Low Carbon Indexing and Correlation Indices: Implications for Portfolio Management

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Abstract:

This article deals with the construction of a tracker of low carbon index (such as the MSCI low carbon) and its performance in a portfolio management application. The tracker is built from raw data with PCA, factor detection and DCC models techniques. The portfolio application is a standard Markowitz application with and without the desired low carbon index. The data is composed of financial data in addition to commodities. Another related topic is discussed in the article, i.e. the performance of correlation indices (constructed similarly to the low carbon index but in a DCC framework) with respect to financial stress on the market (proxied by the St Louis Fed Stress Index) and with main competitor the VIX correlation index. Results are interesting for a broad array of applications in the financial industry.

JEL Codes: C58; F37; G12; Q54

Keywords: Low Carbon; Correlation Index; Factor Model; Financial Stress; DCC; VIX

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1. Introduction

Climate change has wide-ranging impacts on human lives throughout the world. According to a World Bank report by Fay et al. [2015], global warming may trap into poverty up to 100 million people by 2030. The transition to a low carbon economy has become a cornerstone of new environmental and development policies. A low carbon economy is characterized by reduced electricity consumption, controlled emissions of pollutants and especially a low carbon-intensity of human-related production activities. This societal shift calls for changes of paradigms, as well as tremendous energy innovations. The Stern Review [2007] has documented that the costs of inaction with regard to climate change could add up to 20% of the world's GDP, compared with only 1% if decisive action is enacted. The Nobel-prize winner IPCC [2007] has underlined as well the GDP losses that could occur due to global warming, ranging from 4% in 2030 to 12% in 2100.

Against this background, the financial industry attempts to develop new low carbon indexes, that select only a subset of companies with a reduced environmental impact (i.e., reduced energy consumption or explicit reduction in greenhouse gases emissions), to reduce long-term risks. To name a few, Merrill Lynch has launched in 2008 the MLCX Global CO_2 Emissions Index in 2008. Meanwhile, S&P has proposed in 2009 the S&P U.S. Carbon Efficient Index that measures the performance of a large sample of US companies with a low carbon footprint. WilderHill has created a pure-play Clean Energy Index by including stocks based on their significance for clean energy, technological influence, and relevance to pollution prevention. However, the construction of such indexes appears as a "black-box", once the user has read the abbreviated white papers available for public use.

This article is devoted to the analysis of low carbon indexes with practical applications to portfolio management. To cope with the "black-box" drawback of existing indexes, the empirical study is based on the replication of the MSCI low carbon index, by means of principal component analysis (PCA) and factor modelling. Therefore, the construction of the low carbon tracker index is entirely transparent and data-driven. Then, its performance is assessed by comparing the performance of Markowitz mean-variance portfolios with and without the low carbon tracker index. To assess further its robustness, the portfolio with low carbon asset will be tested in a cointegration framework.

International stock markets being highly integrated [Chan et al., 1997; Bracker et al., 1999], another area of research in this article is related to correlation dynamics. Indeed, the growth process entails an increase in correlation between stock markets. For portfolio managers, inter-sectoral correlations are less prevalent, therefore greater diversification can be achieved by relying on sectoral indices.

Correlation indices have gained momentum in the financial industry thanks to option prices [Driessen et al., 2009]. Moreover, the Chicago Board of Exchange (CBOE) has developed correlation indicators as part of its broad array of financial data available to the public, based on implied correlation on the S&P 500, known as CBOE Implied Correlation Indexes (ICI). However, their use shall not be restricted to the sphere of derivatives, as several scholars have extended the concept of correlation risk to optimal portfolio choice [Krishnan et al., 2009; Buraschi et al., 2010].

In this article, we will thoroughly check the correlation between low carbon assets and traditional assets (equities, bonds, FX). Besides, we will compare the performance of a cross-market correlation index (including explicitly low carbon assets) with that of the CBOE's ICI in predicting a broad measure of financial stress constructed by the St-Louis Fed.

This work relates to another strand of literature dedicated to futures markets, where researchers typically aim at evaluating the diversification benefits of correlation indices, by resorting to time-varying correlations and stress events studies (see, e.g. Lien and Yang [2006]; Park and Jei [2010]). More precisely, the correlation index literature is drawn from the options literature, as published by Skintzi and Refenes [2005]. Only a few scholars have attempted to build correlation indices with standard closing prices for equities, bonds, FX and commodities, i.e. from a cross market perspective.

This articles mixes several methodological tools (PCA and factor models) to construct a correlation index based on Dynamic Conditional Correlations (including low carbon assets) to predict financial stress, very close in the spirit to the paper by Jobst et al. [2015]. Last but not least, a “horse-race” is conducted between the new correlation index and that of the CBOE Implied Correlation index (from the S&P 500 options literature) in order to gauge their respective predictive power. Each empirical section has been approved by applying the necessary robustness checks.

The remainder of the article is structured as follows. Section 2 details the methodology and dataset. Section 3 contains the empirical results. Section 4 concludes.

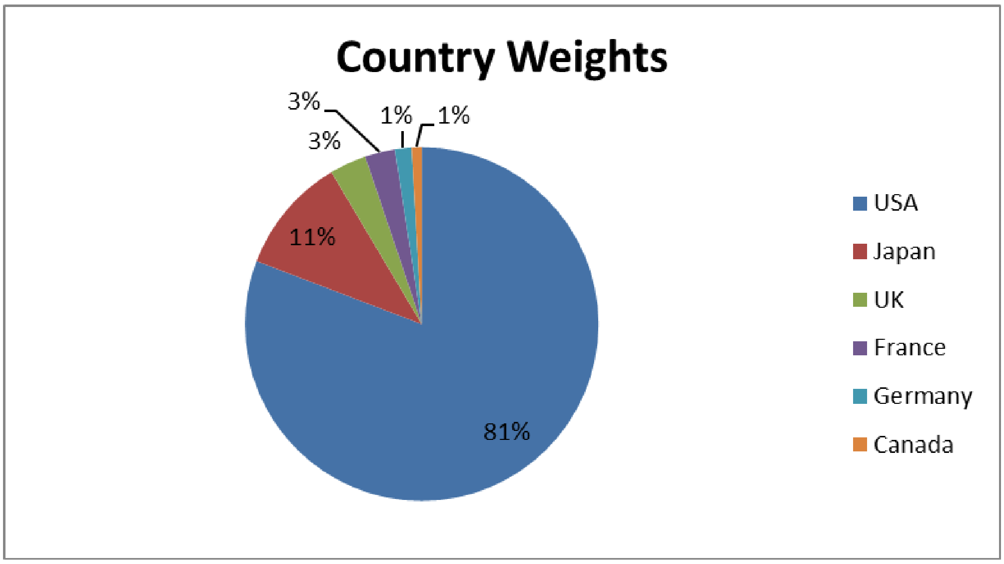
2. Methodology and data

The motivation to build a tracker on the MSCI Low Carbon Index is to provide a transparent methodology to retrieve the weights of the index constituents (in percentage), absent experts’ additions and entirely data-driven. By following this methodology, the practitioner can then tailor a low carbon index suited to her/his own needs and activities.

2.1 Dataset

Data with a daily frequency has been extracted from Bloomberg during the period ranging from November 30, 2010 to January 1, 2015, i.e. totalling 1068 observations. The data is composed of 330 companies that are listed on the main stock exchanges (DJIA, CAC40, DAX, TSX, HSE, NIKKEI, MIB, FTSE).

The companies were selected to match the sector and industry coverage of the MSCI Low Carbon index, as indicated in its methodology white paper [MSCI, 2014]. For instance, in our setting, the total Health Care sector represents 12,23% of the subset of companies. The financial sector captures 22,33% of the index, with 73 companies. Only 38 companies are selected from the industrial sector (11.67%), due to a selection of low-carbon activities only. These characteristics match those of the MSCI Low Carbon index. Further details are provided in Figure 1.



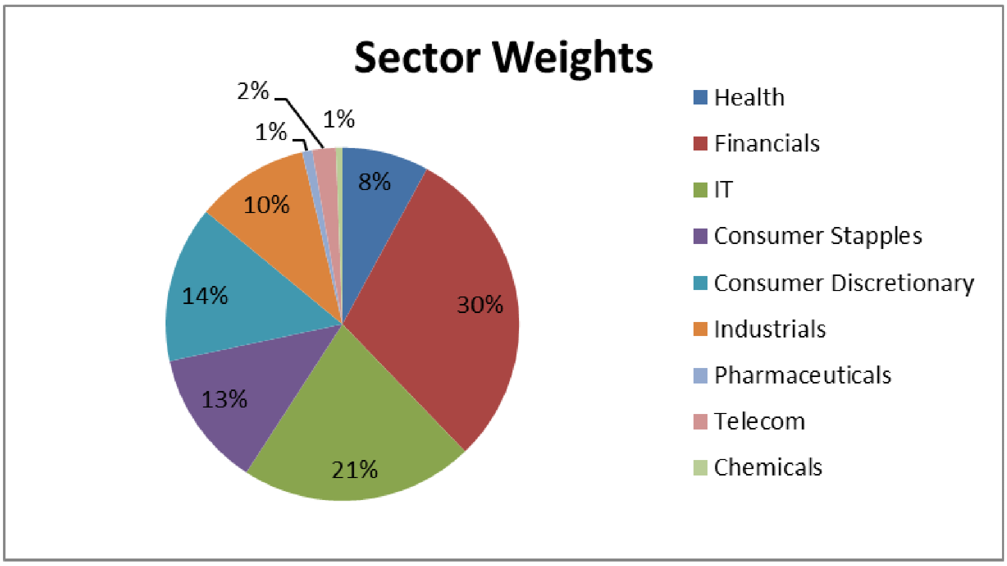


Fig.1. Country and Sector Weights of the MSCI Low Carbon Index Tracker

2.2 Methodology

The econometric methodology to build the tracker unfolds in several steps as detailed below. Initially, we detail the successful replication of the MSCI low carbon index. Then, we explain how to construct correlation indices based on pairwise DCC estimates.

2.2.1 Automatic choice detection for the number of factors

The Alessi-Barigozzi-Capasso (ABC) criterion by Alessi et al. [2010] is implemented to determine the appropriate number of factors needed to extract principal compents from the full database of 330 companies.

The result is displayed in Figure 2.

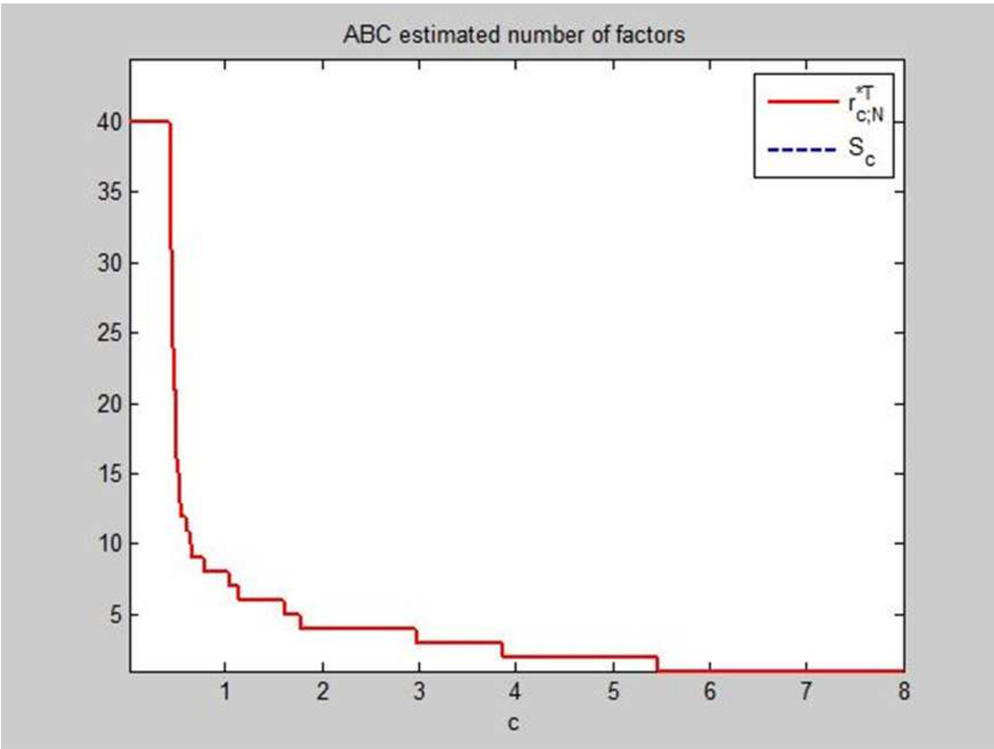


Fig.2. ABC criterion results for the low carbon tracker dataset

Visually, we observe that at least 5 factors are needed to accurately model the dynamics of the underlying data. This number is rounded upwards; therefore 6 factors will be selected during the course of the principal components extraction.

2.2.2 *Principal components analysis, factor modeling and tracker construction*

PCA is run on the 330 companies with a choice of 6 factors. This computational procedure returns the weight of each company for each of the 6 factors (for a review, see Stock and Watson [2002a, b]).

The contribution of a selected company to the tracker is computed based on its average weight across the 6 factors. In other words, we do not favor one factor over another (based on purely statistical grounds), and set their influence to be equal to construct the index tracker. The composition of the MSCI low carbon tracker index (in percentage terms) is reproduced in the Appendix.

In Figure 3, we represent the performance of the tracker against the MSCI Low Carbon, as well as the leading international equity indexes S&P 500 and EuroStoxx 600.

Visually, these graphs reveal that our methodology has been able to replicate successfully the targeted MSCI Low Carbon index, since both series (the tracker and its MSCI counterpart) vary closely together. From November 30, 2010 to July 31, 2011, the tracker is under-representing the variations of the index. From 2012 until November 30, 2014, the tracker seems to slightly over-shoot the behavior of the underlying index.

Interestingly, the tracker appears also moving closely in sync with the S&P 500, since we only notice one episode where the tracker moves away from it during November 2013. The comments are broadly similar with respect to the Eurostoxx 600: the two series move closely together, with the tracker being above the European equity index from September 30, 2011 to November 30, 2014.

Following these descriptive comments, we compute model validation statistics known as the Excess Returns (ER) and Tracking Errors (TE), in order to assess statistically the performance of the index replication exercise.

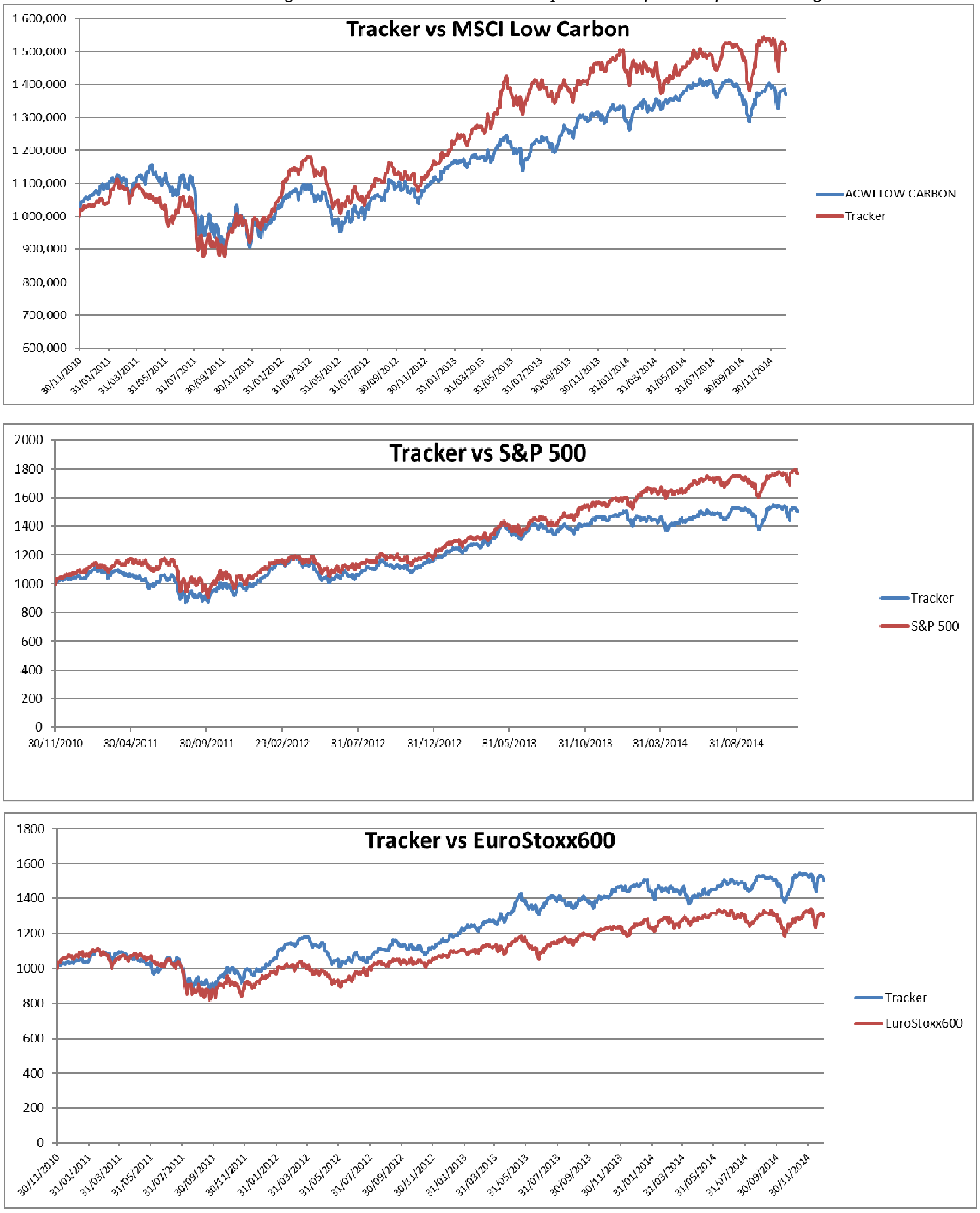


Fig.3. Tracker represented versus the MSCI Low Carbon Index, as well as S&P500 and Eurostoxx 600 equity indexes

Formally, the TE is defined as the root mean squared error between the tracker index return noted $r_{t,tracker}$, and the MSCI Low Carbon index return noted $r_{t,MSCI}$. T is the terminal period.

$$TE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_{t,tracker} - r_{t,MSCI})^2} \quad (2.1)$$

Next, the ER is the average difference between the tracker index return and the MSCI Low Carbon index return:

$$ER = \frac{1}{T}\sum_{t=1}^{T}(r_{t,tracker} - r_{t,MSCI}) \quad (2.2)$$

For a review of these performance metrics in the index tracking literature, see Beasley et al. [2003], Dose and Cincotti [2005], Chen and Kwon [2012].

Table 1 provides the TE and ER for each comparison between the tracker versus the MSCI Low Carbon, S&P 500 and Eurostoxx 600 indexes.

Table 1. Index tracking performance metrics

Series	**ER**	**TE**
Tracker vs. MSCI Low Carbon	0,055787797	1,860898
Tracker vs. S&P 500	0,097714473	2,186142
Tracker vs. Eurostoxx 600	0,097713511	2,185076

Note: TE stands for Tracking Error. ER stands for Excess Returns.

Model validation tests confirm the remarkable performance of our methodology to track the underlying MSCI Low Carbon and equity markets indices. Indeed, the TE and ER scores are very low, on average around zero with two decimals. We have therefore demonstrated the ability of our methodology to construct an efficient tracker of the benchmark portfolio.

2.2.3 Building correlation indices

This section builds on the notations by Koch [2014]. Consider n time series of returns under the hypothesis of absence of serial autocorrelation. Define a white noise vector of mean zero $\varepsilon_t = r_t - \mu$, with r_t the $n \times 1$ vector of returns, and μ the vector of anticipated returns.

Returns exhibit a contemporaneous correlation under the form:

$$\sum_t := \mathrm{E}_{t-1}[(r_t - \mu)(r_t - \mu)'] \qquad (2.3)$$

Besides, this contemporaneous variance can vary through time, depending on past information.

The GARCH-DCC model unfolds in two steps. The first step takes into account the conditional heteroskedasticity. It consists in estimating, for each of the n series of returns r_{it}, the conditional volatility σ_{it} from a GARCH(p,q) model. Let D_t be a diagonal matrix with these conditional volatilites, i.e. $D_{i,it} = \sigma_{it}$ and, for all $i \neq j$, $D_{i,jt} = 0$. Standardized residuals write:

$$v_t = D^{-1}_t (r_t - \mu) \qquad (2.4)$$

Standardized residuals have a unitary conditional volatility. Define the matrix that corresponds to the Constant Conditional Correlation (CCC) model by Bollerslev [1990]:

$$\bar{R} = \frac{1}{T} \sum_{t=1}^{T} v_t v_t' \qquad (2.5)$$

The second step consists in generalizing Bollerslev's CCC model in order to capture correlation dynamics, hence the name of *Dynamic Conditional Correlation* by Engle [2002]. DCC correlations write:

$$Q_t = \bar{R} + \propto (v_{t-1} v'_{t-1} - \bar{R}) + \beta (Q_{t-1} - \bar{R}) \qquad (2.6)$$

with $Q_{i,jt}$ the correlation between r_{it} and r_{jt} at time t.

Based on subset of 16 series selected from the full dataset[b], we have launched a loop to compute the corresponding [n*(n-1)]/2 pairs, i.e. 120 iterations of the DCC model.

Once the dynamic conditional correlations have been stored, we can investigate briefly the most significant ones, as reproduced in Table 2.

Natural Gas NBP UK & VSTOXX	-1,29%	MSCI Low Carbon & SP500	0,69%
Crude Oil WTI & VSTOXX	-0,58%	Aluminium & US 10y T-Bill	1,96%
EUR-USD & CBOE VIX	-1,13%	Crude Oil WTI & US 10y T-Bill	1,40%
Nikkei 225 & CBOE VIX	-1,62%	MSCI Low Carbon & EUROSTOXX 600	0,70%
CBOEVIX & Aluminium	-2,17%	SP500 & EUROSTOXX 600	0,60%
Crude Oil WTI & CBOE VIX	-4,34%	USD-JPY & US 10y T-Bill	0,49%
CBOEVIX & US 10y T-Bill	-7,93%	Nikkei 225& US 10y T-Bill	0,50%
Gold & US 10y T-Bill	-0,37%	CBOE VIX & VSTOXX	0,55%
USD-JPY & CBOE VIX	-0,86%	Natural Gas NBP UK & CBOEVIX	0,96%
VSTOXX & Corn	-0,48%	Crude Oil WTI & Aluminium	0,66%

Table 2. Top-ten DCC correlations (positive on the left hand-side and negative on the right hand-side)

[b] The MSCI Low Carbon, the S&P 500, the Crude Oil Brent, the Natural Gas NBP UK, the Nikkei 225, the Nasdaq, the CBOE VIX, the VSTOXX, the Crude Oil WTI, the 10-Year US T-Bill, the USD-EUR / USD-JPY / USD-GBP exchange rates, Gold, Aluminium, and Corn futures from a cross-asset management perspective?

The main information that can be gleaned from Table 2 can be summarized as follows. First, in case of negative correlations, greater bond yields tend to decrease market uncertainty as proxied by the VIX. Commodity prices (such as Aluminium) seems counter-cyclical with respect to market uncertainty. Second, in the case of positively correlated series, we notice that the MSCI Low Carbon and the S&P 500 go hand-in-hand.

The correlation index is built from the 120 time-varying correlations by resorting to automatic factor detection (6 factors were also needed), PCA and factor modelling similarly to the methodology developed in Section 2.2. For each series, index weight is obtained by averaging the influence of each factor (i.e., we do not favour one factor over another based on purely statistical grounds). Once the correlation index has been created, we can evaluate its performance in a horse race versus the CBOE ICI, including as low carbon asset either the MSCI Low Carbon original index or its tracker.

3. Empirical results

3.1 Mean-variance portfolio optimization with and without Low Carbon indexes

Consider the mean-variance approach (Markowitz [1952]):

$$\max_{\omega} U = \omega'\mu - \frac{\delta}{2}\omega'\Sigma\omega \qquad (3.1)$$

with U the investor's utility, ω the vector of portfolio weights, $\sum$ the covariance matrix, μ the vector of return estimates, and δ the risk aversion coefficient. Upper volatility bounds are added as a constraint in the optimization strategy:

$$\sqrt{\omega'\Sigma\omega} \leq \hat{\sigma} \qquad (3.2)$$

Two investor types are distinguished:

(i) A *Conservative* investor with a maximum desired volatility of 5% p.a. (e.g. risk aversion coefficient equal to 10). Typically, the investor holds 80% bonds, 15% stocks, and 5% commodities.

(ii) An *Aggressive* investor with a maximum desired volatility of 15% p.a. (e.g. risk aversion coefficient equal to 2). Typically, the investor holds 60% stocks, 20% bonds and 20% commodities.

Strategic weights are indicators typically used in the industry by asset managers and practitioners. They are to be followed as a rough guide for portfolio allocation, and set as flexible upper/lower bounds in the optimization problem.

From a cross-market perspective, we construct the following portfolios:

(1) The *benchmark portfolio* composed of equities (S&P 500, Nasdaq, CBOE VIX, Eurostoxx 600, Nikkei 225), bonds (US 10-year T-Bill), and commodities (Gold, Crude Oil WTI Crude Oil Brent, Natural Gas NBP UK, Natural Gas Henry Hub).

(2) The *extended portfolios* including as well either the original MSCI Low Carbon index, or its tracker.

Table 3 reports the portfolio gains for each portfolio depending on the investor type.

Table 3. Mean-variance portfolio optimization results

Investor Type	**Risk**	**Return**
Conservative		
Benchmark Portfolio	4,50%	3,23%
Extended Portfolio with MSCI Low Carbon	2%	3,71%
Extended Portfolio with Tracker	2,75%	3,80%
Aggressive		
Benchmark Portfolio	11,30%	8,45%
Extended Portfolio with MSCI Low Carbon	6,40%	5,08%
Extended Portfolio with Tracker	8,34%	6,84%

Several comments arise. First, the extended portfolio with tracker dominates the Conservative strategy, with a higher return and only slightly higher risk than the extended portfolio with the original MSCI index. The benchmark portfolio underperforms in this setting.

Second, the benchmark portfolio dominates the Aggressive strategy, delivering much higher returns than alternative portfolios with low carbon series. On the downside, the investor must accept a significantly higher level of risk to achieve this performance.

Regarding portfolio weights, in its aggressive investor type, the benchmark portfolio is composed of 64,85% of equities, 31,70% of bonds and only 3.45% of commodities. For Low Carbon extended portfolios, in their conservative investor type, commodities (including either the MSCI or its tracker) rise up to 6% (relaxing the upper bound for the 5% portfolio weight constraint invested into commodities) whereas the bulk of this portfolio is still invested in US T-Bill (80%).

Another look at the performance of the *extended* portfolio (with Low Carbon asset) can be obtained from the estimation of a Vector Error-Correction Model (VECM, Johansen [1991]) with one lag.

Table 4. VECM Error-Correction Mechanism for a reduced form of the extended portfolio with MSCI Low Carbon asset

	D(EUROSTOXX600)	**D(OAT_10Y)**	**D(EUR_USD)**	**D(BRENT)**	**D(MSCI)**
Error Correction:	0.016370 [1.16532]	-2.80E-07 [-0.10445]	-0.000104 [-2.46711]	-0.015903 [-1.98980]	0.171638 [3.59687]

Note: D(.) refers to the first-differenced series. Coefficient estimates are reproduced, with *t*-statistics under brackets.

Table 4 provides the results for a reduced form of the extended portfolio with the MSCI Low Carbon index. Error-correction terms are mostly significant, with a negative sign registered for the exchange rate and the Crude Oil Brent series, indicating their predominant role in the adjustment towards the long-run equilibrium.

As depicted in Figure 4, the cointegration relationship appears stationary. As a robustness check, we have therefore demonstrated that the market practitioner could successfully implement a VECM model with his/her own Low Carbon tracker in order to capture long-run trends in the portfolio under management.

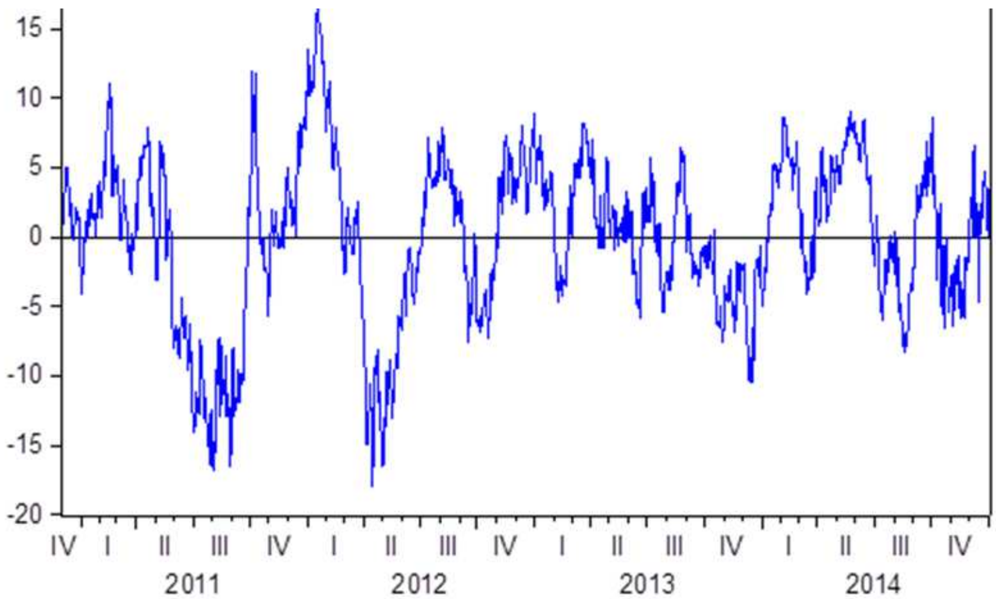


Fig.4. Cointegration relationship for a reduced form of the extended portfolio with MSCI Low Carbon asset

3.2 Predicting financial stress based on correlation indices

In the remainder of the empirical application, we are interested in gauging the explanatory power of correlation indices with respect to the stress level on financial markets.

A widely-accepted measure of financial stress in the literature can be found at the St-Louis Federal Reserve, under the form of a stress index composed of interest rates, returns spreads and other forward-looking indicators. The St-Louis Fed Financial Stress Index is shown in Figure 5.

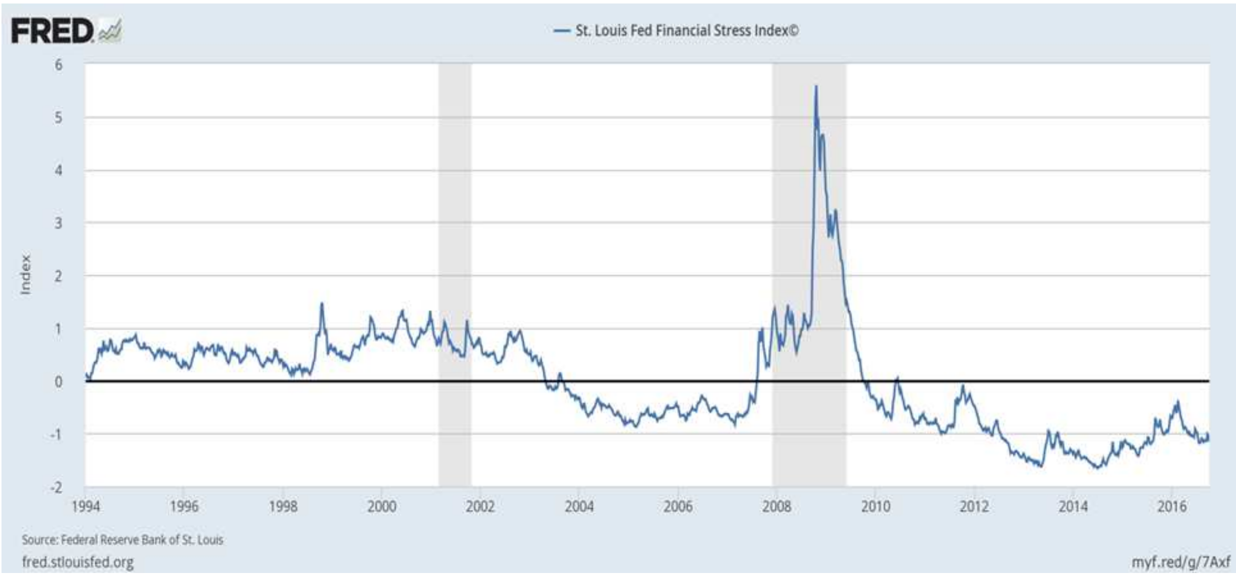


Fig.5. St-Louis Fed Financial Stress Index

Compared to the benchmark level of stress being zero (the solid black line), we remark that there was little stress on financial markets between 1994 and 2003 (except the dot-com bubble burst of the years 2001-2002). Relatively to this ‘tranquil’ period, the years 2007-2010 have been characterized by a surge in financial stress in the aftermath of the 2008 sub-primes crisis in the USA, before resuming quiet territories amidst Central Banks non-conventional monetary policies.

In what follows, we set up an original regression model in order to predict the financial stress based on correlation indices:

$$\Delta Stress_t = \alpha + \beta 1\ \Delta Correlation\_Index_t + \beta 2\ \Delta CBOE\_ICI_t + \varepsilon_t \quad (3.3)$$

with $\Delta Stress_t$ the first-differenced value of the St-Louis Fed Financial Stress Index at time t, α_i the constant term, β1 and β2 the estimated coefficients for, respectively, $Correlation\_Index_t$ the correlation index built from the cross-market dataset and low carbon tracker used in this article, and $CBOE\_ICI_t$ the S&P 500 options counterpart built by the CBOE. ε_t is the error term.

Table 5. Predicting financial stress based on correlation indices: a horse-race between the CBOE ICI and broad cross-market correlation indices (including low carbon)

Dependent Variable: **ΔSTRESS$_t$**
Method: Least Squares
Included observations: 1066 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0.897554	0.835586	1.074162	0.2830
ΔCorrelation_Index$_t$	0.004062	0.006211	0.653948	0.5133
ΔCBOE_ICI$_t$	-0.044176	0.020313	-2.174721	0.0299
R-squared:	0.6187			

Note: Ljung-Box-Pierce test confirms residuals are not autocorrelated (available upon request).

Ordinary Least-Squares regression results are reproduced in Table 5. They indicate, by and large, that financial stress can be significantly explained by the CBOE ICI (at the 5% level), whereas the correlation index (including low carbon) fails to do so. Financial stress therefore seems weakly impacted by a broad cross-market correlation index.

To further ascertain this result, we conduct a sensitivity analysis based on rolling regressions (with a window of 200 observations) for the coefficient estimates β_1 and β_2. Detailed computer outputs have been stored and are not reproduced for brevity. Figure 6 displays this picture.

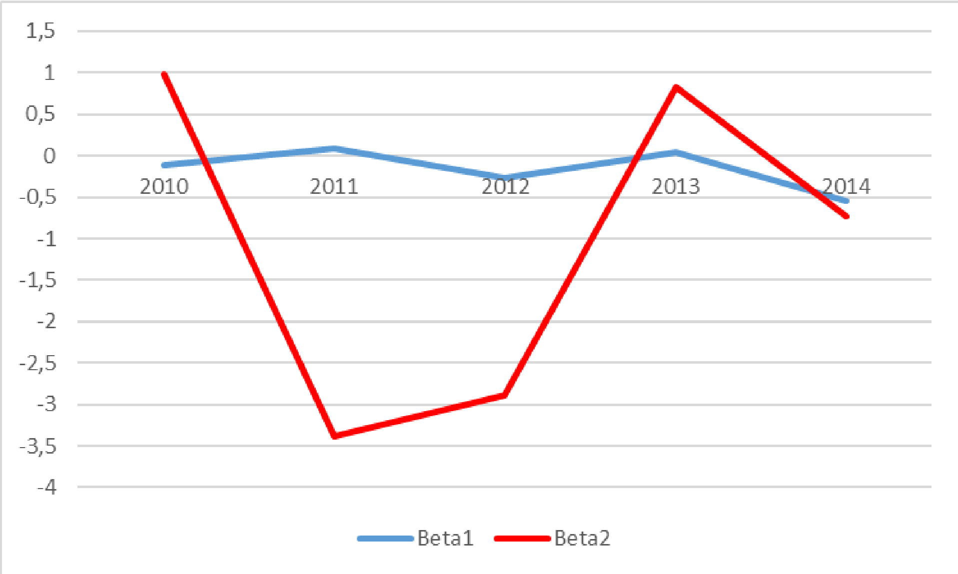


Fig.6. Rolling regression results for the influence of β_1 and β_2

The sensitivity analysis reveals that the influence of the CBOE ICI coefficient (aka, β_2) on financial stress is not stable through time, therefore it cannot be claimed either as winner of the horse-race. The main implication for portfolio managers would be that, essentially, broad cross-market correlation indices (including stocks, bonds and commodities such as low carbon) would be *less* impacted during crises periods than the S&P 500.

4. Conclusion

This article details step-by-step an innovative methodology to construct a tracker of a Low Carbon index, e.g. the MSCI. Several uses of such an index tracker are advanced, one of them being part of broad cross-market correlation indices.

In the portfolio optimization exercise, the inclusion of a Low Carbon index (either the original MSCI or its tracker) is profitable for the Conservative-type of investor, where it dominates the benchmark portfolio. Only a small percentage of the portfolio weights (below 6%)

invested into commodities (including low carbon) allows to reach this conclusion, which has interesting implications from a cross-asset management perspective. However, an Aggressive-type investor would dominate a portfolio composed of Low Carbon indexes, at the expense of a much higher risk profile. As robustness check, a cross-market vector error-cointegration with low carbon asset can be formulated to long-run trends, with a predominant role played by the oil price.

In the correlation index application (extending the present factor modelling exercise to the DCC framework), we reach the main result that – during periods of high financial stress – broad cross-market indices (including low carbon assets or trackers) are less impacted than any S&P 500-based (implied) correlation index. Hence, we reclaim the main interest in building tailored version of our (low carbon and correlation) indexes in order to achieve greater diversification benefits.

<u>Appendix</u>: Basket Weights of the MSCI Low Carbon Tracker

Company	Tracker Weight	Company	Tracker Weight	Company	Tracker Weight
APPLE	1,76%	Western Digital	0,43%	Bank of America Corp	0,51%
MICROSOFT	1,05%	Western Union Co	0,24%	The Bank of New York Mellon Corp.	0,51%
GENERAL ELECTRIC	0,80%	Xerox Corp.	0,36%	BB&T Corporation	0,22%
JOHNSON & JOHNSON	0,75%	Xilinx Inc	0,29%	Berkshire Hathaway	0,21%
WELLS FARGO & CO	0,71%	Yahoo Inc.	0,20%	BlackRock	0,17%
AMAZON.COM	0,64%	Altria Group Inc	0,28%	Block H&R	0,13%
JP MORGAN CHASE & CO.	0,64%	Archer-Daniels-Midland Co	0,13%	Boston Properties	0,18%
PROCTER & GAMBLE	0,58%	Brown-Forman Corporation	0,16%	Capital One Financial	0,17%
GOOGLE 'A'	0,56%	Campbell Soup	0,25%	CBRE Group	0,25%
Bed Bath & Beyond	0,30%	The Clorox Company	0,28%	Charles Schwab Corporation	0,19%

BorgWarner	0,19%	The Coca Cola Company	0,24%	Chubb Corp.	0,18%
Darden Restaurants	0,27%	Coca-Cola Enterprises	0,17%	Cincinnati Financial	0,15%
Dollar Tree	0,70%	Colgate-Palmolive	0,24%	Citigroup Inc.	0,44%
Ford Motor	0,31%	ConAgra Foods Inc.	0,27%	CME Group Inc.	0,15%
Genuine Parts	0,16%	Constellation Brands	0,20%	Comerica Inc.	0,24%
Harley-Davidson	0,13%	Costco Co.	0,27%	Crown Castle International Corp.	0,22%
Home Depot	0,15%	CVS Caremark Corp.	0,19%	Discover Financial Services	0,11%
Interpublic Group	0,48%	Dr Pepper Snapple Group	0,25%	E*Trade	0,30%
Johnson Controls	0,14%	Estee Lauder Cos.	0,21%	Equifax Inc.	0,17%
Mohawk Industries	0,14%	General Mills	0,28%	Essex Property Trust Inc	0,16%
Nordstrom	0,13%	Kellogg Co.	0,31%	Fifth Third Bancorp	0,21%
Omnicom Group	0,14%	Keurig Green Mountain	3,11%	Franklin Resources	0,16%
PVH Corp.	0,18%	Kimberly-Clark	0,28%	General Growth	0,15%

				Properties Inc.	
Ross Stores	0,21%	Kroger Co.	0,20%	Genworth Financial Inc.	0,70%
Stanley Black & Decker	0,11%	McCormick & Co.	0,24%	Goldman Sachs Group	0,25%
TJX Companies Inc.	0,19%	Molson Coors Brewing Company	0,15%	Hartford Financial Svc.Gp.	0,37%
Urban Outfitters	0,11%	Mondelez International	0,27%	HCP Inc.	0,16%
Wyndham Worldwide	0,14%	Monster Beverage	0,23%	Host Hotels & Resorts	0,18%
AUTONATION	0,57%	PepsiCo Inc.	0,25%	Huntington Bancshares	0,22%
AUTOZONE	0,38%	Philip Morris International	0,21%	Intercontinental Exchange	0,17%
BEST BUY	0,46%	Reynolds American Inc.	0,27%	Invesco Ltd.	0,24%
CABLEVISION SYS.	0,50%	Smucker (J.M.)	0,28%	JPMorgan Chase & Co.	0,24%
CARMAX	0,45%	Sysco Corp.	0,25%	KeyCorp	0,20%

CARNIVAL	0,47%	The Hershey Company	0,25%	Kimco Realty	0,16%
CBS 'B'	0,72%	Tyson Foods	0,17%	Legg Mason	0,21%
CHIPOTLE MEXN.GRILL	0,43%	Wal-Mart Stores	0,24%	Leucadia National Corp.	0,21%
COACH	0,73%	Walgreens Boots Alliance	0,13%	Lincoln National	0,37%
COMCAST 'A'	0,52%	Whole Foods Market	0,18%	Loews Corp.	0,19%
D R HORTON	0,76%	3M Company	0,20%	M&T Bank Corp.	0,16%
DISCOVERY COMMS.'A'	0,44%	Ametek	0,16%	Macerich	0,15%
EXPEDIA	0,55%	Amphenol Corp A	0,14%	Marsh & McLennan	0,15%
FOSSIL GROUP	0,65%	Boeing Company	0,14%	McGraw Hill Financial	0,12%
GAMESTOP 'A'	0,57%	C. H. Robinson Worldwide	0,10%	MetLife Inc.	0,34%
GAP	0,45%	Caterpillar Inc.	0,12%	Moody's Corp	0,13%
GARMIN	0,44%	Cintas Corporation	0,16%	Morgan Stanley	0,54%
GOODYEAR TIRE & RUB.	0,89%	Corning Inc.	0,12%	NASDAQ OMX Group	0,11%
HARMAN INTL.INDS.	0,57%	CSX Corp.	0,12%	Northern Trust	0,21%

				Corp.	
HASBRO	0,32%	Cummins Inc.	0,24%	People's United Financial	0,17%
KOHL'S	0,45%	Danaher Corp.	0,17%	Plum Creek Timber Co.	0,16%
L BRANDS	0,46%	Deere & Co.	0,16%	PNC Financial Services	0,22%
L'OREAL	0,15%	Delta Air Lines	0,23%	Principal Financial Group	0,18%
LVMH	0,11%	Dover Corp.	0,14%	Progressive Corp.	0,15%
ACCOR	0,19%	Dun & Bradstreet	0,16%	Prologis	0,17%
BRITISH AMERICAN TOBACCO	0,10%	Eaton Corporation	0,13%	Prudential Financial	0,19%
ROLLS-ROYCE HOLDINGS	0,20%	Emerson Electric Company	0,15%	Public Storage	0,19%
KDDI	0,32%	Expeditors Int'l	0,15%	Regions Financial Corp.	0,45%
Accenture plc	0,26%	Fastenal Co	0,14%	Simon Property Group Inc	0,17%
Adobe Systems Inc	0,25%	FedEx Corporation	0,13%	State Street Corp.	0,24%

Akamai Technologies Inc	0,48%	FLIR Systems	0,14%	SunTrust Banks	0,32%
Alliance Data Systems	0,24%	Flowserve Corporation	0,12%	T. Rowe Price Group	0,19%
Alphabet Inc Class A	0,22%	Fluor Corp.	0,20%	The Travelers Companies Inc.	0,16%
Altera Corp	0,39%	General Dynamics	0,17%	Torchmark Corp.	0,17%
Analog Devices, Inc.	0,29%	Grainger (W.W.) Inc.	0,13%	U.S. Bancorp	0,21%
Applied Materials Inc	0,33%	Honeywell Int'l Inc.	0,16%	Unum Group	0,15%
Autodesk Inc	0,42%	Ingersoll-Rand PLC	0,15%	Ventas Inc	0,14%
Automatic Data Processing	0,30%	Iron Mountain Incorporated	0,20%	Vornado Realty Trust	0,15%
Broadcom Corporation	0,32%	Jacobs Engineering Group	0,10%	Wells Fargo	0,20%
CA, Inc.	0,26%	AT&T Inc	0,22%	Weyerhaeuser Corp.	0,11%
Cisco Systems	0,34%	CenturyLink Inc	0,20%	Zions Bancorp	0,28%
Citrix Systems	0,43%	Frontier Communications	0,18%	STANDARD CHARTERED	0,13%
Cognizant Technology Solutions	0,27%	Level 3 Communications	0,27%	BARCLAYS	0,46%

Computer Sciences Corp.	0,31%	Verizon Communications	0,24%	ROYAL BANK OF SCTL.GP.	0,43%
eBay Inc.	0,31%	MS&AD INSURANCE GP.HDG.	0,49%	AVIVA	0,19%
Electronic Arts	0,34%	DAIWA SECURITIES GROUP	0,17%	PRUDENTIAL	0,14%
EMC Corp.	0,28%	CHIBA BANK	0,41%	AXA	0,41%
F5 Networks	0,55%	BANK OF YOKOHAMA	0,43%	CAP GEMINI	0,17%
Fidelity National Information Services	0,23%	NOMURA HDG.	0,64%	SAP	0,13%
First Solar Inc	0,86%	SHIZUOKA BANK	0,42%	CARREFOUR	0,19%
Fiserv Inc	0,30%	FUKUOKA FINANCIAL GP.	0,45%	DANONE	0,17%
Harris Corporation	0,27%	RESONA HOLDINGS	0,40%	ALCATEL-LUCENT	0,47%
Hewlett Packard Enterprise	0,28%	CREDIT SAISON	0,57%	SANOFI	0,11%
Intel Corp.	0,25%	SUMITOMO MITSUI FINL.GP.	0,38%	BASF	0,11%
International Bus. Machines	0,27%	SONY	0,63%	K + S	0,11%

Intuit Inc.	0,28%	HITACHI CON.MCH.	0,43%	BAYER	0,13%
Juniper Networks	0,53%	CASIO COMPUTER	0,46%	FRESENIUS MED.CARE	0,18%
KLA-Tencor Corp.	0,35%	FUJITSU	0,45%	MERCK KGAA	0,14%
Lam Research	0,33%	TOSHIBA	0,53%	3M	0,20%
Linear Technology Corp.	0,32%	SHARP	0,83%	JOHNSON & JOHNSON	0,25%
Mastercard Inc.	0,28%	TOYOBO	0,35%	MERCK & COMPANY	0,20%
Microchip Technology	0,29%	KIKKOMAN	0,37%	PFIZER	0,22%
Micron Technology	0,68%	TAKARA HDG.	0,55%	UNITEDHEALTH GROUP	0,14%
Microsoft Corp.	0,24%	UNITIKA	0,56%	GLAXOSMITHKLINE	0,21%
Motorola Solutions Inc.	0,27%	TORAY INDS.	0,43%	ASTRAZENECA	0,19%
NetApp	0,34%	HONDA MOTOR	0,32%	SHIRE	0,14%
Netflix Inc.	0,80%	TOYOTA TSUSHO	0,49%	Gilead Sciences Inc	0,09%
Nvidia Corporation	0,42%	KAWASAKI HEAVY INDUSTRY	0,57%	Allergan	0,12%
Oracle Corp.	0,27%	PIONEER	0,80%	Amgen Inc	0,14%
Paychex Inc.	0,28%	ISUZU MOTORS	0,58%	Bristol-Myers	0,24%

				Squibb	
QUALCOMM Inc.	0,30%	ACE Limited	0,16%	Medtronic	0,15%
Red Hat Inc.	0,39%	AFLAC Inc	0,22%	ASTELLAS PHARMA	0,29%
Salesforce.com	0,44%	Affiliated Managers Group Inc	0,21%	CHUGAI PHARM.	0,42%
SanDisk Corporation	0,46%	Allstate Corp	0,18%	DAIICHI SANKYO	0,28%
Seagate Technology	0,54%	American Express Co	0,14%	SUMITOMO DAINIPPON PHA.	0,43%
Symantec Corp.	0,33%	American International Group, Inc.	0,25%	Eisai	0,31%
Teradata Corp.	0,36%	American Tower Corp A	0,18%	KYOWA HAKKO KIRIN	0,38%
Texas Instruments	0,30%	Ameriprise Financial	0,21%	SHIONOGI	0,39%
Total System Services	0,28%	Apartment Investment & Mgmt	0,11%	TAKEDA PHARMACEUTICAL	0,31%
Verisign Inc.	0,23%	Assurant Inc	0,14%	CATAMARAN	0,18%
Visa Inc.	0,21%	AvalonBay Communities, Inc.	0,14%	EXTENDICARE	0,27%

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