Essays on Conditional Pricing of Finnish Stocks

MARKKU MALKAMÄKI

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Markku Malkamäki

Contents

1 Aim and Scope of the Study

The Sharpe (1964) – Lintner (1965) version of the CAPM states that the expected return on an asset is positively and exactly linearly related to its systematic risk, which is measured by the beta coefficient of the asset. However, the CAPM is not testable, as stated in Roll (1977), because the true market portfolio is not observable. Therefore, the CAPM is merely a statement about the mean-variance efficiency of a given market portfolio. Thus, we test empirically whether the observed stock market portfolio is mean-variance efficient. The test is, of course, a joint test of whether a given portfolio is mean-variance efficient and whether the market is information efficient.

Prior evidence from unconditional tests of the CAPM has been mixed regarding the mean-variance efficiency of the Finnish stock market index and the implied positive pricing of the beta risk (see eg Korhonen (1977), Berglund (1986) and Malkamäki (1991)). The first two essays of this study provide a thorough analysis of the mean-variance efficiency of the Finnish stock market index and the pricing of the firm-specific (unconditional or conditional) beta risk. The first essay employs two static OLS models and OLS and maximum likelihood (ML) time-varying-parameter models to estimate the betas. It is found that the mean-variance efficiency is always rejected and the average risk premium takes a negative sign when the OLS estimates of the market risk are used to capture the cross-section of expected returns. However, this result appears to be due to spurious OLS beta estimates. We draw this conclusion because when the betas are forecasted using a mean-reverting AR1 model, the mean-variance efficiency of the market index is not rejected and the price of risk is found to be positive.

The second essay examines the robustness of the above results in four asset-return samples using a static OLS and dynamic ML procedure to estimate the betas. A pooled data analysis is performed in addition to second-pass Fama–MacBeth (1973) regressions. It is shown that in every case the analysis on OLS betas leads to rejection of the mean-variance efficiency of the market index and the price of market risk is negative and statistically significant. The corresponding tests on the time-varying betas produce the opposite results. The mean-variance efficiency of the market index is not rejected in any of the samples. Furthermore, the price of market risk turns out positive and statistically significant, especially for the stock return data set that most closely resembles the normal distribution. The data employed in these two essays covers all Finnish common stocks listed on the Helsinki Stock Exchange throughout the period 1972–1989. The tests are carried out on end-of-month returns in excess of a short term interest rate for the first time in Finland. Some additional testing of robustness is provided through the use of monthly and quarterly nominal returns.

The third and fourth essays examine (1) the time-series predictability of Finnish stock market returns, (2) the conditional variation of the cross-section of expected returns, according to the time-varying risk parameters of the CAPM, and (3) the pricing of Finnish stocks when business conditions, interest-based variables, certain macrovariables and foreign stock markets are used as conditioning information. The relevance of these topics for research is discussed in Fama (1991).

The third essay examines the time-series predictability of Finnish stock market returns. This is accomplished by employing cointegration and Granger causality analysis on the stock markets in the United States, the United Kindom, Germany, Sweden and Finland. The first three nations are the largest trading partners of the two small open Nordic economies, Finland and Sweden. The tests are carried out using standard univariate vector autoregressive (VAR) models and a system of VAR models under the assumption of multivariate cointegration, first introduced in Johansen (1988). Fama (1991) points out that stock returns can be predictable in an efficient market. Accepting this proposition Dwyer and Wallace (1992) show that there is no general equivalance between the existence of arbitrage opportunities and cointegration or a lack of it. It follows that no conclusions regarding market efficiency are drawn in the third essay.

The cointegration analysis suggests that the stock markets are cointegrated, having one cointegrating vector when prices are in local currencies or in Finnish markkas and two cointegrating vectors when prices are in US dollars. It is also found that the Finnish and Swedish markets may deviate from the equilibrium path without having a significant impact on the three other markets, which indicates that the causality is from other stock markets to Finland and Sweden. The Finnish stock market is always found to be predicted by the German market, instead of the Swedish market as previously suggested, and also by the UK market when returns are in local currencies or in Finnish markkas. The Swedish stock market is Granger caused by the

UK market instead of the US market, as previously suggested. The data covers the period 1974—1989.

The fourth essay studies the driving forces of predictable variation in Finnish stock returns in excess of the short term interest rate. This essay involves a joint hypothesis regarding the rationality (efficiency) of the Finnish stock market and the model employed. The dynamics of Ferson and Harvey's (1991) methodology is extended and applied within the Sharpe—Lintner CAPM. It is found that the market risk is conditionally priced in the Finnish stock market. Most of the predictable variation of stock returns is attributed to the time-varying risk premium, which supports the hypothesis of rational behavior by Finnish investors in setting prices in the stock market. However, the conditional residual term accounted for a larger part of the predictable variation of the returns than is found in the US market. Expectation concerning changes in the future order stock for Finnish industry and unexpected changes in inflation are found to capture the variation in the risk premium; and unexpected changes in inflation, in combination with an instrument, estimated in the third essay, for the lagged influence of Finnish, German, Swedish, UK and US stock market returns on the Finnish market, are found to predict firm-specific excess returns.

The essays are closely related to each other, especially essays 1, 2 and 4, which examine conditional pricing of Finnish stocks within the S-L CAPM, whereas essay 3 provides an additional conditioning instrument for essay 4. Thus, it is perhaps most convenient to read them in numbered order. However, this is not necessary as each essay is also an independent study. Methodological issues in asset pricing tests on thin stock markets (eg Finland) and interpretation of the results in light of the theory and prior results are taken up extensively in this study. Some explicit suggestions that may be relevant for investment services and investors are also given. Much has also been omitted. This study does not, for example, examine anomalies or Black's (1972) and Merton's (1973) versions of the CAPM. Nor does it consider Ross's (1976) arbitrage pricing theory (APT) or multifactor applications of the APT (such as Chen et al. (1986)). Explicit discussion of the information efficiency of the Finnish stock market is avoided largely because the topic is ambiguous, as pointed out in Fama (1991).

The remainder of the study is organized as follows. Section two discusses the methodologal aspects of the tests of the CAPM, especially for a thin stock market such as that of Finland. Some concluding remarks are given in section 3, after which the essays are presented.

2 Methodological Aspects of the Tests

The CAPM itself is not testable, as stated in Roll (1977). Hence, the only hypothesis concerning the model that can actually be tested empirically is whether an observed stock market portfolio is mean-variance efficient in the sense of Markowitz (1959). But the test, in fact, is a joint test of whether the given portfolio is mean-variance efficient and whether the market is information efficient. Another problem here is that the true beta coefficient, β_i, in the CAPM cannot be observed and has to estimated. The betas are usually estimated by applying Sharpe's well-known time-series regression (TSR) model, ie the market model. However, the estimated beta is a combination of the "true" beta and a measurement error. This error is a matter of great concern, since it induces an errors-in-variables problem into the mean-variance analysis and risk premium estimates.

Within the Sharpe–Lintner CAPM, the time-series model, through which the betas are commonly estimated is expressed in terms of excess returns as:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \tag{1}$$

where r_{it} = excess return on asset i at time t,
α_i = intercept term,
β_i = beta coefficient of asset i,
r_{mt} = excess return on the stock market portfolio at time t,
ε_{it} = random error term.

Since the Fama and MacBeth (1973) introduced their seminal univariate test of the CAPM, betas have been estimated iteratively from this regression model to get a time series of "rolling" beta estimates. The second step in their methodology is to run a cross-sectional regression (CSR) of expected returns on the estimated betas. They performed the following CSR for each month:

$$r_{it} = \lambda_{0t} + \lambda_{1t}\hat{\beta}_{it-1} + e_{it}, \tag{2}$$

where r_{it} = expected excess return implied by the CAPM on asset i for period t
λ_{0t} = intercept term (H_0: $\lambda_{0t} = 0$ according to the CAPM)
λ_{1t} = risk premium
$\hat{\beta}_{it-1}$ = beta coefficient estimated from the previous period
e_{it} = random error term.

The final estimates of the intercept and the ex-post risk premium are the sample means of the time series of these coefficients. The computation of standard errors is based on the assumption that the time series of the cross-sectional estimates are independent and identically distributed. However, the independence assumption is not strictly satisfied due to the use of the beta estimates instead of the "true" betas. The errors-in-variables (EIV) problem is also introduced in the second-pass regression by regressing the returns on betas which are measured with error. Due to the EIV problem, the CSR estimates are biased and inconsistent in small samples (for a review of EIV problems, see eg Lehmann (1992) and Shanken (1992)). An additional drawback of univariate tests is pointed out in Bradfield and Affleck-Graves (1991). They show that in certain cases the lack of statistical power of the univariate tests is so evident that the risk-return relationship entailed in the CAPM, even if true, is nearly impossible to detect.

The hypothesis of mean-variance efficiency explicitly implies that λ_0 is not significantly different from zero, since an asset's expected return should be positively and exactly linearly related to its systematic risk within the S-L CAPM.[1] Given an efficient proxy for the true market index, the true beta risk is priced by the market (see eg Roll (1977)). Nevertheless, the estimate of the risk premium may be statistically insignificant according to the tests due to the biased beta estimates, which gives academics and investment analysts good reason to search for an adequate method of estimating betas.

[1] Another way to test the ex-post mean-variance efficiency of an portfolio is to test whether the time series estimate α_i is significantly different from zero. The power of the test can be increased by employing the multivariate test of Gibbons (1982), Stambaugh (1982) or Gibbons et al. (1989).

2.1 Beta Estimation

The TSR of equation (1) is usually run iteratively over five-year periods to get the beta estimates for each asset or for a portfolio of assets. Shanken (1992) shows that the measurement error for beta declines as the estimation period T increases and that the cross-sectional lamda estimator converges to its true value as T goes to the infinity. This implies that the true beta is constant over time. However, the time-variation of the betas is theoretically rational and has been found in many studies (see eg Ball and Kothari (1989), Fama and French (1992)).[2] The time-variation of the betas implies that the five-year beta estimation period is already quite long and could hardly be lengthened. This is also a relevant criticism of the contemporaneous multivariate tests of the CAPM (see eg Gibbons, Shanken and Ross (1989)). These tests are statistically efficient, but they do not allow for time-variation in beta.

Another way of reducing the measurement error in beta is to minimize the variance of the error term in the TSR. This is most commonly achieved by grouping assets into portfolios if the errors are not perfectly correlated cross-sectionally. If the residuals are not perfectly correlated, there is a diversification effect, and the residual variance of the portfolio will be less than that of any individual asset in the portfolio. The problem is that one must find a sorting variable that is highly correlated with the true betas and uncorrelated with the estimation error. Random selection of assets would solve this problem, but it would not provide the necessary dispersion in the beta estimates. Substantial dispersion of the betas is necessary in the CSR since the betas are the only explanatory variables in the cross-section of asset returns.

Another problem with the grouping approach is that it can support a false theory because individual asset deviations from exact linearity can cancel out in the portfolios.[3] Moreover, Ball and Kothari (1989)

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[2] The non-statiority of Finnish stock betas is reported in Korhonen (1977), Berglund et al. (1989), Martikainen (1991) and Malkamäki (1992a). On the other hand, Knif (1989) and Malkamäki (1992a) show that Finnish common stock betas in most cases follow a stationary AR1 process and that the AR1 parameter is seldom statistically significant. The slightly contradictory results can be due to the invertion of the hypothesis tested.

[3] This can be the case if the deviations are not related to the betas (see also Roll (1977)). An example of such a reason for deviation could be that the risk associated with higher moments of the asset returns is priced.

suggest that alternative grouping methods of securities may very well have crucial effects on beta values. Lo and MacKinley (1990) employ Monte Carlo simulations and show, for example, that sorting portfolios by size creates potentially significant biases in the test statistics of asset pricing models. Shanken and Weinstein (1990) replicate the Chen et al. (1986) multifactor study and show that the latter's results are sensitive to the assets and grouping methods employed. All these studies (and many others) indicate that the search for an optimal beta estimation method will continue.

The security grouping approach is actually not useful in the context of a thin stock market because there are only a limited number of listed stocks. Furthermore, a firm's stocks may be divided into different types of stocks (eg common and preference shares and restricted and unrestricted stocks on the Helsinki Stock Exchange). The potential diversification effect in portfolio formation would be very limited. Another problem is that a sorting variable that would provide the needed dispersion in betas would have to be found.[4] Thus individual stocks are usually examined in Finnish studies. This approach avoids the caveats related to portfolio formation but must confront non-normality in some of the stock returns, which also may bias the inferences of the CSR.

There are two additional problems in applying the two-pass regression approach in the analysis. These are the possible existence of autocorrelation in the TSR residuals and heteroscedasticity in the TSR and CSR residuals. If the residual variance turns out to vary over time, a common solution is to use the weighted least squares regression method. The problem with autocorrelation in TSR residuals is usually reduced by measuring the returns over one-month (instead of shorter) intervals. These problems can also be reduced by using conditional estimation methods.

Time variation of betas has been documented recently by a number of researchers, as reviewed above.[5] Malkamäki (1992a and b) shows that it is crucial to allow betas to vary over time in tests of the CAPM and states that the use of static betas in making investment

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[4] For example, firm size, which is commonly used as a sorting variable in US studies, does not generate the required dispersion of betas in other countries.

[5] A driving economic force behind the time-varying beta coefficient could be, for example, a change in leverage or riskiness of a firm's investment projects (see eg Chan (1985), Ball and Kothari (1989), Chan and Chen (1991) and Fama and French (1992)).

decisions will lead to a loss of wealth. There are, in fact, at least three relevant estimation procedures available for testing models with time-variation in the betas.[6] Bollerslev, Engle and Wooldridge (1988) and Ng (1991) employ different versions of the multivariate generalized autoregressive conditional heteroskedasticity (GARCH) method in modelling the conditional covariances as a function of past conditional covariances. However, Nelson (1991) states that there are at least three major drawbacks involved in the GARCH models, and he develops a univariate exponential ARCH model that does not suffer from these drawbacks. A multivariate version of his univariate model or some other satisfactory improvement on the ARCH models is still needed to avoid these problems when using the models in asset pricing applications.

Harvey (1989) applies the generalized method of moments (GMM) of Hansen (1982) to allow conditional covariances to vary in a test of the CAPM. This procedure involves expected returns conditional on the "true" market information set. A problem here is that the true market information set is not observed. Instead, a subset of observable variables, called instrumental variables, is employed. A problem with observable variables is that the thinner a capital market is the more the quality of conditioning information can suffer. Furthermore, it is assumed in the GMM applications that a linear function relates conditional expectations to the information set.

Time-varying-parameter (TVP) models are the third possibility for controlling time variation in the betas. We can estimate TVP models, for example, by applying the Kalman filter technique. This technique provides insight into how a rational investor would revise his beta estimates in a Bayesian fashion in response to new information and generates i.i.d. error terms. Chan (1985), perhaps, was the first to apply the Kalman filter methodology to beta estimation. He estimates static and dynamic betas for US size-sorted stock portfolios and finds that Kalman filtered time-varying betas outperform OLS betas in forecasting the future betas and in explaining the cross-sectional distribution of expected returns. Knif (1989) applies Kalman filter techniques to model the time variation of firm-specific market risk in Finnish common stock data. He finds that the betas are time varying. However, most betas of Finnish common stocks follow a stationary autoregressive (AR1) process. Östermark (1990) finds that conditional

[6] This and the next two paragraph are adopted from Malkamäki (1992a).

market risk estimates ourperform static beta estimates in tests of the asset pricing models. De Jong et al. develop the Kalman filter AR1 market model further by incorporating a GARCH model with t-distributed errors. They find that firm-specific betas and the variance of the error term are time varying in the Dutch stock market. Their evidence of the time variation of betas is quite straightforward.

Berglund and Knif (1992) and Malkamäki (1992a,b and d) apply the same mean-reverting AR1 model that generates the most accurate firm-specific beta estimates in the Finnish stock market, according to Knif (1989). To express the estimated parameter vector, the market model (1) is conveniently written in state space form as:

$$r_{it} = X_t' \theta_t + \varepsilon_t, \tag{3}$$

where $X_t' = [1, r_{mt}]$

$\theta_t' = [\alpha_{it}, \beta_{it}]$

ε_t = random error with variance v_t.

The parameter vector θ_t is actually assumed to vary according to the stationary first order autoregressive model[7]

$$\theta_t - \bar{\theta} = F(\theta_{t-1} - \bar{\theta}) + u_t, \tag{4}$$

where $\bar{\theta}$ = mean vector of the parameters

F = weights for the AR1 and mean parameters

u_t = random error with covariance matrix M_t.

The authors also employ the betas forecasted on the basis of these estimated ML betas in cross-sectional analysis in order to further reduce the EIV problem.[8] However the CSR tests carried out differ

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[7] For details, see eg Knif (1989), Malkamäki (1992a) or Harvey (1991).

[8] The forecasting model is ($\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta}$), where ω is the parameter value of the AR1 term in F (see equation (6)). I am grateful to Tom Berglund and Johan Knif for advising me to use forecasted betas in the CSRs.

from each other (these methods, data and results are discussed in the next subsection). Moreover, these authors compute static OLS beta estimates iteratively over five-year periods. In addition to these beta estimates, Malkamäki (1992a) employs also three-year OLS beta estimates and dynamic Kalman-filtered OLS betas which are assumed to follow a random walk. This enables him to show that only the use of AR1 betas provides support for the mean-variance efficiency of the Finnish stock market index.

2.2 Estimation of the Risk Premium

Lehmann (1992) provides an extensive discussion on errors-in-variables bias and the ways to mitigate it by using information on the sampling error in estimated betas. This subsection discusses briefly the procedures employed to mitigate the EIV problem in Malkamäki (1992a,b and d). The results are also discussed and compared with Berglund and Knif (BK) (1992) because their paper is closely related to the first two essays of this study.

Essays 1, 2 and 3 apply the ML Kalman Filter procedure (along with other estimation procedures), which produces minimum-mean-square beta estimates. These beta estimates always converge towards the mean due to the mean-reverting AR1 model employed. Thus, extreme effects of errors in the beta estimates are expected to be reduced. As the final step in estimating the betas, the mean-reverting AR1 model is used to compute the forecasted beta series. The second-pass regression is run over the forecasted betas in order to further reduce the EIV problem, at least to some extent.[9] This will be the case if the residual variance of the market model changes over time and is dependent on the time variation of the betas.

Malkamäki (1992a), using the traditional procedure, regresses expected monthly returns (observed ex post returns) on the estimated betas. However, instead of getting Fama–MacBeth iterative CSRs, he runs this regression only once with pooled return and beta series. This is done by constructing only one composite return vector for all firms' returns and one corresponding beta vector for the entire period analysed. The first 25 observations are the February 1977 excess returns and corresponding betas for each firm. Observations 26–50 are

[9] This methodology is used also in Berglund and Knif (1992).

the respective observations for March 1977, and so on. Therefore, his monthly analysis includes 3875 observations in these two vectors for the period 1977:2—1989:12. This implies that our tests of the risk premium have extremely high degrees of freedom. The pooled data estimation procedure avoids the above criticism regarding standard deviations in the univariate tests and has the nice feature of giving greater weight to those observations that are highly correlated with each other, as compared to the standard univariate tests. It also enables one to examine whether the assumption of a constant risk premium should be relaxed. A drawback of this method is that it implies an assumption that the cross-sectional and time-series variability (error variance) are equal. The inferences reported in the essay are heteroscadasticity corrected, according White (1980).

Malkamäki (1992b) employs the traditional Fama—MacBeth univariate tests and the above pooled-data tests. Significancy tests of the risk premium are extended by an analysis of the number of statistically significant CSRs. It is shown in the essay that the CSRs are more often statistically significant than would be expected under randomness. This indicates that the beta risk is cross-sectionally priced and that the risk premium is time varying, as the corresponding Fama—MacBeth premiums are not statistically significant. On the other hand, the pooled data regression in the essay suggests that the index is mean-variance efficient and that the average risk premium is statistically significant at the 10 % level. Berglund and Knif (1992) also use weighted least square (WLS) regression to mitigate EIV bias in the CSR analysis. The weight used in their CSRs is the variance of one-step ahead prediction errors from the forecasting model of betas expressed in footnote 9 in the previous subsection. They find that their correction that is dependent on their estimation methodology has the greatest effect in monthly analysis in favor of the positive average risk premium, which has the t-value of 2.05. However, bi-monthly and quarterly risk premiums are not statistically significant.[10]

Essay four of this study goes one step further. It applies Ferson and Harvey's (1991) methodology to examine the pricing of beta risk and the driving forces of predictable variation in Finnish stock returns. The methodology employ completely avoids the inference problem of the univariate tests. It is found in the essay that the risk premiums

[10] Mean-variance tests of this study cannot be compared with Berglund and Knif, since they do not report these test statistics. It should also be noted that the data and periods studied in Malkamäki and Berglund and Knif differ slightly.

estimated in the monthly CSRs are conditionally priced. Expectation concerning changes in the future order stock for Finnish industry and unexpected changes in inflation are found to capture the variation in the risk premium reasonably well. This result is extremely promising, since the data employed include the year 1989, which is found to be very problematic in the unconditional tests of the risk premium in essays 1 and 2. Furthermore, most of the predictable variation in stock returns is attributed to the time-varying risk premium, which supports the hypothesis of rational behavior by Finnish investors in setting prices in the market.

2.3 Cointegration and Causality

Several papers have recently examined interdependencies in international stock markets. For example, Eun and Shim (1989), Hamao et al. (1990) and King and Wadhwani (1990) find that stock markets are in many cases less than fully integrated, which implies that shocks are transferred from one market to another. Furthermore, Kasa (1992) suggests that international stock markets move together in the long run. Virtanen and Yli-Olli (1987) was the first study showing that foreign (Swedish) stock returns predict Finnish returns.

The third essay of this study examines the time-series predictability of Finnish stock market returns in a broader context. This is accomplished by applying Johansen's (1988) multivariate cointegration and Granger causality analysis to stock markets in the United States, United Kingdom, Germany, Sweden and Finland. In this methodology, the short-term causalities are simultaneously analysed conditional on the long-term relations, thus using all information contained in the data. The first three nations are the largest trading partners of the two small open Nordic economies, Finland and Sweden.[11] Furthermore, Sweden is Finland's second biggest trading partner. If foreign stock market returns contain relevant information for Finnish investors in setting prices in the market, it should be useful to examine the stock markets of countries whose real economies are most important to Finnish exporters. The motivation for the third essay in this study is that it provides an instrument for the lagged influence of

[11] This brief discussion of the third essay omits the results with respect to the Swedish market (see Malkamäki (1992c) for details).

Finnish, German, Swedish, UK and US stock market returns on the Finnish market. This instrument is used in the forth essay as one of the conditioning variables.

The tests for causality performed here find their roots in the regression technique of Granger (1969). Time series used in Granger causality analysis should be stationary in order to apply standard inference techniques. Differencing the logarithmic stock prices once usually produces stationarity, and hence we conlude that the series have a unit root, ie they are integrated of order one, I(1). On the other hand, Granger (1981) showed that even in the case that all the variables in a vector are stationary only after differencing, there may be linear combinations of those variables which are stationary without differencing, ie the variables may be cointegrated. Cointegration of a vector of variables implies that the number of unit roots in the system is less than the number of unit roots in the corresponding univariate series. This implies that the variables share at least one common (stochastic) trend.

Engle and Granger (1987) showed that a cointegrated system can be represented in an error-correction structure that incorporates both changes and levels of variables such that all the elements are stationary. The levels of variables contain long-term information, which is lost when differencing the data, except in the unlikely event that short-term effects are identical to long-term effects. Error-correction models (ECM) allow for testing the possibility of differences in short-run and long-run dynamics. If a set of variables is cointegrated, the ECM term should be included when estimating a dynamic model. Otherwise, the model is mis-specified and relevant information is omitted.

Cointegration tests are usually carried out using the Engle—Granger (1987) two-step procedure, which may employ either a static linear regression or a dynamic linear model. Johansen (1988) presents an efficient autoregressive formulation of the multivariate error-correction model. His multivariate cointegration approach allows for the simultaneously analysis of hypothetical long-run relations and short-term dynamics, using a maximum likelihood estimation procedure. This approach relaxes the assumption that the cointegrating vector is unique and takes into account the error structure of the underlying process. It also allows for several tests regarding the cointegrating vectors and for tests of weak exogeneity among the variables. The multivariate model is developed further in Johansen and Juselius (1990) Johansen (1991) and Johansen (1992). The tests in essay (3) are carried out using standard univariate vector autoregressive (VAR) models and a system of VAR models under the assumption of Johansen's multivariate cointegration.

The key findings of the essay (in the context of this study) are that the stock markets are cointegrated and that the Finnish market may deviate from the equilibrium path without having a significant impact on the other markets, which indicates that the causality is from the other markets to Finland. The Finnish stock market is also found to be predicted by the German market, instead of the Swedish market, as previously suggested, and also by the UK market when returns are in local currencies or in Finnish markkas. These results are not sensitive to inflation differences, since all the analyses were performed on nominal and real stock market indices. Dwyer and Wallace (1992) show that there is no general equivalance between the existence of arbitrage opportunities and cointegration, or a lack of it. Thus, no explicit conclusions as to market efficiency are drawn in the third essay.

2.4 A Note on the Data

The data used in essays 1, 2 and 4 cover stocks listed on the Helsinki Stock Exchange throughout the period 1972–1989. The analyses are carried out with end-of-month and, to some extent, end-of-quarter returns, which are measured as logarithmic changes in the indices. Monthly excess returns are computed by using the one-month return for the three-month Eurorate on the Finnish markka. The interest rate series is constructed and introduced in Malkamäki (1992a). The lack of data on short term interest rates prior to January 1972 was the limiting factor in the data. Observations on end-of-month days without a transaction in a stock are bid prices for that day. The HSE market index, which is used here, is value weighted (see Berglund–Wahlroos–Grandell (1983)). In this index, prices are corrected for cash dividends, splits, stock dividends and new issues. The correction is based on the principle that all income from a stock is reinvested in the stock with no transaction cost. No portfolios are formed for the analysis as is usually done in US studies. This is because of the extremely limited number of actively traded stocks. Instead, four asset samples are included in the second essay. The first sample includes all 25 restricted[12] ordinary stock series listed throughout the period analysed. The second sample includes the 16 most traded restricted stocks for the period. The third sample includes the 15 return series that most closely resemble the normal distribution. Sample 1 is also enlarged to form sample 4 by introducing a corporate bond return index into the analysis. The corporate bond return index is first introduced in Malkamäki (1992b). Essays 1 and 4 employ only the sample.

Essay 3 uses stock market indices of the United States, United Kindom, Germany, Sweden and Finland for the period 1974–1989. End-of-month stock market logarithmic price indices in local currencies, constructed by Morgan Stanley Capital International, are employed for all the countries except Finland, as the MSCI index was not calculated for Finland until the late 1980s. For Finland, the HSE index is used, as in the other essays. This index is similar to the MSCI. The log price series for each country are presented in the essay. In the indices, prices are corrected for dividends, splits, stock dividends and new issues. The correction is based on the principle that all income from a stock is reinvested in that stock with no transaction cost.

All the analyses are conducted using the indices in local currences, US dollars and Finnish markkas, and the foreign exchange risk is not hedged. Furthermore, the hypothetical impact of inflation is eliminated here by repeating the analysis with indices reduced by the corresponding short term money market rates (see Appendix 1 for these index values). End-of-month foreign exchange rates were collected from the Bank of Finland's archives. The corresponding one-month Euromarket deposit rates were taken from the DRI and Nomura databanks. The Finnish one-month interest rate was adopted from Malkamäki (1992a).

[12] Only domestic investors are allowed to buy restricted stocks.

3 Concluding Remarks

The first two essays suggest that more effort should be expended in search of an adequate beta estimation method. In the case of small stock markets, as in Finland, it is crucial to allow for time variation in firm-specific betas in a dynamic way. Investors should clearly not base their investment desisions on the unconditional OLS betas commonly published by investment services. They could, instead, consider the mean-reverting AR1 betas employed here. However, more sophisticated models of risk evaluation might perform even better.

The third essay shows that Finnish stock market returns can be predicted by Finland's own and certain foreign stock market indices. Both lagged prices and lagged returns for these markets appeared to contain information relevant to Finnish stock market returns. Essay 4 goes one step further to show that lagged market prices and returns also predict Finnish firm-specific returns. However, the key finding of the fourth essay is that the risk premium is conditionally priced. It also finds that most of the predictable variation in stock prices is attributable to the time-varying risk premium, which supports the hypothesis of Finnish investors' rationality in setting prices in the market.

There would seem to be three fruitful ways in which to extend this study. One could further examine the time variation of the betas. It would be very useful to find out to which firm-specific and/or economic variables the time-varying betas are related. The beta risk could also be modelled in a more flexible framework than the stationary AR1 model, which is employed here. An example of such a study is provided in de Jong et al. (1992). The second route is motivated by Yli-Olli et al. (1989). They find that there are three common factors in the Finnish stock market. An attempt could be made to identify these factors, as is done in Östermark (1989) and Martikainen (1990). It might also be useful to replicate the Malkamäki (1992d) study in a multifactor context in order to find out whether additional risk factors are conditionally priced. Finally, the ex ante mean-variance efficiency of the Finnish stock market index could be examined, for example, using the approach of Harvey (1989).

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Markku Malkamäki

In the Defence of the CAPM: Evidence Using Time-Varying Betas on a Thin Stock Market

Abstract

This paper examines the Sharpe—Lintner CAPM using time-varying-parameter models in addition to the static market model. Prior evidence does not support the CAPM in that it suggests that market risk is not priced or that the price of the beta risk is significantly negative for a thin European stock market, eg the Finnish stock market. This paper shows explicitly that this phenomenom is due to static ordinary least squares beta estimates which are spurious. We reduce the errors-in-variables problem by estimating firm-specific betas using Kalman filter techniques and employ the betas forecasted on the basis of these estimated betas in a cross-sectional analysis. Analysis of pooled data shows that the price of conditional risk is positive and that the mean-variance efficiency of the market index cannot be rejected. These results support the CAPM. The data covers all Finnish common stocks listed on the Helsinki Stock Exchange throughout the period 1972—1989.

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1 Introduction

The CAPM states that the expected return on an asset is positively and linearly related to its systematic risk, which is measured by the beta coefficient of the asset. The Sharpe (1964)—Lintner (1965) version of the model states that

$$E(R_i) = R_f + \beta_i E(R_M - R_f), \tag{1}$$

where $E(R_i)$ = expected return on asset i
R_f = risk-free rate of interest
β_i = systematic risk coefficient (beta) for asset i
$E(R_M\text{-}R_f)$ = expected return on the market portfolio in excess of the risk-free rate.

The CAPM is not testable, as stated in Roll (1977), because the true market portfolio is not observable. Therefore, the CAPM, as applied in empirical research, is merely a statement about the mean-variance efficiency of a given market portfolio. Thus, we test empirically whether an observed stock market portfolio is mean-variance efficient. The test is then a joint test of whether the given portfolio is mean-variance efficient and whether the market is information efficient.

Unfortunately, the true beta coefficient, β_i, in the CAPM cannot be observed. In the traditional two-pass approach, beta is estimated by applying Sharpe's well-known time-series regression (TSR) model, ie the market model, which is expressed below in terms of excess returns:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \tag{2}$$

where r_{it} = excess return on asset i at time t
α_i = intercept term
β_i = beta coefficient of asset i
r_{mt} = excess return on the stock market portfolio at time t
ε_{it} = random error term.

In their seminal paper, Fama and MacBeth (1973) introduce an iterative technique for estimating the second-pass cross-sectional regression (CSR). They revise the TSR each month in order to get a series of "rolling" beta estimates for each asset and compute the following CSR on the beta estimates for each month:

$$r_{it} = a_t + \lambda_t \hat{\beta}_{it-1} + e_{it}, \tag{3}$$

where r_{it} = expected excess return implied by the CAPM on asset i for period t (here monthly return over the entire period analysed)

a = intercept term (H_0: $a_t = 0$ according to the CAPM)

λ_t = risk premium

$\hat{\beta}_{it-1}$ = beta coefficient estimated for the previous period

e_{it} = random error term.

In univariate tests of the CAPM, the betas are generally estimated over a five year period prior to each CSR.[1] The final estimates of the intercept and risk premium are the sample means of the time series of these coefficients. The computation of standard errors is based on the assumption that the time series of the estimates are independent and distributed identically to the means of the final estimates. However, the independence assumption is not strictly satisfied due to the use of the estimated betas instead of "true" betas. We also introduce an errors-in-variables (EIV) problem in the second-pass regression by regressing the returns on betas which are measured with error. Due to the EIV problem, our CSR estimates are biased and inconsistent in small samples (for a review of EIV problems, see eg Shanken (1992)). Moreover, Bradfield and Affleck-Graves (1991) show that in certain cases the lack of statistical power of the univariate tests is so evident that the risk-return relationship implied by the CAPM, even if true, is nearly impossible to detect.

However, most earlier studies of Finnish stock market data follow this approach. These studies do not support the existence of a robust positive risk-return relationship as implied by the CAPM. The most

[1] Methodological aspects of alternative unconditional and conditional beta estimation methods and CAPM tests are discussed in the next section.

puzzling result is obtained in Malkamäki (1991) with monthly and quarterly stock market data on excess returns. He runs Fama–MacBeth OLS regressions in a multifactor context, as in Ferson and Harvey (1991), and finds that the price of market risk is negative and statistically significant. A recent paper by Fama and French (1992) also employs a version of the above unconditional univariate tests. They find strong evidence that the betas are weaker in capturing the cross-section of expected returns than firm size and book-to-market equity. However, since the latter variables are directly available, whereas the betas include a measurement error of unknown size, statistical tests might favor firm size and book-to-market equity as explanatory variables.

This paper examines the risk-return question raised by Malkamäki (1991) in the context of the Sharpe–Lintner CAPM using data from the thin Finnish stock market. The CAPM's systematic risk is estimated by employing the traditional OLS rolling beta procedure and, as alternatives, two different kinds of time-varying-parameter models. The time series for the beta coefficient of each stock is estimated by applying Sharpe's (1964) market model. We estimate the rolling OLS betas over five- and three-year periods of time. The dynamic beta estimates are computed by applying OLS and maximum likelihood (ML) Kalman filter techniques.

We proceed by testing whether the market risk, either static or time varying, is priced by the market. We regress, as usual, expected monthly returns on the estimated betas. However, this regression is run with pooled returns and betas. This is done by constructing only one composite return vector for all firms' returns and one corresponding beta vector for the entire period analysed.[2] Therefore, the monthly analysis includes 3875 observations in these two vectors for the period 1977:2–1989:12. This implies that the tests of the risk premium have extremely high degrees of freedom, ie the tests are powerful. The pooled data estimation procedure avoids the above criticism regarding standard deviations in the univariate tests. The pooled regression also has the nice feature of giving greater weight to those observations that are highly correlated with each other, as compared to the standard

[2] Regression over the pooled data implies an assumption that the cross-sectional and time-series variability (error variance) are equal. The first 25 observations are the February 1977 excess returns and corresponding betas for each firm. Observations 26–50 are the respective observations for March 1977.

univariate tests. As a final topic, this paper examines whether the assumption of a constant risk premium should be relaxed.

The paper tries to do five things. First, the short-term interest rate is computed from the Eurofutures market for the Finnish markka. This makes it possible to analyse excess returns of this kind for the first time using Finnish stock returns. Second, static and dynamic monthly estimates for the beta time series are computed. Third, the data is pooled in order to increase the power of the tests in analysing the pricing of risk and its potential variation. Fourth, the CAPM is tested in its restricted and unrestricted forms to analyse the accuracy of the beta estimates obtained using different estimation methods. Finally, the paper explicitly shows that time-varying beta estimates improve the empirical results substantially in line with the basic risk-return assumption of the CAPM. Furthermore, the Finnish stock market index turns out to be mean-variance efficient.

The remainder of the paper is organised as follows. Section 2 discusses the methodological problems of estimating constant and time-varying betas and the risk premium. Section 3 describes the Kalman filter technique. The next section describes the data and economic conditions in Finland during the period studied. Empirical results are presented in section 5 and, finally, the key findings and some conclusions are presented in section 6.

2 Methodological Aspects of Beta Estimation

2.1 Constant Beta Models

Let us assume that a firm's true beta is constant over time. There are two ways to reduce the measurement error in the TSR. First, we could lengthen the common five year time period employed in the beta estimation. On the other hand, empirical analysis suggests that the betas are non-stationary, which implies that five years is a reasonably long period for their estimation. This is also a relevant criticism of contemporaneous multivariate tests of the CAPM (see eg Gibbons, Shanken and Ross (1989)). These tests are statistically efficient but do not allow for time variation in beta.

The second possibility is to minimize the variance of the error term in the TSR. This is most commonly achieved by grouping securities into portfolios if the errors are not perfectly correlated cross-sectionally. The problem is that we should find a sorting variable that is highly correlated with the true betas and uncorrelated with the estimation error. However, Ball and Kothari (1989) and Shanken and Weinstein (1990) show that alternative grouping methods of securities may easily have crucial affects for beta values and lead to spurious results as well. The security grouping approach is actually not available on thin stock markets because there are only a limited number of listed stocks, and different kinds of stock series are involved (eg common and preference shares and restricted and unrestricted stock series on the Helsinki Stock Exchange). The potential diversification effect in portfolio formation would be very limited. If we do not form portfolios, we have to face another statistical problem: non-normality of certain individual asset returns.

There are two additional problems in applying the two-pass regression approach in the analysis. These are the possible existence of autocorrelation in the TSR residuals and heteroscedasticity in the TSR and CSR residuals. The problem with autocorrelation in TSR residuals is usually reduced by measuring the returns over one month (instead of shorter) intervals. If the residual variance turns out to be changing, one common solution is to use the weighted least squares regression method. Another solution is to apply conditional asset pricing models.

2.2 Time-Varying Beta Models

Time variation of the market risk has been documented recently by a number of reserchers. There are, in fact, at least three relevant estimation procedures available for modelling time variation in the betas. Bollerslev, Engle and Wooldridge (1988) and Ng (1991) employ different versions of the multivariate generalized autoregressive conditional heteroskedasticity (GARCH) method in modelling the conditional covariances as a function of past conditional covariances. However, Nelson (1991) states that there are at least three major drawbacks involved in the GARCH models, and he develops a univariate exponential ARCH model that does not suffer from these drawbacks. A multivariate version of his univariate model or some other satisfactory improvement on the ARCH models is still needed to avoid these problems when applying the models in asset pricing applications.

Harvey (1989) applies the generalized method of moments (GMM) to allow conditional covariances to vary in a test of the CAPM. This procedure involves expected returns conditional on the true market information set. A problem here is that the true market information set is not observed. Instead, a subset of observable variables, called instrumental variables, is employed. A problem with observable variables is that the thinner a capital market is the more the quality of conditioning information suffers. Further, we assume in the GMM applications that a linear function relates conditional expectations to the information set.

Time-varying parameter (TVP) models are the third possibility for controlling time variation in the betas. We can estimate TVP models, for example, by applying the Kalman filter technique. This technique provides insight into how a rational investor would revise his beta estimates in a Bayesian fashion in response to new information. A driving economic force behind the time-varying beta coefficient could be, for example, a change in leverage or riskiness of a firm's investment projects. Chan (1985) applies the Kalman filter to US size-sorted stock portfolios. He finds that Kalman filtered time-varying betas outperform OLS betas in forecasting the future betas and in explaining the cross-sectional distribution of expected returns. Knif (1989) applies Kalman filter techniques to model time variation of firm-specific market risk in Finnish common stock data. He finds that the betas are time varying. However, most betas of Finnish common stocks follow a stationary autoregressive (AR1) process. De Jong et al. develop the Kalman filter AR1 market model further by incorporating a GARCH model with t-distributed errors. They find that firm-specific betas and the variance of the error term are time varying also in the Dutch stock market. The evidence of time variation of betas is quite straightforward. This paper examines whether time-dependent betas are able to explain the risk-return puzzle found in Malkamäki (1991).

3 Beta Estimation

Four different estimation procedures are applied here to compute the betas. We run Sharpe's well known OLS regression, ie the market model of equation (2), in order to get the rolling beta estimates. The betas are computed over five and three-year time periods prior to each cross-sectional regression. The market model is also estimated by applying the dynamic Kalman filter OLS and ML estimation procedures, which account for time variation in the betas. The first Kalman filter application is the OLS random walk (for the OLS version, see eg Doan, Litterman and Sims (1984), Cuthbertson (1988) and Knif (1989)). In this approach, only ex ante and current information are used in evaluating the initial values for filtering and in updating the parameter vector and its covariance matrix in the Kalman equations. This is in accordance with the real situation, in which investors try to estimate a beta conditional on the information available at the time. The market model is now conveniently written in state space form as

$$r_{it} = X_t' \theta_t + \varepsilon_t, \tag{4}$$

where $X_t' = [1, r_{mt}]$

$\theta_t' = [\alpha_{it}, \beta_{it}]$

ε_t = random error with variance v_t.

The parameter vector θ_t is assumed to vary over time according to the random walk transition equation

$$\theta_t = \theta_{t-1} + u_t, \tag{5}$$

where u_t = random error with covariance matrix M_t.

The random errors ε_t and u_t are independent of each other. The corresponding variance v_t and covariance matrix M_t are estimated. If we also have initial values for θ_{t-1} and its covariance matrix Σ_{t-1}, then the updated estimates for Σ_t and θ_t, given r_{it} and X_t, are obtained from the following Kalman equations:

$$\Sigma p = \Sigma_{t-1} + M_t, \tag{6}$$

where Σp = one-step-ahead prediction based on the prior information for the covariance matrix of the new parameter vector.

$$F = X_t' \Sigma p X_t + v_t, \tag{7}$$

where F = one-period prediction for the variance of the new parameter vector.

$$K_t = \Sigma p X_t F^{-1}, \tag{8}$$

where K_t = Kalman gain, ie the correction weight based on the one-step-ahead prediction for the covariance matrix Σp and variance F.

$$\tilde{r}_{it} = r_{it} - X_t' \theta_{t-1}, \tag{9}$$

where $\tilde{r}_{it}$ = one-step-ahead prediction error.

$$\Sigma_t = \Sigma p - \Sigma p X_t F^{-1} X_t' \Sigma p, \tag{10}$$

where Σ_t = updated estimate of the covariance matrix of the new parameter vector.

$$\theta_t = \theta_{t-1} + K_t \tilde{r}_{it}, \tag{11}$$

where θ_t = updated estimate of the parameter vector.

The initial values of V_t, M_t, θ_{t-1} and Σ_{t-1}, as well as the parameters for tightness in the Kalman filter estimation, were obtained by the method suggested in Doan, Litterman and Sims (1984). The initial values were estimated an ordinary least squares regression of the market model over the period 1972:2–1975:1. The initial estimate of the variance, V_t, was weighted by 0.9 and the relative tightness on time variation for the parameter vector was assumed to be 0.1. The initial covariance matrix was assumed to be that of the OLS estimation, which implies that overall tightness was assumed to be one. The Kalman filter estimation covered the period 1975:2–1989:12. As one observes, only ex ante and current information are used in this Kalman filter technique. This is in accordance with the real situation, in which investors evaluate the time variation in the betas.

The maximum likelihood Kalman filter procedure employed is based on the study of Knif (1989) (see also Goodrich (1989)). Knif found that Finnish common stock betas change according to a stationary first order autoregressive (AR1) process with a constant coefficient. The parameter vector is now assumed to vary according to the AR1 model, that is,

$$\theta_t - \bar{\theta} = F(\theta_{t-1} - \bar{\theta}) + u_t, \tag{12}$$

where $\bar{\theta}$ = vector of parameter means
F = weights for the AR1 and mean parameters
u_t = random error with covariance matrix M_t.

The state space representation for the market model is now

$$\begin{aligned} r_{it} &= \begin{bmatrix} x'_t & x'_t \end{bmatrix} \begin{bmatrix} \bar{\theta}_t \\ \theta_t - \bar{\theta}_t \end{bmatrix} + \varepsilon_t \\ &= B'_t \gamma_t + \varepsilon_t \end{aligned} \tag{13}$$

and for the parameter vector,

$$\gamma_t = \begin{bmatrix} \bar{\theta} \\ \theta_t - \bar{\theta}_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & F \end{bmatrix} \begin{bmatrix} \bar{\theta}_{t-1} \\ \theta_{t-1} - \bar{\theta}_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ u_t \end{bmatrix} \tag{14}$$

$$= A\gamma_{t-1} + e_t,$$

where $\underline{F}$ = $\underline{d}$iag $[\omega_1, \omega_2]$
$\bar{\theta}_1 = \bar{\theta}_{t-1}$ for all t
e_t = random error with covariance matrix N_t.

Only the following updating Kalman equations need to be revised.

$$\Sigma_p = A_t\Sigma_{t-1}A'_t + N_t, \tag{15}$$

where Σ_{t-1} = covariance matrix of γ_{t-1},

$$\tilde{r}_{it} = r_{it} - X_tA_t\gamma_{t-1}, \tag{16}$$

$$\gamma_t = A_t\gamma_{t-1} + K_t\tilde{r}_{it}. \tag{17}$$

This AR1 model collapses into the random walk model if the A matrix is equal to one. However, the estimation technique is now quite different. In the first phase, a maximum likelihood solution for the parameter vector is computed using the above forward recursive Kalman equations, which use only past and current information. Next, information from the whole sample period is employed to find another set of ML estimators by applying the backward recursions of the Kalman smoother (see Goodrich (1989) for details). As a final step, the mean-reverting AR(1) model is used to compute the forecasted beta series. The second-pass regression is run over the forecasted betas in order to reduce the EIV problem, at least to some extent. This will be the case if the changing residual variance of the market model is dependent on the time variation in the betas.

4 The Data

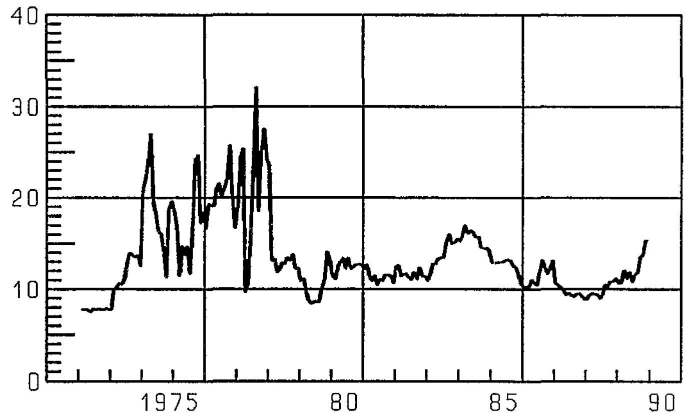
The stock market data employed here consist of end-of-month excess returns for all the common stocks listed on the Helsinki Stock Exchange (HSE) for the whole period covered, 1972:2–1989:12 (Table 1).[3] The lack of short term interest rate data prior to 1972:1 was the limiting factor. The HSE market index used here is value weighted, as described in Berglund – Wahlroos – Grandell (1983). Prices are corrected for cash dividends, splits, stock dividends and new issues. Corrections are based on the principle that all income from a stock is reinvested in the stock with no transaction costs. In this study, returns are measured as changes in logarithmic indices.

Table 1. **Stocks included in the analysis. All restricted ordinary stocks listed throughout the period 1972–1989.**

Stock	Designation
Bank of Åland Ltd K	AB
Effoa-Finland Steamsip Co Ltd K	EFFO
Enso-Gutzeit Ltd A	ENSOA
Fiskars Corporation	FISKK
Huhtamäki Corporation K	HUHTK
Instrumentarium Corporation	INSTA
Kemi Corporation	KEMI
Kesko Corporation	KESK
KANSALLIS-OSAKE-PANKKI	KOP
Kymmene Corporation	KYMI
Lassila & Tikanoja Ltd	LASS
Lohja Corporation A	LOHJA
Nokia Corporation	NOKIK
Otava Publishing Company Ltd	OTAVK
Partek Corporation	PART
Rauma-Repola Corporation	RAUM
Finnish Sugar Co Ltd I	SOKEI
Stockman A	STOCA
Suomen Trikoo Corp. A	TRIK
Union Bank of Finland Ltd A	SYPA
Tamfelt Group K	TAMF
Tampella Ltd	TAMP
Talous-Osakekauppa Co	TAOK
Wärtsilä Co I	WARTI
United Paper Mills Ltd K	YHTYK

[3] Observations for end-of-month days without a transaction in a stock are bid prices for that day.

Figure 1. **Approximated three month interest rate on the Finnish markka, 1972—1989**



It is convenient to run asset pricing tests in the excess returns form. To do this, a short-term interest rate was constructed and employed for the first time in a study of Finnish asset market returns (Figure 1). The Bank of Finland created the market for US dollar forwards in January 1972. Since then, the shortest maturity continously traded each month has been a three month forward contract. To compute the end-of-month time series for a three-month interest rate, end-of-month data were collected on three-month currency forward premia and US dollar interest rates. The three-month interest rate for the Finnish markka was then computed by summing the premia and the US interest rates. For the monthly analysis here, the one-month return implicit in the three-month Euromarket return for the Finnish markka had to be used, ie the interest rate yield curve was assumed to be flat between the one and three month maturities.

As seen in Figure 1, the short-term interest rate was extremely volatile in the 1970s after the first oil crisis. There was a recession in Finland after the crisis, and on several occasions speculation occurred concerning a possible devaluation of the Finnish markka. The Bank of Finland devaluated the markka two times in 1977 and once again in February 1978, which considerably reduced the volatility of short term interest rates. The end of February 1978 is also the first point at which Chow's (1983) test is applied to examine whether the assumption of constant price of risk should be relaxed. Our hypothesis is that major changes in economic conditions are likely to change the pricing of market risk. However, we do not argue that the risk premium is constant over any period even though we must assume it in order to test for the structural breaks in the risk premium.

Table 2. **Summary statistics for excess returns (per cent per month), 1972:2–1989:12 (215 observations)**

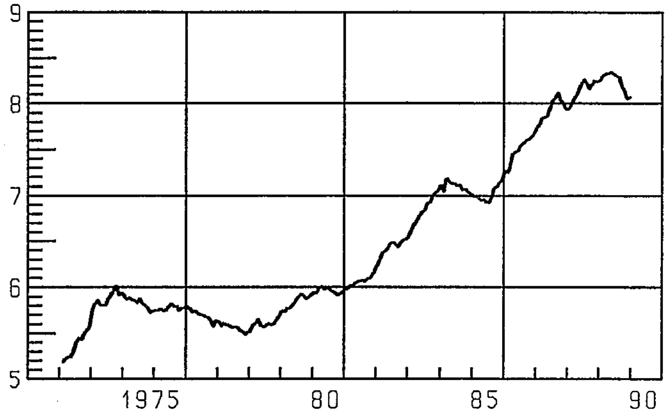
Stock	Mean	St.dev.	Skewness	Kurtosis
AB	0.746	10.683	1.332	16.702
EFFO	0.423	8.204	0.348	1.448
ENSOA	-0.234	7.922	0.645	3.114
FISKK	1.292	7.252	0.296	1.959
HUHTK	0.782	6.610	1.056	2.655
INSTA	1.156	7.118	0.607	3.206
KEMI	-0.360	10.646	-0.694	4.457
KESK	0.658	5.147	1.060	2.481
KOP	0.104	6.644	0.751	4.821
KYMI	-0.002	6.410	0.597	1.908
LASS	1.298	9.240	1.336	7.143
LOHJA	0.930	7.333	0.141	0.295
NOKIK	-0.009	6.910	0.159	0.684
OTAVK	1.234	9.496	1.773	10.212
PART	0.522	6.594	0.242	0.555
RAUM	0.034	6.741	1.042	2.112
SOKEI	0.694	8.094	0.762	2.001
STOCA	0.895	6.645	0.521	2.684
SYPA	0.433	6.083	1.230	4.425
TAMF	0.717	9.835	-0.486	6.468
TAMP	0.051	7.788	1.276	5.215
TAOK	1.866	9.520	-0.031	1.863
TRIK	0.136	11.697	0.255	6.330
WARTI	0.613	7.480	0.764	1.155
YHTYK	0.707	7.459	0.380	0.934
VWI[a]	0.254	4.230	0.265	0.976

[a] Stock market index return.

Summary statistics of monthly excess returns for 25 firms and for the market index are shown in Table 2. Statistics are reported also for three subperiods according our structural analysis: 1972:2–1978:2, 1978:3–1984:3 and 1984:4–1989:12 (see Appendix 1). The statistics show that the mean varied greatly from period to period. The monthly return distribution is, on the average, always somewhat skewed to the right and leptokurtic, as is usual. The first period ends with the third devaluation of the markka descriped above. The second period ends at 1984:3 for two reasons: First, unrestricted shares, ie shares that foreign investors are allowed to buy, have been listed separately on the Helsinki Stock Exchange since January 1984. This may have changed the pricing of Finnish stocks. Another major change was made by the Bank of Finland, which first gave foreign banks access to central bank financing in April 1984. This meant in practice that competition was greatly enhanced in the Finnish money market.

We considered five additional significant changes in the Finnish economy that might have affected the risk return relationship. The first of these occurred at the end of December 1981 when the sharp rise in the stock market index began (Figure 2). Another break point occurs at the end of October 1982. The Finnish markka was devaluated twice in that month. The third change was a partial abolition of the regulation of average rates on bank lending to the public. This change took place at the end of April 1983 and increased banks' activity in the money market. The next potential break point, after March 1984, is at the end of December 1986, when the market for certificates of deposit was introduced in Finland. The last stability test is done because of the stock market crash of October 1987.

Figure 2. **Helsinki Stock Exchange market index, 1972–1989**



5 Empirical Results

5.1 Market Risk Estimates

The well known "rolling" beta estimation method introduced in Fama and MacBeth (1973) is applied here. The betas are estimated from the traditional market model described by equation 2. Since market risk is known to be non-stationary, we compute the OLS betas for three-year periods as well as for the traditional five year period. The OLS and ML Kalman filter techniques, which allow for conditional time variation in the betas, are also applied.

Table 3. **Summary statistics for estimated beta series (155 observations per series)**

Stock	5 year beta Mean	St. dev.	3 year beta Mean	St. dev.	KF RW Mean	St. dev.	KF AR1 Mean	St. dev.
AB	0.655	0.146	0.627	0.143	1.014	0.127	0.748	0.000
EFFO	0.614	0.175	0.553	0.250	1.254	0.248	0.888	0.005
ENSOA	0.758	0.258	0.767	0.406	1.377	0.186	1.010	0.005
FISKK	0.657	0.194	0.630	0.274	0.759	0.055	0.795	0.005
HUHTK	0.948	0.436	0.918	0.495	0.577	0.195	0.495	0.018
INSTA	0.872	0.106	0.910	0.164	0.416	0.205	0.868	0.002
KEMI	1.171	0.598	1.134	0.821	0.875	0.074	0.913	0.037
KESK	0.556	0.139	0.576	0.202	0.424	0.174	0.670	0.024
KOP	1.136	0.223	1.083	0.325	1.193	0.074	1.069	0.001
KYMI	1.008	0.137	1.088	0.241	0.284	0.344	0.935	0.009
LASS	0.754	0.194	0.751	0.279	0.351	0.132	0.711	0.021
LOHJA	1.231	0.131	1.210	0.241	0.979	0.052	1.202	0.010
NOKIK	1.112	0.224	1.157	0.293	0.851	0.128	1.074	0.006
OTAVK	0.543	0.392	0.479	0.297	1.421	0.010	0.684	0.102
PART	1.020	0.194	0.989	0.309	0.838	0.096	1.086	0.002
RAUM	1.103	0.208	1.071	0.304	1.377	0.201	0.993	0.011
SOKEI	0.932	0.145	0.888	0.225	1.173	0.152	0.928	0.010
STOCA	0.879	0.194	0.921	0.346	0.572	0.088	0.870	0.003
SYPA	0.940	0.091	0.912	0.135	1.398	0.216	1.010	0.018
TAMF	0.967	0.520	0.971	0.720	0.781	0.063	0.908	0.101
TAMP	0.935	0.462	0.935	0.553	0.710	0.040	0.935	0.063
TAOK	0.471	0.326	0.607	0.599	-0.124	0.397	0.474	0.002
TRIK	1.005	0.212	0.901	0.556	1.184	0.178	1.042	0.388
WARTI	1.307	0.329	1.300	0.460	0.572	0.131	1.001	0.000
YHTYK	1.278	0.186	1.247	0.304	0.963	0.108	1.153	0.011
Mean	0.914	0.249	0.905	0.358	0.849	0.147	0.899	0.034
St.dev.	0.237	0.135	0.231	0.178	0.402	0.092	0.186	0.079

All the beta estimate are revised monthly. The first five-year period for beta estimation is 1972:2—1977:1 and the corresponding three-year period is 1974:2—1977:1. We then proceed by dropping and adding one observation and repeating the computation. Table 3 presents summary statistics for all the beta series. The time series for three-year betas are more volatile than those for five-year betas. Surprisingly, both of the Kalman filtered beta series are a lot less volatile (especially the ML betas) than the statically estimated betas. Correlation between the monthly beta series is highest for the static betas and lowest between the static betas and the OLS (RW) Kalman filter betas (Table 4).

Table 4. **Correlation matrix for estimated beta series (3875 observations)**

Variable	B5Y	B3Y	BKFRW	BKFAR1
B5Y	1.000			
B3Y	0.756	1.000		
BKFRW	0.023	-0.050	1.000	
BKFAR1	0.430	0.311	0.417	1.000

Variables in the cross-moment matrix:

B5Y	=	five-year beta estimation period.
B3Y	=	three-year beta estimation period.
BKFRW	=	Kalman filter (RW) beta.
BKFAR1	=	Kalman filter (AR1) beta, forecasted betas given by $(\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta})$.

A closer look at the estimated beta series was found to be very interesting. For this purpose, we included three beta series for one firm in the same figure along with the mean value for the AR1 beta estimates (see Appendix 2). The figures show clearly that the statically estimated betas vary greatly in magnitude. These beta estimates typically vary between 0.3 and 2.0, five-year betas having a slightly smaller range of variation. It is somewhat perplexing that an ongoing firm's beta should vary so much. Furthermore, shocks to the beta estimates seem to persist over time. This is evident in the beta estimates for the forest industry companies (Kemi, Kymi, Tamf, Tamp and Yhtyk). The Finnish markka was devaluated in April 1977. This shock caused a dramatic drop in the betas after three or five years, depending on the length of the estimation period.

The series for both the RW (OLS) and AR1 (ML) Kalman filter betas are more stable by nature, as was, of course, expected for the AR1 betas, which are mean reverting. The AR1 maximum likelihood estimation results are available in Appendix 3. The ML beta estimates are even more mean reverting than those of Knif (1989:154). The beta values for a firm typically vary within a range of 0.2. However, the Random Walk OLS beta series do display dramatic jumps in the beta values in the late 1980s, particularly in 1989.[4] This indicates that there has been a sudden change in investors' expectations regarding the future earnings of certain companies. There are several reasonable explanations for this phenomenom: first, the collapse of trade with the Soviet Union, which had a drastic impact on certain companies only. Second, the EEC's proposal to start negotiations with the EFTA countries in order to create a large European Economic Area. Third, the revaluation of the Finnish markka in March 1989. Fourth, the Bank of Finland raised the cash reserve requirement several times, which reduced banks' earnings.

5.2 Pricing of Risk

The Sharpe–Lintner version of the CAPM is usually tested by iterating the CSR described by equation 4. Instead of iterating monthly, we performed just one regression using the pooled data for the whole period. The model was estimated with and without the constant. Strictly speaking, we assume that the CAPM holds in the restricted version of the estimation and obtain an estimate of the implied risk premium. On the other hand, the unrestricted regression is, strictly speaking, a test of the mean-variance efficiency of the market index or a test of the risk premium implied by the one-factor capital asset pricing model, where the prespecified factor is the market index.

Table 5 gives the results of these regressions. The estimated risk premium of the restricted regressions is positive and highly significant. This is a direct result of the positive mean premium for stocks, which

[4] Note that the scale in the figures is extremely large for the Kalman filter betas. This creates the impression that the Kalman filter series hardly varies at all before the mid-1980s.

makes the slope coefficient positive. The regressions on the Kalman filter AR1 betas have the highest t-values, implying that the ML beta forecasts best capture the variation in excess returns.

Table 5. **Monthly average risk premiums associated with the stock market index (per cent per month), 1977:2–1989:12 (3875 observations for 25 ordinary stocks)**

Model	a^{cd}	λ^{cd}	σ^{ce}
Restricted[a]			
5 year beta	-	0.696 (5.63)	7.975
3 year beta	-	0.684 (5.55)	7.975
Kalman filter RW Ex ante	-	0.768 (5.52)	7.971
Kalman filter AR1 ML	-	0.949 (6.79)	7.957
Unrestricted[b]			
5 year beta	1.791 (5.00)	-0.994 (-2.85)	7.949
3 year beta	1.295 (4.38)	-0.456 (-1.60)	7.954
Kalman filter RW Ex Ante	1.128 (3.82)	-0.290 (-0.91)	7.956
Kalman filter AR1 ML	0.615 (0.85)	0.297 (0.37)	7.957

[a] Model estimated: $r_{it} = \lambda\beta_{it-1} + e_{it}$.

[b] Model estimated: $r_{it} = a + \lambda\beta_{it-1} + e_{it}$.

[c] All coefficients are multiplied by 100.

[d] Heteroscedasticity-consistent t-values in parenthesis, White (1980).

[e] Standard error of estimate.

The three first unrestricted regressions imply that the CAPM is not valid or that the index is not mean-variance efficient, because the constant has significant t-values. Surprisingly, the risk premium is negative and highly significant for the regression on five-year beta estimates. This supports the results of Malkamäki (1991). These betas have been commonly employed in CSRs for about fifteen years to test the validity of the CAPM. However, the three-year and OLS-Kalman-filter beta regressions do not give significant estimates for the negative risk premium.

The fourth regression on the forecasted ML betas gave quite different results. The constant is not significant, ie we do not reject the mean-variance efficiency of the market index. Furthermore, the coefficient of the price of risk is now positive, as in the CAPM, but not statistically significant.

In the above tests, it was assumed that the risk-return relationship does not change over time. However, it is well known that this is not the case. Our pooled data enables us to test whether the price of risk is affected by certain prespecified shocks to the Finnish economy as described in section 4. For this purpose, we carry out the well-known Chow tests for stability of the risk premium (Chow 1983). The model is now always estimated with a constant. Each test for a break covers two years of data before and after the break. This implies that there are 1196 degrees of freedom in the F-value analysis. The outcome of these tests is presented in Table 6. The evidence shows that the risk premium is not constant over time. There are at least five clear breaks in the risk-return relationship in the entire period. The outcome was almost exactly the same regardless of the beta series employed.

Table 6. **Chow tests for structural breaks in the risk return relationship**

Suggested break at the end of		F-value	P-value
February	1978	33.05	0.00
December	1981	15.96	0.00
October	1982	0.02	0.98
April	1983	13.40	0.00
March	1984	11.10	0.00
December	1986	0.36	0.70
September	1987	32.50	0.00

Model estimated: $r_{it} = a + \lambda\beta_{it-1} + e_{it}$.

The model is estimated for a two-year period before and after a tested break point and for the combined four-year period. The F-tests have 1196 degrees of freedom.

Next, the same regression analyses were performed for subperiods (see Table 7). The periods are based on the empirical finding in Malkamäki (1991) that the risk premium varied around zero between 1978:3 and 1984:3 and was clearly negative after 1984:3. The first period, which is very short, was included because the break at the end, 1978:2, is extremely significant. All regressions gave the same result for the middle period: the risk premium is not significant. However, the regression on ML betas has a positive sign for the price of risk. The period after 1984:3 is interesting. The price of risk is negative and clearly significant in the regressions computed over the static estimates for betas. The risk premium has a negative sign in the Kalman filter beta regressions but it is not significant. The last time period studied excludes the periods before 1978:3 and after 1988:12. The latter period is excluded because of the drastic slowdown of the Finnish economy that started in early 1989. The risk-return relationship implied by the CAPM is strongest for this period. The regression on the ML beta series does not reject the mean-variance efficency of the market index and has a positive t-value of 1.25 for the risk premium coefficient. Although the premium is not unconditionally priced, its sign and size gives reason to believe that the risk premium may be conditionally priced, as turned out to be the case eg in Ferson and Harvey (1991). Malkamäki (1992b), in fact, finds strong evidence that time-varying market risk (AR1) is conditionally priced in Finland also.

Table 7. **Monthly average risk premiums associated with the stock market index[a] (per cent per month) for different subperiods**

Period	a^{b}	λ^{b}	σ^{bc}
77:2–78:2			
5 year beta	-2.416 (-2.16)	0.614 (0.52)	5.904
3 year beta	-2.244 (-2.95)	0.401 (0.59)	5.912
Kalman filter RW	-1.765 (-1.89)	-0.074 (-0.07)	5.916
Kalman filter AR1	0.475 (0.37)	-2.550 (-1.77)	5.895
78:3–84:3			
5 year beta	1.861 (4.45)	-0.54 (-1.34)	7.093
3 year beta	1.357 (3.78)	-0.020 (-0.06)	7.097
Kalman filter RW	1.910 (3.79)	-0.663 (-1.21)	7.094
Kalman filter AR1	0.258 (0.25)	1.205 (1.06)	7.092
84:4–89:12			
5 year beta	2.772 (4.12)	-2.185 (-3.16)	8.967
3 year beta	2.232 (3.71)	-1.559 (-2.52)	8.977
Kalman filter RW	1.034 (2.71)	-0.149 (-0.37)	8.992
Kalman filter AR1	0.962 (0.87)	-0.056 (-0.05)	8.993
78:3–88:12			
5 year beta	2.428 (6.44)	-1.053 (-2.91)	7.986
3 year beta	1.829 (5.70)	-0.399 (-1.27)	7.998
Kalman filter RW	1.446 (4.06)	0.024 (0.06)	7.997
Kalman filter AR1	0.472 (0.58)	1.11 (1.25)	7.993

[a] Model estimated: $r_{it} = a + \lambda\beta_{it-1} + e_{it}$. Heteroscedasticity consistent t-values in parenthesis, White (1980).

[b] All the coefficients are multiplied by 100.

[c] Standard error of estimate.

6 Conclusions

This paper is an empirical analysis of the Sharpe–Lintner version of the CAPM for the thin Finnish stock market. Two unconditional and conditional sets of the market risk parameters of firms were computed. The unconditional beta of a firm was computed by the traditional OLS rolling beta technique, assuming that the beta is constant over a period of five/three years. As an alternative approach, we employed dynamic OLS and ML Kalman filter techniques, which account for time variation in market risk. It was found that the mean of returns, the systematic risk and the pricing of systematic risk vary over time. The puzzling prior result that the regression on the static OLS betas gives a negative and statistically significant coefficient for the risk premium was also found. It is shown that this phenomenom is strongest after April 1984. The ML Kalman filter betas too are unable to explain the cross section of returns. More research is needed to explain this phenomenom. However, the ML Kalman filter beta estimates here clearly capture best the excess returns on Finnish shares. In the restricted regressions, the regression on these betas had the largest risk premium, as well as the highest t-value. In the unrestricted regressions, the regression on the ML betas was the only one with a positive coefficient for the risk premium, and it was also relatively highly significant when the periods that were extraordinary for the Finnish economy were excluded from the analysis. Furthermore, this regression does not reject the mean-variance efficiency of the market index, as the others do.

The existence of a positive risk-return relationship, suggested in this paper in connection with time-varying betas, was found in a subsequent study to be robust and statistically significant in four alternative Finnish asset samples by Malkamäki (1992a). Furthermore, Malkamäki (1992b) employs the methodology of Ferson and Harvey (1991) and finds that the risk premium estimated using the same AR1 betas as here is conditionally time varying, in accord with US results.

The results of this paper strongly suggest that more effort should be expended in search of an adequate beta estimation method. In the case of small markets such as in Finland, it is crucial to allow time variation in firm-specific betas in a dynamic way that dampens the impact of market shocks on the beta estimation. This evidence, together with the findings of Ball and Kothari (1989), Shanken and Weinstein (1990) and Fama and French (1992), suggests that problems in beta estimation may play an important role also in tests of capital asset pricing models with US data.

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Appendix 1.1

Summary statistics for excess returns (per cent per month), 1972:2—1978:2 (73 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	-0.234	11.341	-0.891	5.441
EFFO	-0.758	6.695	-0.243	1.797
ENSOA	-1.732	8.098	-0.027	3.707
FISKK	0.199	6.573	-0.103	0.044
HUHTK	-0.157	5.375	2.353	8.174
INSTA	0.623	7.574	0.343	0.517
KEMI	-1.191	8.916	0.162	1.704
KESK	-0.434	5.058	1.772	4.584
KOP	-0.857	6.867	0.063	0.404
KYMI	-0.926	6.521	0.231	2.054
LASS	-0.069	8.549	2.660	13.570
LOHJA	-0.215	7.519	0.648	0.988
NOKIK	-0.738	6.290	0.180	0.742
OTAVK	0.967	11.330	2.331	13.188
PART	-0.829	6.709	-0.007	0.096
RAUM	-0.881	7.280	1.131	1.873
SOKEI	-0.375	7.859	0.849	1.956
STOCA	-1.082	5.825	0.650	1.750
SYPA	-0.077	6.822	1.143	2.630
TAMF	-0.913	12.530	-0.756	4.601
TAMP	-2.466	6.961	0.071	0.501
TAOK	2.786	8.880	0.760	2.176
TRIK	-0.739	8.292	1.057	3.638
WARTI	-1.414	7.328	0.700	1.242
YHTYK	-0.483	7.854	0.421	0.466
VWI[a]	-0.721	4.406	0.942	2.167

[a] Stock market index return.

Appendix 1.2

Summary statistics for excess returns (per cent per month), 1978:3–1984:3 (73 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	1.263	7.092	0.067	2.436
EFFOA	0.655	6.433	-0.338	2.210
ENSOA	0.307	5.710	0.983	2.273
FISKK	0.931	5.492	0.108	1.176
HUHTK	2.584	7.120	0.992	3.180
INSTA	2.318	5.577	1.938	5.857
KEMI	-1.538	12.402	-1.469	5.919
KESK	0.748	3.368	-0.118	0.329
KOP	1.538	6.459	2.683	13.159
KYMI	0.178	5.365	0.512	2.742
LASS	1.993	6.848	0.029	1.367
LOHJA	2.052	6.423	-0.183	0.790
NOKIK	0.645	6.016	0.112	2.406
OTAVK	1.459	5.017	-0.090	1.482
PART	1.311	4.980	1.299	3.060
RAUM	0.680	6.502	1.264	2.163
SOKEI	2.189	7.682	0.820	1.867
STOCA	2.333	6.608	0.502	6.768
SYPA	1.005	5.551	2.423	13.827
TAMF	1.853	6.335	1.338	3.601
TAMP	0.659	6.517	0.695	3.246
TAOK	2.388	9.657	-0.332	3.069
TRIK	1.421	12.346	-1.345	10.440
WARTI	2.813	7.230	0.681	0.538
YHTYK	1.672	7.087	0.512	1.865
VWI[a]	1.172	3.278	0.000	2.024

[a] Stock market index return.

Appendix 1.3

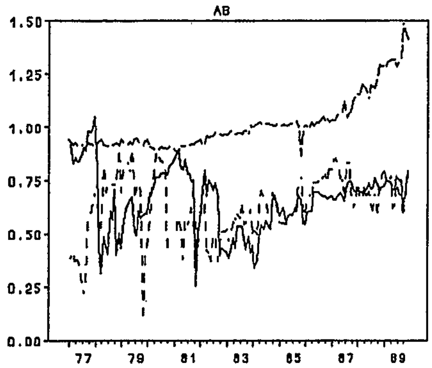
Summary statistics for excess returns (per cent per month), 1984:4–1989:12 (69 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	1.236	12.885	3.124	21.096
EFFO	1.427	10.860	0.442	0.010
ENSOA	0.776	9.476	0.982	4.491
FISKK	2.830	9.166	0.212	1.523
HUHTK	-0.131	6.926	0.400	-0.257
INSTA	0.490	7.974	0.590	4.397
KEMI	1.766	10.143	0.274	0.629
KESK	1.718	6.468	0.654	0.815
KOP	-0.397	6.431	-0.251	0.953
KYMI	0.784	7.228	0.896	1.039
LASS	2.008	11.774	0.937	4.501
LOHJA	0.954	7.859	-0.021	-0.151
NOKIK	-0.211	8.309	0.198	-0.181
OTAVK	1.280	11.003	1.028	1.963
PART	1.118	7.740	0.176	-0.319
RAUM	0.321	6.380	0.876	3.277
SOKEI	0.245	8.629	0.770	2.655
STOCA	1.466	7.073	0.373	0.642
SYPA	0.367	5.822	0.457	-0.182
TAMF	1.241	9.549	0.316	4.861
TAMP	2.073	9.125	1.986	5.879
TAOK	0.340	9.973	-0.261	0.593
TRIK	-0.298	13.915	1.176	3.198
WARTI	0.429	7.363	1.175	2.586
YHTYK	0.944	7.350	0.342	1.260
VWI[a]	0.314	4.737	0.042	0.241

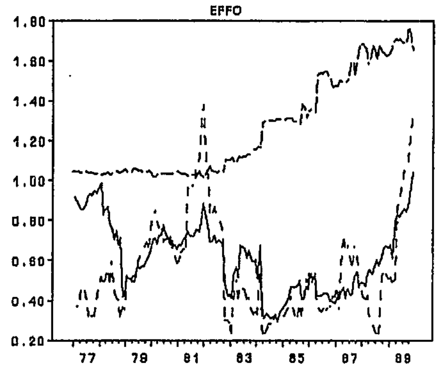
[a] Stock market index return.

Appendix 2

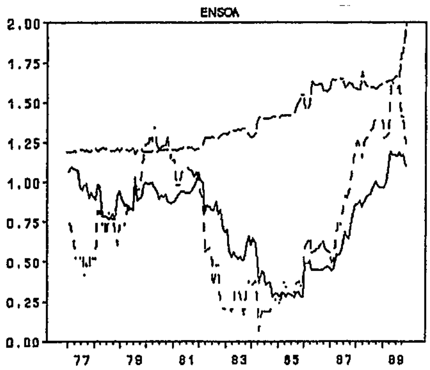
Monthly Beta Series for 25 Stocks



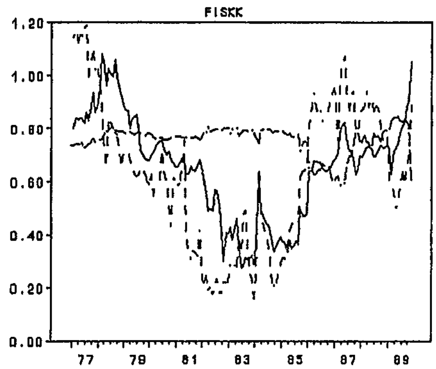
$\overline{\beta}$ = .748



$\overline{\beta}$ = .889

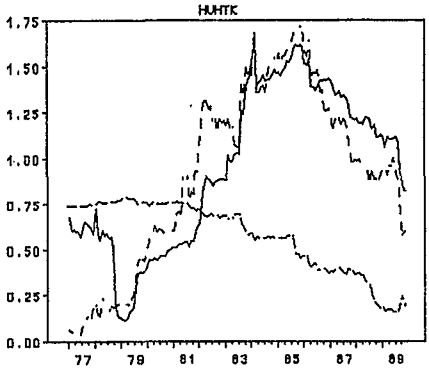


$\overline{\beta}$ = 1.011

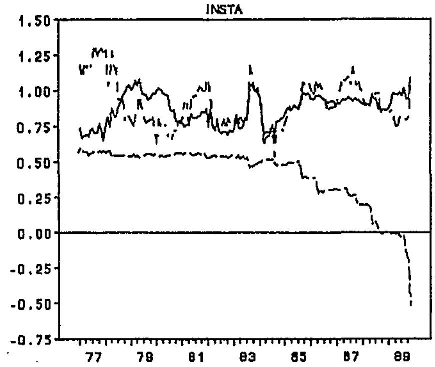


$\overline{\beta}$ = .795

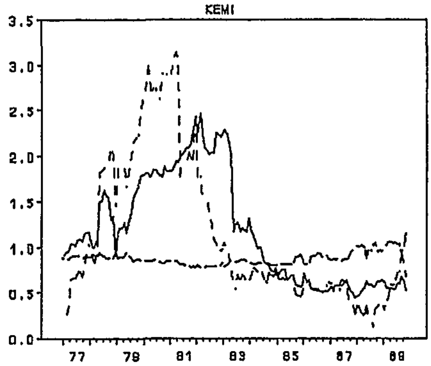
———	5 year estimation period
-----	3 year estimation period
–-–-	Kalman filter (random walk) estimates
$\overline{\beta}$ =	mean beta in AR1 parameter equation



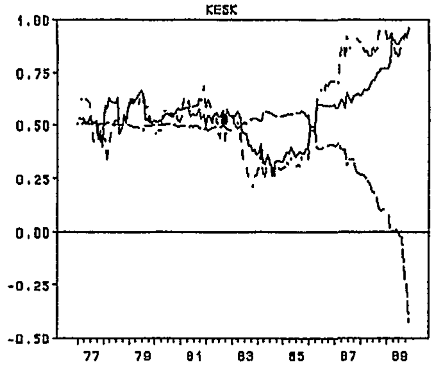
$\bar{\beta}$ = .968



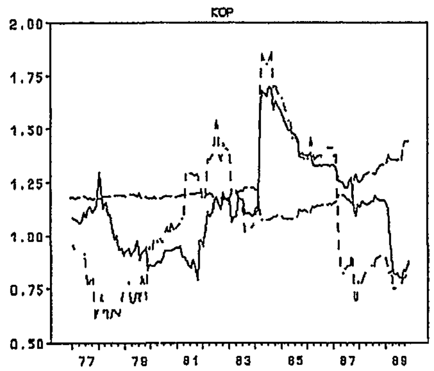
$\bar{\beta}$ = .868



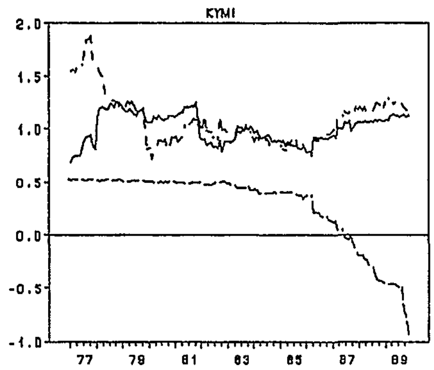
$\bar{\beta}$ = .914



$\bar{\beta}$ = .671

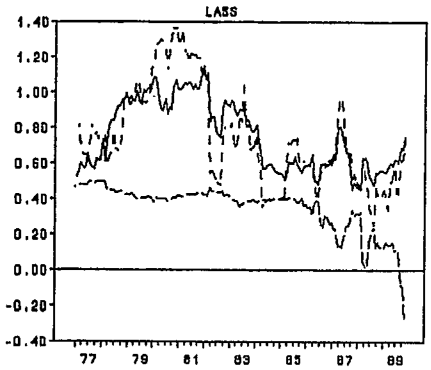


$\bar{\beta}$ = 1.067

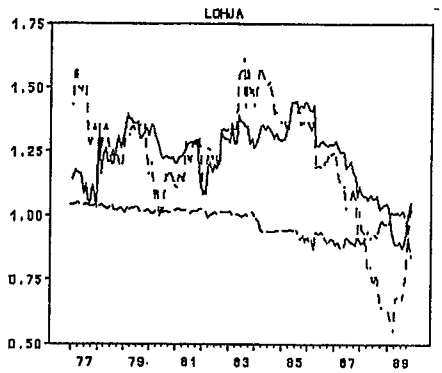


$\bar{\beta}$ = .934

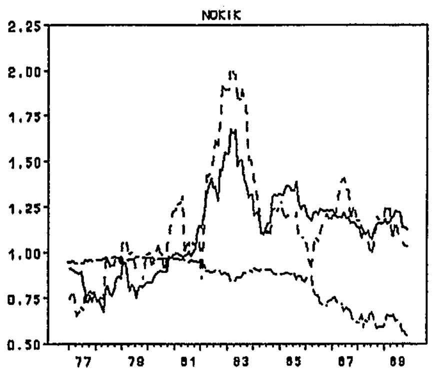
———	5 year estimation period
-----	3 year estimation period
—-—	Kalman filter (random walk) estimates
$\bar{\beta}$ =	mean beta in AR1 parameter equation



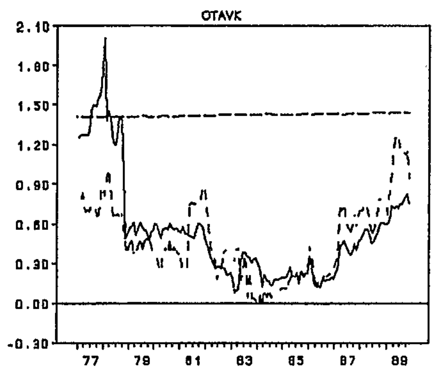
$\bar{\beta}$ = .710



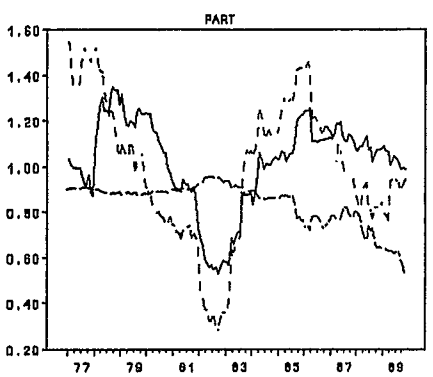
$\bar{\beta}$ = 1.202



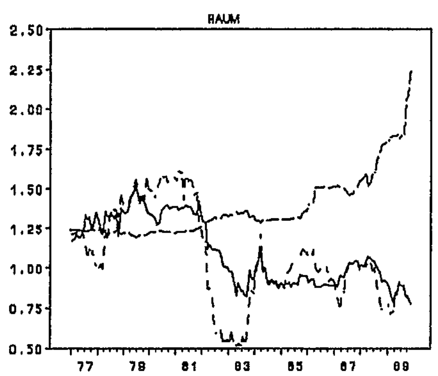
$\bar{\beta}$ = 1.075



$\bar{\beta}$ = .689

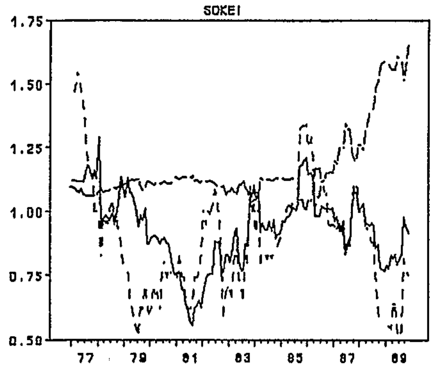


$\bar{\beta}$ = 1.086

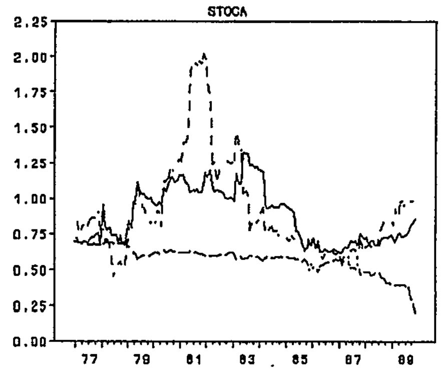


$\bar{\beta}$ = .993

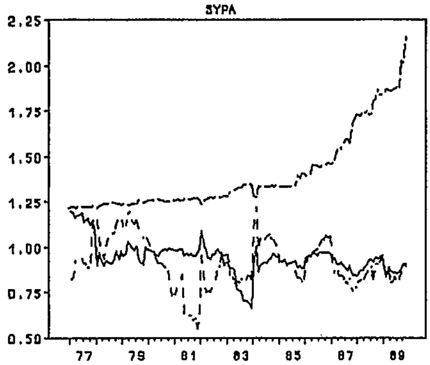
——	5 year estimation period
-----	3 year estimation period
-.---	Kalman filter (random walk) estimates
$\bar{\beta}$ =	mean beta in AR1 parameter equation



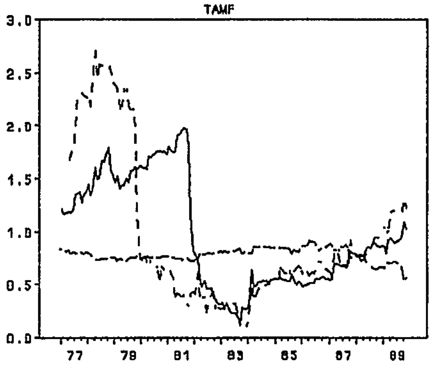
$\bar{\beta}$ = .993



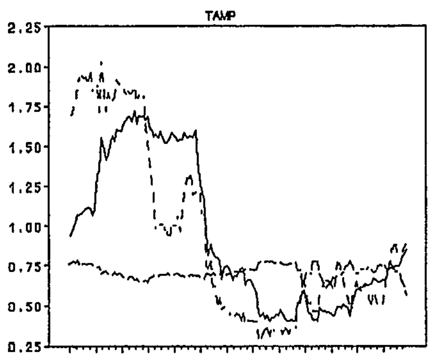
$\bar{\beta}$ = .870



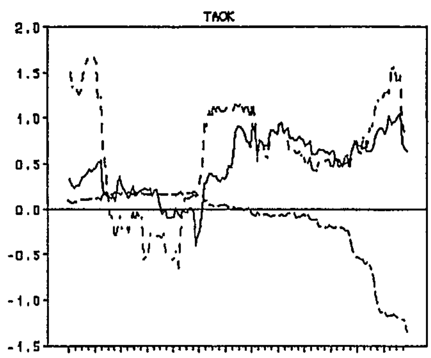
$\bar{\beta}$ = 1.011



$\bar{\beta}$ = .909

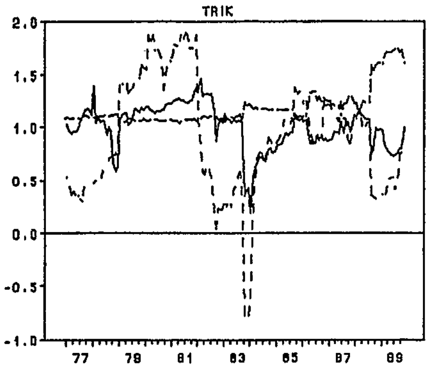


$\bar{\beta}$ = .948

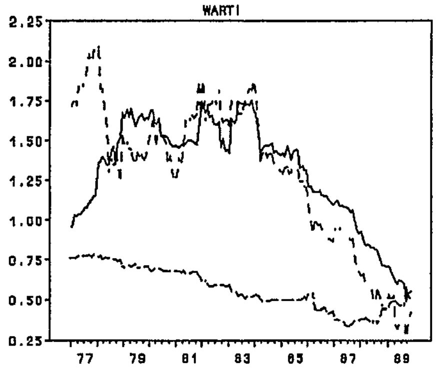


$\bar{\beta}$ = .474

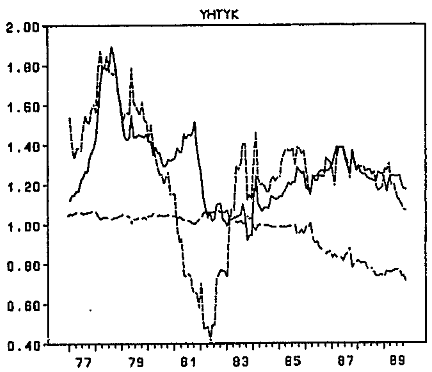
——	5 year estimation period
-----	3 year estimation period
—---	Kalman filter (random walk) estimates
$\bar{\beta}$ =	mean beta in AR1 parameter equation



$\bar{\beta}$ = 1.039



$\bar{\beta}$ = 1.001



$\bar{\beta}$ = 1.153

——— 5 year estimation period
----- 3 year estimation period
-.-.- Kalman filter (random walk) estimates
$\bar{\beta}$ = mean beta in AR1 parameter equation

Appendix 3

Maximum likelihood estimation results for the Kalman filter AR1 specification (estimation period 1972:2–1989:12)

STOCK	ω	$\bar{\beta}$	q	σ^2	α	R^2	P(F)
AB	-.0902	.7483*	.0016	.0104	.0049	.0954	.9995
EFFO	-.0227	.8885*	.4523	.0046	.0035	.1844	1.0
ENSOA	.0172	1.0106*	.6726	.0035	-.0052	.2575	1.0
FISKK	.0322	.7953*	.2926	.0035	.0126*	.2258	1.0
HUHTK	.4469*	.9676*	.4967	.0019	.0020	.2981	1.0
INSTA	-.0346	.8680*	.0989	.0036	.0097*	.2580	1.0
KEMI	-.0797	.9139*	1.1405	.0079	-.0057	.1317	1.0
KESK	-.2138	.6707*	.1303	.0016	.0055*	.2955	1.0
KOP	.0027	1.0664*	.3458	.0016	-.0031	.3859	1.0
KYMI	.0694	.9342*	.2063	.0022	-.0013	.3590	1.0
LASS	.2163	.7103*	.1765	.0074	.0120*	.0938	.9994
LOHJA	-.0785	1.2017*	.0221	.0026	.0073*	.4318	1.0
NOKIK	-.0526	1.0748*	.1426	.0025	-.0036	.4354	1.0
OTAVK	.1064	.6889	2.8235	.0035	.0116*	.1357	1.0
PART	-.0104	1.0863*	.2200	.0021	.0031	.4179	1.0
RAUM	-.0472	.9927*	.3495	.0022	-.0038	.3930	1.0
SOKEI	.0329	.9927*	.5949	.0039	.0050	.2550	1.0
STOCA	-.0626	.8699	.0788	.0030	.0072	.2844	1.0
SYPA	.0431	1.0106*	.5339	.0011	.0011	.5006	1.0
TAMF	.3272	.9094*	.9270	.0062	.0079	.1870	1.0
TAMP	.7896*	.9484	.0262	.0045	.0006	.2410	1.0
TAOK	.0383	.4740	.1097	.0085	.0176*	.0419	.8982
TRIK	-.2379	1.0390*	4.5252	.0050	.00005	.1222	1.0
WARTI	.2530	1.001*	.0009	.0038	.0044	.3001	1.0
YHTYK	.0587	1.1527*	.3089	.0026	.0052	.4426	1.0

Estimated model: $r_{it} = \alpha_t + \beta_t r_{mt} + \varepsilon_t$,

where α_t = constant $\qquad \sigma^2 = \mathrm{var}(\varepsilon_t)$

$\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta} + v_t \qquad q = \mathrm{var}(v_t)$

ESSAY 2

Markku Malkamäki

Conditional Betas and the Price of Risk in a Thin Asset Market: A Sensitivity Analysis

Abstract

This paper examines the sensitivity of tests of the Sharpe–Lintner CAPM to different beta estimation methods and asset-return samples in a thin European asset market, ie the Finnish asset market. A time-varying-parameter model is introduced as an alternative to the static market model. We also employ pooled data in the analysis in addition to second-pass Fama–MacBeth regressions. The tests are, furthermore, carried out with four asset-specific samples. It is shown that in every case, the analysis on OLS betas leads to rejection of the mean-variance efficiency of the market index and the price of market risk is statistically significant, but negative. The corresponding tests on the time-varying betas indicate just the opposite. We are not able to reject the mean-variance efficiency of the market index in any of the samples. The price of market risk turns out positive and statistically significant, especially for the stock-return data set that most closely resembles the normal distribution.

I am grateful to Tom Berglund, G. Geoffrey Booth, David Bradfield, Pierre Hillion, Johan Knif, Erkki Koskela, Heikki Koskenkylä, Avri Ravid, Juha Tarkka, Jouko Vilmunen, Matti Virén and William Ziemba for helpful comments. This research has benefited from workshops at the Bank of Finland, the Finnish Economic Association and the University of Vaasa. A previous version of this paper appeared in Bank of Finland Discussion Papers.

1 Introduction

Recently, a number of empirical papers have focused on the time variation of conditional expected returns, variances and covariances in tests of the Sharpe–Lintner CAPM. Almost all conditional tests of the CAPM employ US data. Some empirical papers support the single-period CAPM, whereas others reject it. Most of the tests are conducted using the generalized method of moments (GMM)[1] or various versions of autoregressive conditional heteroscedasticity (ARCH)[2] models. However, these methods rely on strong assumptions. Nelson (1991) discusses the drawbacks of ARCH models. GMM involves expected parameters conditioned on the true market information set, which is unobservable. We, instead, employ a subset of observable instrumental variables. This may be a relevant problem at least in thin capital markets where time series of, for example, market-based interest rates are not available. Further, GMM tests assume that a linear function relates conditional expectations to the information set.

This paper examines the Sharpe–Lintner CAPM using a time-varying-parameter model in place of the traditional static market model. We demonstrate the crucial role of time-varying market risk in the thin Finnish asset market. Traditional cross-sectional regressions (CSR) on the static OLS betas reject for all asset samples the mean-variance efficiency of the stock market index and imply that the price of market risk is significantly negative. Abel (1988) and Backus and Gregory (1988) provide two hypotheses under which the negative risk premium could be explained. Abel argues that the risk premium is not necessarily positive in a general equilibrium when the investor's preference is not logarithmic. Backus and Gregory show that in their theoretical world the relationship between conditional mean and variance is nonlinear. This implies that even if one succeeds in modelling the conditional variance correctly, there need be no predictable relation between it and the risk premium.

However, empirical evidence found in this study suggests that dynamic beta estimation procedures have substantial impacts on the

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[1] See eg Harvey (1989).

[2] See eg Bollerslev, Engle and Wooldridge (1988), Bodurtha and Mark (1991) and Ng (1991).

risk premium in favor of a positive, linear risk-return relationship. In this sense, the results from the CSRs on the time-varying betas are contrary to the conclusions cited above. We are not able to reject the mean-variance efficiency of the market index in any of the four asset samples employed. The market risk is priced in the manner of the CAPM, most evidently in the stock return data set that most closely resembles the normal distribution. The risk-return relationship is notably weaker in a data set of the most-traded stocks. This finding does not support the prior understanding that the errors-in-variables problem due to nonsynchronous trading produces highly spurious results in tests of the CAPM.

Prior evidence from unconditional tests of the CAPM has generally led to rejection of the positive risk return relationship for all data sets. The unconditional market risk is usually rewarded in US studies[3] but is not rewarded in studies using data from other asset markets, as, for example, in studies of the Finnish stock market (see eg Korhonen (1977) and Berglund (1986)).

The poor performance of the CAPM on thin markets may be largely a result of serious errors-in-variables problems. Berglund, Liljeblom and Löflund (1989) and Martikainen (1991) show that OLS-betas for thinly traded stocks tend to be downward biased and are little improved by the use of several correction procedures that account for thin trading. The same authors and Knif (1989) provide evidence that Finnish firms' betas are not stable. Knif applies Kalman filter techniques in order to model time variation in the market risk. He shows that Finnish common stock betas usually follow a stationary autoregressive process (AR1).

Malkamäki (1992a) examines the Sharpe–Lintner CAPM using time-varying-parameter models as alternatives to the static market model. The monthly data employed covers all Finnish common stocks listed throughout the period 1972–1989. He computes two alternative rolling beta estimate series, assuming that the betas are constant over a period of three or five years. As an alternative approach, he applies dynamic OLS and maximum likelihood (ML) Kalman filter techniques which account for the time variation in the market risks. He computes a pooled regression over the return and estimated beta series instead of Fama–MacBeth (1973) second-pass regressions in order to increase the

[3] However, for example Fama and French (1992) found that the unconditional beta is not unconditionally priced.

power of the tests and avoid at least to some extent the problems involved in the univariate tests. Malkamäki finds that every analysis on the OLS betas (static or dynamic) rejects the mean-variance efficiency of the market index and gives a negative price for the market risk. However, regression over the forecasted, mean-reverting ML betas does not reject the mean-variance efficiency of the market index and the price of average market risk clearly takes a positive sign but is not statistically significant at conventional levels. He tests the CAPM also in the restricted form and finds that the regression over the ML betas gives the highest risk premium and the corresponding test statistic for significance. Furthermore, the hypothesis of constant risk premium is rejected.

Berglund and Knif (1992) perform Fama–MacBeth tests using Finnish common stock data from 1970–1988. They analyse the changes in test statistics for the risk premium of the CAPM in quarterly returns when time-varying betas are used instead of constant betas. They find that the risk premium is negative but not significant in the constant beta regression and positive but not significant in the time-varying beta regression. Berglund and Knif also run cross-sectional regressions of monthly, bi-monthly and quarterly stock returns over the predicted time-varying beta series and find in each case a positive average risk premium that is not statistically significant. However, a weighted least squares correction that gives less weight to the betas that have high prediction variance improves their results considerably, and the monthly risk premium turns out to be statistically significant. Further, they find a non-linear relationship between ex post risk premiums and returns.

The purpose of this paper is to test the robustness of the findings in Malkamäki (1992a) and Berglund and Knif (1992) and to provide further analysis of the risk-return relationship implied by the Sharpe–Lintner CAPM and mean-variance efficiency of the stock market index. We perform a modified version of the Fama–MacBeth univariate tests and the pooled regression introduced in Malkamäki (1992a) in four asset samples. We estimate static betas with five-year OLS regressions and time-varying estimates for the betas using the ML Kalman filter procedure as in Berglund and Knif (1992) and Malkamäki (1992a). All tests for the risk premium are also carried out on the subperiods that were employed in Malkamäki (1992a). The data covers all listed Finnish common stock excess returns and an index for corporate bond returns.

The remainder of this paper is organized as follows. Section two discusses the methodological problems in estimating the betas and risk premiums in thin asset markets. The next section describes the data. The empirical results are presented in section four, and section five concludes with the key findings of the paper.

2 The Model and Methodological Considerations

The CAPM states that expected returns on an asset are linearly related to the systematic risk, which is measured by the asset's beta. The Sharpe–Lintner version of the model in the excess-return form is:

$$E(r_i) = \beta_i E(r_m), \tag{1}$$

where $E(r_i)$ = Expected excess return for security i

$$\beta_i = \frac{\operatorname{cov}(r_i, r_m)}{\operatorname{var}(r_m)}$$

$E(r_m)$ = Expected excess return for the market.

Actually, the CAPM is not testable, as stated in Roll (1977), because the true market portfolio is not observable. Therefore, the CAPM, as applied in empirical research, is just a statement about the mean-variance efficiency of a given market portfolio. Thus, we test whether the observed stock market portfolio is mean-variance efficient. The test is then a joint test of whether the given market portfolio is mean-variance efficient and whether the CAPM is the correct model.

Unfortunately, we don't observe the true beta coefficient, β_i, of the CAPM. The beta is usually estimated, under the assumption of constant market risk, by computing an OLS regression over Sharpe's well-known time series (TSR) market model

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \tag{2}$$

where r_{it} = excess return on asset i at time t
α_i = intercept term
β_i = beta coefficient of asset i
r_{mt} = excess return on the stock market portfolio at time t
ε_{it} = random error term.

Fama and MacBeth (1973) in their seminal paper introduce an iterative technique to test the CAPM. They revise the TSR each month in order to get a series of "rolling" beta estimates for each asset and compute the following second-pass cross-sectional regression (CSR) each month:

$$r_{it} = a_t + \lambda_t \hat{\beta}_{it-1} + e_{it}, \tag{3}$$

where r_{it} = expected excess return implied by the CAPM on asset i for period t (here monthly or quarterly return),
a_t = intercept term (= 0 according to the CAPM),
λ_t = risk premium at time t,
β_{it-1} = beta coefficient estimated for the previous period,
e_{it} = random error term.

In the literature, the betas are generally estimated, according to a rule of thumb, over a five-year period of time prior to each CSR. The final Fama–MacBeth estimates for the intercept and risk premium are the sample means from the time series of these coefficients. To calculate the standard errors, it is assumed that the time series of the cross-sectional estimates are independent and identically distributed with the means of final estimates. However, the independence assumption is not strictly satisfied because of the use of estimated betas instead of "true" betas. An errors-in-variables (EIV) problem is introduced in the second-pass regression of returns on betas that are subject to measurement error. Due to the EIV problem, the CSR estimates are biased and inconsistent in small samples (for a review of these EIV problems, see eg Shanken (1992) and for thin markets, Malkamäki (1992a)).

In addition to the Fama–MacBeth tests, this paper includes a pooled data analysis, as in Malkamäki (1992a). The latter avoids at least to some extent the criticism regarding the standard deviations used in the univariate tests. This is done by constructing a single composite return vector for all return series and a corresponding beta vector for the entire period analysed.[4] Altogether, there are 3875 observations in these two vectors in the monthly analysis over the time period 1977:2–1989:12. This implies that our tests of the risk premium have extremely high degrees of freedom, ie the tests are powerfull. Model 3 is now rewritten as

$$r_{it} = a + \lambda\hat{\beta}_{it-1} + e_{it}. \tag{4}$$

Note that lamda now has no time subscript. The pooled regression has the nice feature of giving greater weight to those observations that have high correlations with each other, as compared to standard univariate tests.

The market model (2) is also estimated by applying the dynamic Kalman filter estimation procedure, which accounts for time variation in the betas. The model is now rewritten in state space form as

$$r_{it} = X_t'\theta_t + \varepsilon_t, \tag{5}$$

where $X_t' = [1, r_{mt}]$
$\theta_t' = [\alpha_{it}, \beta_{it}]$
ε_t = random error with variance v_t.

According to Knif (1989), the parameter vector θ_t is actually assumed to vary according to the stationary first order autoregressive (AR1) model

[4] Regression over the pooled data implies an assumption that the cross-sectional and time-series variability (error variance) is the same. The first 25 observations are the February 1977 excess returns and corresponding betas for each firm. The observations 26–50 are the respective observations for March 1977.

$$\theta_t - \bar{\theta} = F(\theta_{t-1} - \bar{\theta}) + u_t, \tag{6}$$

where $\bar{\theta}$ = mean vector of the parameters
F = weights for the AR1 and mean parameters
u_t = random error with covariance matrix M_t.

The state space representation for the market model is now

$$r_{it} = \begin{bmatrix} X'_t & X'_t \end{bmatrix} \begin{bmatrix} \bar{\theta}_t \\ \theta_t - \bar{\theta}_t \end{bmatrix} + \varepsilon_t \tag{7}$$

$$= B'_t \gamma_t + \varepsilon_t$$

and for the parameter vector,

$$\gamma_t = \begin{bmatrix} \bar{\theta}_t \\ \theta_t - \bar{\theta}_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & F \end{bmatrix} \begin{bmatrix} \bar{\theta}_{t-1} \\ \theta_{t-1} - \bar{\theta}_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ u_t \end{bmatrix} \tag{8}$$

$$= A\gamma_{t-1} + e_t,$$

where F = diag $[\omega_1, \omega_2]$
$\bar{\theta}_t$ = $\bar{\theta}_{t-1}$ for all t
e_t = random error with covariance matrix N_t.

The random errors ε_t and e_t are independent of each other. The corresponding variance v_t and covariance matrix N_t are estimated. We employ the ML method to estimate minimum mean square values for γ_{t-1} and its covariance matrix Σ_{t-1}. The estimates for Σ_t and γ_t, given r_{it} and X_t, at each time t are updated by means of the Kalman filter updating equations (Appendix 1).

The Kalman filter technique is actually a three-step procedure.[5] First, a maximum likelihood solution for the parameter vector is found

[5] For details concerning the maximization algorithms, see Goodrich (1989).

using the above forward recursive Kalman equations, which use past and current information. Next, information from the whole sample period is used to find another set of ML estimators by applying the backward recursions of the Kalman smoother. As a final step, the mean-reverting AR1 model is employed to generate the forecasted betas. The forecasted betas are employed in the CSR and pooled-data analyses. The EIV problem is reduced at least to some extent in the case of the mean-reverting AR1 model by using forecasted betas as the independent variable in the second-pass regressions. This is the case assuming that the changing residual variance of the market model is dependent on the time variation of beta.

3 Description of the Data

The data used in this study cover the period 1972–1989. The lack of data on short-term interest rates prior to January 1972 was the limiting factor. The analyses are carried out with end-of-month and, to some extent, end-of-quarter returns, which are measured as logarithmic changes in the indices. Observations on end-of-month days without a transaction in a stock are bid prices for that day. The stock market data consist of end-of-month returns on all the common stocks listed on the Helsinki Stock Exchange. The HSE market index, which is used here, is value weighted (see Berglund–Wahlroos–Grandell (1983)). In the index, prices are corrected for cash dividends, splits, stock dividends and new issues. The correction is based on the principle that all income from a stock is reinvested in the stock with no transaction cost. No portfolios are formed for the analysis as is usually done in US studies. This is because of the extremely limited number of actively traded stocks. Instead, four asset samples are included (Table 1). The first sample includes all 25 restricted ordinary stock series listed throughout the period analysed. The second sample includes the 16 most traded restricted stocks for the period. The third sample includes the 15 return series that most closely resemble the normal distribution. Sample 1 is also enlarged to form sample 4 by introducing a corporate bond return index into the analysis.

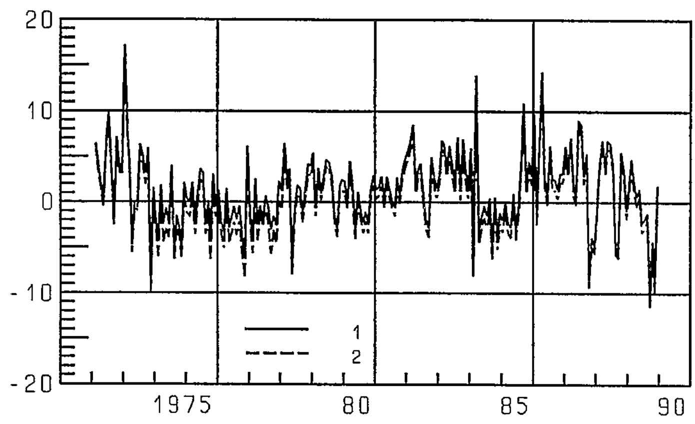
Table 1. **Asset samples employed in the study**[a]

Sample	Assets
1	all (25) common stocks listed throughout the period 1972–1989.
2	the 16 most traded common and preferred stocks
3	the 15 return series that most closely resemble a normal distribution
4	sample 1 and a corporate bond return index

[a] See Appendices 2.1–2.3 for firm names.

Asset-pricing tests are convenient to run in excess-returns form. To compute excess returns, we use the one-month return for the three-month Eurorate on the Finnish markka. This interest rate series is introduced in Malkamäki (1992a). Figure 1 shows the corresponding nominal and excess market returns employed in the analysis.

Figure 1. **Monthly returns for the Helsinki Stock Exchange**

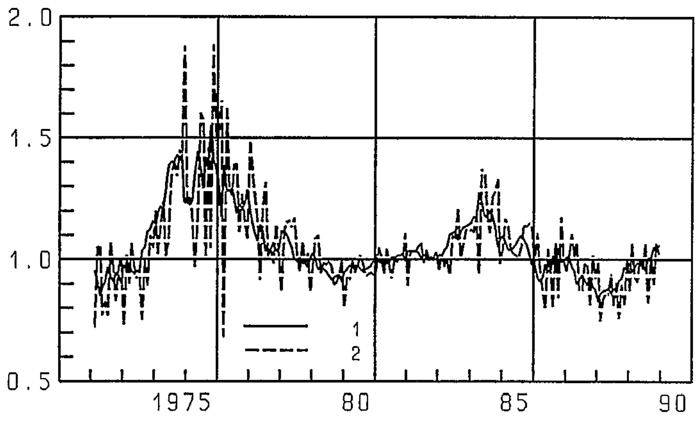


1 Nominal returns
2 Excess returns

The corporate bond return index is based on the corporate bond yield series described in Alhonsuo, Söderlund and Tarkka (1989). The series includes corporate bonds maturing in three to six years. The bond-return index was computed by using an approximate average bond maturity of four years. The duration for the assumed bond was computed by using the corresponding average bond yield over 1972—1989. This enables us to compute the one-month-holding-period return for the corporate bonds (Figure 2).

Summary statistics of the monthly real returns on 27 assets and the stock market general index are shown in Table 2. Statistics are also given for three subperiods: 1972:2—1978:2, 1978:3—1984:3 and 1984:4—1989:12 (see Appendices 3.1—3.3). The first period ends with a devaluation of the Finnish markka. The second period ends in 1984:3 for two reasons: (1) Unrestricted shares, ie shares that foreign investors are allowed to buy, have been listed separately on the Helsinki Stock Exchange since January 1, 1984. Another major change was initiated by the Bank of Finland, which gave the right to central bank financing to foreign banks from April 1, 1984. This meant in practice that short-term money markets started to function freely in Finland for the first time. For a closer description, see Malkamäki (1992a).

Figure 2. **Monthly interest rates and returns on corporate bonds**



1 Monthly rate of interest
2 Monthly rate of return

Table 2. **Summary statistics for excess returns on assets (per cent per month), 1972:2–1989:12 (215 observations)**

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	0.746	10.683	1.332	16.702
EFFO	0.423	8.204	0.348	1.448
ENSOA	-0.234	7.922	0.645	3.114
FISKK	1.292	7.252	0.296	1.959
HUHTK	0.782	6.610	1.056	2.655
INSTA	1.156	7.118	0.607	3.206
KEMI	-0.360	10.646	-0.694	4.457
KESK	0.658	5.147	1.060	2.481
KONE	0.432	7.084	1.462	4.969
KOP	0.104	6.644	0.751	4.821
KYMI	-0.002	6.410	0.597	1.908
LASS	1.298	9.240	1.336	7.143
LOHJA	0.930	7.333	0.141	0.295
NOKIK	-0.009	6.910	0.159	0.684
OTAVK	1.234	9.496	1.773	10.212
PART	0.522	6.594	0.242	0.555
RAUM	0.034	6.741	1.042	2.112
SOKEI	0.694	8.094	0.762	2.001
STOCA	0.895	6.645	0.521	2.684
SYPA	0.433	6.083	1.230	4.425
TAMF	0.717	9.835	-0.486	6.468
TAMP	0.051	7.788	1.276	5.215
TAOK	1.866	9.520	-0.031	1.863
TRIK	0.136	11.697	0.255	6.330
WARTI	0.613	7.480	0.764	1.155
YHTYK	0.707	7.459	0.380	0.934
BONDS[a]	-0.054	0.683	-2.71	15.047
VWI[b]	0.254	4.230	0.265	0.976

[a] Corporate bond index return.
[b] Value-weighted stock market index return.

The summary statistics tell us that the mean of returns changes significantly over the periods. The distribution of monthly returns is somewhat skewed to the right and leptokurtic. If we include only the most traded share series, ie sample 2 (not reported separately), it turns out that the skewness is unchanged but the leptokurtosis is slightly negative. The distribution of quarterly return (not reported here) for sample 1 is also positively skewed and negatively leptokurtic. The standard deviation of nominal and excess returns is almost the same as would be expected based on Figure 1.

4 Empirical Results

4.1 Beta Estimation

The first hypothesis tested is that the market risk of individual stocks is constant over time. The constant betas are estimated according to the well-known "rolling" beta estimation procedure introduced in Fama and MacBeth (1973). The alternative hypothesis is that the market risk of individual stocks changes over time. The Kalman filter technique is used to allow for time variation in the beta coefficients (see equation 4 and appendix 1). Three additional sets of OLS beta series are estimated in order to provide additional sensitivity analysis. The market risk coefficients are also computed using monthly nominal and quarterly real returns, suppressing the constant term of the market model (see Table 5).

All the beta estimations are revised monthly. The first estimation period for all the five-year OLS regressions is 1972:2—1977:1. We proceed by dropping the earliest observation and adding the next observation and repeating the estimation procedure. The last estimation period is 1984:12—1989:11. The outcome of the Kalman filter beta estimations is given in Appendix 4. The Appendix shows that most of the betas are actually constant. Table 3 is a correlation matrix of pooled monthly beta series for sample 1. All the five-year OLS beta series have very high correlations with each other (at least 0.968). The Kalman-filtered beta series employs forecasted beta values, which are used again in the second-pass regressions. The correlations between the OLS and dynamic beta series are approximately 0.43.

Table 3. **Correlation matrix of estimated beta series for sample 1 (3875 observations per series)**

Variable	B5Y	B5YNC	B5YN	BKFAR1
B5Y	1.000			
B5YNC	0.968	1.000		
B5YN	0.997	0.972	1.000	
BKFAR1	0.430	0.426	0.439	1.000

Variables in the correlation matrix:

B5Y = five-year beta estimation period, excess returns.
B5YNC = five-year beta estimation period, no constant in the TSR, excess returns.
B5YN = five-year beta estimation period, nominal returns.
BKFAR1 = Kalman filter (AR1) beta, excess returns, forecasted betas used ($\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta}$).

4.2 Tests of the CAPM and Risk Premiums

In the first phase, a modified version of the Fama–MacBeth univariate tests on four asset samples is performed; in the second phase, a pooled regression test. The CSR of equation 3 is computed iteratively for each month. The final estimates of the intercept and risk premium of the CSRs are the sample means of the time series of these coefficients.[6] Table 4 presents the outcome of these tests for the whole sample period. We see that the static OLS beta series always leads to rejection of the mean-variance efficiency of the market and implies a statistically significant negative risk-return relationship. Tests using the time-varying betas do not enable us to reject the mean-variance efficiency of the market index. However, the price of risk is not generally significant.[7]

[6] The methodological problems involved and our attempts to control for them are discussed above.

[7] The market risk coefficient of the bond.return index (RDK36 in Appendix 4) is not significant, especially in the 1980s. One should keep this in mind when interpreting the outcome of sample 4.

Table 4. **Monthly average risk premiums (per cent per month) associated with the stock market general index, 1977:2—1989:12 (155 CSR's)**

	a	λ	$R^{2\,a}$	SSR(%)[b]	P(Q)[c]
Sample 1					
OLS	1.787	-1.058	5.7	15.5	0.0
	(3.67)	(-2.61)			
KFAR1	1.128	-0.281	6.3	18.7	94.4
	(1.85)	(-0.40)			
Sample 2					
OLS	1.664	-0.932	7.8	14.2	21.6
	(3.17)	(-1.98)			
KFAR1	1.375	-0.006	6.9	19.4	26.2
	(1.74)	(-0.68)			
Sample 3					
OLS	0.158	-0.066	8.0	12.3	0.4
	(2.90)	(-1.45)			
KFAR1	0.788	0.219	9.3	25.8	94.7
	(1.22)	(0.30)			
Sample 4					
OLS	1.375	-0.648	4.8	18.1	0.0
	(3.99)	(-2.16)			
KFAR1	0.533	0.357	4.8	14.8	46.0
	(1.62)	(0.76)			

[a] Mean of R^2s in the CSRs (per cent).
[b] Percentage of statistically significant R^2s (at the 10 % level) in the CSRs.
[c] Significance level (based on Ljung–Box test statistics Q(36)) for the risk that there is no autocorrelation in the risk premium series.

The above univariate tests are not necessarily very robust and they say almost nothing about the pricing of market risk in the event that the premiums vary through time, as found eg in Ferson and Harvey (1991). Therefore, we compute another test statistic (SSR(%) in the table), the percentage of statistically significant coefficients of determination at the 10 % level of risk (R^2 greater than 11.84 %) for the cross-sectional regressions. These statistics show that there are many more significant CSRs than would be found randomly. This is an indication that the market risk may be time varying and conditionally priced in the Finnish asset market. The risk-return relationship appears to be positive and quite strong in sample 3, where almost 26 % of the cross-sectional regressions are statistically significant at the 10 % level.[8]

Finally, the Ljung–Box statistic is computed to test whether the estimated risk premium time series are autocorrelated, ie whether risk premiums change systematically over time, conditional on their own histories. The results are quite straightforward. The OLS beta risk premiums tend to be autocorrelated, whereas the Kalman filter beta risk premiums do not. The risk premium is usually assumed to be autocorrelated based on US studies,[9] according to which the volatility of market excess return changes over time. In this context, it is somewhat discouraging that the risk premium associated with the time-varying betas is not time varying conditional on its own past. On the other hand, the number of statistically significant CSRs is clearly higher where time-varying betas are concerned. Furthermore, Malkamäki (1992b) shows that the risk premiums estimated for the forecasted AR1 betas are conditionally time varying when using the same conditioning method but different instruments, as in Ferson and Harvey (1991).

Table 5 contains additional analysis of robustness with the OLS betas in sample 1. The first two restricted regressions suggest that our proxy for the riskless return is reasonably accurate.[10] Strictly speaking, we accept the restricted version of the CAPM model and estimate the implied risk premium. Consequently, the unrestricted regression is a test of the validity of the CAPM or a test of the risk premium implied by the one-factor capital asset pricing model, where the prespecified factor is the market index. The third regression on the monthly nominal returns gives a puzzling result whether we employ excess returns or not. The fourth regression indicates that the price of market risk is negative also for quarterly returns.

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[8] The risk premium series are illustrated in Appendix 6.

[9] See eg Chou et al. (1992).

[10] The mean coefficients of determination in the cross-sectional regressions are not reported for the restricted versions, as they are not comparable to the corresponding R^2s in the unrestricted model.

Table 5. **Monthly and quarterly average risk premiums (per cent per month) associated with stock market general index, 1977:2—1989:12 (155 CSR's)**

	a	λ	R^{2} [a]	SSR(%)[b]	P(Q)[c]
Sample 1, OLS					
Monthly Excess Returns					
— Five-year betas without constant in the CSR	-	0.703 (2.21)	-	-	0.0
— Five-year betas without constant in the TSR and CSR	-	0.701 (2.21)	-	-	0.0
Monthly Nominal Returns					
— Five-year betas	2.850 (5.99)	-1.062 (-2.67)	5.8	15.5	0.0
Quarterly Excess Returns					
— Five-year betas	4.748 (3.17)	-2.221 (-2.12)	5.3	15.7	45.4

[a] Mean of the R^2s in the CSRs (per cent).
[b] Percentage of statistically significant R^2s (at the 10 % level) in the CSRs.
[c] Significance level (based on Ljung—Box test statistics Q(36)) for the risk that there is no autocorrelation in the risk premium series.

Appendices 5.1—5.3 provide a closer look at the results for the subperiods introduced in section 4. The negative price of the OLS market risk is especially clear for the last subperiod. The positive risk-return relationship is most evident for the Kalman-filtered market risk exposures in sample 3 for all periods.

The above results together support the findings of Malkamäki (1992a) in showing that the negative risk-premium phenomenom associated with the OLS betas is robust over the asset samples and that the time-varying market risk is very likely rewarded, especially in the subsample where the returns most closely resemble the normal distribution.

Table 6 gives the correlation matrix for the estimated monthly risk premiums. The estimation methodology for the market risk exposure appears to divide the risk premium series into two parts. Risk premiums computed with static/dynamic beta estimates tend to have the highest correlations with each other. One additional finding concerns the risk premiums computed from the conditional betas. The risk premiums of samples 1 and 4 are highly correlated with the corresponding series of sample 3, whereas the correlation between the corresponding series and sample 2 is considerably lower. The major difference between samples 2 and 3 is that banks are excluded from sample 3. We would suggest that the omission of the banks' return series enhances the risk-return relationship in sample 3, but we do not have clear evidence that this is the case because sample 3 includes five additional firms that are not included in sample 2. However, the financial markets were liberalized in Finland beginning in 1983. The rapid expansion in all relevant financial market aggregates suggests that the nature of the banking business changed considerably (see Malkamäki and Virén (1990)); hence, there could have been a sift in banks' market risk coefficients which cannot be accounted for in this mean-reverting AR1 model.

Table 6. **Correlation matrix for estimated risk premiums**

Variable	5Y25	KF25	5Y16	KF16	5Y15	KF15	5Y26	KF26
5Y25	1.000							
KF25	0.303	1.000						
5Y16	0.463	0.170	1.000					
KF16	0.263	0.527	0.405	1.000				
5Y15	0.738	0.358	0.433	0.306	1.000			
KF15	0.156	0.909	0.187	0.466	0.331	1.000		
5Y26	0.929	0.412	0.476	0.353	0.680	0.265	1.000	
KF26	0.239	0.948	0.162	0.565	0.297	0.869	0.430	1.000

Monthly risk premiums in the correlation matrix:

5Y25 = five-year beta estimation period, all (25) common stocks.
KF25 = Kalman filter (AR1) forecasted beta*, all (25) common stocks.
5Y16 = five-year beta estimation period, 16 most traded stocks.
KF16 = Kalman filter (AR1) forecasted beta*, 16 most traded stocks.
5Y15 = five-year beta estimation period, 15 most normally distributed asset return series.
KF15 = Kalman filter (AR1) forecasted beta*, 15 most normally distributed asset return series.
5Y26 = five-year beta estimation period, 26 assets.
KF26 = Kalman filter (AR1) forecasted beta*, 26 assets.

* Forecasted betas defined by $\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta}$.

The power of the above univariate tests can be increased by applying a pooled regression method. We compute, as usual, monthly returns over the estimated beta series. This is done by constructing a single composite vector of firms' returns and a corresponding beta vector for the period analysed. The tests then have extremely high degrees of freedom (3873 for the entire period), ie the tests are powerful. The pooled regression also has the nice feature of giving greater weight to those observations that have high correlations with each other, compared to the corresponding univariate tests. Furthermore, this method avoids the criticism of the univariate tests' regarding standard deviations computed from the second-pass time-series estimates (for details, see Malkamäki (1992a).[11]

Table 7. **Monthly average risk premiums associated with the stock market index (per cent per month) in the pooled data regression[a] (for sample 3)**

Period	a^b	λ^b	δ^{bc}
1977:2–1989:12	0.241 (0.29)	0.823 (0.91)	7.810
1978:3–1988:12	0.076 (0.08)	1.635 (1.62)	7.778

[a] Model estimated: $r_{it} = a + \lambda\beta_{it} + e_{it}$, where $\beta_{it} = \omega\beta_{it-1} + (1-\omega)\bar{\beta}$. Heteroscedasticity-consistent t-values in parenthesis, White (1980).

[b] All coefficients are multiplied by 100.

[c] Standard error of estimate.

Table 7 gives the pooled regression results for sample 3, where the risk-return relationship turned out to be the strongest in the above analysis. The first regression is computed over the whole sample period. The constant is relatively small and not significant. The risk

[11] Regression over the pooled data implies an assumption that the cross-sectional and time-series variability (error variance) are equal. If this does not hold, the standard deviations are too big, ie the t-values are biased downwards.

premium coefficient is more than twice as big as in Table 4, but the t-value is not significant. The second regression excludes extraordinary periods in the Finnish economy: the periods before 1978:3 and after 1988:12. The Finnish markka was devaluated three times in the excluded period prior to 1978:3 and the Finnish economy turned sharply downward in early 1989. The exclusion of these periods has a major impact on the risk-return relationship. The average risk premium is now statistically significant at the 10 % level and accords with what would be expected based on the average excess returns shown in Table 2.[12]

5 Conclusions

This paper examines the Sharpe–Lintner CAPM in which a time-varying-parameter model serves as an alternative to the traditional static market model. We test the model for the thin Finnish asset market. Prior unconditional tests of the CAPM have usually led to rejection of the mean-variance efficiency of the Helsinki Stock Exchange index and have found that market risk is not priced or, as in recent studies, that the price of market risk is negative. Here, the traditional Fama–MacBeth univariate tests on static OLS betas reject the mean-variance efficiency of the market index and again find a negative risk-return relationship. This result is shown to be very robust, recurring in every one of the four asset samples. The first sample includes all 25 restricted ordinary stocks listed throughout the whole period analysed. The second sample includes the 16 restricted stocks most traded during the period. The third sample includes the 15 return series that most closely resemble the normal distribution. Sample 1 is also enlarged by introducing a corporate bond return index into the analysis.

Two recent papers, Malkamäki (1992a) and Berglund and Knif (1992), suggest that the market index may be mean-variance efficient and the time-varying market risk may be rewarded in the Finnish

[12] The exclusion of the data after 1988 turned out to have a bigger impact in favour of the CAPM. This implies that our betas are not able to account for the dramatic stock price drops within that year. One explanation for this phenomenon is reported in Berglund and Knif (1992). They find a non-linear relationship between ex post risk premiums and returns for Finnish stock market data. However, they excluded the data for 1989.

stock market. The market risk coefficients were allowed to vary over time according to a mean-reverting AR1 model in both of these studies. We examine the robustness of these results in four asset samples and in every case are unable to reject the mean-variance efficiency of the market index. The constant risk premium coefficient is not significant in our standard Fama–MacBeth univariate analysis. However, the number of statistically significant cross-sectional regressions is clearly highest, and statistically significant, in sample 3, ie among the 15 return series that most closely resemble the normal distribution. The pooled regression analysis of sample 3 suggests that the constant risk premium is clearly positive and significant if the two periods that were extraordinary for the Finnish economy are excluded.

The risk-return relationship is notably weaker in the sample of most traded stocks. This finding does not support the prior understanding that the poor performance of the CAPM using data from a thin stock market is due mainly to non-synchronous trading. The evidence here suggests that the non-normality of the return series may be an even bigger problem in tests of asset pricing models. The major difference between samples 2 and 3 is that banks are excluded from sample 3. We leave it for subsequent research to determine whether the omission of the bank returns explains the enhanced risk-return relationship in sample 3.

This paper also showed that the risk-return relationship is sensitive to the time period considered. In particular, the conditional betas are not able to account for the return behavior of stocks under such drastic expectations as in the Finnish economy in 1989. An explanation for this could be, for example, that the risk premium varies over time and, hence, the unconditional tests were unable to capture the price of risk in the extraordinary periods. This hypothesis is actually one of the findings in Malkamäki (1992b). He is able to show, using the whole period tested here, that the risk premium estimated with the AR1 betas is conditionally time varying.

The key contribution of this paper is, however, that investors should clearly not base their investment decisions on the unconditional OLS betas commonly published by investment research services. They could, instead, consider the mean-reverting AR1 betas employed here. However, more sophisticated models of risk evaluation might perform even better. One could also consider correction procedures for thin trading in the context of such models.

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Appendix 1

The forward updating Kalman equations are:

$$\Sigma p = A_t \Sigma_{t-1} A'_t + N_t,$$

where Σp = one-step ahead prediction based on the prior information for the covariance matrix of the new parameter vector.

$$F = X'_t \Sigma p X_t + v_t,$$

where F = one-step-ahead prediction for the variance of the new parameter vector.

$$K_t = \Sigma p X_t F^{-1},$$

where K_t = Kalman gain, ie the correction weight based on the one-step ahead prediction for the covariance matrix Σp and variance F.

$$\tilde{r}_{it} = r_{it} - X_t A_t \gamma_{t-1},$$

where $\tilde{r}_{it}$ = one-step-ahead prediction error.

$$\Sigma_t = \Sigma p - \Sigma p X_t F^{-1} X'_t \Sigma p,$$

where Σ_t = updated estimate for the covariance matrix of new parameter vector.

$$\gamma_t = A_t \gamma_{t-1} + K_t \tilde{r}_{it},$$

where r_t = updated estimate of the parameter vector.

Appendix 2.1

Stocks included in the analysis. Sample 1. All restricted ordinary stocks listed throughout the period 1972–1989

Stock	Designation
Bank of Åland Ltd K	AB
Effoa-Finland Steamsip Co Ltd K	EFFO
Enso-Gutzeit Ltd A	ENSOA
Fiskars Corporation	FISKK
Huhtamäki Corporation K	HUHTK
Instrumentarium Corporation	INSTA
Kemi Corporation	KEMI
Kesko Corporation	KESK
KANSALLIS-OSAKE-PANKKI	KOP
Kymmene Corporation	KYMI
Lassila & Tikanoja Ltd	LASS
Lohja Corporation A	LOHJA
Nokia Corporation	NOKIK
Otava Publishing Company Ltd	OTAVK
Partek Corporation	PART
Rauma-Repola Corporation	RAUM
Finnish Sugar Co Ltd I	SOKEI
Stockman A	STOCA
Union Bank of Finland Ltd A	SYPA
Tamfelt Group K	TAMF
Tampella Ltd	TAMP
Talous-Osakekauppa Co	TAOK
Suomen Trikoo Corp. A	TRIK
Wärtsilä Co I	WARTI
United Paper Mills Ltd K	YHTYK

Appendix 2.2

Stocks included in the analysis. Sample 2. The 16 most-traded restricted stocks

Stock	Designation
Enso-Gutzeit Ltd A	EFFO
Fiskars Corporation	FISKK
Instrumentarium Corporation A	INSTA
Kesko Corporation	KESK
Kone Corporation B (preference share)	KONE
KANSALLIS-OSAKE-PANKKI	KOP
Kymmene Corporation	KYMI
Lohja Corporation A	LOHJA
Nokia Corporation	NOKIK
Partek Corporation	PART
Rauma-Repola Corporation	RAUM
Finnish Sugar Co Ltd I	SOKEI
Union Bank of Finland Ltd A	SYPA
Tampella Ltd	TAMP
Wärtsilä Co I	WARTI
United Paper Mills Ltd K	YHTYK

Appendix 2.3

Stocks included in the analysis. Sample 3. The 15 stocks whose returns that most closely resemble the normal distribution.

Stock	Designation
Effoa-Finland Steamsip Co Ltd K	EFFO
Fiskars Corporation	FISKK
Huhtamäki Corporation K	HUHTK
Kesko Corporation	KESK
Kymmene Corporation	KYMI
Lohja Corporation A	LOHJA
Nokia Corporation	NOKIK
Partek Corporation	PART
Finnish Sugar Co Ltd I	SOKEI
Stockman A	STOCA
Tamfelt Group K	TAMF
Talous-Osakekauppa Co	TAOK
Suomen Trikoo Corp. A	TRIK
Wärtsilä Co I	WARTI
United Paper Mills Ltd K	YHTYK

Appendix 3.1

Summary statistics for the asset excess returns (per cent per month), 1972:2—1978:2 (73 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	-0.234	11.341	-0.891	5.441
EFFO	-0.758	6.695	-0.243	1.797
ENSOA	-1.732	8.098	-0.027	3.707
FISKK	0.199	6.573	-0.103	0.044
HUHTK	-0.157	5.375	2.353	8.174
INSTA	0.623	7.574	0.343	0.517
KEMI	-1.191	8.916	0.162	1.704
KESK	-0.434	5.058	1.772	4.584
KONE	-0.807	6.761	1.766	10.257
KOP	-0.857	6.867	0.063	0.404
KYMI	-0.926	6.521	0.231	2.054
LASS	-0.069	8.549	2.660	13.570
LOHJA	-0.215	7.519	0.648	0.988
NOKIK	-0.738	6.290	0.180	0.742
OTAVK	0.967	11.330	2.331	13.188
PART	-0.829	6.709	-0.007	0.096
RAUM	-0.881	7.280	1.131	1.873
SOKEI	-0.375	7.859	0.849	1.956
STOCA	-1.082	5.825	0.650	1.750
SYPA	-0.077	6.822	1.143	2.630
TAMF	-0.913	12.530	-0.756	4.601
TAMP	-2.466	6.961	0.071	0.501
TAOK	2.786	8.880	0.760	2.176
TRIK	-0.739	8.292	1.057	3.638
WARTI	-1.414	7.328	0.700	1.242
YHTYK	-0.483	7.854	0.421	0.466
BONDS[a]	-0.149	1.084	-1.559	4.574
VWI[b]	-0.721	4.406	0.942	2.167

[a] Corporate bond index return.
[b] Value-weighted stock market index return.

Appendix 3.2

Summary statistics for the asset excess returns (per cent per month), 1978:3—1984:3 (73 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	1.263	7.092	0.067	2.436
EFFOA	0.655	6.433	-0.338	2.210
ENSOA	0.307	5.710	0.983	2.273
FISKK	0.931	5.492	0.108	1.176
HUHTK	2.584	7.120	0.992	3.180
INSTA	2.318	5.577	1.938	5.857
KEMI	-1.538	12.402	-1.469	5.919
KESK	0.748	3.368	-0.118	0.329
KONE	2.426	7.357	2.021	4.749
KOP	1.538	6.459	2.683	13.159
KYMI	0.178	5.365	0.512	2.742
LASS	1.993	6.848	0.029	1.367
LOHJA	2.052	6.423	-0.183	0.790
NOKIK	0.645	6.016	0.112	2.406
OTAVK	1.459	5.017	-0.090	1.482
PART	1.311	4.980	1.299	3.060
RAUM	0.680	6.502	1.264	2.163
SOKEI	2.189	7.682	0.820	1.867
STOCA	2.333	6.608	0.502	6.768
SYPA	1.005	5.551	2.423	13.827
TAMF	1.853	6.335	1.338	3.601
TAMP	0.659	6.517	0.695	3.246
TAOK	2.388	9.657	-0.332	3.069
TRIK	1.421	12.346	-1.345	10.440
WARTI	2.813	7.230	0.681	0.538
YHTYK	1.672	7.087	0.512	1.865
BONDS[a]	-0.030	0.408	-4.826	33.708
VWI[b]	1.172	3.278	0.000	2.024

[a] Corporate bond index return.
[b] Value-weighted stock market index return.

Appendix 3.3

Summary statistics for the asset excess returns (per cent per month), 1984:4–1989:12 (69 observations)

Asset	Mean	St.dev.	Skewness	Kurtosis
AB	1.236	12.885	3.124	21.096
EFFO	1.427	10.860	0.442	0.010
ENSOA	0.776	9.476	0.982	4.491
FISKK	2.830	9.166	0.212	1.523
HUHTK	-0.131	6.926	0.400	-0.257
INSTA	0.490	7.974	0.590	4.397
KEMI	1.766	10.143	0.274	0.629
KESK	1.718	6.468	0.654	0.815
KONE	-0.413	6.739	0.555	0.377
KOP	-0.397	6.431	-0.251	0.953
KYMI	0.784	7.228	0.896	1.039
LASS	2.008	11.774	0.937	4.501
LOHJA	0.954	7.859	-0.021	-0.151
NOKIK	-0.211	8.309	0.198	-0.181
OTAVK	1.280	11.003	1.028	1.963
PART	1.118	7.740	0.176	-0.319
RAUM	0.321	6.380	0.876	3.277
SOKEI	0.245	8.629	0.770	2.655
STOCA	1.466	7.073	0.373	0.642
SYPA	0.367	5.822	0.457	-0.182
TAMF	1.241	9.549	0.316	4.861
TAMP	2.073	9.125	1.986	5.879
TAOK	0.340	9.973	-0.261	0.593
TRIK	-0.298	13.915	1.176	3.198
WARTI	0.429	7.363	1.175	2.586
YHTYK	0.944	7.350	0.342	1.260
BONDS[a]	0.018	0.213	-0.907	1.116
VWI[b]	0.314	4.737	0.042	0.241

[a] Corporate bond index return.
[b] Value-weighted stock market index return.

Appendix 4

Maximum likelihood estimation results for the Kalman filter AR1 specification. 1972:2–1989:12

Asset	ω	$\bar{\beta}$	q	σ^2	α	R^2	P(F)
AB	-.0902	.7483*	.0016	.0104	.0049	.0954	.9995
EFFO	-.0227	.8885*	.4523	.0046	.0035	.1844	1.0
ENSOA	.0172	1.0106*	.6726	.0035	-.0052	.2575	1.0
FISKK	.0322	.7953*	.2926	.0035	.0126*	.2258	1.0
HUHTK	.4469*	.9676*	.4967	.0019	.0020	.2981	1.0
INSTA	-.0346	.8680*	.0989	.0036	.0097*	.2580	1.0
KEMI	-.0797	.9139*	1.1405	.0079	-.0057	.1317	1.0
KESK	-.2138	.6707*	.1303	.0016	.0055*	.2955	1.0
KONEB	-.0294	.7427	.2776	.0035	.0021	.1999	1.0
KOP	.0027	1.0664*	.3458	.0016	-.0031	.3859	1.0
KYMI	.0694	.9342*	.2063	.0022	-.0013	.3590	1.0
LASS	.2163	.7103*	.1765	.0074	.0120*	.0938	.9994
LOHJA	-.0785	1.2017*	.0221	.0026	.0073*	.4318	1.0
NOKIK	-.0526	1.0748*	.1426	.0025	-.0036	.4354	1.0
OTAVK	.1064	.6889	2.8235	.0035	.0116*	.1357	1.0
PART	-.0104	1.0863*	.2200	.0021	.0031	.4179	1.0
RAUM	-.0472	.9927*	.3495	.0022	-.0038	.3930	1.0
SOKEI	.0329	.9927*	.5949	.0039	.0050	.2550	1.0
STOCA	-.0626	.8699	.0788	.0030	.0072	.2844	1.0
SYPA	.0431	1.0106*	.5339	.0011	.0011	.5006	1.0
TAMF	.3272	.9094*	.9270	.0062	.0079	.1870	1.0
TAMP	.7896*	.9484	.0262	.0045	.0006	.2410	1.0
TAOK	.0383	.4740	.1097	.0085	.0176*	.0419	.8982
TRIK	-.2379	1.0390*	4.5252	.0050	.00005	.1222	1.0
WARTI	.2530	1.001*	.0009	.0038	.0044	.3001	1.0
YHTYK	.0587	1.1527*	.3089	.0026	.0052	.4426	1.0
RDK36	-.0294	.7427	.2776	.0035	.0021	.1999	1.0

Estimated model: $r_{it} = \alpha_t + \beta_t r_{mt} + \varepsilon_t$,

where α_t = constant; $\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta} + v_t$; $\sigma^2 = \mathrm{var}(\varepsilon_t)$; $q = \mathrm{var}(v_t)$

Appendix 5.1

Monthly average risk premiums (per cent per month) associated with the stock market index, 1977:2—1984:3 (86 CSR's)

	a	λ	$R^{2\,a}$	SSR(%)[b]	P(Q)[c]
Sample 1					
OLS	1.032	-0.197	5.3	16.3	30.5
	(2.44)	(-0.52)			
KFAR1	0.965	-0.120	6.6	18.6	35.7
	(1.31)	(-0.13)			
Sample 2					
OLS	0.755	0.070	7.3	11.6	57.2
	(1.56)	(0.14)			
KFAR1	0.889	-0.045	6.6	19.8	14.3
	(0.98)	(-0.04)			
Sample 3					
OLS	0.056	0.053	8.6	16.3	82.8
	(1.10)	(1.16)			
KFAR1	0.722	0.411	9.8	27.9	95.2
	(0.86)	(0.43)			

[a] Mean of the rates of determination in the CSR's.
[b] Percentage of statistically significant R^2s (at 10 % level) in the CSR's.
[c] Significance level (based on Ljung–Box test statistics Q(27)) for the risk that there is no autocorrelation in the risk premiums.

Appendix 5.2

Monthly average risk premiums (per cent per month) associated with the stock market index, 1978:3—1984:3 (73 CSR's)

	a	λ	R^2 [a]	SSR(%)[b]	P(Q)[c]
Sample 1					
OLS	1.506	-0.018	5.4	16.4	31.5
	(3.43)	(-0.48)			
KFAR1	1.041	0.329	6.4	17.8	75.2
	(1.29)	(0.34)			
Sample 2					
OLS	0.997	0.338	7.2	17.8	36.4
	(2.01)	(0.66)			
KFAR1	0.840	0.005	6.7	21.9	23.4
	(0.84)	(0.43)			
Sample 3					
OLS	0.079	0.083	8.9	16.4	72.4
	(1.42)	(1.76)			
KFAR1	0.838	0.848	9.7	30.1	99.7
	(0.89)	(0.80)			

[a] Mean of the rates of determination in the CSR's.
[b] Percentage of statistically significant R^2s (at 10 % level) in the CSR's.
[c] Significance level (based on Ljung–Box test statistics Q(24)) for the risk that there is no autocorrelation in the risk premiums.

Appendix 5.3

Monthly average risk premiums (per cent per month) associated with the stock market index, 1984:4—1989:12 (69 CSR's)

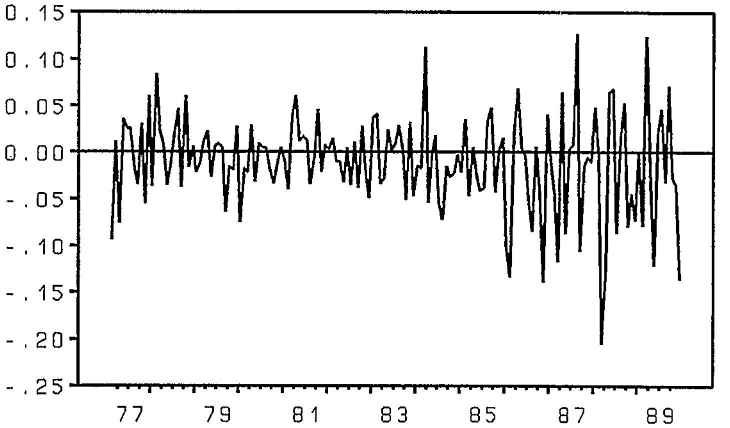
	a	λ	$R^{2\,a}$	SSR(%)[b]	P(Q)[c]
Sample 1					
OLS	2.729	-2.132	6.2	14.5	0.0
	(2.86)	(-2.80)			
KFAR1	1.331	-0.481	5.9	18.8	81.7
	(1.30)	(-0.43)			
Sample 2					
OLS	2.796	-2.181	8.4	17.4	63.4
	(2.80)	(-2.63)			
KFAR1	1.981	-0.013	7.2	10.1	78.6
	(1.43)	(-0.89)			
Sample 3					
OLS	0.285	-0.214	8.5	7.2	0.0
	(2.76)	(-2.64)			
KFAR1	0.870	-0.0002	8.7	23.2	85.8
	(0.85)	(-0.02)			

[a] Mean of the rates of determination in the CSR's.
[b] Percentage of statistically significant R^2s (at 10 % level) in the CSR's.
[c] Significance level (based on Ljung—Box test statistics Q(24)) for the risk that there is no autocorrelation in the risk premiums.

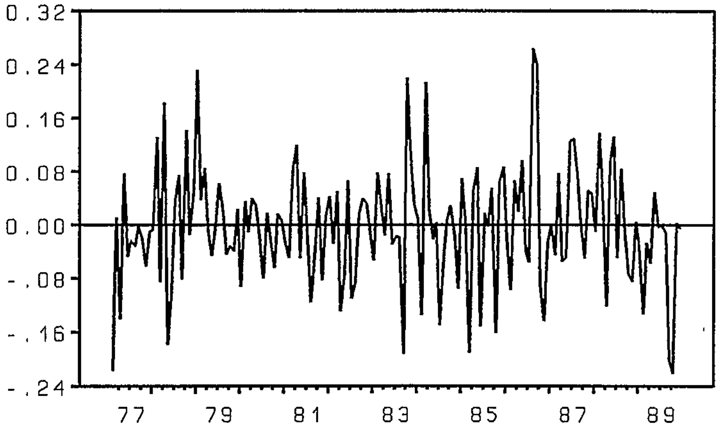
Appendix 6

Estimated time series for the risk premium: alternative samples of assets, estimation methods for the betas and time aggregation of the returns

Sample 1

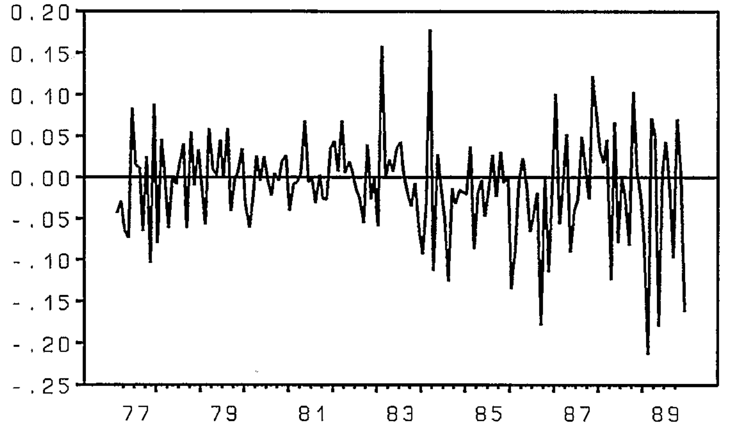


Five Year Estimation Period for Beta Series

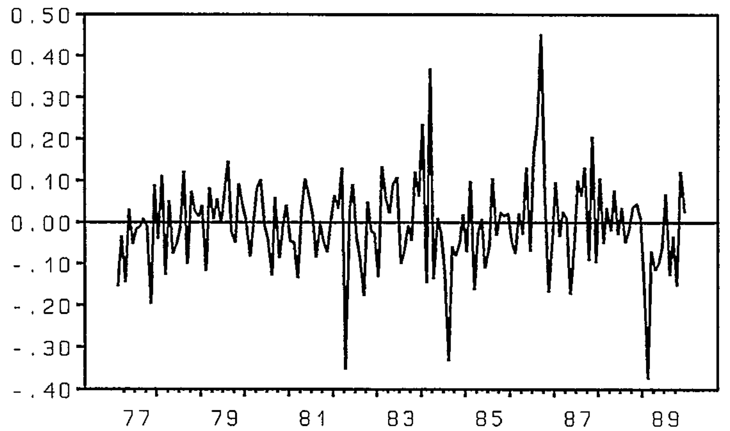


Kalman Filter AR1 Estimation for Beta Series

Sample 2

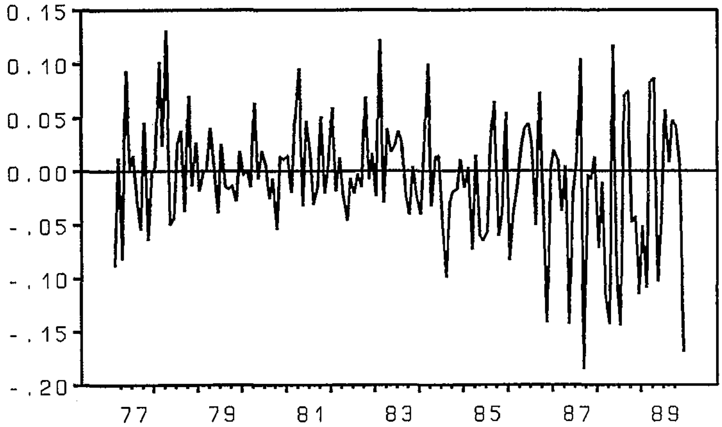


Five Year Estimation Period for Beta Series

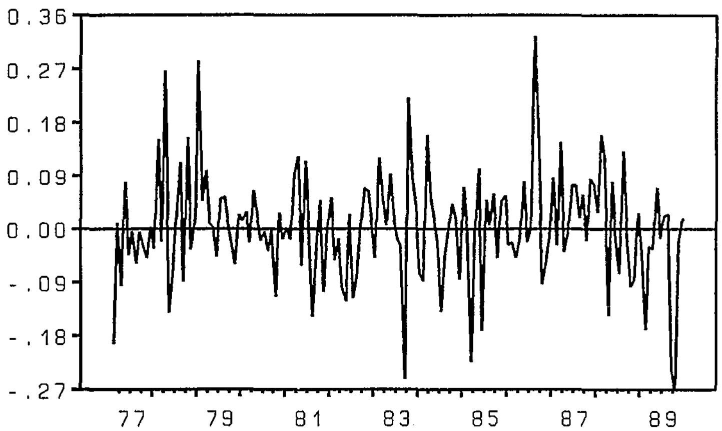


Kalman Filter AR1 Estimation for Beta Series

Sample 3

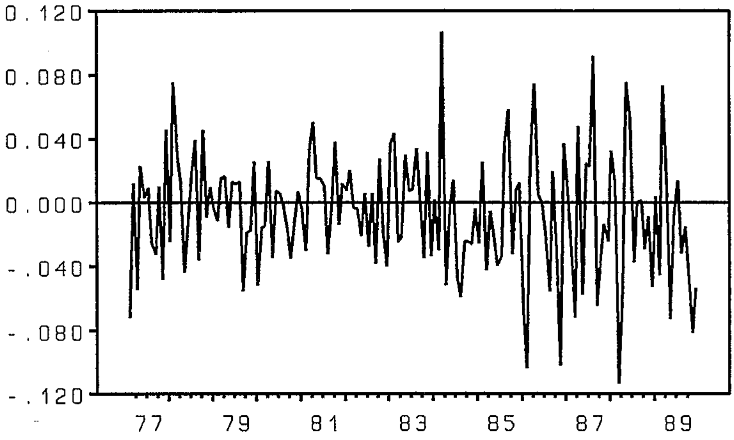


Five Year Estimation Period for Beta Series

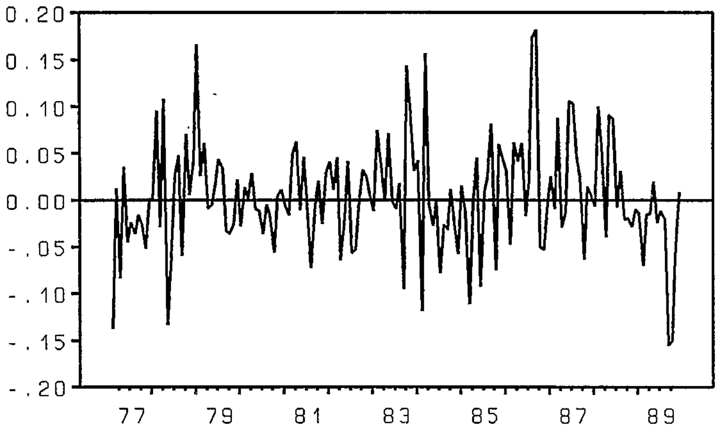


Kalman Filter AR1 Estimation for Beta Series

Sample 4



Five Year Estimation Period for Beta Series



Kalman Filter AR1 Estimation for Beta Series

Markku Malkamäki

Cointegration and Causality of Stock Markets in Two Small Open Economies and Their Major Trading Partners

Abstract

This paper examines cointegration and Granger causality among the stock markets in the United States, the United Kingdom, Germany, Sweden and Finland. The first three nations are the biggest trading partners of the two small open Nordic economies, Finland and Sweden. We apply standard univariate VAR models and a system of VAR models under the assumption of multivariate cointegration, first introduced in Johansen (1988). The cointegration analysis suggests that the stock markets are cointegrated, having one cointegrating vector when prices are measured in local currencies or in Finnish markkas and two cointegrating vectors when prices are measured in US dollars. It is also found that the Finnish and Swedish markets may deviate from the equilibrium path without having a significant impact on the three other markets, which indicates that the causality is from other stock markets to Finland and Sweden. The Finnish stock market is always found to be led by the German market, instead of the Swedish market as previously suggested, and also by the UK market when returns are measured in local currencies or in Finnish markkas. The Swedish stock market is Granger caused by the UK market instead of the US market, as previously suggested. The data covers the period 1974–1989.

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1 Introduction

Several papers have recently considered interdependencies in international stock markets. Interdependencies may be either short-term or long-term relations. The former studies have concentrated on the international transmission of returns and volatility (eg Eun and Shim (1989), Hamao, Masulis and Ng (1990), and King and Wadhwani (1990)) and have found that stock markets are in many cases less than fully integrated. This implies that shocks are transferred from one market to another as meteor showers instead of heat waves in terms of Engle, Ito and Lin (1990) and Ito, Engle and Lin (1991). Studies of the latter type examine whether national stock markets move together in the long run, ie whether they are cointegrated. If they are, the number of stochastic trends is analysed, as eg in Kasa (1992). Kasa argues that there is a single common trend driving the stock markets of the US, Japan, UK, Germany, and Canada. He also raises an interesting question as to what are the sources of this trend. He suggests that a stochastic world economic growth factor could be the underlying force driving national earnings and dividends.

The purpose of this study is to analyse cointegration and order of integration among the stock markets of the United States, the United Kingdom, Germany, Sweden and Finland. The former three nations are the biggest trading partners of the two small open Nordic economies, Finland and Sweden. We consider an unrestricted VAR model for each country in order to carry out traditional Granger causality tests. VAR models are employed under the assumption of multivariate cointegration, first introduced in Johansen (1988), in order to simultaneously analyse the hypothetical long-term relations and short-term dynamics, thus using all the information contained in the data. The short-term causalities are analysed conditional on the long-term relations when applying the Johansen method. We use end-of-month return data of good quality from 1974–1989. All the tests are computed over the returns denominated in (a) local currencies, (b) U.S. dollars and (c) Finnish markkas, in both nominal and excess forms.

The interdependencies among the Nordic and non-Nordic stock markets have been analysed recently by Hietala (1989), Mathur and Subrahmanyam, henceforth MS (1990) and (1991), Malkamäki, Martikainen and Perttunen, henceforth MMP (1991) and Malkamäki, Martikainen, Perttunen and Puttonen, henceforth MMPP (1991). All the authors emphasized that the Nordic stock markets are less than fully integrated. MS employed the Granger causality procedure to analyse interdependencies among Danish, Finnish, Norwegian and Swedish stock market indices. They used monthly (average, mid-month or end-of-month) data provided in IMF satistics for 1974–1985. MS (1990) used the vector autoregressive (VAR) technique and MS (1991) the seemingly unrelated regression (SUR) procedure and found that the Swedish market index led the indices in Denmark, Finland and Norway. The Norwegian market influenced the Danish and Swedish markets, whereas the Danish and Finnish markets did not influence any other markets. However, MS did not test for the cointegration, and the quality of their data was mixed.

These two studies were extended by MMPP (1991). They used daily returns measured in US dollars for February 1988 – April 1990 and also included the world stock index in the analysis. MMPP employed the single equation approach and tested for cointegration by applying the Engle–Granger (1987) two-step procedure. They found no cointegration among the indices but again found that the Swedish stock market led the other Scandinavian markets. However, the other Scandinavian markets did not significantly influence any other markets. The worldwide returns were found to have leading causality for Scandinavian stock market returns.

Recalling the paper by Kasa (1992), one would expect that the stock markets of all industrialized western countries move together in the long run, ie that the indices studied here are cointegrated and cannot drift too far from the equilibrium path. If the stock markets studied here are cointegrated and share a common stochastic trend, long-term gains to international diversification among them are smaller than they would otherwise be, assuming that transitory deviations from trend do not persist too long and that investors have a finite horizon.

Full stock market integration would imply that risk-adjusted stock returns denominated in the numeraire currency are equal in all countries. One would expect that at least the stock markets of the USA and UK would be fully integrated since both markets are of reasonable size and there have not been any significant restrictions on capital movements between them. Regulations have prevented foreign investors from having free access to the Finnish and Swedish stock markets. Furthermore, these markets, as well as the German stock market, have been marked by small capitalization and illiquidity. Such markets are typically characterized by non-synchronous trading.

Therefore, one would not necessarily expect the Finnish and Swedish stock markets in particular to be fully integrated with the UK and US stock markets.

Finland and Sweden are small open economies, highly dependent on exports. Finland's most important trading partners (excluding the former Soviet Union) are Sweden, Germany and the United Kingdom; Sweden's are Norway, Germany, the United Kindom and the United States. If the stock markets of Finland and Sweden are not fully integrated, we expect that they are Granger caused by the stock markets of their major trading partners. Thus, the Finnish market is expected to be led by the German, Swedish and/or UK stock markets and the Swedish market by the German, UK and/or US stock markets.

Our multivariate cointegration analysis suggests that the stock markets examined here are cointegrated, having one common vector when prices are measured in local currencies or in Finnish markkas and two common vectors when prices are in US dollars. The results from the Granger causality analysis of returns in all three currencies contradicts the prior results of MS (1990) and (1991). They emphasized that Sweden's stock market index leads Finland's. Instead of this relationship, this study finds that the Finnish stock market is in all cases led by the German market, as well as the UK market, when returns are measured in local currencies or in Finnish markkas. This contradiction may be due to the fact that the construction of the data differs in these two studies. End-of-month returns are used here for all the countries, whereas MS used somewhat mixed data. The number of relevant lags was also found to be considerably lower in this study.

We also find that the Swedish stock market is Granger caused by the UK market instead of the US market, as suggested in MMPP (1992). However, this contradiction may be due simply to data differences, since MMPP employed daily data from 1988–April 1990. The US stock market is always able to predict the German market. Somewhat surprisingly, the German stock market was also led by the Swedish stock market in all currencies. On the other hand, some evidence was found that the German index was able to predict the UK stock market.

The remainder of this paper is organized as follows. Section two discusses the methodologies employed and the next section describes the data. Empirical results are presented in section four, and section five concludes with the key findings of the paper.

2 Methodology

Time series used in econometric analysis (Granger causality tests here) should be stationary in order to apply standard inference techniques. Stock price series are typically non-stationary. Differencing the logarithmic levels once usually produces stationarity, and hence we conlude that the series have one unit root, ie they are first order integrated, I(1).[1] Thus, standard distributional results apply to the model estimates computed on differenced variables. The presence of unit roots gives rise to stochastic trends with innovations to an integrated process being permanent. On the other hand, Granger (1981) showed that even in the case that all the variables in a vector are stationary only after differencing, there may be linear combinations of those variables which are stationary without differencing, ie the variables may be cointegrated. Cointegration of a vector of variables implies that the number of unit roots in the system is less than the number of unit roots in the corresponding univariate series. This implies that the variables share at least one common (stochastic) trend.[2]

Engle and Granger (1987) first formalized cointegration theory and developed tests for evaluating the existence of equilibrium relationships between the variables. They also showed that a cointegrated system can be represented in an error-correction structure that incorporates both changes and levels of variables such that all the elements are stationary. The levels of variables contain long-term information, which is lost when differencing the data, except in the unlikely event that short-term effects are identical to long-term effects. Error-correction models (ECM) allow for testing the possibility of different short- and long-run dynamics. If a set of variables is cointegrated, the ECM term should be included when estimating a dynamic model. Otherwise, the model is not consistent with the data and relevant information is omitted.[3]

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[1] We should keep in mind the argument of Christiano and Eichenbaum (1990) that it is often extremely difficult to separate trend and difference stationarity from each other. If a variable is trend stationary, innovations to it have no effect on long-run forecasts of it.

[2] Unit roots and Cointegration are described in detail eg in Engle and Yoo (1987), Stock and Watson (1988) and Dolado, Jenkinson and Sosvilla-Rivero (1990).

[3] For a review of cointegration, see Engle and Granger (1987), Johansen and Juselius (1990).

2.1 Granger Causality

A number of causality tests have been proposed and applied in the literature. A review of these tests is given in Geweke, Meese and Dent (1983). The tests for causality performed here essentially employ the regression technique of Granger (1969). A time series {Yt} is said to Granger cause another time series {Xt} if the present X is better predicted using the past values of Y and other relevant information, including the past values of X, than is the case without the past values of Y. The null hypothesis is that there is no causality. The alternative is that {Yt} Granger causes {Xt}. This is tested by means of an F-test of the joint significance of the retained regressors, ie the lagged values of {Yt}.

2.2 Johansen Cointegration

In case of cointegrated variables, the equilibrium error should be included as an additional regressor in the causality tests of stationary variables. Most cointegration tests are carried out using the Engle–Granger (1987) two-step procedure, which may employ either a static linear regression approach or a dynamic linear model procedure. Johansen (1988) presents an autoregressive formulation of the multivariate error-correction model.[4] The multivariate cointegration approach of Johansen allows for the analysis of hypothetical long-run relations and short-term dynamics simultaneously, using a maximum likelihood estimation procedure. This approach relaxes the assumption that the cointegrating vector is unique and takes into account the error structure of the underlying process. It also allows for several tests regarding the cointegrating vectors and for tests of weak exogeneity among the variables. The multivariate model is developed further in Johansen and Juselius (1990) and Johansen (1991). The basic p-dimensional vector autoregressive model with Gaussian errors is

$$X_t = A_1 X_{t-1} + \ldots + A_k X_{t-k} + \mu + \psi D_t + \varepsilon_t, \qquad t = 1,\ldots,T, \qquad (1)$$

[4] Juselius (1990) reviews the differences between these methodologies.

where X_t is a px1 vector of stochastic variables, $X_{-k+1},...,X_0$ are fixed, k is the number of lags, $\varepsilon_1,...,\varepsilon_T$ are i.i.d. $N_p(0,\Sigma)$ and D_t are centred seasonal dummies. It is convenient to rewrite equation 1 in error correction form as

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-k-1} + \Pi X_{t-k} + \mu + \psi D_t + \varepsilon_t, \qquad t=1,...,T \quad (2)$$

where Δ is the difference operator and

$$\Gamma_i = -(I - A_1 - ... - A_i), \qquad i=1,...,k-1$$

$$\Pi = -(I - A_1 - ... - A_k).$$

Now all the long-run information is contained in the levels component ΠX_{t-k}. The hypothesis of cointegration is based on the determination of the rank of the Π-matrix:[5]

$$H_1(r):\ \Pi = \alpha\beta', \qquad (3)$$

where α and β are p x r matrices. The parameters in β are the cointegration vectors and in α the adjustment vectors. Under certain conditions (see Johansen, 1989), the relations $\beta' X_t$ can be interpreted as the stationary relations between nonstationary variables, ie as cointegration relations. In this case, equation (2) can be interpreted as an error-correction model (see eg Engle and Granger (1987) or Johansen (1988)). If the rank of the matrix Π is zero, the model implies that no linear cointegration vectors exist. The model would be still consistent, but would be reduced to the standard VAR model in first differences. If the rank r of the matrix Π is greater than zero, the model would imply r linear cointegration vectors. The formulation of equations (2) and (3) allows us to test alternative hypotheses, such as weak exogeneity, ie causality, on the cointegration space. This is essential if more than one cointegration vector exists.[6]

[5] Details of the estimation procedure are given in Johansen and Juselius (1990).

[6] These tests are applied eg in Johansen and Juselius (1991).

2.3 Unit Roots

Standard Johansen methodology assumes that the variables analysed are first order integrated. The Granger causality tests assume stationary time series. Engle and Granger suggested seven alternative tests for determining the order of integration. We employ the augmented Dickey—Fuller (ADF) test to examine the stationarity of stock prices and returns. The ADF test is based on the following regression:

$$\Delta x_t = \alpha_0 + \phi x_{t-1} + \sum_{i=1}^{n} \beta_i \Delta x_{t-i} + \sum_{j=1}^{11} \gamma_j M_{jt} + \lambda t + e_t, \tag{4}$$

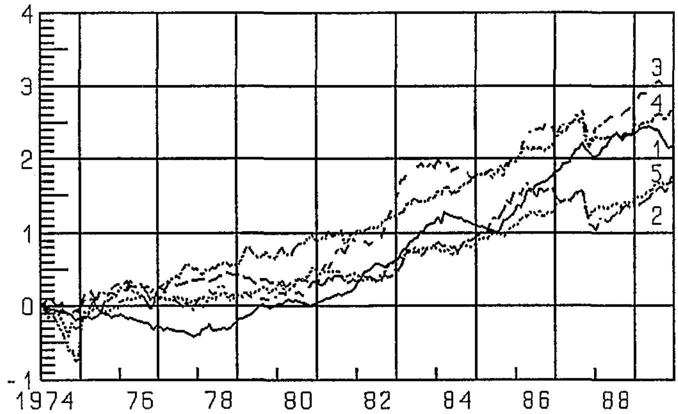
where Δ is the difference operator, M_{jt} are seasonal dummies, t is the trend and e_t is a stationary random error term. The null hypothesis is that x_t is non-stationary, ie that it has a unit root I(1). H_0 is rejected if ϕ is statistically significant. This would imply that the variable is I(0). Christiano and Eichenbaum (1990) state that in many cases it is difficult to provide compelling evidence that a variable is either difference or trend stationary. If a variable is trend stationary, innovations to it have no inpact on its own long-run forecasts. The difference stationarity I(1) would imply that stock prices are best characterized as a stochastic process (eg a random walk process) that does not revert to a deterministic trend path. This would imply that innovations to stock prices persist and contain relevant information on future stock prices.

3 Data

This paper examines interdependencies among the stock markets in the United States, the United Kingdom, Germany, Sweden and Finland. End-of-month stock market logarithmic price indices in local currencies, constructed by Morgan Stanley Capital International, are employed for all the countries except Finland. The MSCI index was not calculated for Finland until the late 1980s. For Finland, another similar index is used (see Berglund et al. (1983)). The log-of-price series for each country are illustrated in Figure 1. In the indices, prices are corrected for dividends, splits, stock dividends and new issues. The correction is based on the principle that all income from a stock is reinvested in that stock with no transaction cost. Stock market returns are measured as changes in logs of prices.

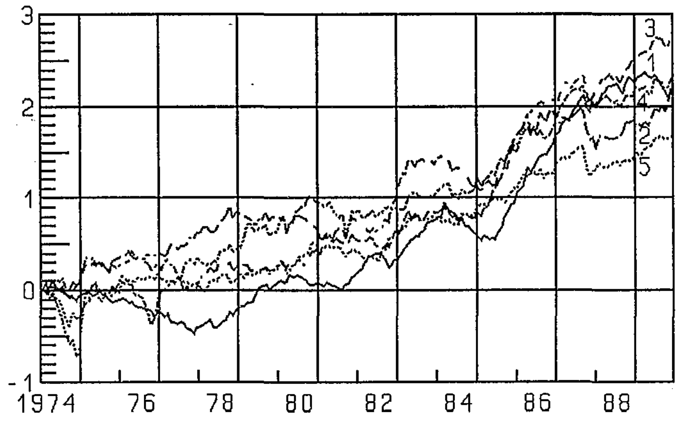
All the analyses are conducted using the indices in US dollars and Finnish markkas. Figures 2 and 3 present these indices. We take dollar and markka investors' points of view in analysing these indices. This implies that the foreign exchange risk is not hedged. Furthermore, the hypothetical impact of inflation is eliminated here by repeating the analysis with indices reduced by the corresponding short-term money market rates (see Appendix 1 for these index values). End-of-month foreign exchange rates were collected from the Bank of Finland's archives. The corresponding one-month Euromarket deposit rates were taken from the DRI and Nomura databanks. The one-month interest rate was not available for the 1970s on the Finnish markka. Therefore, end-of-month data on three-month currency forward prices, currency spot rates and US dollar interest rates were used to compute the corresponding one-month return on the three-month Eurorate for the markka. This interest rate series is introduced in Malkamäki (1992).

Figure 1. **Logarithmic stock market indices, local currencies**



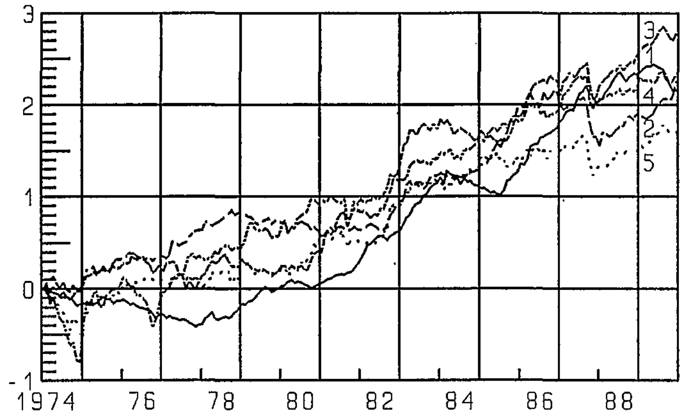
1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Figure 2. **Logarithmic stock market indices, US dollars**



1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Figure 3. **Logarithmic stock market indices, Finnish markkas**



1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Table 1 presents summary statistics for monthly stock market returns in local currencies, US dollars and Finnish markkas. We see from the table that the distributional properties of returns are almost the same regardless of currency denomination. The returns are somewhat skewed to the right in Finland and the UK and to the left in the other countries. Excess kurtosis is present especially in the German, UK and US returns. The Finnish stock market returns were found to be strongly autocorrelated, although the fourth order autocorrelation coefficient was already close to zero. The lower part of the table contains the cross-correlation matrices. The UK and US returns correlate most highly with each other. The Finnish returns correlate least with the returns from the other markets.

Table 1. **Summary statistics for nominal stock market returns (per cent/100 per month), 1974:1–1989:12 (192 observations)**

Return	Symbol	Mean	St. dev.	Skew.	Ex. Kurt.	ρ_1	ρ_2	ρ_3
Local currencies								
Finland	FIN	0.011	0.039	0.160	0.776	0.276	0.282	0.208
Germany	GER	0.009	0.051	−0.694	4.130	0.098	−0.023	0.072
Sweden	SWE	0.016	0.060	−0.164	1.241	0.165	0.024	0.104
UK	UK	0.014	0.072	0.337	7.632	0.079	−0.096	0.086
US	US	0.009	0.048	−0.563	3.633	0.034	−0.064	0.005
US dollars								
FIN	–	0.011	0.046	0.433	0.811	0.186	0.243	0.231
GER	–	0.012	0.061	−0.169	0.984	0.019	0.078	0.081
SWE	–	0.014	0.064	−0.124	0.147	0.059	0.009	0.104
UK	–	0.012	0.080	0.529	4.595	0.070	−0.065	0.061
US	–	0.009	0.048	−0.563	3.633	0.034	−0.064	0.005
Finnish markkas								
FIN	–	0.011	0.039	0.160	0.776	0.276	0.282	0.208
GER	–	0.121	0.055	−0.354	2.174	0.084	−0.006	0.089
SWE	–	0.148	0.063	−0.362	1.215	0.110	0.023	0.072
UK	–	0.012	0.077	0.278	5.434	0.106	−0.104	0.076
US	–	0.009	0.056	−0.453	4.173	0.023	−0.005	−0.005

Correlation matrix, returns in local currencies

Variable	FIN	GER	SWE	UK	US
FIN	1.000				
GER	0.139	1.000			
SWE	0.318	0.325	1.000		
UK	0.102	0.384	0.390	1.000	
US	0.135	0.401	0.419	0.584	1.000

Correlation matrix, returns in US dollars

Variable	FIN	GER	SWE	UK	US
FIN	1.000				
GER	0.313	1.000			
SWE	0.374	0.385	1.000		
UK	0.223	0.403	0.415	1.000	
US	0.109	0.341	0.402	0.515	1.000

Correlation matrix, returns in Finnish markkas

Variable	FIN	GER	SWE	UK	US
FIN	1.000				
GER	0.108	1.000			
SWE	0.296	0.313	1.000		
UK	0.098	0.329	0.377	1.000	
US	0.152	0.342	0.445	0.501	1.000

4 Empirical Results

4.1 Unit Root Tests

Both the cointegration and Granger causality tests assume that the order of integration of variables is known. The standard Johansen methodology, applied here, assumes that the variables are first-order integrated. The Granger causality tests assume stationary time series. The augmented Dickey–Fuller (ADF) test reviewed in subsection 2.3 is performed here to examine the stationarity of stock prices and returns in local currencies. Two lags were found to suffice (n=2). The critical values for the t-test are tabulated in Fuller (1976).

Table 2. **Augmented Dickey–Fuller Unit Root tests for stock market indices in local currencies**

Variable	FIN	GER	SWE	UK	USA
Δx_t = first difference Regression coefficient					
ϕ (ADF-test)	−2.36	−1.66	−1.88	-4.32^c	−2.94
Order of integration	I(1)	I(1)	I(1)	I(0)/I(1)	I(1)
γ_j (t-test for seasonals)	$-2.22\ M_9$ $2.56\ M_{12}$	$-2.17\ M_5$	$-2.13\ M_8$ $2.02\ M_{12}$	$2.20\ M_1$ $4.39\ M_{12}$	$2.92\ M_{12}$
λ (t-test for trend)	2.70	1.78	2.25	4.38	3.17
Δx_t = second difference Regression coefficient					
ϕ (ADF-test)	-5.01^c	-6.72^c	-6.51^c	-7.38^c	-7.89^c
Order of	I(0)	I(0)	I(0)	I(0)	I(0)
γ_j (t-test for seasonals)	$-2.02\ M_8$ $-2.45\ M_9$ $-2.01\ M_{10}$	$-2.15\ M_5$	$-1.92\ M_5$ $-2.15\ M_8$	$2.24\ M_1$	–
λ (t-test for trend)	−1.36	0.58	1.32	0.21	1.22

Augmented Dickey–Fuller model, see equation 4.
Reported t-values are heteroscedastic consistent.
$^{a-c}$ correspond to significance levels of 10 % (−3.15), 5 % (−3.45), and 1 % (−3.73) respectively. The critical values (in parentheses) are tabulated in Fuller (1976).

The outcome of the analysis is presented in Table 2. The results indicate that the stock price series (except for UK) are non-stationary. According to the ADF test, the UK prices are quite clearly trend-stationary, which is seen also in Figure 1. However, a closer analysis revealed that the ADF test value for ϕ is very sensitive to the first few observations of the UK prices and the test value is not significant even at the 10 % level, as the 12 first observations are excluded. This suggests that the UK prices are also first-order integrated. Further statistics, provided in table 4.5 and 8, also support this view.[7] Differencing the levels once produces stationarity in all cases. We conclude, therefore, that all the price series have one unit root, ie they are first order integrated, I(1). Thus, the standard distributional results apply to the model estimates.

4.2 A Standard VAR Model

A standard vector autoregression model is fit to the data before testing for cointegration. This is done in order to compare our results with those in MS (1990) and (1991). According to the Akaike and Schwartz information criteria, only one or two lags, respectively, are needed in the VAR models for stock market returns.

The results given in Table 3 indicate that the Finnish index is Granger caused by its own and the German lags. We do not find clear causality from Sweden to Finland. This contradicts the prior results of MS (1990) and (1991). They emphasized that the Swedish stock index leads the Finnish index by one month. The results may differ due to the fact that the quality of the data here is better than that in MS and/or that three indices which are likely to explain index returns in Sweden as well as in Finland are included here. These alternatives were examined further and it turned out that the Swedish stock market causes the Finnish market if the other markets are excluded. But if any of the three other indices is included, the Swedish market loses its ability to lead. Furthermore, the Swedish market is not able to lead the Finnish market even when the other markets are excluded for the period 1974—1985, which was tested in MS. This indicates that the primary reason for the contradiction is the better quality of data here. However, the inclusion of Germany altered the results most when the whole data sample was used.

[7] See section 2.3 for a closer discussion of the extremely strong implications that would apply if the UK prices were trend-stationary.

Table 3. **VAR estimation for stock market returns in local currencies, 1974—1989**

Significance of lags 1 and 2

	Constant	Lag 1 FIN	Lag 1 GER	Lag 1 SWE	Lag 1 UK	Lag 1 USA	Lag 2 FIN	Lag 2 GER	Lag 2 SWE	Lag 2 UK	Lag 2 USA
FIN	0.005	0.160	0.083	0.106	0.017	-0.064	0.232	-0.142	0.011	0.064	0.014
(t)	(1.72)	(2.13)	(1.34)	(1.99)	(0.35)	(0.89)	(3.12)	(2.36)	(0.21)	(1.35)	(0.19)
GER	0.009	0.014	0.056	0.166	-0.080	0.161	-0.265	-0.027	0.027	0.121	-0.137
(t)	(2.19)	(0.14)	(0.67)	(2.30)	(1.25)	(1.66)	(2.64)	(0.33)	(0.37)	(1.89)	(1.38)
SWE	0.012	0.026	0.052	0.115	-0.080	0.238	0.054	0.026	-0.009	0.020	-0.128
(t)	(2.53)	(0.21)	(0.51)	(1.30)	(1.02)	(1.98)	(0.43)	(0.26)	(0.10)	(0.26)	(1.05)
UK	0.015	0.140	0.030	-0.038	0.083	0.024	-0.129	0.220	-0.113	-0.141	0.019
(t)	(2.75)	(0.95)	(0.25)	(0.36)	(0.90)	(0.17)	(0.89)	(1.87)	(1.08)	(1.52)	(0.13)
USA	0.010	0.020	-0.054	0.094	0.035	-0.008	-0.094	0.138	-0.095	0.007	-0.086
(t)	(2.48)	(0.19)	(0.65)	(1.31)	(0.56)	(0.08)	(0.94)	(1.71)	(1.32)	(0.12)	(0.88)

Marginal significance of retained regressors by nation

Variable	FIN[a]	GER[a]	SWE[a]	UK[a]	USA[a]
FIN	0.000	0.028	0.135	0.365	0.649
GER	0.030	0.761	0.067	0.096	0.080
SWE	0.868	0.849	0.431	0.587	0.068
UK	0.497	0.171	0.515	0.235	0.978
USA	0.641	0.195	0.189	0.845	0.681

[a] Marginal significance of F-test (P(F-test)) for retained regressors by nation.

The Swedish stock market is led by the US stock market if a marginal risk of 6.8 % is accepted. The German stock returns are affected by lags of all the markets included here except its own. The leading ability of Finnish returns is surprising, and it is hard to find an economic explanation for it. The UK and US stock markets are not Granger caused by any markets.

The corresponding analysis with the excess returns in local currencies was performed with almost identical results (see Appendix 2A). This implies that inflation differentials do not play a significant role in the tests. Appendices 2B and 2C present the results from the VAR estimation on nominal returns in US dollars and Finnish markkas. One can see from Appendix 1B that the behavior of the US dollar in the period studied has significant effects on the tests. The US stock market clearly leads the German and Swedish markets here. The German market has lead capability for the UK market. The Finnish stock market is now affected only by its own lags. It is somewhat puzzling that the Finnish market still has some impact on the German market. However, these results indicate that the strong appreciation and subsequent depreciation of the US dollar had a marked impact on economic expectations in the other markets. This implies that expectations regarding the value of the US dollar contain information that is relevant to investors in the determination of stock prices. The corresponding analysis of the returns in Finnish markkas indicates that markka markets contain less relevant information for stock market investors.

4.3 Cointegration and Causality Tests

4.3.1 Indices in Local Currencies

The empirical analysis begins with model (2) and the reduced rank hypothesis (3). Model (2) is estimated assuming that there are linear trends in the data. The motivation for the assumption is straightforward, based on Figures 1—3 and Table 2. The presence of linear trends in the model implies that no restrictions are imposed on the constant term, which alters the rank inference as shown in Johansen and Juselius (1990). The common trends will show up in the estimation of the constant term but not in the cointegration relations. However, it was found that an explicit linear trend in the cointegration relations alters the results considerably and that the trend term produces high t-values. This indicates that there is some linear growth in the data which the model is unable to account for.[8] Therefore, model (2) was reformulated as:[9]

[8] Johansen and Juselius (1991) provide more detailed discussion regarding restrictions on the constant term and linear trends.

[9] Seasonals are added later on.

$$\Delta X_t = \Gamma_1 X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-k-1} + \Pi X_{t-k} + \mu + \lambda t + \varepsilon_t, \qquad t=1,...,T, \qquad (5)$$

where t is the trend.

The number of cointegration vectors is considered in Table 4. The hypothesis $r \leq 1$ is not rejected according to maximal eigenvalue and trace tests in the 90 percent quantile. This indicates that there is at most one cointegration relation in the data. Our test procedures provide mixed results regarding the hypothesis r=0. The trace test rejects the hypothesis, whereas the maximal eigenvalue test does not. Johansen and Juselius (1991) got similar results and state that the ambiguity of the tests is due to their low power in cases where the cointegration relation is close to the nonstationary boundary. In such a case, it is reasonable to accept the existence of the cointegration relation.[10]

Table 4. **Maximal eigenvalue and trace tests for the cointegration rank, k=3[a]**

H(r)	Eigenvalue λ_i	ME[b] test $-T\ln(1-\lambda_i)$	Crit. value[c] $\lambda_{max}(.90)$	Trace test $-T\Sigma\ln(1-\lambda_i)$	Crit. value[c] $\lambda_{trace}(.90)$
$r \leq 4$	.023	4.388	6.691	4.388	6.691
$r \leq 3$	.035	6.800	12.783	11.188	15.583
$r \leq 2$	.043	8.315	18.959	19.502	28.436
$r \leq 1$	.103	20.551	24.917	40.053	45.248
$r = 0$	.137	27.811	30.818	67.864	65.956

[a] Number of lags in the VAR.
[b] Maximal eigenvalue.
[c] Critical values are tabulated in Johansen and Juselius (1990:208), Table A2.

[10] See also Johansen and Juselius (1990) 183—192.

The coefficient estimates of the cointegration vectors α and β are found in Table 5. The cointegration vector β can be interpreted as an error-correction mechanism. The excess price effect is derived through the estimated long-term equilibrium relation (standardized for Finland) and given by

$$FIN = 2.51*GER + .558*SWE - 6.024*UK - .724*USA.$$

The corresponding α coefficients indicate the average speed of adjustment towards the estimated long-term equilibrium state. The α coefficients indicate that the eigenvector is least important for Finnish stock prices and most important for UK stock prices. Finnish prices may be slow to adjust, for example, due to restrictions on capital flows during the period studied or to high adjustment costs and other short-run effects which tend to lengthen the time during which the prices deviate from the equilibrium path. Such effects could be present in Finland, for example, because of the strong business cycles due to both the central role of the forest industry in the economy and the deregulation of financial markets.

Table 5. **Stationary cointegration vector and its weights (eigenvalue .137)**

	Beta	Alfa
FIN	1.000	–.007
GER	–2.510	–.019
SWE	–.558	–.015
UK	6.024	–.040
USA	.724	–.018

The maximum likelihood estimates for model (5) are presented in Table 6. All the coefficients and statistics are now based on the assumption of one cointegration relation. In comparing the short-term dynamics with those of Table 3, we notice that all the markets except the Swedish market Granger cause the Finnish market at lag 1, Germany and the United Kingdom having the strongest influence. According to Table 3, the German market was the only one that led the Finnish market.[11] The German market is influenced at lag one by the US and German markets and at lag two by the Swedish market. The puzzling causality from Finland to Germany is now absent from the short-term dynamics.[12]

The long-term relations are shown in the middle of the Table 6. The Π matrix ($\Pi = \alpha\beta'$ for $H_1(1)$) implied by model (5) is provided with its standard deviations. The lower part of the table gives the estimated coefficients for the constant and trend terms. Both coefficients have significant t-values in all regressions except for that of the Finnish returns.

[11] We estimated model (6) also by adding monthly-centered seasonals. They did not generally produce high t-values. The German stock market turned out to be the only one to have a statistically significant t-value (2.9 at lag one) in the VAR model for Finnish returns. The US stock market lost its leading ability for Swedish returns. The univariate residual statistics wei :omewhat better for Finland but worse for Sweden. The short-term dynamics are presented in Appendix 3. Detailed results are available from the author on request.

[12] The corresponding analysis of the stock indices in the excess short-term money market rate gave results very similar to those in Table 6.

Table 6. **Maximum likelihood estimates for the restricted model based on one cointegration vector (r=1), local currencies**

Short-term relations (Γ_1 and Γ_2 matrices and t-values for the estimates)

	Lag 1					Lag 2				
	FIN	GER	SWE	UK	USA	FIN	GER	SWE	UK	USA
FIN	.156	.222	.066	–.163	.105	.012	.034	.086	–.069	.011
(t)	(2.0)	(2.9)	(1.0)	(2.6)	(2.0)	(.2)	(.7)	(1.8)	(.9)	(.1)
GER	.021	–.264	.005	–.085	.164	.030	–.037	.175	.160	–.134
(t)	(.2)	(2.6)	(.1)	(1.0)	(2.3)	(.4)	(.6)	(2.7)	(1.7)	(1.4)
SWE	.022	.040	.016	–.018	.113	–.007	–.045	.065	.230	–.132
(t)	(.2)	(.3)	(.2)	(.2)	(1.3)	(.1)	(.6)	(.8)	(1.9)	(1.1)
UK	.171	–.102	–.081	.094	–.038	–.107	.171	–.032	.033	.037
(t)	(1.2)	(.7)	(.7)	(.8)	(.4)	(1.1)	(1.9)	(.4)	(.2)	(.3)
USA	.021	–.102	–.101	.082	.092	–.093	.078	.061	–.013	–.087
(t)	(.2)	(1.0)	(1.2)	(1.0)	(1.3)	(1.3)	(1.2)	(.9)	(.1)	(.9)

Long-term relations (PI-matrix and its standard deviations)

FIN	–.007	.018	.004	–.044	–.005
(σ)	.004	.010	.002	.025	.003
GER	–.019	.048	.011	–.114	–.014
(σ)	.006	.014	.003	.033	.004
SWE	–.015	.037	.008	–.089	–.011
(σ)	.007	.017	.004	.042	.005
UK	–.040	.100	.022	–.239	–.029
(σ)	.008	.019	.004	.047	.006
USA	–.018	.046	.010	–.111	–.013
(σ)	.005	.014	.003	.033	.004

Coefficients for the constant and trend

Constant	.149	.395	.307	.831	.380
(t)	(1.6)	(3.3)	(2.0)	(5.0)	(3.2)
Trend	.001	.002	.001	.003	.002
(t)	(1.8)	(3.4)	(2.2)	(4.9)	(3.4)

Table 7. **Misspecification tests for the model**

Autocovariance/correlation matrix of the residuals

.001195				
.110115	.002101			
.306551	.270815	.003277		
.121483	.391312	.397623	.004092	
.147598	.375645	.409087	.551412	.002055

Univariate analysis of the residuals (Box–Pierce Q, ARCH, skewness, excess kurtosis and Jarque-Bera tests)

B–P.Q(47)/44	ARCH(3)	SKEW.	EX.KURT.	J–B.NORM.
.929	8.168	–.072	1.525	18.485
1.067	5.911	–.639	2.400	58.189
.622	9.773	–.094	.620	3.311
1.034	25.649	–.254	3.822	117.075
.731	1.698	–.594	2.747	70.533

Autocorrelation; 2*(1/SQRT(T)) = .14548, lag 1–8

–.017	–.037	.059	–.009	.037	–.071	.116	.030
–.011	.001	.038	–.105	–.075	–.067	–.051	.061
.006	–.023	.095	.081	–.000	–.003	–.021	–.129
.032	–.086	.117	–.011	–.177	–.065	–.029	–.116
–.005	–.026	.006	–.053	.112	–.054	–.079	–.067

Table 7 gives some misspecification statistics for the estimated model. The results are quite satisfactory. The residuals are not autocorrelated and the ARCH effect is clearly observed only in equation 4 (UK). There is excess kurtosis and slight skewness to the left, especially in equations 2, 4 and 5, and the Jarque-Bera test indicates that the residuals for these equations are clearly not normally distributed.[13] This violates the validity of the t-values to some extent in these equations. The non-normality of the residuals in equations 2, 4 and 5 is not surprising, recalling that the purpose of including the German, UK and US stock returns was to explain return behavior in Finland and Sweden, not vice versa. Actually, the statistics indicate that additional lags or variables would be needed to model non-Nordic stock returns. However, the t-values for the parameter estimates in the

[13] The Box–Pierce Q-statistic is distributed as $\chi^2(47)/44$, ARCH test as $\chi^2(3)$ and Jarque-Bera test statistics for normality $\chi^2(2)$.

equations for Finland (1) and Sweden (3) are realiable. This enables as to make inferences concerning these markets, which are our main concern.

Table 8. **Test for some known parameters in the cointegration vector beta**

	Beta
FIN	.0
GER	1.0
SWE	.0
UK	–1.0
USA	–1.0

Some restriction tests performed for the beta vector are presented in Table 5. The Finnish and Swedish stock markets were restricted to have no impact on the cointegration relation, and the other stock markets to have a coefficient of 1 or –1 (see Table 8). We were not able to reject the null hypothesis. The probability of erroneous rejection of the null hypothesis was as high as .58. This implies that the Finnish and Swedish stock markets may deviate from the equilibrium path without having a statistically significant impact on the other three markets. The reverse does not necessarily hold.[14] The short-term dynamics conditional on the restricted beta vector were almost identical to those presented in Table 6.

[14] The German, UK and/or US stock markets are likely to be weakly exogenous in the cointegration relation, implying that the direction of causality is from these countries to Finland and Sweden. Examples of these tests are provided in Johansen and Juselius (1991). We do not test for weak exogeneity since we assume that all stock indices are dependent variables and thus include them all also in the analysis of short-term effects. However, these tests are a topic for further research.

4.3.2 Indices in US Dollars

We repeated the above analysis on the stock market indices transformed into US dollars. Table 9 gives the results. The maximal eigenvalue and trace tests for cointegration rank imply that the indices share two cointegration vectors. One can argue that the second cointegration vector appeared as a result of the transformation of the indices and thus reflects the impact of fluctuations on the value of the US dollar. The second cointegration vector seems to have the greatest impact on Finnish, Swedish and US stock prices. The speed of adjustment towards the equilibrium is fastest in the US and Finland. The relatively high speed of adjustment in Finnish stock prices is reasonable if the second cointegration vector reflects the common impact of changes in the value of the US dollar, since the US dollar is the dominant currency in Finnish foreign trade. In Swedish foreign trade the Swedish krona (SEK) is dominant. Therefore, one would not expect the Swedish stock market to have a large alfa coefficient for the cointegration vector 2.

The results here are slightly different from those of Kasa (1992). He did not find a single cointegration vector in monthly real stock market indices. However, he included the stock markets of Japan and Canada, instead of Finland and Sweden in his study and reported his results for two lags in the model specification instead of three, as employed here. Kasa analysed mainly higher order VAR models including 10–15 lags (10 lags in quarterly models). The misspecification tests performed here on the alternative models with monthly data indicated that three lags already produces some signs of overparameterization in the residual sum of squares.

The short-run dynamics of returns in US dollars are slightly different from those found in the previous section. The Finnish stock market is now led only by the German market at lag 1. The German market is caused by the US market at lags 1 and 2 and by the Swedish market at lag 2. The UK stock market has a clear leading ability at lag 2 for the Swedish market. Somewhat surprisingly, the t-value for the German stock market to Granger cause the US market at lag 1 is as high as 1.9. The corresponding t-value is 2.2 when the corresponding analysis is carried out with excess indices, which indicates that the German stock market actually is able to lead the US market, at least in this data set.

Table 9. **Maximum likelihood estimates for the restricted model based on two cointegration vectors (r=2), indices in USD**

Eigenvalues	.159	.119	.060	.038	.007
Maximal eigen-value test	32.688	23.848	11.599	7.234	1.404
Trace test	76.773	44.086	20.237	8.638	1.404

The two stationary cointegration vectors and their weights[a]

Beta 1	1.000	1.572	−1.576	−3.957	.495
Alfa 1	.008	.041	.017	.066	.021
Beta 2	1.000	−.831	−1.866	−.873	4.025
Alfa 2	−.025	.006	.003	−.010	−.038

Short-term relations (Γ_1 and Γ_2 matrices and t-values for the estimates)[a]

	Lag 1					Lag 2				
	FIN	GER	SWE	UK	USA	FIN	GER	SWE	UK	USA
FINUSD	.044	.194	.053	−.053	.077	.011	−.043	.043	.018	−.001
(t)	(.5)	(2.3)	(.8)	(.8)	(1.2)	(.2)	(.2)	(.8)	(.2)	(.0)
GERUSD	−.141	−.208	−.069	.031	.249	.131	−.081	.152	.147	−.250
(t)	(1.3)	(1.9)	(.8)	(.4)	(2.9)	(1.6)	(1.2)	(2.2)	(1.3)	(2.2)
SWEUSD	−.007	.022	.030	.051	.043	.024	−.093	.018	.283	−.192
(t)	(.1)	(.2)	(.3)	(.5)	(.5)	(.3)	(1.2)	(.2)	(2.3)	(1.6)
UKUSD	.066	.008	−.136	.165	.048	−.020	.152	−.031	.032	−.041
(t)	(.5)	(.1)	(1.2)	(1.5)	(.4)	(.2)	(1.7)	(1.7)	(.2)	(.3)
USAUSD	−.028	−.166	−.081	.097	.096	−.045	.023	.026	.048	−.075
(t)	(.3)	(1.9)	(1.1)	(1.4)	(1.4)	(.7)	(.4)	(.5)	(.5)	(.8)

Univariate analysis of the residuals (Box–Pierce Q, ARCH, skewness, excess kurtosis and Jarque-Bera tests)

B–P.Q(47)/44	ARCH(3)	SKEW.	EX.KURT.	J–B.NORM.
.838	3.472	.186	.757	5.597
.815	5.032	−.270	1.009	10.310
.901	.777	−.154	−.081	.798
.880	23.717	−.087	2.195	38.168
.704	.873	−.621	2.895	78.152

[a] Restricted matrices based on 2 cointegration vectors.

Univariate misspecification analysis shows that the residuals are more normally distributed in the US dollar data than in local currency data. The non-normality found here is due mainly to excess kurtosis. However, one should keep in mind that inferences concerning the non-Nordic countries are based on the t-values, which may be biased to some extent.

4.3.3 Indices in Finnish Markkas

The above analysis was repeated with the data converted into Finnish markkas (see Table 10). From Table 10 it is clear that the results are very similar to those with returns in local currencies. Again, there is only one cointegration vector among the stock market indices, although the speed of adjustment towards the equilibrium is now somewhat slower. The short-run dynamics are also very similar to those reported in subsection 4.3.1. The lead capabilities of the UK stock market for the Finnish market, the US market for the German market and the German market for the UK market are now somewhat stronger. The UK stock market returns are no longer able to predict the Swedish returns. However, analysis with the indices in excess Finnish short-term money market rates indicates that the Swedish stock market is led by the UK market. The similarity of the empirical results with indices in local currences and in Finnish markkas indicates that the Finnish currency market contains almost no information of relevance to international stock market investors, which is intuitively realistic.

Table 10. **Maximum likelihood estimates for the restricted model based on one cointegration vector (r=1), indices in FIM**

Eigenvalues	.153	.084	.064	.037	.022
Maximal eigen-value test	31.393	16.585	12.520	7.134	4.151
Trace test	71.782	40.389	23.805	11.285	4.151

The stationary cointegration vector and its weight[a]

BETA	1.000	.831	−2.624	−6.200	4.077
ALFA	−.003	.020	.009	.041	.003

Short-term relations (Γ_1 and Γ_2 matrices and t-values for the estimates)[a]

	Lag 1					Lag 2				
	FIN	GER	SWE	UK	USA	FIN	GER	SWE	UK	USA
FINFIM	.142	.206	.091	−.102	.108	.012	.028	.060	−.116	−.030
(t)	(1.8)	(2.7)	(1.6)	(1.8)	(2.0)	(.2)	(.6)	(1.4)	(1.9)	(.5)
GERFIM	.011	−.276	.008	−.045	.239	.097	−.031	.133	.065	−.176
(t)	(.1)	(2.5)	(.1)	(.6)	(3.1)	(1.3)	(.5)	(2.1)	(.8)	(2.0)
SWEFIM	.078	.048	.067	−.018	.053	.025	−.024	.014	.158	−.105
(t)	(.6)	(.4)	(.7)	(.2)	(.6)	(.3)	(.3)	(.2)	(1.5)	(1.0)
UKFIM	.260	.003	−.046	.111	.063	−.054	.236	−.005	−.142	−.086
(t)	(1.7)	(.0)	(.4)	(1.0)	(.6)	(.5)	(2.7)	(.1)	(1.2)	(.7)
USAFIM	.070	−.118	−.035	.042	.118	−.049	.092	.024	−.091	−.015
(t)	(.6)	(1.0)	(.4)	(.5)	(1.4)	(.6)	(1.4)	(.3)	(1.0)	(.2)

Univariate analysis of the residuals (Box−Pierce Q, ARCH, skewness, excess kurtosis and Jarque-Bera tests)

B−P.Q(47)/44	ARCH(3)	SKEW.	EX.KURT.	J−B.NORM.
.914	6.999	−.123	1.371	15.274
.984	6.378	−.514	1.731	31.924
.786	6.578	−.302	.752	7.334
.997	13.245	−.360	3.512	101.183
.758	1.127	−.588	4.747	188.327

[a]Restricted matrices based on 1 cointegration vector.

5 Conclusions

This paper examines interdependencies among the stock markets in the United States, the United Kingdom, Germany, Sweden and Finland, testing for cointegration and order of integration. The former three nations are the biggest trading partners of the two small open Nordic economies, Finland and Sweden. First, the unrestricted VAR model for each country is considered in order to carry out the traditional Granger causality tests. The VAR models are also employed under the assumption of multivariate cointegration, first introduced in Johansen (1988), in order to analyze the hypothetical long-run relations and short-term dynamics simultaneously, thus using all the information contained in the data. In this approach, the short-term causalities are analysed conditional on the long-term relations. The data consist of end-of-month observations over 1974—1989. All the tests are performed on the variables denominated in (a) local currencies, (b) US dollars and (c) Finnish markkas, in both nominal and excess return form.

The multivariate cointegration analysis suggests that the stock markets examined here are cointegrated, having one cointegration vector when prices are measured in local currencies or in Finnish markkas and two cointegration vectors when prices are in US dollars. This implies that these stock markets have a long-run steady-state relationship and cannot drift too far from the equilibrium path. On the other hand, it was found that the Finnish and Swedish stock markets may deviate from the equilibrium path without having a significant impact on the other three markets, which indicates that the direction of causality is from the other stock markets to Finland and Sweden. The order of cointegration implies that there are several common stochastic trends driving national stock market prices. We suggest that the economic forces behind a trend could be, for instance, expectations regarding the future state of the world economy and the value of the US dollar.

The results of Granger causality tests indicate that the US and UK stock markets are fully integrated. This implies that risk-adjusted stock returns are equal in these countries in the numeraire currency. However, the Finnish, German and Swedish stock market returns could be predicted with the US and UK returns. More specifically, the Finnish stock market was Granger caused by the German and UK stock markets, the Swedish stock market by the UK market and the German stock market by the US market. This implies that Finnish, Swedish and German stock markets are not fully integrated with the bigger stock markets included in the study. The leading ability of the German and UK markets for the Finnish market is not surprising since these nations are among the biggest trading partners of Finland. The United States and United Kindom are also among the biggest trading partners of Sweden and Germany.

It seems that stock returns in smaller markets do not adjust instantaneously to new information. However, this does not necessarily indicate market inefficiency, since abnormally high returns are not necessarily earned. The low degree of integration of the Finnish and Swedish stock markets may be due to significant restrictions on portfolio investments of foreign investors in the period studied. Furthermore, the market capitalization of these markets, as well as of the German stock market, has been relatively small and trading relatively modest most of the time, which generally implies non-synchronous trading.

The results of Granger causality tests contradict the prior understanding that the Swedish stock market index leads the Finnish market (see pg. 119 above). This contradiction is due to the more efficient estimation technique used here and to the inclusion of the stock market indices of Germany, the United Kingdom and the United States, which are likely to explain index returns in Sweden as well as in Finland. However, the improved quality and homogeneity of data turned out to be the most apparent reason for the contradiction. The end-of-month returns are used here for all the countries, whereas somewhat mixed data was used in the earlier studies. The number of relevant lags was also found to be considerably smaller in this study. It was further found that the Swedish stock market is Granger caused by the UK market instead of the US market, as suggested earlier. This contradiction may be due simply to the data differences, as earlier results were obtained with daily data for 1988—April 1990.

This study could be extended, for instance, by analysing whether the low rate of integration found here could be used in trading to earn abnormally high returns on stock market index futures. One might also expect that the causal relations found here could be found in the Asian stock markets as well.

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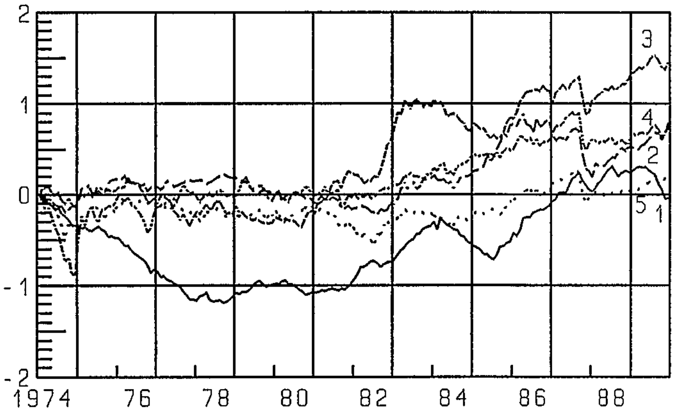
Appendix 1

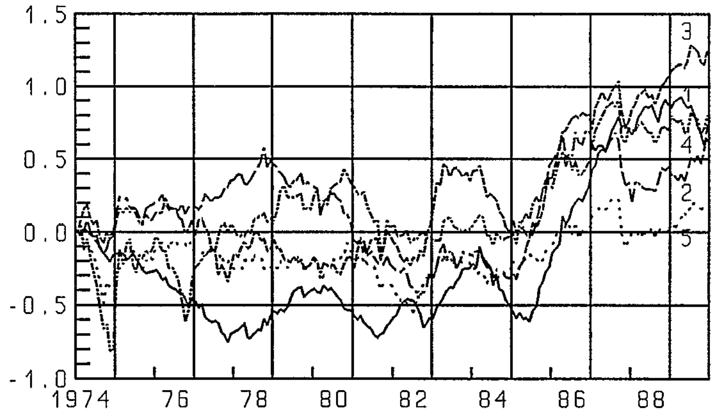
Logarithmic stock market indices in excess short-term money market rate, alternative currencies

Figure 1. **Indices in excess local money market rates, local currencies**



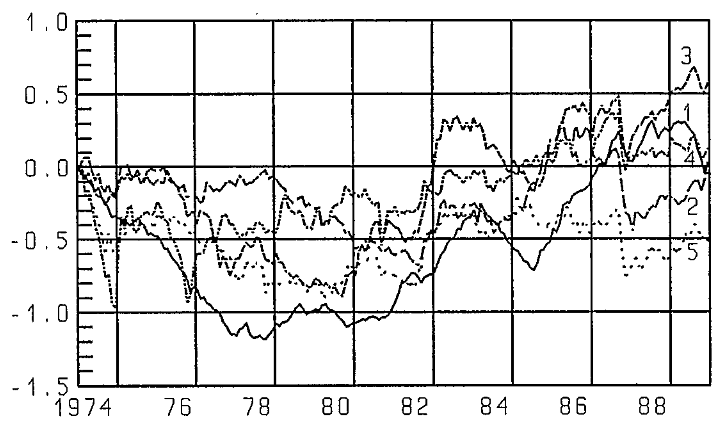
1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Figure 2. **Indices in excess US money market rate, US dollars**



1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Figure 3. **Indices in excess Finnish money market rate, Finnish markkas**



1 Finland
2 Germany
3 Sweden
4 United Kingdom
5 United States

Appendix 2A

VAR estimation for excess stock returns in local currencies, 1974–1989

Variable	FIN[a]	GER[a]	SWE[a]	UK[a]	USA[a]
FINE	0.000	0.032	0.150	0.359	0.700
GERE	0.045	0.758	0.106	0.091	0.074
SWEE	0.739	0.872	0.487	0.579	0.069
UKE	0.539	0.167	0.443	0.253	0.966
USAE	0.688	0.185	0.184	0.840	0.751

[a] Marginal significance of F-test (P(F-test)) for retained regressors by nation.

Appendix 2B

VAR estimation for stock market returns in US dollars, 1974–1989

Variable	FIN[a]	GER[a]	SWE[a]	UK[a]	USA[a]
FIN	0.004	0.461	0.428	0.601	0.970
GER	0.069	0.247	0.171	0.066	0.020
SWE	0.885	0.486	0.990	0.236	0.008
UK	0.798	0.010	0.326	0.350	0.872
USA	0.491	0.113	0.236	0.876	0.518

[a] Marginal significance of F-test (P(F-test)) for retained regressors by nation.

Appendix 2C

VAR estimation for stock market returns in Finnish markkas, 1974–1989

Variable[a]	FIN[a]	GER[a]	SWE[a]	UK[a]	USA[a]
FIN	0.000	0.055	0.226	0.473	0.684
GER	0.009	0.883	0.042	0.260	0.173
SWE	0.727	0.779	0.915	0.662	0.035
UK	0.385	0.210	0.251	0.118	0.862
USA	0.591	0.144	0.272	0.905	0.540

[a] Marginal significance of F-test (P(F-test)) for retained regressors by nation.

Appendix 3

Short-run dynamics when 11 seasonal dummies are added to the model, k=3, local currencies

	Lag 1					Lag 2				
	FIN	GER	SWE	UK	USA	FIN	GER	SWE	UK	USA
FIN	.142	.230	.077	–.113	.101	.017	.036	.057	–.076	–.009
(t)	(1.8)	(2.9)	(1.2)	(1.8)	(1.8)	(.3)	(.7)	(1.1)	(1.0)	(.1)
GER	–.017	–.273	.012	–.083	.183	.015	–.032	.158	.151	–.115
(t)	(.2)	(2.6)	(.1)	(.9)	(2.4)	(.2)	(.5)	(2.3)	(1.5)	(1.1)
SWE	–.064	.083	.047	.078	.122	–.008	–.084	.024	.209	–.156
(t)	(.5)	(.6)	(.4)	(.7)	(1.3)	(.1)	(1.0)	(.3)	(1.7)	(1.3)
UK	–.014	–.086	–.066	.166	–.086	–.133	.119	–.086	.107	.038
(t)	(.1)	(.6)	(.6)	(1.4)	(.9)	(1.3)	(1.3)	(.9)	(.8)	(.3)
USA	–.035	–.114	–.118	.075	.082	–.079	.095	.038	.016	–.076
(t)	(.3)	(1.1)	(1.4)	(.9)	(1.1)	(1.1)	(1.4)	(.6)	(.2)	(.8)

ESSAY 4

Markku Malkamäki

Conditional Risk and Predictability of Finnish Stock Returns

Abstract

This paper studies the driving forces of predictable variation in Finnish stock returns. The dynamics of Ferson and Harvey's (1991) methodology are extended and applied within the Sharpe–Lintner CAPM. We find that market risk is conditionally priced in the thin Finnish stock market. Most of the predictable variation of stock returns is attributed to the time-varying risk premium, which supports the hypothesis of rational behavior by Finnish investors in setting stock prices. However, the conditional residual term accounted for a larger part of the predictable variation of the stock returns than is found in the US market.

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1 Introduction

The predictability of stock returns has been documented in several recent studies. Keim and Stambaugh (1986) reported this phenomenom first for US returns, and they were followed by Campbell (1987), Fama and French (1988), Poterba and Summers (1988) and others. Virtanen and Yli-Olli (1987) were the first to find return predictability in the Finnish stock market. Similar results were reported later, eg in Knif and Högholm (1991) and Malkamäki (1992c). There are two major explanations for this predictability. Either the market is inefficient or the required rate of return is changing over time. Both explanations have been supported by empirical evidence. If the asset pricing models provide a reasonable description of the expected returns of assets, then the predictable variation in the expected returns should be driven by variation in (1) risk exposures, ie the betas, (2) the price of beta, ie the risk premiums, and/or (3) the riskless rate of return.

Ferson and Harvey (FH) (1991) specify a list of risk factors similar to Chen, Ross and Roll (1986). However, FH focus on predictable variation in expected asset returns in order to analyse the relative importance of the above explanations (1) and (2) for predictability of US monthly portfolio returns. FH suggest that if the rational expectations hypothesis is true, then the expected returns implied by an asset pricing model should mimick the expected returns generated by the type of regression analysis that they employ in the study. If this holds, the predictable variation in the model's returns is driven by predictable variation in the betas, the price of betas or a combination of the two, ie if the predictable variation in the model's expected returns closely matches the predictable variation from the regression analysis in forecasting stock returns, then the rational expectations view is supported.

FH (1991) found that most of the predictability (some 81 %) is driven by changes in the expected betas and expected price of betas. They called what is left over "the part due to market inefficiency". This part was generally small (some 10 %). They also found that the primary source of predictability was the time variation in the expected risk premiums — not the betas. Interestingly, the market risk was only weakly priced on average, yet it was extremely important in accounting for variation in the predicted returns in the US stock portfolios.

Recent conditional tests of the Sharpe–Lintner CAPM with Finnish data suggest that market risk is rewarded in the Finnish stock market if the betas are allowed to vary through time according to a mean-reverting AR1 process (see Berglund and Knif (1992) and Malkamäki (1992a) and (1992b)). This provides motivation to replicate the study of FH (1991) to find out to what extent the Kalman filtered, conditional firm-specific betas and conditional market risk premium are able to explain the return predictability in the Finnish stock Market.

This paper aims to extend FH (1991) in four ways. Firstly, we replicate the FH (1991) study with greater dynamics in the parameter estimation for the CAPM, as the betas are allowed to vary through time according to a mean-reverting AR1 process. Secondly, we employ firm-specific betas and thus, in this sense, allow far more idiosyncratic variation in the betas. Thirdly, empirical analysis on the source of the predictable variation in the expected returns is carried out for a thin security market, ie the Finnish stock market. Moreover, the data employed here include the highly volatile years around the 1987 stock market crisis. Finally, we use stock returns in excess of the short-term money market rate (used for the first time in Malkamäki (1992c)) in analysing the predictability of Finnish returns.

This paper finds that most of the predictable variation is due to the time-varying risk parameters of the CAPM. Actually, almost none of the predictability was attributed to the betas. However, the conditional residual term mimics fairly well the predictable variation, suggesting that the inefficiency factor in the sense of FH (1991) is considerably larger for the Finnish stock market than for the US market. Our findings concerning the risk premium are very similar to those of FH, ie that the risk premium is conditionally time varying and that the conditional risk premium is the primarly source of predictability. Expectation concerning changes in the future order stock for Finnish industry and unexpected changes in inflation are found to capture the variation in the risk premium; and the unexpected changes in inflation, in combination with an instrument for the lagged influence of Finnish, German, Swedish, UK and US stock market returns on the Finnish market, are found to predict firm-specific excess returns fairly well.

The remainder of the paper is organized as follows. Section two discusses the methodologies employed. Section three describes the stock market data and conditioning variables. Empirical results are presented in the next section, and section five concludes with the key findings of the paper.

2 Methodologies

2.1 Conditional Market Risk

The CAPM states that expected returns on an asset are linearly related to the systematic risk, which is measured by the asset's beta. The Sharpe–Lintner version of the model in excess-return form is:

$$E(r_i) = \beta_i E(r_m), \tag{1}$$

where $E(r_i)$ = expected excess return for security i

$\beta_i = \dfrac{\mathrm{cov}(r_i, r_m)}{\mathrm{var}(r_m)}$

$E(r_m)$ = expected excess return for the market.

Actually, the CAPM is not testable, as stated in Roll (1977), because the true market portfolio is not observable. Therefore, the CAPM, as applied in empirical work, is just a statement about the mean-variance efficiency of a given market portfolio. Thus, in our empirical analysis, we test whether the observed stock market portfolio is mean-variance efficient. The test is then a joint test of whether the given market portfolio is mean-variance efficient and whether the market is information efficient.

Unfortunately, the true beta coefficient, β_i, implied by the CAPM cannot be observed. It is usually estimated, under the assumption of constant market risk, by computing iteratively an OLS regression over Sharpe's well-known time series (TSR) market model. However, we relax the assumtion of constant market risk and estimate the market model (2) by applying the dynamic Kalman filter estimation procedure, which accounts for time variation in the betas. The market model is now rewritten in state space form as

$$r_{it} = X_t' \theta_t + \varepsilon_t, \tag{2}$$

where $X_t' = [1, r_{mt}]$
$\theta_t' = [\alpha_{it}, \beta_{it}]$
ε_t = a random error with variance v_t.

The parameter vector θ_t is assumed to vary according to the stationary first order autoregressive (AR1) model (see also Knif (1989) and Malkamäki (1992a,b))

$$\theta_t - \bar{\theta} = F(\theta_{t-1} - \bar{\theta}) + u_t, \tag{3}$$

where $\bar{\theta}$ = mean vector of the parameters
F = weights for the AR1 and mean parameters
u_t = random error with covariance matrix M_t.

The state space representation of the market model is now

$$\begin{aligned} r_{it} &= \begin{bmatrix} X'_t & X'_t \end{bmatrix} \begin{bmatrix} \bar{\theta}_t \\ \theta_t - \bar{\theta}_t \end{bmatrix} + \varepsilon_t \\ &= B'_t \gamma_t + \varepsilon_t \end{aligned} \tag{4}$$

and the parameter vector

$$\begin{aligned} \gamma_t &= \begin{bmatrix} \bar{\theta}_t \\ \theta_t - \bar{\theta}_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & F \end{bmatrix} \begin{bmatrix} \bar{\theta}_{t-1} \\ \theta_{t-1} - \bar{\theta}_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ u_t \end{bmatrix} \\ &= A\gamma_{t-1} + e_t, \end{aligned} \tag{5}$$

where $\underline{F}$ = $\underline{d}$iag $[\omega_1, \omega_2]$
$\bar{\theta}_1 = \bar{\theta}_{t-1}$ for all t
e_t = random error with covariance matrix N_t

The random errors ε_t and e_t are independent of each other. The corresponding variance v_t and covariance matrix N_t are estimated. The maximum likelyhood (ML) method is employed to estimate minimum mean square values for γ_{t-1} and its covariance matrix Σ_{t-1}. The estimates for the Σ_t and γ_t, given r_{it} and X_t, are updated at each time t by means of the Kalman filter updating equations (see eg Harvey (1989) or Malkamäki (1992a)).

The Kalman filter technique used here is actually a three-step procedure.[1] First, a maximum likelihood solution for the parameter vector is found by means of the above forward recursive Kalman equations, which use past and current information. Next, the information from the whole sample period is used to find another set of ML estimators by applying the backward recursions of the Kalman smoother. As a final step, the AR(1) model is employed to estimate the forecasted beta series.

The forecasted betas are used later in Fama and MacBeth (1973)-type cross-sectional (CSR) analyses of the price of risk and in conditional tests of predictability. In the first phase, the following second-pass CSR is estimated for each month:

$$r_{it} = \lambda_{0t} + \lambda_{1t}\hat{\beta}_{it-1} + e_{it}, \tag{6}$$

where r_{it} = expected excess return implied by the CAPM on asset i for period (month) t

λ_{0t} = intercept term (= 0 according to the CAPM),

λ_{1t} = risk premium at time t

$\hat{\beta}_{it-1}$ = beta coefficient estimated for the previous period

e_{it} = random error term.

The final Fama–MacBeth estimates for the intercept and risk premium are the sample means from the time series of these coefficients. In the univariate test of the CAPM, the estimates for the intercept and average risk premium are the sample means from the time series of these coefficients. The computation of the standard errors is based on the assumption that the time series of cross-sectional estimates are independent and distributed identically with the means of the final

[1] For details on the maximization algorithms, see Goodrich (1989).

estimates. However, we know that the independence assumption is not strictly satisfied due to the use of estimated betas instead of true betas as the explanatory variable. An errors-in-variables (EIV) problem is introduced in the second-pass regression, since the betas are subject to measurement error (for a review of EIV problems, see eg Shanken (1991) and for thin markets, Malkamäki (1992a). The EIV problem is reduced at least to some extent in the case of the mean-reverting AR1 model, since forecasted betas are used as the independent variable in the second-pass regressions. This procedure reduces the EIV problem assuming that the changing residual variance of the market model is dependent on the time variation of beta.[2]

2.2 Predictable Variation of Stock Returns

Conditional Risk Premium

The monthly risk premiums from the CSR are regressed on the instrumental varibles in order to see whether the variation in premiums can be explained by the instruments. If the risk premiums are constant over time, then the regression of these coefficients on the information variables should not be significant. The model is

$$\lambda_{1t} = \delta_0 + \delta_1 Z_{1,t-1} + \delta_2 Z_{2,t-1} + \delta_3 Z_{3,t-1} + \varepsilon_{jt}, \tag{7}$$

where λ_t represents the estimated risk premium associated with the market risk and Z_{t-1} represents an instrumental variable with a lag structure (not necessarily t–1).

[2] The critisism regarding the standard deviations of the univariate tests could be avoided at least to some extent by eg computing just one regression over pooled return and beta series, as in Malkamäki (1992a) or using a weighted least squares approach, as eg in Berglund and Knif (1992). Since our primary interest is in the source of predictability, we proceed to test it.

Decomposition of the Predictable Variation

The CSR provides the following decomposition of the driving forces of predictable variation in stock returns:

$$r_{it} = \{\beta_{i,t-1}\lambda_{1t}\} + \{\lambda_{0t} + \varepsilon_{it}\}.^{3} \tag{8}$$

The first term is related to the cross-sectional structure and price of the conditional market risk. The second term ($\lambda_{0t} + \varepsilon_{it}$) is not related to systematic risk and should be unpredictable, assuming that the CAPM is the correct model and the pricing of stocks is rational in the sense of Ferson and Harvey (1991).[4]

Two variance ratios can be formed. The first one (VR1) is the ratio of the variance of the model's conditionally predicted returns to the variance of expected returns from a linear regression on the set of instruments (Z). That is

$$VR1 = \frac{Var\,[E(\beta_{i,t-1}\lambda_{1t}|Z)]}{Var\,[E(r_{it}|Z)]}, \tag{9}$$

where the expected values are obtained by regressing on the information variables. The second variance ratio (VR2) is the ratio of the variance of the conditional part of a return that is not explained by the model to the variance of the conditionally expected return. Thus

$$VR2 = \frac{Var\,[E(r_{it} - \beta_{i,t-1}\lambda_{1t}|Z)]}{Var\,[E(r_{it}|Z)]}. \tag{10}$$

If most of the predictable variation in returns is due to the changing structure of the risk parameters, then VR1 should be close to one and VR2 close to zero.

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[3] The conditional variance decomposition is:
$Var\{r_{it}|Z\} = Var\{\beta_{i,t-1}\lambda_{1t}|Z\} + Var\{\lambda_{ot} + \varepsilon_{it}|Z\} + Cov\{(\beta_{i,t-1}\lambda_{1t}, \lambda_{ot} + \varepsilon_{it})|Z\}.$

[4] Ferson and Harvey provides a discussion of cases where predictability may enter via the λ_{0t} term also.

Risk Premium vs. Risk Sensitivity

A further decomposition of variance ratios reveals whether time-varying expected risk premium or time-varying risk sensitivities drive the predictable variation in stock returns. The variance is decomposed as:

$$\mathrm{Var}\,[E(\lambda\beta)\,|Z] = [E(\beta)]^2\mathrm{Var}\,[E(\lambda\,|Z)] + [E(\lambda)]^2\mathrm{Var}\,[E(\beta\,|Z)] + \text{interaction term,} \tag{11}$$

where $E(\lambda)$ and $E(\beta)$ are the unconditional means of estimated parameters and $E[\lambda|Z)$ and $E(\beta|Z)$ are linear projections on the λ and β on the instruments. The interaction term arise because of covariance between the time-varying risk premiums and betas.

3 The Data

This study uses end-of-month stock returns in excess of the short-term interest rate on all 25 restricted[5] ordinary stocks listed on the Helsinki Stock Exchange (HSE) throughout the period 1972–1989 (see Table 1). Returns are measured as logarithmic changes in the indices. The HSE market index, which is used here, is value weighted (see Berglund–Wahlroos–Grandell (1983)). In the index, prices are corrected for cash dividends, splits, stock dividends and new issues. The correction is based on the principle that all income from a stock is reinvested in that stock with no transaction cost. No portfolios are formed for the analysis, as is usually done in US studies. This is because of the extremely limited number of actively traded stocks. The excess returns are computed by using the one-month return entailed in the three-month Eurorate on the Finnish markka. This interest rate series is introduced in Malkamäki (1992a). The whole period is used to estimate the betas. Predictability analyses are carried out on data beginning with 1977, as in Malkamäki (1992a and 1992b).

[5] Only domestic investors are allowed to buy restricted stocks. An observation at an end-of-month day when there was no transaction in a stock is the last bid price for that day.

Table 1. **Stocks included in the analysis: all restricted ordinary shares listed throughout the period 1972–1989**

Stock	Designation
Bank of Åland Ltd K	AB
Effoa-Finland Steamsip Co Ltd K	EFFO
Enso-Gutzeit Ltd A	ENSOA
Fiskars Corporation	FISKK
Huhtamäki Corporation K	HUHTK
Instrumentarium Corporation	INSTA
Kemi Corporation	KEMI
Kesko Corporation	KESK
KANSALLIS-OSAKE-PANKKI	KOP
Kymmene Corporation	KYMI
Lassila & Tikanoja Ltd	LASS
Lohja Corporation A	LOHJA
Nokia Corporation	NOKIK
Otava Publishing Company Ltd	OTAVK
Partek Corporation	PART
Rauma-Repola Corporation	RAUM
Finnish Sugar Co Ltd I	SOKEI
Stockman A	STOCA
Suomen Trikoo Corp. A	TRIK
Union Bank of Finland Ltd A	SYPA
Tamfelt Group K	TAMF
Tampella Ltd	TAMP
Talous-Osakekauppa Co	TAOK
Wärtsilä Co I	WARTI
United Paper Mills Ltd K	YHTYK

Table 2. **Summary statistics for the excess returns (per cent per month) for 1972:2–1989:12 (215 observations)**

Asset	Mean	St.dev.	Skewness	Kurtosis
	Excess Returns			
AB	0.746	10.683	1.332	16.702
EFFO	0.423	8.204	0.348	1.448
ENSOA	-0.234	7.922	0.645	3.114
FISKK	1.292	7.252	0.296	1.959
HUHTK	0.782	6.610	1.056	2.655
INSTA	1.156	7.118	0.607	3.206
KEMI	-0.360	10.646	-0.694	4.457
KESK	0.658	5.147	1.060	2.481
KOP	0.104	6.644	0.751	4.821
KYMI	-0.002	6.410	0.597	1.908
LASS	1.298	9.240	1.336	7.143
LOHJA	0.930	7.333	0.141	0.295
NOKIK	-0.009	6.910	0.159	0.684
OTAVK	1.234	9.496	1.773	10.212
PART	0.522	6.594	0.242	0.555
RAUM	0.034	6.741	1.042	2.112
SOKEI	0.694	8.094	0.762	2.001
STOCA	0.895	6.645	0.521	2.684
SYPA	0.433	6.083	1.230	4.425
TAMF	0.717	9.835	-0.486	6.468
TAMP	0.051	7.788	1.276	5.215
TAOK	1.866	9.520	-0.031	1.863
TRIK	0.136	11.697	0.255	6.330
WARTI	0.613	7.480	0.764	1.155
YHTYK	0.707	7.459	0.380	0.934
VWI[a]	0.254	4.230	0.265	0.976

[a] The stock market index return.

Summary statistics for monthly excess returns for 25 firms and for the HSE market index are shown in Table 2. The statistics indicate that the return distributions are somewhat skewed to the right and leptokurtic, as is usual (see eg Taylor (1986)).

We use three information variables, which are usually called instruments in the literature. These varibles are assumed to describe the information that investors use to set prices in the stock market (see Table 3). The instruments are FSM, an instrument for the influence of lagged excess returns on the stock markets in Finland, Germany, Sweden, the United Kingdom and the United States, UNEXINF, change in unexpected inflation, and BARIP, expected change in order stock for Finnish industry.[6] FSM is based on Malkamäki (1992c). He applied Johansen's (1988) multidimensional vector autoregressive (VAR) technique, which accounts also for the multivariate cointegration of stock market indices in the above countries and found that the Finnish stock market is clearly Granger caused by these countries' market returns with Germany having the strongest foreign impact. FSM is the fit of the VAR model for the Finnish stock market. The second instrument, UNEXINF, is the difference between actual and forecasted inflation. The forecast is obtained from an ARIMA (1,0,1)(0,0,2) model for percentage changes in the seasonally unadjusted consumer price index.[7] The third instrument, BARIP, is an estimate of the aggregated future cash-flow expectations of firms. BARIP is the percentage change in negative answers regarding expected change in order stock for Finnish industry in the quarterly questionaire of the Confederation of the Finnish Industries. The monthly series is interpolated from the quarterly series.

Table 3. **Instrumental variables**

Instrument	Definition
FSM	An instrument for influence of lagged stock market returns in Finland, Germany, Sweden, UK and US.
UNEXINF	Change in unexpected inflation.
BARIP	Expected change in future order stock for Finnish industry.

[6] We also tried most of the instruments that are commonly employed in US studies (see also next paragraph). However, these variables did not show any forecasting power for excess stock returns or risk premium.

[7] The model is stable according to the F-test at the 5 % level of significance.

Summary satistics for the instruments are given in Table 4. Only FSM is somewhat skewed and leptokurtic. The lower part of the table shows that cross-correlation of the insrumental variables is not a matter of concern. However, one should keep in mind that all the instruments are generated variables. Pagan (1984) discusses econometric issues concerning generated variables and shows that their use may lead to biased estimates in OLS regressions. On the other hand, the market-based instrumental variables most commonly used in US studies were tested here as conditioning instruments before turning to the generated variables, but no significant relations were found. The variables studied include change in the difference between long- and short-term interest rates, change in the difference between medium and short-term interest rates, nominal and real three month Euromarket returns for the Finnish markka, a bond return index, nominal inflation and real per capita growth of personal consumption (seasonally adjusted). From preliminary analysis of the above instruments, we concluded that the information that is relevant to Finnish investors in setting stock prices differs from that which is relevant in the US market.

Table 4. **Summary statistics for the instrumental variables, 1972:2–1989:12**

Instrument	Mean	Std. dev.	Skew.	Ex. Kurt.
FSM	–.032	.021	–.834	3.396
UNEXINF	.005	.006	.069	–.227
BARIP	–4.300	10.230	–.348	–.043

Correlation matrix

Instrument	FSM	UNEXINF	BARIP
FSM	1.000		
UNEXINF	.176	1.000	
BARIP	–.085	–.044	1.000

4 Empirical Results

4.1 Unconditional vs Conditional Price of Risk

Cross-sectional regressions of the excess returns on the conditional betas are performed for each month. The model estimated is that of equation (6). The slope coefficient for the betas is the monthly risk premium. The results from these regressions are reported in Table 5. The upper part of the table gives the results from the unconditional analysis of the price of beta risk. These results are taken from Malkamäki (1992b). The table shows that the unconditional price of risk is not significant for the period 1977:2—1989:12, and furthermore, the sign of the coefficient is negative. The t-ratios reported in parenthesis are calculated as in Fama—MacBeth (1973). The hypothesis tested, as in numerous other studies, is that the mean premium equals zero. However, as stated in FH (1991), a premium may be the most significant premium even if it has zero mean. This is possible if the premium is changing through time or there is a sudden structural change in the return-generating process for a particular period, as reported in Booth et al. (1991) or there are several structural changes, as found in Malkamäki (1992a). In such a case, our tests of the significance of average risk premium would be weak.

We test the conditional pricing of market risk by regressing the ex post risk premiums from the monthly cross-sectional regressions on the instrumental variables in order to detect the predictable variation in the premium. If the conditional ex post risk premium is constant, the regression should not detect a significant relation. The outcome of this test is given in the lower part of Table 5. We see that some of the observed variability of the ex post risk premium can be explained by the instruments. The coefficient of determination, 8.7 %, is reasonable in light of the results of FH. Note also that the period studied here includes two extraordinary periods for the Finnish economy, which are found to have a dominating role in unconditional tests of the CAPM. These are the period of three devaluations, 1977:4–1978:2, and the year 1989, when the drastic slowdown of the Finnish economy started. Malkamäki (1992a and 1992b) shows that these periods have a strong impact on the risk-return relationship under the assumption of constant risk premium. The above analysis shows that the conditioning instruments are able to predict the behavior of the ex post premium also for these extraordinary periods.

Table 5. **Unconditional and conditional price of market risk 1977:2—1989:12 (155 observations)**

Unconditional model

λ_0	λ_1	R^2
0.011	−0.003	6.3
(1.85)	(−0.40)	

The model estimated is: $r_{it} = \lambda_{0t} + \lambda_{1t}\beta_{it-1} + e_{it}$, where β_{it-1} is actually a beta forecasted for the period t based on the mean-reverting AR1 model: $\beta_t = \omega\beta_{t-1} + (1-\omega)\bar{\beta}$.

Conditional model[a]

δ_0	δ_1	δ_2	δ_3	R^2	DW
0.051	0.161	−2.559	0.005	8.7	2.16
(1.28)	(0.78)	(−2.08)	(3.26)		

The model estimated is: $\lambda_{it} = \delta_0 + \delta_1 FSM(t) + \delta_2 UNEXINF(t-3) + \delta_3 BARIP(t-4) + u_t$. BARIP was second-order differenced in the regression (see text).

[a] Heteroscedasticity-consistent t-values in parenthesis, White (1980).

UNEXINF and BARIP turned out to have the greatest effect on the risk premium, BARIP having the strongest influence according to the t-statistics. BARIP had significant t-values and coefficients of same size but opposite sign at lags 4 and 5. It was, therefore, differenced a second time in order to increase the power of the regression analysis. It follows from the second-order differencing that the positive regression coefficient implies a decrease in the expected ex post risk premium as the percentage of negative answers regarding the future order stock for Finnish industry increases, which seems reasonable enough. The negative coefficient of the unexpected inflation at lag 3 implies that an unanticipated increase in inflation reduces the expected ex post premium associated with stock investments. This supports the view that unexpected inflation is bad news for Finnish stock investors. A lag structure of this size between economic variables and stock price reactions is also found in Virtanen and Yli-Olli (1987). A possible explanation for this is that macro-information is usually available with a lag of several months.

4.2 Decomposing the Predictable Variation

The cross-sectional regression provides a decomposition of the predictable variation in stock returns. The first term is related to the cross-sectional structure of risk. The second term is a residual that should be unpredictable (see equation (8)). The estimated λ's and β's are assumed to be unbiased estimates of the "true" parameter values. Therefore, we construct artificial data which satisfy the hypothesis that the model captures the predictable variation of the returns when conditioning on the instruments (Z) (see also FH (1991)). We compute mean-centred residuals mcu_{it} by subtracting the mean of $\lambda_{ot} + \varepsilon_{it}$ from $\lambda_{ot} + \varepsilon_{it}$ ($\lambda_{ot} + \varepsilon_{it} = r_{it} - \lambda_{1t}\beta_{i,t-1}$) and form the pseudo-returns (r_i) as the sum $mcu_{it} + \lambda_{1t}\beta_{i,t-1}$. Two variance ratios can be formed based on the above components. The first one, VR1, is the ratio of the variance of the model's predicted returns $E(\lambda\beta|Z)$ to the variance of expected (pseudo) returns (see equation (9)). The expected values are obtained from a linear regression on the instruments. The second variance ratio, VR2, is the ratio of the variance of the expected part of a return that is not explained by the model, ie the mean-centred residual, to the variance of the expected return (see equation (10)). This ratio is compared to VR1. If the first variance ratio is close to unity, then most of the predictable variation in returns is due to the changing structure of risk.

Ferson and Harvey (1991) found that some 81 % of the predictability in US returns was driven by changes in the expected betas and expected price of betas. Table 6 gives the corresponding analysis with Finnish stock data. The variance ratio VR1 has, in all cases except three, a bigger value than VR2, which indicates that the predictability of Finnish returns is driven mainly by the component that is related to the cross-sectional structure of risk and the cross-section of expected returns. We characterize this part of predictability as rational. The irrational source of predictability is driven by the variance of the expected error term in equation (10). This component, VR2, clearly has a smaller mean than VR1. We do not have a specific test for the significance of the variance ratios. However, the irrational component of the predictability seems to be bigger in Finland than in the US.

Table 6. **Decomposition of predictable variation of stock-specific returns, 1977:6—1989:12 (151 observations)**

Stock	VR1	VR2
AB	1.056	0.768
EFFO	1.342	0.438
ENSOA	1.361	0.475
FISKK	1.752	1.704
HUHTK	0.900	0.776
INSTA	4.434	3.384
KEMI	1.349	0.898
KESK	4.115	2.835
KOP	1.680	1.424
KYMI	1.307	0.553
LASS	1.077	1.392
LOHJA	2.652	0.512
NOKIK	1.301	0.428
OTAVK	0.913	1.270
PART	3.118	2.045
RAUM	6.884	2.960
SOKEI	1.314	0.859
STOCA	1.190	0.440
SYPA	2.399	1.346
TAMF	1.371	0.129
TAMP	1.110	0.908
TAOK	1.438	1.253
TRIK	1.406	1.449
WARTI	2.666	0.608
YHTYK	3.996	1.704
Mean	2.085	1.222

$$VR1 = \frac{\mathrm{Var}[E(\lambda\beta|Z)]}{\mathrm{Var}[E(r|Z)]}$$

$$VR2 = \frac{\mathrm{Var}[E(r-\lambda\beta|Z)]}{\mathrm{Var}[E(r|Z)]} = \frac{\mathrm{Var}[E(mcu|Z)]}{\mathrm{Var}[E(r|Z)]}$$

The variance ratios are often greater than one, which indicates that the covariance of the numerators in the variance ratios is negative. It should be noted that the conditioned return in the denominator is the firm-specific pseudo-return instead of the portfolio return used in Ferson and Harvey. This implies that we also condition an aggregate variable, ie the risk premium, in addition to the firm-specific betas in the numerator, whereas only the firm-specific returns are conditioned in the denominator. It is not surprising, given this background, that the conditional variance of the denominator is often smaller than that of the numerator.

A closer look at the conditioning regressions reveals that BARIP is the major source of negative covariation.[8] This is illustrated clearly by the t-values for BARIP on pseudo-returns (Appendix 1A) and mean-centred residuals (Appendix 1D), given that BARIP was the most significant forecasting instrument for the ex post risk premium. Appendix 1A shows that ENSOA, LOHJA, NOKIK, TAMF and WARTI are the only stocks whose returns BARIP is able to predict significantly. None of these firms has significant t-value on BARIP in Appendix 1D, and all of these firms have reasonable VR2 values in Table 6. This evidence suggests that the high VR2 values are due to the data construction method, where the negative covariance between the $\lambda\beta$s and mcus is introduced via the estimated λ term if returns on a stock are not predicted by BARIP.

All in all, the large variance ratios seem to be related to small sample problems, which at times introduce extra variability, via the λ term, to the artificial data used in the numerator of the variance ratios. However, the extra variance is approximately the same in both of the numerators and hence does not alter the relative order of size between the two.

Appendix 1A also shows further that the coefficients of determination for regressions of the pseudoreturns are reasonable enough. The interpretation of FSM is quite straightforward. It is the most significant predictor of firm-specific returns, having a significant t-value (at the 5 % level) in 14 regressions. Unexpected inflation turned up with a significant t-value in 11 regressions out of 25.

[8] See Appendix 1, which gives the results of the conditioning regressions.

4.3 Risk Premium vs Risk Sensitivity

The numerator of the first variance ratio, VR1, can be decomposed further to determine whether the time-varying expected risk premium or risk sensitivities are driving the predictable variation in the excess stock returns. In the third variance ratio, VR3, the variance of the conditional risk premium is multiplied by the square of the unconditional mean of the betas (see equation (11)). The interaction terms arise because of covariance between the time-varying risk premium and the betas. $E(\lambda)$ and $E(\beta)$ are the unconditional means – which are assumed to be constants. The constancy assumption is accurate at least with respect to the betas, according to Malkamäki (1992a), who found that the betas of the stocks analysed here follow a stationary AR1 process.

Table 7 shows us that some 61 % of the rational part of predictability is due to the predictable variation of the risk premium. No predictable variation is attributed to the conditional betas, according to VR4 in the table. This supports the findings of FH. They also pointed out that the variance of expected risk premium is on the order of the variance of expected stock returns, and the betas are on the order of 1.0. Furthermore, Malkamäki (1992a) found that the mean-reverting AR1 betas employed here are in most cases constant. Thus, it is not surprising that the predictable variation of Finnish stock returns is attributed to the time-varying risk premium.

Table 7. **Decomposition of predictable variation between betas and the price of the betas, 1977:6–1989:12 (151 observations)**

Stock	**VR3**	**VR4**	**Inter-action effects**
AB	61.092	0.0000	38.908
EFFO	61.104	0.0000	38.896
ENSOA	61.350	0.0000	38.650
FISKK	61.252	0.0000	38.748
HUHTK	60.561	0.0000	39.439
INSTA	61.121	0.0000	38.879
KEMI	59.516	0.0000	40.484
KESK	61.664	0.0000	38.336
KOP	61.103	0.0000	38.897
KYMI	60.598	0.0000	39.402
LASS	59.436	0.0000	40.564
LOHJA	61.056	0.0000	38.944
NOKIK	61.417	0.0000	38.583
OTAVK	59.072	0.0002	40.928
PART	61.084	0.0000	38.916
RAUM	61.312	0.0000	38.688
SOKEI	61.438	0.0000	38.562
STOCA	61.135	0.0000	38.865
SYPA	60.683	0.0000	39.317
TAMF	58.387	0.0000	41.613
TAMP	60.863	0.0000	39.137
TAOK	61.139	0.0000	38.861
TRIK	64.004	0.0004	35.996
WARTI	61.094	0.0000	38.906
YHTYK	61.022	0.0000	38.978
Mean	60.900	0.000	39.100

$$VR3 = \frac{[E(\beta)]^2 Var[E(\lambda|Z)]}{Var[E(\lambda\beta|Z)]} \times 100$$

$$VR4 = \frac{[E(\lambda)]^2 Var[E(\beta|Z)]}{Var[E(\lambda\beta|Z)]} \times 100$$

5 Conclusions

This paper studies the driving forces of predictable variation in Finnish stock returns. We apply a modified version of the research design of Ferson and Harvey (1991) in order to divide the driving forces of predictabity into rational and irrational parts. However, the analysis is conducted within the Sharpe–Lintner CAPM instead of using the multifactor approach of FH. The rational expectations view is supported in the analysis if the predictable variation of excess stock returns is driven by predictable variation in the betas, the price of the betas or a combination of the two. We allow for greater dynamics in the beta estimation than FH, since the betas are allowed to vary over time according to a mean-reverting AR1 process. We also use firm-specific returns instead of portfolio returns as in FH.

We find that market risk is conditionally priced on the thin Finnish stock market. Finnish investors were found to use change in unexpected inflation, expected change in future order stock for Finnish industry and an instrument for the influence of lagged excess returns on stock markets in Finland, Germany, Sweden, the United Kingdom and the United States, in setting prices in the stock market. The interest-based variables that have been found to be relevant information to US investors did not succeed as conditioning variables in this analysis. Most of the predictable variation in the stock returns is attributed to the time-varying risk premium, which supports the rational behavior of Finnish investors in setting the prices in the market. However, the conditional residual term accounted for a greater part of the predictable variation of the stock returns than that which was found by Ferson and Harvey. The bigger "irrational" part of predictability may be partly due to the data employed, as we used firm-specific returns instead of portfolio returns. Another reason could be that the CAPM is not an adequate model. A conditional multifactor replication of this study could provide further information concerning the pricing of Finnish stocks.

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Appendix 1A

Pseudo-returns (r_{it}) conditioned on the instruments* 1977:2—1989:12 (155 observations)

r_{it}	Constant	FSM(t)	UNEXINF(t–3)	BARIP(t–4)	R^2	DW
AB	0.030	0.789	–1.328	0.001	3.3	2.47
	(1.79)	(1.96)	(–0.93)	(0.76)		
EFFO	0.028	0.675	–1.631	0.002	5.1	1.71
	(1.97)	(2.00)	(–1.36)	(1.59)		
ENSOA	0.028	0.751	–1.072	0.003	8.0	1.96
	(2.20)	(2.51)	(–1.01)	(2.44)		
FISKK	0.026	0.672	–1.274	0.000	4.1	1.92
	(2.11)	(2.26)	(–1.21)	(0.01)		
HUHTK	0.022	0.581	–0.858	0.001	3.7	1.76
	(1.90)	(2.12)	(–0.88)	(0.78)		
INSTA	0.010	0.399	0.325	0.001	2.4	2.15
	(0.90)	(1.48)	(0.34)	(1.09)		
KEMI	0.010	–0.151	–3.391	0.001	3.3	2.19
	(0.55)	(–0.34)	(–2.16)	(0.34)		
KESK	0.013	0.286	–1.089	0.000	2.8	1.47
	(1.59)	(1.44)	(–1.54)	(0.13)		
KOP	0.032	0.614	–3.014	–0.000	10.8	2.42
	(3.18)	(2.54)	(–3.51)	(–0.26)		
KYMI	0.032	0.652	–2.663	0.002	11.2	1.75
	(3.25)	(2.77)	(–3.18)	(1.47)		
LASS	0.021	0.276	–2.812	–0.001	3.6	1.97
	(1.37)	(0.75)	(–2.16)	(–0.61)		
LOHJA	0.020	0.384	–2.019	0.003	7.2	2.19
	(1.77)	(1.42)	(–2.10)	(2.38)		
NOKIK	0.036	0.773	–2.634	0.002	11.1	1.88
	(3.11)	(2.85)	(–2.73)	(2.02)		
OTAVK	0.022	0.282	–2.958	–0.001	5.0	2.31
	(1.60)	(0.87)	(–2.57)	(–0.71)		
PART	0.026	0.579	–1.864	0.000	6.2	2.05
	(2.51)	(2.36)	(–2.14)	(0.40)		
RAUM	0.004	–0.028	–1.225	0.001	2.3	1.99
	(0.33)	(–0.11)	(–1.37)	(1.27)		
SOKEI	0.034	0.868	–1.531	0.002	6.5	1.86
	(2.55)	(2.77)	(–1.38)	(1.08)		
STOCA	0.029	0.531	–2.828	0.002	9.2	1.89
	(2.70)	(2.08)	(–3.11)	(1.38)		
SYPA	0.027	0.596	–1.990	0.001	8.7	1.90
	(2.97)	(2.76)	(–2.60)	(0.85)		
TAMF	0.022	0.457	–1.523	0.004	6.5	1.81
	(1.69)	(1.49)	(–1.39)	(2.54)		
TAMP	0.039	0.894	–2.395	0.001	8.4	1.85
	(3.07)	(3.00)	(–2.26)	(0.49)		
TAOK	0.017	0.461	–0.533	0.001	1.1	2.20
	(1.03)	(1.21)	(–0.39)	(0.30)		
TRIK	0.036	1.046	–0.868	0.000	2.9	2.38
	(1.69)	(2.05)	(–0.48)	(0.08)		
WARTI	0.016	0.373	–1.072	0.003	4.4	1.99
	(1.27)	(1.28)	(–1.04)	(2.09)		
YHTYK	0.021	0.484	–1.533	0.002	4.1	2.06
	(1.76)	(1.69)	(–1.51)	(1.24)		

* The model estimated: $r_{it} = \gamma_o + \gamma_1 FSM(t) + \gamma_2 UNEXINF(t\text{-}3) + \gamma_3 BARIP(t\text{-}4) + e_{it}$

Appendix 1B

Parameters of the CAPM ($\beta_{i,t-1}\lambda_{1t}$) conditioned on the instruments*
1977:6–1989:12 (151 observations)

$\beta_{i,t-1}\lambda_{1t}$	Constant	FSM(t)	UNEXINF(t–3)	BARIP(t–4)	R^2	DW
AB	0.013	0.176	–1.864	0.003	8.7	2.16
	(1.28)	(0.71)	(–2.12)	(3.09)		
EFFO	0.016	0.207	–2.214	0.004	8.7	2.15
	(1.27)	(0.71)	(–2.12)	(3.09)		
ENSOA	0.018	0.236	–2.500	0.005	8.7	2.15
	(1.27)	(0.71)	(–2.11)	(3.09)		
FISKK	0.014	0.186	–1.975	0.004	8.7	2.16
	(1.27)	(0.71)	(–2.12)	(3.09)		
HUHTK	0.009	0.111	–1.275	0.002	8.7	2.17
	(1.29)	(0.67)	(–2.18)	(3.05)		
INSTA	0.015	0.205	–2.164	0.004	8.7	2.15
	(1.28)	(0.71)	(–2.13)	(3.09)		
KEMI	0.017	0.216	–2.337	0.004	8.9	2.17
	(1.32)	(0.72)	(–2.17)	(3.10)		
KESK	0.012	0.147	–1.715	0.003	8.6	2.17
	(1.25)	(0.67)	(–2.18)	(3.04)		
KOP	0.019	0.252	–2.664	0.005	8.7	2.16
	(1.28)	(0.71)	(–2.12)	(3.09)		
KYMI	0.017	0.222	–2.338	0.004	8.8	2.15
	(1.30)	(0.72)	(–2.13)	(3.10)		
LASS	0.013	0.174	–1.797	0.003	8.8	2.15
	(1.30)	(0.74)	(–2.14)	(3.11)		
LOHJA	0.021	0.281	–2.976	0.006	8.7	2.15
	(1.27)	(0.71)	(–2.11)	(3.11)		
NOKIK	0.019	0.252	–2.664	0.005	8.7	2.16
	(1.27)	(0.71)	(–2.11)	(3.09)		
OTAVK	0.013	0.178	–1.724	0.003	8.5	2.10
	(1.29)	(0.76)	(–2.08)	(3.04)		
PART	0.019	0.257	–2.707	0.005	8.7	2.15
	(1.28)	(0.72)	(–2.12)	(3.09)		
RAUM	0.018	0.242	–2.458	0.005	8.7	2.16
	(1.28)	(0.74)	(–2.11)	(3.09)		
SOKEI	0.016	0.219	–2.303	0.004	8.7	2.16
	(1.28)	(0.72)	(–2.12)	(3.10)		
STOCA	0.015	0.204	–2.167	0.004	8.7	2.16
	(1.28)	(0.71)	(–2.12)	(3.09)		
SYPA	0.018	0.240	–2.514	0.005	8.7	2.16
	(1.28)	(0.72)	(–2.12)	(3.10)		
TAMF	0.018	0.239	–2.255	0.004	8.3	2.12
	(1.39)	(0.76)	(–2.02)	(3.04)		
TAMP	0.017	0.252	–2.238	0.004	8.5	2.11
	(1.32)	(0.81)	(–2.03)	(3.09)		
TAOK	0.008	0.110	–1.182	0.002	8.7	2.16
	(1.27)	(0.70)	(–2.13)	(3.09)		
TRIK	0.022	0.376	–2.499	0.005	7.5	2.15
	(1.46)	(1.04)	(–1.94)	(2.78)		
WARTI	0.018	0.236	–2.494	0.005	8.7	2.16
	(1.28)	(0.71)	(–2.12)	(3.09)		
YHTYK	0.020	0.267	–2.871	0.005	8.7	2.16
	(1.26)	(0.70)	(–2.12)	(3.09)		

* The model estimated: $\beta_{i,t-1}\lambda_{1t} = \gamma_o + \gamma_1 FSM(t) + \gamma_2 UNEXINF(t\text{-}3) + \gamma_3 BARIP(t\text{-}4) + e_{it}$

Appendix 1C

Betas ($\beta_{i,t-1}$; see also table 5) conditioned on the instruments[*] 1977:2–1989:12 (155 observations)

$\beta_{i,t-1}$	Constant	FSM(t)	UNEXINF(t–3)	BARIP(t–4)	R^2	DW
AB	0.748	–0.000	0.001	0.000	0.8	2.47
	(99518.80)	(–0.72)	(0.86)	(0.14)		
EFFO	0.890	0.022	–0.089	0.000	1.8	2.03
	(940.11)	(1.00)	(–1.11)	(0.78)		
ENSOA	1.010	–0.020	–0.149	0.000	2.8	1.90
	(1029.67)	(–0.86)	(–1.80)	(0.30)		
FISKK	0.795	0.004	–0.015	–0.000	0.4	1.62
	(783.77)	(0.16)	(–0.17)	(–0.75)		
HUHTK	0.501	0.145	–0.153	0.000	3.8	0.59
	(168.23)	(2.05)	(–0.61)	(1.21)		
INSTA	0.868	0.006	–0.030	–0.000	1.7	1.95
	(2308.55)	(0.71)	(–0.93)	(–1.06)		
KEMI	0.907	–0.169	0.347	–0.000	1.3	2.39
	(147.68)	(–1.16)	(0.67)	(–0.56)		
KESK	0.670	0.037	0.388	–0.000	1.0	2.77
	(163.73)	(0.38)	(1.12)	(–0.24)		
KOP	1.069	0.002	0.005	0.000	0.9	1.77
	(9129.67)	(0.72)	(0.48)	(0.71)		
KYMI	0.932	–0.035	0.224	0.000	2.9	2.12
	(630.81)	(–0.99)	(1.79)	(0.63)		
LASS	0.711	0.007	0.137	–0.001	1.4	1.10
	(197.70)	(0.08)	(0.45)	(–1.37)		
LOHJA	1.202	0.001	0.002	0.000	0.0	2.37
	(669.97)	(0.03)	(0.01)	(0.26)		
NOKIK	1.075	–0.001	–0.105	–0.000	1.1	2.36
	(1077.99)	(–0.04)	(–1.24)	(–0.12)		
OTAVK	0.681	–0.167	–0.535	–0.004	4.0	1.75
	(39.89)	(–0.41)	(–0.37)	(–2.38)		
PART	1.086	–0.008	0.006	0.000	2.2	1.93
	(3978.36)	(–1.17)	(0.25)	(1.38)		
RAUM	0.993	–0.019	–0.043	–0.000	0.5	2.11
	(544.64)	(–0.45)	(–0.28)	(–0.67)		
SOKEI	0.926	–0.027	0.287	0.000	4.6	1.86
	(533.24)	(–0.66)	(1.96)	(1.67)		
STOCA	0.870	0.003	–0.033	–0.000	0.4	2.59
	(1571.35)	(0.22)	(–0.70)	(–0.14)		
SYPA	1.010	–0.051	–0.407	0.000	2.2	1.80
	(337.98)	(–0.72)	(–1.61)	(0.17)		
TAMF	0.871	–1.029	0.458	0.000	4.4	1.31
	(52.30)	(–2.61)	(0.33)	(0.12)		
TAMP	0.916	–0.332	0.515	–0.001	2.6	0.10
	(102.19)	(–1.56)	(0.68)	(–1.12)		
TAOK	0.473	–0.019	0.002	–0.000	4.5	1.70
	(1529.85)	(–2.59)	(0.07)	(–0.37)		
TRIK	1.065	1.227	3.495	–0.007	1.4	2.77
	(16.34)	(0.79)	(0.64)	(–1.00)		
WARTI	1.001	0.003	0.004	0.000	14.6	1.22
	(35954.78)	(4.05)	(1.89)	(1.97)		
YHTYK	1.153	–0.002	–0.042	–0.000	0.4	1.96
	(591.44)	(–0.03)	(–0.26)	(–0.66)		

[*] The model estimated: $\beta_{i,t-1} = \gamma_o + \gamma_1 FSM(t) + \gamma_2 UNEXINF(t\text{-}3) + \gamma_3 BARIP(t\text{-}4) + e_{it}$

Appendix 1D

Mean-centred residuals (mcu_{it}) conditioned on the instruments* 1977:2—1989:12 (155 observations)

(mcu_{it})	Constant	FSM(t)	UNEXINF(t–3)	BARIP(t–4)	R^2	DW
AB	0.017	0.612	0.536	–0.002	1.7	2.43
	(0.82)	(1.24)	(0.30)	(–0.93)		
EFFO	0.012	0.468	0.583	–0.002	1.4	2.02
	(0.66)	(1.06)	(0.37)	(–0.84)		
ENSOA	0.010	0.515	1.427	–0.001	2.4	2.28
	(0.60)	(1.33)	(1.04)	(–0.78)		
FISKK	0.012	0.486	0.701	–0.004	4.4	1.94
	(0.78)	(1.30)	(0.53)	(–2.16)		
HUHTK	0.013	0.470	0.417	–0.001	2.2	1.78
	(0.98)	(1.49)	(0.37)	(–0.92)		
INSTA	–0.005	0.195	2.489	–0.003	4.2	2.12
	(–0.34)	(0.53)	(1.89)	(–1.60)		
KEMI	–0.007	–0.368	–1.055	–0.004	2.6	2.08
	(–0.33)	(–0.78)	(–0.63)	(–1.66)		
KESK	0.002	0.139	0.626	–0.003	3.6	1.92
	(0.13)	(0.48)	(0.60)	(–2.22)		
KOP	0.013	0.362	–0.350	–0.005	6.9	2.25
	(0.86)	(0.98)	(–0.27)	(–3.13)		
KYMI	0.015	0.430	–0.325	–0.003	3.1	1.98
	(1.04)	(1.23)	(–0.26)	(–1.76)		
LASS	0.008	0.102	–1.016	–0.004	3.3	2.09
	(0.43)	(0.23)	(–0.63)	(–2.11)		
LOHJA	–0.001	0.103	0.957	–0.003	2.0	2.34
	(–0.07)	(0.27)	(0.71)	(–1.56)		
NOKIK	0.017	0.522	0.030	–0.002	2.8	2.18
	(1.05)	(1.40)	(0.02)	(–1.47)		
OTAVK	0.009	0.104	–1.234	–0.004	4.0	2.21
	(0.54)	(0.25)	(–0.85)	(–2.29)		
PART	0.007	0.322	0.843	–0.005	6.0	2.12
	(0.44)	(0.91)	(0.67)	(–2.85)		
RAUM	–0.014	–0.270	1.233	–0.003	3.7	1.91
	(–0.99)	(–0.79)	(1.02)	(–2.04)		
SOKEI	0.017	0.649	0.772	–0.003	3.3	1.96
	(0.99)	(1.57)	(0.53)	(–1.47)		
STOCA	0.014	0.327	–0.660	–0.002	2.2	1.95
	(0.89)	(0.91)	(–0.52)	(–1.48)		
SYPA	0.009	0.356	0.524	–0.004	4.6	2.05
	(0.61)	(1.02)	(0.42)	(–2.43)		
TAMF	0.004	0.218	0.731	–0.001	0.6	2.31
	(0.23)	(0.60)	(0.57)	(–0.47)		
TAMP	0.021	0.643	–0.157	–0.004	4.9	2.28
	(1.33)	(1.69)	(–0.12)	(–2.14)		
TAOK	0.008	0.351	0.649	–0.002	0.9	2.27
	(0.41)	(0.74)	(0.39)	(–0.78)		
TRIK	0.014	0.670	1.630	–0.004	3.8	2.28
	(0.62)	(1.27)	(0.87)	(–1.84)		
WARTI	–0.002	0.137	1.422	–0.002	1.6	2.08
	(–0.13)	(0.35)	(1.03)	(–1.06)		
YHTYK	0.001	0.217	1.339	–0.004	3.6	2.10
	(0.05)	(0.55)	(0.95)	(–2.07)		

* The model estimated: $(mcu_{it}) = \gamma_o + \gamma_1 FSM(t) + \gamma_2 UNEXINF(t\text{-}3) + \gamma_3 BARIP(t\text{-}4) + e_{it}$

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