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Behavioral explanation of beta variation: French market case

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ABSTRACT: In this study, we test whether investor learning, herding, and prospect theory explain the variation of beta across different return regimes and return frequencies. Empirically, we use quantile regressions to analyze beta change on the French financial market from January 2000 to December 2012.
For daily data, we find a larger estimated impact of systematic shocks on extreme quantiles of firm's returns as compared to intermediate quantiles. The beta pattern is probably symmetrically suggesting that whatever the type of shocks have similar effects. This finding can be explained by herding behavior and investor learning. These behaviors lead to beta- increasing in the extreme returns case.
For monthly data, beta evolves asymmetrically across return regimes with a greater impact of the market in the lower tail of returns distribution. This finding provides strong evidence in favor of prospect theory explanation. Overall, constant beta estimated by ordinary-least squares overestimates the systematic risk of stock in normal times and underestimate the risk in extreme conditions or financial crisis.

KEYWORDS: systematic risk, quantile regression, investor learning, herding, prospect theory, behavioral finance

1 INTRODUCTION

The relationship risk- return is a fundamental financial relationship that affects expected rates of return on every existing asset investment. The most common pricing model proposed to describe this relation is the Capital Asset Pricing Model "CAPM", developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The model proposes that high-expected returns are associated with high levels of risk. Particularly, CAPM suggests that the expected return on an asset above the risk-free rate is linearly related to the non-diversifiable risk as measured by the asset's beta. Substantial empirical work has been conducted to investigate the validity of the model. The CAPM assumes that beta of a stock is constant over time, while empirical literature shows that beta may be varied with data frequency (daily, weekly or monthly) and different regimes of returns. Then, several models have been developed to incorporate the time varying beta (e.g. [6]).

Behavioral finance introduces the investor behavior to understanding the evolution of beta over time. According to Hwang and Salmon [7] the beta becomes biased in the presence of herding behavior. This behavior leads investors to change their beliefs to follow the performance of the overall market more than they should in the CAPM. In other words, they ignore the equilibrium in the CAPM and try to move towards the return for each asset with the market (e.g. [9]).

Moreover, Patton and Verardo [15] propose learning behavior as an explanation the time varying beta. They show a temporary increase of beta around quarterly announcements days. Verardo and Patton suggest that this finding can be explained by investors learning about the profitability of a given firm using information about other firms.

More recently, Savor and Wilson [14] show that the stock market has much higher returns in the days of macroeconomic announcements. Their model is based on the dependence of stock market returns on macroeconomic variables such as expected economic growth in the long term and inflation. Intuitively, the market tends to exercise badly in the days of macroeconomic announcements which make the investment more risky.

In 1979, Kahneman and Tversky demonstrate that investors behave as if maximizing an S-shaped value function. This value function is defined on the basis of gains and losses rather than levels of wealth and it is concave (risk-averse) in the domain of gains and convex (risk-seeking) in the domain of losses, both measured relative to a reference point. More importantly, prospect theory can provide additional explanation of the asymmetric beta. Indeed, if investors are risk-seeking (risk-averse) over losses, beta is expected to be higher (lower) in negative (positive) market conditions.

This paper considers the hypothesis that investor behavior affects the beta and provides economic explanations of his variation. Particularly, we test if investor learning, herding, and prospect theory explain the variation of beta across different return regimes and return frequencies. This study adds to the existing literature by analyzing betas for different return regimes and return frequencies within a quantile regression framework. The main advantage of quantile regression over least-squares regression is its robustness to extreme observations in the dependent variable.

The rest of the paper is organized as follows. Section 2 presents literature review. Section 3 describes the hypotheses, the methodology and the data. Section 3 presents the empirical results. Section 6 concludes the paper.

2 LITTERATURE REVIEW

The CAPM assumes that beta of a stock is constant over time, while empirical literature shows that beta may be changed with data frequency (daily, weekly or monthly) and may vary with investor behavior. Several studies demonstrate that the variation of stock betas can be explained by investor behavior such as investor learning, herding and loss aversion in prospect theory.

Patton and Erardo [15] provide evidence that individual stocks betas increase significantly amount on days of quarterly earnings announcements, and revert to their average levels two to five days later. They explain this finding by investor learning, such as investors interpret the profitability of a company given by using information for other companies.

Baur and Schulze [2] demonstrate that the beta of individual stocks varies across the entire return distribution and that the variation depends on the return frequency. Their results show that there is a symmetric increase of beta in extreme conditions of the market for daily data and an asymmetric reaction of beta for weekly data. They explain this finding with investor learning and herding for shorter investment horizons and prospect theory for longer investment horizons.

Calvo and Mendoza [5] develop a model in which investors preferences are characterized by an indirect expected utility function. They show that relative information costs at shock can lead to herding behavior if these costs are too expensive to prevent investors from collecting and interpreting this information. In the context of changing betas, their argument can be applied to the following situation: if a major shock affects the market and investors do not have time to collect and interpret information (or the information costs are too expensive), they follow the market which leads to higher betas in period of extreme shocks.

In the same way, Hwang and Salmon [7] show that beta-herding increases with the market sentiment. Specifically, if market sentiment is positive (negative), stocks returns tend to increase (decrease), independently of their systematic risk, which will increase (decrease) the beta herding. Their results confirm a significant positive relationship between beta herding and market sentiment. Boujelbène Abbes [4] found that herding behavior increases volatility in financial markets during crisis period.

In 1979, Kahneman and Tversky have analyzed the decision making under risk and they proposed the prospect theory which incorporates human emotions to better describe the human decision. The S-shaped value function described by Kahneman and Tversky [11] is concave over gains (risk aversion for gains) and convex over losses (risk-seeking for losses) and, it is steepest in the loss domain. Based in this theory, Baur and Schulze [2] suggest that stock's returns exhibit higher volatility in a loss regime (negative returns) as compared to gain regime (positive returns). Moreover, the cross-sectional dispersion of returns is larger in a loss regime than in a gain regime. Also, investor behavior affects a firm's beta. If investors are risk-seeking in adverse market conditions, betas will be higher than in more favorable market conditions. Empirically, Baur and Schulze [2] show that the beta varies across different firm-specific return regimes conforming to the value function in Prospect Theory.

3 HYPOTHESES, METHODOLOGY AND DATA

3.1 HYPOTHESES

By considering the literature presented above, we test three major hypotheses in our empirical work:

H1: Investor learning explains the symmetric increase in the stocks- beta for the extreme daily return.
H2: Herding bias explains the symmetric increase in U-shaped beta for the extreme daily returns.
H3: Prospect theory explains the asymmetric variation in the stocks-beta under different regimes for monthly returns.

3.2 METHODOLOGY

Allen et al. [1] suggest that the traditional OLS regression becomes less effective when it comes to analyze the extreme returns, which are often a major interest for investors and risk managers. Based in this suggestion we use the quantile regression to test the three hypotheses described above. The estimator of the quantile regression is not affected by the observations found in the extreme quantiles. Also, the technique of quantiles provides estimates of beta for different regimes of returns which is in conformity with a fundamental proposal of prospect theory.

We estimate the following model:

$$R_{it} = a_i + b_i R_{mt} + v_{it}, \quad (1)$$

$$Q_r (\tau \mid R_{it}) = a_i (\tau) + b_i (\tau) R_{mt} \quad (2)$$

Where, R_{it} is the return of stock *i* at time *t;* R_{mt} is the market return and $Qr (\tau \mid R_{it})$ is the τ -th conditional quantile of a stock's return R_{it}, assumed to be linearly dependent on the market return R_{mt}.

This model is estimated with the quantile regression method and can thus assess the impact of R_{mt} on different quantiles of R_{it}.This approach provides estimates of the coefficients and (pseudo-) R squares for any conditional quantile for each stock.

3.3 DATA AND VARIABLES

We use daily and monthly data of the *CAC40* index and all constituent stocks of this index from January 2000 until December 2012. The basic variables of this study are individual stock returns and market return. An individual stock return is defined as follows:

$$R_{it} = \frac{P_{it} - P_{it-1} + D_{it}}{P_{it-1}} \quad (3)$$

Where, P_{it} and P_{it-1} represent respectively the price of stock *i* at time *t* and *t-1* and D_{it} : dividend of stock *i* at time *t*.

Figures 1 plots the movements of daily returns on the CAC40 index. The Figure indicates that CAC 40 index exhibits lower volatility in period of 2004-mid2007. This finding is confirmed to the results of Ellouz S. [8]. But, during the period from July-2007 until 2009, return index shows enhanced volatility reflecting the impact of 2007- US crisis on the French market. This finding supports the results of Jayech et al. (2011) reporting the presence of financial contagion during the subprime mortgage crisis of 2007 in French market.

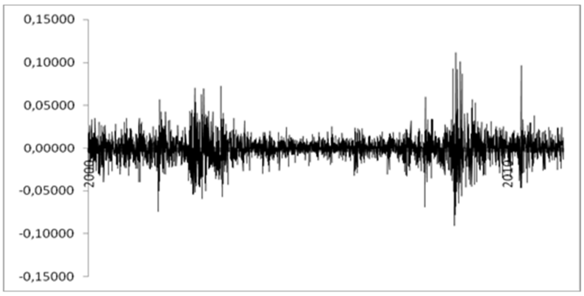

Fig. 1. Monthly moving of CAC40 index returns

Table 1 reports descriptive statistics on daily returns of CAC40 index and the 40 firms which currently constitute this index. This table provides information on the number of observations, mean, median, maximum, minimum, standard deviation, the skewness, the kurtosis, the Jarque-Bera test, the ADF test, and the critical value of 1%.

The CAC40 index has an average positive return, but very low, with a minimum of -0.0903 and a maximum of 0.1118.

The normality test results show that the distributions of CAC 40 and all listed firms are not normal (Skewness ≠ 0 and kurtosis ≠ 3). The results of stationary test show that CAC40 return and the 40 firms' series are stationary.

Table 1. Descriptive statistics for cac40 index and its constitutes

	CAC	ACCOR	AIR LIQ	ALC	ALS	A M	AXA	BNP
Mean	0,00001	0.000442	0.000399	-0.000179	9.85e-05	0.000669	0.000124	0.000351
Median	0.000204	0	0.000592	0.000000	0.000000	0.000605	0.000000	0.000000
Max	0,1118	0,2248	0,11	0,4054	0,5072	0,2844	0,2187	0,209
Min	-0,0904	-0,1947	-0,086	-0,177	-0,5533	-0,3019	-0,1841	-0,1724
Std. Dev.	0.015556	0.031963	0.017291	0.035588	0.044644	0.029737	0.028921	0.024332
Skewness	0.227334	0.276980	0.147524	0.639076	0.495506	-0.004645	0.716064	0.724125
Kurtosis	8.408.287	7.558.571	6.772.959	1.213.685	3.101.652	1.626.973	1.072.089	1.379.666
J-B	3.561.756	2.549.823	1.731.205	10291.90	95029.33	17322.44	7.456.098	14348.61
Test ADF	-2.507.721	-2.520.065	-2.153.723	-2.499.536	-2.491.252	-2.309.313	-2.420.446	-1.895.956
Crit V 1%	-3.961.223	-3.961.223	-3.961.229	-3.961.222	-3.961.223	-3.961.960	-3.961.223	-3.961.236
	BOUYG	**CAP G**	**CAR**	**CR AGR**	**DAN**	**E D F**	**E I N**	**EADSP**
Mean	9.30e-05	-0.000168	-0.000183	0.000151	0.000307	0.000114	0.000596	0.000344
Median	0.000000	-0.000388	-0.000520	-0.000359	0.000000	0.000277	0.000000	0.000000
Max	0,169595	0,263889	0,099495	0,263158	0,101887	0,159794	0,14167	0,134002
Min	-0,143587	-0,229656	-0,110351	-0,133663	-0,104969	-0,104782	-0,125364	-0,263179
Std. Dev.	0.024630	0.030164	0.019593	0.026272	0.016332	0.020016	0.017218	0.026318
Skewness	0.350828	0.251363	-0.003397	0.683826	0.139754	0.224226	0.617342	-0.126666
Kurtosis	7.852.665	8.404.112	6.399.242	1.200.918	7.344.604	9.557.033	1.021.806	8.522.747
J-B	2.906.919	3.561.861	1.397.179	8.317.412	2.291.819	2.516.155	6.484.136	3.695.807
Test ADF	-1.978.226	-2.486.552	-2.094.617	-8.185.728	-9.374.203	-5.945.359	-1.008.080	-9.321.293
Crit V 1%	-3.961.232	-3.961.222	-3.961.229	-3.961.865	-3.961.207	-3.964.632	-3.961.207	-3.961.207
	F T	**GDF S**	**GEN**	**LAF**	**LVMH**	**MICH**	**NAT**	**OREAL**
Mean	-0.000361	0.000954	0.000273	-6.78e-05	0.000333	0.000450	0.000189	0.000193
Median	-0.000867	0.000000	0.000000	0.000000	0.000000	0.000218	0.000000	0.000000
Max	0,255014	2,969332	0,238938	0,139091	0,169014	0,165535	0,388047	0,147292
Min	-0,161966	-0,792819	-0,155556	-0,114303	-0,122644	-0,102053	-0,37193	-0,111183
Std. Dev.	0.027388	0.061853	0.026541	0.022147	0.021476	0.022802	0.028513	0.018309
Skewness	0.885233	3.747.415	0.366064	0.070227	0.499674	0.213458	0.752767	0.217888
Kurtosis	1.252.454	1.840.787	9.978.724	7.048.813	8.477.951	6.863.854	3.585.161	7.251.988
J-B	11348.19	4.09e+08	5.953.767	1.984.559	3.749.221	1.827.247	130770.8	2.209.063
Test ADF	-8.585.884	-9.318.776	-8.633.003	-9.105.640	-9.129.250	-8.995.653	-8.844.661	-9.678.489
Crit V 1%	-3.961.207	-3.961.208	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.207
	PERN	**PEUG**	**PPR**	**PUB G**	**REN**	**SA G**	**SAN**	**SCH EL**
Mean	0.000635	0.000193	4.87e-07	0.000295	0.000290	0.000314	0.000280	0.000394
Median	0.000000	0.000000	-0.000435	0.000000	0.000000	0.000000	0.000000	0.000000
Max	0,113227	0,138259	0,179319	0,160093	0,1625	0,185921	0,146612	0,163745
Min	-0,136332	-0,141349	-0,128315	-0,120925	-0,145038	-0,225	-0,103488	-0,20398
Std. Dev.	0.019263	0.022807	0.023104	0.024048	0.026235	0.024917	0.019070	0.022716
Skewness	0.151959	0.229431	0.487618	0.332652	0.081061	0.158086	0.164712	-0.015402
Kurtosis	9.250.566	6.670.026	9.162.710	7.380.566	7.396.315	1.133.204	6.770.633	9.464.977
J-B	4.735.332	1.654.097	4.707.295	2.373.834	2.340.206	8.406.482	1.732.276	5.050.457
T ADF	-9.830.721	-8.682.214	-8.829.981	-8.747.914	-8.733.705	-9.361.693	-9.366.517	-9.020.662
C V 1%	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.207	-3.961.209
	STM EL	**S E**	**TECH**	**TOTAL**	**UNIB R**	**V C S**	**V ENV**	**VINCI**
Mean	-0.000242	-2.19e-05	0.000701	0.000239	0.000601	0.001368	6.91e-05	0.000661
Median	-0.000767	-0.000309	0.000924	0.000580	0.000648	0.000520	0.000000	0.000000
Max	0,170646	0,137214	0,169988	0,136376	0,119111	0,257976	0,16103	0,181284
Min	-0,126543	-0,088538	-0,191888	-0,091904	-0,167722	-0,160698	-0,411088	-0,124367
Std. Dev.	0.027891	0.020431	0.026176	0.017781	0.017598	0.026011	0.022712	0.019916
Skewness	0.334631	0.567433	-0.099516	0.310993	-0.225891	0.403541	-2.700.925	0.674855
Kurtosis	5.392.802	9.449.638	8.214.196	8.428.431	8.996.500	8.954.328	6.041.358	1.139.686

J-B	7.464.688	1.282.999	3.292.253	3.608.690	4.372.603	4.365.745	276709.2	8.745.786
T ADF	-8.700.128	-4.583.570	-9.492.434	-9.314.982	-9.483.463	-9.460.089	-7.536.478	-9.315.160
C V 1%	-3.961.207	-3.970.921	-3.961.207	-3.961.208	-3.961.207	-3.961.207	-3.962.648	-3.961.207

	VIV
Mean	-0.000197
Median	0.000000
Max	0,224731
Min	-0,25523
Std. Dev.	0.025668
Skewness	-0.523853
Kurtosis	2.035.003
J-B	36531.50
T ADF	-8.352.558
C V 1%	-3.961.207

Note: the full names of the CAC 40 constitutes are presented in the annex.

3.4 RESULTS

This section presents the estimation results of 40 quantile regressions based on the time-series for each firm for daily and monthly data (each regression yields 9 different quantile coefficient estimates for beta). Table 1 and 2 present a summary of the estimation results for several selected quantiles, respectively for daily and monthly data. The tables contain two types of coefficient estimate, the ordinary least square (OLS) coefficient and the quantile regression coefficient (QR).

3.4.1 DAILY DATA

Table 1 show that the average coefficient estimate for beta based on a least-squares regression model is 0,855. Indeed, the estimate of beta by Least Square provides a constant measure across time. An alternative is a time-varying beta obtained by fitting a quantile regression model. For all quantiles, the coefficient of market return is significantly positive.

The average estimate of beta coefficients for the quantile 10% is 0,928; it decreases to 0,903 for the quantile 50% and increases to 0,968 for the quantile 90%. Consequently, we note the presence of U-shape pattern.

Table 2. OLS and quantile regression results for 40 firms, daily data

	a	b
OLS -Coef	0,0248 (0,765)	0,8547 (40,8904)
EST QR (10%)	-0,0187 (-27,5589)	0,9285 (27,3882)
EST QR (20%)	-0,0109 (-26,6382)	0,9146 (31,205)
EST QR (30%)	-0,0065 (-19,7879)	0,9081 (32,1309)
EST QR (40%)	-0,0031 (-10,5279)	0,9027 (32,0055)
EST QR (50%)	-0,0001 (-0,4261)	0,9026 (32,351)
EST QR (60%)	0,0029 (9,5579)	0,9055 (32,4184)
EST QR (70%)	0,0065 (18,6611)	0,9085 (31,5762)
EST QR (80%)	0,0112 (25,2002)	0,9159 (29,3659)
EST QR (90%)	0,0198 (27,488)	0,9292 (27,5874)

To better presenting the beta variation across quantiles, we present in figure 2 the evolution of the beta coefficients for different quantiles. The graph clarifies the U-shaped pattern of the coefficients across quantiles.

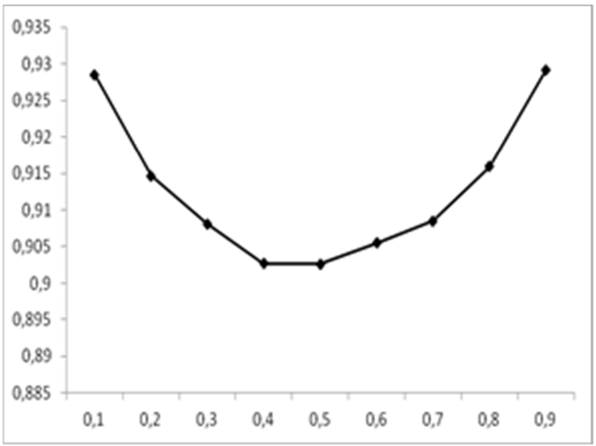

Fig. 2. The evolution of beta across quantiles - daily data

We show that aggregate market affects differently individual stock returns depending on the firm's return regime. Indeed, the figure indicates the larger estimated impact of the market on return-extreme quantiles as compared to intermediate quantiles. Indeed, beta increases in the tails of the distribution. This increasing is probably symmetry suggesting that whatever the type of shocks have similar effects. This finding can be explained by herding behavior. In the event of appearance of shock on the market, the investor does not find time to interpret information; he will follow the market trend what involves, leading to an increase in beta in the extreme return case. This result confirms our second hypothesis suggesting that herding bias explains the symmetrical increase in U-shaped beta for the extreme daily returns.

An alternative explanation for the beta variation is the investor learning. If large return surprises occur, beta increases, affecting extreme quantiles' returns. If news announcements are small or within a "normal" range, investors do not use this information for other firms and beta does not increase. The variation of betas and its U-shape pattern across quantiles support our first hypothesis suggesting that betas are regime-dependent. This finding can be explained with a theoretical model where investors learn about the profitability of other firms by using information on a given firm.

3.4.2 MONTHLY DATA

Table 3 presents the coefficient estimates of beta for monthly data. The average estimate of the beta coefficients for the quantile 10% is 0,899, while the value of the coefficient decreases to 0,773 for the quantile 50% and it is 0,472 for the quantile 90%. Consequently, the positive impact of market returns on individual stocks' returns decreases for lower quantiles to higher quantiles. Moreover, the Least Squared beta (0.8185) overestimates the risk in lower quantiles and underestimates the risk in intermediate and higher quantiles which can affect the investor and manger decisions.

Table 3. OLS and quantile regression results for 40 firms, monthly data

	a	b
OLS- Coef	0,0085 (0,6228)	0,8185 (4,3998)
EST QR (10%)	-0,09 (-7,0506)	0,8989 (3,5445)
EST QR (20%)	-0,0542 (-5,4807)	0,8537 (3,543)
EST QR (30%)	-0,0315 (-3,5489)	0,8304 (3,679)
EST QR (40%)	-0,0143 (-1,5813)	0,7975 (3,4042)
EST QR (50%)	0,0025 (0,2475)	0,7735 (3,1284)
EST QR (60%)	0,01945 (1,9005)	0,7281 (3,0595)
EST QR (70%)	0,03895 (3,5635)	0,6448 (2,7737)
EST QR (80%)	0,06335 (5,1918)	0,5865 (2,5214)
EST QR (90%)	0,1003 (6,2577)	0,4717 (2,3699)

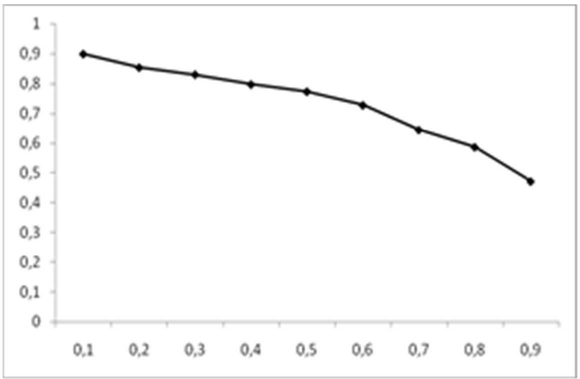

Fig. 3. The evolution of beta quantiles, monthly data

We show an asymmetrical evolution of beta across quantiles with a higher estimated impact of shocks if the stock exhibits extreme negative returns than if the stock exhibits average or extreme positive returns. Indeed, beta is 0.899 in the quantile 10% and it is 0.472 in the quantile 90%. This asymmetrical variation of beta cannot be explained by learning investor or herding behavior since they suggest a symmetrical evolution of beta. This finding is consistent with the fundamental proposition of prospect theory which models the differential behavior of investors when faced with losses or gains. According to prospect theory investors are risk-seeking over losses and risk-averse over gains, which leads them to gamble in falling markets and prefer “no gamble” in rising markets. This behavior explains the cross-sectional dispersion asymmetry in falling and rising markets. Indeed, in a loss-regime, investors are risk-seeking and thus increase the range of possible return realizations across firms. Similarly, in a gain-regime investors are risk-averse and thus decrease the range of possible return realizations across firms.

The difference between monthly and daily results can be explained by the change of investor behavior at different investment horizons. By differentiating between gains and losses, prospect theory provides a convening explanation to monthly results. Indeed, it is reasonable to assume that investors change their behavior following an estimation of gains and losses on a monthly basis and not on a daily basis. Therefore, it is not surprising that prospect theory can explain the results for monthly return frequencies, but not for daily.

4 CONCLUSION

One of the most striking patterns in the financial markets is the variation of beta. In this study, we examine on the French market, the ability of behavioral finance to explain the beta change. Empirically, Investor learning, herding and prospect theory are applied to explain the variation in beta across different return regimes and return frequencies. The main contribution of this paper is the application of quantile regression to the analysis of beta change. Quantile regression is a suitable tool to analyze variation of beta in the extreme tails of aggregate returns distribution.

For daily data, we find a strong impact of aggregate and systematic shocks depending on stocks' return regimes. The impact of systematic shocks in stock return tends to be larger extreme returns than in normal return regimes. This variation can be explained by the herding behavior suggesting that investor follows the market trend in the appearance of new information. This behavior leads to beta increasing in the extreme returns case.

In addition, the increase in beta is more robust in the good announcements than in the bad announcements. This result can be explained with investor learning. In case of larger return surprises, beta increases affecting extreme quantiles' returns. But, in case of smaller or normal return surprises, investors do not use this information for other firms and beta does not increase.

For monthly data, beta evolves asymmetrically across return regimes with a greater impact of the market in the lower tail of returns distribution than in the upper tail of returns distribution. This finding provides strong evidence in favor of prospect theory explanation. Indeed, in a loss-regime, investors are risk-seeking and thus increase the range of possible return realizations across firms. Similarly, in a gain-regime investors are risk-averse and thus decrease the range of possible return realizations across firms.

Overall, constant beta estimated by ordinary-least squares overestimates the systematic risk of stock in normal times and underestimate the risk in extreme conditions or financial crisis. This finding has fundamental implications for investors and portfolio managers.

ABBREVIATIONS

CAC40 Composition	Abbreviation
ACCOR	*ACCOR*
AIR LIQUIDE	*AIR LIQ*
ALCATEL	*ALC*
ALSTOM	*ALS*
ARCELORMITTALREG	*A M*
AXA	*AXA*
BNP PARIBASACT.APARIBAS ACT.A	*BNP*
BOUYGUES	*BOUYG*
CAP GEMINI	*CAP G*
CARREFOUR	*CAR*
CREDIT AGRICOLE	*CR AGR*
DANONE	*DAN*
EUROPEAN AERONAUTIC DEFENCE AND SPACE COMPANY	EADSP
ELECTRICITE DE FRANCE	*E D F*
ESSILOR INTERNATIONAL	*E I N*
France TELECOM	*F T*
GDFSUEZ	*GDF S*
OREAL	*OREAL*
LAFARGE	*LAF*
LVMH	*LVMH*
MICHELIN	*MICH*
NATIXIS	*NAT*
PERNOD RICARD	*PERN*
PEUGEOT	*PEUG*
PPR	*PPR*
PUBLICIS GROUPE	*PUB G*
RENAULT	*REN*
SAINT GOBAIN	*SA G*
SANOFI	*SAN*
SCHNEIDER ELECTRIC	*SCH EL*
GENERALE	*GEN*
STMICRO ELECTRONICS	*STM EL*
SUEZ ENVIRONNEMENT COMPANY	*S E*
TECHNIP	*TECH*
TOTAL	*TOTAL*
UNIBAIL RODAMCO	*UNIB R*
VALLOURE CUSINE SATUBESDELOR	*V C S*
VEOLIA ENVIRONEMENT	*V ENV*
VINCI	*VINCI*
VIVENDI	*VIV*

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