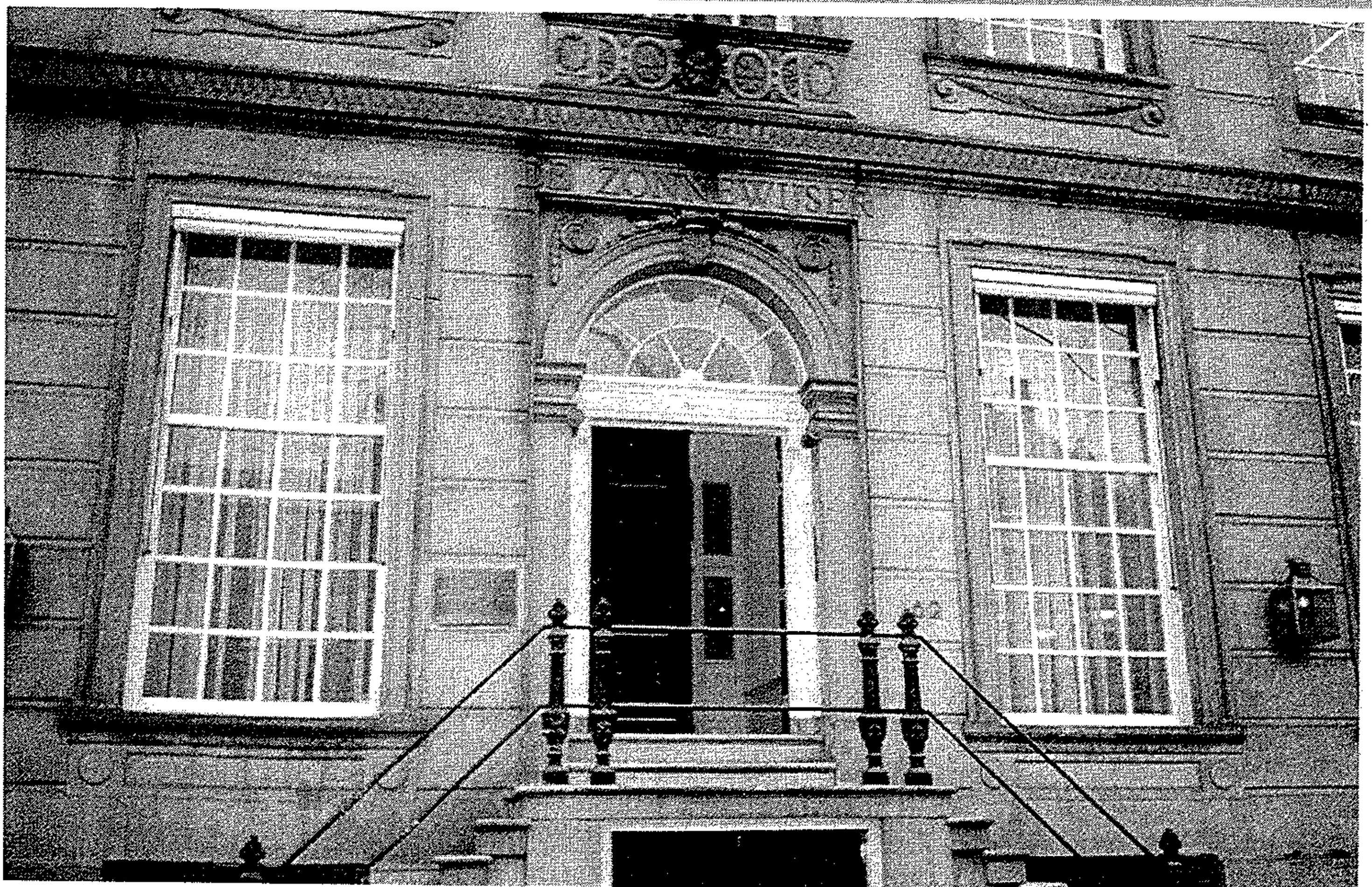
In The Money

jaargang 2, nummer 3, maart 1997



Bedrijf in Beeld: Kempen & Co, *Merchant Bank*

Estimating Systematic Risk

Financiële Fragiliteit en Banken

FAM Financierings Associatie Maastricht

ING GROEP

SIGMA Maastricht

Estimating Systematic Risk

In the Presence of Thin Trading and Conditional Heteroscedasticity

Albert Corhay
University of Liège and University of Maastricht
Alireza Tourani Rad and Jean-Pierre Urbain
University of Maastricht

In this paper we propose to use a dynamic version of the market model which allows estimation of the systematic risk of a firm which is not affected by the return measurement interval. We also extent the model to incorporate the non-normality and non-constancy of variances of stock returns. Our objective is not to build an explicit stochastic model dealing with, or explaining, non-synchronous trading but well to provide a simple framework for the estimation of the systematic risk component in the presence of thin and non-synchronous trading.

Consistent with the CAPM literature, we view the simple Market Model as an equilibrium model which relates the return of a given security linearly to the market return. This enables us to view the beta (ß) as an equilibrium parameter that has to be estimated and should be the same whatever the interval length used to measure returns. However, for reasons such as non-synchronous trading, this equilibrium relationship will certainly not hold for each period of time so that one would have to model the price adjustment process.

We use an Autoregressive Distributed Lag model (ADL) allowing for both leads and lags in the returns in order to integrate the potential effects of late news arrivals and cross-serial correlation in returns. This type of flexible estimation method would result in nearly identical estimates of ß whatever the interval length used. For a given security *i*, our dynamic model is:

$$R_{it} = \alpha_i + \sum_{j=-m_1}^{m_2} \beta_{ij} R_{mt+j} + \sum_{k=1}^{p} \gamma_{ik} R_{it-k} + u_{it}$$

where u_{it} is i.i.d. normally distributed with constant variance. Based on $max(p, m_2)$ initial values, the beta of the security *i* is then estimated as the long run effect of R_m on R_i:

$$\hat{\beta}_i = \frac{\sum_{j=-m_1}^{m_2} \hat{\beta}_{ij}}{1 - \sum_{k=1}^{p} \hat{\gamma}_{ik}}$$

The model is also extended to take into account non-normality and time-varying conditional second moment. We however restrict ourselves to a GARCH(1,1) process.

We first estimate the market model for various interval lengths of returns. We subdivided the firms into five levels of trading based on the number of days (1 day to 5 days) which were traded on average per week and we calculated the average beta, as well as the average market value for each level of trading. The market value of a firm has been measured at the middle point of the sample period. The results are presented in the table for interval lengths of 1, 10 and 20 days.

> The differences in the estimated betas are smaller when the GARCH dynamic model is used

It can be concluded that there are variations in the systematic risk depending on the interval length used to calculate the returns. The beta coefficient of small and less traded firms has a downward bias. This also suggests that the size effect discovered by Banz (1981) can be caused by a bias in the estimation of the beta coefficient of the small firms.

The results for the Dynamic GARCH model are presented in the table. Average beta coefficients appear to be closer to each other for the Dynamic GARCH model than for the other two models, the OLS and the Dynamic with no adjustment for heteroscedasticity. The average beta of portfolio 1 varies from 0.286 for one day interval to 0.343 and 0.610 for 10 and 20 days intervals, average beta of portfolio 2 from 0.298 to 0.408 and 0.518, average beta of portfolio 3 from 0.556 to 0.648 and 0.798, average beta of portfolio 4 from 0.801 to 0.902 and 0.904 and average beta of portfolio 5 from 1.070 to 1.090 and 1.076. These results are further confirmed by the values of the Mean Squared Errors (MSE).

It can be concluded that when we compare the evolution of the average betas according to the length of the interval for the three methods, the differences in the estimated betas are smaller when the GARCH dynamic model is used. This reveals, first, that the dynamic model provides estimates that are much closer to each other than those obtained using the market model for different intervals and, secondly, that allowing a GARCH structure on the error terms, make the differences quite small for many firms. This suggests that this model can to a large extent alleviate the problem of the intervalling effect.

ITM

Table : Average Beta Per Level Of Trading

Average number of days traded per week	Number of firms	Average Market value (1.000.000 BF)	1-day interval (1867 observations) Average betas, leads and lags				
				Dynamic model			
			OLS	OLS	GARCH	leads	lags
1	3	104	0,143	0,112	0,286	0,67	1,33
2	12	2274	0,143	0,291	0,298	0,33	1,00
3	29	2417	0,227	0,571	0,556	0,21	1,90
4	42	19051	0,640	0,832	0,801	0,64	0,98
5	14	111340	0,967	1,149	1,070	1,07	1,00

Average number of days traded per week	Number of firms	Average Market value (1.000.000 BF)	10-days interval (186 observations) Average betas, leads and lags				
				Dynamic model			
			OLS	OLS	GARCH	leads	lags
1	3	104	0,284	0,538	0,343	0,00	1,00
2	12	2274	0,460	0,563	0,408	0,25	0,42
3	29	2417	0,694	0,804	0,648	0,21	0,38
4	42	19051	0,929	0,971	0,902	0,26	0,62
5	14	111340	1,112	1,100	1,090	0,29	0,07

Average number of days traded per week	Number of firms	Average Market value (1.000.000 BF)	20-days interval (93 observations) Average betas, leads and lags				
				Dynamic model			
			OLS	OLS	GARCH	leads	lags
1	3	104	0,295	0,947	0,610	0,00	2,66
2	12	2274	0,542	0,631	0,518	0,08	0,42
3	29	2417	0,778	0,865	0,798	0,38	0,34
4	42	19051	0,945	0,923	0,904	0,29	0,38
5	14	111340	1,104	1,120	1,076	0,14	0,14