Testing the CAPM: Evidences from Italian Equity Markets

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Abstract

The aim of the following work is to exploit principal econometric tecniques to test the Capital Asset Pricing Model theory in Italian equity markets. CAPM is a financial model which describes expected returns of any assets (or asset portfolio) as a function of the expected return on the market portfolio. In this paper I will firstly explain the meaning of the market risk and I will measure it via the estimation of beta coefficients, which, in this view, are seen as a measure of assets' sensitivity to market portfolio fluctuations. The theoretical framework is based on the Sharpe (1964) and Lintner (1965) version of the CAPM and on the Pettengill's hypothesis (1995) over the relationship between betas and returns. Secondly, I will test the presence of specific effects which usually occur in financial markets; in particular, I will check the presence of the well-known January effect and detect the existence of structural breaks over the considered period of time.

1 Introduction: CAPM as a linear regression model

The CAPM theory affirms that in a world where investors have homogeneous expectations about expected returns and covariances of individual assets, in the absence of transaction costs, taxes and trading restrictions of any kind, the market portfolio, which represents the aggregations of all individual porfolios, is mean variance efficient and gives the maximum expected return for a given level of risk.

A first representation of the CAPM (Sharpe and Lintner version) posits that the expected return on an asset is given by:

$$E(R_{it}) = R_f + \beta_{im} (R_{tm} - R_f) \tag{1}$$

where:
R_{it} = expected risky return of i-th asset at time t;

R_{tm} = risky return on the market portfolio at time t;
R_f = riskless return.

$$\beta_{im} = \frac{cov\left(R_{it}, R_{tm}\right)}{var\left(R_{tm}\right)}{}^{1} \tag{2}$$

β can be seen as the best measure of the asset risk and indicates how strong fluctuations in j-th asset returns are related to movements of the market as a whole.

Sometimes this coefficient can be interpreted as a measure of the market risk, or as the risk which can't be eliminated by diversification and it is equal to the covariance of the portfolio return.

Empirical tests of the Sharpe-Lintner version of CAPM have focused on three implications:

1. The intercept is zero;
2. Beta completely captures the cross sectional variation of expected excess returns[2];
3. the market risk premium, $E\left(Z_m\right)$, is positive.

A second representation of the CAPM (Black et al. (1972) version) predicts that:

$$E\left(R_{it}\right) = \gamma_0 + \gamma_1 \beta_i \tag{3}$$

where:
$E\left(R_{it}\right)$ = expected return on i-th asset
γ_0 = expected return on the porfolio
$\gamma_1 = E\left(R_{mt} - R_{ft}\right)$, expected risk premium of the market porfolio

The CAPM assumes that the expected market excess return $E\left(R_{mt} - R_{ft}\right)$ is positive. Under the positive expected market excess return, Equation (3) denotes a positive linear relation between expected returns and betas.

Finally, Pettengill et al. (1995) argued that there should be a positive relationship between beta and return when the excess market return is positive and a negative relationship when the excess market return is negative; they suggested to divide into up market months and down market months the sample. The hypotheses, predicted by Pettengrill et al. are:

1. $H_0 : \Upsilon_2 = 0$;
2. $H_a : \Upsilon_2 > 0$;
3. $H_0 : \Upsilon_3 = 0$;

[1] In terms of excess returns: $E\left(Z_i\right) = \beta_{im} E\left(Z_m\right)$, where $Z_i = R_i - R_f$ and Z_m is the excess return on the market portfolio of asset.

[2] When a risk-free asset exists, γ_0 will be the risk-free return

4. $H_a : \Upsilon_3 > 0$.

where Υ_2 and Υ_3 are the average values of the coefficients of the two subsamples (up market months and down market months).

In empirical tests of the model betas are usually estimated in a time-series regression. Subsequently, a cross-sectional regression of the form

$$r_{jt} - r_f = \beta_j \left(r_{mt} - r_f \right) + \varepsilon_{jt} \tag{4}$$

is estimated for each month of the sample period, where ε_{jt} represents the error term:

$$\varepsilon_{jt} = u_{jt} - \beta_{jumt}{}^{3} \tag{5}$$

u_{jt} = unexpected returns on j-th asset
u_{mt} = unexpected returns on the market portfolio.

Finally, a statistical framework is summarized for the estimation.

Define Z_t as an $(Nx1)$ vector of excess returns for N assets (or portfolios of assets). For these N assets, excess returns can be described using the excess-return market model:

$$Z_t = \alpha + \beta Z_{mt} + \varepsilon_t \tag{6}$$

$$E\left(\varepsilon_t\right) = 0 \tag{7}$$

$$E\left(\varepsilon_t \varepsilon_t\prime\right) = \Sigma \tag{8}$$

$$E\left(Z_m\right) = \mu_m \qquad E\left(\left(Z_{mt} - \mu_m\right)^2\right) = \sigma_m^2 \tag{9}$$

$$Cov\left(Z_{mt}, \varepsilon_t\right) = 0 \tag{10}$$

β is the $(Nx1)$ vector of betas, Z_{mt} is the time period t market portfolio excess return, and α and ε are $(Nx1)$ vectors of asset return intercepts and disturbances, respectively. The implication of the Sharpe-Lintner version of the CAPM is that all of the elements belonging to the vector α are zero.

[3] We can write the following relations: $\beta_j = E\left(u_{jf}, u_{mt}\right) / var\left(u_{mt}\right)$ and $\varepsilon_{jt}(r_{mt} - r_f) = E\left((u_{jt} - \beta_{jumt})u_{mt}\right) = E\left(u_{jtm}, u_{mt}\right) - \beta_j E\left(u_{mt}^2\right)$.

2 Empirical Evidence

2.1 Dataset

Tests were performed using a fifteen-year sample of monthly returns within six sectors of stocks listed on the Milan Stock Exchange. Automobile industry return for the Industrial macrosector, Distribution Services and Media industries return for the Services macrosector and Insurance, Bank and Construction industries return for Financials macrosector have been used. Furthermore, the MIB index was used as a proxy of the market portfolio, and the three-month Italian Tresury bill return was used for the risk free rate. The sample extends from January 1990 until February 2005.

Tests were conducted for the overall period and for three five-year subperiods. Furthermore, I considered September 11th 2001 as a date to evaluate the presence of structural breaks.

The main sources for the data was Datastream and Borsa Italiana Spa[4].

2.2 Descriptive statistics

As a first step, I show some summary statistics of the database. Table 1 presents summary statistics of market returns differentiating between Up months and Down months, from January 1990 to February 2005. On average, the number of Up months are slightly higher than the number of Down months.

Furthermore, Table 2 shows summary statistics of industries averege returns which are almost all positive, exception made for the Automobile industry, which have filed a -0.00193 average return over the entire period.

[4] http:\\www.borsaitaliana.it

1. Number of Up and Down months			
Index	Total sample	Up Months	Down Months
Mib	180	95	85

2. Average and standard deviation (SD)			
	Total sample	Up months	Down months
Average	0.0068802	0.0552466	-0.0471763
SD	0.067619	0.0505576	0.0357842

Figure 1: Summary Statistics of Market Returns with the Difference of Up Months and Down Months (January 1990 - February 2005)

	Industry					
	Bank	Automobile	Distribution	Insurance	Media	Construction
Returns						
Average	0.0060405	-0.00193	0.0078428	0.0065389	0.0080191	0.0037143
SD	0.0755826	0.0965766	0.0810311	0.0734844	0.1112349	0.0690041

Figure 2: Summary Statistics of Industries Averege Returns (January 1990 - February 2005)

2.3 Regressions. Interpretation of coefficients.

I estimated the validity of CAPM for six industry portfolios, using the Sharpe and Lintner version and I regressed excess returns of industry portfolios upon the excess return of market index proxy (MIB), initially not including an intercept (results are shown in Table 3).

Industry	Bank	Automobile	Distribution	Insurance	Media	Construction
Excess mr						
Overall	1.021	1.083	0.849	0.951	1.047	0.726
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
1st period	0.93	1.31	0.833	0.942	0.651	0.695
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
2nd period	1.045	0.908	0.816	0.891	1.2	0.786
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
3 rd period	1.127	1.104	0.961	1.116	1.388	0.637
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
R^2 (*)	0.832	0.573	0.497	0.765	0.4	0.503
Adj R^2	0.831	0.57	0.494	0.764	0.397	0.5
S (*)	0.031	0.062	0.057	0.035	0.086	0.048

(*) overall period

Figure 3: CAPM regression (without intercept)

Results regard the estimations on beta coefficients, which represent a sensitivity coefficient explaining how sensitive the value of the industry porfolios is with respect to the market fluctuations. As the table 3 clearly shows, this sensitivity is relatively high for Automobile and Media industries, whilst it is relatively low for Construction and Distribution. This means, for instance, that an excess return on the market of 10% corresponds to an expected excess return on the Automobile industry of 10.83%.

As for the economic interpretation of results, the relatively high value of the beta coefficient in the Automobile industry shuld not be surprising, since durable goods are very sensitive to market movements. During recessions households reduce wages and the demand for cars decreases as well. Otherwise, we observe rather a strange result which regards the low sensitivity value of the Construction industry; in fact, the sensitivity of this sector to overall market fluctuactions usually is higher than the sensitivity evaluated in our sample, and it is often more correlated with the business cycle trend.

Assuming that the conditions required for the distributional results of the OLS estimator are satisfied, I tested the (null) hypothesis that $\beta_j = 1$ by the meaning of an F-test. By the obtained evidence, the null can be rejected for Distribution and Construction industries, whilst it can be accepted for Bank, Automobile, Insurance and Media. That is, the last four industries expected returns on the industry portfolio has been very close to expected returns on the overall market as the following explanation shows.

Suppose that $\beta = 1$; then the following expressions can be written:

$$E\left(R_{ti}\right) = R_f + 1 * \left(E\left(R_{tm}\right) - R_f\right)$$

$$E\left(R_{ti}\right) = E\left(R_{tm}\right)$$

That is, the expected return on the i-th porfolio is exacltly equal to the expected return on the market.

As suggested by Cambell et al. (1997) we have performed the same test again over three equi-partitioned subsamples (first period 1990/1995; second period 1995/2000; third period 2000/2005).

Results of Table 3 show that Bank, Insurance, Distribution and Construction industries have recorded a steady trend over the last fifteen years.

On the other hand, Automobile and Media industries have filed a more variable trend; expecially the Media industry has shown a very high sensitivity coefficient over the last five years ($\beta = 1.388$), whilst over the first five years the same coefficient was only equal to 0.651. These different results could be due to some particular conditions which Automobile and Media markets have faced over the last years.

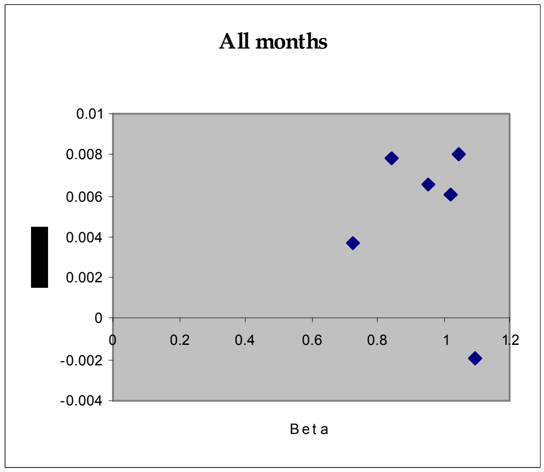
Media industy has faced some remarkable technological breaktroughs and, loosely speaking, the dimension of the market has become increasingly big. Furthermore, Media industry focalized on different technologies (Internet, broadband connections, mobile telecommunications and so on), which are in a development phase within the product life cycle framework. One of the main feature of this phase is the possibility of gaining market leaderships, associated with higher profits, which resolves into higher stock prices.

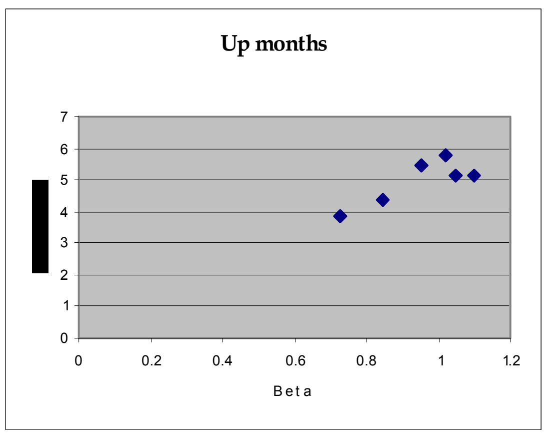
I intend to make a step further in the analysis. As the CAMP theory assumes that the only relevant variable in the regression is the excess return on the market porfolio, any other variable should have a zero coefficient, constant term included. This is precisely what I want to prove. For doing this, another regression of the previous model (Sharpe and Lintner version) have been run, this time including a constant term. Results of the regression are shown in Table 4 (they are only referred to the overall period). The main goal is to evaluate the validity of CAPM by testing whether the intercept term is zero. Results show that we can accept the null hypothesis for each industry, which means that the intercept term is really equal to zero. Indeed, we can accept the validity of CAPM at the 5% level; industry porfolios are expected to have a return which is exactly equal to what CAPM predicts.

Industry	Bank	Automobile	Distribution	Insurance	Media	Construction
constant	0	0	0	0	0	-0.001
P>|t|	0.668	0.044	0.648	0.994	0.898	0.706
Excess mr	1.022	1.097	0.846	0.951	1.046	0.728
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.832	0.582	0.493	0.764	0.398	0.502
Adj R^2	0.831	0.58	0.49	0.762	0.394	0.499
s	0.031	0.062	0.057	0.035	0.086	0.048

Figure 4: CAPM regression (with intercept)

Note also that beta coefficients are very close to those estimated without the presence of a constant term. In Appendix some useful scatter graphs of regressions are available.





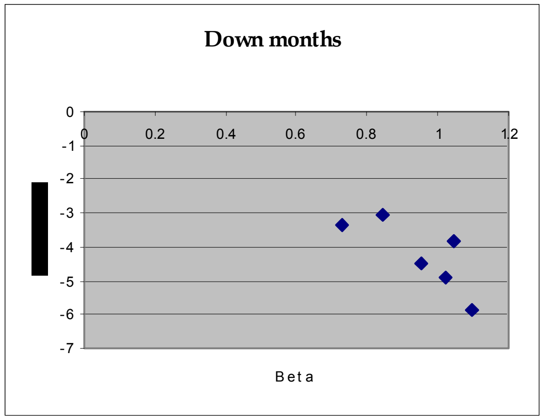


Figure 1-3: Relation between return and beta obtained with MIB index - Down months (January 1990 - February 2005)

At the end of the analysis, I investigated the relation between the sign of market returns and beta coefficients, by exploiting the Pettengill's hypothesis. Figure 1 is a scatter diagram obtained from the average portfolio return and the average portfolio beta in the six industries of our sample. This graph shows the existence of a flat relation between the average return and betas.

Furthermore, Figure 2 and 3 also represent a scatter diagram obtained from the average portfolio return and the portfolio betas conditioned to the sign of the market excess return; in particular, Figure 2 shows the situation when the market excess return is positive, whilst Figure 3 the situation when is negative. From the two diagrams it is easy to recognize the existence of a clear ex post positive and negative linear relationships between returns and betas when the market is Up and Down. The comparison of Figure 1, 2 and 3 naturally motivates to differentiate up markets from down markets. This occurs as there must be some probability where investors expect that the realized return on a low beta portfolio will be greater than the return on a high beta portfolio.

In the end, two dinstinct conditional regressions were run, in which condition upon the sign of the market excess return was involved. As Table 5 shows, there is a significant difference between values which parameters assume in Up months and in Down months.

2.4 Market Imperfections

I move now to detect the presence of a famous effect which often occur in studies on financial markets, the so called "January effect". As the theory of market imperfections states, there would be some evidence that, *ceteris paribus*, returns in January are higher than in other months, due to several reasons[5].

[5] The most quoted causes are seasonality in risk premium or expected returns, tax-loss selling effects, "window dressing" effects and year-end transactions of cash.

Industry	Bank	Automobile	Distribution	Insurance	Media	Construction
Total Months	1.022	1.097	0.846	0.951	1.046	0.728
Up Months	0.962	1.062	1.07	0.892	1.452	0.734
Down Months	1.053	1.248	0.908	0.966	0.915	0.843

Figure 5: CAPM regression - Comparison Between Total Months, Up Months and Down months excess returns

For detecting the presence of the January effect I included a dummy variable in the model and tested whether the latter was significant or not (results are shown in Table 6). The evidence seems to strongly deny the presence of January effect at the 5% level, so that the dummy variable is not statistically significant.

To complete the analysis of market imperfections I used some Measures of Fit for comparing the model which does not contain the dummy variable with the other one, with the January dummy included. I did that to evaluate the existance of misspecification forms. I named the model which does not contain the January dummy as "Model A" and the model which does as "Model B". Results show (Table 7) that the inclusion of the January dummy substancially does not modify the values of the main indicators. In particular, the Log Likelihood indicators are exactly the same in model A and B and the same holds for R^2, AIC and BIC.

We can concluded that January dummy does not explain anything new for the model and the January dummy can be considerd as an irrelevant variable.

Industry	Bank	Automobile	Distribution	Insurance	Media	Construction
constant	0	-0.1	0.002	0	0.002	-0.003
P>|t|	0.687	0.041	0.524	0.787	0.756	0.076
Excess mr	1.022	1.093	0.852	0.956	1.055	0.716
P>|t|	0.000	0.000	0.000	0.000	0.000	0.000
January dummy	0	0.007	-0.011	-0.009	-0.015	0.023
P>|t|	0.978	0.682	0.475	0.318	0.502	0.390
R^2	0.832	0.582	0.494	0.765	0.339	0.51
s	0.031	0.062	0.057	0.035	0.086	0.048

Figure 6: CAPM regression (with intercept and January dummy)

Bank	Model A	Model B
Log-Lik Intercept Only	211.347	211.347
D(178)	-743.729	-743.730
R2	0.832	0.832
AIC	-4.110	-4.098
BIC	-1668.075	-1662.883
Log-Lik Full Model	371.864	371.865
LR(1)	321.034	321.035
Prob > LR	0.000	0.000
Adjusted R2	0.831	0.830
AIC*n	-739.729	-737.730
BIC'	-315.841	-310.649

Automobile	Model A	Model B
Log-Lik Intercept Only	166.657	166.657
D(178)	-490.594	-490.766
R2	0.583	0.583
AIC	-2.703	-2.693
BIC	-1414.941	-1409.919
Log-Lik Full Model	245.297	245.383
LR(1)	157.280	157.452
Prob > LR	0.000	0.000
Adjusted R2	0.580	0.578
AIC*n	-486.594	-484.766
BIC'	-152.087	-147.066

Distribution	Model A	Model B
Log-Lik Intercept Only	198.288	198.288
D(178)	-518.893	-519.412
R2	0.493	0.495
AIC	-2.861	-2.852
BIC	-1443.239	-1438.566
Log-Lik Full Model	259.446	259.706
LR(1)	122.317	122.837
Prob > LR	0.000	0.000
Adjusted R2	0.490	0.489
AIC*n	-514.893	-513.412
BIC'	-117.124	-112.451

Insurance	Model A	Model B
Log-Lik Intercept Only	216.732	216.732
D(178)	-693.450	-694.467
R2	0.764	0.765
AIC	-3.830	-3.825
BIC	-1617.797	-1613.621
Log-Lik Full Model	346.725	347.234
LR(1)	259.987	261.004
Prob > LR	0.000	0.000
Adjusted R2	0.763	0.763
AIC*n	-689.450	-688.467
BIC'	-254.794	-250.618

Media	Model A	Model B
Log-Lik Intercept Only	140.872	140.872
D(178)	-373.082	-373.542
R2	0.398	0.399
AIC	-2.050	-2.042
BIC	-1297.428	-1292.695
Log-Lik Full Model	186.541	186.771
LR(1)	91.339	91.798
Prob > LR	0.000	0.000
Adjusted R2	0.395	0.393
AIC*n	-369.082	-367.542
BIC'	-86.146	-81.412

Construction	Model A	Model B
Log-Lik Intercept Only	226.979	226.979
D(178)	-579.684	-582.888
R2	0.503	0.511
AIC	-3.198	-3.205
BIC	-1504.030	-1502.041
Log-Lik Full Model	289.842	291.444
LR(1)	125.725	128.929
Prob > LR	0.000	0.000
Adjusted R2	0.500	0.506
AIC*n	-575.684	-576.888
BIC'	-120.532	-118.544

January Effect - Comparison Between Model A and Model B

2.5 Goodness-of-fit

In the regressions of CAPM the typical goodness-of-fit indicator R^2 has not only a statistical meaning, but it also has a precise economic interpretation. This point can be better understood by writing the variance of the return on portfolio in the following fashion:

$$V\left(r_{jt}\right)=\beta_j^2 V\left(r_{jt}\right)+V\left(\varepsilon_{jt}\right) \tag{11}$$

The first component represents the variance of the market index, whilst the second the so called idiosyncratic risk. As a consequence it is possible to write:

$$Total\ risk = market\ risk + idiosyncratic\ risk$$

The theory of CAPM affirms that diversification can only eliminate the idiosyncratic risk, but cannot cancel out the market risk and, for this reason, the market risk is rewarded whilst the idiosyncratic risk is not. R^2 indicator can be seen as an estimate of the relative importance of market risk for each of the industry porfolios.

For example, with respect to the the Bank industry, we can see that 83.2% of the risk (variance) of the industry portfolio is due to the market, whilst the idiosyncratic risk is only equal to 16.8%. This 83.2% is a very high value and means that the Bank industry appears to be well diversified.

Otherwise, other sectors show a lower R^2; especially the Media industry, whose level is only equal to 39.8%, appears to be worse diversified, with an higher idiosyncratic risk.

2.6 Structural breaks

Test on the existence of structural breaks was performed using the September 11th 2001 as a break date. The choice of the date was due to the belief that the aftermaths of events occured on September 11th would have radically changed the market trend. In particular I mantained that the magnitude related to the impact of those events was so strong to affect in a dramatic way the stock markets.

Firstly, monthly returns have been observerd to collapse within every industry in September 2001. The most significant case was the Insurance industry, whose share prices lost up to 19%.

Secondly, I performed a Chow test (results in Table 10). In particular, if a structural break occured at a given moment of time, say t_i, then the slope of betas was expected to be significatively different from the outcomes derived running two separate regressions for two different periods, say $P_1 \in [t_0; t_i]$ and $P_2 \in [t_i; t_2]$ and from the regression run over the overall period, say$P_t = P_1 + P_2$. Technically, the Chow test can be performed by running an F test, whose expression is:

$$F = \frac{[SSR_{pooled} - (SSR_1 + SSR_2)}{(SSR_1 + SSR_2)} \cdot \frac{n-2(k+1)}{k+1}$$

The null hypothesis imposes that:

$$\beta_t < t_i = \beta_t > t_i$$

The rejection of the null, which supposes the equality of betas before and after the break date, strongly supports the existance of two different values of betas, which also implies that slopes of obtained fitted lines are different.

Since F-distribution is a right-skewed distribution, we performed the Chow test at the 10% significance level ($\alpha = 0.10$). As results show the null hypothesis can be (weakly) rejected for the Bank and the Insurance industries and the existence of a structural break accepted, whilst the null accepted and the existence of a structural break refused for all the other industries.

This is not a very surprising result. As it can be imagined, Bank and Insurance were those sectors which suffered more than others to the September 11th effect, due to the international turmoils of financial markets.

	SSRpooled	n	Df1	Df2	F-test	P-value	Reject H_0	SB
banc	0.177412303	180	176	2	12.972364	0.07415941	Yes	Yes
auto	0.717688561	180	176	2	-19.780776	1	No	No
dist	0.590745833	180	176	2	-15.216238	1	No	No
assi	0.223706548	180	176	2	11.086009	0.08621282	Yes	Yes
medi	1.32644903	180	176	2	4.552848	0.19697472	No	No
cost	0.421557028	180	176	2	6.3983454	0.14457066	No	No

Figure 7: Structural breaks - September 11th 2001

3 Conclusions

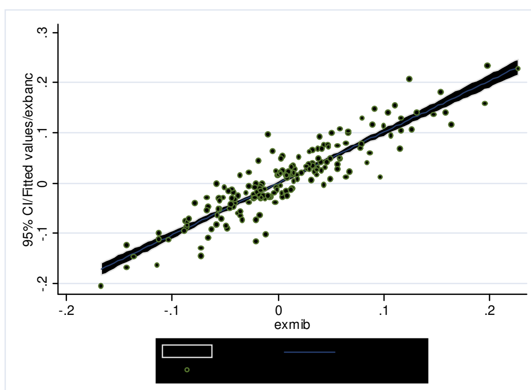
Results of the work seems to confirm the validity of the three Sharpe-Lintner CAPM empirical tests.

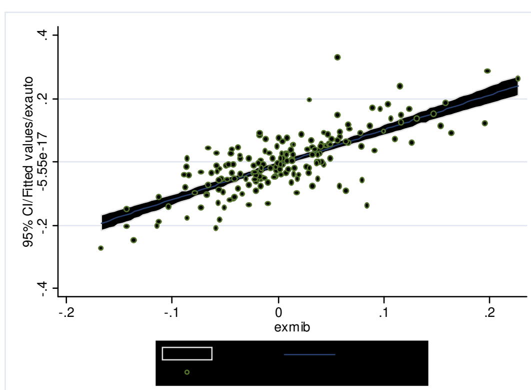
First of all, the evidence has shown that intercepts of regressions are equal to zero, so that the CAMP theory, which assumes that the only relevant variable in the regression is the excess return on the market porfolio, has been respected.

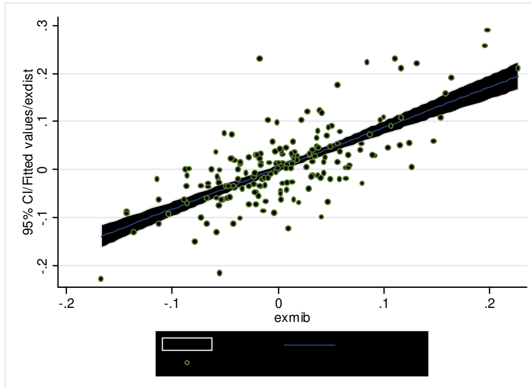
As a consequence of this, it can be said that betas completely capture the cross sectional variation of expected excess returns and can be seen as a measure of the asset risk. Furthermore, I have analyzed how different trends have been occured with respect to different industries of the sample.

In the end, the relation between the sign of market returns and beta coefficients was tested and the existance of an ex post positive (when the market is at an Up state) and negative (when the market is at a Low state) relationships between returns and betas was detected.

4 Appendix



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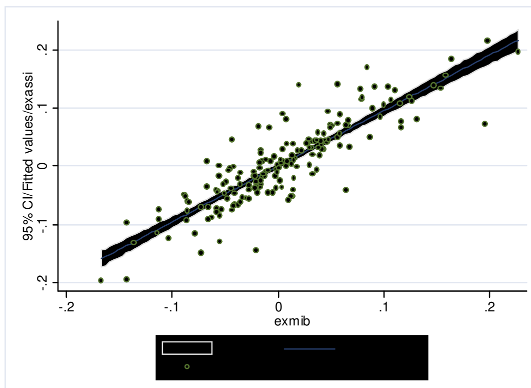
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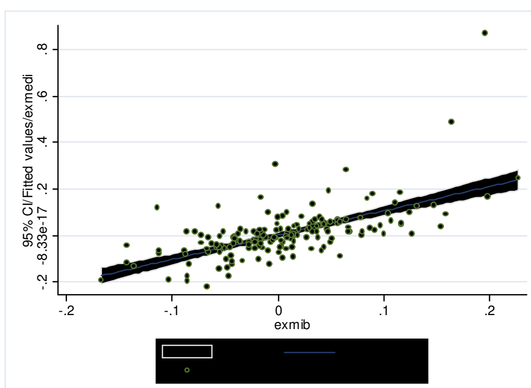
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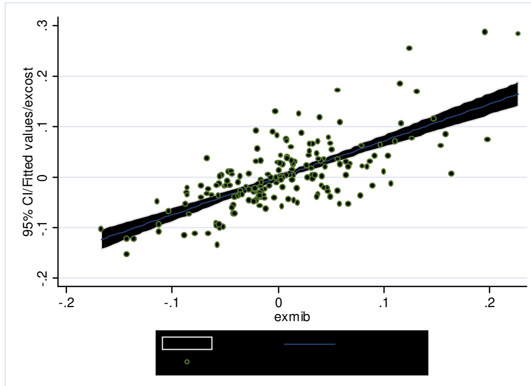

Scatter Graphs of Regressions (overall period): Bank, Automobile, Distribution, Assurance, Media, Construction

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