CONTRIBUTI DI RICERCA CRENOS

CLUSTERING MUTUAL FUNDS BY RETURN AND RISK LEVELS

Francesco Lisi

Edoardo Otranto

WORKING PAPERS

2008/13

CENTRO RICERCHE ECONOMICHE NORD SUD
(CRENoS)
UNIVERSITÀ DI CAGLIARI
UNIVERSITÀ DI SASSARI

Il CRENoS è un centro di ricerca istituito nel 1993 che fa capo alle Università di Cagliari e Sassari ed è attualmente diretto da Raffaele Paci. Il CRENoS si propone di contribuire a migliorare le conoscenze sul divario economico tra aree integrate e di fornire utili indicazioni di intervento. Particolare attenzione è dedicata al ruolo svolto dalle istituzioni, dal progresso tecnologico e dalla diffusione dell'innovazione nel processo di convergenza o divergenza tra aree economiche. Il CRENoS si propone inoltre di studiare la compatibilità fra tali processi e la salvaguardia delle risorse ambientali, sia globali sia locali.
Per svolgere la sua attività di ricerca, il CRENoS collabora con centri di ricerca e università nazionali ed internazionali; è attivo nell'organizzare conferenze ad alto contenuto scientifico, seminari e altre attività di natura formativa; tiene aggiornate una serie di banche dati e ha una sua collana di pubblicazioni.

www.crenos.it
info@crenos.it

CRENOS – CAGLIARI
VIA SAN GIORGIO 12, I-09100 CAGLIARI, ITALIA
TEL. +39-070-6756406; FAX +39-070- 6756402

CRENOS - SASSARI
VIA TORRE TONDA 34, I-07100 SASSARI, ITALIA
TEL. +39-079-2017301; FAX +39-079-2017312

Titolo: CLUSTERING MUTUAL FUNDS BY RETURN AND RISKL EVELS

Clustering mutual funds by return and risk levels*

Francesco Lisi
Dipartimento di Scienze Statistiche,
Università di Padova,
Via Cesare Battisti 241/243, 35121 Padova, Italy
e-mail: lisif@stat.unipd.it

Edoardo Otranto
Dipartimento di Economia, Impresa e Regolamentazione and CRENoS,
Università di Sassari,
Via Torre Tonda 34, 07100 Sassari, Italy
e-mail: eotranto@uniss.it

Abstract

Mutual funds classifications, often made by rating agencies, are very common and sometimes criticized. In this work, a three-step statistical procedure for mutual funds classification is proposed. In the first step time series funds are characterized in terms of returns. In the second step, a clustering analysis is performed in order to obtain classes of homogeneous funds with respect to the risk levels. In particular, the risk is defined starting from an Asymmetric Threshold-GARCH model aimed todescribe minimum, normal and turmoil risk. The third step merges the previous two. An application to 75 European funds belonging to 5 different categories is given.

Keywords: Cluster, distance, GARCH models, risk
JEL Codes: C22, G11, G23

*We are grateful to the participants of the MAF 2008 conference, in particular to Alessandra Amendola, Giuseppe Storti, Umberto Triacca. This work was supported by Italian MIUR under Grant 2006137221_001.

1 Introduction

The number of mutual funds has grown dramatically over the last years. This has led to a number of classification schemes that should give reliable information to investors on features and performance of funds. Most of these classifications are produced by national or international rating agencies. For example, Morningstar groups funds into categories according to their actual investment style, portfolio composition, capitalization, growth prospects, etc. This information is then used, together with that related to returns, risks and costs, to set up a more concise classification commonly referred as Star Rating (see [11] for details). Actually, each rating agency has a specific owner evaluation method and also national associations of mutual funds managers keep and publish their own classifications.

Problems arise as, in general, classes of different classifications do not coincide. Also, all classification procedures have some drawback; for example, they are often based on subjective information and require long elaboration time (see, for example, [15]).

In the statistical literature, classification of financial time series received only relatively small attention. In addition, to the best of our knowledge, there are not comparisons among different proposed classifications and those of the rating agencies. Some authors use only returns for grouping financial time series. For example, [15] propose a classification scheme which combines different statistical methodologies (principal component analysis, clustering analysis, Sharpe's constrained regression) applied on past returns of the time series. Also the clustering algorithm proposed by [9], referring to different kinds of functions, is based only on return levels. Other authors based their classifications only on risk and grouped the assets according to the distance between volatility models for financial time series ([12], [2], [13], [14], [8]). Risk-adjusted returns, i.e. returns standardized through standard deviation, are used for clustering time series by [4]. This approach is interesting, but using the unconditional variance as a measure of risk and ignoring the dynamics of volatility seems too simplistic.

In this paper, a classification based only on the information contained in the net asset value (NAV) time series is considered. It rests on the simple and largely agreed idea that two very important points in evaluation of funds are return and risk levels. In order to measure the return level, the mean annual net period return is considered. As regards the riskiness, in the time series literature, it is commonly measured in terms of conditional variance (volatility) of a time series. As well known, volatility is characterized by a time-varying behavior and clustering effects, which imply that quiet (low volatility) and turmoil (high volatility) periods alternate. In order to account both for the time-varying nature of volatility and for its different behavior in quiet and turmoil periods, an asymmetric version of the standard Threshold GARCH model ([5], [17]), is considered in this work.

The whole classification scheme consists of three steps: the first groups funds with respect to returns whereas the second with respect to riskiness. In particular, the whole risk is decomposed in constant minimum risk, time-varying standard risk and time-varying turmoil risk. Following [12], [13] and [14], the clustering related to volatility is based on a distance between GARCH models, which is an extension of the AR metric introduced by ([16]). Lastly, the third step merges the results of the first two steps to obtain a concise classification.

The method is applied to 75 funds belonging to five categories: aggressive balanced funds, prudential balanced funds, corporate bond investments, large capitalization stock funds, monetary funds. In order to make a comparison with the classification implied by the Morningstar Star Rating, which ranges from 1 to 5 stars, our clustering is based on 5 "stars" as well. As expected, our classification does not coincide with the Morningstar Rating because it is only partially based on the same criteria. Nevertheless, in more than 82% of the considered funds the two ratings do not differ for more than one star.

The paper is organized as follows. Section 2 describes how the risk is defined. Section 3 contains an application and the comparison of our clustering with the Morninstarg Rating classification. Section 4 concludes.

2 Risk modelling

In this section the reference framework for fund riskiness modelling is described. Let y_t be the time series of the NAV of a fund and r_t the corresponding log-return time series. We suppose that the return dynamics can be described by the following model:

$$\begin{aligned} & r_t = \mu_t + \varepsilon_t = \mu_t + h_t^{1/2} u_t, \qquad t = 1, ..., T \\ & \varepsilon_t \mid I_{t-1} \sim N(0, h_t) \end{aligned} \tag{2.1}$$

where $\mu_t = E_{t-1}(r_t)$ is the conditonal expectation and u_t is an i.i.d. zero-mean and unit variance innovation. The conditional variance h_t follows an asymmetric version of the Threshold GARCH(1,1) process ([5], [17]), which stresses the possibility of a different volatility behavior in correspondence of high negative shocks. We refer to it as Asymmetric Threshold GARCH (AT-GARCH) model. Formally, the conditional variance can be described as:

$$\begin{aligned} & h_t = \gamma + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta S_{t-1} \varepsilon_{t-1}^2 \\ & S_t = \begin{cases} 1 & if \quad \varepsilon_t < \varepsilon_t^* \\ 0 & otherwise \end{cases} \end{aligned} \tag{2.2}$$

where γ, α, β, δ are unknown parameters, whereas ε_t^* is a threshold identifying the turmoil state. The value of ε_t^* could represent a parameter to be estimated, but in this work we set it equal to the first decile of the empirical distribution of ε. On the whole, this choice maximizes the likelihood and the number of significant estimates of δ. Also, the first decile seems suitable because provides, through the parameter δ, the change in the volatility dynamics when high - but not extreme - negative returns occur.

The purpose of this work is to classify funds in terms of gain and risk. While the net period return is the most common measure of gain, several possible risk measures are used in literature. However, most of them look at specific aspects of riskiness: standard deviation gives a medium constant measure; Value-at-Risk tries to estimate an extreme risk; the time-varying conditional variance in a standard GARCH model focuses on the time-varying risk, and so on.

In this paper we make an effort to jointly looking at risk from different points of view. To do this, following [13], we consider the squared disturbances ε_t^2 as a proxy of the instantaneous volatility of r_t. It is well known that ε_t^2 is a conditionally unbiased, but very noisy, estimator of the conditional variance and that realized volatility and intra-daily range are, in general, better estimators ([1], [3], [10]). However, the adoption of ε_t^2 in our framework is justified by practical motivations because intra-daily data are not available for mutual funds time series and, thus, realized volatility or range are not feasible. Starting from (2.2), after simple algebra, it can be shown that, for an AT-GARCH(1,1), ε_t^2 follows the ARMA$(1,1)$ model:

$$\varepsilon_t^2 = \gamma + (\alpha + \delta S_{t-j} + \beta)\,\varepsilon_{t-1}^2 - \beta\left(\varepsilon_{t-1}^2 - h_{t-1}\right) + \left(\varepsilon_t^2 - h_t\right), \tag{2.3}$$

where $(\varepsilon_t^2 - h_t)$ are uncorrelated, zero-mean errors.

The AR(∞) representation of (2.3) is:

$$\varepsilon_t^2 = \frac{\gamma}{1-\beta} + \sum_{j=1}^{\infty}(\alpha + \delta S_{t-j})\beta^{j-1}\varepsilon_{t-j}^2 + \left(\varepsilon_t^2 - h_t\right), \tag{2.4}$$

from which it is easy to derive the expected value at time t given past information

$$E_{t-1}(\varepsilon_t^2) = \frac{\gamma}{1-\beta} + \sum_{j=1}^{\infty}(\alpha + \delta S_{t-1})\beta^{j-1}\varepsilon_{t-j}^2. \tag{2.5}$$

This representation splits the expected volatility, $E_{t-1}(\varepsilon_t^2)$, considered as a whole measure of risk, in three positive parts: a constant part, $\gamma/(1-\beta)$, representing the minimum risk level which can be reached given the model; the time-varying standard risk $(\sum_{j=1}^{\infty}\alpha\beta^{j-1}\varepsilon_{t-j}^2)$ and the time-varying turmoil risk $(\sum_{j=1}^{\infty}(\delta S_{t-j})\beta^{j-1}\varepsilon_{t-j}^2)$, the last two being dependent on past information. Of course, the estimation of expression (2.5) requires a finite truncation.

In order to classify funds with respect to all these three risk components, we propose considering the distance between an homoskedastic model and a GARCH(1,1) model. Using the metric introduced by [12] and re-considered by [14], in the case of specification (2.2) this distance is given by:

$$\frac{\alpha + \delta S_{t-1}}{\sqrt{(1-\beta^2)}}. \tag{2.6}$$

The previous analytical formulation allows us to provide a vectorial description of the risk of each fund. In particular, we characterize the *minimum constant risk* through the distance between the zero-risk case ($\gamma = \alpha = \beta = \delta = 0$) and the $\alpha = \delta = 0$ case

$$v_m = \frac{\gamma}{1-\beta}. \tag{2.7}$$

The *time-varying standard risk* is represented, instead, by the distance between a GARCH(1,1) model ($\delta = 0$) and the corresponding homoskedastic model ($\alpha = \beta = \delta = 0$)

$$v_s = \frac{\alpha}{\sqrt{(1-\beta^2)}}. \tag{2.8}$$

Lastly, the *turmoil risk* is described by the difference of the distance between an AT-GARCH model, and the homoskedastic model and the distance measured by (2.8):

$$v_t = \frac{\delta}{\sqrt{(1-\beta^2)}}. \tag{2.9}$$

The whole risk is then characterized by the vector $[v_m, v_s, v_t]'$. If an extra-element, accounting for the return level, $\bar{r}$, is considered, each fund may be featured by the vector:

$$\mathbf{f} = [\bar{r}, v_m, v_s, v_t]'.$$

In order to obtain groups of funds with similar return and risk levels, some clustering algorithm can be easily applied directly to $\mathbf{f}$ or to some function of the elements of $\mathbf{f}$. For example, in the next section risk will be defined as the average of v_m, v_s and v_t.

3 An application

As an application of the previous described procedure, the daily time series of NAV of 75 funds of the Euro area and belonging to five different categories were considered. The five typologies are the aggressive balanced, prudential balanced, corporate bond investments, large capitalization stock and monetary funds. Data, provided by Bloomberg, range from 1/1/2002 to 18/2/2008, for a total of 1601 observations for each series.

Our experiment consists in providing a classification of these funds, characterizing each group in terms of return and riskiness (following the definitions of constant minimum, time-varying standard and time-varying turmoil risk) and comparing our classification with that produced by the Morningstar star rating.

For each fund the return time series was considered and for each calendar year the net percentage return was computed; finally the average of the one-year returns, $\bar{r}$, was used to represent the gain.

To describe riskiness, first model (2.1) - (2.2) was estimated for each fund. When parameters were not significant at 5% level, they were set equal to zero and the corresponding constrained model was estimated. Of course, before accepting the model the absence of residual ARCH effects in the standardized residuals was checked. Parameter estimation allowed us to calculate the risks defined as in (2.7), (2.8) and (2.9) and to characterize the funds by the elements $\bar{r}, v_m, v_s, v_t$ or by some their function.

With these vectors a clustering analysis was performed. In the clustering, a classical hierarchical algorithm with the Euclidean distance was used, whereas distances between clusters are calculated following the average-linkage criterion (see, for example, [7]).[1] In particular, the classification procedure followed three steps:

1. the series were classified in three groups, referring only to the degree of gain, i.e $\bar{r}$ low, medium and high;
2. the series were classified in three groups only with respect to the degree of risk (low, medium and high). To summarize the different kinds of risk, the average of the three standardized risks was computed for each series. Standardization is important because of the different magnitudes of risks; for example, minimum risk generally has an order of magnitude lower than that of the two other risks;
3. the previous two classifications were merged combining the degree or gain and risk so as to obtain a rating from 1 to 5 "stars"; in particular, denoting with

[1] The clustering was performed also using the Manhattan distance and the single-linkage and complete-linkage criteria. Results are very similar.

h, m and l the high, medium and low levels respectively and with the couple (a, b) the levels of gain and risk (with $a, b = h, m, l$), stars were assigned in the following way:

1 star for (l, h) (low gain and high risk);

2 stars for (l, m), (l, l) (low gain and medium risk, low gain and low risk);

3 stars for (m, h), (m, m), (h, h) (medium gain and high risk, medium gain and medium risk, high gain and high risk);

4 stars for (m, l), (h, m) (medium gain and low risk, high gain and medium risk);

5 stars for (h, l) (high gain and low risk).

Of course, this is a subjective definition of stars, nevertheless it seemed reasonable to us.

As in [13], the quality of the clustering was measured using the C-index ([6]). This index assumes values in the interval $[0, 1]$, assuming small values when the quality of the clustering is good. In our experiments, we always obtained $C \leq 0.1$.

Table 1 lists the step-by-step results of the classification procedure for the group of monetary funds. The left part of the table shows the classification based on the risk evaluation and the global rating provided by Morningstar. The central part lists the elements characterizing the funds (one-year average return, constant minimum, time-varying standard and time-varying turmoil risks). Note that v_m assumes very small values (due to the small values of $\hat{\gamma}$) and that only the last fund presents a turmoil risk.[2] The right part of the table shows the results of the three-step classification procedure. The *Gain* column contains the classification in high, medium and low gain obtained by the clustering of step 1; the *Risk* column contains the classification in high, medium and low risk obtained by the grouping of step 2; lastly, the *Stars* column shows the five-group classification described in step 3.

The differences with respect to the Morningstar rating are not large: the classification is the same in 8 cases over 15, in 6 cases it does not differ for more than one star and only in one case (the 14th fund) the two classifications differ for 2 stars.

The same procedure was applied to the other four categories and results are summarized and compared with the Morningstar classification in Table 2. Clearly, the classifications are different because they are based on different criteria and definitions of gain and risk. However, in 82.7% of cases the two classifications do not differ for more than one star. This is evident looking at Table 3, in which the empirical probability function of the differences in stars and the corresponding cumulative distribution function are shown. Moreover, excluding the Corporate Bond Investments, which present the largest differences between the two classifications, the percentage of differences equal to or less than 1 increases up to 90% while the remaining 10% differs by two stars. In particular, the classifications relative to the Aggressive Balanced and the Monetary funds seem very similar between the two methodologies.

4 Some concluding remarks

In this paper a clustering procedure to classify mutual funds in terms of gain and risk has been proposed. It refers to a purely statistical approach, based on few tools

[2] On the whole, instead, parameter δ resulted significant in 11 cases (about the 14% of funds).

Table 1: Monetary funds: Morningstar classification and details of the clustering procedure.

Morningstar						Clustering		
Risk	Stars	Return	v_m	v_s	v_t	Gain	Risk	Stars
low	3	2.25	4.77E-09	0	0	medium	low	4
below average	5	2.66	0	0.087	0	high	low	5
below average	3	2.08	7.01E-08	0.171	0	low	medium	2
below average	3	2.26	5.71E-08	0	0	medium	low	4
below average	3	2.34	0	0.180	0	medium	medium	3
below average	3	2.26	0	0.231	0	medium	medium	3
average	2	1.70	1.93E-07	0	0	low	low	2
average	2	1.87	0	0.144	0	low	medium	2
average	4	2.41	0	0.208	0	medium	medium	3
above average	2	2.05	0	0.155	0	low	medium	2
above average	4	2.71	1.91E-07	0.385	0	high	high	3
above average	2	2.10	0	0.234	0	low	medium	2
above average	3	1.96	0	0.145	0	low	medium	2
high	5	2.28	1.29E-06	0	0	medium	medium	3
high	1	1.80	0	0.151	0.333	low	high	1

Table 2: Comparison of Morningstar and Clustering Classification.

							differences in stars			
Stars		1	2	3	4	5	0	1	2	3
Aggr. Bal.	Clustering	2	4	7	1	1	7	6	2	
	Morningstar	0	3	8	4	0				
Prud. Bal.	Clustering	0	2	6	7	0	4	9	2	
	Morningstar	0	2	9	4	0				
Corp. Bond	Clustering	1	0	3	2	9	3	5	5	2
	Morningstar	0	3	10	2	0				
Stock	Clustering	0	1	2	11	1	4	10	1	
	Morningstar	1	3	6	5	0				
Monetary	Clustering	1	6	5	2	1	8	6	1	
	Morningstar	1	4	6	2	2				

Table 3: Empirical probability and cumulative distribution functions of differences in stars (percentages).

Empirical probability function					
0	1	2	3	4	5
34.7	48.0	14.7	2.6	0.0	0.0
Empirical cumulative distribution function					
0	1	2	3	4	5
34.7	82.7	97.4	100	100	100

to characterize return and risk. The method is model-based, in the sense that the definition of risk is linked to the estimation of a particular Threshold GARCH model, which characterizes quiet and turmoil states of financial markets.

The risk is evaluated simply considering an equally-weighted average of three different kinds of risk (constant minimum risk, time-varying standard risk and time-varying turmoil risk). Different weights could also be considered but at the cost of introducing a subjectivity element.

Surprisingly, in our application, this simple method provided a classification which does not show large differences with respect to the Morningstar classification. Of course, this exercise could be extended to compare our clustering method with other alternative classifications. A very interesting application would be using this approach in asset allocation or portfolio selection problems.

References

[1] Andersen, T.G., Bollerslev, T.: Answering the skeptics: yes, standard volatility models do provide accurate forecasts. International Economic Review **39**, 885–905 (1998)

[2] Caiado, J., Crato, N.: A GARCH-based method for clustering of financial time series: International stock markets evidence. MPRA Paper **2074** (2007)

[3] Christensen K., Podolskji M.: Realized range-based estimation of integrated variance. Journal of Econometrics **141**, 323–349 (2007)

[4] Da Costa, Jr. N., Cunha, S., Da Silva, S.: Stock selection based on cluster analysis. Economic Bulletin **13**, 1–9 (2005)

[5] Glosten, L.R., Jagannathan, R., Runkle, D.E.: On the relation between expected value and the nominal excess return on stocks. Journal of Finance **48**, 1779–1801 (1993)

[6] Hubert, L. and Schultz, J.: Quadratic assignment as a general data-analysis strategy. British Journal of Mathematics, Statistics and Psychology **29**, 190-241 (1976)

[7] Johnson, S.C.: Hierarchical clustering schemes. Psychometrika **2** 241–254 (1967)

[8] Kalantzis, T., Papanastassiou, D.: Classification of GARCH time series: an empirical investigation. Applied Financial Economics **18** 1–6 (2008)

[9] Lytkin, N.I., Kulikowski, C.A., Muchnik, I.B.: Variance-based criteria for clustering and their application to the analysis of management styles of mutual funds based on time series of daily returns. DIMACS Technical Report **2008-01** (2008)

[10] Martens M., van Dijk D.: Measuring volatility with realized range. Journal of Econometrics **138**, 181–207 (2007)

[11] Morningstar: The Morningstar rating methodology. Morningstar Methodology Paper (2007).

[12] Otranto, E.: Classifying the markets volatility with ARMA distance measures. Quaderni di Statistica **6** (2004) 1–19.

[13] Otranto, E.: Clustering heteroskedastic time series by model-based procedures. Computational Statistics and Data Analysis (2008) doi:10.1016/j.csda.2008.03.020

[14] Otranto, E., Trudda, A.: Evaluating the Risk of Pension Funds by Statistical Procedures. In: Lakatos, G.M. (ed.): Transition Economies: 21st Century Issues and Challenges, pp. 189-204. Nova Science Publishers, Hauppauge (2008)

[15] Pattarin, F., Paterlini, S. and Minerva, T.: Clustering financial time series: an application to mutual funds style analysis. Computational Statistics and Data Analysis, **47**, 353–372 (2004)

[16] Piccolo, D.: A distance measure for classifying ARIMA models. Journal of Time Series Analysis **11**, 153–164 (1990)

[17] Zakoian, J.M.: Threshold heteroskedastic models. Journal of Economic Dynamic and Control **18**, 931-955 (1994)

Ultimi Contributi di Ricerca CRENoS

I Paper sono disponibili in: http://www.crenos.it

08/12 *Adriana Di Liberto, Francesco Pigliaru, Piergiorgio Chelucci,* "International TFP Dynamics and Human Capital Stocks: a Panel Data Analysis, 1960-2003"

08/11 *Giorgio Garau, Patrizio Lecca ,* "Impact Analysis of Regional Knowledge Subsidy: a CGE Approach"

08/10 *Edoardo Otranto,* "Asset Allocation Using Flexible Dynamic Correlation Models with Regime Switching"

08/09 *Concetta Mendolicchio, Dimitri Paolini, Tito Pietra,* "Investments In Education In A Two-Sector, Random Matching Economy"

08/08 *Stefano Usai,* "Innovative Performance of Oecd Regions"

08/07 *Concetta Mendolicchio, Tito Pietra, Dimitri Paolini,* "Human Capital Policies in a Static, Two-Sector Economy with Imperfect Markets"

08/06 *Vania Statzu, Elisabetta Strazzera,* "A panel data analysis of electric consumptions in the residential sector"

08/05 *Marco Pitzalis, Isabella Sulis, Mariano Porcu,* "Differences of Cultural Capital among Students in Transition to University. Some First Survey Evidences"

08/04 *Isabella Sulis, Mariano Porcu,* "Assessing the Effectiveness of a Stochastic Regression Imputation Method for Ordered Categorical Data"

08/03 *Manuele Bicego, Enrico Grosso, Edoardo Otranto,* "Recognizing and Forecasting the Sign of Financial Local Trends Using Hidden Markov Models"

08/02 *Juan de Dios Tena, Edoardo Otranto,* "A Realistic Model for Official Interest Rates Movements and their Consequences"

08/01 *Edoardo Otranto,* "Clustering Heteroskedastic Time Series by Model-Based Procedures"

07/16 *Sergio Lodde,* "Specialization and Concentration of the Manufacturing Industry in the Italian Local Labor Systems"

07/15 *Giovanni Sulis,* "Gender Wage Differentials in Italy: a Structural Estimation Approach"

07/14 *Fabrizio Adriani, Luca G. Deidda, Silvia Sonderegger,* "Over-Signaling Vs Underpricing: the Role of Financial Intermediaries In Initial Public Offerings"

07/13 *Giovanni Sulis,* "What Can Monopsony Explain of the Gender Wage Differential In Italy?"

07/12 *Gerardo Marletto,* "Crossing the Alps: Three Transport Policy Options"

07/11 *Sergio Lodde* "Human Capital And Productivity Growth in the Italian Regional Economies: a Sectoral Analysis"

07/10 *Axel Gautier, Dimitri Paolini,* "Delegation, Externalities and Organizational Design"

07/09 *Rinaldo Brau, Antonello E. Scorcu, Laura Vici,* "Assessing visitor satisfaction with tourism rejuvenation policies: the case of Rimini, Italy"

07/08 *Dimitri Paolini,* "Search and the firm's choice of the optimal labor contract"

07/07 *Giacomo Carboni,* "Shape of U.S. business cycle and long-run effects of recessions"