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► **To cite this version:**

Hayette Gatfoui, Christian Walter. Less Can Be More!. *Journal of Money, Investment and Banking*, 2007, 9, pp.59-77. hal-04515402

HAL Id: hal-04515402

<https://hal.science/hal-04515402>

Submitted on 21 Mar 2024

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Less Can Be More!¹

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December 2007

Abstract

We focus here on the specific management style of a French insurance company SMA BTP. The employed management style allows the management team to improve its diversified portfolio's return. Indeed, the stock sub-portfolio of this insurance company outperforms some known benchmarks such as Euro Stoxx index, CAC 40 French stock index or Euro Stoxx 50 index. We show that SMA BTP's specific management style is optimal in the lens of two basic important criteria, namely the portfolio's excess return and its performance persistence. Such a persistence profile is driven by the trade-off between portfolio diversification and performance concentration.

JEL Codes: C52, G12.

Keywords: asset allocation, asset selection, concentration, excess return, market timing, performance, stock-picking.

1 Introduction

Focusing on a positive long term real return under a regulatory risk setting,⁴ any insurance company seeks to optimize the management of its asset portfolio. The optimization process is usually envisioned as beating the market even if common thought tells that any investor can only do as well as the market at best (see Ibbotson & Kaplan (2000), and Surz & Price (2000)). Such an investment target requires therefore to question both the investment style as well as the investment decisions made by the insurance company. Under this framework, we study the optimization process handled by a French insurance company - SMA BTP - whose asset portfolio outperforms some known market benchmarks. Specifically, SMA BTP's portfolio incorporates stocks, bonds or interest rate assets as well as money market assets (i.e., short term assets). Our study focuses on the stock component of its global asset portfolio.⁵

More precisely, SMA BTP's management style reduces only to asset/security selection (i. e., a one-step 'active' management style or bottom-up investment/management style). Specifically, the investment decision about the global portfolio is motivated by both a liquidity constraint on the portfolio and asset quality concerns. First, new assets aimed at being added to the global portfolio are bought with available cash (i.e., insurance company's available and non-invested funds, or funds resulting from sales of short term assets). Second, high/medium quality assets are targeted at the global portfolio's level. Namely, the global and stock portfolios composition only depends on market opportunities⁶ (i.e., no dependency on a given benchmark but rather a trade-off between stock-picking and market timing ability). Consequently, the portfolio's concentration in stocks may be high given the targeted risk level, and the global portfolio's turnover may be usually low (depending on the frequency of occurrence of market opportunities).⁷ In particular, the low turnover pattern of SMA BTP stock portfolio is quite worthwhile insofar as Carhart (1997) shows the negative impact of turnover (as well as expenses) on performance.

Literature first ascribes portfolio/fund performance⁸ to five determinants such as expenses, size,⁹ time since portfolio/fund's inception, performance persistence (see Annaert *et al.* (2001) for those four first determinants), and investment/management style (see Ibbotson & Kaplan (2000)). Ibbotson & Kaplan (2000) show that asset allocation policy explains a high part of funds' returns due to the long term strategy they focus on. Moreover, pension funds and balanced mutual funds policy brings no added value relative to their related market benchmarks due to timing effect, security selection, management fees, and expenses. However, SMA BTP's security selection process reveals to generate excess return as compared to Euro Stoxx, CAC40 index, and Euro Stoxx 50 index benchmarks.¹⁰ Second, literature focuses generally on performance persistence to discriminate between portfolios/funds. Indeed, though Jensen (1968) finds no evidence of persistence, Grinblatt & Titman (1992), Elton *et al.* (1993), and Elton *et al.* (1996b) find evidence of a long term persistence effect. In the same way, a short term performance persistence effect is found by Hendricks *et al.* (1993), Goetzmann & Ibbotson (1994), Brown & Goetzmann (1995), Wermers (2000), Bollen & Busse (2001,2005), and Busse & Irvine (2002). In accordance with previous research, SMA BTP's stock portfolio performance seems to persist over time (at least on a short term horizon). The foundation of such a persistence feature can be questioned. Indeed, Goetzmann & Ibbotson (1994) argue that

inferior as well as superior performance persist over time whereas Agarwal *et al.* (2004) and Christopherson *et al.* (1998) underline that bad performers persist while good performers may not persist (i. e., an existing chance factor). Differently, Boyson & Cooper (2004) show that less experienced managers tend to outperform more than experienced managers.

Our study proposes an introductory analysis of a given portfolio's performance, namely the stock component of a French insurance company's global portfolio. Specifically, we propose a pure performance and a pure persistence approach while considering only one fund and focusing on its gross daily return over time (no assessment of the management's effectiveness). Our results are twofold. First, we find that the portfolio under consideration beats the market and we propose an assessment of this stylized fact. Second, we check whether the portfolio's excess performance over the studied time horizon comes either from its diversification profile or its concentration profile (i.e., identifying a limited core of assets driving the global portfolio's performance). The concentration profile results probably from the market timing ability and the stock picking ability of the management team over time.

Assessing the impact of investment style consistency on SMA BTP's stock portfolio, our paper is organized as follows. Section 2 introduces the data set under consideration as well as some portfolio and stock features (e.g., asymmetry, weights). Section 3 computes some classic performance measures, and studies the stock portfolio's performance as well as the contributions of a given set of constituent assets (performance concentration). Section 4 further investigates the performance persistence profile of our stock portfolio. Finally, section 5 draws some concluding remarks and insights for future research.

2 Data and empirical features

We introduce here our data set as well as some corresponding empirical features.

2.1 Data

We consider daily data ranging from January 2nd, 2002 to November 16th, 2005, namely 1010 observations per series. Our study focuses on the daily values of SMA BTP's stock portfolio (i.e., the stock portfolio's total

Table 1: Ten most contributive stocks to the portfolio

Stock	<i>i</i>
Areva SA	1
Bouygues SA	2
Essilor International	3
Pernod Ricard SA	4
Royal Dutch Shell	5
Sanofi-Aventis SA	6
Spir Communication SA	7
Technip SA	8
Total SA	9
Vinci SA	10

capitalization in euros) as well as daily stock prices (in euros) of the ten most contributive stocks of the portfolio in terms of cash profits. These ten stocks are assets that belonged to SMA BTP's stock portfolio over our studied time horizon, and which generated an important portion of the portfolio's total cash profits. The positive contribution of such assets to SMA BTP's stock portfolio comes from both the asset selection process (i.e., stock picking ability) as well as the buy and sell strategy (i.e., market timing ability) established by the management (i.e., choosing the time when to list or delist a given stock in the portfolio, and deciding to delist partially or totally a specific stock in the portfolio). Moreover, the positive contribution of such assets to the stock portfolio comes also from the convenient behavior of those ten stocks relative to the other constituent stocks of the portfolio over time. Namely, these ten core stocks explain more than 35 percent of the positive portfolio's performance (i.e., core assets contributing significantly and positively to the portfolio's global daily return over time, or equivalently performance concentration). We label P_t the current value of SMA BTP's stock portfolio, and S_t^i the current price (i.e., at current time t) of contributive stock i (see table 1).

We also consider r_t the daily three-month Euribor rate of return, which represents our risk free rate proxy. And finally, we take into account three daily stock market indices, namely DJ Euro Stoxx, CAC 40 and DJ Euro Stoxx 50, which represent three different market benchmarks. We label those three market benchmarks DJES, CAC40, and DJES50 respectively. More-

Table 2: Descriptive statistics for asset returns

Asset	Min.	Max.	Mean	Std Dev.	Skewness	Excess kurtosis
SMA BTP	-5.0324	5.4538	0.0201	1.1250	0.0273	3.4654
DJES	-5.1797	6.1498	-0.0005	1.3317	0.0356	3.0227
CAC40	-6.0448	7.0022	-0.0021	1.4859	0.0709	3.5553
DJES50	-6.3621	7.0802	-0.0111	1.5529	0.0476	3.2521
Euribor	0.0054	0.0098	0.0069	0.0014	0.9497	-0.8614
1	-8.0852	11.8686	0.0840	1.7193	0.4939	4.8209
2	-9.7556	11.4926	0.0285	1.9644	0.2719	4.6673
3	-7.3663	9.4033	0.0717	1.6440	0.5388	4.8419
4	-7.0291	10.1494	0.0706	1.5066	0.5352	4.2322
5	-10.4295	6.6412	-0.0092	1.5942	-0.7155	5.0540
6	-10.2367	8.9006	-0.0215	1.8906	-0.0954	3.1268
7	-17.8637	14.8555	0.0436	1.7393	-0.9128	21.1628
8	-21.3212	15.6972	0.0189	2.3463	-0.6201	11.2051
9	-6.5457	7.2375	0.0303	1.5455	-0.1629	2.4280
10	-7.3422	6.8259	0.0672	1.3330	0.2320	3.0786

over, we compute the corresponding continuous daily returns for the stock portfolio, its ten most contributive stocks, and the considered stock market indices as follows $R_t^P = \ln\left(\frac{P_t}{P_{t-1}}\right)$, $R_t^i = \ln\left(\frac{S_t^i}{S_{t-1}^i}\right)$ and $R_t^j = \ln\left(\frac{S_t^j}{S_{t-1}^j}\right)$ for $t \in \{2, \dots, 1010\}$, $i \in \{1, \dots, 10\}$, and $j \in \{\text{DJES}, \text{CAC40}, \text{DJES50}\}$ (i.e., 1009 observations per series). Any return is expressed on a percentage basis. Thus, we can compute the related daily risk premia as the difference between daily returns and the risk free rate, namely $(R_t^i - r_t)$ for stock i as an example.

2.2 Empirical features

We compute key descriptive statistics for the asset returns under consideration as well as their related market risk premia. Results are displayed in tables 2 and 3.

As regards returns, excluding Euribor three-month rate, we find that standard deviations range from 1.1250 to 2.3463, and excess kurtosis estimates are positive (i.e., the empirical probability distributions of returns are sharper

Table 3: Descriptive statistics for asset risk premia

Asset	Min.	Max.	Mean	Std Dev.	Skewness	Excess kurtosis
SMA BTP	-5.0394	5.4467	0.0132	1.1251	0.0246	3.4634
DJES	-5.1888	6.1407	-0.0074	1.3318	0.0331	3.0209
CAC40	-6.0540	6.9951	-0.0090	1.4860	0.0685	3.5538
DJES50	-6.3716	7.0709	-0.0180	1.5530	0.0453	3.2506
1	-8.0942	11.8595	0.0771	1.7194	0.4933	4.8186
2	-9.7626	11.4856	0.0216	1.9645	0.2705	4.6662
3	-7.3742	9.3974	0.0648	1.6440	0.5380	4.8415
4	-7.0378	10.1403	0.0637	1.5066	0.5339	4.2306
5	-10.4389	6.6321	-0.0161	1.5942	-0.7172	5.0559
6	-10.2460	8.8913	-0.0284	1.8907	-0.0967	3.1259
7	-17.8697	14.8497	0.0367	1.7393	-0.9125	21.1601
8	-21.3309	15.6888	0.0120	2.3464	-0.6212	11.2059
9	-6.5552	7.2284	0.0234	1.5456	-0.1646	2.4281
10	-7.3479	6.8181	0.0603	1.3331	0.2310	3.0767

than the corresponding¹¹ Gaussian ones). Moreover, asset returns are generally positively skewed (i.e., right-skewed) except for five stocks. Namely, Royal Dutch Shell, Sanofi-Aventis SA, Spir Communication SA, Technip SA, and Total SA stock returns are negatively skewed (i.e., left-skewed).¹² As regards asset risk premia relative to the three-month Euribor rate of return, the same results as the previous case apply here. Clearly, asset returns as well as related market risk premia exhibit asymmetric and non-normal empirical probability distributions. However, SMA BTP portfolio's risk premium and market benchmarks' risk premia are close to each other in terms of skewness and kurtosis considerations (see Figure 1). However, we can identify five different stock groups in terms of skewness and kurtosis closeness of risk premia, namely (1-3-4), (2-10), 5, (6-9) and (7-8) clusters. As a rough guide, we also display some relevant Kendall and Spearman correlation coefficients. Indeed, the asymmetric nature of return distributions requires using non-parametric correlation measures. All the computed correlation coefficients are significant at a 1% level of bilateral test (see tables 4 and 5).

Whatever the correlation measure under consideration, we get strong and significant correlation coefficients between SMA BTP portfolio's return and stock index returns as well as between SMA BTP portfolio's market risk

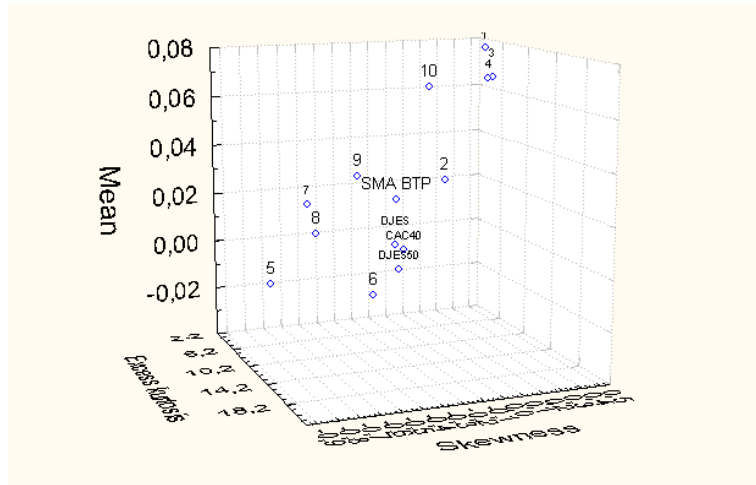


Figure 1: Average asset risk premia vs skewness and kurtosis.

Table 4: Kendall (and Spearman) correlation matrix for asset return

Asset	SMA BTP	DJES	CAC40	DJES50
SMA BTP	1.0000	0.8273 (0.9540)	0.8596 (0.9696)	0.8075 (0.9437)
DJES		1.0000	0.8669 (0.9704)	0.9360 (0.9935)
CAC40			1.0000	0.8606 (0.9691)
DJES50				1.0000

Table 5: Kendall (and Spearman) correlation matrix for asset risk premia

Asset	SMA BTP	DJES	CAC40	DJES50
SMA BTP	1.0000	0.8272 (0.9540)	0.8594 (0.9696)	0.8075 (0.9438)
DJES		1.0000	0.8669 (0.9703)	0.9360 (0.9935)
CAC40			1.0000	0.8605 (0.9691)
DJES50				1.0000

Table 6: Sharpe Index in percent

Asset	SMA BTP	DJES	CAC40	DJES50
Sharpe Index	1.1715	-0.5533	-0.6041	-1.1577

premium and stock index risk premia. Then, we exhibit the strong link prevailing between SMA BTP portfolio and market conditions (as represented by our three market benchmarks).

3 Performance analysis

We analyze SMA BTP portfolio’s performance, and explain how SMA BTP portfolio’s performance is generated (i.e., identify the source of performance). Namely, we investigate some performance concentration grounds among others.

3.1 Classic performance measures

We apply three classic performance measures to SMA BTP portfolio’s return, which are commonly used on financial markets. These measures are respectively known as Sharpe index, Treynor index, and finally Jensen’s alpha. First, Sharpe index expresses as follows for any portfolio P :

$$Sharpe\ Index_P = \frac{\bar{R}_P - \bar{r}}{\sigma_P} \quad (1)$$

where $\bar{R}_P = \frac{1}{1009} \sum_{t=2}^{1010} R_t^P$ (i.e., arithmetic mean of P portfolio’s return),

$\bar{r} = \frac{1}{1009} \sum_{t=2}^{1010} r_t$ (i.e., arithmetic mean of the risk free rate proxy between

01/02/2002 and 11/16/2005), and $\sigma_P = \sqrt{Var(R_P)}$ (i.e., standard deviation or volatility of portfolio’s return) over our studied time horizon.¹³ This index is widely used to assess diversified and undiversified portfolios. It measures the portfolio’s market risk premium per unit of total risk. The values obtained for SMA BTP stock portfolio’s return, and available stock market indices are displayed in table 6.

Table 7: Treynor Index in percent for SMA BTP portfolio

Benchmark	DJES	CAC40	DJES50
β	0.8180	0.7414	0.6953
Treynor Index	1.6103	1.7766	1.8945

Only SMA BTP portfolio exhibits a positive Sharpe index whereas stock market indices exhibit a negative index. Hence, SMA BTP portfolio seems to be more interesting (i.e., it is outperforming) than the considered market benchmarks in terms of generated return, and in the lens of Sharpe measure. Though Sharpe ratio may be inappropriate when asset returns follow non-Gaussian distributions, Eling & Schuhmacher (2006) show that it yields the same ranking across hedge funds as other more appropriate performance measures.

Second, Treynor index expresses as follows for any portfolio P :

$$Treynor\ Index_P = \frac{\bar{R}_P - \bar{r}}{\beta_P} \quad (2)$$

where $\beta_P = \frac{Cov(R_P, R_M)}{Var(R_M)}$ according to the CAPM definition such that R_M represents the market portfolio's return (see Sharpe (1964)). The other variables remain unchanged. This index is mainly used to assess diversified portfolios. Differently, this index measures the portfolio's market risk premium per unit of systematic risk (as defined by Sharpe's beta in the CAPM). Given that we consider three possible market benchmarks, we can compute three benchmark-based Treynor indices (see table 7).

As regards beta estimates, SMA BTP portfolio is positively linked to the financial market while absorbing market shocks (i.e., beta estimates are below unity). We also notice that SMA BTP stock portfolio is the less sensitive to DJ Euro Stoxx 50 market benchmark whereas it is the most sensitive to DJ Euro Stoxx index. Whatever the market benchmark under consideration, SMA BTP portfolio's Treynor index is positive. As expected, the higher index level is achieved for DJ Euro Stoxx 50 benchmark whereas the lowest is achieved for DJ Euro Stoxx benchmark.

Finally, Jensen's alpha was formerly introduced by Jensen (1968) as an extension of Sharpe's CAPM. For any portfolio P , Jensen's alpha is defined as follows for each time t ranging from 2 to 1010:

Table 8: Jensen’s alpha for SMA BTP portfolio (daily basis)

Market proxy	α	Student t_α	β	Student t_β	$R^2(\%)$	DW
DJES	0.0192	2.1671	0.8180	122.9251	93.7522	2.1573
CAC40	0.0198	2.7637	0.7414	153.5272	92.1098	2.0859
DJES50	0.0257	2.5783	0.6953	108.4237	95.9028	2.1412

$$R_t^P - r_t = \alpha_P + \beta_P (R_t^j - r_t) + \varepsilon_t \quad (3)$$

where R_t^j is the market portfolio’s return at time t for $j \in \{\text{DJES, CAC40, DJES50}\}$; R_t^P is the portfolio’s return¹⁴ at time t ; r_t is the risk free rate proxy; β_P represents the portfolio’s sensitivity to the financial market; α_P is a constant term of regression known as Jensen’s alpha; and ε_t is a random normal error with zero expectation and constant variance. Recall that $(R_t^P - r_t)$ and $(R_t^j - r_t)$ represent the market risk premia of portfolio P and market portfolio j respectively. Specifically, Jensen’s alpha represents the portfolio’s abnormal performance on a risk-adjusted basis,¹⁵ namely the non-equilibrium return that the portfolio brings in over the considered investment horizon. Jensen’s alpha represents that part of the portfolio’s return, which results from the portfolio’s specific features (i.e., idiosyncratic profile) apart from market conditions (see table 8 where DW is the Durbin Watson statistic).

For all market benchmarks, Jensen-type regressions are highly significant (i.e., high explanatory power), and exhibit significant regression coefficients (i.e., high level of related Student statistics). Specifically, Jensen’s representation allows for capturing the main evolution of SMA BTP portfolio’s return from day to day. To sum up our results, we notice that beta estimates are all positive, which underlines a positive link with the financial market. However, SMA BTP portfolio’s is shown to absorb market shocks (i.e., beta estimates are below unity). Finally, daily Jensen’s alpha are all positive (i.e., abnormal returns leading to a gain in value for an investment in the portfolio). On an annual basis, corresponding abnormal returns are 6.9110%, 7.1373%, and 9.2410% for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market indices respectively. Consequently, despite its strong link with financial market conditions, SMA BTP portfolio generates a positive excess return (relative to the risk free rate), which results from its idiosyn-

cratic patterns. We underline therefore a performance feature of SMA BTP portfolio whose composition allows for absorbing market shocks. Moreover, classifying the abnormal returns (i.e., idiosyncratic excess returns) of SMA BTP stock portfolio from the lowest to the highest level leads to DJ Euro Stoxx-, CAC 40-, and DJ Euro Stoxx 50-based estimates respectively. The highest abnormal return is obtained for DJ Euro Stoxx 50 market benchmark as expected from table 7.

3.2 Performance concentration

A portfolio's final return usually results from the achievement of a small number of substantial increases rather than the accumulation of many small increases in return. Moreover, such variations tend to cluster over time (i.e., clustering effect). Such a feature explains the asymmetric nature of the changes in asset market prices. Along with these empirical facts, we try to exhibit the most important assets triggering and/or driving SMA BTP stock portfolio's performance (i.e., most contributive assets to the portfolio's global performance). We address the question of how to exhibit the impact of the core set of stocks generating SMA BTP portfolio's performance. Indeed, one idiosyncratic pattern regarding SMA BTP stock portfolio consists of a core set of ten specific stocks driving the portfolio's global performance (i.e., a limited number of key assets), namely performance concentration. Hence, we investigate such a performance concentration feature that may explain the observed performance level.

We realize our performance investigation in four steps. The first step considers the correlation prevailing between SMA BTP portfolio and related relevant stocks. The second step computes some key performance measures (i.e., Sharpe and Treynor indices). The third step undertakes Jensen-type regressions for such relevant stocks. The fourth step finally considers SMA BTP portfolio after excluding from its composition all the most relevant stocks that initially generate a non-negligible portion of the global performance (i.e., that contributes strongly to SMA BTP portfolio's positive excess return).

We consider the ten most contributive stocks to SMA BTP portfolio in terms of generated cash profits (i.e., core stocks). As regards our first step, we display the corresponding non-parametric correlation coefficients between

Table 9: Kendall (and Spearman) correlation coefficients between SMA BTP portfolio and contributive stock risk premia

Stock	Correlation coefficients	Stock	Correlation coefficients
1	0.2315 (0.3375)	6	0.5006 (0.6750)
2	0.4974 (0.6729)	7	0.1537 (0.2244)
3	0.1768 (0.2580)	8	0.2631 (0.3726)
4	0.2099 (0.2998)	9	0.5488 (0.7307)
5	0.5038 (0.6835)	10	0.2665 (0.3833)

SMA BTP portfolio's risk premium and the corresponding ten stock risk premia (see table 9).

All the displayed correlation coefficients are positive (as expected) and significant at a 1% bilateral test level. Recall that the impact of the contributive stocks also depends on the related assigned weights in SMA BTP portfolio (as compared to the other constituent stocks' weights). The higher the assigned weight of a contributive stock in the portfolio is, the more SMA BTP portfolio takes advantage of the stock's positive contribution to its cash profits (i.e., its market value's improvement or increase).

As regards our second step, we display in tables 10, 11, and 12 some key performance measures (i.e., Sharpe and Treynor indices) as well as related details (e.g., stock betas for each market benchmark over our time horizon). Performance indices are displayed in percent, and on a daily basis.

First, Sharpe index estimates are positive for all stocks except for Royal Dutch Shell and Sanofi-Aventis SA assets over our studied investment horizon. Such a feature underlines the efficiency of the management's policy in terms of asset selection as well as listing or delisting decision making over time. Indeed, having negative indices for Royal Dutch Shell and Sanofi-Aventis SA stocks shows that their performance is globally bad over the whole investment horizon. However, SMA BTP management has taken advantage of the good behavior and contribution of those two stocks while

Table 10: Sharpe Index for the ten most contributive stocks

Stock	Sharpe Index	Stock	Sharpe Index
1	4.4873	6	-1.5008
2	1.0982	7	2.1109
3	3.9427	8	0.5129
4	4.2289	9	1.5146
5	-1.0133	10	4.5254

Table 11: Beta estimates for the ten most contributive stocks

Stock	β_{DJES}	β_{CAC40}	β_{DJES50}
1	0.42804	0.37309	0.34868
2	0.99752	0.90827	0.83865
3	0.31782	0.29501	0.25698
4	0.26561	0.24161	0.21840
5	0.89619	0.80576	0.78441
6	0.94095	0.88613	0.82315
7	0.23699	0.20938	0.18705
8	0.65050	0.57130	0.52639
9	0.90919	0.84084	0.79760
10	0.36936	0.33502	0.30453

keeping them in the stock portfolio, and avoided their bad contribution while delisting those assets from its stock portfolio (when the management team considered that the time to delist completely or partially such stocks has arrived). The good global performance of the eight other stocks is highlighted by their corresponding positive Sharpe index estimates.

Second, we also display the beta estimates of the ten most contributive stocks to SMA BTP portfolio in a Treynor index computation prospect. Notice that all the beta estimates are positive for all market benchmarks, underlining then a positive link with financial market conditions. However, those beta estimates remain below unity, which highlights the absorbing feature of such stocks (i.e., they absorb market shocks).

Finally, Treynor index estimates are globally positive for all stocks apart from Royal Dutch Shell and Sanofi-Aventis SA assets over our investment horizon. The same remark as the Sharpe index framework holds for those

Table 12: Treynor Index for the ten most contributive stocks

Stock	Treynor Index for DJES	Treynor Index for CAC40	Treynor Index for DJES50
1	18.0159	20.6693	22.1164
2	2.1615	2.3739	2.5710
3	20.4528	22.0341	25.2948
4	23.9748	26.3566	29.1576
5	-1.8015	-2.0037	-2.0582
6	-3.0140	-3.2004	-3.4453
7	15.4844	17.5258	19.6182
8	1.8491	2.1054	2.2850
9	2.5734	2.7826	2.9335
10	16.3238	17.9972	19.7992

stocks. Notice that classifying stocks from the lowest to the highest Sharpe index level leads to Sanofi-Aventis SA, Royal Dutch Shell, Technip SA, Bouygues SA, Total SA, Spir Communication SA, Essilor International, Pernod Ricard SA, Areva SA, Vinci SA. Differently, classifying stocks from the lowest to the highest Treynor index level leads to Sanofi-Aventis SA, Royal Dutch Shell, Technip SA, Bouygues SA, Total SA, Spir Communication SA, Vinci SA, Areva SA, Essilor International, and Pernod Ricard SA whatever the market benchmark under consideration. Both Sharpe and Treynor index estimates lead to the same classification for the first six stocks and a ranking divergence for the last four stocks. The last four stocks exhibit positive skewness and close mean and excess kurtosis values (see Figure 1).

As regards Jensen's alpha computation, we unfortunately obtain insignificant alpha estimates. We do not display related results for parsimony reasons. Such results may come from the time series profile of our ten most contributive returns. However, computation details and statistics remain available from the authors upon request. To bypass such a feature, we rather consider SMA BTP stock portfolio while removing the related most contributive stocks from it. We call this new portfolio SMA BTP degenerate portfolio. First, removing the most contributive stocks lowers highly Sharpe index level, which becomes 0.4159 now. Second, we display in tables 13 and 14 the results for Treynor and Jensen performance measures.

As compared to the initial portfolio, SMA BTP degenerate stock port-

Table 13: Treynor Index in percent for the degenerate portfolio

Asset	DJES	CAC40	DJES50
β	0.8829	0.7958	0.7462
Treynor Index	0.5731	0.6359	0.6781

Table 14: Jensen's alpha for the degenerate portfolio (daily basis)

Market proxy	α	Student t_α	β	Student t_β	$R^2(\%)$	DW
DJES	0.0125	1.2604	0.8830	118.6222	93.2987	2.0166
CAC40	0.0131	1.4442	0.7958	130.1344	94.36546	1.9105
DJES50	0.0197	1.6907	0.7464	99.1195	90.6603	1.9679

folio exhibits higher beta estimates whatever the market benchmark under consideration. Hence, SMA BTP stock portfolio becomes more sensitive to financial market conditions after removing the most contributive stocks. We also notice that SMA BTP stock portfolio remains the less sensitive to DJ Euro Stoxx 50 market benchmark whereas it remains the most sensitive to DJ Euro Stoxx market index. Moreover, the related Treynor index estimates (i.e., for the degenerate stock portfolio) are lowered by three times as compared to their corresponding values for the initial portfolio. Then, SMA BTP portfolio's performance drops strongly after the most contributive stocks' removal.

Though all Jensen-type regressions as well as market risk premium coefficient estimates are significant (i.e., good explanatory power and significant beta estimates), Jensen's alpha estimates of the degenerate portfolio are insignificant whatever the market benchmark under consideration (i.e., low corresponding Student statistics). Indeed, SMA BTP portfolio's daily alpha drops by 0.0067%, 0.0067%, and 0.0060% respectively for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market benchmarks after removing the most contributive stocks. Removing the most contributive stocks from SMA BTP portfolio cancels then the idiosyncratic feature that underlies the initial SMA BTP portfolio's performance. Consequently, all our previous findings and results emphasize a concentration effect in SMA BTP stock portfolio's performance.

4 Performance persistence

We exhibited previously SMA BTP stock portfolio's performance and related features. We address now the question of how to analyze such a performance persistence at least in a short term viewpoint. Recall that a stock portfolio's performance may result from three dimensions after excluding risk free rate benefits as well as common global market performance.¹⁶ Namely, performance may come from market timing as well as asset allocation ability, stock picking ability of managers, and finally the risk level-based management of the portfolio. These three sources of performance usually result from skills, which are peculiar to managers. We focus on the performance persistence that is due to SMA BTP stock portfolio's specific patterns such as stock picking and market timing issues. Namely, we consider the portfolio's performance apart from risk free rate as well as market-based performance trends.

4.1 A time-varying measure

We focus on SMA BTP portfolio's performance over time, namely performance persistence. Such an investigation requires undertaking a dynamic study over time, and therefore exhibiting time-varying Jensen's alpha. Indeed, the performance measures that we used previously are computed on a static basis, and then no more appropriate here. To this end, we undertake Jensen-type regressions while applying the flexible least square (FLS) estimation methodology.

We employ a linear estimation method, which can deal with correlated observations, is robust to data outliers, and presents many advantages. First, among the set of time-varying parameter models, the FLS method allows for stochastic parameters, which are generated by a non-stationary process. Second, the FLS method allows for estimating processes that may encompass specification errors. Third, FLS methodology can be used to investigate data processes, which are described by approximately linear measurement relations and gradual state evolutions (see Kalaba & Tesfatsion (1988,1990)). Finally, the FLS estimation process can capture systematic and potential idiosyncratic time-variations (see Kalaba & Tesfatsion (1989,1996), and Kladroba (2005)).

Consider the following time-varying Jensen linear regression for any portfolio P and time $t \in \{2, \dots, 1010\}$:

$$R_t^P - r_t = \alpha_t^P + \beta_t^P (R_t^j - r_t) + \varepsilon_t \quad (4)$$

where all the parameters are defined as in (3) case except that alpha and beta coefficients (i.e., α_t^P and β_t^P) are now time-varying. The FLS methodology requires to rewrite equation (4) while setting the following two equations for $t \in \{2, \dots, 1010\}$ and $(t + 1) \in \{3, \dots, 1010\}$ respectively:

$$y_t = x_t \beta_t + \varepsilon_t \quad (5)$$

$$\beta_{t+1} = \beta_t + \eta_t \quad (6)$$

where $\beta_t = (\alpha_t^P \ \beta_t^P)'$ is the unknown 2×1 vector of regression coefficients, $y_t = R_t^P - r_t$ is the endogenous variable, and $x_t = (1 \ R_t^j - r_t)$ is the 1×2 vector of exogenous variables. Moreover, we set $E[\varepsilon_t] = E[\eta_t] = E[\varepsilon_t \eta_t'] = E[\varepsilon_t \eta_{t'}'] = E[\varepsilon_t \varepsilon_{t'}'] = E[\eta_t \eta_{t'}'] = 0$, $E[\varepsilon_t \varepsilon_t'] = \Sigma$, and $E[\eta_t \eta_t'] = \Omega$ whatever times t and t' in $\{2, \dots, 1010\}$ such that $t \neq t'$.¹⁷ Usually, (ε_t) and (η_t) residual processes are assumed to be white noises, and in the most classic case, they are assumed to be Gaussian white noises. In particular, equation (5) is called measurement equation (i.e., it refers to the approximately linear profile of the risk premium's evolution over time) whereas equation (6) is called dynamic equation (i.e., it refers to the gradual evolution of the risk premium's state). Hence, (ε_t) is the measurement error of the model whereas (η_t) is the dynamic specification error of the model.

The FLS estimation methodology focuses on the sum of squared residual measurement errors that is added to the sum of squared residual dynamic errors. This global squared residual error sum is commonly known as the objective function. Moreover, in this objective function, the sum of squared residual dynamic errors is weighted by a given positive coefficient that is called 'incompatibility' cost. For a given incompatibility cost, the FLS methodology attempts to estimate the optimal coefficient sequences (i.e., (α_t^P) and (β_t^P) for $t \in \{2, \dots, 1010\}$) that yield minimal pairs of squared residual dynamic error and squared residual measurement error sums (i.e., the residual efficiency frontier) conditional on a given set of observations (y_t) . The sum of squared residual measurement errors $r_M^2(\beta)$, sum of squared residual dynamic errors

$r_D^2(\beta)$, and the related objective or cost function $C(\beta)$ take respectively the following forms:

$$r_M^2(\beta) = c_M(\beta) = \sum_{t=2}^{1010} (y_t - x_t \beta_t)^2 = \sum_{t=2}^{1010} (\varepsilon_t)^2 \quad (7)$$

$$r_D^2(\beta) = c_D(\beta) = \sum_{t=2}^{1010} (\beta_{t+1} - \beta_t) (\beta_{t+1} - \beta_t)' = \sum_{t=2}^{1010} (\eta_t) (\eta_t)' \quad (8)$$

$$C(\beta) = \sum_{t=2}^{1010} (y_t - x_t \beta_t)^2 + \sum_{t=2}^{1010} (\beta_{t+1} - \beta_t) \Upsilon (\beta_{t+1} - \beta_t)' \quad (9)$$

where $\Upsilon = \begin{pmatrix} \mu_\alpha^P & 0 \\ 0 & \mu_\beta^P \end{pmatrix}$ is the incompatibility cost matrix, and μ_α^P and μ_β^P are two incompatibility cost parameters. Hence, the FLS methodology targets to determine a state sequence $(\hat{\beta}_t^{FLS})$, which minimizes the incompatibility cost function $C(\beta)$ so that $(\hat{\beta}_t^{FLS}) = \arg \min_{(\beta_t, t \in \{2, \dots, 1010\})} \{C(\beta)\}$. By

the way, the sum of squared residual measurement errors penalizes the equation errors whereas the sum of squared residual dynamic errors penalizes the coefficient variations. Therefore, a small incompatibility cost yields a reduced importance of coefficient variations in the objective function. As a result, we get more volatile coefficient time-paths (i.e., highly fluctuating coefficients over time). Differently, a high incompatibility cost penalizes severely coefficient variations. As a result, we obtain very smooth or even nearly constant time-paths for our regression coefficients.

On a practical viewpoint, a convenient state sequence is reached once we get residuals, which conform to FLS key assumptions. Namely, the convenient state sequence is such that we get white noise residuals (i.e., stationary uncorrelated and constant variance residuals roughly speaking). Given this basic framework and after running FLS regression (4), our estimation process yields $\mu_\alpha^P = 100\,000$ and $\mu_\beta^P = 1$. We checked the soundness of our residual while considering successively their classic and partial autocorrelation coefficients until lag 16 (i.e., stationary and independency assumptions), and related Ljung-Box statistics (i.e., white noise assumption). For parsimony

Table 15: Statistics on SMA BTP portfolio’s daily alphas vs stock market indices (in percent)

Asset	Min. Max.	Mean	Median	Std Dev.	Skewness	Excess kurtosis
DJES	0.0137 0.0232	0.0163	0.0154	0.0023	1.8797	2.2793
CAC40	0.0202 0.0253	0.0226	0.0224	0.0015	0.0635	-1.4692
DJES50	0.0231 0.0287	0.0265	0.0271	0.0017	-0.7218	-0.7024

reasons, we do not report these statistics, which remain available from the authors upon request. Notice that econometric results show a stable evolution of SMA BTP portfolio’s alpha (i.e., high incompatibility cost or smooth idiosyncratic excess return relative to the risk free rate) as well as a highly more volatile evolution of SMA BTP portfolio’s beta (i.e., low incompatibility cost or very high sensitivity to the financial market).

As a rough guide, we report some relevant statistics for obtained alpha and beta time series relative to each market benchmark under consideration (see tables 15 and 17). We also draw the corresponding graphs (see Figures 2 and 3).

As regards Jensen-type alphas, classifying their average values from the lowest to the highest level yields DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50-based estimates. First, corresponding annual average estimates are 5.8793%, 8.1517%, and 9.5553% respectively for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market benchmarks. Second, corresponding empirical distribution probabilities behave quite differently. Indeed, DJ Euro Stoxx- and CAC40-based alpha estimates are right-skewed whereas DJ Euro Stoxx 50-based alpha estimates are left-skewed. By the way, DJ Euro Stoxx-based alpha estimates exhibit a positive excess kurtosis whereas CAC40- and DJ Euro Stoxx 50-based alpha estimates exhibit a negative excess kurtosis. Moreover, obtained alpha time series generally exhibit very low standard deviations, which underlines the stable evolution of obtained alpha sequences over time.¹⁸ For further investigation and backtesting prospects, we study

Table 16: SMA BTP portfolio's persistence analysis

Market Index	a	b	c	R^2 (%)
DJES	0.9963 (5345.9756)	-0.00000175 (-2.0330)	0.00005271 (17.0653)	99.9965
CAC40	0.9987 (3514.1669)	-0.00000219 (-2.5193)	0.00002986 (4.6074)	99.9919
DJES50	0.9991 (3032.6551)	-0.00000235 (-2.1642)	0.00002335 (2.6487)	99.9891

the performance property of alpha time series for all market benchmarks. To this end, we run the following linear regression for any portfolio P , and $t \in \{3, \dots, 1010\}$:

$$\alpha_t^P = c + a \alpha_{t-1}^P + b I_{t-1}^j + v_t \quad (10)$$

where a , b , and c are classic regression coefficients; I_{t-1}^j is a dummy variable that is unity when excess return $(R_{t-1}^j - r_t)$ of market index j is negative and zero else; and finally v_t is a random regression error (i.e., white noise). On one side, we check for some market dependency while introducing I_{t-1}^j variable (i.e., to check for the soundness of our estimation process and results). On the other side, the degree of persistence, or equivalently, the lifetime of a shock to alpha estimates depends on the autoregressive part of those alpha estimates (i.e., regression coefficient a). Table 16 exhibits related results where corresponding Student statistics are displayed between parentheses. All regressions exhibit a very high explanatory power. Hence, regression coefficient estimates yield two major issues. First, alpha time series evolve in a stable way for all market benchmarks since slope coefficient a lies below unity. Second, they exhibit an extremely low or quasi-zero dependency relative to the financial market. (Recall that alpha estimates are already considered on a percentage basis, and represent the abnormal or idiosyncratic excess return of SMA BTP portfolio).

As regards beta estimates in table 17, their average values are quite high but still remain below unity, which underlines again the absorbing feature of SMA BTP stock portfolio. However, related standard deviations are far more higher than the ones observed for alpha estimates. Indeed, they range

Table 17: Statistics on SMA BTP portfolio’s daily betas vs stock market indices

Asset	Min. Max.	Mean	Median	Std Dev.	Skewness	Excess kurtosis
DJES	0.1453 1.2445	0.8185	0.8301	0.1423	-0.6368	1.6540
CAC40	0.1691 1.1118	0.7526	0.7573	0.1154	-0.2267	1.2728
DJES50	0.0390 1.1955	0.7129	0.7253	0.1516	-0.4729	1.0617

between 11.5418% and 15.1623% respectively. Moreover, corresponding empirical probability distributions are left-skewed, and exhibit a positive excess kurtosis whatever the market benchmark under consideration (i.e., empirical distributions are sharper than the corresponding Gaussian ones, namely normal distributions with same first and second order moments).

Plotted graphs (see Figures 2 and 3) confirm previous statistical results. Indeed, Figure 2 shows the general evolution of SMA BTP portfolio’s alpha around some fixed constant level. Differently, Figure 3 shows the strong volatile behavior of beta estimates obtained from Jensen-type FLS regressions.

4.2 Lucky manager or real performer?

We investigate whether such a persistent performance results from a small number of stocks in the portfolio. Namely, we investigate concentration properties for SMA BTP portfolio’s performance persistence. For this purpose, we consider SMA BTP degenerate portfolio, and achieve a study that is quite similar to that of the previous section (see tables 18 and 19).

As regards Jensen-type alpha estimates, the same remarks as the previous section apply (i.e., low standard deviations and same features for empirical probability distributions). Annual corresponding values for average alpha estimates are 1.8187%, 4.2954%, and 6.3272% respectively for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market benchmarks. Moreover, removing

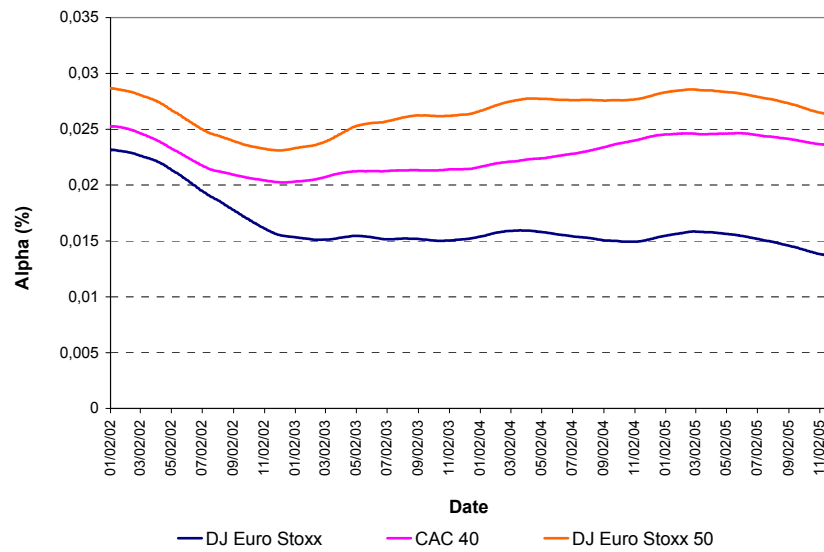


Figure 2: Jensen-type alphas obtained for SMA BTP portfolio (FLS estimates)

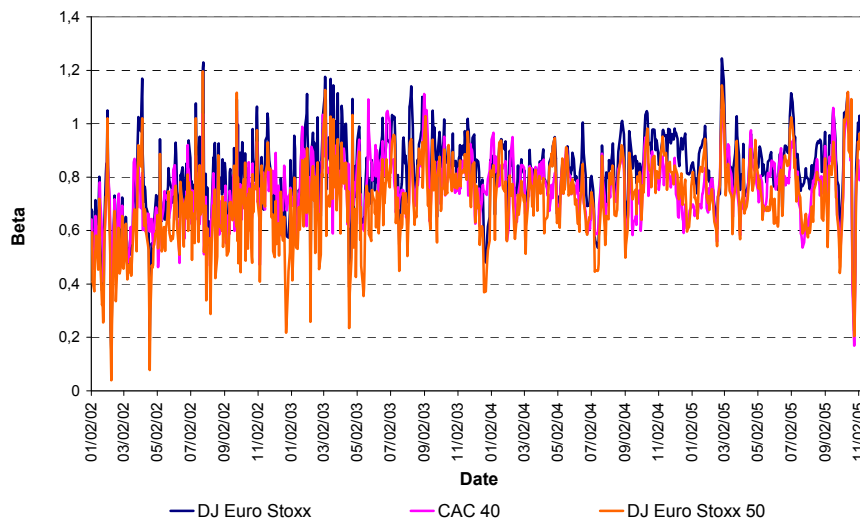


Figure 3: Jensen-type betas obtained for SMA BTP portfolio (FLS estimates)

Table 18: Statistics on SMA BTP degenerate portfolio's daily alphas vs stock market indices (in percent)

Asset	Min. Max.	Mean	Median	Std Dev.	Skewness	Excess kurtosis
DJES	0.0024 0.0126	0.0051	0.0037	0.0027	1.5338	1.3296
CAC40	0.0089 0.0151	0.0119	0.0115	0.0019	0.3483	-1.0502
DJES50	0.0154 0.0202	0.0176	0.0176	0.0011	-0.3309	-0.2903

Table 19: Statistics on SMA BTP degenerate portfolio's daily betas vs stock market indices

Asset	Min. Max.	Mean	Median	Std Dev.	Skewness	Excess kurtosis
DJES	0.2723 1.3773	0.8863	0.8965	0.1456	-0.2106	0.7717
CAC40	0.3811 1.2736	0.8060	0.7975	0.1280	0.3147	0.4856
DJES50	0.1305 1.3542	0.7662	0.7663	0.1646	-0.2450	0.5689

the most contributive stocks from SMA BTP portfolio reduces average alpha estimates by 0.0112%, 0.0107%, and 0.0089% respectively (i.e., a drop of 68.7117%, 51.7699%, and 33.5849% respectively in the initial alpha levels) for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market benchmarks. Incidentally, corresponding daily median estimates drop by 0.0117%, 0.0109%, and 0.0095% respectively (i.e., a drop of 75.9740%, 48.6607%, and 35.0554% respectively in the initial median alpha levels). Hence, the idiosyncratic part of SMA BTP portfolio's excess return is then heavily impacted given that the abnormal side of its return is strongly weakened.

As regards beta estimates, the same remarks as the previous section also apply. Incidentally, related standard deviations are far more higher than initial beta ones, and range from 12.8021% to 16.4559% respectively. Moreover, removing the most contributive stocks from SMA BTP portfolio increases av-

erage beta estimates by 0.0678, 0.0484, and 0.0533 (i.e., their level) respectively for DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50 market benchmarks. Hence, the idiosyncratic part of SMA BTP portfolio's excess return is then heavily impacted. Therefore, removing the most contributive stocks from the portfolio increases its sensitivity to the financial market while offsetting some of its specific features.

As a rough guide, we also plot the corresponding graphs of time-varying alpha and beta estimates (see Figures 4 and 5).

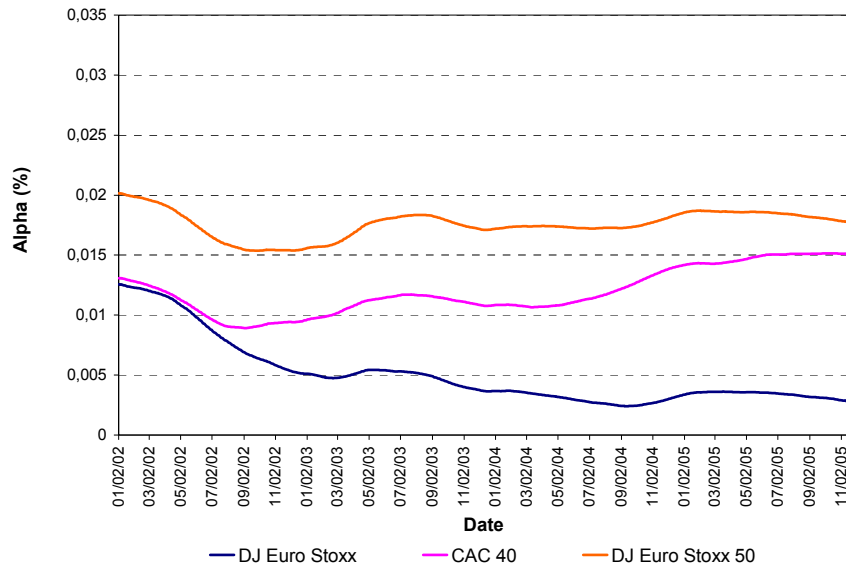


Figure 4: Jensen-type alphas obtained for SMA BTP degenerate portfolio (FLS estimates)

For each market benchmark, alpha time series still seems to evolve around some constant level in a stable way over time. Though Figure 4 shows extremely low alpha estimates for SMA BTP degenerate portfolio, these estimates are still strictly positive. Such an appealing result underlines the good diversification side of SMA BTP initial portfolio as well as SMA BTP degenerate portfolio. Even after the most contributive stocks' removal, SMA BTP degenerate portfolio still succeeds in bringing in a positive idiosyncratic excess return over our investment horizon (although this specific excess return component is small). For an overview, we give the respective non-parametric

Table 20: Correlations between SMA BTP initial and SMA BTP degenerate portfolios' daily alphas vs stock market indices

Asset	Spearman	Kendall
DJES	0.6246	0.4865
CAC40	0.8222	0.5863
DJES50	0.7525	0.5843

correlation coefficients of SMA BTP initial portfolio's alphas with the alphas of its degenerate counterpart for each market benchmark (see table 20).

Obtained correlation coefficients are all positive and significant at a 1% bilateral test level. Such an issue may result from the general diversification dimension of SMA BTP portfolio.

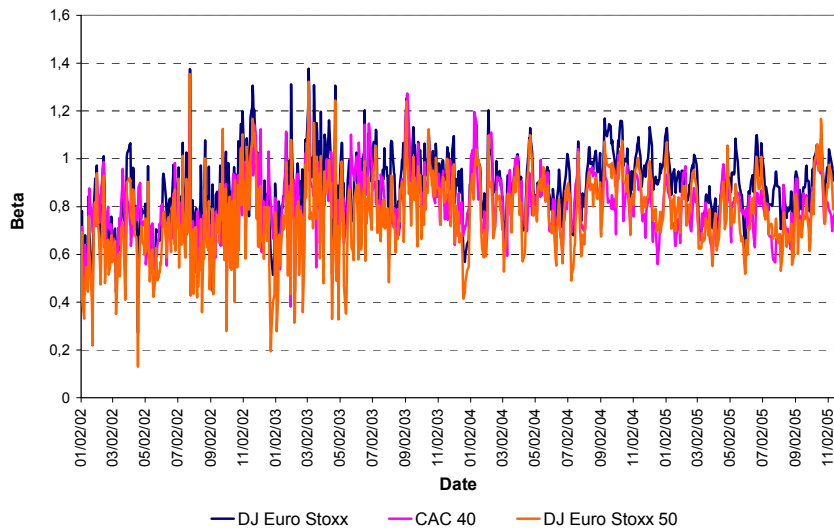


Figure 5: Jensen-type betas obtained for SMA BTP degenerate portfolio (FLS estimates)

Previous plots (see Figures 4 and 5) confirm the statistical results above mentioned. Indeed, Figure 4 shows the general evolution of SMA BTP degenerate portfolio's alpha around some fixed constant level over time apart from DJ Euro Stoxx case. Specifically, regarding DJ Euro Stoxx benchmark,

corresponding alpha estimates evolve in a stable way around some slightly decreasing trend. And, Figure 5 shows the highly volatile behavior of beta estimates for the Jensen-type FLS regression. Moreover, beta estimates are, on an average basis, higher for SMA BTP degenerate portfolio than SMA BTP initial portfolio. Consequently, results show clearly the concentration feature of SMA BTP portfolio's performance as well as the significance of portfolio diversification. Our study highlights therefore the well-known trade-off between concentration and diversification, commonly named as 'conversification'.

5 Concluding remarks

We studied the behavior of SMA BTP insurance company stock portfolio's return as well as its corresponding features. Our main focus targeted SMA BTP stock portfolio's performance as well as its performance persistence. By the way, we investigated some potential grounds that may justify such a persistence feature. Indeed, we shed light on some concentration feature of performance.

For this purpose, we realized a two-step study encompassing first a static analysis for performance study, and then a dynamic study for persistence investigation. The first step resorted to well known performance measures such as Sharpe and Treynor indices as well as Jensen's alpha. This step was based on three different market benchmarks such as DJ Euro Stoxx, CAC 40, and DJ Euro Stoxx 50. On a daily basis, SMA BTP portfolio reveals to outperform the three market benchmarks over our investment horizon. Moreover, its excess return relative to the risk free rate (i.e., its market risk premium) exhibits a positive abnormal return (i.e., a positive idiosyncratic excess return). Such results highlight the performing side of SMA BTP stock portfolio. Indeed, the positive realized abnormal return results from the superior analysis skill of SMA BTP portfolio manager (i.e., SMA BTP internal scoring methodology and fundamental valuation process, see Grinblatt *et al.* (1995) for example).

The second step achieved a dynamic analysis of this performance feature while employing the FLS regression methodology to infer both time-varying alpha and beta estimates. Alpha time series evolve in a stable way whereas beta time series evolve in a highly volatile way over time for all market benchmarks. Moreover, alpha estimates remain strictly positive over our in-

vestment horizon (i.e., showing a positive idiosyncratic portfolio performance over time), and beta estimates are positive and remain below unity (i.e., SMA BTP portfolio is shown to absorb market shocks). By the way, we also realized a stability analysis, which showed the stable property of SMA BTP portfolio's alpha estimates whatever the market benchmark under consideration. Finally, we investigated the concentration feature of the portfolio's performance while removing its most contributive stocks (i.e., considering a degenerate portfolio). We found that alpha estimates are heavily impacted since they are highly lowered. Such a pattern underlines the concentration structure of SMA BTP portfolio. Incidentally, the degenerate portfolio becomes more sensitive to the financial market (i.e., higher beta estimates over time, on average). However, even after removing SMA BTP stock portfolio's most contributive stocks, we noticed two appealing issues. As a first point, SMA BTP degenerate portfolio's alpha estimates still remain positive over our investment horizon after the most contributive stocks' removal (although we get low alpha estimates). As a second point, SMA BTP degenerate portfolio's alpha time series also evolve in a stable way over time. Such features then underline the good diversification side of SMA BTP stock portfolio as well as the management skills (i.e., asset selection policy as well as listing/partial or total delisting decision making).

Consequently, managing a portfolio requires to arbitrate between two essential dimensions, namely portfolio diversification and concentration in a performance prospect. Such an issue yields two main questions. First, we noticed that results were slightly different in level, depending on the employed market benchmark. Hence, to assess soundly a portfolio's performance, one should define in a universal way what a market benchmark should be. Indeed, such a proxy is supposed to represent the latent factor that is common to any asset in the financial market (see Gatfaoui¹⁹ (2006a,b), Roll (1978)). Second, we noticed the portfolio's concentration feature that has to be balanced with the well known diversification principle in portfolio management. Consequently, we should address the question of how to target soundly a concentration level as well as the corresponding goal (see Walter (1999)). Should concentration be aimed at targeting performance apart from risk level and diversification considerations or should it be considered in the lens of those two dimensions?

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Notes

¹We are grateful to Hubert Rodarie Chief Financial Officer (hubert_rodarie@smabtp.fr) at SMA BTP company, and to SMA BTP insurance company for funding this research. We also thank SMA BTP management team for their helpful remarks and comments (e.g., Hubert Rodarie, Philippe De Surmont, Mohamed Majri).

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⁴For example, accounting and prudential rules imply upper bounds for asset weights in the global portfolio.

⁵Regulatory European rules yield SMA BTP company to concentrate its stock portfolio on Euro zone assets. The part of SMA BTP's portfolio that can be invested in foreign assets is limited to 20% at most.

⁶SMA BTP's internal scoring methodology drives the asset selection process while classifying assets in three categories. The first class deals with core assets in the stock portfolio, and relates to firms that exhibit possible growth opportunities (i.e., convenient and lasting returns). The second class deals with assets aimed at being temporarily included in the portfolio. Although those assets exhibit an unsatisfying return level, their return is improving over time. Finally, the third class deals with rejected assets since such stocks exhibit low returns as well as bad fundamentals. Consequently, SMA BTP stock portfolio's performance depends on the ability of the management team to identify profit opportunities in the financial market (i.e., selling over-valued stocks and buying under-valued stocks, see Siegel (2002)). Such an issue requires to evaluate the stock portfolio's absolute return rather than its relative return since benchmarking management is not targeted here.

⁷Core assets generally represent two thirds of the stock portfolio's global capitalization. And, the portfolio's concentration depends on the management's targets (i.e., it ranges generally from 70 to 100 stock issuers at most). Moreover, core assets remain in the stock portfolio between three to five years on average, and the portfolio's turnover ratio lies between 20 percent and 30 percent on average.

⁸Annaert *et al.* (2001) first underline the fact that performance or excess return can come from risk factors, which are not taken into account. Second, current performance is usually linked with past historical performance (i.e., momentum effect).

⁹Elton *et al.* (1996a) exhibit a relationship between size and fund performance. However, such a relationship can be altered by a survivorship bias.

¹⁰Usually, a benchmark index gives the manager information about the general market

risk level.

¹¹Namely, we refer to the Gaussian, or equivalently the normal distributions with the same expectations and variances as the empirical distributions of asset returns.

¹²We can also conclude that those stocks are leptokurtic given previous results.

¹³Namely, for time $t \in \{2, \dots, 1010\}$.

¹⁴Instead of considering a portfolio P , we can also consider any stock i while running a Jensen-type regression.

¹⁵The risk measure is Sharpe's beta here, namely the systematic risk level.

¹⁶Indeed, common global market performance benefits to any investor or manager in the market.

¹⁷Namely, (ε_t) and (η_t) are mutually and serially independent processes. Basically, (β_t) is distributed independently of (ε_t) and (η_t) whatever time t .

¹⁸Notice that median daily alpha values are close to average daily alphas (see table 15).

¹⁹This author investigates the latent factor common to stock returns in the market while employing different filtering methods.