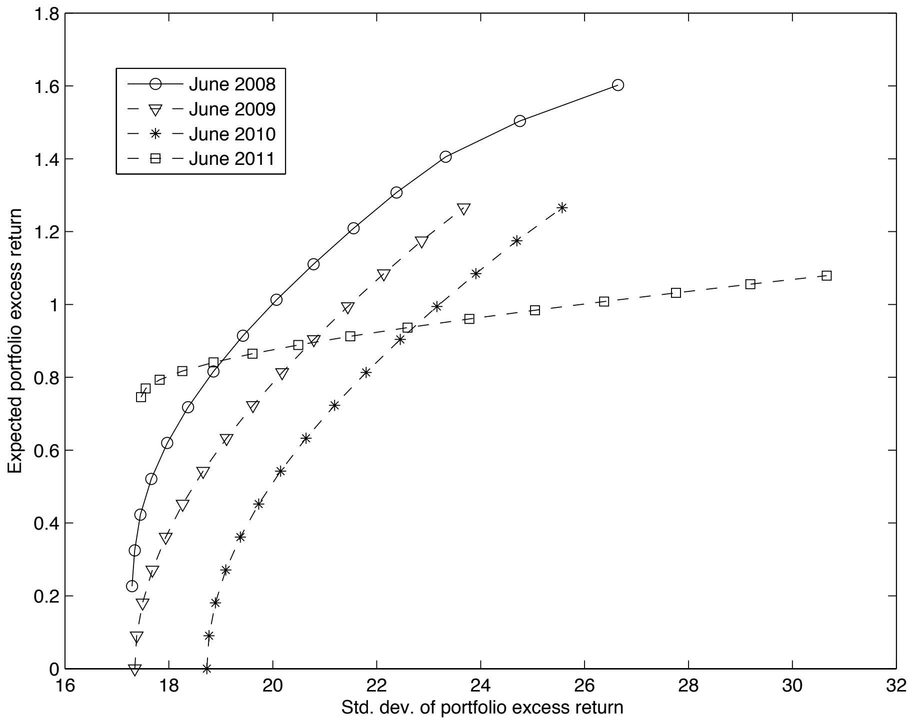


Figure 2: Movement of mean-variance frontiers from DCC-FIGARCH model

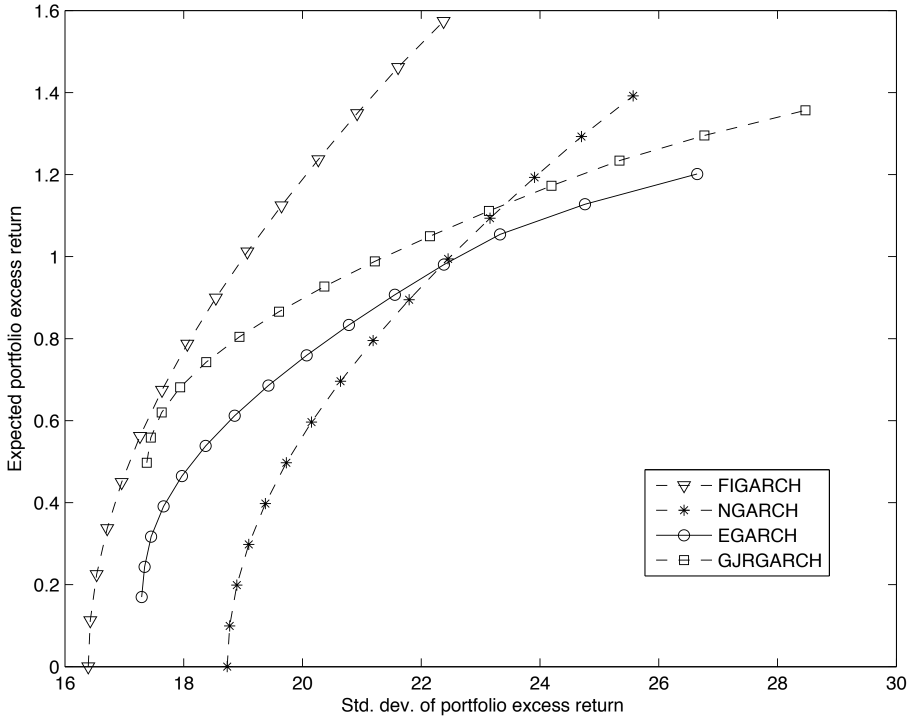
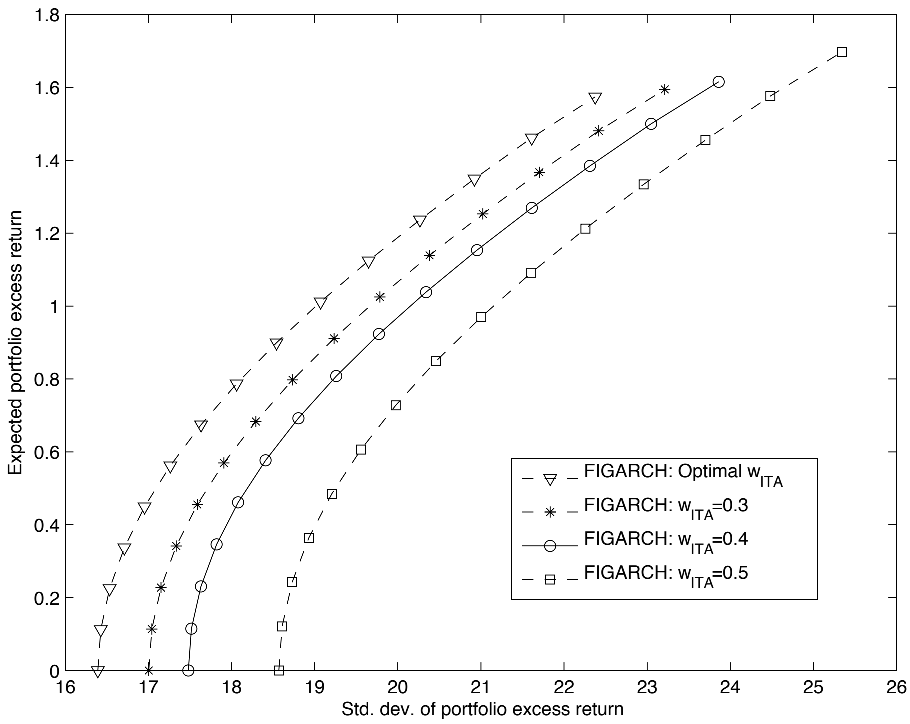


Figure 3: Mean-variance frontiers with fixed weight on Italian fund index



Legend: This plot is obtained by fixing the weight on Italian funds fixed to w_{ITA}, and by computing asset-allocation plans by optimizing the weights for French and German fund indices. The underlying forecasting model is the DCC-FIGARCH.