ACADEMY OF ECONOMIC STUDIES
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PORTFOLIO CONSTRUCTION STRATEGIES USING COINTEGRATION

-DISSERTATION PAPER-

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1. Introduction

Traditional methods used by financial institutions for portfolio construction and risk management are based on security return covariance matrices. Since these matrices are notoriously difficult to estimate and very unstable in time, they often fail to be consistent with market conditions. Moreover mean-variance approach has nothing to ensure that the tracking error of a portfolio relative to a benchmark is stationary. Therefore, traditional portfolios can drift virtually anywhere, unless they are frequently rebalanced, which will imply considerable transaction costs with negative influence on the overall portfolio performance.

At the root of the problem stays the fact that mean-variance approach can be used only with respect to stationary variables. By differencing the financial price variables, which generally prove to be integrated of order one, we are faced with the inconvenience of losing a great deal of information contained in that prices, and consequently of detecting any stochastic trends that prices might follow. Cointegration enables us to avoid this drawback because it measures how the prices, and not the returns, are moving together in the long run, having in contradiction to the classical correlation concept the advantage of using the entire set of information from the price levels. Moreover, cointegrating vectors can explain the long run behavior of cointegrated series, while correlation doesn't have this feature, being unstable as any short run measure. However, cointegration based methods are not excluding in any way correlation based methods as short term instruments.

Pioneered by Engle and Granger (1987), cointegration has become a powerful technique used for detecting common stochastic trends from multivariate time series, thus enabling us to model the system's dynamics both on the long and short run. If there exists a linear combination of non-stationary variables which is found to be stationary, we say that these variables are cointegrated. The linear combination is called cointegrating vector, and indicates the long run equilibrium of the multivariate system. The presence of cointegration cannot tell us where the system will be on the long run, but it can tell us that wherever one variable will be, the others will be right along with it. In other words, we can say that the above linear combination describes a mean-reverting process.

The literature on cointegrated time series has been expanding at an exponential rate. Starting with the fundamental work of Engle and Granger (1987) have been created new tests for cointegration amongst which we mention the ones of Engle and Yoo (1987) and Johansen (1988). Likewise, many studies focused on distributional properties of the various estimation and inference methods, namely: Phillips and Oularis (1990), Johansen (1991) and MacKinnon (1991).

In financial markets area, cointegration analysis has been used in certain directions. In order to test the efficiency of futures markets, we can employ cointegration to verify whether exists a cointegrating vector, formed by spot and futures prices, that has the property of mean-reversion. To this end we mention the papers of MacDonald and Taylor (1988), Brenner and Kroner (1995), Ackert and Racine (1998), and Alexander (1999b). Cointegration has also been used to test the efficiency of forex markets. Since on an efficient forex market the cross rate is non-stationary, it results that two exchange rates (in logs) cannot be cointegrated. However has been empirically found that three or more exchange rates can be cointegrated: Alexander and Johnson (1992) and Alexander (1995).

Regarding equity markets, cointegration is used to assess the degree of co-movement between the countries' markets or relative to an index. If equity markets from two or more countries are cointegrated, then they share at least one common stochastic trend, which makes them move together in time. One consequence of this fact, is that the advantages of international diversification will disappear on the long run, so that the longer term investors will not benefit from out-of-country portfolios. This idea was studied in their papers by Taylor and Tonks (1989) and Kasa (1992). However Garrett and Spyrou (1996) have argued against this idea, showing that the benefits of international diversification are very little (or even at all) eroded if the returns are reacting very slowly (or are not reacting at all) due to the common stochastic trend.

With respect to fixed-income instruments' markets, empirical studies show that from the n maturities of the yield curve, every one of the n-1 spreads represents a cointegrating vector, if the spreads are mean-reverting. We mention the papers of Alexander and Johnson (1994) and of DeGennaro, Kunkel and Lee (1994).

Another field of cointegration applicabillity is option pricing. Duan and Pliska (1996) have created a pricing model based on cointegrated brownian motions. The model contains an ECM which ensure the correction of deviations away from the equilibrium as well as the stationarity of the spread between the two asset prices.

Returning to the use of cointegration in portfolio management, an area tackled by the present dissertation, we mention, as a headstone, the paper of Lucas (1997). In this paper, it is studied the asset allocation problem in the presence of cointegrated time series, as well as the link between the number of cointegrating relations and the optimal asset allocation. According to Lucas, cointegration affects both strategic and tactical allocation, the cointegrating combinations having a reduced long run variability and therefore a reduced long run risk. Lucas investigates the effects of mis-specification of cointegration rank: underestimating this rank leads to the loss of investment opportunities, while overestimating this rank doesn't have any substantial adverse effect on short run financial policy.

Pindyck and Rothenberd (1992) argue that a basket of equities should be cointegrated with the whole equity index provided that the index weights are stable in time. From the same point of view, a basket of equity indices from different countries should be cointegrated with a regional or international index. This idea was further explored by Alexander (1999), DiBartolomeo (1999), Alexander and Weddington (2001) and Alexander and Dimitriu (2002). DiBartolomeo uses cointegration between MSCI EAFE and component country indices to portfolio construction, which enables him to avoid the assumptions of normality and stationarity of returns, assumptions required by the mean-variance approach. In order to obtain the cointegrating vector, he makes use of Monte

Carlo simulations, thus constructing a great number of random portfolios (depending of certain restrictions) out of which are selected the ones that are cointegrating. Alexander uses cointegration to set up index-tracking strategies as well as market neutral hedging strategies. In the first case, Alexander shows that it is possible, to obtain a portfolio with a higher return and a smaller risk relative to a benchmark. In the second case, Alexander shows that cointegration may lead to a positive excess return, irrespective of market direction, and with a low volatility.

Our paper continues the line of research of cointegration as a method for portfolio construction. Using a simple algorithm of finding the optimal composition of cointegrating portfolios, we implement and test two types of portfolios.

First type, the *clone portfolio*, tries to track an equity index plus a spread, using only a part of original index components, and also to obtain higher performances in terms of returns and volatility.

Second type, the *arbitrage portfolio*, aims to generate riskless arbitrage returns, in any state of the nature. To this end, we construct two cointegrating portfolios: o long portfolio, which clone a benchmark plus a spread, and a short portfolio, which clone a benchmark minus a spread. The arbitrage portfolio will be given by the difference of the above portfolios, and will earn approximately the sum of the absolute values of the two spreads . Using five years of daily data of Morgan Stanley Capital International (MSCI) stock indices for the countries participating at “Euro” currency, as well as the same amount of data for the regional EURO MSCI Index, we are able to implement the above mentioned strategies. Another novelty brought by this paper is that it investigates the behavior of the main strategies (portfolios) under two different assumptions or sub-strategies : unmanaged portfolios vs. monthly rebalanced portfolios. After constructing the main strategies we performed a number of tests to assess the overall performances of the models during the testing period. The results were encouraging even if the portfolios were left unmanaged.

The remainder of the paper is organized as follows: section 2 presents theoretically how to implement the two portfolio strategies and how a portfolio manager can assess the overall performances of the models; section 3 describes the data and presents the estimation and back-testing results; finally, in section 4 we draw the conclusions.

2. Portfolio Construction Strategies Using Cointegration

Traditional mean-variance portfolios are seeking the weights of component securities so as to minimize the total variance of portfolio for a given level of return. Constructing portfolios according to this classical approach, investors will soon realize that there is nothing to ensure the mean-reversion of the error relative to a given benchmark. Moreover, in their attempt to bring the portfolio back in line with the benchmark, they will incur virtually unlimited transaction costs, which can reduce, sometimes considerably, portfolio return. Using cointegration, we can now build portfolios with a stationary tracking error, resulting strategies having fewer transaction costs, greater return, and a smaller risk than in the case of Markowitz traditional method.

2.1. Cloning strategies

2.1.1.General presentation

These strategies aim to construct a portfolio, that clones a given benchmark, in terms of return and volatility, and preferably with the use of a small number of assets. The correlation of this clone portfolio with the market will be very high. Therefore this passive strategy will suit a more risk averse investor segment. To enhance the performance of the strategy, one could choose to clone an *artificial* benchmark, that is a benchmark plus a positive spread per annum, thus producing a greater excess return. To implement this type of portfolio, we will use not the correlation matrix, but the cointegration, in this way benefiting of the entire set of information from the asset prices. If the portfolio and the benchmark are cointegrated then the tracking error will describe a white noise process, with zero mean, and small variance.

The cointegration method that will be used is that introduced by Engle and Granger (1987). The reason of choosing EG, instead of the more powerful technique of Johansen and Juselius, is that we know a priori that we have a single cointegrating relation, that is we know for sure that we cannot have more than one set of weights in our clone portfolio.

Additional arguments for EG are referring to its simplicity and to its main criterion of minimizing the variance, which for portfolio risk management is far more important than Johansen's criterion of maximizing the stationarity.

Once we ensured that the candidate asset price series are non-stationary, we will estimate a cointegrating regression, having as dependent variable the price series of the benchmark, and as independent variables the candidate clone portfolio components. Estimation will be made using a prespecified window of data, called *calibration period*. More formally, we will estimate by OLS the following equation:

$$\log(P_{benchmark,t}) = c + \sum_{i=1}^{n} \beta_i \cdot \log(P_{Ai,t}) + \varepsilon_t \qquad (1)$$

where: $P_{benchmark}$ is the time series of (daily) benchmark price; P_{Ai} is the time series of asset "i"; β_i are the estimated coefficients from the above regression, coefficients that after normalization will play the role of portfolio weights; and ε is residual series, which is nothing but the tracking error.

It must be emphasized, that applying OLS to non-stationary variables is allowed only in the special case of cointegration. If residual series ε is non-stationary the coefficients will inconsistent and any inference based on them is incorrect. If ε is stationary, then the portfolio and the benchmark are cointegrated, and coefficients are super-consistent, converging very rapidly to the real values.

2.1.2. A simple algorithm of optimization

To fully benefit of the common stochastic trend followed by the asset prices that will compose the clone portfolio, it is paramount to select from the candidate assets, the basket that is the most cointegrated with the benchmark.

Definition 1. We will call *cointegrating portfolio* the linear combination $PC = \sum_{i=1}^{m} \beta_i \cdot \log(P_{Ai})$, m <= n, with the property that $\log(P_{benchmark})$ is cointegrated with PC, n being the number of available assets.

Definition 2. We say that cointegrating portfolio $PC_1 = \sum_{i=1}^{m_1} \beta_i \cdot \log(P_{Ai})$ *is more cointegrated (in Engle Granger sense)* than portfolio $PC_2 = \sum_{i=1}^{m_2} \beta_i \cdot \log(P_{Ai})$, if noting $\varepsilon_j = \log(P_{benchmark}) - PC_j, j = 1,2$ then t-stat (ε_1) < t-stat (ε_2), where t-stat is taken from the unit root test applied to residual ε_j.

Definition 3 (optimality) . Let $\Pi = \left\{ PC_j \mid j = \frac{n!}{(n-k)!k!} \right\}$ be the set of all cointegrating portfolios that can be formed with the n assets, using the same calibration period. Let $\mathrm{E} = \left\{ \varepsilon_j \mid \varepsilon_j = \log(P_{benchmark}) - PC_j, j = 1,2 \ldots \frac{n!}{(n-k)!k!} \right\}$ be the set of residual series corresponding to the above portfolios. We say that PC_k is *optimal cointegrating portfolio* if and only if t-stat(ε_k) < t-stat(ε_h) for $\forall h \neq k$.

From the above definitions, results it is not sufficient to verify the stationarity of residual series. We will also need to ensure there we cannot find a portfolio more cointegrated. The criterion we will use, is minimizing t-stat from the unit root test of residual.

Unlike the approach used by Alexander (1999 and 2001), and by DiBartolomeo (1999), in the first case using heat maps, and in the second using Monte Carlo simulations, in the present paper we propose a relatively simple method for finding the most cointegrated portfolio. The method consists of a few steps or rounds, by which we test all portfolio possibilities. These steps are:

Step 1. Estimate the cointegrating regression using the whole set of assets, and perform the unit-root test on residual, ADF_0.

Step 2. Eliminate successively variable "i" from the regression, for every i=1…n. Extract for every case the residuals and perform the UR tests. From the n resulting values ADF_{01}, ADF_{02},…ADF_{0N} we choose the smaller one (the more negative). Suppose this value is

ADF_{0j}, 1<=j<=N, then the variable j is completely eliminated from the optimization of portfolio. By doing so we obtain the most cointegrated portfolio at this round.

Step 3. We now have n-1 variables. We will proceed again with pulling out of the regression variables for every i=1…n-1. The n-1 residuals will have the UR t-stat values ADF_{j1}, ADF_{j2},…$ADF_{jN-1.}$ We pick from these values the more negative one. If this value is ADF_{jk}, 1<=k<=N-1, then variable k will be eliminated from portfolio.

….

We continue to eliminate variables from portfolio 1) up to a minimum number m, set according to the preference of the investor; or 2) until we reach the optimal portfolio. For this case the optimal portfolio is the one corresponding to the combination that leads to the minimum UR t-stat taking into account all steps possible. Regarding this matter we can make an observation: suppose that at step "p-1" we find a combination with the smallest ADF (or PP) UR test by that time, and at following step "p" the minimum UR t-stat is greater than the one from the previous step, we can conclude that the portfolio at step "p-1" is optimal. Once the t-stat become increasing, it means that we can no longer find more cointegrated portfolios, because we tend to move away from the common stochastic trend that glued the series together in the long run.

2.1.3. Back-testing the model

Every cloning strategy can be defined by several elements, called parameters. Thus, cloning portfolios will be characterized by: a spread above the target benchmark; the data window used in cointegration, called calibration period; number n of assets; other preferences.

Once we have found the optimal composition of the cloning portfolio, we will move to the back-testing sequence. This back-testing is made over a period following the calibration period, called testing period. There is a variety of tests that can be done to assess the overall performance of the model.

1. Rolling window EG cointegration tests. Are made at a specified frequency (monthly, daily) rolling a window, of the same size with calibration period, over the testing period. It shows the extent to which the tracking error remains stationary with time passage.

2. Differential return between the cloning strategy and the benchmark. If we decide a periodical rebalance of portfolio, then we will have the same allocations only until the next rebalancing. Portfolio value will therefore be given by: $P_{t+j}^{clona} = \sum_{i=1}^{N} w_t^i \cdot P_{t+j}^{Ai}$.

3. Information ratio, given by the ratio between average annual return and the annualized volatility.

4. Turnover index and transaction costs. By TO we understand the sum of absolute values of weights modification. To obtain the index, we divide the above value by 2 (200%), which corresponds to the situation where we switch from one set of assets to another.

Transaction costs are computed as a percentage applied to the dollar value of the turnover: $C_t^{tranzactionare} = a(\%) \cdot \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-\Delta t} \right| P_{Ai,t}$.

5. Volatility of strategies' returns and of the tracking error. We can compute both the historical and conditional EWMA volatilities.

6. Correlation between the benchmark and the cloning portfolio, and between the error and the benchmark. We can compute both the historical and conditional EWMA correlation coefficients.

7. Distributional properties of the tracking error (e.g. Skewness, and Kurtosis).

2.2. Arbitrage Strategies

2.2.1. General Presentation

This type of strategies aims to construct a self-financing portfolio, which will generate positive returns irrespective of market direction, with a low volatility and in conditions of zero correlation with the market. To ensure the self-financing of the strategy, we construct two cointegrating portfolios: o long portfolio, which clone a benchmark plus a spread, and a short portfolio, which clone a benchmark minus a spread. The arbitrage portfolio will be given by the difference of the above portfolios, and will earn approximately the sum of the absolute values of the two spreads .

After setting up the two artificial benchmarks (by adding / subtracting a spread uniformly distributed on the whole benchmark series), we will clone the two portfolios, estimating initially the following cointegrating regressions:

$$\log(P_{benchmark\_plus,t}) = c_1 + \sum_{i=1}^{n} \beta_i \cdot \log(P_{Ai,t}) + \varepsilon_t \tag{2}$$

$$\log(P_{benchmark\_minus,t}) = c_2 + \sum_{i=1}^{n} \gamma_i \cdot \log(P_{Ai,t}) + u_t \tag{3}$$

If simultaneously the residuals ε and u are stationary, then each of the two portfolios will be cointegrated with its benchmark. The *arbitrage portfolio* can now be determined by the difference of the first two. The weights of the component assets are given by: $w\_arbitrage_{i,t} = w\_plus_{i,t} - w\_minus_{i,t}$.

To explain the low correlation of the arbitrage portfolio with the benchmark, we will analyze separately the two returns of the component portfolios:

$$R_{plus,t} = \alpha_{plus} + \rho_{plus} \frac{\sigma_{plus}}{\sigma_{benchmark\_plus}} R_{benchmark\_plus,t} + \varepsilon_{plus,t} \tag{4}$$

$$R_{minus,t} = \alpha_{minus} + \rho_{minus} \frac{\sigma_{minus}}{\sigma_{benchmark\_minus}} R_{benchmark\_minus,t} + \varepsilon_{minus,t} \tag{5}$$

where $\rho_{plus/minus}$ is the correlation coefficient of the long / short portfolio with the market; $\sigma_{plus/minus}$ is the volatility of the long / short portfolio.

The arbitrage return is given by:

$$R_{arbitrage,t} = R_{plus,t} - R_{minus,t} =$$

$$= \alpha_{plus} - \alpha_{minus} + \rho_{plus}\frac{\sigma_{plus}}{\sigma_{benchmark\_plus}}(R_{benchmark,t} + s_{plus}) - \rho_{minus}\frac{\sigma_{minus}}{\sigma_{benchmark\_minus}}(R_{benchmark,t} - s_{minus}) +$$

$$+ \varepsilon_{plus,t} - \varepsilon_{minus,t} =$$

$$= \alpha_{plus} - \alpha_{minus} + R_{benchmark,t}(\rho_{plus}\frac{\sigma_{plus}}{\sigma_{benchmark\_plus}} - \rho_{minus}\frac{\sigma_{minus}}{\sigma_{benchmark\_minus}}) + s_{plus}\rho_{plus}\frac{\sigma_{plus}}{\sigma_{benchmark\_plus}} +$$

$$+ s_{minus}\rho_{minus}\frac{\sigma_{minus}}{\sigma_{benchmark\_minus}} + \varepsilon_{plus,t} - \varepsilon_{minus,t} \qquad (6)$$

where s_{plus} and s_{minus} are the spreads added/subtracted from the benchmark. If the two cointegrating portfolios succeed in cloning their benchmark, then ρ_{plus} and ρ_{minus}, as well as relative volatilities $\frac{\sigma_{plus}}{\sigma_{benchmark\_plus}}$ and $\frac{\sigma_{minus}}{\sigma_{benchmark\_minus}}$ will converge to one. This will make the second term from the right-hand side of relation (6) to converge to zero. But this is nothing but the beta β of the arbitrage portfolio. We have now demonstrated the market neutrality of these strategies.

2.2.2. Back-testing the model

As in the case of cloning strategies, we will employ o number of back-tests during the testing period. These tests are:

1. Rolling window EG cointegration tests for both component portfolios. Are made at a specified frequency (monthly, daily) rolling a window, of the same size with calibration period, over the testing period. It shows the extent to which the tracking errors remain stationary with time passage.

2. Arbitrage portfolio return

3. Turnover index and transaction costs. Since the arbitrage portfolio is given by the difference of the long and the short portfolios, the strategies' transaction costs will be smaller than the sum of transaction costs of the two portfolios managed separately (see relation 7).

$$C_t^{tranzactionare} = a(\%) \cdot \sum_{i=1}^{N} \left| (wplus_{i,t} - w\min us_{i,t}) - (wplus_{i,t-\Delta t} - w\min us_{i,t-\Delta t}) \right| P_{Ai,t} \tag{7}$$

4. Volatility of strategies' returns and of the component portfolios. We can compute both the historical and conditional EWMA volatilities.

5. Correlation between the benchmark return and the arbitrage portfolio return. We can compute both the historical and conditional EWMA correlation coefficients.

6. Distributional properties of the two tracking errors (e.g. Skewness, and Kurtosis).

3. Cointegration-Based Portfolios Using MSCI Equity Indices

3.1. Data

In order to construct and test the cloning and arbitrage strategies described in section 2, we employ five years of daily data, from 30.04.1997 to 02.05.2002, for the equity indices of the countries participating at "Euro" currency as well as for the equity index for the entire zone. The data is available online from Morgan Stanley Capital International (MSCI), a source very often quoted in financial literature. The MSCI indices are computed in USD and weighted with the market capitalization. The five years of data are divided in two sub-periods: calibration period (first 4 years) and testing period (last year). Series, transformed first in logarithms, are presented in table 1.

Table 1. Description of data

	Series name	Description
1	LAUSTRIA	MSCI Austria Equity Index
2	LBELGIUM	MSCI Belgium Equity index
3	LFINLAND	MSCI Finland Equity index
4	LFRANCE	MSCI France Equity index
5	LGERMANY	MSCI Germany Equity index
6	LGREECE	MSCI Greece Equity index
7	LIRELAND	MSCI Ireland Equity index
8	LITALY	MSCI Italy Equity index
9	LNETHERLANDS	MSCI Netherlands Equity index
10	LPORTUGAL	MSCI Portugal Equity index
11	LSPANIA	MSCI Spain Equity index
12	LEURO	MSCI EURO Equity index
13	LEUROPLUS	MSCI EURO Equity index plus a spread of 2% p.a. uniformly distributed
14	LEUROMINUS	MSCI EURO Equity index minus a spread of 2% p.a. uniformly distributed

3.2. Unit-Root Tests

We will use both the Augmented Dickey-Fuller Test and Phillips-Perron Test. For the ADF tests we have selected the number of lags that eliminates autocorrelation of residuals according to the maximum lag criterion, that is we select the maximum lag for which the probability is less than 5% confidence level. When we couldn't apply this criterion we have applied Akaike Information Criterion (AIC). The entire set of results, for a number of 8 to 0 lags, is presented in Appendix 1. The summary of the ADF and PP tests is presented in Table 2.

Table 2. Summary of ADF and PP unit-root tests

SERIES NAME	LEVEL H_0: I(1)		1st DIFFERENCE H_0:I(2)	
	ADF	PP	ADF	PP
LAUSTRIA	-1.3486	-1.3106	-14.193	-30.204
LBELGIUM	-1.5335	-1.5288	-22.442	-27.482
LFINLAND	-1.5032	-1.5032	-23.882	-31.784
LFRANCE	-1.7885	-1.8555	-13.466	-30.489
LGERMANY	-2.4285	-2.4833	-24.485	-31.096
LGREECE	-1.6926	0.3044	-27.935	-27.82
LIRELAND	-1.9361	-1.9505	-11.654	-29.874
LITALY	-2.7667	-2.7434	-19.905	-31.657
LNETHERLANDS	-3.2274	0.5743	-14.919	-30.6205
LPORTUGAL	-2.1695	-2.1538	-28.238	-28.2155
LSPANIA	-2.6999	-2.6750	-23.13	-29.3702
LEURO	-2.1495	-2.3121	-13.698	-29.5797
LEUROPLUS	-2.1292	-2.2662	-13.698	-29.5797
LEUROMINUS	-2.1488	-2.3793	-13.698	-29.5797

MacKinnon critical values for rejection of hypothesis of a unit root:
1% significance level -3.4394
5% significance level -2.8647

We can observe that for all series we can reject the null hypothesis of unit-root only after taking the first difference. We will therefore conclude that all series are non-stationary, being integrated of order one. In the case of LNETHERLANDS, if we use ADF we can reject hypothesis of unit-root in level at 5%, but if we apply PP we find that the series is I(1) too.

3.3. Implementing The Cloning Strategy

We will try to construct and test a portfolio that clones MSCI EURO equity index plus a spread of 2% p.a., uniformly distributed (all returns were augmented with 0.00008 per trading day, assuming 250 such days per year). We will employ Engle-Granger cointegration method, and then the optimization algorithm presented in section 2.1.2.

We start by estimating the following cointegrating regression:

$$LEUROPLUS_t = c + \sum_{i=1}^{11} \beta_i \cdot \log(P_{Ai,t}) + \varepsilon_t \qquad (8)$$

where $\log(P_{Ai}) \in$ {LAUSTRIA, LBELGIUM, LFINLAND, LFRANCE, LGERMANY, LGREECE, LIRELAND, LITALY, LNETHERLANDS, LPORTUGAL, LSPAIN} are independent candidate variables, and LEUROPLUS is considered dependent variable.

We extract de residual series, named RESID00, and test its stationarity. Since UR t-stat is –4.937256 we can conclude that the residual is stationary. Although we have found cointegration, we are not stopping here. We will try, using the algorithm, to find the most cointegrated portfolio.

We will estimate EG cointegrating regressions, eliminating successively one series at a time, and extracting residuals. We will eliminate completely, at every step, one single series according to the minimum ADF t-stat criterion. The results are presented in Tables from 3 to 7 from the Appendix 2. We can observe that in order to obtain a portfolio more and more cointegrated (an error more and more stationary) we need to eliminate first Finland index, second Netherlands index, third Spain index, and fourth Belgium index. From table 7, we observe that a further attempt to optimize the portfolio composition will end up in obtaining a suboptimal portfolio, because eliminating the Austrian equity index from portfolio will lead to an error less stationary (ADF t-stat of –7.0568) comparing to the previous round (ADF t-stat of –7.2266). We will conclude that previous round gives us the most cointegrated portfolio.

Since we have just found the optimal composition of cloning portfolio, we will determine the weights of the component assets, by estimating equation:

$$LEUROPLUS_t = c + \beta_1 LAUSTRIA_t + \beta_2 LFRANCE_t + \beta_3 LGERMANY_t + \beta_4 LGREECE_t + \\ + \beta_5 LIRELAND_t + \beta_6 LITALY_t + \beta_7 LPORTUGAL_t + \varepsilon_t$$

The output of the econometric software Eviews 3 are presented in table 8.

Table 8. Coefficients of EG cointegration regression for de cloning portfolio

Dependent Variable: LEUROPLUS
Method: Least Squares
Sample: 4/30/1997 5/02/2001
Included observations: 1046

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LAUSTRIA	-0.04919	0.003945	-12.4691	0.0000
LFRANCE	0.586314	0.00798	73.47163	0.0000
LGERMANY	0.317436	0.006915	45.90446	0.0000
LGREECE	-0.02272	0.001998	-11.3686	0.0000
LIRELAND	0.051311	0.005324	9.637921	0.0000
LITALY	0.211019	0.006652	31.72453	0.0000
LPORTUGAL	-0.08221	0.005488	-14.9816	0.0000
C	-0.25137	0.033517	-7.49981	0.0000

We verify the cointegration of the cloning portfolio with the benchmark, by applying phase two of Engle-Granger method. We extract the residual series, named EROARE1, and test its stationarity using ADF, taking from 8 to 0 lags. The results are shown in Table 9.

Table 9. Phase two of EG cointegration test

SERIES: EROARE1									
ADF test- level (with constant)		MacKinnon critical values*:			1%:	-5.2651	5%:		-4.7211
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-7.2266	-6.9066	-6.8898	-6.7195	-6.3057	-6.294	-6.1159	-6.1312	-6.072
prob_lgmax	4.95E-13	0.39655	0.51545	0.64591	0.15633	0.59208	0.66239	0.18689	0.84608
AIC	-8.7071	-8.705	-8.7026	-8.7005	-8.6995	-8.697	-8.6943	-8.6938	-8.6919
SBC	-8.6976	-8.6907	-8.6836	-8.6767	-8.671	-8.6637	-8.6562	-8.6509	-8.6442

* another set of critical values will be used for EG ADF tests; they are calculated from the response surfaces of MacKinnon (1991)

Looking at table 9, we observe the number of lags is the same no matter what criterion we use. Both the maximum lag probability and AIC indicates lag zero. The value of ADF t-stat is in this case –7.2266, which shows a powerful cointegrating relation among variables.

After normalizing the coefficients so that they sum to unity, we have found the cloning portfolio weights (see table 22 from Appendix 3).

3.4. Back-testing the cloning strategy

We will proceed with assessing the overall performances of the model, using the tests describes in section 2.1.3.

3.4.1. Rolling window EG cointegration tests

We will examine the behavior of the cloning portfolio during the testing period. We have analyzed separately the sub-strategies of leaving the portfolio unmanaged for a whole year, and the sub-strategy of rebalancing its weights every month. We have implemented the rolling window tests, using different codes written in Eviews programming language. The window size was 4 years, and the frequency was monthly and daily. The results are depicted in Figures 1 and 2 from Appendix 4. Based on these figures it can be inferred that even left unmanaged the portfolio stays most of the time cointegrated at 1% significance level. Towards the end of the testing period the portfolio looses from its stationarity, which means a possible increase of the risk, especially when the ADF test breaks the 5% critical value.

If we rebalance monthly the portfolio (see Figures 3 and 4 Appendix 4), we are able to obtain an error with an increasing stationarity, which translates in smaller and more mean-reverting errors, with positive influences on the portfolio returns.

3.4.2. Differential return between the cloning strategy and the benchmark

Table 10. Return of cloning portfolio vs. benchmark return

		$R_{MSCI\ EURO}$	R_{PClone}	$R_{PClone\ Rebal}$	$R_{MSCI\ EURO}$ cumulated	R_{PClone} cumulated	$R_{PClone\ Rebal}$ cumulated
May	2001	-7.6830%	-6.8367%	-6.7542%	-7.6830%	-6.8367%	-6.7542%
Jun	2001	-4.0890%	-2.6386%	-2.8392%	-11.7720%	-9.4753%	-9.5935%
Jul	2001	0.1812%	0.0639%	0.0944%	-11.5907%	-9.4114%	-9.4991%
Aug	2001	-5.1310%	-4.5884%	-4.9981%	-16.7217%	-13.9998%	-14.4972%
Sep	2001	-13.2248%	-15.7097%	-14.4758%	-29.9465%	-29.7094%	-28.9729%
Oct	2001	4.1796%	4.8391%	4.8078%	-25.7670%	-24.8703%	-24.1652%
Nov	2001	4.7549%	4.7061%	4.2784%	-21.0121%	-20.1642%	-19.8867%
Dec	2001	2.9018%	3.3577%	3.1018%	-18.1102%	-16.8065%	-16.7850%
Jan	2002	-6.2934%	-6.2711%	-5.9570%	-24.4036%	-23.0777%	-22.7420%
Feb	2002	-0.6254%	-0.1915%	-0.0479%	-25.0290%	-23.2692%	-22.7899%
Mar	2002	5.4747%	6.3870%	5.8837%	-19.5542%	-16.8822%	-16.9062%
Apr	2002	-2.2441%	-3.1133%	-2.2029%	-21.7983%	-19.9955%	-19.1091%

In Table 10 are presented the returns of the cloning portfolio, for both the unmanaged and rebalanced substrategies, comparing to benchmark return.

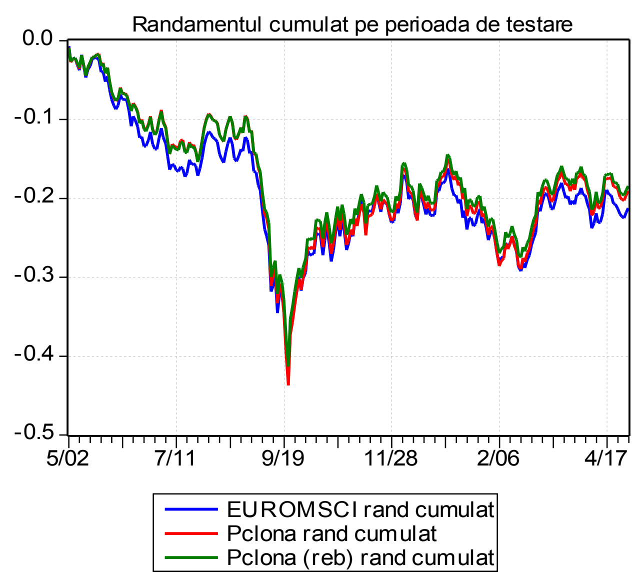

Figure 5. Cumulated returns during testing period of the two substrategies

Even there were difficult times in European equity markets, during testing period, both cloning strategies have managed to generate a higher return then the market. We observe that the excess returns were very close to the 2% p.a. spread that was proposed. In the case of rebalanced sub-strategy, due to the increased level of tracking error stationarity we obtain even a greater excess return (+2.58%) than the 2% planned.

Figure 5 describes the cumulated returns of cloning portfolio, under the two sub-strategies. We can observe how, at any time, the rebalanced strategy generates higher returns. However, one must interpret with caution this result, because by now we didn't take into account the transaction costs, which may change dramatically the situation.

3.4.3. Information Ratio

We can assess the risk-adjusted returns by calculating IR, the ratio of average annual return and volatility. The results shown in Table 11, indicate a better risk-adjusted performance of unmanaged cloning portfolio, even if has a smaller return (a greater loss) and a greater market risk.

Table 11. Iratio for the benchmark and cloning portfolio

	R_{CloneP}	$R_{CloneP\ Rebal}$	$R_{MSCI\ EURO}$
μ	-19.988%	-19.383%	-22.092%
σ	23.959%	22.696%	22.999%
IRatio	-0.83424	-0.85403	-0.96055

3.4.4. Turnover index and transaction costs

We have computed turnover index for the rebalanced strategy. Table 12 from Appendix 5, shows a small turnover, ranging from 0.28% to 4.13% every month, due to the stationarity of tracking error.

Regarding the transaction costs, we have studied their impact on the rebalanced strategy's returns, taking into account three different percentages 0.1%, 0.2% and 0.5%. The returns of the rebalanced cloning portfolios were computed in Table 14 from Appendix 5, based on the monthly normalized allocations taken from rolling cointegrating regressions, and shown in Table 22a from Appendix 3. The conclusion was that the cloning portfolio has the greatest return (minimum loss) even after accounting for the transaction costs. Moreover, even if we are faced with a brokerage fee of 50 bp, the cloning portfolio still generates a smaller loss than the benchmark (-20.5285% comparing to –21.7983%).

3.4.5. Volatility of strategies' returns and of the tracking error

We have computed the unconditional (historical) and conditional EWMA volatilities, using a look-back period of 30 days, and a smoothing coefficient λ=0.94 (see figure 6).

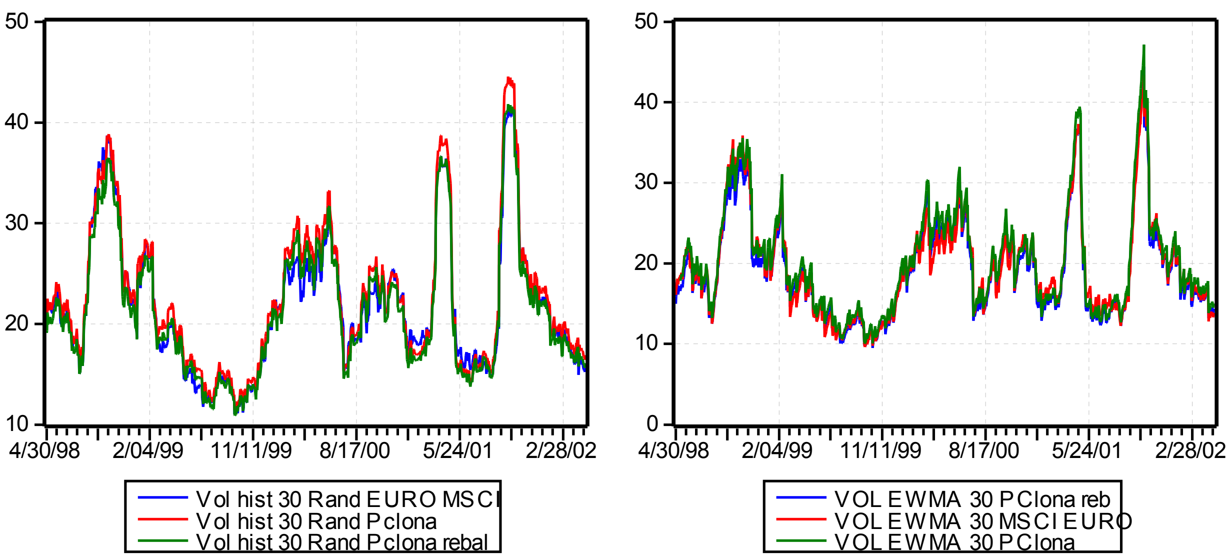

Figure 6. a) Historical 30 day volatility b) conditional EWMA volatilities with λ=0.94

We observe a great deal of similarity between cloning portfolio returns volatility and the volatility of market returns. Even if the cloning portfolio is composed of about a half of the assets in the MSCI EURO index, the shape of volatilities is almost identical. We can see how the terrorist attack of September 11th is "felt" identically by the benchmark and the clone portfolio. Regarding the two sub-strategies, it can be observed that the rebalanced portfolio has the smallest volatility, while the unmanaged one has the greatest volatility.

We have computed too, the volatility of the tracking error (excess return).

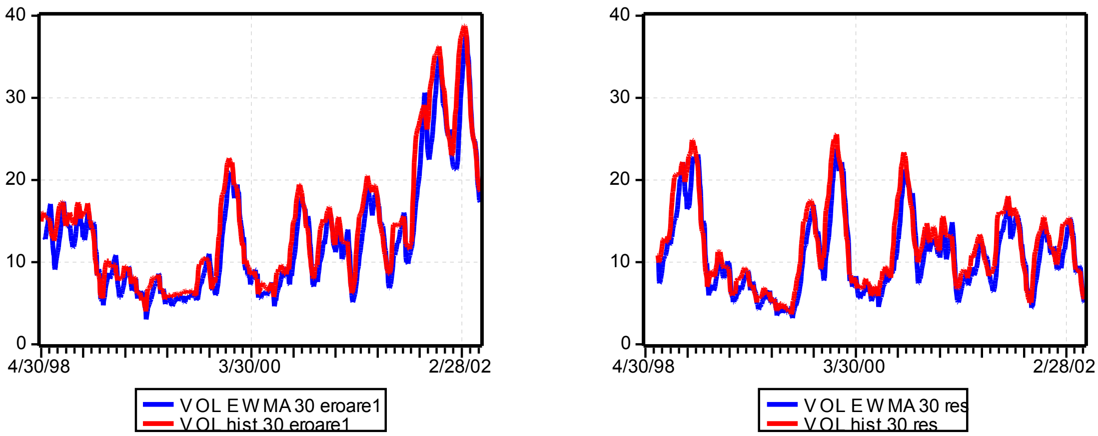

Figure 7. Historical and EWMA volatilities of the excess return for the two sub-strategies

From figure 7, we can observe a greater variability of excess returns, during the testing period, when we choose to let the portfolio unmanaged. The better performance of the rebalanced portfolio, is due to the more powerful stationarity, as explained in section 3.4.1.

3.4.6. Correlation between the benchmark and the cloning portfolio, and between the error and the benchmark.

The results are depicted in Figures 8 and 9. We can draw the conclusion that the cloning strategy generates portfolios very strong correlated with the benchmark, at any moment correlation coefficients being situated above the level of 0.94. Moreover, the residuals of this type of strategy ranged between –0.2 and +0.4, oscillating around the zero value.

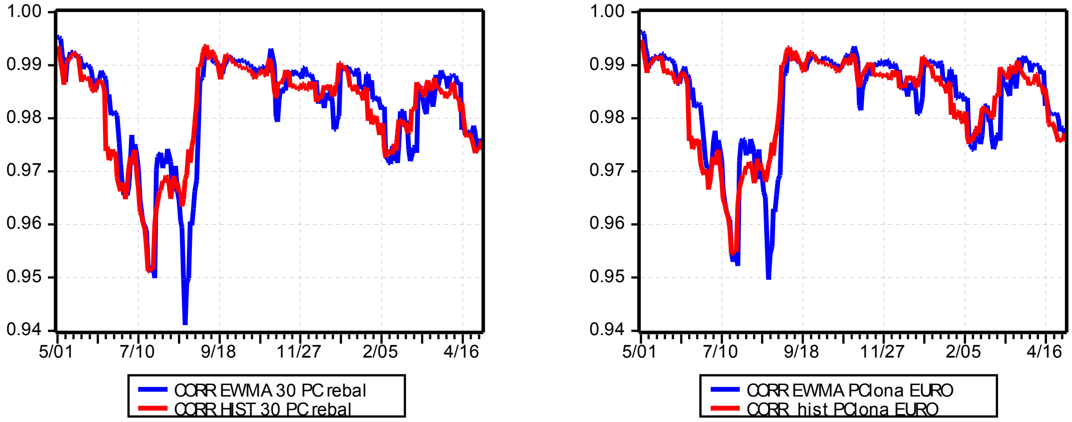

Figure 8. Historical and EWMA correlations between

a) rebalanced portfolio and market **b) unmanaged portfolio and market**

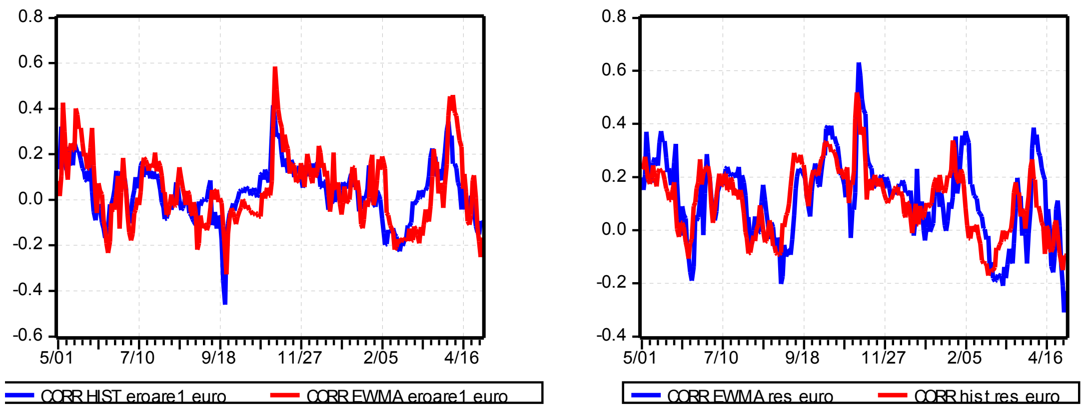

Figure 9. Historical and EWMA correlations between

a) market and unmanaged residual **b) market and rebalanced residual**

3.4.7. Distributional properties of the tracking error

To shed even more light on the overall performance of the cloning strategy we have analyzed the higher order moments (table 15 from Appendix 6). For the both substrategies (unmanaged and rebalanced) the skewness was negative, indicating a tendency of cloning portfolio to over-perform the market. Kurtosis is for both substrategies under 3, the platykurtic distribution indicating a smaller frequency of tracking error extreme movements than in the case of normal distribution.

3.5. Implementing The Arbitrage Strategy

As was discussed in section 2.2.1., in order to implement the arbitrage strategy, we need to construct two portfolios. The so-called long portfolio was already created and tested in previous sections, so we will focus on the short portfolio. The artificial benchmark used in this case, was MSCI EURO index minus 2% p.a. We start again by estimating a cointegrating regression, from which we are eliminating one variable at a time. We apply the same simple algorithm until we find the optimal cointegrating portfolio (with the minimum UR t-stat of the error). The summary of the optimization algorithm are presented in Table 16 from Appendix 2. We observe again that any further optimization leads to suboptimal portfolios (-6.25 comparing to –6.43 from the previous round).

Having found the optimal components of the short portfolio, we are now able to determine the actual weights. So we will estimate the following cointegrating regression:

$$LEUROMINUS = c + \beta_1 LBELGIUM + \beta_2 LFINLAND + \beta_3 LGREECE + \beta_4 LIRELAND + \\ + \beta_5 LNETHERLANDS + \beta_6 LPORTUGAL + \varepsilon$$

The results were, as shown in Table 17, the following:

Table 17. EG cointegrating regression coefficients for short portfolio

Dependent Variable:LEUROMINUS
Sample: 4/30/1997 5/02/2001
Included observations: 1046

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LBELGIUM	0.048556	0.005851	8.299036	0.0000
LFINLAND	0.193238	0.001956	98.81191	0.0000
LGREECE	0.020864	0.003528	5.913643	0.0000
LIRELAND	-0.076175	0.007751	-9.828342	0.0000
LNETHERLANDS	0.404709	0.012000	33.72456	0.0000
LPORTUGAL	0.354806	0.006464	54.88697	0.0000
C	0.741652	0.068012	10.90479	0.0000

Once again, we verify the stationarity of the residual series, using lags from 8 to 0. (see Table 18). The correct value of the ADF t-stat, which must be compared with the critical value, is –6.4368, indicating a strong cointegration at 1% significance level.

Table 18. Second phase of EG method for short portfolio

SERIES: EROARE2									
ADF test- level (with constant)			MacKinnon critical values*:		1%:		-5.2651 5%:		-4.7211
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-6.4368	-6.3819	-6.0351	-5.9576	-5.7165	-5.9316	-5.9387	-6.0686	-6.1248
prob_lgmax	0	0.7722	0.7537	0.851	0.3689	0.1049	0.5906	0.2099	0.7148
AIC	-7.5673	-7.5646	-7.5675	-7.5647	-7.5626	-7.5626	-7.5601	-7.5587	-7.5584
SBC	-7.5578	-7.5503	-7.5485	-7.5409	-7.5341	-7.5293	-7.522	-7.5159	-7.5107

The weights of the short portfolio are now obtained by normalizing the coefficients (see Table 22 from Appendix 3). Since we have determined both component portfolios, we can determine the weights of arbitrage portfolio by doing a simple subtraction. To save space, we are not reproducing here the initial weights, but we are reminding that the sum of weights must be zero.

3.6. Back-testing the arbitrage strategy

3.6.1. Rolling window EG cointegration tests

We have used the same approach as in section 3.4.1. Since the unmanaged short portfolio remained cointegrated, only at an unsatisfactory 10% level of confidence, we have focused on the rebalanced strategy. The resulting rolling window tests are depicted in Figure 10 from Appendix 4. The direct effect of rebalancing consisted once again of a more stationary tracking error, so that in 10 months out of 12 the portfolio remained cointegrated at 1% significance level (Figure 10 middle panel).

3.6.2. Arbitrage portfolio return

We will analyze arbitrage portfolio returns starting with the performances of the two long and short component portfolios, considering the unmanaged and the rebalanced sub-strategies. From Table 19 and more visually from the Figure 11, we observe how the losses of the long portfolio were more than compensated by the returns of the short portfolio.

Table 19. Cumulated returns of the arbitrage strategy

		R_{LONG}	R_{SHORT}	$R_{ARBITRAGE}$	R_{LONG} REBALANCED	R_{SHORT} REBALANCED	$R_{ARBITRAGE}$ REBALANCED
May	2001	-6.8367%	9.0058%	2.1691%	-6.7542%	7.1222%	0.3680%
Jun	2001	-9.4753%	17.0103%	7.5349%	-9.5935%	10.2975%	0.7040%
Jul	2001	-9.4114%	16.0273%	6.6159%	-9.4991%	10.5551%	1.0560%
Aug	2001	-13.9998%	22.4745%	8.4747%	-14.4972%	15.9052%	1.4080%
Sep	2001	-29.7094%	28.4680%	-1.2414%	-28.9729%	30.7009%	1.7280%
Oct	2001	-24.8703%	22.8646%	-2.0057%	-24.1652%	26.2612%	2.0960%
Nov	2001	-20.1642%	19.7057%	-0.4585%	-19.8867%	22.3347%	2.4480%
Dec	2001	-16.8065%	17.4388%	0.6323%	-16.7850%	19.5690%	2.7840%
Jan	2002	-23.0777%	22.3647%	-0.7130%	-22.7420%	25.8940%	3.1520%
Feb	2002	-23.2692%	23.5181%	0.2489%	-22.7899%	26.2619%	3.4720%
Mar	2002	-16.8822%	18.8532%	1.9710%	-16.9062%	20.7142%	3.8080%
Apr	2002	-19.9955%	22.9627%	2.9671%	-19.1091%	23.2691%	4.1600%

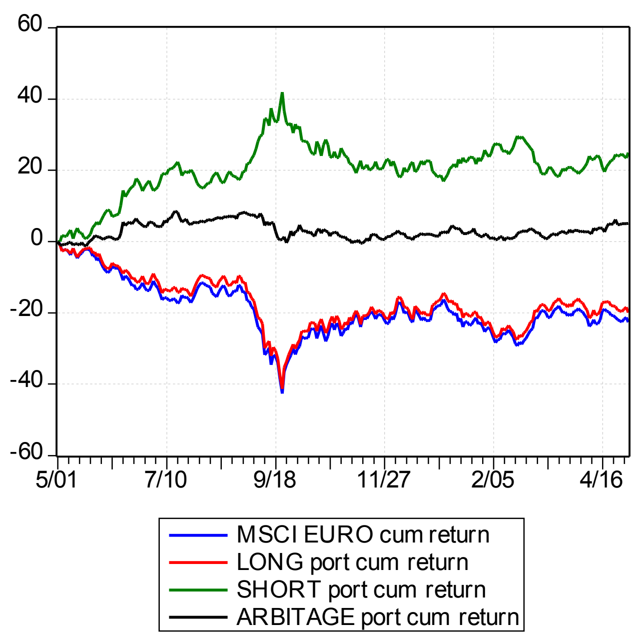

Figure 11. Cumulated returns of the arbitrage strategy with monthly rebalancing

Considering monthly rebalancing, the arbitrage returns were 4.16% comparing with 2.96% in the case of unmanaged portfolios. Again this differential can be explained by the greater stationarity (quantified by a smaller ADF t-stat) of the rebalanced tracking errors.

3.6.3. Turnover index and transaction costs.

We have computed turnover index not only for the arbitrage portfolio, but also for the two component portfolios. The results are reported in Table 12 from the Appendix 5. We can observe how for the entire arbitrage strategy TO index has situated between a minimum value of 0.65% and a maximum value of 6.47% per month. It must be emphasized that always the arbitrage turnover was smaller than the sum of the components' turnover.

Regarding the important issue of transaction costs, we have calculated both these values (Table 20 from Appendix 5) and their effects on the returns generated by the rebalanced arbitrage strategy (Table 21 Appendix 5). Again we have used three brokerage fees: 10bp, 20 bp, and 50 bp. The arbitrage strategy remains efficient after accounting for the brokerage fees. Moreover, if we deduct, as a stress-test, an exaggerated (relative to liquidity of these markets) fee of 50 bp the strategy is still able to produce a positive return. At the other extreme, if the portfolio manager had been able to negotiate a brokerage fee of 10 bp, the rebalanced arbitrage returns would have been greater than in the unmanaged case. As an observation, if the component portfolios had been managed separately, the arbitrage portfolio would have lost the benefits of transaction costs savings, and consequently the returns would have been smaller.

3.6.4. Volatility of arbitrage portfolio returns

We have computed the historical and conditional EWMA volatility of arbitrage portfolio, considering not only the monthly rebalancing of the weights, but also the unmanaged case. The results are depicted in Figure 12.

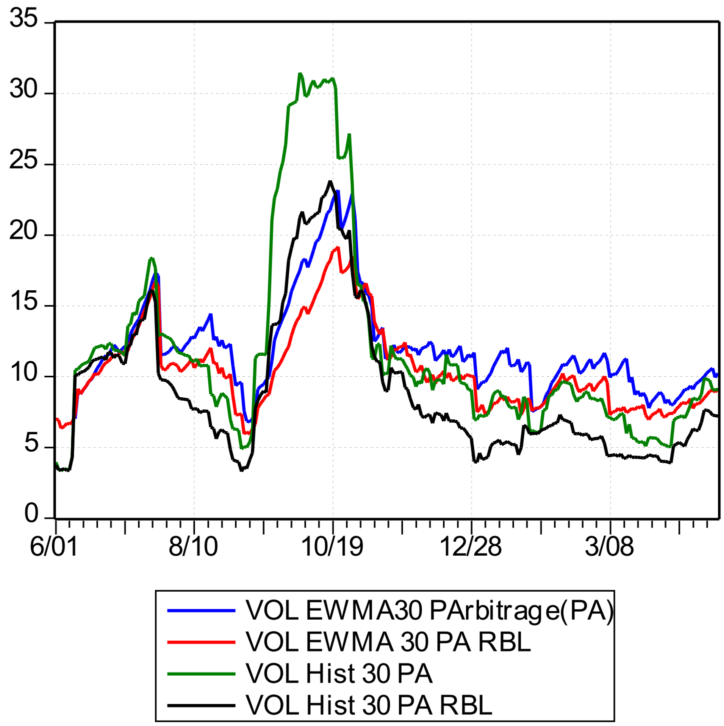

Figure 12. Historical and EWMA volatilities of the arbitrage returns for the two sub-strategies

We observe how, during the testing period, volatility of the rebalanced (RBL) arbitrage strategy was noticeable smaller comparing to the unmanaged strategy, irrespective of the way of computation. Quantitatively, the mean volatility of the rebalanced arbitrage portfolio returns was 9% p.a., while in the unmanaged case the mean volatility was 12%. More important is that the both substrategies have had a market risk, as measured by volatility, two times smaller than market risk of MSCI EURO index.

3.6.5. Correlation between the benchmark return and the arbitrage portfolio return

We have computed historical and EWMA correlation coefficients between arbitrage portfolio returns and EURO MSCI returns. From Figure 13, we observe that by rebalancing the component portfolios, we obtain a much lower correlation than in the case we leave the portfolios unmanaged. If we calculate the mean correlation coefficients over the testing period, we obtain for the unmanaged case a value of 0.30, while for the rebalanced case we report a correlation of 0.055 which is very close to market neutrality

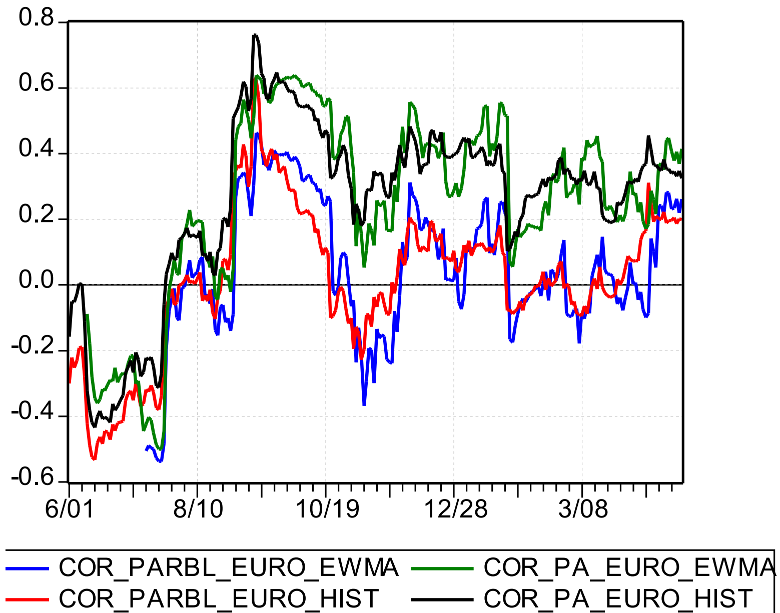

Figure 13. Correlation between MSCI EURO returns and arbitrage returns

3.6.6. Distributional properties of the two tracking errors

Since the tracking error of the long portfolio has been analyzed in section 3.4.7, in the following we will focus on the short portfolio error. The values of the descriptive statistics have been reported in Table 15 from Appendix 6. Being a short portfolio, a positive skewness indicates portfolio tendency over-perform the benchmark. This tendency is the more pronounced the more stationary is the error. Again we observe a platykurtic distribution of errors, indicating a smaller frequency of extreme movement than in the case of a normal distribution.

4. Conclusions

This paper has proposed to analyze the extent to which the cointegration technique may be employed in portfolio construction. To this end we have implemented and tested two types of strategies: cloning strategies and arbitrage strategies.

Using a simple algorithm we succeeded to find a portfolio that systematically over-performed the benchmark in terms of returns, had a smaller volatility, and moreover was composed of a smaller number of assets than the original benchmark. Once found, the cloning strategy remained cointegrated with the benchmark during the entire testing period, even if the portfolio was left unmanaged. When we tried to rebalance the weights with a monthly frequency, the results were even more appealing, obtaining a portfolio not only more cointegrated than in the first case, but also with a greater excess return and a reduced risk. The performances of the model persisted even after accounting for brokerage fees.

The second strategy aimed to produce a positive return in all states of the nature. We therefore constructed back-to-back two cloning strategies: a long one and a short one. These two portfolios remained the most cointegrated with their benchmarks when we rebalanced the weights every month. The enhanced stationarity of the tracking errors, gained this way, made it possible for the arbitrage portfolio to generate positive risk-free returns after deducting the corresponding transaction costs. Regarding the management of cloning and arbitrage strategies, our analysis leaded to the conclusion that the advantage of cointegration is obvious irrespective of our decision to leave unmanaged or to rebalance the portfolios. However, from a risk management point of view we recommend the rebalancing, because the unmanaged strategy will sooner or later result in an increased level of volatility.

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APPENDIX 1 – ADF Unit-Root Tests using from 8 to 0 lags

Series:LAUSTRIA

ADF test- level (with constant)		MacKinnon critical values:			1%:	-3.4394	5%:		-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.2055	-1.3041	-1.2504	-1.3486	-1.4182	-1.3242	-1.3111	-1.3314	-1.3419
prob_lgmax	0.228	0.0258	0.2683	0.0304	0.1401	0.0586	0.799	0.7014	0.8081
AIC	-5.9508	-5.953	-5.9513	-5.953	-5.9525	-5.9534	-5.9509	-5.9495	-5.9468
SBC	-5.9413	-5.9388	-5.9323	-5.9292	-5.924	-5.9201	-5.9128	-5.9066	-5.8991
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-30.182	-22.832	-17.442	-14.677	-14.193	-13.116	-12.053	-11.226	-10.754
prob_lgmax	0	0.2434	0.0353	0.1589	0.05	0.7513	0.7486	0.8574	0.5909
AIC	-5.9533	-5.9517	-5.9531	-5.9525	-5.9537	-5.9512	-5.9497	-5.947	-5.9443
SBC	-5.9438	-5.9375	-5.9341	-5.9287	-5.9251	-5.9179	-5.9116	-5.904	-5.8966

Series:LBELGIUM

ADF test- level (with constant)		MacKinnon critical values:			1%:	-3.4394	5%:		-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.4425	-1.6174	-1.5335	-1.5087	-1.4818	-1.4667	-1.444	-1.4069	-1.3587
prob_lgmax	0.1492	0	0.0371	0.5151	0.9226	0.7755	0.9428	0.2364	0.4997
AIC	-5.8855	-5.907	-5.9083	-5.9058	-5.9031	-5.9003	-5.8977	-5.8962	-5.894
SBC	-5.8761	-5.8928	-5.8893	-5.8821	-5.8746	-5.867	-5.8596	-5.8533	-5.8463
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-27.688	-22.442	-18.813	-16.313	-14.694	-13.354	-12.8	-12.157	-11.571
prob_lgmax	0	0.0313	0.4766	0.8771	0.7316	0.9877	0.2151	0.4691	0.5536
AIC	-5.9064	-5.908	-5.9056	-5.9029	-5.9002	-5.8976	-5.8962	-5.8941	-5.8916
SBC	-5.8969	-5.8937	-5.8866	-5.8792	-5.8716	-5.8643	-5.8581	-5.8512	-5.8438

Series:LFINLAND

ADF test- level (with constant)		MacKinnon critical values:			1%:	-3.4394	5%:		-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.5032	-1.4921	-1.485	-1.4836	-1.4507	-1.4767	-1.4772	-1.4641	-1.4814
prob_lgmax	0.1328	0.6025	0.08	0.6199	0.7993	0.6327	0.1792	0.9754	0.933
AIC	-4.2725	-4.2699	-4.27	-4.2673	-4.2648	-4.2624	-4.2613	-4.2584	-4.2557
SBC	-4.263	-4.2557	-4.251	-4.2436	-4.2363	-4.2292	-4.2232	-4.2156	-4.208
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-31.766	-23.882	-19.462	-16.499	-14.861	-14.041	-12.832	-11.863	-10.793
prob_lgmax	0	0.0798	0.6219	0.7957	0.6364	0.1813	0.969	0.927	0.3562
AIC	-4.2697	-4.2698	-4.2671	-4.2647	-4.2623	-4.2611	-4.2583	-4.2555	-4.2535
SBC	-4.2602	-4.2555	-4.2481	-4.241	-4.2337	-4.2278	-4.2202	-4.2126	-4.2058

Series:LFRANCE

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.8593	-1.8538	-1.8331	-1.8197	-1.8302	-1.829	-1.8033	-1.7885	-1.7203
prob_lgmax	0.063	0.0722	0.0478	0.3254	0.9251	0.2827	0.8795	0.0381	0.7602
AIC	-5.7565	-5.7568	-5.7577	-5.7557	-5.7529	-5.7511	-5.7484	-5.7497	-5.7481
SBC	-5.747	-5.7426	-5.7387	-5.732	-5.7244	-5.7178	-5.7103	-5.7068	-5.7004

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-30.536	-23.574	-19.61	-16.688	-15.303	-13.742	-13.466	-12.548	-11.975
prob_lgmax	0	0.0461	0.3207	0.9308	0.2805	0.8818	0.0381	0.7624	0.4502
AIC	-5.7554	-5.7564	-5.7544	-5.7516	-5.7498	-5.7472	-5.7485	-5.7472	-5.7454
SBC	-5.7459	-5.7421	-5.7354	-5.7278	-5.7213	-5.7138	-5.7104	-5.7042	-5.6977

Series:LGERMANY

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.4929	-2.5012	-2.4285	-2.3624	-2.3235	-2.3514	-2.2719	-2.1725	-2.1614
prob_lgmax	0.0127	0.2074	0.0047	0.495	0.5594	0.5331	0.0906	0.0651	0.8529
AIC	-5.5079	-5.5067	-5.5115	-5.5102	-5.5081	-5.5056	-5.5056	-5.5065	-5.5036
SBC	-5.4985	-5.4924	-5.4926	-5.4865	-5.4796	-5.4723	-5.4675	-5.4636	-5.4559

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-31.116	-24.485	-19.134	-16.2	-14.207	-13.727	-13.409	-12.456	-11.891
prob_lgmax	0	0.0037	0.5356	0.6039	0.5794	0.0787	0.0574	0.8156	0.4524
AIC	-5.5026	-5.5078	-5.5068	-5.5048	-5.5022	-5.5026	-5.5038	-5.501	-5.4988
SBC	-5.4931	-5.4936	-5.4878	-5.481	-5.4737	-5.4692	-5.4657	-5.4581	-5.4511

Series:LGREECE

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.5793	-1.6926	-1.6625	-1.6263	-1.5722	-1.5465	-1.5165	-1.4329	-1.3966
prob_lgmax	0.1143	0	0.4592	0.9316	0.1982	0.9139	0.6629	0.2088	0.4824
AIC	-4.7871	-4.8054	-4.8031	-4.8006	-4.7994	-4.7969	-4.7943	-4.7942	-4.792
SBC	-4.7776	-4.7912	-4.7841	-4.7769	-4.7709	-4.7636	-4.7562	-4.7514	-4.7443

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-27.935	-21.628	-18.029	-16.39	-14.578	-13.475	-12.969	-12.311	-11.92
prob_lgmax	0	0.4294	0.8942	0.183	0.9471	0.6333	0.1956	0.4616	0.2522
AIC	-4.8046	-4.8023	-4.8	-4.799	-4.7965	-4.794	-4.7942	-4.792	-4.7906
SBC	-4.7951	-4.7881	-4.781	-4.7752	-4.768	-4.7607	-4.7561	-4.7491	-4.7429

Series:LIRELAND									
ADF test- level (with constant)			MacKinnon critical values:		1%:		-3.4394	5%:	-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-1.9183	-1.9361	-1.8509	-1.8553	-1.8211	-1.7927	-1.7869	-1.7403	-1.7642
prob_lgmax	0.0551	0.0111	0.0613	0.9346	0.5689	0.4844	0.5265	0.9117	0.6419
AIC	-5.8218	-5.8272	-5.8277	-5.8248	-5.8232	-5.8208	-5.8185	-5.8161	-5.8135
SBC	-5.8124	-5.813	-5.8087	-5.8011	-5.7947	-5.7875	-5.7804	-5.7733	-5.7658
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-29.946	-23.302	-18.859	-16.047	-14.69	-13.627	-12.626	-11.588	-11.654
prob_lgmax	0	0.0512	0.9941	0.6199	0.4388	0.4798	0.8573	0.6923	0.0348
AIC	-5.8255	-5.8263	-5.8234	-5.8219	-5.8196	-5.8174	-5.8151	-5.8124	-5.8145
SBC	-5.816	-5.8121	-5.8044	-5.7982	-5.7911	-5.784	-5.777	-5.7695	-5.7668

Series:LITALY									
ADF test- level (with constant)			MacKinnon critical values:		1%:		-3.4394	5%:	-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.7385	-2.7156	-2.7342	-2.7667	-2.7043	-2.7538	-2.7366	-2.7186	-2.7286
prob_lgmax	0.0062	0.5316	0.6756	0.0324	0.5434	0.1516	0.1191	0.1044	0.6123
AIC	-5.5729	-5.5704	-5.5678	-5.5694	-5.5672	-5.5666	-5.566	-5.5658	-5.5632
SBC	-5.5634	-5.5561	-5.5488	-5.5457	-5.5386	-5.5333	-5.528	-5.5229	-5.5155
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-31.655	-22.869	-19.905	-16.595	-15.392	-13.203	-12.827	-11.701	-10.52
prob_lgmax	0	0.6803	0.0336	0.5292	0.1585	0.1133	0.1095	0.5929	0.1649
AIC	-5.5652	-5.5625	-5.564	-5.562	-5.5612	-5.5607	-5.5605	-5.5579	-5.557
SBC	-5.5557	-5.5483	-5.545	-5.5383	-5.5327	-5.5274	-5.5224	-5.515	-5.5093

Series:LNETHERLANDS									
ADF test- level (with constant)			MacKinnon critical values:		1%:		-3.4394	5%:	-2.8647
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-3.6034	-3.5835	-3.5226	-3.4183	-3.3336	-3.3408	-3.2274	-3.104	-3.0749
prob_lgmax	0.0003	0.0545	0.0021	0.4688	0.6491	0.5571	0.0589	0.3427	0.737
AIC	-5.8052	-5.8067	-5.8141	-5.8119	-5.8094	-5.8071	-5.8078	-5.8063	-5.8036
SBC	-5.7958	-5.7925	-5.7951	-5.7882	-5.7809	-5.7738	-5.7697	-5.7635	-5.7559
ADF first difference (with constant)									
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-30.605	-24.513	-20.042	-17.335	-15.579	-14.919	-13.996	-12.738	-11.752
prob_lgmax	0	0.0012	0.387	0.5585	0.4757	0.0456	0.2978	0.8022	0.809
AIC	-5.7964	-5.8041	-5.8026	-5.8007	-5.7983	-5.7996	-5.799	-5.7964	-5.7937
SBC	-5.7869	-5.7899	-5.7836	-5.7769	-5.7698	-5.7663	-5.7608	-5.7534	-5.7459

Series:LPORTUGAL

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.0346	-2.1695	-1.9042	-1.8596	-1.8887	-1.854	-1.8669	-1.8294	-1.8726
prob_lgmax	0.0419	0	0.3949	0.8009	0.6457	0.4005	0.5485	0.6199	0.4307
AIC	-5.7993	-5.8146	-5.824	-5.8218	-5.8192	-5.817	-5.8144	-5.8125	-5.8103
SBC	-5.7898	-5.8004	-5.805	-5.798	-5.7907	-5.7837	-5.7763	-5.7696	-5.7626

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-28.283	-22.044	-18.154	-15.603	-14.428	-12.953	-11.909	-10.895	-10.531
prob_lgmax	0	0.3517	0.8613	0.7017	0.3579	0.6009	0.6744	0.4748	0.4664
AIC	-5.812	-5.8224	-5.8204	-5.8176	-5.8156	-5.813	-5.8112	-5.8088	-5.8064
SBC	-5.8025	-5.8082	-5.8014	-5.7939	-5.787	-5.7797	-5.7731	-5.7659	-5.7587

Series:LSPAIN

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.671	-2.6999	-2.6905	-2.5772	-2.601	-2.5648	-2.5221	-2.4418	-2.373
prob_lgmax	0.0076	0.0031	0.0527	0.5833	0.6757	0.4153	0.5765	0.3342	0.2849
AIC	-5.5178	-5.5233	-5.5242	-5.5229	-5.5204	-5.5182	-5.5157	-5.5144	-5.5134
SBC	-5.5083	-5.509	-5.5052	-5.4992	-5.4919	-5.4849	-5.4777	-5.4715	-5.4657

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-29.487	-23.13	-19.143	-16.668	-15.187	-13.983	-13.236	-11.878	-10.906
prob_lgmax	0	0.0467	0.5565	0.6493	0.3971	0.5581	0.3233	0.2942	0.4618
AIC	-5.5182	-5.5192	-5.5184	-5.5158	-5.5138	-5.5115	-5.5105	-5.5099	-5.5079
SBC	-5.5087	-5.5049	-5.4995	-5.4921	-5.4853	-5.4782	-5.4724	-5.467	-5.4602

Series:LEURO

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.3129	-2.2896	-2.2907	-2.239	-2.2072	-2.2197	-2.1861	-2.1495	-2.1079
prob_lgmax	0.02073	0.00651	0.00215	0.53742	0.60394	0.32053	0.63691	0.01996	0.38319
AIC	-5.7857	-5.7901	-5.7964	-5.7942	-5.7917	-5.7899	-5.7873	-5.79	-5.788
SBC	-5.7763	-5.7759	-5.7774	-5.7705	-5.7632	-5.7566	-5.7493	-5.7471	-5.7404

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-29.686	-24.013	-19.627	-16.491	-15.116	-13.878	-13.698	-12.266	-11.618
prob_lgmax	0	0.00205	0.53505	0.60577	0.31967	0.63828	0.02036	0.37694	0.6689
AIC	-5.787	-5.7933	-5.7913	-5.789	-5.787	-5.7846	-5.7874	-5.7856	-5.7832
SBC	-5.7775	-5.779	-5.7723	-5.7652	-5.7585	-5.7513	-5.7493	-5.7427	-5.7355

Series:LEUROPLUS

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.2647	-2.2256	-2.2448	-2.1973	-2.1625	-2.181	-2.1507	-2.1292	-2.0825
prob_lgmax	0.02353	0.00678	0.00205	0.52874	0.61314	0.31393	0.62738	0.01926	0.39004
AIC	-5.7855	-5.7899	-5.7962	-5.7941	-5.7915	-5.7897	-5.7872	-5.7899	-5.7879
SBC	-5.776	-5.7756	-5.7772	-5.7703	-5.763	-5.7564	-5.7491	-5.747	-5.7403

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-29.686	-24.013	-19.627	-16.491	-15.116	-13.878	-13.698	-12.266	-11.618
prob_lgmax	0	0.00205	0.53505	0.60577	0.31967	0.63828	0.02036	0.37694	0.6689
AIC	-5.787	-5.7933	-5.7913	-5.789	-5.787	-5.7846	-5.7874	-5.7856	-5.7832
SBC	-5.7775	-5.779	-5.7723	-5.7652	-5.7585	-5.7513	-5.7493	-5.7427	-5.7355

Series:LEUROMINUS

ADF test- level (with constant) MacKinnon critical values: 1%: -3.4394 5%: -2.8647

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-2.3839	-2.4056	-2.3562	-2.2947	-2.272	-2.2676	-2.2261	-2.1488	-2.1222
prob_lgmax	0.01713	0.00577	0.00246	0.56297	0.57762	0.34019	0.66479	0.02209	0.36395
AIC	-5.7861	-5.7907	-5.7967	-5.7945	-5.792	-5.7901	-5.7875	-5.79	-5.7881
SBC	-5.7766	-5.7764	-5.7777	-5.7707	-5.7635	-5.7568	-5.7494	-5.7471	-5.7404

ADF first difference (with constant)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
t-stat	-29.686	-24.013	-19.627	-16.491	-15.116	-13.878	-13.698	-12.266	-11.618
prob_lgmax	0	0.00205	0.53505	0.60577	0.31967	0.63828	0.02036	0.37694	0.6689
AIC	-5.787	-5.7933	-5.7913	-5.789	-5.787	-5.7846	-5.7874	-5.7856	-5.7832
SBC	-5.7775	-5.779	-5.7723	-5.7652	-5.7585	-5.7513	-5.7493	-5.7427	-5.7355

APPENDIX 2 Optimization algorithm

Table 3. Engle-Granger cointegration tests (round 1)

SERIES NAME	ADF H0: I(1) vs I(0)
RESIDAU	-4.7471
RESIDBE	-4.7094
RESIDFI	-6.6327
RESIDFR	-6.1154
RESIDGE	-4.7469
RESIDGR	-5.2723
RESIDIR	-4.6777
RESIDIT	-4.9688
RESIDNE	-5.4707
RESIDPO	-3.9057
RESIDSP	-6.3582

Table 4. Engle-Granger cointegration tests

(round 2, after eliminating Finland index)

SERIES NAME	ADF H0: I(1) vs I(0)
RESID01AU	-7.1659
RESID01BE	-6.4796
RESID01FR	-6.5213
RESID01GE	-5.0125
RESID01GR	-6.318
RESID01IR	-6.4678
RESID01IT	-5.8177
RESID01NE	-7.3124
RESID01PO	-5.4401
RESID01SP	-6.8202

Table 5. Engle-Granger cointegration tests

(round 3, after eliminating Finland and Netherlands)

SERIES NAME	ADF H0: I(1) vs I(0)
RESID02AU	-7.0592
RESID02BE	-7.1881
RESID02FR	-6.3224
RESID02GE	-5.2677
RESID02GR	-6.9923
RESID02IR	-7.0693
RESID02IT	-6.0594
RESID02PO	-6.2361
RESID02SP	-7.3568

APPENDIX 2 (continued)

Table 6. Engle-Granger cointegration tests

(round 4, eliminated: Finland, Netherlands and Spain)

SERIES NAME	ADF H0: I(1) vs I(0)
RESID03AU	-7.1127
RESID03BE	-7.2266
RESID03FR	-5.5149
RESID03GE	-5.8952
RESID03GR	-7.0518
RESID03IR	-6.8181
RESID03IT	-6.893
RESID03PO	-6.9268

Table 7. Engle-Granger cointegration tests
(suboptimal round)

SERIES NAME	ADF H0: I(1) vs I(0)
RESID04AU	-7.0568
RESID04FR	-5.525
RESID04GE	-4.8763
RESID04GR	-6.4989
RESID04IR	-6.7358
RESID04IT	-6.8774
RESID04PO	-6.0192

Table 16. Short portfolio optimization summary

	Residual Series	ADF t-stat
round 1	r_ge	-5.8476
round 2	r_01fr	-6.2491
round 3	r_02au	-6.2563
round 4	r_03it	-6.2609
round 5	r_04sp	-6.4368
round 6	r_05ne	-6.2523

APPENDIX 3. Asset allocations

Tabel 22a. Asset allocation of the long portfolio monthly rebalanced

Month		austria	france	germany	greece	ireland	italy	portugal
May	2001	-4.86%	57.94%	31.37%	-2.24%	5.07%	20.85%	-8.12%
Jun	2001	-4.52%	60.53%	29.86%	-2.41%	5.78%	18.46%	-7.70%
Jul	2001	-4.63%	60.91%	29.41%	-2.18%	5.32%	18.04%	-6.87%
Aug	2001	-4.68%	61.06%	28.78%	-1.87%	4.68%	18.11%	-6.08%
Sep	2001	-4.83%	60.75%	28.76%	-1.74%	4.39%	18.48%	-5.80%
Oct	2001	-5.03%	62.89%	27.25%	-1.69%	4.57%	16.82%	-4.82%
Nov	2001	-5.30%	63.71%	26.67%	-1.71%	4.75%	16.25%	-4.37%
Dec	2001	-6.04%	64.97%	25.96%	-1.77%	5.16%	15.26%	-3.55%
Jan	2002	-6.29%	65.64%	25.82%	-1.88%	5.59%	14.45%	-3.32%
Feb	2002	-6.27%	65.62%	26.06%	-1.87%	5.48%	14.44%	-3.46%
Mar	2002	-5.72%	64.34%	27.97%	-1.55%	3.63%	15.80%	-4.46%
Apr	2002	-5.53%	63.88%	28.70%	-1.54%	3.15%	16.18%	-4.84%
May	2002	-5.45%	63.57%	29.28%	-1.48%	2.90%	16.59%	-5.41%

Tabel 22b. Asset allocation of the short portfolio monthly rebalanced

Month		belgium	finland	greece	ireland	netherlands	portugal
May	2001	5.13%	20.43%	2.21%	-8.05%	42.78%	37.51%
Jun	2001	4.92%	20.34%	1.14%	-5.77%	43.72%	35.65%
Jul	2001	5.30%	21.06%	-0.59%	-1.85%	43.49%	32.59%
Aug	2001	6.13%	21.74%	-1.90%	0.57%	42.75%	30.70%
Sep	2001	6.83%	21.80%	-2.43%	1.18%	43.66%	28.96%
Oct	2001	6.77%	21.08%	-2.55%	1.55%	45.71%	27.45%
Nov	2001	5.75%	20.08%	-1.91%	1.05%	48.51%	26.52%
Dec	2001	4.86%	19.11%	-1.37%	0.35%	51.33%	25.72%
Jan	2002	4.84%	18.75%	-1.23%	0.00%	52.29%	25.34%
Feb	2002	4.88%	18.55%	-1.21%	0.07%	52.69%	25.02%
Mar	2002	3.70%	18.36%	-1.41%	2.01%	52.59%	24.75%
Apr	2002	1.50%	18.03%	-1.32%	3.46%	52.71%	25.62%
May	2002	-1.78%	17.40%	-0.95%	4.49%	53.64%	27.19%

APPENDIX 3 (continued)

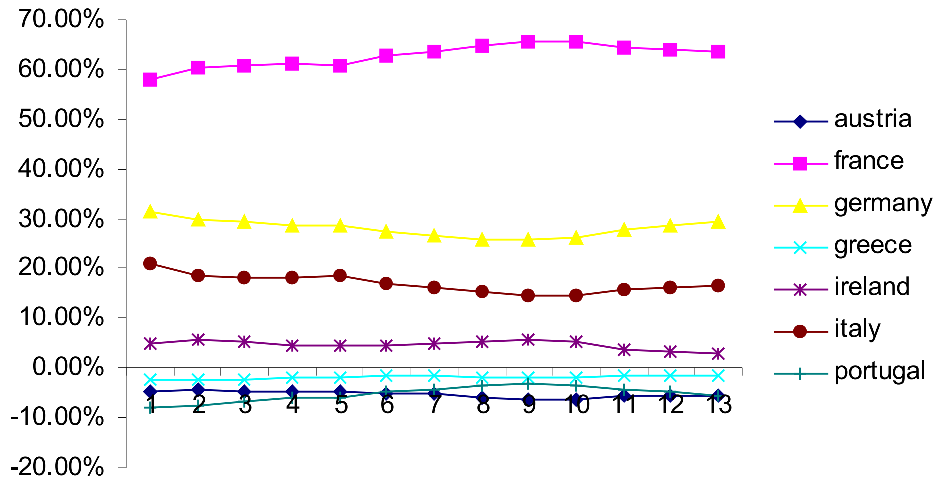

Figure A. The weights of the long cloning portfolio during testing period

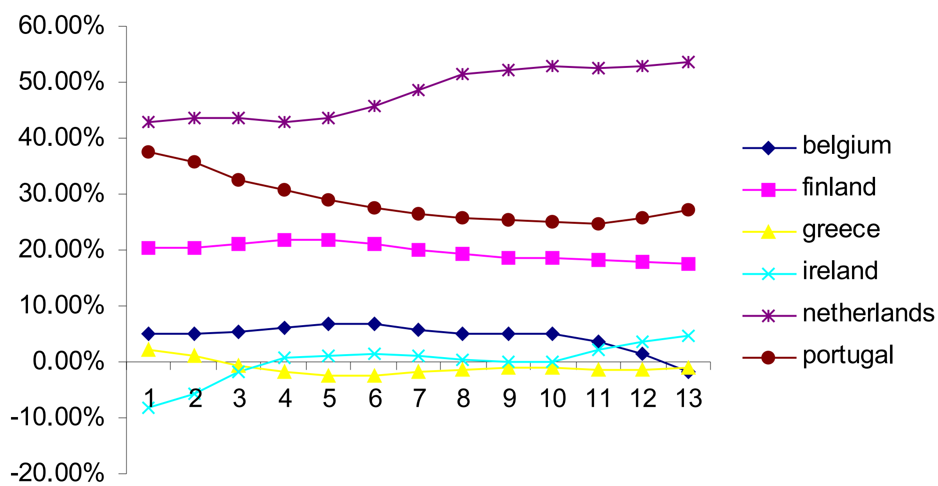

Figure B. The weights of the short cloning portfolio during testing period

APPENDIX 4

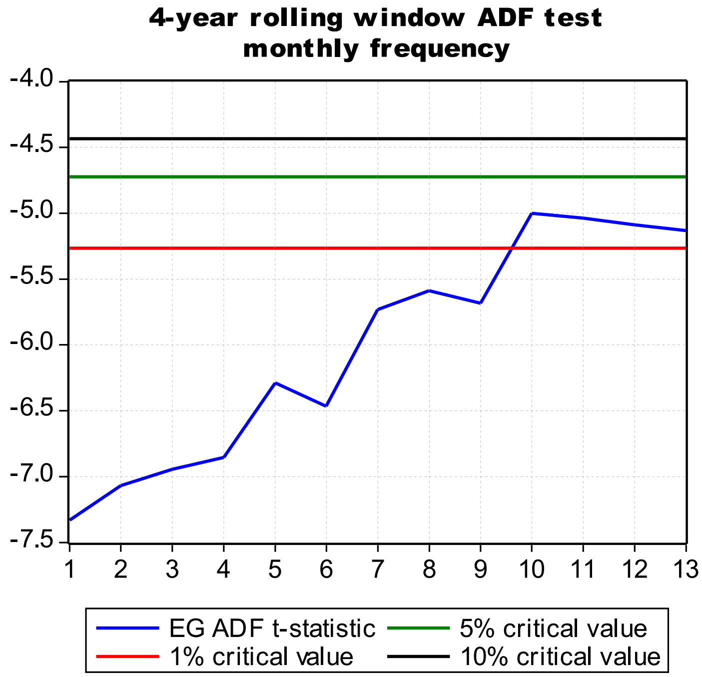

Figure 1. Monthly EG rolling cointegration tests for the unmanaged portfolio

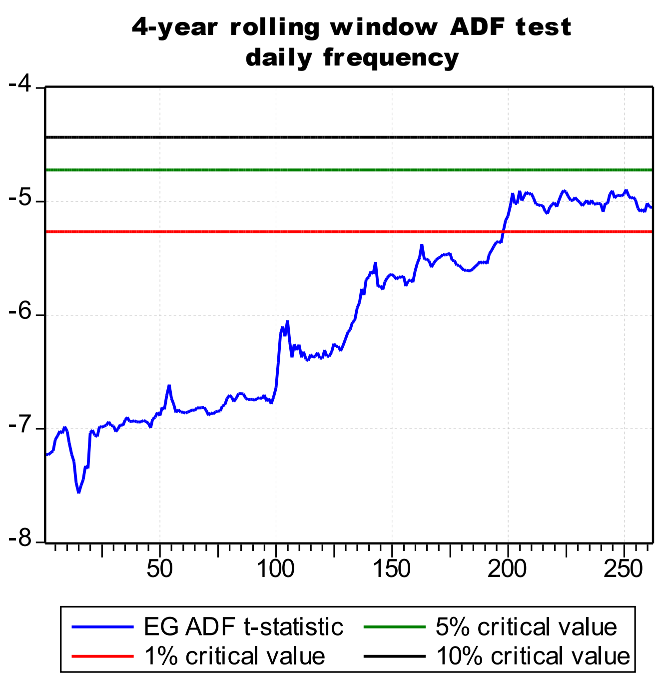

Figure 2. Daily EG rolling cointegration tests for the unmanaged portfolio

APPENDIX 4 (continued)

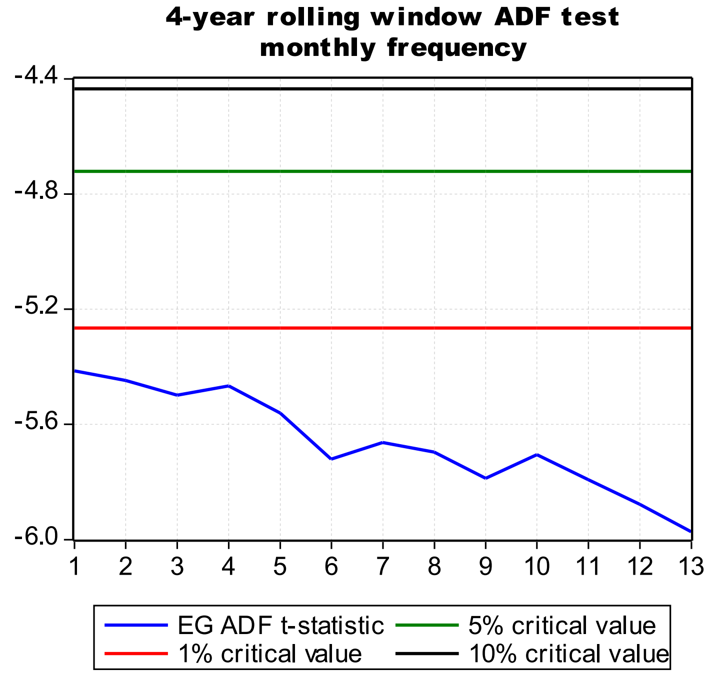

Figure 3. Monthly EG rolling cointegration tests for the rebalanced portfolio

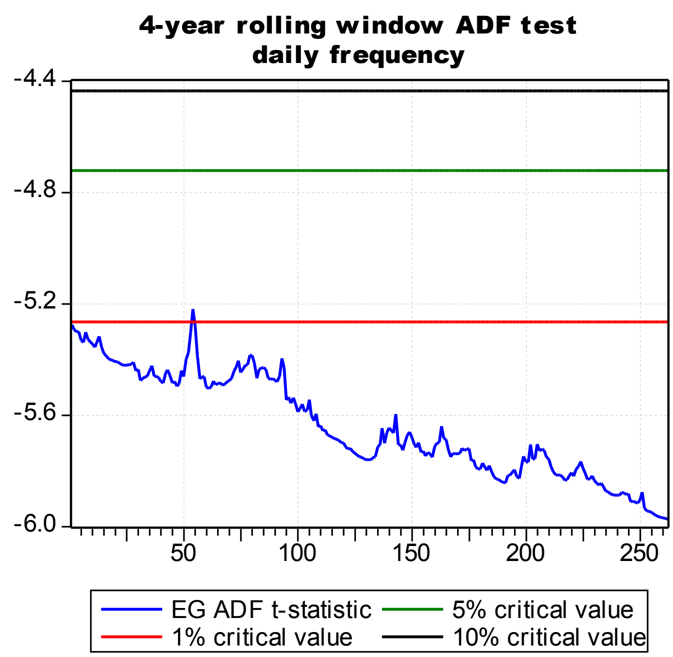

Figure 4. Daily EG rolling cointegration tests for the rebalanced portfolio

APPENDIX 4 (continued)

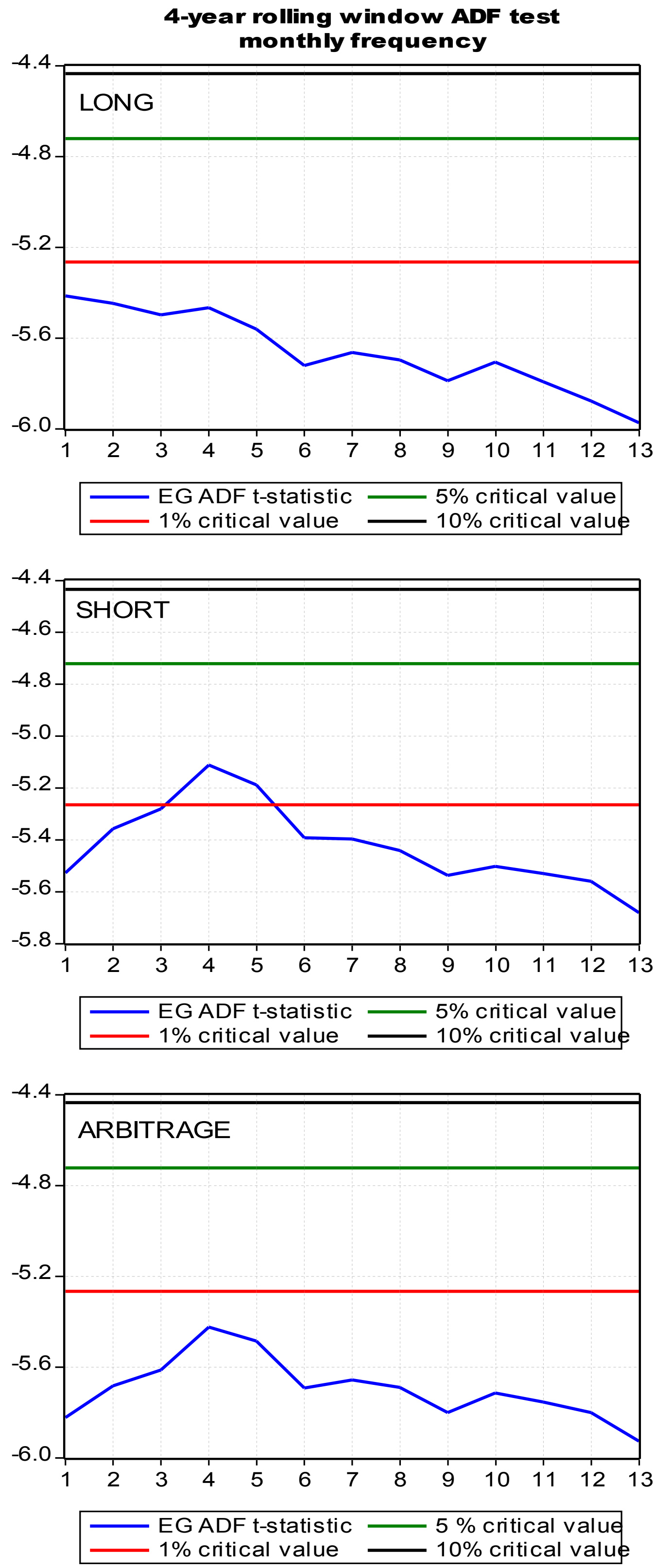

Figure 10. Rolling ADF tests for the long, short and arbitrage portfolios

APPENDIX 5.

Table 14.
The effects of transaction costs on the returns generated by the rebalanced cloning strategy

a=0.1%		a=0.2%		a=0.5%	
Net rebalanced cloning return	**Cumulated net rebalanced cloning return**	**Net rebalanced cloning return**	**Cumulated net rebalanced cloning return**	**Net rebalanced cloning return**	**Cumulated net rebalanced cloning return**
-6.8065%	-6.8065%	-6.8587%	-6.8587%	-7.0155%	-7.0155%
-2.8562%	-9.6627%	-2.8733%	-9.7320%	-2.9243%	-9.9397%
0.0792%	-9.5836%	0.0639%	-9.6680%	0.0183%	-9.9215%
-5.0072%	-14.5907%	-5.0163%	-14.6843%	-5.0436%	-14.9650%
-14.5178%	-29.1085%	-14.5598%	-29.2441%	-14.6858%	-29.6508%
4.7897%	-24.3188%	4.7716%	-24.4725%	4.7173%	-24.9335%
4.2476%	-20.0713%	4.2167%	-20.2558%	4.1241%	-20.8094%
3.0859%	-16.9854%	3.0699%	-17.1859%	3.0222%	-17.7872%
-5.9603%	-22.9457%	-5.9637%	-23.1495%	-5.9736%	-23.7608%
-0.0983%	-23.0441%	-0.1488%	-23.2983%	-0.3000%	-24.0608%
5.8675%	-17.1766%	5.8513%	-17.4470%	5.8026%	-18.2582%
-2.2164%	-19.3930%	-2.2299%	-19.6769%	-2.2703%	-20.5285%

Table 21.
The effects of transaction costs on the returns generated by the rebalanced arbitrage strategy

a=0.1%		a=0.2%		a=0.5%	
Net rebalanced arbitrage return	**Cumulated net rebalanced arbitrage return**	**Net rebalanced arbitrage return**	**Cumulated net rebalanced arbitrage return**	**Net rebalanced arbitrage return**	**Cumulated net rebalanced arbitrage return**
0.2885%	0.2885%	0.2090%	0.2090%	-0.0296%	-0.0296%
0.2630%	0.5515%	0.1900%	0.3990%	-0.0290%	-0.0586%
0.2906%	0.8420%	0.2291%	0.6281%	0.0448%	-0.0138%
0.3159%	1.1580%	0.2798%	0.9079%	0.1716%	0.1578%
0.2486%	1.4066%	0.1773%	1.0852%	-0.0369%	0.1209%
0.3040%	1.7106%	0.2401%	1.3252%	0.0482%	0.1691%
0.2759%	1.9866%	0.1999%	1.5251%	-0.0283%	0.1409%
0.3055%	2.2921%	0.2750%	1.8001%	0.1834%	0.3243%
0.3595%	2.6516%	0.3511%	2.1512%	0.3257%	0.6500%
0.2474%	2.8990%	0.1747%	2.3259%	-0.0432%	0.6068%
0.2886%	3.1875%	0.2411%	2.5670%	0.0989%	0.7056%
0.2900%	3.4775%	0.2279%	2.7950%	0.0419%	0.7475%

APPENDIX 5 (continued)

Table 12. Turnover index for the arbitrage strategy and its components

Month	TO(%) Long	TO(%) Short	TO(%) Arbitrage
May-01	4.06	3.22	6.40
Jun-01	1.45	5.02	6.47
Jul-01	1.31	3.93	5.25
Aug-01	0.78	2.27	3.05
Sep-01	3.36	2.42	5.60
Oct-01	1.45	3.44	4.89
Nov-01	2.50	3.37	5.87
Dec-01	1.31	1.10	2.42
Jan-02	0.28	0.52	0.65
Feb-02	4.13	1.95	5.81
Mar-02	1.31	2.53	3.83
Apr-02	1.13	3.91	4.98

Table 20. Transaction costs incurred by the rebalanced arbitrage strategy

Turnover	Transaction costs		
	a = 0.1%	a = 0.2%	a = 0.5%
0.730018	0.00073	0.001460035	0.00365009
0.614461	0.000614	0.001228921	0.0030723
0.360800	0.000361	0.000721601	0.001804
0.713716	0.000714	0.001427431	0.00356858
0.639610	0.00064	0.001279219	0.00319805
0.760510	0.000761	0.001521021	0.00380255
0.305218	0.000305	0.000610435	0.00152609
0.084584	8.46E-05	0.000169168	0.00042292
0.726422	0.000726	0.001452844	0.00363211
0.474294	0.000474	0.000948588	0.00237147
0.620287	0.00062	0.001240574	0.00310143

APPENDIX 6. Distributional properties of cloning errors

Table 15.
Distributional properties of cloning errors

Error	Long P	Long rbl P	Short P	Short rbl P
Mean	0.010147	0.001207	0.006660	0.002074
Median	0.011981	0.002274	-0.006811	-0.005947
Maximum	0.032453	0.014586	0.080644	0.049457
Minimum	-0.020394	-0.020299	-0.051729	-0.026488
Std. Dev.	0.011858	0.007568	0.034781	0.021043
Skewness	-0.358671	-0.449998	0.601555	0.721445
Kurtosis	2.232754	2.301240	1.976044	2.103339