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DO BUSINESS CYCLES EXHIBIT BENEFICIAL INFORMATION FOR PORTFOLIO MANAGEMENT? AN EMPIRICAL APPLICATION OF STATISTICAL ARBITRAGE

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Abstract. An advantageous statistical arbitrage strategy should exhibit a zero-cost trading strategy for which the expected payoff should be positive. In practical applications, however, the abnormal returns often are out-of-sample not significant. The statistical model being suggested here results in an estimated portfolio exhibiting in-sample a cointegration relationship with the artificial stock index. The portfolio returns exhibited out-of-sample a mean of 10.44% p.a., whereas the volatility was one third lower in comparison to the benchmark's volatility. Accounting for trading costs of 2.94% p.a. on average, the annual returns of the estimated portfolio are out-of-sample still 6.83% higher than the market returns. As a result, the model involves implicitly advantageous market timing.

1. Introduction

Probably the most basic principle of capital markets may be that equilibrium market prices are rational resulting in ruling out arbitrage opportunities. If market circumstances allow for arbitrage, the consequence will be strong pressure so that the market equilibrium will be restored immediately. Hence, capital markets should satisfy a "no-arbitrage condition". The arbitrage pricing theory (APT) as introduced by Ross (1976), however, is based on three key propositions: First, asset returns may be explained by a factor model. Second, there are sufficient assets to diversify away any idiosyncratic risk. The third is that efficient security markets ought not to allow for the persistence of arbitrage possibilities. In contrast to the Capital Asset Pricing Model (CAPM), the APT is based on the idea of factor risk, but the factors influencing the asset returns remain unknown.

Fama and French (1992) identify the firm's size and the ratio of book-to-market value as the two main determinants of the cross-sectional expected returns. Schwert (2002) argues that effects, such as the size effect or the book-to-market effect seem to have weakened over time or simply disappeared after the paper that highlighted those empirical observations were published. Even though Schwert (2002) states that practitioners constructed investment vehicles that implemented arbitrage strategies implied by some research cause the anomalies to disappear, the research that aims to figure out arbitrage opportunities and market anomalies is still large. However, as long as the economic theory involved is little and the detected anomalies are rather based on empirical facts these forces seem to vanish over time.

Basically, there are two possibilities to figure out arbitrage opportunities: On the one hand, the investor may employ active investment strategies. Active strategies are pursued if the investor is convinced that the market does not work efficient. In accordance to van Montefort,

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Visser and van Draat (2008), active investment strategies have several disadvantages: First, they implicate high research and trading costs, which lower any returns gained. The second is that active investment strategies apart from that often involve high risks, imposing the return required higher. The third main disadvantage is that active strategies presuppose extensive knowledge about stocks and the underlying stock markets. On the other hand, with the averaged lower costs of investing passively the different disadvantages of active strategies are major reasons to develop passive strategies as the alternative to figure out arbitrage opportunities. An arbitrage opportunity arises basically if an investor can earn profits without making a net investment and without bearing any risk. In real life, however, arbitrage opportunities occurring are rather based on statistical arbitrage theory as pointed out by Bondarenko (2003). The concept of statistical arbitrage opportunities (SAO) involves three main issues: In a finite time horizon, the SAO exhibits first of all a zero-cost trading strategy for which the expected payoff should be first of all positive. Second, the conditional expected payoff in every final state of the economy is nonnegative. The third issue in contrast to pure arbitrage opportunities is that a SAO may exhibit negative payoffs only stochastically provided that the average payoff in each final state is nonnegative.

In line with the seminal work of Markowitz (1959), Sharpe (1964), Lintner (1965), and Black (1972), the traditional statistical tool for portfolio optimization and, consequently, SAO is correlation analysis of assets returns focusing on minimizing the variance of a tracking error. Alexander (1999), however, introduces the cointegration approach for portfolio modeling. Cointegration, as defined and developed by Granger (1981) and Engle and Granger (1987), is a property of some nonstationary time series. If two or more nonstationary time series are cointegrated, a linear combination relationship being stationary is said to exist. In the context of portfolio theory, whether the value series of a fixed weight portfolio of assets with nonstationary prices is stationary, the assets will exhibit a cointegrated set. The set of asset weights generating such a portfolio is called the cointegrating vector.

The aim of statistical arbitrage trading strategies accounting for cointegration analysis, can be to exploit long- or short-run relationships between equities and an underlying stock market, for instance. Alexander, Giblin and Weddigton (2001) investigated the performance of various long-short trading strategies worked out in the S&P 100 stock market. The S&P 100 Index which is a subset of the S&P 500® measures the performance of 100 companies in the US-stock market which exhibit the highest market capitalization. Alexander, Giblin and Weddigton (2001) construct long-short portfolios optimized on different model parameters like training period, composed tracking error and number of stocks being contained in the portfolio. Apart from that their models based on cointegration analysis exhibit robust alphas with low volatility and no autocorrelation. Thereby, the optimization procedure rests upon a black box selection algorithm.

In another application of statistical arbitrage strategies that is especially relevant to my line of research, Alexander and Dimitriu (2005) construct portfolios tracking artificial indices and trading on their spread. This approach is often referred to as "enhanced indexation". They highlight that the response of statistical arbitrage portfolios on eventful samples, like strong market declines, exhibit poor performances irrespective if cointegration analysis is applied or not. Furthermore they find that the best performance is achieved by strategies tracking narrow spreads up to plus 5% hedged with the portfolio tracking the real underlying benchmark. The wider the spread the more volatile the abnormal returns without the compensation of additional returns. However, cointegration-optimal statistical arbitrage strategies clearly dominate their correlation based counterparts over a sample spanning ten years resulting in stable out-of-sample alphas and low volatility as long as narrow spreads are tracked, only.

Malkiel's (1995) studies the consistency of mutual funds performance. His studies' outcome is that the evidence performance being consistent from one period to the next is suggestive, but it is inconclusive. However, mutual funds that go out of business tend to be poor performers. Consequently, Malkiel's (1995) studies are possibly subject to survivorship bias. The challenging question still remains: Is it possible to find an asset allocation strategy exhibiting a portfolio that beats the benchmark continuously?

The presence of cointegration relationships presents a number of considerable benefits for a passive trading strategy. To the best of my knowledge, though, there are no dispositive studies that investigate statistical arbitrage strategies accounting for cyclical patterns which assets may exhibit during the business cycle, for instance. In this work, however, I attempt to remedy this.

Portfolio managers' attempt to perform better than the benchmark often results in an increase of the portfolio volatility often referred to as being the risk-return trade-off. In this work a passive trading strategy shall be suggested exhibiting significantly higher profits (i.e. 48.85% gross return) and lower volatility (i.e. 30% lower volatility) out-of-sample compared to the underlying Index. Apart from cointegration analysis, the strategy depicts an implicit market timing associated with business cycle movements entailing temporarily under- respectively overpricing of various business sectors. The trading strategy should ensure figuring out sectors that switch from underpriced to overpriced, while assuming the stochastic trend to hold within the out-of-sample period. Thus, business cycle movements can be exploited by the investors.

2. Background

In compliance with Kitchin (1923) who analyzes cycles and trends in economic factors, minor business cycles averaging 40 months in length. Keynes (1936) and Hicks (1950) argue that major economic time series respond asymmetric over different phases of the business cycle. Even if Neftci (1984) mentions that trends are difficult to figure out, the link between stock market and business cycle is well documented as stated by Chauvet (1998). Industrial production and capacity utilization are two main indicators and guideposts for monitoring swings in corporate profits through the business cycle. Taylor (1997) underlines, that year-on-year peaks in industrial production growth, basically, occur simultaneously with peaks in nonfinancial corporate profits.

Even though the cyclical behavior of prices are well documented in the literature, as pointed out by Smith (1992), the stochastic properties of sectors, respectively, prices may change over time. For instance, during the boom of 1999/2000, the telecommunication sector showed the following cyclical patterns: During the peak in the stock market, the companies operating in the latter sector were overpriced. As a result, the telecommunication sector was seen to be cyclical[1]. *Figure 1* provides an overview of the cyclical patterns with respect to the S&P 500 index and the investment funds DWS *Telemedia* which invests mainly in the US-telecommunication sector[2]. The time series runs from 01.08.1995 until 31.07.2009.

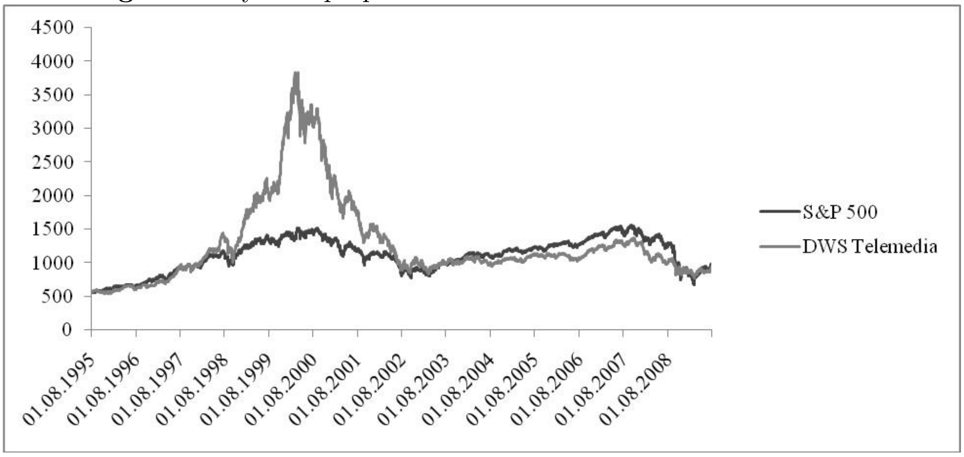
The first empirical fact that a model should account for, can be summarized as follows: Stock market sectors respond different in various phases of the business cycle. Sectors which exhibit a beta larger than one during one cycle can exhibit a beta smaller than one during another cycle. Even if other economists, like Schumpeter (1955), argue that the typical business cycle[3] indicates a duration of rather 7-11 years, a period between three and four years may be considered as being the lower-bound of a business cycle. Consequently, a model should comprise at least the information comprehended by the business cycle's lower bound. During business cycles various sectors may respond differently, whereas the stochastic patterns may change from one business cycle to the next one.

[1]For instance, even though the EPS of the stock „Deutsche Telekom AG“ was negative in 1999, the stock exhibited peak prices which were larger than EUR 100.

[2]The mutual funds DWS *Telemedia* (ISIN: DE0008474214 WKN: 847421) that was launched on 04/07/1994 invest in equities from the telecommunications, media and communications industries with a geographical focus on the U.S. The benchmark is the MSCI World Telecommunication Services. DWS Investments, a member of Deutsche Bank Group is one of the world's leading asset management company (see www.dws.com).

[3]Identified in 1860 by the French economist Clement Juglar.

Figure 1. Cyclical properties of the telecommunication sector



Note: The prices of the investment funds DWS Telemedia is multiplied by the factor 14.35 in order to make the issue visible.

Furthermore, stock markets exhibit the following empirical characteristics: Keown and Pinkerton (1981) figure out that the cumulative abnormal return of target companies regarding a takeover is starting to generate positive abnormal returns already two to three weeks before the announcement day[4]. Moreover, Busse and Green (2002) report stock price reactions occurring before the CNBC reports. Magnus (2008) observes also inefficiencies in stock markets and rejects the weak-form efficient market random walk hypothesis. Therefore, in the following it will be assumed that historical stock prices reflect the whole information given at any point in time, respectively, time window. Hence, the second assumption is that stochastic trends of stock prices, respectively, sectors can be anticipated as their historical prices provide implicitly the whole information needed.

Stochastic trends with respect to different sectors should be relatively stable during the business cycle[5]. Even if the market tends to hyperbolize, especially in case of a speculative bubble is formed up, Blanchard and Watson (1982) point out that the sector will adjust the stronger the more excessive the bubble has been. Consequently, the third assumption is that sectors which are overpriced in the first time window will be underpriced in the next one, since markets show empirically a tendency of exaggeration. Just like the overpricing of the telecommunication and internet sector in the year 1999/2000 being studied by Jensen (2005) and Harmantzis (2004), the same happened to the financial sector under the bubble formation of the year 2007/2008 as described by Baker (2008) and Soros (2008).

Furthermore, there are several works available that employ cointegration theory to other fields of research. Bossaerts (1988), for instance, developed a test of cointegration and applied it to size-based and industry-based stock portfolios. His results provide substantial evidence of cointegration. Furthermore, Corhay et al. (1993), who studied the relationships among regional stock markets to find potential gains from international diversification, figured out cointegration relationships among stock prices in several European countries. Gregoriou and Rouah (2001) examined hedge fund investments. They tested common stochastic trends between the ten largest hedge funds of different styles and the equity market indices of the S&P 500, the MSCI World, the Russell 2000, as well as the NASDAQ index from January 1991 through December 2000. They found evidence of cointegration with the stock market indices for only two of the hedge funds. In accordance to Gregoriou and Rouah (2001) there is a tendency of large hedge funds to allocate assets over a wide range of investment instruments, such as futures, swaps,

[4]Keown and Pinkerton (1981) analyzed a sample of 194 companies that were targets of takeover attempts.
[5]See illustration 1 as an example.

currencies and options, for instance. Hence, the performance of these hedge funds will not be strongly tied to standard benchmarks.

3. Statistical Model

The model suggested by Alexander and Dimitriu (2005) involves two major drawbacks: First, when constructing the artificial index they add, respectively, subtract uniformly distributed returns only. As a consequence the hypothetical index being tracked exhibits the same volatility as the ordinary index which seems to be not plausible as higher returns should be correlated with higher risk. Second, their model does not account for a switching trend within the in-sample time window, but operates with an ordinary linear trend only. Consequently, their model does not capture the information being involved in the business cycle. Therefore, another statistical model should be presented which is able to account for these drawbacks.

The approach can be divided into two parts. First, the methodology concerning the weight allocation will be described. Considering this, a rolling time window of four years is taken into account in order to estimate weights that will be hold constant one year ahead. Second, the overall out-of sample window employing the estimated weights will be priced afterwards in order to figure out the overall as well as average performance.

Since it is assumed that there are sectors in the economy that respond differently in various phases of the business cycle, the stochastic process of each sector should exhibit information whether a sector within the current phase under consideration is under- or overpriced. Consequently, a sector that is underpriced within the first phase of the cycle is assumed to exhibit a stronger price increase compared to other sectors during the following phase. As stochastic trends are explored, Alexander (1999) points out that the information which is necessary is involved in the price process rather than in the process of the corresponding asset returns being detrended. In contrast to Alexander (1999) who uses log prices, in the following, transformed time series should be employed as follows: Given the returns R_{it}, where $R_{it} = (P_{it} - P_{it-1}) \times 100/P_{it-1}$and P_{it} denotes the price of mutual funds i at time t and the index $i = 1, ..., 11$ denotes the index concerning the mutual funds being employed as substitutes for the business sectors (see table 1), and given the index returns $R_t^{S\&P500}$ the time series are retrended in the following way:

$$y_t = 100 + \sum_{j=1}^{t} R_j^{S\&P500} \tag{3.1}$$

$$x_{it} = 100 + \sum_{j=1}^{t} R_{ij} \tag{3.2}$$

The transformed time series y_t and x_{it} have basically two important features: Testing for cointegration shows that the transformed time series are not cointegrated with the ordinary time series in price levels, but exhibit a strong cointegration relationship with the logarithm of the latter instead. Roughly spoken, the transformation (1) and (2), respectively, is like the logarithm a kind of linearization. Furthermore, when taking the first differences Δy_t or Δx_{it} it is ended up with the ordinary return series $R_t^{S\&P500}$ and R_{it} again[6]. This feature may be important later when the significance of the model's trend-parameter will be tested. Since it is operated with integrated time series, the linear trend-parameter corresponds to the alpha of Sharp's (1964) index model which involves asset returns. If the trend-stationary stochastic process is significant even within the out-of-sample windows, the model will perform well.

The optimization procedure being applied here should meet two requirements: It should provide an estimation of asset allocations that first of all exhibit the same stochastic patterns like the underlying stock index and second, imbed a trend stationary stochastic process such that the portfolio erases from the benchmark while generating stable positive abnormal returns

[6]Illustration 1 exhibits the transformed time series corresponding to equation (1) and (2).

within the out-of-sample period. The first point ensures that the portfolio can be priced with the benchmark at all, whereas the second point should assure that the portfolio outperforms the index. Therefore, the trend stationary stochastic process being involved must be stable over time. Alexander and Dimitriu (2005) emphasize that cointegration as statistical tool ensures that the constructed portfolio is tied closely to the benchmark, irrespective of the system's position.

In accordance to the third assumption, one is looking for an asset combination (i.e. sector allocation) exhibiting a portfolio that switches from underpriced during the first part of the in-sample-period to overpriced in the second part of the in-sample-period, assuming the stochastic trend to hold in the out-of-sample (i.e. one year ahead). As the lower bound of a business cycle is three to four years, each step employs a rolling time window of four years of daily data to estimate the weight allocation that will be hold constant one-year ahead. This is also in line with Alexander and Dimitriu (2005) who use a large data set of three years to estimate asset weights.

Concerning the optimization procedure it is essential to construct the artificial index (i.e. the index plus a positive return) which serves as independent variable and should be tracked tightly by the portfolio. Consequently, the artificial index y_t^* is needed for estimating the quasi-maximum likelihood function. In accordance to the assumptions, it should always be possible to find sectors which switch from underpriced to overpriced or vice versa, irrespective of what is the current status of the business cycle or, respectively, the stock index.

The artificial index return series $R_t^{*S\&P500}$ is constructed as follows: One sets out from the ordinary index returns $R_t^{S\&P500}$ and adds simply returns which satisfy the requirements above. In contrast to Alexander and Dimitriu (2005) who draw uniform distributed returns to construct the artificial index, here, stochastic returns $\overline{R_t}$ are drawn that are normally distributed with $E(\overline{R_t}) = \overline{R_t}$ and $VAR(\overline{R_t}) = VAR(R_t^{*S\&P500})$ in order to maintain the same stochastic patterns like the index ensuring the likelihood function to generate more stable weights. Apart from that one major issue in theoretical finance is the positive correlation between risk and return. Alexander and Dimitriu's (2005) model does not account for the latter issue because adding uniform distributed returns only does not entail that the artificial index's volatility increases. Furthermore, both distributions should exhibit the same volatility like the underlying stock index. Hence, one may get the following artificial index returns:

$$R_t^{*S\&P500} = R_t^{S\&P500} + \delta_t \overline{R_t} \tag{3.3}$$

with $\delta_t = -1$ for $t \in T_1$, $\delta_t = 1$ for $t \in T_2$ and $\overline{R_t}\tilde{\ } N(\overline{R_t}, VAR(R_t^{*S\&P500}))$. The dummy variable δ_t ensures the stochastic process $\overline{R_t}$ to switch after two years. Note that $E(R_t^{*S\&P500}) = E(R_t^{S\&P500})$ via construction as the expectation of $\overline{R_t}$ evens out with respect to the whole in-sample window per definition. In other words, the expected return of the artificial index is the same like the ordinary stock market return, but the volatility is higher being in line with finance theory. Therefore, the information is passed straight into the transformed price process of the artificial index, y_t^* which in accordance to equations (1)-(3) may be given by:

$$y_t^* = 100 + \sum_{j=1}^{t} R_j^{S\&P500} + \delta_t \sum_{j=1}^{t} \overline{R_t} \tag{3.4}$$

Figure 2 shows the ordinary and artificial index with respect to the first run of the optimization procedure. The first in-sample rolling time window runs from 01.08.2000-31.07.2004, while the estimated weights are hold constant one year ahead (i.e. 01.08.2004-31.07.2005 for the first run).

The next stage is to figure out a combination of sectors exhibiting stochastic patterns like y_t^*. As the price level, irrespective if in natural form or in logarithm, contains in contrast to the return processes in accordance to the second assumption additional information about stochastic trends, it should be possible, given the set of sectors, to find a trend stationary stochastic process which exhibits asymptotically the same properties like the artificial index. As the duration of the business cycle is in accordance to Kitchin (1923) at least 40 months, one may assume the stochastic trend to be relatively stable within an out-of-sample period of at least one year ahead. Grobys (2009a) suggests employing the following optimization procedure: Estimating first the quasi-maximum log-likelihood function including the whole set of N sectors being given by:

$$\log L(\theta,t) = -\frac{T}{2}\log(2\cdot\pi) - \frac{T}{2}\log\sigma^2 - \frac{1}{2}\sum_{t\in T}(\frac{(\varepsilon_t)^2}{\sigma^2}) \tag{3.5}$$

where:

$$\varepsilon_t = y_t^* - \sum_{i=1}^{N} a_i^2 x_{it} \tag{3.6}$$

Estimating the squared parameters ensures that the weights are positive. Afterwards the parameter vector $\widehat{a}$ can easily be obtained by taking the estimators' square roots. Furthermore, the standardizing restriction is imposed that the parameters $\widehat{a}_i$ may sum up to one. Thereby, Grobys' (2009a) suggestion is adopted and the parameters are standardized via $\widehat{a}_i^* = \widehat{a}_i \big/ \sum_{i=1}^{N}\widehat{a}_i$. Alexander and Dimitriu (2005) point out that testing for cointegration is essential when operating with time series in price levels or their logarithms (here: with transformed price processes). As long as cointegration holds, the allocated weights should cause a mean reversion of the tracking error ε_t so that the error term $\varepsilon_t = y_t^* - \beta_{P^*}P_t^*$, where $P_t^* = \sum_{i=1}^{N}\widehat{a}_i^* x_{it}$, should result in a time series exhibiting stationarity and mean reversion, even out-of-sample. (Note: β_{P^*} can easily be obtained via OLS estimation of the equation $y_t^* = c + \beta_{P^*}P_t^* + \varepsilon_t$).

After estimating the portfolio weight allocation concerning the first time window, it must be tested if the portfolio $P_t^* = \sum_{i=1}^{N}\widehat{a}_i^* x_{it}$ exhibits in-sample a cointegration relationship with the index or the artificial index. As a consequence, there are two possibilities of testing for cointegration: Either one employs the artificial index y_t^* and the constructed portfolio P_t^* or the transformed index y_t and P_t^* are employed. Grobys (2009a) though, mentions that applying the ordinary index and P_t^* involves the major drawback that the test statistic can be significant even if the constructed portfolio will exhibit a significant negative trend. Consequently, it might be better to use the artificial index and P_t^*. The test statistic being employed is the trace-test as introduced by Johansen (1988) and should not contain a trend term as long as the artificial index is employed.

Furthermore, if the test statistic suggests that cointegration does not hold, it should be possible to maximize the quasi-maximum likelihood function by employing the return series of the artificial index returns $R_t^{*S\&P500}$ as substitute for y_t^* and R_{it} as substitute for x_{it}. However, this approach can result in an unstable out-of sample behavior because it would be based on correlation, only. In fact, Alexander and Dimitriu (2005) show that the out-of sample error based on correlation analysis can be very sample specific and exhibit random walk behavior because correlation does not cause mean-reversion in stochastic processes. Despite that all out-of-sample time series put together can exhibit a cointegration as shown in the next section. The latter is the main condition because an investor is generally rather interested in the overall performance after the investment period.

Afterwards the sector portfolio should be priced respect to the overall out-of-sample process in order to see whether the trend component is statistically significant. As four years of daily data is used to estimate the weight allocation one year ahead, the out-of-sample period runs, as a consequence, from 01.08.2004-31.07.2009. Since it is operated here with integrated stochastic processes, Grobys (2009b) suggests unlike Treynor and Black (1973) employing Vector-Error-Correction Models (VECM) for pricing the cointegration portfolio's out-of-sample process. Thereby, he points out three major reasons for employing the more sophisticated VECM: First, the beta estimators of the cointegration model are super consistent in contrast to the beta estimators of the corresponding traditional index model. Second, as a result of the latter long-run forecasts regarding the portfolio's out-of-sample behaviour leads to more sufficient estimates because the cointegration relationship causes the portfolio and the benchmark to be tied together through the beta. Third, using the VECM representation may apart from that exhibit an estimate with respect to the average rebalancing time. This may give a clue of how actively a mutual fund is managed.

Figure 2. The S&P 500 and the artificial stock index S&P 500*

Note: S&P 500=y_t^*. The indices are standardized to be 100 concerning t=01.08.2000.*

If the gain is statistically significant, the trend component will be significant, too. Hence, one should estimate the VECM of the following form:

$$\Delta Y_t = \alpha(\beta' Y_{t-1} - \mu_0 - \mu_1 t) + \sum_{j=1}^{l} \Gamma_j \Delta Y_{t-1} + u_t \qquad (3.7)$$

where $\Delta Y_t = (\Delta P_t^*, \Delta y_t)$, Γ_j are parameter matrices and $u_t\,\tilde{}\,N(0, \sum)$. Note that the vector ΔY_t contains the ordinary returns series of both, the estimated sector portfolio and the index as $\Delta Y_t = R_t^{S\&P500}$. Afterwards the trend μ_1 parameter is tested for significance. According to the seminal work of Johansen (1991), the corresponding test statistic will be chi-square distributed with one degree of freedom.

4. Limitations of the Dataset

In this work, the S&P 500 index (i.e. benchmark) will be employed as the investment funds being analyzed invest mainly in the US-stock market. In accordance to Brown, Goetzmann, Ibbotson and Ross (1992), the investor faces basically a survivorship bias because mutual funds that perform unsuccessful over some time tend to go out of business. As a consequence, the access to mutual funds corresponding to different business sectors is limited.

Since it is also difficult to explore long time horizons due to the survivorship bias, in the following work nine years of daily data is considered, only. The overall period under consideration starts on the 01.08.2000 and ends on the 31.07.2009. Table I provides an overview of the mutual funds being employed as well as their target sectors and the percentage of the amount invested in US-stocks. Each mutual funds provider as well as the index provider in principle report on the same day. The dataset shows, however, that there are exceptions. Therefore, those days are taken into account only, where both of them publish their prices. As a result, 2184 trading days are investigated.

Table I. Mutual funds and business sectors

Mutual funds	**Sector**	**% in US-market**[7]	**i**
Allianz Logistics&Services	Logistics and Services	59.60	1
DWS Finanzwerte	Banks and Financial Service	12.50	2
DWS Nordamerika	US-Stock market	86.50	3
DWS PharmaMed	Pharma and Health	69.30	4
DWS Telemedia	Telecommunication and Media	41.10	5
DWS Energiefonds	Energy	50.10	6
DWS Rohstoffonds	Commodity	9.50	7
DWS Technologiefonds	Technology	73.40	8
DWS Gold plus	Gold	n.a.	9
DWS Bonds	Bonds (mid-term)	n.a.	10
DWS Internet	Internet and Services	91.60	11

5. Results

The rolling time window of the first in-sample period runs from 01.08.2000-31.07.2004 and includes 953 observations. The weights are holding constant for the first out-of sample period running from 01.08.2004-31.07.2005 and including 248 observations. Furthermore, the artificial index in accordance to equations (2)-(3) is constructed with $E(\overline{R_t}) = 0.06$ and $VAR(\overline{R_t}) = VAR(R_t^{S\&P500})$. Consequently, the artificial index is expected to perform 15% p.a. worse than the ordinary Index during the first part of the in-sample time window running from 01.08.2000-31.07.2002, while performing 15% p.a. better than the index during the second part of the first in-sample period running from 01.08.2002-31.07.2004. Moreover, the variance concerning the normally distributed process $\overline{R_t}$ is via construction the same like the ordinary stock index's variance. Five in-sample/out-of sample periods could be investigated as shown in table II. As trading costs differ between the mutual funds employed and as they arise for buying fund shares only[8], table II exhibits the absolute difference of the weight distribution for each rebalancing moment, too as well as the incurring trading costs.

Regarding the last sample, the optimization procedure showed that it is not possible to find a linear combination which maximizes the likelihood function given the set of mutual funds. Therefore, the weights are allocated by estimating the quasi-log-likelihood of the returns series, instead of the transformed price series. Samples 1-4 exhibit weight allocations estimated by employing the transformed price processes and, hence, by applying cointegration.

[7]The information is available for free on the provider's homepage, as of 14.11.2009.

[8]Note for the analysis it does not matter if the costs are imposed for buying or selling the shares.

Table II. Weight allocations after each rebalancing moment

Run	Mutual funds/Sector	$Weight(i)$	$\Delta Weight(i)$	Trading costs	In-sample	Issue fee[9]
1	Allianz Logistics&Services	0.00	-	0.0000		5%
1	DWS Finanzwerte	0.12	+0.12	0.0000	01.08.2000-31.07.2004	4%
1	DWS Nordamerika	0.00	-	0.0000		5%
1	DWS PharmaMed	0.13	+0.13	0.0000	Out-of-sample	4%
1	DWS Telemedia	0.02	+0.02	0.0000		5%
1	DWS Energiefonds	0.00	-	0.0000	01.08.2004-31.07.2005	5%
1	DWS Rohstoffonds	0.00	-	0.0000		5%
1	DWS Technologiefonds	0.00	-	0.0000	Observations	5%
1	DWS Gold plus	0.55	+0.55	0.0000	953	3%
1	DWS Bonds	0.11	+0.11	0.0000	Costs	2%
1	DWS Internet	0.06	+0.06	0.0000	-	0%
Run	Mutual funds/Sector	$Weight(i)$	$\Delta Weight(i)$	Trading costs	In-sample	Issue fee
2	Allianz Logistics&Services	0.00	-	0.0000		5%
2	DWS Finanzwerte	0.01	-0.11	-0.0044	01.08.2001-31.07.2005	4%
2	DWS Nordamerika	0.07	+0.07	0.0000		5%
2	DWS PharmaMed	0.04	-0.09	-0.0036	Out-of-sample	4%
2	DWS Telemedia	0.14	+0.12	0.0000		5%
2	DWS Energiefonds	0.32	+0.32	0.0000	01.08.2005-31.07.2006	5%
2	DWS Rohstoffonds	0.03	+0.03	0.0000		5%
2	DWS Technologiefonds	0.00	-	0.0000	Observations	5%
2	DWS Gold plus	0.01	-0.54	-0.0162	956	3%
2	DWS Bonds	0.36	+0.25	0.0000	Costs	2%
2	DWS Internet	0.00	-0.06	0.0000	2.42%	0%
Run	Mutual funds/Sector	$Weight(i)$	$\Delta Weight(i)$	Trading costs	In-sample	Issue fee
3	Allianz Logistics&Services	0.28	+028	0.0000		5%
3	DWS Finanzwerte	0.00	-0.01	-0.0004	01.08.2002-31.07.2006	4%
3	DWS Nordamerika	0.00	-0.07	-0.0035		5%
3	DWS PharmaMed	0.00	-0.04	-0.0016	Out-of-sample	4%
3	DWS Telemedia	0.00	-0.14	-0.0070		5%
3	DWS Energiefonds	0.00	-0.32	-0.0160	01.08.2006-31.07.2007	5%
3	DWS Rohstoffonds	0.68	+0.65	0.0000		5%
3	DWS Technologiefonds	0.03	+0.03	0.0000	Observations	5%
3	DWS Gold plus	0.00	-0.01	-0.0003	975	3%
3	DWS Bonds	0.01	-0.35	-0.0070	Costs	2%
3	DWS Internet	0.00	-	0.0000	3.58%	0%

[9] The issue fees are published on the mutual funds provider's homepage and are as of 16.11.2009.

Run	Mutual funds/Sector	$Weight(i)$	$\Delta Weight(i)$	Trading costs	In-sample	Issue fee
4	Allianz Logistics&Services	0.00	-0.28	-0,0140		5%
4	DWS Finanzwerte	0.02	+0.02	0,0000	01.08.2003-31.07.2007	4%
4	DWS Nordamerika	0.00	-	0,0000		5%
4	DWS PharmaMed	0.00	-	0,0000	Out-of-sample	4%
4	DWS Telemedia	0.21	+0.21	0,0000		5%
4	DWS Energiefonds	0.00	-	0,0000	01.08.2007-31.07.2008	5%
4	DWS Rohstoffonds	0.13	-0.55	-0,0275		5%
4	DWS Technologiefonds	0.32	+0.29	0,0000	Observations	5%
4	DWS Gold plus	0.00	-	0,0000	938	3%
4	DWS Bonds	0.31	+0.30	0,0000	Costs	2%
4	DWS Internet	0.00	-	0,0000	4.15%	0%
Run	Mutual funds/Sector	$Weight(i)$	$\Delta Weight(i)$	Trading costs	In-sample	Issue fee
5	Allianz Logistics&Services	0.00	-	0		5%
5	DWS Finanzwerte	0.00	-0.02	-0.0008	01.08.2004-31.07.2008	4%
5	DWS Nordamerika	0.00	-	0		5%
5	DWS PharmaMed	0.38	+0.38	0	Out-of-sample	4%
5	DWS Telemedia	0.00	-0.21	-0.0105		5%
5	DWS Energiefonds	0.00	-	0	01.08.2008-31.07.2009	5%
5	DWS Rohstoffonds	0.00	-0.13	-0.0065		5%
5	DWS Technologiefonds	0.00	-0.32	-0.016	Observations	5%
5	DWS Gold plus	0.53	+0.53	0	986	3%
5	DWS Bonds	0.09	-0.22	-0.0044	Costs	2%
5	DWS Internet	0.00	-	0	4.54%	0%

Figure 4 plots the out-of-sample time series of the estimated portfolio P_t^* and the S&P 500. The out-of sample period contains 1231 observations. The statistical properties can be summarized as following: The portfolio returns exhibited out-of-sample a mean of 10.44% p.a., whereas the underlying stock index S&P 500 exhibited a mean of only 0.67% concerning the same period. The standard deviation of the latter was 24.08% p.a., whereas the constructed portfolio exhibited a standard deviation of only 17.30% p.a. Furthermore, the return distributions of both showed leptokurtic properties because the kurtoses were higher than three and at the same time skewed. However, the estimated portfolio returns' kurtosis was 6.51 in contrast to 13.55 which was the value of the S&P 500's kurtosis.

Choosing a Bartlett window of $\sqrt{N} = 35$ (N denotes the number of included observations), as suggested by Chatfield (1975), the spectral densities of the S&P 500 returns showed a high contribution of frequencies $\pi \in (\pi/2, \pi)$, which may explain it's noisy behavior, whereas the spectrum of the estimated sector portfolio returns revealed a smoother and at the same time more equally contribution for both, low and high frequencies. Figure 3 provides an overview of the spectral densities with respect to a Bartlett window of $\sqrt{N} = 35$.

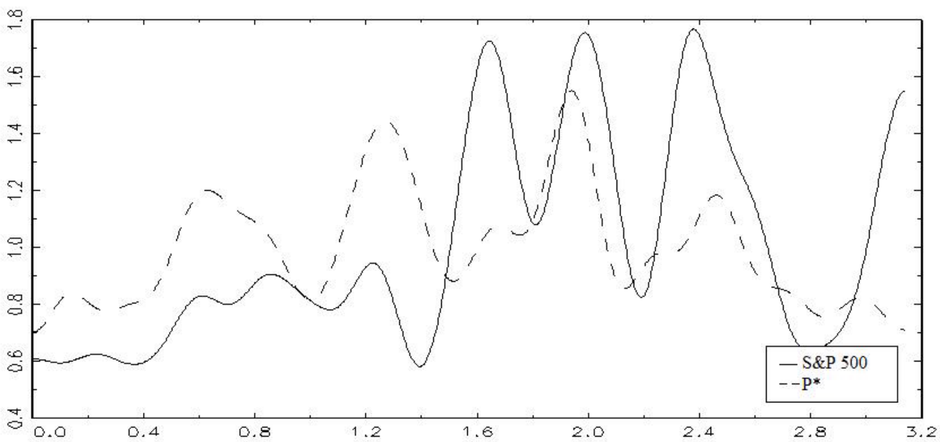
Regarding the whole out-of-sample period, the portfolio exhibited a return before trading costs which was 48.85% higher compared to the market return. At the same time the volatility was on average 1/3 lower (i.e. 17.30% p.a.) than the market's volatility (i.e. 24.08% p.a.).

Accounting for trading costs (see table 2) of 2.94% p.a. on average, the annual returns of the estimated portfolio are out-of-sample still 6.83% p.a. higher than the market returns.

There are two issues to clarify: First, although the constructed cointegration portfolio outperforms the underlying index, in case of the estimated portfolio exhibits another stochastic trend at all, it could hardly work as a hedge for the underlying stock market (i.e. S&P 500). Second, even though the cointegration portfolio outperforms the index it has to be investigated whether the gain is statistically significant.

Concerning the first point, the trace-test is performed in order to determine, whether the portfolio exhibits the same stochastic properties like the S&P 500. Note that the portfolio is a hypothetical process consisting of the stock index and an added stochastic process being normally distributed when taking the first differences. As a result, it may not be for sure that both time series exhibit the same stochastic patterns. The trace-test statistic should include a constant and trend component. Running the trace-test with respect to the overall out-of-sample process, the test statistic exhibited a p-value of 0.1093 and consequently the alternative hypothesis of cointegration will not be accepted on a 5% significance level. As the trace-statistic rejects cointegration, other tests could be run for investigating if cointegration holds. As the hypothesis of cointegration is rejected by a narrow margin only, a second test is run.

Figure 3. Spectrum of the estimated Sector Portfolio and the S&P 500



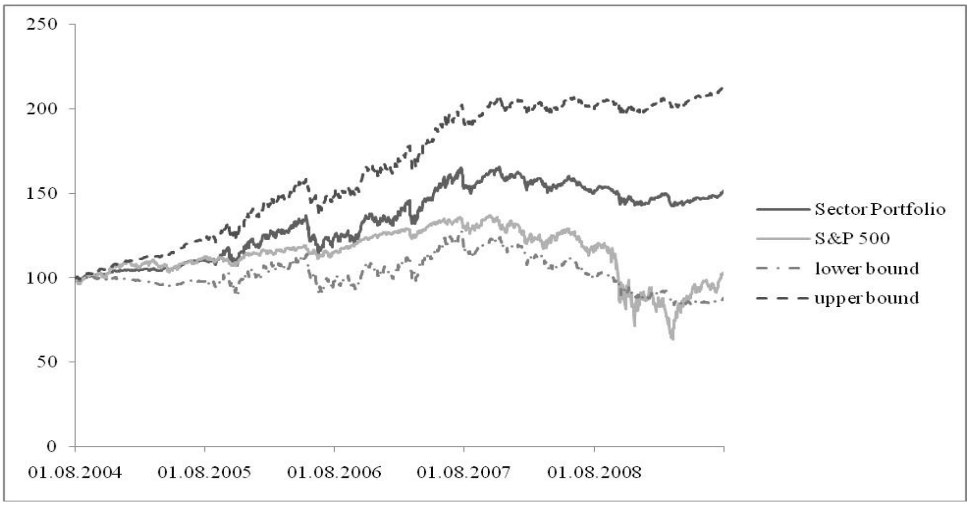
In contrast to the trace test the Saikkonen & Lütkepohl test as presented by Lütkepohl and Krätzig (2007) shows a p-value of 0.0802. As a result, the hypothesis of cointegration is only supported if taking into account a significance level of 10%. If there remains uncertainty whether cointegration holds or not there are other tests for cointegration available as described further by Greene (2008). In the following though, it is assumed that cointegration holds, even if the assumption is not supported on a 5% significance level.

But is the gain statistically significant? Since the Schwarz Criterion suggests a lag order of one, one may get in accordance to equation (7) the following estimated VECM[10]:

$$\begin{pmatrix} d(P_t^*) \\ d(y_t) \end{pmatrix} = \begin{pmatrix} \underset{(-4.601)}{-0.026} \\ \underset{(-0.703)}{-0.006} \end{pmatrix} \left(\begin{pmatrix} 1.000 & \underset{(-8.560)}{-0.654} \end{pmatrix} \begin{pmatrix} P_{t-1}^* \\ y_t \end{pmatrix} + \begin{pmatrix} \underset{(-3.287)}{-30.095} & \underset{(-16.283)}{-0.051} \end{pmatrix} \begin{pmatrix} \mu_0 \\ \mu_1 \end{pmatrix} \right) \quad (5.1)$$
$$+ \begin{pmatrix} \underset{(-0.566)}{-0.015} & \underset{(15.253)}{0.287} \\ \underset{(-2.467)}{-0.097} & \underset{(-4.684)}{-0.135} \end{pmatrix} \begin{pmatrix} d(P_{t-1}^*) \\ d(y_{t-1}) \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

[10]Note t-values in parenthesis.

Figure 4. Sector Portfolio and the S&P 500 out-of-sample



The upper and lower bound are 95% bootstrap confidence intervals using 20.000 bootstrap replications.

As it is operated with the transformed price series like shown in equations (1)-(2), the vector ΔY_{it} contains fittingly the ordinary returns of the portfolio returns and the S&P 500 stock index returns. The log-likelihood shows a value of -3959.71 and is larger compared to both models, the VECM including only a constant term (log-likelihood value: -3967.69) concerning the error correction and the VECM including no determining components at all (log-likelihood value: -3967.70). Furthermore, the test statistic λ_t concerning the pair of the hypothesis:

$$H_0 : \mu_1 = 0 \tag{5.2}$$

against:

$$H_1 : \mu_1 > 0 \tag{5.3}$$

is in accordance to Johansen (1991) asymptotically chi-square distributed with one degree of freedom and results in a test-statistic of $\lambda_t = 265.14$ being higher than the corresponding critical value (the corresponding p-value is 0.0000). Consequently, the trend component is with respect to this VECM framework statistically significant within the out-of-sample window. Furthermore, the beta-estimator in this VECM is 0.65 as shown in equation (8) and consequently, the abnormal return may be given by $\widehat{\alpha}_t = R_t^{P^*} - R_t^{S\&P500} = \Delta(P^*) - \Delta(y_t)$, where $E(\alpha_t) = 10.04\%$ p.a.[11] As a result, it could be shown that it is possible to estimate weight allocations exhibiting a portfolio that overforms the benchmark continuously even within a passive strategy framework.

6. Discussion

Two main outcomes can be recorded as follows: First, the constructed sector portfolio exhibits the same stochastic properties like the index and hence, may act as a hedge of the latter. Second, the trend component is highly statistically significant even out-of-sample and accounts

[11]Note the beta-estimator is super consistent (in contrast to using the ordinary index model as pricing model).

for expected abnormal returns of 12.75% p.a. (i.e. 0.051 in daily terms) and realized abnormal gross returns of 10.44% p.a.

Taking into account a four years period of daily data, it is possible to figure out trend stationary stochastic processes which the data implicitly involves. The stochastic trend is relatively stable over a one year period out-of-sample as long as cointegration holds. Due to the business cycle being represented here through the stock index sectors respond differently in various phases within the cycle. This information is implicitly cached in the price information. The sectors involved are represented here by the mutual funds that are primarily active in different business sectors. Irrespective of the system's position, it is possible to run the same optimization procedure which leads to cointegrated portfolios concerning four of five out-of-sample periods. However, the optimization procedure regarding the weight allocation of the last period (i.e. 31.07.2008-01.08.2009) is based on the return series instead. The overall out-of-sample portfolio exhibited a cointegration relationship with the benchmark[12].

The more extreme the trend stationary stochastic process is chosen the less stable will be the cointegration relationship. Even though Alexander and Dimitriu (2005) investigated less stable cointegration relationships for trading spreads of larger than 5%, accounting for a switching trend within the cointegration relationship seems to work as an implicit market timing factor. As a result, stable cointegration relationships involving trends corresponding to double digit annual returns (i.e. higher than 10% p.a.) are thoroughly possible as shown here. An evaluation of the estimated portfolio's volatility indicates a very similar pattern to that reported by Alexander, Giblin and Weddigton (2001) who point out that the constructed portfolio's volatility remains low.

While Alexander and Dimitriu (2005) suggest a calibration period of 10 days while trading the spread of the long/short portfolios here the estimated portfolio is rebalanced only once in a year due to the high trading costs of up to 5% p.a. Rebalancing portfolios is expansive. Even if the spread of 10% p.a. is in accordance to Alexander and Dimitrui (2005) stable and statistically significant out-of-sample their trading strategy is not beneficial when accounting for trading costs. Taking into account average trading costs of 0.25% p.a. for each portfolio, for instance (i.e. the long- and short-position), rebalancing 25 times a year[13] (i.e. every 10 days) results in trading costs of 12.50% p.a. and as a consequence the profit becomes negative (i.e. -2.50% on average). The trading strategy suggested here, though, exhibits a net return of 7.50% p.a. instead.

Apart from that Alexander and Dimitriu (2005) expose that cointegration-optimal statistical arbitrage strategies exhibit advantages only if taking into account long time horizon spanning ten years. In this work it is shown that the constructed trend is statistically significant with respect to the VECM framework even though five years out-of-sample is taken into account, only.

While Alexander, Giblin and Weddigton (2001) take into account 100 assets in order to figure out the best suitable linear combination exhibiting cointegration the data set being employed here is limited to 11 assets, only. The results of the previous section showed that the limitations of the data set do not affect the trading strategy introduced here. However, it may be worth mentioning that the more sectors the model involves the more parsimonious the model may be. Furthermore, the long/short strategy in a fund of funds framework like presented here is limited: The short position is always the index because going short in funds is not possible. Apart from that the artificial index being employed here is constructed by adding, respectively, subtracting returns which have an expectation of 15%. The results show a realized abnormal returns being 4.56% lower on average. The remaining question may still be if it is possible to construct portfolios exhibiting even higher abnormal returns. It is not clear which is actually the abnormal return's upper bound when applying passive strategies for statistical arbitrage.

[12]As long as significance level of 10% is taken into account.

[13]Here it is assumed that the investor faces on average 250 trading days a year.

7. Concluding Remarks

The general benefits of cointegration relationships in statistical arbitrage frameworks are clear. The estimated portfolio and the artificial index are tied together in the long run even one year ahead. Accounting for a linear switching trend with respect to the artificial index being tracked, the estimated portfolio exhibits lower volatility and higher returns compared to the benchmark, whereas the stochastic patterns remain similar which ensures arbitrage opportunities. As a result, it could be shown that it is possible to perform continuously better than the benchmark by employing more sophisticated statistical arbitrage strategies.

Concerning the model being employed here, it may be worth to underline that it is operated with stochastic returns exhibiting the same volatility as the underlying index in order to construct the artificial index. In comparison Alexander and Dimitriu (2005) employ uniform distributed returns. The more realistic the artificial index will be constructed the more parsimonious the optimization procedure should work. Hence, it may be an advantage to operate with artificial indices exhibiting higher volatilities than the ordinary index. Consequently, generating an artificial index that exhibits the same leptokurtic properties like the underlying stock index should be most parsimonious.

The knowledge of stochastic trends being implicitly incorporated in the price information may establish a wide area of research regarding asset allocation management. However, the data may even exhibit non-linear trends that can be exploited. The model being introduced here is applied to the most intuitive framework, namely the business cycle. During a business cycle, some sectors begin to overprice while others remain underpriced. The same may be true in other systems. Globalization, for instance, is seen to be two-sided: On the one hand, there are researchers who are worried about a loss of welfare due to wage dumping or price falls in goods due to the globalization procedure. On the other hand, globalization discloses benefits when considering the financial markets: A good market timing may ensure participating in economic growth of smaller economies that exhibit higher growth rates. This point may be important to account for concerning asset-, portfolio-, and pension-management especially if the growth rates of large and well developed economies become smaller over time.

Furthermore, there may be further need of research concerning the most adequate calibration period. Rebalancing portfolios is expansive due to the trading costs involved. The more often the estimated portfolio is rebalanced the more the portfolio returns will be diminished. In this work the estimated sector portfolio is rebalanced only annually. However, the optimal rebalancing time remains unclear. Within a statistical arbitrage framework, the portfolio should be rebalanced as soon as the trend becomes unstable (i.e. insignificant) which may be different and depend on the system's, respectively, market's position.

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