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EXECUTIVE SUMMARY OF THE THESIS

A Markov-Switching dynamic approach to non-linear hedge fund risk exposures

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1 Introduction

Due to the increase popularity of HF and the increasing presence of HF data collected by institutions, a plenty of studies have been performed during last 25 years with the aim to study HF industry and assess hedge funds performance. The first innovative study on HF performance saw its light in 1997 with Hsieh and Fung which extended Sharpe (1992) asset-class based style regression[1] (that in turn was an extension of CAPM of Sharpe 1964). While Sharpe's focus was to mimic the performance of mutual funds that implement a strategy of buy and hold of asset classes, Fung and Hsieh (1997,2001) were oriented to replicate HF performance which used also dynamic trading strategies like short-selling, derivatives and leverage. They clustered individual funds into five different strategies of trading through common factor analysis. One of them, "trend-follower", exhibited returns that were *not linear* but large and positive during the best and worst performing months of the global equity market, mimicking lookback straddles payoffs. Afterwards, Agarwal and Naik (2004) accomplished a broader study discovering that non-linear option payoffs were found not only in risk arbitrage and trend follower HFs but also on a wider range of HF strategies. To replicate HFs dynamic strategies Fung and Hsieh (2004) included in their model five non-linear PTFS (primitive-trend-following-factors) represented by the monthly returns of

[1] An asset-based model is a univariate or multivariate regression where risk factors are securities; when class of securities are gathered together and proxied with market indices, it is called asset-class based model.

lookback straddles on commodities (PTFSCOM), currencies (PTFSFX), 3-months interest rates (PTFSIR), stocks (PTFSSTK) and government bonds (PTFSBD).

Although studying HFs risk exposures using cross-sectional regressions is useful to get a preview of hedge fund non-linear returns, there is a weakness as this perspective do not help investors in a practical way to choose where to invest. Indeed, static regressions don't give insights on dynamic risks exposures according to existing market regimes.

A further improvement is quantile analysis of market versus HFs returns, but market states are exogenously imposed and hidden trends are not visible.

This is why a new current of relatively recent alternative studies has become established in the literature having as main objective the research of structural breaks and patterns in HFs returns. Examples are to be found with Billio et al. (2010) and Stafylas et al.(2018). Following this new stream of studies our thesis wants to assist investors in having a better knowledge of the determinants of Hedge Fund risk and performance during different cycles of the market, since we found a covering gap of HF performance evaluation during last few years.

2 General analysis

We started by performing a general analysis of different HFs strategies. We used HFR equal-weighted strategy monthly indexes to proxy the behaviour of 10 well-known HFs strategies in the literature: Global Macro (GM), Emerging Markets (EM), Equity Hedge (EH), EH-Market Neutral (EH-N), Event Driven (ED), ED-Distressed (ED-D), ED-Merger Aribitrage (ED-M), Relative Value (RV), RV-Convertible Arbitrage (RV-CA), RV-Corporate Arbitrage (RV-A).

Then, we compared them to SP500. Results are reported in table 1.

We found that they all exhibit non-normal returns with HFs strategy indexes returns less volatile than SP500. Skewness is lower than 0 with the exception of GM and Kurtosis is in most cases higher than 3.

In addition, Global Macro, Equity Market Neutral and Relative value returns have the lowest variances. Moreover, all the indexes exhibit positive monthly mean with Emerging Markets and Event Driven Distressed the highest. Sharpe ratio is larger for Event-Driven strategies and Relative value. Considering Sortino ratio and Upside potential showed in table 2 GM is the best strategy followed by ED-D.

In order to find patterns in hedge funds returns we define the concept of "negative (positive) window" if for 3 months in a row the index strategy returns are negative (positive). We opted for 3 months following the outcomes of Agarwal, Naik (2000) HFs study in which the authors, using HFR net-of-fee returns, found that the extent of persistence is highest at the quarterly horizon for hedge funds and, whenever present, is unrelated to the type of strategy (directional or non-directional) followed by the fund.

Looking at table 3 we are able to claim with even more evidence that Global Macro can face crises better than everyone else while defending quite well in bull periods maintaining consistent small positive returns, RV-Distressed is the most performing but much riskier than GM, EH-Market Neutral is the less risky overall and RV-Convertible Arbitrage has the worst profile of profitability and risk.

3 Empirical analysis

3.1 First Model

We have implemented cross sectional multiple linear regressions with linear risk factors. We have included specific regressors according to availability, low collinearity, high correlation with strategies and what other authors used. Risk factors taken into account are:

- SP500 (proxy of global equity market of developed countries)
- MSCI ACWI EM IMI (proxy of global equity market of emerging countries)
- MOM (Momentum, proxy of investing in previous months higher performance stocks)
- DVIX (Delta VIX, proxy of global market volatility trend)
- SMB (Small-Minus-Big, proxy of excess returns of small cap vs large cap stocks)
- CRSPRD (Credit Spread, proxy of excess return of global corporate yields over global sovereign yields)
- TRSPRD (Term Spread, proxy of excess return of global sovereign yields vs risk-free)
- ENERGY (Global Energy Index)
- METAL (Global Metal Index)
- RAWM (Global Agricultural Raw Materials index)

The regression is written as:

$$HF_t = \alpha_i + \sum_{J=1}^{K} \beta_{i,j} F_J + \varepsilon_t$$

Where HF_t denotes the HF strategy return at time t, K the total number of risk factors, $F_{1,t}, \dots, F_{K,t}$ are the values of the factors at time t, $\beta_1, \dots, \beta_K$ are the relevant sensitivities and ε_t is a i.i.d zero mean random variable with ω^2 variance. Results are displayed in table 4.
Then, we have compared the results obtained carrying out a second multiple linear regression reported in table 5 adding non-linear PTFS risk factors. They contribute to highlight more HFs non-linear returns and are useful to assess Global Macro and EH-Neutral trend-following strategies but they still don't allow to overcome the limitations of a static model.

3.2 Second model

With a view of binding market states performances to HFs returns simplifying the comprehension for the investor we have decided to avoid the inclusion of option-like risk factors and adopt a Markov-Switching dynamic regime regression on SP500 equity risk factor as done by Billio et al. in 2010 and, with a different equity risk factor, Stafylas et al. in 2018. We suppose that the random variable of interest R_t is defined by the value of an unobserved discrete state random variable s_t that follows a discrete Markovian stochastic process S_t. We have assumed 3 hidden regimes for the market like Billio et al. (2010) because information criteria AIC and BIC are minimized and this assumption is coherent with the literature that recognizes the market to exhibit 3 regimes. Similarly to Billio (2010), we named "down-market" and "up-market" the regimes which show respectively the lowest and highest mean while we changed the name moving from "tranquil" to "tranquil for now" to characterize the regime with 0-like mean but high variance. Below we report AIC and BIC of MS model with 2 and 3 regimes as well as means and standard deviations of the 3 regimes.

	AIC	BIC
2 regimes	-934,78	-927,67
3 regimes	-960,44	-949,78

3 regimes	μ	σ
Tranquil for now	0,0121	0,0254
Down Market	-0,0426	0,0467
Up market	0,0831	0,0181

We can represent the model as:

$R_t = \mu(s_t) + \sigma(s_t)\varepsilon_t$ with

$\varepsilon \sim iid\ N(0,1)$

$t = 1, 2, \dots T$

R_t = market return at time t

$\mu(s_t)$ = intercept at regime s_t

$\sigma(s_t)$ = standard deviation at regime s_t

Transition matrix is:

$$P = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix}$$

Using the ergodic (unconditional) probability π of each of the n different regimes to initialize the process, we are able to obtain a matrix of state probabilities with dimension number regimes x number of observations of R_t. Afterwards, through Viterbi algorithm we can estimate the hidden most likely state sequence of the Markovian process S_t and so attribute to each observation R_t a state s_t ranging from 0 to 2.

Since our final scope is to assess HFs performance during different states of the market, we divide each HF strategy pool of returns in three regimes performing three different regressions according to S_t. In this way we are able to infer how much the index strategy HF is exposed to each of risk factors belonging to the correspondent regime according to the market states. Below we show the formalization of the 3 regressions:

$HF_t = \alpha(s_t) + \sum_{i=0}^{I} \vartheta_i(s_t) F_{it} + \omega(s_t)\varepsilon_t$ with

$\varepsilon \sim iid\ N(0,1)$

$i = 1, 2, \dots I$ with I that indicates the number of risk factors

$t = 1, 2, \dots T$ with T that indicates the total number of observations

HF_t = hedge fund strategy return at period t

$\alpha(s_t)$ = intercept of the regime s_t

$\vartheta_i(s_t)$ = sensitivity factor i at regime s_t

F_{it} = risk factor i at time t

$\omega(s_t)$ = standard deviation of the regime s_t

In order to discern suitable regressors for different states of the market we carried out 3 stepwise regressions, one for each regime for each strategy. Results are reported in table 6.

4 Findings

We found that almost all HF strategies, with the except of Global Macro, are positive exposed to SMB (small minus big) factor during the 3 market periods under analysis. This is a clear sign of liquidity risk that HFs suffer due to lock-up period as reported by Getmanski et al. (2004), Aragon (2006) and Billio et al. (2010). Moreover, we discover that Credit spread positive exposure to market regimes is present both during tranquil periods and distressed ones, contrary to Billio's findings which see HFs to be exposed only during down-market. We think that this could derive by the high variance that characterizes tranquil regime and so higher risk associated to it.

We report the common behavior of HFs to invest in commodities, especially energy, during distressed periods or high-variance ones demonstrated by Billio et al. (2010), Stafylas et al. (2018). Moreover, we have found GM to be the best strategy in terms of risk-return tradeoff. Evidences are small but consistent positive return, positive skewness and low kurtosis of the return's distribution, complete neutrality during the extreme regimes of the market and insurance strategy during tranquil market to set a floor on losses.

Finally, we have proved the HFs behavior to flew to investments in commodity in periods of instability as reported by Billio (2010) and Stafylas (2018), with energy which is preferred to metal and raw materials in down-market periods.

5 Tables

				Whole period					
Strategy	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev**	**Sharpe**	**Skeweness**	**Kurtosis**	**Jarque bera**	**p value**
GM	0,30%	0,20%	5,58%	-3,81%	1,42%	21,37%	0,39	0,59	68,73	1,2E-15
EM	0,49%	0,80%	9,62%	-14,53%	3,11%	15,88%	-0,98	3,13	41,27	1,1E-09
EH	0,33%	0,58%	8,27%	-11,02%	2,45%	13,47%	-0,75	2,94	24,48	4,8E-06
EH-N	0,13%	0,23%	1,85%	-3,02%	0,75%	18,03%	-1,01	2,85	43,98	2,8E-10
ED	0,41%	0,65%	7,03%	-12,53%	1,97%	20,90%	-1,58	8,44	426,40	2,6E-93
ED-D	0,49%	0,64%	6,43%	-11,18%	1,91%	25,71%	-1,40	6,91	248,97	8,6E-55
ED-M	0,27%	0,39%	4,84%	-9,71%	1,16%	23,40%	-2,28	21,89	4059,17	0,0E+00
RV	0,35%	0,50%	3,93%	-9,90%	1,31%	27,09%	-3,37	22,50	4576,19	0,0E+00
RV-CA	0,35%	0,44%	9,74%	-16,09%	2,03%	17,50%	-2,61	23,83	4957,55	0,0E+00
RV-A	0,35%	0,56%	4,47%	-11,14%	1,68%	20,54%	-2,58	15,35	1924,12	0,0E+00
SP500	0,42%	0,86%	12,68%	-17,02%	4,41%	9,61%	-0,55	1,06	53,42	2,5E-12

Table 1: The table reports a descriptive performance analysis together with higher moments of returns for HF strategy and SP500 index during the period from February 2001 to July 2022

Strategy	Mean	Mean +	Std. dev -	Sharpe	Rank	Sortino	Rank	Up. Potential	Rank	Weight rank	Final rank
RV	0,35%	0,63%	1,68%	27,09%	1	21,13%	6	37,31%	10	5,67	6
ED-D	0,49%	0,97%	1,74%	25,71%	2	28,12%	2	55,50%	6	3,33	2
ED-M	0,27%	0,54%	1,20%	23,40%	3	22,75%	3	45,33%	8	4,67	3
GM	0,30%	0,71%	0,74%	21,37%	4	41,10%	1	96,21%	1	2,00	1
ED	0,41%	0,94%	1,85%	20,90%	5	22,31%	4	50,98%	7	5,33	5
RV-A	0,35%	0,75%	1,89%	20,54%	6	18,31%	8	39,86%	9	7,67	8
EH-N	0,13%	0,35%	0,62%	18,03%	7	21,70%	5	56,89%	3	5,00	4
RV-CA	0,35%	0,79%	2,41%	17,50%	8	14,73%	10	32,62%	11	9,67	11
EM	0,49%	1,45%	2,51%	15,88%	9	19,65%	7	57,62%	2	6,00	7
EH	0,33%	1,09%	1,94%	13,47%	10	16,95%	9	56,16%	5	8,00	9
SP500	0,42%	1,89%	3,35%	9,61%	11	12,63%	11	56,40%	4	8,67	10

table 2. The table reports the calculation of performance rating measures on the period February 2001 to July 2022 with the classification according to their values.

Strategy	Windows +	Windows -	Mean	Mean +	Mean -	Std. dev	Std. dev +	Std. dev-
GM	227	29	1,15%	1,56%	-2,03%	2,49%	2,32%	1,08%
EM	229	27	1,84%	3,11%	-8,92%	6,66%	5,41%	6,61%
EH	235	21	1,27%	2,07%	-7,71%	4,90%	4,01%	5,12%
EH-N	239	17	0,60%	0,80%	-2,26%	1,39%	1,11%	1,82%
ED	236	20	1,50%	2,20%	-6,74%	4,24%	3,39%	4,63%
ED-D	233	23	1,75%	2,52%	-6,05%	4,39%	3,53%	4,63%
ED-M	245	11	1,03%	1,22%	-3,19%	2,17%	1,93%	2,99%
RV	243	13	1,29%	1,66%	-5,49%	2,83%	2,16%	4,87%
RV-CA	235	21	1,32%	2,02%	-6,54%	4,72%	3,67%	7,48%
RV-A	232	24	1,28%	1,83%	-4,02%	3,70%	3,12%	4,65%
SP500	240	16	1,57%	2,52%	-12,63%	7,64%	6,73%	6,49%
Strategy	**Sharpe**	**Rank**	**Sortino**	**Rank**	**Up. Potential**	**Rank**	**Weight rank**	**Final rank**
GM	0,46	2	1,07	1	1,44	1	1,33	1
EM	0,28	9	0,28	6	0,47	4	6,33	6
EH	0,26	10	0,25	9	0,40	7	8,67	9
EH-N	0,43	4	0,33	4	0,44	5	4,33	4
ED	0,35	6	0,32	5	0,47	3	4,67	5
ED-D	0,40	5	0,38	2	0,54	2	3,00	2
ED-M	0,47	1	0,34	3	0,41	6	3,33	3
RV	0,46	3	0,27	8	0,34	10	7,00	7
RV-CA	0,28	8	0,18	11	0,27	11	10,00	10
RV-A	0,35	7	0,28	7	0,39	8	7,33	8
SP500	0,21	11	0,24	10	0,39	9	10,00	10

table 3: The table reports descriptive statistics for HFs strategies and SP500 during 3 months rolling-windows during the period February 2001-July 2022 together with their correspondent performance ratio measures and their comparison in ranks.

Risk factors	GM	EM	EH	EH-N	ED	ED-D	ED-M	RV	RV-CA	RV-A
alpha	0,0014*	0,0001	-0,0005	0,0004	0,0012**	0,0023**	0,0013**	0,0015**	0,0009	0,001*
SP500			0,2654**	0,0574**	0,1536**	0,0805**	0,0937**			
EMMKT	0,1685**	0,4954**	0,1857**	0,0229*	0,0706**		0,0621**	0,0509**	0,0580**	0,0413**
SMB		0,1284**	0,4084**	0,1074**	0,3973**	0,3565**	0,28501**	0,1371**	0,1438**	0,1744**
MOM	0,0589**	0,0390**	0,0402**	0,0768**				0,0216**		
DVIX										
TRSPRD	0,1820**							0,153**	0,3008**	0,2068**
CRSPRD	-0,0973**	0,1823**	0,0708**	0,0428**	0,1682**	0,2494**		0,2584**	0,4080**	0,3458**
ENERGY		0,0222**	0,0217**		0,0296**	0,0509**		0,026**		0,0355**
RAWM			0,0341**					0,0398**	0,0949**	
METAL	0,0566**	0,0409**			0,0255**	0,0432**				
std.dev	0,0125	0,0101	0,0071	0,0058	0,0077	0,0102	0,0078	0,0063	0,0122	0,0081
R^2	0,242	0,898	0,918	0,4	0,853	0,721	0,559	0,771	0,643	0,772
ADJ R^2	0,224	0,895	0,915	0,386	0,849	0,714	0,552	0,764	0,634	0,767
Loglikelihood	768,24	824,26	913,43	964,32	894,63	820,44	889,03	943,55	773,21	878,75
parameters	7	8	9	7	8	7	5	9	7	7
AIC	-1522,48	-1632,51	-1808,85	-1914,63	-1773,25	-1626,88	-1768,06	-1869,10	-1532,42	-1743,49
BIC	-1519,60	-1629,22	-1805,15	-1911,75	-1769,96	-1624,00	-1766,00	-1865,40	-1529,53	-1740,61

Table 4: Representation of the stepwise regressions using forward inclusion at 5% p value and backward offset at 10% p value of linear risk factors over dependent variable defined by HFs strategy indexes. **stands for significance at 5%, * stands for significance at 10% using t-test. Data used range from Feb 2001 to July 2022.

Risk factors	GM	EM	EH	EH-N	ED	ED-D	ED-M	RV	RV-CA	RV-A
alpha	0,0011	0,0002	-0,0005	0,0006*	0,0012**	0,0024**	0,0011**	0,0014**	0,0009	0,0011**
SP500			0,2654**	0,0621**	0,1521**	0,0821**	0,0873**			
EMMKT	0,1413**	0,4946**	0,1857**	0,0309**	0,0686**		0,0575**	0,0485**	0,0580**	0,0384**
SMB		0,1103**	0,4084**	0,1078**	0,3929**	0,3595**	0,2732**	0,1251**	0,1438**	0,1570**
MOM	0,0521**	0,0472*	0,0402**	0,0764**				0,0208**		
DVIX	-0,0331*									
TRSPRD	0,2695**			-0,0902**				0,1463**	0,3008**	0,1808**
CRSPRD		0,1863**	0,0708**		0,1585**	0,2273**		0,2438**	0,4080**	0,3197**
PTFSBD	0,0228**		0,0217**		0,0301**	0,0506**		0,0236**		0,0252**
PTFSCOM	0,0566**	0,0505**	0,0341**					0,0420**	0,0949**	
PTFSIR	0,0336**	0,0397**			0,0244**	0,0420**				0,0361**
PTFSFX	0,0136**					-0,0085**				
PTFSSTK	0,0147**	-0,0097**		-0,0088**				-0,0067**		-0,0102**
ENERGY					-0,0037**					-0,0043**
RAWM	0,0218**									
METAL							-0,0081**	-0,0049*		
std.dev	0,0109	0,0999	0,0071	0,0057	0,0076	0,0101	0,0077	0,0062	0,0122	0,0079
R^2	0,436	0,9	0,918	0,430	0,855	0,727	0,569	0,781	0,643	0,785
ADJ R^2	0,411	0,897	0,915	0,414	0,850	0,719	0,560	0,772	0,634	0,777
Loglikelihood	806,26	826,41	913,43	970,95	896,72	823,49	892,08	949,11	773,21	886,28
parameters	12	9	9	8	9	8	6	11	7	10
AIC	-1588,53	-1634,81	-1808,85	-1925,89	-1775,45	-1630,97	-1772,15	-1876,22	-1532,42	-1752,55
BIC	-1583,59	-1631,11	-1805,15	-1922,60	-1771,74	-1627,68	-1769,68	-1871,69	-1529,53	-1748,44

Table 5: Representation of stepwise regressions using forward inclusion at 5% p value and backward offset at 10% p value of linear and non-linear risk factors over dependent variable defined by HFs strategy indexes. **stands for significance at 5%, * stands for significance at 10% using t-test. Data used range from Feb 2001 to July 2022.

	GM	EM	EH	EH-N	ED	ED-D	ED-M	RV	RV-CA	RV-A
alpha										
1	-0,0012	-0,0001	-0,0006	0,0009**	0,0017**	0,0034**	0,0017**	0,0024**	0,0011	0,0019**
2	0,002762	-0,0034	0,0053**	-0,0045**	-0,0035*	-0,006**	0,0003	0	0,0033	-0,0031
3	0,002586	-0,0008	0,0159**	0,0044	0,0043	-0,0024	-0,0557**	0,0113**	0,0119**	0,0057
SP500										
1	0,16115**		0,28**	0,0681**	0,179**		0,1074**			
2			0,1825**		0,1287**					
3							0,797**			
EMMKT										
1	0,20825**	0,4975**	0,1835**		0,0737**		0,0549**	0,0360**	0,0527**	
2		0,4879**	0,2081**				0,1459**			
3		0,5809**								
SMB										
1		0,1496**	0,3926**	0,0869**	0,381**	0,3337**	0,1894**	0,0852**		0,1076**
2			0,3494**		0,5034**	0,3787**	0,3945**	0,2998**		0,4279**
3			0,6544**		0,3587**	0,4112**		0,353**	0,3409**	0,4604**
MOM										
1				0,0403**						
2		0,1076**	0,0943**	0,1545**		0,0908**				
3									-0,0839**	-0,1118**
DVIX										
1		0,0552**		-0,0383**	0,0348**		0,04**		0,0486**	
2										
3			-0,207**		-0,2156**	-0,2044**				
TRSPRD										
1	0,361109**	0,2127**				0,1777**		0,1868**	0,3048**	0,3329**
2										
3							0,8537**			
CRSPRD										
1	-0,173643**	0,2893**	0,1083**		0,2113**	0,4059**		0,27**	0,4738**	0,443**
2		0,1787**	0,0823*	0,117**	0,2135**	0,28**		0,2497**	0,5445**	0,2803**
3										
ENERGY										
1		0,0267**	0,0215**		0,0153**	0,0393**		0,0156**		0,0183**
2	0,0519**	0,047**	0,0325**		0,0393**	0,071**		0,047**		0,0519**
3										
RAWM										
1	0,072140**	0,0651**	0,0348**		0,0322**	0,0518**		0,0395**	0,0747**	
2										
3					0,1264**	0,206**	0,1222**			
METAL										
1				0,0155**	0,0201**	0,0254*				0,0307**
2										
3										
std.dev										
1	0,0107	0,0085	0,0054	0,0044	0,0057	0,00799	0,00614	0,00403	0,00883	0,0051
2	0,0151	0,0128	0,00858	0,00771	0,0103	0,0129	0,0104	0,011	0,0213	0,0133
3	0,0127	0,0123	0,0108	0,00781	0,00741	0,0105	0,00586	0,00501	0,0072	0,00664
R^2	0,32	0,8724	0,897	0,413	0,8332	0,7153	0,5469	0,738	0,5794	0,7512
1	0,417	0,874	0,9	0,349	0,825	0,672	0,354	0,742	0,562	0,775
2	0,112	0,884	0,909	0,519	0,839	0,752	0,619	0,737	0,58	0,732
3	/	0,729	0,793	/	0,852	0,777	0,884	0,711	0,784	0,808
ADJ R^2	0,290	0,863	0,889	0,384	0,819	0,694	0,521	0,722	0,557	0,736
1	0,398	0,868	0,896	0,328	0,816	0,659	0,336	0,732	0,548	0,768
2	0,078	0,872	0,895	0,491	0,823	0,727	0,597	0,716	0,564	0,711
3	/	0,680	0,731	/	0,786	0,678	0,832	0,658	0,719	0,750
Loglikelihood	787,9	844,32	955,52	998,49	941,82	858,22	926,33	1005,06	814,22	945,03
parameters	12	18	20	13	21	19	15	16	14	16
AIC	-1551,8	-1652,64	-1871,04	-1970,98	-1841,64	-1678,44	-1822,66	-1978,12	-1600,44	-1858,06
BIC	-1509,16	-1588,69	-1799,98	-1924,79	-1767,03	-1610,93	-1769,37	-1921,27	-1550,70	-1801,21

Table 6: Results of 3 stepwise regressions, one for each regime defined by Markov-Switching model on SP500, using forward inclusion at 5% value and backward offset at 10% of risk factors over dependent variable defined by HFs strategy indexes. ** stands for significance at 5%, * stands for significance at 10% using t-test. Data used range from Feb 2001 to July 2022. 1,2,3 stand for respectively “tranquil for now”, “down-market” and “up-market”.

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