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Forecasting the Ability of Dynamic versus static CAPM: Evidence from Amman Stock Exchange

Moh'd M. Ajlouni [a]***, Dima W.H. Alrabadi*** [b]***, Tariq K. Alnader*** [c]

ABSTRACT

This study tests whether the dynamic (conditional) Capital Asset Pricing Model (CAPM) outperforms the static one in forecasting the returns of the industrial companies listed in Amman Stock Exchange (ASE) over the period 2000-2011. We investigate the in-sample forecasting ability of CAPM estimated via OLS, GJR-GARCH (1, 1), and Kalman Filter. The results indicate that the dynamic CAPM estimated through GJR-GARCH (1, 1) provide the most accurate in-sample forecasts of stock returns. Moreover, this model shows the lowest values of Akaike Information Criterion and explains the cross section of returns of most sample stocks.

Keywords: Conditional CAPM, Time-Varying Beta, In-Sample Forecast, GARCH, Kalman Filter, Amman Stock Exchange.

INTRODUCTION

The standard CAPM of Sharp (1964) assumes a constant beta coefficient. It assumes that all investors have the same expectations on the means, variances and covariances of returns. Fabozzi and Francis (1978) suggest that stock's beta coefficient may move randomly over time. They test the CAPM with time varying beta. Bollerslev *et al.* (1988) argue that economic agents may have common expectations on the moments of future returns, but these are conditional expectations. Thus, the CAPM that takes conditional expectations into consideration is known as conditional CAPM. Harvey (1989), Ferson and Harvey (1991) and (1993) argue that there is a weakness in the static CAPM because it does not reflect the dynamic nature of beta. Numerous different econometrical methods have been applied to estimate time-varying betas of different stocks in different countries. The Two well known methods are the GARCH models and the Kalman filter approach. The GARCH models use the conditional variance information to generate the conditional beta series. The Kalman approach recursively estimates the beta series from an initial set of priors. Assessing the forecasting performance of CAPM is very important for both academicians and practitioners. Predicting future returns would help investors to take their investment decisions and evaluate the performance of their portfolios, accordingly. Moreover, forecasting returns would help corporations to calculate their cost of capital.

This study compares the in-sample forecasting accuracy between the conditional CAPM with time-varying beta and the unconditional CAPM with constant beta. Our sample consists of the industrial companies listed on ASE over the period 2000 – 2011. The study

[a]Associate Professor, Finance and Banking Sciences Department, Faculty of Economics and Business Administration, Yarmouk University, Jordan.
[b]Assistant Professor, Finance and Banking Sciences Department, Faculty of Economics and Business Administration, Yarmouk University, Jordan.
[c]Master of Finance and Banking Sciences, Yarmouk University, Jordan.
Correspondence: Dima Waleed Hanna Alrabadi, Finance and Banking Sciences Department, Faculty of Economics and Business Administration, Yarmouk University, P.O Box 566, Irbid 21163, Jordan. Tel: 96-22-721-1111 ext. 6856, E-mail: dhws2004@yahoo.co.uk.
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uses three modeling techniques, ordinary least square regression OLS to test the un conditional CAPM, while GJR-GARCH (1,1) technique and Kalman Filter approach are employed to test the conditional CAPM. The results indicate that the dynamic CAPM estimated through GJR-GARCH (1, 1) provide the most accurate in-sample forecasts of stock returns. Moreover, this model shows the lowest values of Akaike Information Criterion and explains the cross section of returns of most sample stocks. The remainder is organized as follows: section 2 describes the objectives of the study, section 3 clarifies its importance, section 4 explains the CAPM, section 5 reviews the related literature, section 6 describes data and methodology, section 7 presents the empirical results and section 8 concludes.

Objectives of the Study

This study aims at testing whether the conditional CAPM outperforms the unconditional version in explaining the cross-section of returns of the industrial companies listed in ASE over the period 2000 – 2011. Moreover, it investigates the in-sample forecasting ability of OLS regression, GJR-GARCH (1,1) technique and Kalman Filter approach.

Importance of the Study

The importance of this study appeared from the lack of studies that empirically test the CAPM with respect to the time variant approach. Its findings may help investors, academicians, practitioners and regulators who use this model to accurately evaluate assets, calculate the required rate of return and the cost of capital and manage their investments more efficiently.

Capital Asset Pricing Model (CAPM)

Sharp (1964) and Lintner (1965) originally proposed Capital Asset Pricing Model (CAPM) to describe the risk-return relationship, following the Markowitz study (1952) of mean variance optimization. The CAPM provides a structure for pricing asset with uncertain returns.

Around the world, CAPM is the most commonly used model in finance to describe the risk-return relationship and predict the price of any asset. The model predicts that asset returns are related to non-diversifiable risk, which is measured by the covariance between the return on this asset and a portfolio composed from all available assets in the market.

The model assumes that there are no sources of risk except the systematic market risk. This risk is measured by a factor called beta. The CAPM depends on several assumptions extended from Markowitz (1952) and Tobin (1958) studies as follows:

- The objective of the investor is to maximize the utility of his terminal wealth.
- Investors choose their investments on the basis of their expected rates of return and variances over a single period horizon.
- All investors completely agree on the joint distribution of the rate of return of assets.
- There are no taxes and transaction cost, or any other market frictions.
- Investors can short-sell any amount of securities and use the proceeds to invest in any other assets.
- All investors have the same time investment horizon.
- All investors can lend and borrow money at the risk free rate.
- Investors are risk averse and price takers.

The previous assumptions and investor's behavior framework were put in a single equation to reflect the risk-return relationship:

$$R_i = Rf + \beta_i (Rm - Rf) \quad (1)$$

Where:

R_i : is the expected rate of return on security (i)

Rf : is the risk free rate of return.

Rm: is the expected rate of return on market portfolio.

β_i : is the security (i) beta, which is equal to the covariance between security's returns and market returns divided by the variance of the market return. A beta value more than one means that the investment is more risky than the market portfolio, while a less than one beta indicates that the investment is less risky than the market. A positive beta represents a positive relationship between the stock return and the market return but a negative beta designates a negative relationship between the stock return and the market return.

Asset risk premium is determined as the difference between its return and the risk free rate, while the market risk premium is the difference between the market return and the risk free rate. There are different uses of CAPM in financial decision such as estimating the cost of capital and the required rate of return, pricing assets and measuring portfolio performance.

CAPM assumes a single period horizon which means a constant beta over time. However, many studies examined the theory and argued that the model is invalid and has drawbacks because beta is time varying besides that there are other factors, affecting the risk premium of assets other than the estimated covariance, like the size of the firm and book to market ratio.

Literature Review

Fabozzi and Francis (1978), Sunder (1980), Bos and Newbold (1984), Collins *et al.*. (1987), Kim (1993), Bos and Fetherstone (1995) and Pettengill *et al.*. (1995) are the pioneering studies which find that beta is time-varying in the US market. Jagannathan and Wang (1996) and Lettau and Ludvigson (2001) also using US data find out that the conditional CAPM performs well in explaining the cross section of average returns. Adrian and Franzoni, (2005) find that a learning version of the conditional CAPM significantly produces smaller pricing errors than those of the standard CAPM for NYSE stocks over the period 1926 to 2004. Studies in different markets around the world find that beta is time-varying as well, see for example, Well (1994) Sweden, Cheng (1997) Hong-Kong, Brook and Faff (1997) Malaysia, Huang (2001) Taiwan, Li (2003) Newzealand, Fraser *et al.*. (2004) UK, Koseoglu and Gokbulut (2012) Turkey. Many other studies compare between the different approaches of estimating time varying betas. Brooks *et al.*. (1998) estimate conditional time varying beta, using three techniques: multivariate generalized ARCH approach, time varying beta market model approach suggested by Schwert and Seguin (1990), Kalman filter technique. Using data for Australian industry firms over the period of 1974-1996, they provide evidence that the best technique to forecast the conditional time dependent betas is the Kalman Filter approach. Faff *et al.*. (2000) examine the three techniques in estimating time-varying beta and find consistent results in the UK market.

Choudry and Wu (2007) investigate the in-sample and out-of-sample forecasting ability of four different GARCH models and the Kalman filter method. The four GARCH models used are the bivariate GARCH, BEKK GARCH, GARCH-GJR and the GARCH-X model. Using a sample of twenty UK companies, they find that Kalman filter is superior to other approaches. Among the GARCH models both GJR and GARCH-X models appear to provide somewhat more accurate forecasts than the bivariate GARCH model. Simillar studies are conducted in emerging markets.

Mergner and Bulla (2008) compare different techniques to model the time varying betas of Pan-European industry portfolios over the period 1987 to

2005. They use weekly data from 18 pan-European sector and apply six different models to investigate the best model describe time varying behavior of sector betas in European context. In addition to the standard constant coefficient model, they estimate bivariate stochastic t-GARCH model, two Kalman filter approaches, bivariate stochastic volatility model estimated via the efficient Monte Carlo likelihood technique as well as markov switching model. Their study find that the random walk process in connection with Kalman Filter model is the best approach to describe and forecast the time varying behavior of betas. From Middle East, Onour (2010) inspects the stability of systematic risk of stock price indices of five sectors in Kuwait stock market over the period 2002-2008. His results provide evidence of time-varying beta values for the five sectors. Banks and real estate sectors have relatively wider range of beta coefficients compared to the other sectors.

ASE is an emerging developing market. Many studies investigate the ability of the static CAPM in explaining the stock returns in ASE and found that investors should depend on other models such as Fama and French three factor model and arbitrage model as pricing models of capital assets (see for example, Al-Otaibi *et al.*. (2009), Al-Mwalla, and Karasneh (2011), Al-Mwalla (2012), Ramadan (2012)).

The studies using time varying beta are unique in ASE, thus the issue is not yet examined. To the best of our knowledge, this is the first study that investigates the forecasting performance of conditional CAPM in ASE.

Data and Methodology

Our data set consist of the monthly excess returns of the industrial companies listed in ASE over the period 1 January 2000 to 31 December 2011. The sample includes 65 companies with available data. Moreover, monthly excess returns of the free float market index are obtained from the ASE's website. This index is calculated using the market value of the free float shares of the companies and not the total number of listed shares of each company. We use three approaches to estimate the CAPM as follows:

Ordinary Lest Squares

OLS is used to estimate the static (unconditional) CAPM as follows (Sharpe, 1964; Lintner, 1965):

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it} \qquad (2)$$

Where: r_{it} is the excess return of stock i in month t. It is calculated as the difference between the monthly stock return and the rate of return on Jordanian government 3-months treasury bills during the month t. Monthly stock return is calculated as follows:

$R_{it} = Ln(P_{it} / P_{it-1})$ Where P_{it} and P_{it-1} is are stock i closing prices at the last trading day of months t and $t-1$, respectively.

r_{mt} is the excess market return in month t. It is calculated using the same formula as used for calculating the rate of return of individual stocks except that instead of stock price the market index value is used.

Newey-West HAC consistent covariance is used to account for heteroskedasticity and serial correlation. Beta values are computed as follows (Sharpe, 1964; Lintner, 1965):

$$\beta_i = COV(r_{it}, r_{mt}) / VAR(r_{mt}) \qquad (3)$$

GARCH

Mean GARCH (M-GARCH) model utilizes conditional variance estimates produced by a GARCH (1,1) model to construct a conditional time varying beta series as follows (Bollerslev, *1990*):

$$E(r_{it} \mid \mathrm{I}_{t-1}) = E(r_{mt} \mid \mathrm{I}_{t-1}) \qquad (4)$$

$$\beta_{i/\mathrm{I}t-1} = COV(r_{it}, r_{mt} \mid \mathrm{I}_{t-1}) / VAR(r_{mt} \mid \mathrm{I}_{t-1}) \qquad (5)$$

Where $E(\mid \mathrm{I}_{t-1})$ is is the mathematical expectation conditional on the information set available to the economic agents last period I_{t-1}

Kalman Filter

The Kalman filter method, originally developed by Kalman (1960) within the context of linear systems, is an iterative computational algorithm designed to calculate forecasts and forecast variances for time series models. It is based on what is called state space model. The general form of a state space model defines an observation (or measurement) equation and a transition (or state) equation, which together express the structure and dynamics of a system (Choudhry and Wu, 2007). The measurement equation describes the relation between observed variables (data) and unobserved state variables. Transition equation describes the dynamics of the state variables based on a minimum set of information from the past such that the future behavior of the system can be completely described by the knowledge of the present state and the future input (Yao and Gao, 2004). Kalman filter recursively forecasts the conditional betas from an initial set of priors; it generates a series of conditional intercepts and beta coefficients for the CAPM.

The CAPM is modified to become an observation equation (Choudhry and Wu, 2007):

$$r_{it} = \beta_{it} r_{mt} + e_{it} \tag{6}$$

Where the dynamic process of the unobserved time varying state vector, β_{it}, is defined by the state equation:

$$\beta_{it} = c_i \beta_{it-1} + e_{it} \tag{7}$$

With c_i denoting the constant transition parameter.

Measures of Forecasting Ability

Mean squared error (MSE) is mainly used to evaluate the in-sample forecasting accuracy of the CAPM. It is calculated for each stock as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{8}$$

Where e_t represents the forecast error defined as the difference between the actual value and the forecasted value of the excess return of the stock in month t.

Moreover, Akaike Information Criteria (AIC) and Log Likelihood ratio (LLR) are used to estimate the overall fit of the models examined. The lower (higher) the AIC (LLR), the better is the overall fit of the model. Finally, we calculate the percentage of stocks with insignificant intercepts, thus an insignificant intercept indicates that the model can explain the cross section of returns of that stock.

Empirical Results

Table 1 shows a zero average return of the industrial companies over the study period. The average market return is .005. Hence, the market portfolio seems to achieve higher rates of return than the industrial sector stocks. The data are not normally distributed. The standard deviation of the stock returns is .127 indicating somehow a high dispersion of returns between the sample stocks. The market return show lower dispersion, thus holding the market portfolio would be less risky than investing in a portfolio of industrial stocks.

Table 1: Descriptive Statistics

Stats	Return for all Industrial Stocks	Market Return	Risk-free rate
Mean	0.000	0.005	0.004
Median	0.000	0.010	0.004
Maximum	3.100	0.150	0.006
Minimum	-1.800	-0.250	0.002
Std. Dev.	0.127	0.055	0.001

Table 2 reports the values of the beta coefficient under the three approaches. The OLS Beta values range from -0.099 to 1.623 with an average of 0.506. The intercept coefficient is insignificant for 76% of the sample companies indicating that the CAPM explains the returns of 44 out of 65 stocks. The GARCH Betas range from -0.054 to 1.549 with an average of 0.447. The intercept coefficient is insignificant for 84% of the companies examined indicating that the CAPM explains the return of 55 out of 65 companies. Finally the results of Kalman filter indicate that Beta values range from -0.094 to 1.619 with an average 0.493. The intercept coefficient is insignificant for 73% of the companies examined. Nearly all beta coefficients are highly significant regardless which approach is applied in estimation.

Table 2: The values of Beta

Companies	OLS Beta	GJR-GARCH Beta	Kalman Beta
company1	0.543	0.434	0.520
company2	0.457	0.400	0.432
company3	0.007	0.001	-0.001
company4	0.501	0.300	0.482
company5	0.842	0.864	0.832
company6	0.384	0.501	0.379
company7	0.605	0.308	0.600
company8	0.247	0.292	0.252
company9	0.820	0.696	0.796
company10	0.410	0.371	0.376
company11	0.119	0.124	0.103
company12	0.281	0.151	0.281
company13	0.417	0.371	0.403
company14	0.510	0.408	0.510
company15	0.447	0.171	0.418
company16	0.952	0.684	0.929
company17	0.534	0.293	0.520
company18	0.826	0.554	0.808
company19	0.500	0.643	0.472
company20	1.623	1.513	1.619
company21	0.385	0.381	0.377

Companies	OLS Beta	GJR-GARCH Beta	Kalman Beta
company22	0.256	0.333	0.247
company23	0.459	0.449	0.457
company24	0.237	0.256	0.214
company25	0.528	0.392	0.510
company26	0.067	0.048	0.058
company27	0.130	0.002	0.102
company28	0.282	0.093	0.271
company29	0.530	0.638	0.517
company30	0.439	0.068	0.418
company31	0.238	0.229	0.226
company32	0.939	0.810	0.928
company33	1.439	1.549	1.441
company34	0.551	0.502	0.530
company35	1.174	1.046	1.184
company36	0.342	0.492	0.325
company37	0.442	0.225	0.427
company38	0.515	0.548	0.508
company39	0.027	0.001	0.010
company40	1.220	0.850	1.191
company41	0.033	0.001	0.023
company42	-0.099	-0.054	-0.094
company43	0.694	0.905	0.669
company44	0.912	0.899	0.877
company45	0.155	-0.001	0.144
company46	-0.006	0.001	-0.012
company47	0.682	0.976	0.682
company48	0.007	0.001	-0.001
company49	1.210	1.013	1.202
company50	0.740	0.908	0.751
company51	0.609	0.545	0.585
company52	0.015	0.004	0.007
company53	0.519	0.632	0.520
company54	0.678	0.687	0.660
company55	0.179	0.115	0.202
company56	0.496	0.365	0.495
company57	0.420	0.182	0.421
company58	0.664	0.694	0.644
company59	0.006	0.243	0.007
company60	0.061	0.051	0.054
company61	1.606	1.470	1.561

Companies	OLS Beta	GJR-GARCH Beta	Kalman Beta
company62	0.301	0.276	0.284
company63	0.540	0.425	0.530
company64	0.385	0.247	0.359
company65	0.851	0.495	0.815
Average	0.506	0.447	0.493
Intercept	76%	84%	73%

Table 3 documents the MSE, AIC, and LLR for all the sample stocks under the OLS, GJR-GARCH and Kalman filter approaches. The result indicates the conditional (dynamic) CAPM estimated through GJR-GARCH outperform the static CAPM and the conditional model estimated through Kalman filter in forecasting the returns of the sample stocks. The average MSE values for GJR-GARCH, OLS, Kalman are 0.01, 0.015 and 0.034, respectively. Moreover, according to other criteria such as the LLR and AIC, the conditional GJR-GARCH approach yield better result. The AIC is lowest under the GARCH approach with an average value of -3.331. At the same time LLR is maximum under the GARCH approach with an average value of 239.362.

These results are consistent with Brooks *et al.*. (2002) who use GARCH model and Kalman Filter approach to test CAPM in UK, using monthly data over the period 1975 to 1995 and find that GARCH based estimates of risk generate the lowest forecast error. However, we disagree with Brooks *et al.*. (1998) who use weekly data from 1987 to 2005 for Pan-European sector and find that Kalman Filter is preferred to describe and forecast the time varying behavior of betas. Similarly, Mergner and Bulla (2008) use six different modeling technique and result that the best technique to examine the conditional time dependent betas is Kalman Filter approach. The contrasting results would be explained by the different levels of efficiency between different stock exchanges taking into consideration that ASE is an emerging stock market.

Table 3: Forecasting Accuracy

	MSE	**MSE**	**MSE**	**AIC**	**AIC**	**AIC**	**LLR**	**LLR**	**LLR**
Companies	OLS	GARCH	Kalman	OLS	GARCH	Kalman	OLS	GARCH	Kalman
company1	0.019	0.02	0.045	-1.106	-3.585	-0.993	81.054	262.311	71.975
company2	0.012	0.012	0.028	-1.585	-2.035	-1.46	115.311	151.534	105.425
company3	0	0	0	-10.573	-11.418	-7.731	720.988	782.419	526.68
company4	0.005	0.005	0.011	-2.484	-2.866	-2.347	179.59	210.941	168.822
company5	0.01	0.011	0.025	-1.697	-1.868	-1.585	123.303	139.577	114.35
company6	0.011	0.011	0.025	-1.671	-1.952	-1.562	121.499	145.601	112.69
company7	0.019	0.02	0.044	-1.115	-3.171	-1.01	81.733	232.737	73.227
company8	0.016	0.016	0.038	-1.261	-3.749	-1.154	91.514	272.173	82.942
company9	0.024	0.024	0.057	-0.858	-2.117	-0.748	63.365	157.383	54.506
company10	0.034	0.034	0.08	-0.523	-1.247	-0.411	39.36	95.139	30.421
company11	0.002	0.002	0.006	-3.193	-3.795	-3.038	230.289	277.357	218.222
company12	0.01	0.01	0.025	-1.694	-2.113	-1.585	123.095	157.082	114.332

	MSE	MSE	MSE	AIC	AIC	AIC	LLR	LLR	LLR
company13	0.004	0.004	0.01	-2.652	-2.75	-2.521	191.621	202.622	181.223
company14	0.021	0.021	0.049	-0.996	-1.466	-0.892	73.212	110.846	64.798
company15	0.009	0.009	0.022	-1.853	-2.198	-1.714	134.454	163.189	123.518
company16	0.012	0.012	0.028	-1.575	-1.628	-1.453	114.607	122.424	104.898
company17	0.005	0.005	0.013	-2.347	-2.849	-2.222	169.78	209.734	159.839
company18	0.01	0.01	0.024	-1.74	-2.336	-1.621	126.427	173.018	116.934
company19	0.02	0.02	0.048	-1.027	-1.647	-0.911	75.435	123.755	66.119
company20	0.014	0.015	0.034	-1.367	-1.582	-1.26	99.724	119.097	91.1
company21	0.012	0.012	0.029	-1.516	-1.692	-1.407	110.399	126.982	101.597
company22	0.015	0.015	0.038	-1.273	-4.261	-1.161	89.166	297.845	80.52
company23	0.009	0.009	0.021	-1.866	-1.989	-1.756	135.427	148.179	126.569
company24	0.008	0.008	0.019	-1.99	-2.297	-1.859	144.31	170.209	133.934
company25	0.004	0.005	0.011	-2.531	-2.542	-2.395	182.982	187.761	172.241
company26	0.005	0.005	0.013	-2.362	-4.264	-2.244	170.89	310.855	161.414
company27	0.011	0.011	0.027	-1.61	-6.972	-1.479	111.468	480.106	101.6
company28	0.033	0.033	0.073	-0.54	-1.583	-0.438	40.598	119.209	32.333
company29	0.055	0.055	0.129	-0.036	-3.655	0.062	4.595	267.362	-3.404
company30	0.011	0.011	0.026	-1.654	-3.775	-1.533	120.276	275.913	110.645
company31	0.033	0.033	0.079	-0.531	-2.657	-0.429	39.976	195.99	31.69
company32	0.011	0.011	0.025	-1.673	-1.715	-1.56	121.585	128.634	112.553
company33	0.037	0.044	0.089	-0.411	-1.563	-0.311	31.371	117.741	23.247
company34	0.006	0.006	0.013	-2.322	-2.372	-2.186	168.038	175.623	157.307
company35	0.008	0.008	0.019	-1.946	-2.048	-1.831	141.133	152.455	131.948
company36	0.026	0.027	0.063	-0.76	-1.502	-0.655	56.338	113.394	47.797
company37	0.012	0.012	0.027	-1.589	-1.786	-1.475	115.608	133.685	106.447
company38	0.006	0.006	0.015	-2.19	-2.344	-2.076	158.613	173.607	149.433
company39	0.001	0.001	0.002	-4.118	-10.334	-3.909	282.056	708.699	266.815
company40	0.024	0.025	0.058	-0.848	-1.086	-0.734	62.628	83.629	53.515
company41	0.003	0.003	0.007	-2.906	-7.164	-2.775	199.639	493.151	189.721
company42	0.078	0.078	0.184	0.319	-3.668	0.414	-20.815	268.238	-28.579
company43	0.012	0.013	0.03	-1.513	-1.896	-1.39	110.177	141.553	100.365
company44	0.009	0.01	0.023	-1.787	-2.102	-1.639	129.76	156.271	118.173
company45	0.006	0.006	0.016	-2.143	-6.555	-2.022	147.756	451.758	138.497
company46	0.001	0.001	0.001	-4.656	-11.053	-4.503	318.631	757.61	307.235
company47	0.016	0.017	0.037	-1.281	-2.048	-1.176	93.618	152.415	85.061
company48	0	0	0	-10.573	-11.418	-7.731	720.988	782.419	526.68
company49	0.01	0.01	0	-1.728	-2.134	463.17	125.565	158.553	-33115.9
company50	0.014	0.015	0	-1.373	-1.505	664.14	100.182	113.625	-47485.3
company51	0.014	0.015	0	-1.386	-1.857	662.86	101.065	138.803	-47393.5
company52	0	0	0	-6.232	-9.208	-5.938	425.746	632.178	404.799

	MSE	MSE	MSE	AIC	AIC	AIC	LLR	LLR	LLR
company53	0.036	0.037	0.085	-0.448	-0.897	-0.348	34.048	70.123	25.908
company54	0.01	0.01	0.024	-1.718	-1.752	-1.599	124.808	131.262	115.316
company55	0.014	0.014	0.032	-1.427	-2.998	-1.308	104.015	220.384	94.544
company56	0.01	0.011	0.024	-1.734	-3.097	-1.625	125.986	227.468	117.202
company57	0.044	0.045	0.105	-0.239	-0.589	-0.141	19.123	48.109	11.087
company58	0.004	0.004	0.009	-2.739	-2.794	-2.59	197.808	205.769	186.189
company59	0.014	0.014	0.032	-1.415	-3.99	-1.309	103.193	291.277	94.568
company60	0.005	0.005	0.011	-2.468	-8.319	-2.346	169.853	571.679	160.531
company61	0.019	0.021	0.047	-1.074	-1.447	-0.938	78.818	109.444	68.084
company62	0.008	0.008	0.018	-2.009	-2.617	-1.886	145.62	193.125	135.862
company63	0.006	0.007	0.015	-2.169	-2.371	-2.052	157.071	175.516	147.708
company64	0.027	0.027	0.064	-0.751	-4.265	-0.641	55.701	310.937	46.835
company65	0.012	0.014	0.03	-1.541	-3.971	-1.405	108.33	280.026	97.976
Average	0.015	0.010	0.034	-1.97	-3.331	25.84	140.315	239.362	-1848.78

Notes: MSE denotes Mean Squared Error. AIC denotes Akaike Information Criteria. LLR denotes Log Likelihood Ratio.

Conclusion

Static beta is beaten. Alternatively, conditional asset pricing models with time varying betas are found to be more efficient in forecasting asset returns. Examining such issue is very important to investors. Their investment decision will be based on the forecasted stock return. Corporations are also interested to forecast their cost of capital. The studies of this area are unique in ASE. To the best of our knowledge, this is the first study that compares the in-sample forecasting accuracy between the conditional CAPM with time-varying beta and the unconditional CAPM with constant beta. Our sample consists of the industrial companies listed on ASE over the period 2000 – 2011. The study uses three modeling techniques, ordinary least square regression OLS to test the un conditional CAPM, while GJR-GARCH (1,1) technique and Kalman Filter approach are employed to test the conditional CAPM. The results indicate that the dynamic CAPM estimated through GJR-GARCH (1, 1) provide the most accurate in-sample forecasts of stock returns. Moreover, this model shows the lowest values of Akaike Information Criterion and explains the cross section of returns of most sample stocks. These results have important implications for the efficient market hypothesis (Fama, 1970). The results indicate that the ASE is efficient at the weak level because excess returns are fairly explained by a dynamic version of the CAPM.

The study recommends future researchers test the CAPM using other techniques such as multivariate GARCH which takes into consideration other factors that affect the stock return, like financial leverage and operation leverage, or to estimate multi-factor models with time varying betas such as Fama French three factor model or Carhart four factor model.

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أفضلية نموذج تسعير الأصول الرأسمالية الديناميكي على النموذج الساكن في التنبؤ بعوائد الأسهم للشركات الصناعية المدرجة في بورصة عمان للأوراق المالية

محمد العجلوني*، ديمة الربضي** وطارق الناظر**

ملخـص

تقوم هذه الدراسة باختبار أفضلية نموذج تسعير الأصول الرأسمالية الديناميكي على النموذج الساكن في التنبؤ بعوائد الأسهم للشركات الصناعية المدرجة في بورصة عمان للأوراق المالية للفترة 2000-2011. وتستخدم الدراسة نموذج تسعير الأصول الرأسمالية المقدر ب OLS, GJR-GARCH (1, 1), and Kalman Filter . وتشير النتائج إلى أن نموذج تسعير الأصول الرأسمالية الديناميكي المقدر بطريقة GJR-GARCH (1, 1) يعطي أدق توقع داخل العينة لعوائد الأسهم، إضافة إلى ذلك؛ فإن هذا النموذج يبين أقل قيم لAkaike Information Criterion ويفسر عوائد الأسهم.

الكلمات الدالة: النموذج الساكن في التنبؤ، تسعير الأصول الرأسمالية الديناميكي، بورصة عمان للأوراق المالية، عوائد الأسهم.

* استاذ مشارك، قسم العلوم المالية والمصرفية، كلية الاقتصاد والعلوم الإدارية، جامعة اليرموك.

** استاذ مساعد، قسم العلوم المالية والمصرفية، كلية الاقتصاد والعلوم الإدارية، جامعة اليرموك.

*** دراسات عليا في العلوم المالية والمصرفية، جامعة اليرموك

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