

New trading risk indexes: application of the shapley value in finance

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Abstract

The aim of this paper is to offer new risk indicators that enable one to classify securities of a portfolio according to their risk degrees. These indexes are issued from a new method of the covariance decomposition based on the Shapley Value. The risk indicators are computed via the well-known Gini coefficient, which is viewed as a new risk measure and compared with the traditional measures related with the modern theory of portfolio. These indicators yield suitable information, which could be used by private or institutional investors to trade strategies on market portfolio.

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1. Introduction

Modern portfolio theory introduced by Markowitz in 1952 is widely used by banks, financial firms, and financial advisers. This theory explores how risk adverse investors construct portfolios in order to optimise expected returns for a given level of market risk. Portfolio theory provides a broad context to understand specific risks and interactions of systematic risks measured by correlations between securities. Quantifying the benefits of diversification principle, this theory has profoundly shaped the management of institutional portfolios, and has motivated the use of passive investment management techniques. Mathematics of portfolio theory is extensively used in financial risk management and constitutes a suitable theoretical support for Value-at-Risk (*VaR*) measures.

VaR computation based on analytic expressions, obtained from the covariance-variance matrix gives suitable information for traders, since it has interesting properties. In particular the property of additivity allows one to decompose the global risk to provide a range of indexes, like marginal and component *VaRs* derived by Garman [1996].

Most studies have revealed that the gaussian paradigm underestimates risks. Other applications are concerned with non-parametric methods like historical simulations (Van Den Goorbergh and Vlaar, [1999]) and semi-parametric estimations using the tail index (Mc Neil and Frey, [2000]).

Furthermore, the decomposition into individual risk contributions is not straightforward for two main reasons:

- the diversification principle states that systematic risks can reduce the global risk of a portfolio, but does not provide information about the most volatile securities;
- specific and systematic component of the portfolio Value-at-risk cannot be aggregated into the overall risk since the function is not separable.

Risk estimation via the Gini decomposition is an alternative. Indeed, one can obtain a new ratio of financial risk in the context of portfolio theory with less restrictive hypotheses on the distributions (Mussard and Terraza, [2004]).

Indeed, decomposable inequality measures allow one to gauge inequalities within and between groups. Consequently, we can define within-risk (specific risks) and between-risk (systematic risk) measures. The covariance matrix can be further decomposed using the Shapley Value. This new decomposition of between-risk measures provides suitable new trading risk indexes. These yield interesting information to classify securities according to different risk degrees.

The aim of this paper is to present the Shapley Value as a new method of risk decomposition (section 2) and the Gini index as a new financial risk measure (section 3). The risk indicators are compared throughout an empirical study (section 4) applied on five securities of the CAC 40 French stock market. We show that the Gini index method is a better measure to classify securities in a portfolio. Section 5 is devoted to the conclusion.

2. Risk Decompositions by the Shapley Value [1953]

In the field of inequality and poverty measurement, a new procedure of decomposition has been proposed. Trannoy in collaboration with Auvray [1992], with Chantreuil [1999], and with Sastre [2002] used the Shapley value algorithm to decompose inequality measures (see also Shorrocks [1999] for inequality and poverty measures). Let us remember the methodology.

Let I be an indicator defined by n factors, which can represent in financial applications, the returns r_k : $k \in K = \{r_1, r_2, \dots, r_k, \dots, r_n\}$. The global risk indicator, estimated on n securities, is given by $I = F(K)$. We define S as the set of factors remaining after the process of security elimination deriving from Shapley's algorithm [$S = K \setminus \{r_k\}$]. Then, $I = F(S)$, corresponds to the I value obtained without taking into account the factors r_k ($r_k \notin S$). We define s , the number of factors, which remains after the successive eliminations of the different factors [$s = |S|$]. So, the indicators are defined by $F: \{S \mid S \subseteq K\} \rightarrow \mathfrak{R}$, where \mathfrak{R} is the Euclidean space of dimension one. The contribution of the factor k to the global risk indicator is (see Shorrocks [1999]):

$$C_k^s(K, F) = \sum_{s=0}^{n-1} \sum_{S \subseteq K \setminus \{r_k\}} \frac{(n-1-s)!s!}{n!} \Delta_k F(S), \quad (1)$$

where:

$$\Delta_k F(S) = F(S \cup \{r_k\}) - F(S) \text{ and } F(\emptyset) = 0. \quad (2)$$

This technique is said to be consistent since the sum of the contributions gives the value of the global indicator (see e.g. Chantreuil and Trannoy, [1999]):

$$\sum_{k=1}^n C_k^s(K, F) = I = F(K). \quad (3)$$

Shapley's algorithm yields the procedure to estimate the risk contribution of a particular asset. For instance, considering two securities i and j ($K = r_i, r_j$), the risk contribution of j to the global risk indicator, measured by the Shapley decomposition, C_j^s , is:

$$C_j^s = \frac{1}{2} (F(r_i, r_j) - F(r_i) + F(r_j) - F(\emptyset)) \quad (4)$$

and the risk contribution of i , C_i^s , is given by:

$$C_i^s = \frac{1}{2} (F(r_j, r_i) - F(r_j) + F(r_i) - F(\emptyset)). \quad (5)$$

The risk contribution of the i -th security is estimated from the difference between the global statistic $F(r_i, r_j)$ and $F(r_j)$ obtained when the i -th security has been eliminated. This difference represents the marginal impact of the i -th security, which is noted: $F(r_i, r_j) - F(r_j)$. This procedure is then implemented from $F(r_i)$, taking the difference between $F(r_i)$ and $F(\emptyset)$ since the i -th asset has been eliminated. The mean of these marginal impacts represents the contribution of the i -th security to the global value of the indicator. Shapley's algorithm can be generalized to obtain the marginal impact of each security into the between-risk proportion of the portfolio. In financial words, the global risk indicator $F(r_i, r_j)$ can be assimilated to the covariance measure between r_i and r_j .

Proposition 1.

The Shapley decomposition of the covariance $cov(r_i, r_j)$ between two securities i and j permits to obtain:

(i) *the contribution of each security to $cov(r_i, r_j)$;*

(ii) *the contribution of each security to the risk related with the diversification principle.*

Proof.

Let us consider a two-asset portfolio where $F: \mathfrak{R}^t \times \mathfrak{R}^t \rightarrow \mathfrak{R}$ represents the covariance between the asset returns on t observations:

$$F(r_j, r_i) = cov(r_i, r_j). \quad (6)$$

When the i -th security has been eliminated, via Shapley's algorithm, j is therefore the unique security of the portfolio. Thus:

$$F(r_j) = cov(r_j, r_j) = \sigma_j^2, \quad (7)$$

where σ_j^2 is the variance of j . The same result is obtained when j has been eliminated:

$$F(r_i) = cov(r_i, r_i) = \sigma_i^2. \quad (8)$$

Therefore, it is possible to bring out the contribution of the j -th security to the covariance $cov(r_i, r_j)$:

$$C_j^s = \frac{1}{2} (cov(r_i, r_j) - \sigma_i^2 + \sigma_j^2 - \sigma_0^2), \quad (9)$$

where the variance of the empty set is: $\sigma_0^2 = 0$.

The same procedure is applied to compute the contribution of the i -th security to the covariance $cov(r_i, r_j)$:

$$C_i^s = \frac{1}{2} (cov(r_i, r_j) - \sigma_j^2 + \sigma_i^2 - \sigma_0^2). \quad (10)$$

Proposition 1 (i) is then completed:

$$C_j^s + C_i^s = \frac{1}{2} (cov(r_i, r_j) - \sigma_i^2 + \sigma_j^2) + \frac{1}{2} (cov(r_i, r_j) - \sigma_j^2 + \sigma_i^2) = cov(r_i, r_j). \quad \blacksquare \quad (11)$$

In accordance with the modern theory portfolio, the variance of the portfolio is:

$$\sigma_p^2 = \sum_{i=1}^n \omega_i^2 \sigma_i^2 + 2 \sum_{i=2}^n \sum_{j=1}^{i-1} \omega_i \omega_j cov(r_i, r_j), \quad (12)$$

where ω_i stands for Markowitz's weights associated with the i -th security. Afterward, the decomposition of systematic risks (say between-security risk σ_b^2) using the Shapley Value (11) is:

$$\sigma_b^2 = 2 \sum_{i=2}^n \sum_{j=1}^{i-1} \omega_i \omega_j (C_i^s + C_j^s). \quad (13)$$

Therefore, the contribution of the i -th security ($\forall i = 1, \dots, n$) to the between-security risk is:

$$\sigma_{bi}^2 = 2 \sum_{i \neq j}^n \omega_i \omega_j C_j^s, \quad (14)$$

such that,

$$\sigma_b^2 = \sum_{i=1}^n \sigma_{bi}^2. \quad \blacksquare \quad (15)$$

Finally, Shapley's decomposition method enables one, on the one hand, to measure individual contributions of between-security risk proportions, and on the other hand, to obtain a separable measure of the covariance between the securities.

Proposition 2.

The Shapley decomposition of the covariance $cov(r_i, r_j)$ between two securities i and j and the decomposition of the specific risk yield the contribution of the i -th security to the overall amount of the risk portfolio.

Proof.

The specific risk decomposition, say the within-security risk (since it relies on each security), is straightforward:

$$\sigma_w^2 = \sum_{i=1}^n \omega_i^2 \sigma_i^2. \quad (16)$$

Then, we obtain the contribution of the i -th security ($\forall i = 1, \dots, n$) to σ_w^2 :

$$\sigma_{wi}^2 = \omega_i^2 \sigma_i^2. \quad (17)$$

Combining equations (14) and (17), one can obtain the contribution of the i -th security to the risk portfolio σ_p^2 :

$$\sigma_{pi}^2 = (\sigma_{bi}^2 + \sigma_{wi}^2). \quad (18)$$

and a new risk-trading index (RTI), that is, the relative contribution of the i -th security to σ_p^2 :

$$\text{RTI} = \frac{\sigma_{pi}^2}{\sigma_p^2}. \quad \blacksquare \quad (19)$$

This ratio measures the risky security of a portfolio and therefore provides a new classification of the securities in accordance with a risk scale. Then, the Shapley decomposition of the covariance facilitates financial information and individual's predictions, whatever they are institutional investors or little investors.

The principal criticism of this approach is that the risk index depends on the variance estimation method. As Dagum [1997] states, the one-way variance analysis is debatable since it is based on the following assumptions: (i) the observations are statically independent and (ii) the studied observations are normally distributed. Even if the normality enables one to involve losses and gains in the distribution tail (throughout derivatives measures such as Value-at-Risk), we aim at obtaining alternatives to these well-known models. The Gini index appears as a solution since it both represents a dispersion measure, a concentration measure and an inequality measure. It can be seen as a new non-parametric indicator of risk, which takes benefit from a more simple use with a clear interpretation based on risk decomposition.

3. The Gini decomposition as a risk measure of portfolios

The well-known Gini index (G) is included in the close interval $[0,1]$ and is usually applied on income distributions. The Gini decomposition is a non-parametric method used when a population is divided into several subgroups. Dagum [1997] have shown that, it is possible to separate the indicator in two components: the within-group inequalities and the between-group inequalities. Using this technique, it is possible to establish a link between the risk of a security and the Gini concentration coefficient. A strong concentration represents a risky security, and conversely.

3.1 Risk definition and the Gini ratio

In order to define the Gini risk measure in accordance with intuition, we can imagine that all the returns of a portfolio securities are written on bowls, which are put in an urn. Then, we draw two bowls at random with repetition. The risk is defined as the return difference (in absolute values) of the two bowls. For instance, let us consider that an individual possesses a portfolio with the following initial value: $V_0 = 10000\text{€}$. The expected gap between the two bowls drawn at random is given by $2 \times \mu \times G$, where μ is the mean return of all the securities, and G the Gini ratio computed on all the returns of the portfolio securities. The potential loss of the investor is expressed as follows:

$$\text{Loss} = 2 \times \mu \times G \times 10000 > 0, \forall G. \quad (20)$$

If the gap between two returns is extremely high, the loss of the individual is important. We observe the contrary, when the return difference is low.¹

3.2 A reformulation of the between-security Gini via the Shapley Value [1953]

Dagum's [1997] article indicates that the Gini coefficient is separated into a within-group component G_w (from now on within-security measure) and a between-group component G_{gb} (say between-security measure):

$$G = G_w + G_{gb}, \text{ where} \quad (21)$$

¹ Let us remark that $2 \times \mu \times G$ is the Gini mean difference (1912). Pyatt (1976) associates the Gini index with a game where all individuals can participate and where it is possible to choose (randomly) the income of another person or to keep its own income.

$$G_w = \frac{\sum_{i=1}^n \sum_{t=1}^{n_i} \sum_{s=1}^{n_i} |r_{it} - r_{is}|}{n^2 n_i^2 2\mu}, \quad (22)$$

$$G_{gb} = \frac{\sum_{i=2}^n \sum_{j=1}^{i-1} \sum_{t=1}^{n_i} \sum_{s=1}^{n_j} |r_{it} - r_{js}|}{n^2 n_i^2 \mu} \quad \forall i, j = 1, \dots, n. \quad (23)$$

n_i is the number of observations of the i -th security, and μ the mean return computed on all the security returns.

The risk portfolio G is then decomposed in the sum of the volatility of each security and the sum of the volatility associated with the interactions between the security pairs. In other words, the Gini decomposition enables one to conceive, like the variance, a conceptual dissociation between within-security risk and between-security risk by dividing the overall risk into two components: the within-security index (G_w) and the between-security index (G_{gb}).

Proposition 3. *The Gini decomposition, associated with the decomposition of the between-security index via the Shapley Value, permits to measure the contribution of each security to G_{gb} .*

Proof.

The observation share of the i -th security in the set of all observations (of n securities) is p_i and the sum of returns of the i -th security in the sum of all the return securities, s_i , are given by:

$$p_i = \frac{n_i}{N}, \quad s_i = \frac{n_i \mu_i}{N \mu}, \quad (24)$$

where n_i is the number of observations of the i -th security, N the overall number of observations ($n \times n_i$), and μ_i the mean returns of the i -th security. Following Dagum [1997], one can obtain²:

$$G = G_w + G_{gb} \quad (25)$$

$$\Leftrightarrow G = \sum_{j=1}^n G_{jj} p_j s_j + \sum_{j=2}^n \sum_{i=1}^{j-1} G_{ji} (p_j s_i + p_i s_j), \quad (26)$$

$$\text{where } G_{ij} = \frac{\sum_{t=1}^{n_i} \sum_{s=1}^{n_j} |r_{it} - r_{js}|}{n_i n_j (\mu_j + \mu_i)} \quad \forall i, j = 1, \dots, n, \quad (27)$$

is the Gini index between the returns of the i -th and the j -th securities, and where,

$$G_{ii} = \frac{\sum_{t=1}^{n_i} \sum_{s=1}^{n_i} |r_{it} - r_{is}|}{2n_i^2 \mu_i}, \quad \forall i = 1, \dots, n. \quad (28)$$

The Shapley decomposition of the interaction between the i -th and the j -th securities is:

$$G_{ij} = \frac{1}{2} (G_{ij} - G_{ii} + G_{jj}) + \frac{1}{2} (G_{ij} - G_{jj} + G_{ii}), \quad (29)$$

where the contributions of the j -th and the i -th securities to G_{ij} are respectively:

$$C_j^s = \frac{1}{2} (G_{ij} - G_{ii} + G_{jj}), \quad C_i^s = \frac{1}{2} (G_{ij} - G_{jj} + G_{ii}). \quad (30)$$

Thus,

² See the computation of the Gini ratio of Dagum, Mussard, Seyte and Terraza [2002] for explanations and computational assistance.

$$G_{gb} = \sum_{j=2}^n \sum_{h=1}^{j-1} (C_j^s + C_h^s)(p_j s_i + p_i s_j). \quad (31)$$

Therefore, the contribution of the j -th security to the between-security risk $[G_{gb}]$ is given by:

$$C_j^{gb} = \sum_{i \neq j}^n C_j^s (p_j s_i + p_i s_j). \quad \blacksquare \quad (32)$$

Corollary 2.

The decomposition of G_{gb} (the between-security index) by the way of the Shapley Value allows one to measure the contribution of each security risk to the overall risk and then evaluate the most volatile securities of the portfolio.

Proof.

We know it is possible to gauge the contribution of each security to the within-security index. In particular, the contribution of the j -th security is given by:

$$C_j^w = G_{jj} p_j s_j. \quad (33)$$

Consequently, the contribution of the j -th security to the whole risk is:

$$C_j^p = C_j^w + C_j^{gb} = G_{jj} p_j s_j + \sum_{i \neq j}^n C_j^s (p_j s_i + p_i s_j). \quad (34)$$

Then, we can provide a risk trading index based on the Gini coefficient (RTIG):

$$RTIG = \frac{C_j^w + C_j^{gb}}{G} = \frac{G_{jj} p_j s_j + \sum_{i \neq j}^n C_j^s (p_j s_i + p_i s_j)}{G}. \quad \blacksquare \quad (35)$$

The RTIG measures the contribution of the j -th security to the overall risk portfolio, and then, yields a classification of each security from the most risky to the least risky.

Finally, we obtain two risk trading indexes, RTI and RTIG. This leads us to make some empirical comparisons between them.

4. Illustration on French securities

The empirical analysis is devoted to the portfolio of five French securities, which are studied in accordance with their closing prices: Accor, Michelin, Carrefour, Wanadoo, and TF1 (which are securities of the CAC 40 French index). Using Markowitz's methodology (1952), the portfolio is constituted with a 17,3% for Accor, 40,7% for Michelin, 34,2% for Carrefour, 3,8% for Wanadoo, and with a 4% for TF1. The studied period is: 01/02/2001 – 12/31/2002. This represents 508 observations. We make a distinction between the sample of estimation, that is, the first 400 observations, and the sample of forecast, that is, the 108 last observations. The sample of forecast can yield 108 potential losses, which offer information of the risk portfolio. To estimate the participation of each security and each period to the overall risk, first we calculate the $RTIG \times 100$. For $t = 108$, exhibit 1 gives a classification of securities from the most to the least risky.

Exhibit 1

Classification of the securities via the RTIG (%), $t = 108$

1) Accor	2) Carrefour	3) Michelin	4) TF1	5) Wanadoo
158.03	2.89	-2.71	-3.09	-55.13

Given these results, the decision-makers can say (in $t = 108$) that Accor and Carrefour increase the risk of the portfolio, whereas the other securities diminish the risk. Indeed,

Michelin decreases the risk portfolio with a 2.71%, and Wanadoo decreases the overall risk with a 55.13%.

Taking the average of the Gini risk index on the whole forecast period, we obtain the following classification (see exhibit 2):

Exhibit 2
Classification of the securities via the RTIG average (%)

1) Accor	2) Carrefour	3) Wanadoo	4) TF1	5) Michelin
46.12	26.71	11.13	9.92	6.09

These results confirm that Accor is the most volatile security of the portfolio but now Michelin is the least risky security during the forecast period ($t = 1, \dots, 108$).

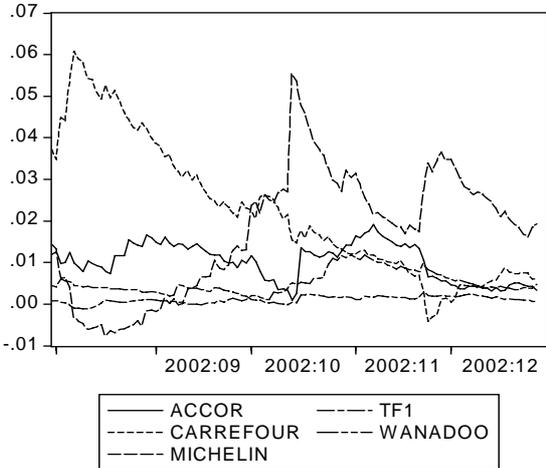
The second classification is concerned with the RTI indicator (in $t = 108$).

Exhibit 3
Classification of the risk via RTI (%), $t = 108$

1) Michelin	2) Carrefour	3) Wanadoo	4) Accor	5) TF1
57.03	17.82	14.26	9.68	1.19

The results are different compared with the Gini ratio decomposition. Michelin seems to be the most risky security while TF1 is the least risky. Therefore, the evolution of these percentages during the whole period of forecasting is of interest.

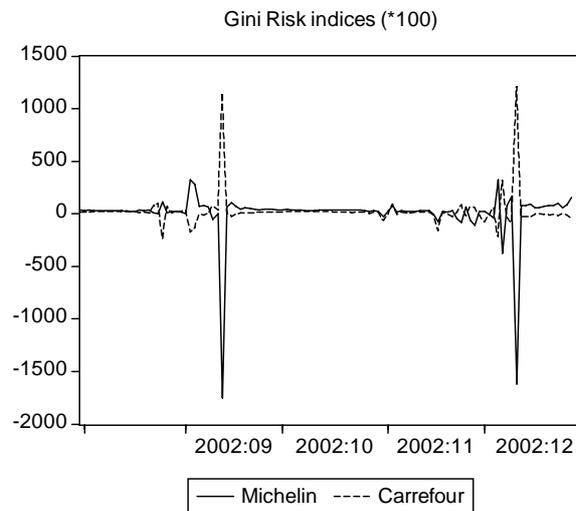
Exhibit 4
RTI of each security (%): $t = 1, \dots, 108$



On the one hand, exhibit 4 indicates that Michelin and Carrefour can be extremely volatile. On the other hand, following the decomposed *Variance* risk measure, it is difficult to interpret the results since the variance indicator does not distinguish the “good” risk from the “bad” risk according to the preference of the investors. From this index, it is impossible to say that a security can diminish the overall risk of a portfolio. Contrary to this, the Gini risk enables one to select the securities that tend to decrease the overall risk portfolio.

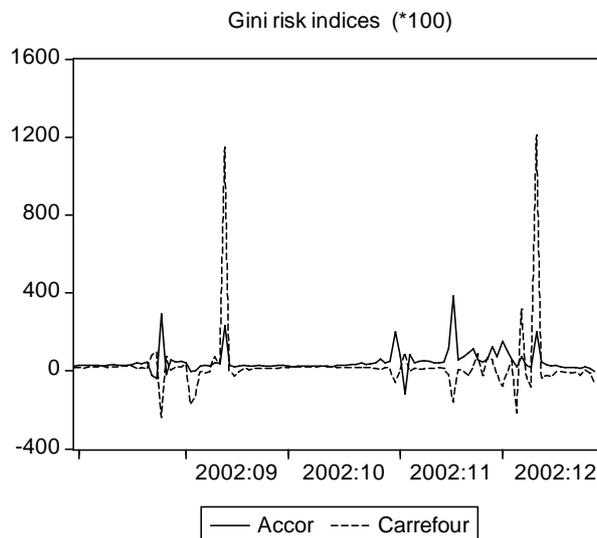
Representing the risk index issued from the Gini decomposition (exhibit 5), we strengthen the fact that Michelin is extremely volatile, in the good sense, since it reduces the risk of the portfolio whereas Carrefour increases the potential losses.

Exhibit 5
RTIG (%) of Michelin and Carrefour: $t = 1, \dots, 108$



We can notice that Michelin yields some powerful negative variations, that is, a strong decrease of the risk portfolio. On the other hand, we have seen (exhibit 2) that in average Accor is the most risky share. But, we observe that Carrefour provides the strongest positive variations, that is, the most important growths of the risk portfolio [see exhibit 5 and 6].

Exhibit 6
RTIG (%) of Accor and Carrefour: $t = 1, \dots, 108$



5. Conclusion

The main objective of this paper was to describe a technique of assessing the risk contributions of each security in a portfolio using the Shapley Value and to define two risk trading indexes (RTI and RTIG) according to a precise risk definition. In the Gini Risk Index (RTIG), the risk relies on the expected difference between two returns drawn at random with

repetition. Contrary to the variance ratio (RTI), this new risk index avoids the difficulties associated with the gaussian assumptions and the essential Markowitz's theory. Calculating the marginal contribution of each title, the two techniques yield suitable information for investors. The main difference between the two measures relies on the computation of the return volatility. The RTIG ratio involves all the pairwise return differences. This implies that the risk portfolio depends on a wider quantity of information, whereas the RTI risk index includes only the return differences with the mean return portfolio. Then, it seems reasonable to pay attention to this new decomposed index that can be used in finance and in others fields where it is necessary to set up a risk classification.

References

- Auvray C. et Trannoy A. (1992)**, « Décomposition par source de l'inégalité des revenus à l'aide de la Valeur Shapley », *Journées de Microéconomie Appliquées*, Sfax, Tunisie.
- Chantreuil, F., and Trannoy, A. (1999)**, "Inequality Decomposition Values: The Trade-off Between Marginality and Consistency", Working Paper 9924, THEMA.
- Dagum, C. (1997)**, "A New Approach to the Decomposition of the Gini Income Inequality Ratio", *Empirical Economics* 22(4), 515-531.
- Dagum, C., Mussard, S., Seyte, F. and Terraza, M. (2002)**, *Program for Dagum's Gini Decomposition*, available on <<http://www.lameta.univ-montp1.fr/online/gini.html>>.
- Franses, P. and Paap, R. (1999)**, "Forecasting with Periodic Autoregressive Time Series Models", Working Paper, Erasmus University, Rotterdam.
- Garman, M. (1996)**, "Improving on VaR", *Risk* 9(5), 61-63.
- Gini C. (1912)**, « Variabilità e mutabilità », *Memori di Metodologia Statistica*, Vol. 1, *Variabilità e Concentrazione*. Libreria Eredi Virgilio Veschi, Rome, p. 211-382.
- JP. Morgan (1996)**, *Riskmetrics*, Technical Document.
- Mc Neil, A.J. and Frey, R. (2000)**, "Estimation of Tail Related Risk Measures for Heteroscedastic Financial Time Series: an Extreme Value Approach", *Journal of empirical finance* 7(3-4), 271-300.
- Markowitz H. (1952)**, "Portfolio selection", *Journal of finance* 7, 77-91.
- Mussard S. and Terraza V. (2004)**, "Méthodes de décomposition de la volatilité d'un portefeuille : une nouvelle estimation des risques par l'indice de Gini", *Revue d'Economie Politique* 4, 557-571.
- Mussard S. and Terraza V. (2006)**, « The Shapley Decomposition for Portfolio Risk », *Applied Economics letters*, forthcoming
- Pyatt G. (1976)**, « On the Interpretation and Disaggregation of Gini Coefficients », *Economic Journal* 86, 243-25.
- Sastre M. et A. Trannoy (2002)**, « Shapley inequality decomposition by factor components: Some methodological issues », in P. Moyes, C. Seidl and A.F. Shorrocks (eds.), *Inequalities: Theory, Experiments and Applications*, *Journal of Economics* 9, 51-90.
- Shapley L. (1953)**, "A Value for n-person Games", in: H. W. Kuhn and A. W. Tucker, eds., *Contributions to the Theory of Games*, Vol. 2, Princeton University Press.
- Shorrocks A. F. (1999)** "Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value", *Mimeo*, University of Essex.
- Van Den Goorbergh R., Vlaar P. (1999)**, "Value at Risk Analysis of Stock Returns, Historical Estimation, Variance Techniques or Tail Index Estimation?" Working Paper, Holland.