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SHORT-TERM RETURNS AND THE PREDICTABILITY OF FINNISH STOCK RETURNS*

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The predictability of Finnish stock returns is studied using the framework of Ferson and Harvey (1993). We employ a conditional asset pricing model where risk premia and risk sensitivities are conditioned on a range of financial information variables. In particular, we study the effect of the return interval on the predictability of short-term stock returns. Using daily, weekly, and monthly returns on Finnish size and industry-sorted portfolios, we find that the predictability of returns increases with the length of the return interval, but so does the power of the conditional pricing model to explain the predictability. Consistent with the earlier results, we report that the time variation in risk premium accounts for most of the predictability. However, the results also show a sizable positive interaction between the beta and the risk premium which seems to increase for smaller companies. (JEL G12, G14)

1. Introduction

A number of studies have shown the stock returns to be predictable. Stock portfolio returns are shown to be predictable, among others, with lagged portfolio returns (Fama and French, 1988a) and return volatility (French, Schwert and Stambaugh, 1987), with financial information, like the short term interest rates (Fama and Schwert, 1977) and the term structure of the interest rates (Campbell, 1987), with market and asset specific attributes, like the dividend yield (Fama and French, 1989) and the price-earnings ratio (Keim and Stambaugh, 1986), and with some common economic variables (Ferson and Harvey, 1991).[2]

Recent papers have studied the nature of the predictability in more detail. Ferson and Harvey (1991) found that the conditional CAPM is able to capture most of the predictable variation in the size and industry portfolio returns. They studied also whether the predictability can be attributed to beta or risk premia and found that most of the predictability comes from the time-varying risk premia, not the risk sensitivity. Ferson and Harvey (1993) studied the conditional CAPM on 18 developed markets with several global risk factors and found their model able to capture on average clearly more

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[1] *Good surveys of these studies can be found, among others, in Fama (1991) and Hawawini and Keim (1995).*

than half of the total predictable variation in the market returns. More recently, Harvey (1995) found global one-factor model to be able to explain on average only twelve percent of the predictability across eight emerging markets.

Further research has found that the predictability increases with the length of the return interval, although this result could be due to the poor power of the test due to the small sample sizes for long return intervals (cf., Kirby, 1997). For example, Fama and French (1988b) report that the dividend yield is able to explain more than twenty percent of the variation in five year returns. Ferson and Korajczyk (1995) found using multi-factor asset pricing model and month, quarterly, annual, and two-year returns that the model seems to be able to explain most of the predictability of long-term returns and that the results are not highly sensitive to the return interval. However, the short-term return predictability (i.e., horizons shorter than one month) has been given less attention.

This paper studies the short-term time series predictability of the stock returns. Using the framework in Ferson and Harvey (1993) and Harvey (1995), we investigate the short-term predictability of equity asset returns using a conditional asset pricing model. The expectations are allowed to vary linear on a predetermined selection of financial variables. In particular, we are interested in studying how different short-term return intervals affect model's ability to explain the predictability and how the results from the asset pricing model behave in different time-aggregation levels. Furthermore, we study whether the model can explain the predictability because of the time-varying risk-premium or beta.

There are a few studies on the predictability of Finnish stock returns. Malkamäki (1993) studied the predictability of monthly stock returns of 25 firms using three conditioning instruments. Using the two-pass cross-sectional approach in Ferson and Harvey (1991), he finds the asset pricing model to be able to explain most of the predictability, though the model produces too much time-variation in the returns and shows surprisingly high values for the unexplained part. He also finds the time-varying risk-premia component to account for most of the predictability. Knif and Högholm (1993) study the predictability of monthly, bimonthly, and quarterly market returns and volatilities with several macroeconomic variables and forecasting methods. They find that the variables generally have quite low predictability power.[3]

The results in this paper show that the predictability increases with the length of the return interval but so does the power of the conditional pricing model to capture the predictability. Consistent with earlier results, we report that the time-variation in risk premium accounts for most of the predictability. However, the results also show that there is a sizable interaction effect between beta and risk premium, especially for smaller companies.

The remainder of this paper is organized as follows. In the next section, the asset pricing model is presented together with a few considerations of the methodological and econometric questions at hand. Section 3 gives some descriptive statistics of the economic risk factors and information variables, and of the portfolios in this study. Section 4 presents the main empirical findings. First, the predictability power of the selected information variables is studied. Second, we test how large proportion of the predictability is explained by the model. Third, we decompose the predictability to that caused by the time-varying beta and by the risk premia. Finally, we perform some additional diagnostic tests. Concluding comments are given in section 5.

2. *Research Methodology*

2.1. Asset Pricing and Predictability

The predictability of stock returns using lagged observations or other information variables is not in itself evidence for or against the

[3] *Malkamäki (1993) employed three instrument variables: a measure for influence of lagged stock market returns in several countries, change in unexpected inflation, and an estimate of the aggregated future cash-flow expectations of the firms. Knif and Högholm (1993) used lagged market returns from the Stockholm Stock Exchange, changes in the import and export price indices, changes in the producer and consumer price indices, and an index for the industrial production.*

market efficiency, since the joint hypothesis underlying such analyses is a joint hypothesis of the market efficiency and some model of equilibrium. This means that if this joint hypothesis is rejected, the rejection cannot be attributed either to the market inefficiency or to the incorrect pricing model. Thus, it can be argued that the predictability is either a finding against the efficiency or that the pricing model is wrong. However, assuming market efficiency and correct asset pricing model, the predictability of the expected returns must come from the predictable time-variation in the risk-premium and risk sensitivities.

Using the conditional capital asset pricing model to describe the expected returns across the portfolios, we focus on its ability to explain the variation in the expected returns in different return intervals. Letting Ω_{t-1} represent the information available publicly to investors at time *t-1* to set prices at time *t*, we can write the conditional capital asset pricing model in the excess return form using the following equation:

$$(1) \quad E[r_{it}|\Omega_{t-1}] = \frac{Cov(r_{it}, r_{mt}|\Omega_{t-1})}{Var(r_{mt}|\Omega_{t-1})} E[r_{mt}|\Omega_{t-1}]$$

where $E[r_{mt}|\Omega_{t-1}]$ and $E[r_{it}|\Omega_{t-1}]$ are the conditional expected return at time *t* on market portfolio and asset *i*, respectively, in excess of the risk-free rate known at time *t-1*.

Following Ferson and Harvey (1991, 1993), we construct two unconditional ratios[4]: VR1 and VR2. VR1 is the ratio of the variance of the expected returns given by the conditional asset pricing model to the variance of the predicted returns given by the statistical model. Thus, VR1 measures how much of the predictable variation in the asset returns is explained by the pricing model. On the other hand, VR2 is the measure of the part that is not explained by the model. The ratios are defined as follows for each asset *i=1, ..., N*:

$$(2) \quad VR1_i = \frac{Var(\beta_{imt}(\Omega_{t-1})E[r_{mt}|\Omega_{t-1}]))}{Var(E[r_{it}|\Omega_{t-1}])}$$

and

$$(3) \quad VR2_i = \frac{Var\big(E[r_{it}|\Omega_{t-1}]-\beta_{imt}(\Omega_{t-1})E(r_{mt}|\Omega_{t-1})\big)}{Var(E[r_{it}|\Omega_{t-1}])}$$

where $\beta_{imt}(\Omega_{t-1})$ is the conditional beta for portfolio *i*. The denominator in both (2) and (3) is the variance of the predicted returns from the statistical model. The variance of the predictable part explained by the model is $Var(\beta_{imt}(\Omega_{t-1})E[r_{mt}|\Omega_{t-1}])$. The part that is not explained by the model is the remaining part.

Intuitively, VR1 is approximately the percentage of the statistical model's R-square that is explained by the pricing model. If the model captures the predictable variation of the asset returns, VR1 should be close to one and VR2 close to zero. However, it should be noted that the equation (2) does not restrict the sum of the ratios to be one, and it is possible that the variation implied by the model is higher than what it really is, giving VR1-ratios higher than one.

Now, it is possible to decompose the predictability further so that we can see the relative importance of the predictable variation coming from the risk premia and from the risk sensitivity. Following Ferson and Harvey (1993), we use the following unconditional decomposition:[5]

$$(4) \quad Var(E[\beta_{imt}r_{mt}|\Omega_{t-1}]) = E[\beta_{imt}]^2 Var(E[r_{mt}|\Omega_{t-1}]) + E[r_{mt}]^2 \mathrm{Var}(\beta_{imt}(\Omega_{t-1})) + \phi_i$$

where the terms on the right hand side represent the predictability component attributable to risk premia and to the beta, respectively. The term ϕ_i is a remainder term that represent the interaction between the expected risk premia and the beta that is due to their correlation through time. Intuitively, this could happen, for example, during an economic recession when higher required rate of return is accompanied with increase in company risk profile.

[4] *Using unconditional ratios gives only an average picture of the predictability, since it is likely that there are periods when the model cannot capture the predictability as well as during other periods. See, for example, Pesaran and Timmermann (1995) who find that the degree to which stock returns are predictable seems to increase when returns are more volatile.*

[5] *Using Taylor series expansion. Also see, e.g., Mood, Gaybill, and Boes (1974).*

In general, earlier empirical results have found that the time-variation in betas contributes only a relatively small amount to the time-variation in the expected asset returns. This finding is not surprising, since if we consider the equation (4), we can see that the first term on the right dominates the second term since the average beta is usually on the order of 1.0, while the average risk premium is only a few percents depending on the return interval. This does not, however, mean that the time-variation in the betas is unimportant, the results merely point out that when the predictability is concerned, time-variation in the risk premia is dominant relative to the time-variation in the beta.

2.2. Research methodology

Empirical testing of the previous models encounters two problems. First, the complete and true information set Ω_{t-1} is not observable and therefore we have to use a subset of the information. Letting a subset $Z_{t-1} \subset \Omega_{t-1}$ to represent the information that is available to econometrician, and assuming that this subset describes the state of the real-world, we can write the models conditional on Z_{t-1}.[6] Second, we have to make further assumptions of how to model the expectations. In general, we do not know the conditional distribution function or the functional form of the regression curve that delivers the expectations. However, if we assume that the asset returns and conditioning variables are jointly elliptically distributed, we can model the conditional expectations using a linear regression function of the conditioning variables (cf. Harvey, 1989 and Ferson and Harvey, 1991).

Using the information set Z_{t-1} to represent the information that investors use to form their expectations, assuming linear expectations and that we can proxy expected returns with the realized returns, we can write the expected asset and market returns as $E[r_{it}|Z_{t-1}]=Z_{t-1}\delta_i$ and $E[r_{mt}|Z_{t-1}]=Z_{t-1}\gamma$, respectively. Similarly, we approximate conditional betas as a linear function[7] of the information variables: $\beta_{im}(Z_{t-1})=Z_{t-1}\kappa_i$. Now, the conditional capital asset pricing model (1) and linear expectations imply the following three conditional moment conditions:[8]

$$\text{(5)} \qquad \begin{aligned} E_t[r_{it} - Z_{t-1}\delta_i] &= 0 \\ E_t[r_{mt} - Z_{t-1}\gamma] &= 0 \\ E_t[(r_{mt} - Z_{t-1}\gamma)^2(Z\kappa_i) - (r_{it} - Z_{t-1}\delta_i)(r_{mt} - Z_{t-1}\gamma)] &= 0 \end{aligned}$$

where r_{it} represents the return on assets i, r_{mt} represents the market factor returns, Z_{t-1} is the conditioning information variables set, δ_i and γ are the coefficients from the linear projection of the asset and factor returns on the information set, and $Z_{t-1}\zeta_i$ are fitted conditional betas. The first two lines represent linear regressions of the asset returns on the information variables. The third line delivers asset betas. To derive the third moment condition, we use the fact that the beta can be written as follows $Z_{t-1}\kappa_i=E[u_{it}u_{mt}|Z_{t-1}]/E[u^2_{mt}|Z_{t-1}]$.[9]

To calculate the VR1-ratios, we add the following unconditional moment conditions for assets $i = 1,\ldots, n$:

$$\text{(6)} \qquad \begin{aligned} E[Z_{t-1}\delta_i - \mu_i] &= 0 \\ E[Z_{t-1}\kappa_i(Z_{t-1}\gamma) - \mu_i - \alpha_i] &= 0 \\ E[(Z_{t-1}\delta_i - \mu_i)VRI_i - Z_{t-1}\kappa_i(Z_{t-1}\gamma) - \mu_i - \alpha_i)^2] &= 0, \end{aligned}$$

where the first condition calculates the average expected returns for test assets (μ_i), the second line defines the mean (unconditional) pricing error (α_i), and the last line delivers the variance ratio. Note that α_i is also analogous to the traditional Jensen's measure. The capital asset pricing model sets the restriction that alpha should be zero if the model is correct and the market is efficient with respect to the information set and choice of market portfolio.

Correspondingly, we can find out the VR2-ratio by replacing the last two equations in (6)

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[6] *This is a strong assumption, which could affect the results. For discussion see, e.g., Harvey (1989 and 1991) and Dumas and Solnik (1995).*

[7] *Probably the first researchers to use this conditional specification for the betas were Rosenberg and Marathe (1979). More recent studies include Campbell (1987), Shanken (1990) and Ferson and Harvey (1991, 1993, 1996), among others.*

[8] *See Ferson and Harvey (1993), Harvey (1995), and He et al., (1996).*

[9] *This is based on the fact that $Cov(r_{it},r_{mt})=Cov(E[r_{it}]+u_{it}, E[r_{mt}]+u_{mt})=Cov(u_{it},u_{mt})$, and the fact that the realized asset return is the sum of its expected value plus an innovation term. Conditional variance can be derived similarly.*

with the following unconditional moment conditions:

$$
\begin{aligned}
(7)\qquad & E[Z_{t-1}\delta_i - Z_{t-1}\kappa_i\,(Z_{t-1}\gamma) - \mu_{2i}] = 0 \\
& E[(Z_{t-1}\delta_i - \mu_i)VR2_i \\
& \quad - (Z_{t-1}\delta_i - Z_{t-1}\kappa_i(Z_{t-1}\gamma) \\
& \quad - \mu_{2i})^2] = 0
\end{aligned}
$$

To decompose the predictability using equation (4) further into the part explained by the variance of the risk premium or of the beta, we add the following moment conditions to (5):

$$
\begin{aligned}
(8)\qquad & E[Z_{t-1}\kappa_i(Z_{t-1}\gamma) - \mu_{1i}] = 0 \\
& E[Z_{t-1}\kappa_i - \mu_{2i}] = 0 \\
& E[Z_{t-1}\gamma_i - \mu_3] = 0 \\
& E[(Z_{-1}\kappa_i(Z_{t-1}\gamma) - \mu_{1i})\Gamma_{1i} - \mu_{2i}^2(Z_{t-1}\gamma - \mu_3)^2] = 0
\end{aligned}
$$

where μ_{1i} is the mean fitted value from the model, μ_{2i} is the mean conditional betas, μ_{3i} is the mean conditional risk premium, and Γ_{1i} is a measure of the predictability due to the time-varying risk premia. Similarly, we can calculate similar measure for beta by replacing the last condition in (9) with the following one:

$$
\begin{aligned}
(9)\qquad & E[(Z_{-1}\kappa_i(Z_{t-1}\gamma) - \mu_{1i})\Gamma_{2i} \\
& \quad - \mu_{3i}^2(Z_{t-1}\kappa_i \\
& \quad - \mu_{2i})^2] = 0
\end{aligned}
$$

where Γ_{21} is a measure of the predictability due to the time-varying beta. Note that the measures should add up to one. The difference is caused by their correlation through time.

2.3 Econometric considerations

There are two predominant approaches to estimate conditional asset pricing models. The first one is the two-step cross-sectional approach by Fama-MacBeth (1973). The second one is the time series approach employed here. Moment conditions (5)–(9) imply orthogonality conditions on expectation errors[10] (cf., Ferson and Harvey, 1993) that can be tested with the generalized method of moments[11] (GMM), using Z_{t-1} as instrumental variables in the conditional moments.

The GMM estimator is efficient in the class of instrumental variable estimators defined by the orthogonality conditions (Greene, 1997). The GMM does not rely upon the assumption of the normally distributed residual. Since short-term asset returns usually exhibit non-normal distribution, the GMM is usable for all return intervals.

The GMM includes, however, a few practical difficulties. One of the main difficulties is the optimization problem. The estimation system comes easily far too large to be estimated using the GMM.[12] On the other hand, the ratio of the ratio of the parameters to the time series observations can be too high (e.g., Cochrane, 1997, recommends that this ratio should be below 1/10). On the other hand, the system could become too "broad" or complicated, if several assets are included at the same time in the estimation which is indicated by the singularity problem. Since the system above is exactly identified, we are not so much concerned with the number of the parameters. However, the system would become too complicated if all portfolios are estimated at the same time. Thus, we use separate estimations for each portfolio.

3. Data and Summary Statistics

All stock market return series, money and foreign currency market series are provided by the Department of Finance at the HANKEN Swedish School of Economics and Business Administration. Series are based on the origi-

[10] Note that the true condition implied by the theory is $E[u_t|Z_{t-1}]=0$. However, since we do not know the expectations functional, we usually test only one type of functional. The most often used approach is to use a necessary but not sufficient orthogonality condition of the residual and the conditioning variables, i.e., $E[u_tZ_{t-1}]=0$ (or $E[u_t(Z_{t-1}]=0$).

[11] The GMM was first introduced by Hansen (1982). It has ever since been used for a wide range of econometric applications. Currently, the GMM-approach is the predominant approach for the parameter estimation and hypothesis testing of the conditional asset pricing models.

[12] Another frequent problem is caused by the use of numerical derivatives that could cause that the solution may not converge to the global minimum or converge at all. (Zhou, 1994). However, all systems above are exactly identified which reduces this problem. In fact, the coefficients should be identical to the OLS estimates.

nal data from the Helsinki Stock Exchange and the Bank of Finland. Portfolio returns are calculated by the author (see Vaihekoski, 1997, for more information).

3.1. Test assets

We examine the behavior of daily, weekly, and monthly portfolio excess returns from January 1987 to December 1996. This period is chosen because competitively determined short-term interest rates have existed during the whole time period. Seven industry and six size-sorted portfolios are formed using companies quoted on the main list of the Helsinki Stock Exchange.[13] If a company has several listed series only one series – the most actively traded – is selected.

Portfolio returns are proxied by the value-weighted average of the selected stock returns. Industry portfolios are formed by sorting firms at the end of the calendar year to groups based on their industry classification given by Talouselämä. Only those companies that are listed throughout the year are included in the industry portfolios. To keep the industry portfolios as similar as possible for all time frequencies, we update the weights only at the end of each year and keep them constant throughout the year. The size portfolios are, on the other hand, revised and weighted using the information from the day before the next period. Companies are included in the size portfolios from the end of the period they became listed until the period before they are removed from the exchange list.

The market portfolio return is proxied by the return on the HEX yield-index from the Helsinki Stock Exchange.[14] It is value-weighted, adjusted for splits and issues, and includes (gross) dividends. Both the market and the portfolio returns are calculated as the difference in the logarithms of the relevant (adjusted) daily indices. Longer return intervals are calculated using sums of the daily returns. Weekly returns are the sum of the returns from Thursday to the next Wednesday. Excess returns are calculated by subtracting the risk-free rate from the returns. Risk-free rate is approxied by continuously compounding the 1-month Interbank Helibor rate for the appropriate length of time.

3.2. Information variables

Selecting conditioning information variables is always problematic. Naturally, the variables given by the theory are the most prominent choices. The variables should also be easily observable and available before the investment period. However, the amount of the variables cannot be too large, since redundant variables could reduce the power of the tests and deteriorate small sample properties of the GMM estimation (cf., Hamilton, 1994). On the other hand, the omission of right conditioning information can lead to erroneous conclusions regarding the conditional mean-variance efficiency of a portfolio (Hansen and Richard, 1987; see also Dumas and Solnik, 1995, and Hansen and Richards, 1987).

The time-aggregation level and the availability of data also limit the set of the information variables. A more frequent data gives usually fewer alternatives (e.g., using frequencies shorter than one month practically forces one to exclude all macro-economic variables from the study). The choice of the conditioning variables also depends on the moment conditions at hand. For example, the relevance of the information variables probably differs for betas and risk premium. In addition, statistical reasons could force us to exclude some variables if the same variables are also used as risk factors.

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[13] *The number of portfolios is rather limited since the number of quoted companies has been throughout the period less than one hundred. Using only six size portfolios, we try to reduce the thin trading effect in small firm portfolio returns. Typically, the number of companies per portfolio is around 5–10 for size and at times even less for industry portfolios.*

[14] *Since the HEX yield-index is not available prior to 1990, the WI-index is used instead. Both indexes are value-weighted and corrected for cash dividends, splits, stock dividends and new issues. The main difference between the WI-index and the HEX-index is how the dividends are handled. In the WI-index the dividends are reinvested back to the paying stock, whereas in the HEX-index the dividends are reinvested in the market. Other smaller differences include, among others, what price is used when the transaction price is not available (see Berglund, Wahlroos, and Grandell, 1983, and Hernesniemi, 1990).*

Since we use the information variables to model both expected asset returns, market risk premia, and betas, we choose a wide range of variables. The following variables are selected: lagged market return, change in the three-month Interbank rate, a measure of the interest rate volatility, interest rate term premium, change in the FIM exchange rate index, a measure of the currency market volatility, and a January-dummy (see Table 3.1). Although the variables reflect mostly local of nature, it is clear that they also reflect also the relation between the Finnish economy and international markets.[15] All information variables are measured with a one-period lag, and considered to be publicly known.

$R_{m,t-1}$ is the lagged equity market return. It is selected following numerous earlier studies (see, e.g., Gibbons and Ferson, 1985; Ferson and Harvey, 1991; Ferson and Harvey, 1996), though its use is somewhat controversial. Ferson (1995) argues that it could be statistical by nature. However, the return time series exhibit often high degrees of first-order serial correlation, which is well known by the market participants.[16]

$dIB3_{t-1}$ is the change in the 3-month Helibor calculated as the difference from the end of the previous period.[17] Short-term interest rates are found in many studies to be powerful variable explaining the future stock and bond return behavior (see, e.g., Fama and Schwert, 1977; Ferson, 1989; Shanken, 1990). Interest rates typically contain information of the future inflation, and of the expected asset returns as well as of the risk premium per se (cf., Campbell, Lo, and MacKinlay, 1997).

SD_{t-1} is a measure of the interest rate yield spread (term premia). Since yield series are not readily available for horizons longer than one year during the sample period, we measure the yield spread as the difference in 1-month and 12-month annual Helibor rates. This captures part of the shape of the yield curve. Theoretically, the yield spread is related to the expected interest rate changes. It also contains information of the expected inflation, economic growth and economic activity (see, e.g., Estrella and Hardouvelis, 1991). It has been found to be a significant predictor of the stock returns for example by Campbell (1987), Fama and French (1989), Harvey (1989).

dFX_{t-1} is the change in the trade-weighted FIM currency index as calculated by the Bank of Finland. It summarizes movements in the value of the Finnish currency. It also reflects changes in the currency regimes (e.g., devaluations) which in turn affects the relative competitive advantages of the Finnish companies. In addition, movements in the exchange rate affect international investors risk premium requirement for the Finnish market. Exchange rate variables have been previously used, among others, by Dumas and Solnik (1995), and Bekaert and Harvey (1995).

Table 3.1: Information variables

Symbol	Definition
$R_{m,t-1}$	Lagged equity market return.
$dIB3_{t-1}$	Change in the Interbank three-month Helibor (per annum) rate.
SD_{t-1}	Difference between 1- and 12-month Helibor rates.
$Vol(IB1)_{t-1}$	Volatility of the interest rates measured as a weighted sum of the last twelve absolute changes in the one-month Helibor interest rate.
dFX_{t-1}	Change in the trade-weighted exchange rate index.
$Vol(USD)_{t-1}$	Volatility of the exchange rates measured as a weighted sum of the last twelve absolute changes in the FIM/USD exchange rate.
JAN_{t-1}	January dummy – one during January, zero otherwise.

[15] *The use of only local risk factors and information variables is based on the assumption of segmented markets and clearly a simplification of the reality. However, this is quite standard approach in many asset pricing tests. Furthermore, the assumption of segmented market is a priori fairly valid for the sample period, since final restrictions on foreign ownership were not removed until early 1993. On the other hand, many of the variables also reflect relationship between Finnish and global economy. For example, the exchange rate related variables reflect the competitiveness of the Finnish companies as well as the devaluation pressure against Finnish markka.*

[16] *A good discussion of the sources of the autocorrelation can be found in Campbell, Lo, and MacKinlay (1997).*

[17] *Three-month rate is selected instead of one-month rate because it is frequently used as the basis rate for new company loans in Finland. Hence, it is expected to reflect more accurately the prevailing market demand for loanable funds and for the financing costs of the companies.*

Vol(IB1)$_{t-1}$ and **Vol(USD)**$_{t-1}$ are proxies for the Finnish interest rate and currency exchange rate volatility. They are calculated using the method presented in Shanken (1990).[18] It can be shown that the interest and exchange rate volatilities can affect firm's investment behavior.[19] Hence, the prevailing market volatility can be of great importance to companies. Furthermore, the volatility is also one of the main factors to the pricing of the other assets. Similar measure of the exchange rate volatility has been used by Löflund (1994) on the Swedish market.

The last information variable **JAN**$_{t-1}$ is a January indicator variable. It has a value of one if the period ends in January, zero otherwise (i.e., in the weekly data, the variable gets value one if the week ends in January). It has been selected because previous studies have found that the month of January seems to predict the returns of the common size ranked stock portfolios (see, e.g., Keim, 1983; on the Finnish stock market, see Berglund, 1986). Especially, the return on the small stocks is likely to be larger in January. January indicator is earlier used in asset pricing tests by Gibbons and Ferson (1985), Ferson and Harvey (1991), and Dumas and Solnik (1995), among others.

3.3 Summary statistics

Table 3.2 presents the descriptive statistics for the risk factor and information variables. Realized excess returns for the Finnish equity market are only slightly positive on average during the whole sample period. Average realized excess returns have been 4.2, 0.9, and 1.1 percent per annum when calculated over daily, weekly, and monthly periods, respectively.[20] Consistent with the earlier studies, market returns show increasing non-normality for shorter return intervals, and the hypothesis of the normal distribution is rejected for daily and weekly returns. Market returns also show evidence of surprisingly strong positive first order autocorrelation. For example, an autocorrelation of 24.1% for monthly returns implies that close to 5.9% of the variation in the market return is predictable using lagged returns (cf., Campbell, Lo, and MacKinlay, 1997).

Most of the information variables also exhibit high autocorrelation, which seems to be caused by significant first-order partial autocorrelation. This raises the question whether the variables can be regarded stationary as required by the GMM. However, using the Augmented Dickey-Fuller test we reject the unit root for most of the series. In addition, it could also be argued that most of the series exhibit mean-reverting characteristics on the long run.

Panel B shows that the variables have quite low pairwise correlation with a few exceptions. The highest pairwise correlation is between interest rate volatility and term structure measures (around 0.5[21]), but for most of the variables the correlation is typically less than 0.2. This indicates that none of the variables is redundant statistically *a priori*. The correlation seems to either increase or decrease with the time-aggregation level, for a given variable.

[18] *Volatility is calculated by taking a weighted average of the 12 previous absolute differences in the one-month interest rate or in the FIM/USD exchange rate, respectively. Weights give more emphasis on more recent values.*

[19] *See e.g. Dixit and Pindyck (1994). They show that although increased uncertainty of the future interest rates can increase the incentive to invest, it usually leads to the postponement of investments, since it increases the incentive to wait and to see whether the interest rates rise or fall. They also show using the real options approach that various sources of uncertainty (like the interest rate and exchange rate volatility here) are in fact more important on investment decisions than does the overall level than these variables.*

[20] *Mean and standard deviation of the returns are annualized (approximately) to make them comparable across daily, weekly, and monthly periods. Means are multiplied with the average number of trading periods in a year, i.e., with 251, 52, and 12 for daily, weekly, and monthly returns, respectively. Standard deviations are multiplied with their square roots. The fact that the annualized daily excess return is highest is a result of declining interest rates during the sample period and the use of higher frequency of observations. Note that the annualization hides the fact that the ratio of the standard deviation to average return is much higher for shorter periods which makes the use of realized returns to proxy for expected returns as such more questionable for shorter period returns.*

[21] *This is as expected since there are theoretical models that suggest a relationship between the level of interest rates volatility and the shape of the yield curve (cf., e.g., Litterman, Scheinkman, and Weiss, 1991)*

Table 3.2: Descriptive statistics for the daily, weekly, and monthly time series

The descriptive statistics are calculated for the market portfolio and the conditioning variables. The first four sample central moments are small sample adjusted (cf. Smillie, 1966). The null hypothesis of the normal distribution is tested using Bera-Jarque Wald-test with the p-value provided in the table. Sample sizes are 2510 daily, 521 weekly, and 120 monthly observations from January, 1987 to December, 1996.

TIME SERIES	Data Frequency	Mean	Standard Deviation	Skewness	Excess Kurtosis	Normality p-value	Autocorrelation[a] ρ_1	ρ_2	ρ_3
Panel A: Summary statistics									
ECONOMIC VARIABLES									
Excess equity market return ($\mathbf{r_{mt}}$)	Daily	0.000	0.011	–0.606	14.601	0.000	0.198*	0.027	0.024
	Weekly	0.000	0.030	–0.285	3.384	0.000	0.096*	0.110*	0.130*
	Monthly	0.001	0.071	–0.092	0.213	0.819	0.241*	–0.013	0.119
INFORMATION VARIABLES									
Equity market return ($\mathbf{R_{mt-1}}$)	daily	0.000	0.011	–0.607	14.661	0.000	0.197*	0.025	0.023
	weekly	0.002	0.033	–0.289	3.423	0.000	0.091*	0.104*	0.125*
	monthly	0.009	0.070	–0.060	0.271	0.803	0.227	–0.032	0.104
Change in 3-month rate ($\mathbf{dIB3_{t-1}}$)	daily	–0.000	0.002	–6.433	197.982	0.000	–0.073*	–0.081*	0.115*
	weekly	–0.000	0.004	0.353	24.179	0.000	–0.029	0.074	0.071
	monthly	–0.000	0.008	–1.022	6.132	0.000	0.134	0.073	–0.167
Interest rate volatility ($\mathbf{Vol(IB1)_{t-1}}$)	daily	0.001	0.002	5.923	50.682	0.000	0.975*	0.933*	0.884*
	weekly	0.003	0.004	2.613	8.077	0.000	0.970*	0.919*	0.864*
	monthly	0.007	0.005	0.861	–0.018	0.001	0.972*	0.947*	0.911
Term premium ($\mathbf{SD_{t-1}}$)	daily	–0.003	0.012	2.389	14.034	0.000	0.960*	0.926*	0.906*
	weekly	–0.003	0.012	2.288	11.001	0.000	0.854*	0.752*	0.680*
	monthly	–0.002	0.010	1.239	2.500	0.000	0.647*	0.466*	0.323*
Change in currency index ($\mathbf{dFX_{t-1}}$)	daily	0.000	0.005	18.194	539.959	0.000	–0.121*	0.013	–0.126
	weekly	0.000	0.010	7.728	101.211	0.000	–0.081	–0.037	0.074
	monthly	0.001	0.019	3.232	18.280	0.000	0.051	0.024	–0.061
FX volatility ($\mathbf{Vol(USD)_{t-1}}$)	daily	0.023	0.013	3.447	20.035	0.000	0.956*	0.908*	0.863*
	weekly	0.053	0.024	1.764	3.677	0.000	0.947*	0.896*	0.843*
	monthly	0.114	0.049	1.562	2.064	0.000	0.951*	0.892*	0.829*

Panel B: Correlation matrix

DAILY SERIES	$\mathbf{R_{mt}}$	$\mathbf{dIB3_{t-1}}$	$\mathbf{Vol(IB1)_{t-1}}$	$\mathbf{SD_{t-1}}$	$\mathbf{dFX_{t-1}}$	$\mathbf{Vol(USD)_{t-1}}$
$\mathbf{R_{mt-1}}$	1.000					
$\mathbf{DIB3_{t-1}}$	–0.147	1.000				
$\mathbf{Vol(IB1)_{t-1}}$	–0.011	–0.104	1.000			
$\mathbf{SD_{t-1}}$	0.005	0.101	0.561	1.000		
$\mathbf{dFX_{t-1}}$	0.077	–0.219	0.121	0.067	1.000	
$\mathbf{Vol(USD)_{t-1}}$	0.084	–0.113	0.311	0.255	0.120	1.000
WEEKLY SERIES	$\mathbf{R_{mt}}$	$\mathbf{dIB3_{t-1}}$	$\mathbf{Vol(IB1)_{t-1}}$	$\mathbf{SD_{t-1}}$	$\mathbf{dFX_{t-1}}$	$\mathbf{Vol(USD)_{t-1}}$
$\mathbf{R_{mt-1}}$	1.000					
$\mathbf{dIB3_{t-1}}$	–0.181	1.000				
$\mathbf{Vol(IB1)_{t-1}}$	–0.017	–0.102	1.000			
$\mathbf{SD_{t-1}}$	0.018	0.205	0.448	1.000		
$\mathbf{dFX_{t-1}}$	0.017	–0.103	0.151	0.163	1.000	
$\mathbf{Vol(USD)_{t-1}}$	0.193	–0.146	0.238	0.212	0.105	1.000
MONTHLY SERIES	$\mathbf{R_{mt}}$	$\mathbf{dIB3_{t-1}}$	$\mathbf{Vol(IB1)_{t-1}}$	$\mathbf{SD_{t-1}}$	$\mathbf{dFX_{t-1}}$	$\mathbf{Vol(USD)_{t-1}}$
$\mathbf{R_{mt-1}}$	1.000					
$\mathbf{dIB3_{t-1}}$	0.300	1.000				
$\mathbf{Vol(IB1)_{t-1}}$	–0.117	–0.104	1.000			
$\mathbf{SD_{t-1}}$	0.016	0.229	0.492	1.000		
$\mathbf{dFX_{t-1}}$	–0.043	–0.084	0.248	0.250	1.000	
$\mathbf{Vol(USD)_{t-1}}$	0.256	–0.198	0.234	0.162	0.030	1.000

[a] Sample standard errors for autocorrelation coefficients are given by $\sqrt{(1+r_1^2+...+r_q^2)}/\sqrt{T}$, where q is the number of lags (* denotes significance at the 5%-level).

Table 3.3 presents the descriptive statistics for the size and industry portfolios. Almost all portfolios show negative average realized returns during the sample period. Contrary to U.S. studies, size portfolios show almost monotonic positive relationship between size and realized returns. Clearly, smallest companies show the worst performance. This is probably due to the recession in the Finnish economy in the early 1990s which hit the small companies more severely than bigger companies since they are more dependant on the domestic markets.

Negative average realized portfolio returns and near zero excess market returns raise a question whether we can proxy expected returns using realized returns. However, it is suggested that the premium could be negative at times as long as some of its moments are time-varying (cf., Harvey and Siddique, 1994) or at the certain states of the world (cf., Boudoukh, Richardson, and Smith, 1993). Moreover, it is reasonable to assume that the *expected* excess returns have been positive for the most part even if the sample realizations have been negative. Thus, we follow the standard approach used in most of the previous studies.

Similar to the market returns, the normality of the portfolio returns is rejected for daily and weekly portfolio returns, and in some cases also for monthly returns. Skewness is mostly negative showing evidence of extreme negative returns consistent with the idea of negative jumps in stock prices. Kurtosis seems to decrease with size in weekly and monthly returns reflecting the probably thin trading effect in the portfolios of small-sized companies.

Portfolios also exhibit high positive first order autocorrelation which is in line with the findings that positive cross-correlations cause portfolios to exhibit positive autocorrelation though individual stocks could exhibit negative autocorrelation (cf., Campbell, Lo, and MacKinlay, 1997). Interestingly, weekly returns show lowest autocorrelation whereas monthly returns show highest values. It could be argued that this is caused by the thin trading which has the strongest effects on the daily returns and decreasing effect on longer time-aggregation levels. On the other hand, monthly returns show clearer evidence of a drift term that causes higher autocorrelation.

4. Empirical Results

4.1 Predictability of returns

The predictability of daily, weekly, and monthly asset returns is studied by regressing them on the information variables. This is done to find out whether the asset returns are statistically predictable and how the predictability is affected by the use of different return intervals. In addition, we want to ensure ourselves that the selected variables are able to pick up the variation in the asset returns. The results of the regression analysis are summarized in Table 4.1.

Panel A in Table 4.1 shows the adjusted R^2 statistics from the regression of the asset return on the information variables. We also report the significance of the R^2 statistics using an F-test to test whether all coefficients are jointly zero (p-values are reported). In addition, we test whether the variables other than the lagged market return are jointly significant.

Similar to earlier studies, the results support the predictability of the asset returns and it seems to increase when longer return intervals are used. Daily returns show typically 2–4 percent adjusted R^2 statistics. Weekly returns show slightly higher adjusted R^2 statistics, typically 3–5 percent. Monthly returns show surprisingly high degree of predictability. Almost 15 percent of next month's market returns can be predicted using the selected forecasting variables. Similarly, the R^2 statistics are on average over 15 percent for the size portfolios and over 12 percent for the industry portfolios. In most cases, the predictability is found significant (i.e., the regressions coefficients on the instruments in the regressions are not jointly zero). Variables other than lagged market return are also found significant in almost all cases (results not reported).

In order to study which variables have been most capable to predict the returns, we report the cross-sectional Wald-test statistic with the p-values in parentheses for each variable in Panel B where we have used Newer and West

Table 3.3: Summary statistics for the excess portfolio returns

The descriptive statistics are calculated for the excess size and industry portfolio returns. The first four sample central moments are small sample adjusted (cf. Smillie, 1966). The null hypothesis of the normal distribution is tested using Bera-Jarque Wald-test with the p-value provided in the table. Sample sizes are 2510 daily, 521 weekly, and 120 monthly observations from January, 1987 to December, 1996.

PORTFOLIOS	Mean % p.a.[a]	Std. Dev. % p.a.[a]	Skewness	Excess Kurtosis	Bera-Jarque p-value	Autocorrelations[b] ρ_1	ρ_2	ρ_3
Size portfolios								
Daily returns								
Largest	0.7	21.2	–0.895	15.949	0.000	0.164*	–0.001	–0.005
2	–0.7	19.8	–0.380	7.318	0.000	0.160*	0.023	0.023
3	–0.2	19.1	–0.728	11.004	0.000	0.115*	0.053*	0.053
4	–1.0	20.2	–2.062	35.826	0.000	0.034	0.060*	0.060*
5	–8.2	20.1	–0.939	13.058	0.000	0.006	0.067*	0.067*
Smallest	–9.1	22.0	–0.478	9.550	0.000	0.035	0.082*	0.082*
Weekly returns								
Largest	–1.0	26.5	–0.554	3.318	0.000	0.054	0.090*	0.139*
2	–5.0	22.6	0.332	5.119	0.000	0.110*	0.074	0.114*
3	–6.1	21.5	–0.611	8.484	0.000	0.175*	0.148*	0.140*
4	–3.8	21.2	–0.282	4.670	0.000	0.135*	0.219*	0.144*
5	–12.1	21.0	–0.152	6.362	0.000	0.103*	0.065	0.084
Smallest	–10.6	26.7	–1.369	16.473	0.000	0.129*	0.056	0.073
Monthly returns								
Largest	–1.5	27.0	–0.171	0.018	0.746	0.210*	0.026	0.089
2	–3.0	25.4	–0.105	1.054	0.056	0.252*	–0.019	0.140
3	–2.6	26.2	–0.257	2.419	0.000	0.253*	0.070	0.076
4	–2.7	25.3	0.232	1.844	0.000	0.252*	0.019	0.219*
5	–7.4	25.7	0.549	1.579	0.000	0.216*	0.150	0.050
Smallest	–13.9	28.5	–0.493	4.306	0.000	0.205*	0.139	0.104
Industry portfolios								
Daily returns								
Banking & Other Financial	–14.7	37.0	1.476	29.871	0.000	0.121*	–0.079*	–0.047*
Forestry	3.6	25.4	0.243	9.292	0.000	0.141*	–0.002	0.015
Trade & Transport	2.0	20.9	–0.263	6.949	0.000	–0.049*	0.006	0.020
Metal & Electronics	3.7	21.4	0.106	3.317	0.000	0.092*	–0.006	0.035
Food Industry	3.8	25.7	–0.660	10.623	0.000	–0.158*	–0.002	0.016
Housing & Construction	–12.4	31.2	–1.760	23.119	0.000	0.066*	0.001	0.049*
Multi-Business	6.8	24.3	–0.742	11.399	0.000	0.166*	0.053	-0.016
Weekly returns								
Banking & Other Financial	–16.6	40.9	1.545	15.829	0.000	–0.035	–0.044	0.017
Forestry	1.2	28.6	0.006	2.459	0.000	0.074	–0.033	0.070
Trade & Transport	-0.9	21.1	0.146	3.425	0.000	0.055	0.128*	0.109*
Metal & Electronics	0.2	23.9	–0.106	1.536	0.000	0.122*	0.037	0.102*
Food Industry	0.9	22.0	–0.434	3.266	0.000	–0.076	0.042	–0.035
Housing & Construction	–15.5	32.1	–0.708	6.651	0.000	0.154*	0.053	0.134*
Multi-Business	3.8	29.0	–0.679	6.464	0.000	0.067	0.131*	0.089*
Monthly returns								
Banking & Other Financial	–17.8	33.5	0.261	0.715	0.000	0.214*	0.001	0.230*
Forestry	0.6	29.6	0.132	0.086	0.824	0.089	0.053	–0.091
Trade & Transport	–1.1	23.3	–0.022	–0.209	0.892	0.273*	0.026	0.195*
Metal & Electronics	0.6	27.5	0.263	0.188	0.457	0.114	–0.190*	0.187
Food Industry	0.7	21.8	0.075	1.584	0.002	–0.002	0.084	0.075
Housing & Construction	–15.5	35.8	–0.080	1.840	0.000	0.221*	–0.085	0.192*
Multi-Business	3.8	31.9	–0.177	0.760	0.173	0.265*	0.027	0.081

[a] Mean and standard deviation are annualized by multiplying them with 251, 52 and 12, and their square roots, respectively.
[b] Sample standard errors for autocorrelation coefficients are given by $\sqrt{(1+r_1^2+...+r_q^2)}/\sqrt{T}$, where q is the number of lags (* denotes significance at the 5%-level).

Table 4.1: Analysis of predictability in excess asset returns

Returns on equity market portfolio, six size and seven industry portfolios are regressed on lagged information variables using daily, weekly, and monthly data frequencies. The information variable set consists of lagged equity market return, change in three-month Interbank interest rate, measures of the interest rate and exchange rate volatility, a measure of the interest rate term-structure, change in the trade-weighted FIM currency index, and a January dummy. An F-test is used to examine if the conditioning variables are jointly able to explain the movements in excess asset returns. The p-value for the F-test is provided in the panel A. Wald-test is used to test if the coefficients are significantly different from zero jointly across assets. The Wald test statistic together with the p-value is given in panel B. Sample sizes are 2510 daily, 521 weekly, and 120 monthly observations from January, 1987 to December, 1996.

TIME SERIES	Adjusted R^2			F-test		
	daily	weekly	monthly	daily	weekly	monthly
Panel A: F-test results						
Market portfolio						
$E[r_{mt}]$	0.043	0.038	0.147	0.000	0.000	0.001
Size portfolios						
Largest	0.034	0.030	0.086	0.000	0.002	0.016
2	0.042	0.045	0.179	0.000	0.000	0.000
3	0.049	0.059	0.176	0.000	0.000	0.000
4	0.038	0.076	0.271	0.000	0.000	0.000
5	0.052	0.035	0.192	0.000	0.001	0.000
Smallest	0.026	0.082	0.198	0.000	0.000	0.000
Average	0.034	0.047	0.157			
Industry portfolios						
Banking & Other Financial	0.022	0.023	0.215	0.000	0.008	0.000
Forestry	0.031	0.025	0.127	0.000	0.005	0.186
Trade & Transport	0.027	0.049	0.135	0.000	0.000	0.001
Metal & Electronics	0.031	0.020	0.049	0.000	0.014	0.082
Food Industry	0.003	0.016	0.058	0.013	0.030	0.056
Housing & Construction	0.012	0.022	0.173	0.000	0.010	0.000
Multi-Business	0.032	0.034	0.120	0.000	0.001	0.003
Average	0.023	0.027	0.125			

ASSET	Wald Multivariate test on							
	Constant	$R_{m,t-1}$	$dIB3_{t-1}$	$VOLIB1_{t-1}$	SD_{t-1}	dFX_{t-1}	$VOLUSD_{t-1}$	JAN_{t-1}
Panel B: Wald-test results[a]								
Market portfolio								
daily	0.341	10.504*	0.724	10.300*	3.086	0.178	4.806*	1.552
	(0.559)	(0.001)	(0.395)	(0.001)	(0.079)	(0.673)	(0.028)	(0.217)
weekly	8.061*	0.788	0.059	1.719	0.166	1.637	17.701*	7.096*
	(0.005)	(0.375)	(0.809)	(0.190)	(0.684)	(0.201)	(0.000)	(0.148)
monthly	0.382	3.782	3.084	7.593*	0.252	3.160	9.020*	2.968
	(0.536)	(0.052)	(0.079)	(0.006)	(0.615)	(0.075)	(0.003)	(0.085)
Size portfolios								
daily	1.350	62.776*	10.359	26.731*	18.293*	39.451*	11.526	7.974
	(0.987)	(0.000)	(0.169)	(0.000)	(0.011)	(0.000)	(0.117)	(0.335)
weekly	27.418*	39.423*	12.216	11.168	2.166	10.437	46.363*	11.535
	(0.000)	(0.000)	(0.057)	(0.083)	(0.904)	(0.107)	(0.000)	(0.073)
monthly	2.601	53.009*	29.700*	42.717*	11.437	10.387	20.956*	21.056*
	(0.857)	(0.000)	(0.000)	(0.000)	(0.076)	(0.109)	(0.002)	(0.002)
Industry portfolios								
daily	6.341	98.260*	7.348	32.871*	11.999	9.401	14.358*	7.454
	(0.386)	(0.000)	(0.290)	(0.000)	(0.062)	(0.152)	(0.026)	(0.281)
weekly	31.508*	12.275	7.463	9.831	6.870	8.514	56.969*	10.589
	(0.000)	(0.092)	(0.382)	(0.198)	(0.443)	(0.289)	(0.000)	(0.158)
monthly	6.876	27.075*	19.646*	39.492*	7.986	12.772	22.504*	20.540*
	(0.442)	(0.000)	(0.006)	(0.000)	(0.334)	(0.078)	(0.002)	(0.005)

[a]Significant (5%) coefficients are marked with an asterisk (*).

(1987) autocorrelation and heteroscedasticity consistent covariance matrix. The results do not show any clear patterns, apart the significance of the lagged market return which reflects the autocorrelation.[22] In addition, interest rates and US-dollar exchange rate volatility measure are found significant for most of the assets. January indicator is found significant only in the monthly data for the test assets. This could be caused by the fact that the January effect is strongest only part of the month and therefore daily and weekly dummies capture too much noise.

4.2 Conditional capital asset pricing model

In this section, we study if we can explain the statistical predictability of asset returns using the conditional CAPM. We use a GMM-system to test the moment conditions implied by equations (5)–(7). In Table 4.2, we report how much of the predictable variation in the asset returns can be explained by the model (VR1) and what is left unexplained (VR2) together with their standard errors in parentheses. We also report average returns, pricing errors, and their standard errors for each portfolio (all are annualized).

In general, the average pricing errors (Jensen's alpha) are found insignificant almost in all return intervals and portfolios. This gives support for the asset pricing model. However, comparing the average return with the average pricing error, we can see that even after controlling for the risk, the average pricing errors are quite high and their magnitude seems to increase for longer return intervals and for the portfolios of small-sized companies, which could indicate the low power of this test to reject the null hypothesis.

The results show that the model is able to capture most of the predictability (VR1-ratio is bigger than VR2-ratio in 27 cases out of 39). The VR1-ratios are typically between 0.5 and 0.9. Ferson and Harvey (1991 and 1993) results for size and industry portfolios are quite similar (around 0.8), but their VR2s are usually much lower than in our study. We also find that in some cases the VR1-ratios are higher than one. This is caused by the fact that the selected instrument variables produce too much variation in the model with respect to the variation in the statistical model. There can be several explanations for this. For example, sample biases, our selection of information variables and the assumption that the variables enter the expectations with constant and equal weights can affect the results.

Similar to Ferson and Harvey (1991), the ability of the model to explain the predictability reduces almost monotonically with the company size. This is probably partly attributable to the thin trading effect in portfolio returns or to the inefficiency of the market, but it can also be argued that the results indicate a missing risk factor (e.g., liquidity). For the industry portfolios, the results show that the model has been able to explain more of the predictability that what is left unexplained almost in all cases.

Comparing the magnitude of the VR1s and the average VR1/VR2-ratio for daily, weekly, and monthly return intervals shows that the model does a better job explaining the predictability when longer intervals levels are used. This is as expected since shorter interval returns are mainly driven by their variance. On the other hand, it is clear that the time-aggregation cannot explain the fact that the standard one-factor CAPM fails to explain returns on portfolios of small-sized companies.

4.3 Decomposing sources of predictability

Table 4.3 shows the results from the analysis of the sources of the predictability using the GMM on the moment conditions (8) and (9). We report the proportion of the predictability variation explained by the model that can be attributed to the predictability of the risk premia

[22] *Since portfolio returns are based on transaction prices and market returns are based on the average of the bid and ask prices if trading price is not available, a legitimate question is whether we can use market returns as a conditioning variable in an illiquid market. This is especially relevant question with respect to the portfolios of small-sized companies and when daily returns are used due to the non-synchronous trading. However, we have taken several steps to minimize the thin trading effect on the size portfolios. Furthermore, portfolio specific results (not reported) do not show big differences across portfolios and return intervals in the forecasting power of the lagged market return.*

Table 4.2: Predictable variation in the portfolio returns

The predictable variation in the excess returns for six size and seven industry portfolios is studied using daily, weekly, and monthly data. Risk premium and beta are conditioned on the following demeaned variables: lagged equity market return, change in three-month Interbank interest rate, measures of the interest rate and exchange rate volatility, a measure of the interest rate term-structure, change in the trade-weighted currency index, and a January dummy. Results are reported from the following exactly identified GMM estimation

$$u_{1it} = r_{it} - Z_{t-1}\delta_i \qquad u_{4it} = Z_{t-1}\delta_i - \mu_i$$
$$u_{2mt} = r_{mt} - Z_{t-1}\gamma \qquad u_{5it} = Z_{t-1}\kappa_i(Z_{t-1}\gamma) - \mu_i + \alpha_i$$
$$u_{3it} = u_{2mt}^2(Z_{t-1}\kappa_i) - u_{2mt}u_{1it} \qquad u_{6it} = (u_{4it}^2)VR^I{}_i - u_{5it}^2$$

where VR1 measures the predictability explained by the asset pricing model. VR2 is estimated from slightly modified system. It measures the part of the predictability not explained by the model. Estimation is done separately for each asset. Average returns, average pricing errors and its standard error are annualized in the table. Significant (5%) estimates are marked with an asterisk (*). Sample sizes are 2510 daily, 521 weekly, and 120 monthly observations from January, 1987 to December, 1996.

TIME SERIES	Daily return				Weekly returns				Monthly returns			
Average	Average return	Average pricing error α_i	VR1	VR2	Average return	Average pricing error α_i	VR1	VR2	Average return	Average pricing error α_i	VR1	VR2
Size portfolios												
Largest	0.001	–0.034	1.027*	0.048	–0.010	0.001	0.929*	0.126	–0.015	–0.005	1.349*	0.084
		(0.029)	(0.216)	(0.053)		(0.023)	(0.205)	(0.074)		(0.022)	(0.215)	(0.051)
2	–0.007	–0.037	0.754*	0.141	–0.050	–0.092*	0.952*	0.108	–0.030	–0.031	0.836*	0.094
		(0.042)	(0.197)	(0.079)		(0.036)	(0.263)	(0.069)		(0.032)	(0.199)	(0.052)
3	–0.001	–0.006	0.355*	0.306*	–0.001	0.002	0.419*	0.406*	–0.026	0.004	0.574*	0.229*
		(0.048)	(0.111)	(0.111)		(0.042)	(0.143)	(0.160)		(0.046)	(0.165)	(0.089)
4	–0.010	–0.017	0.213*	0.377*	–0.038	–0.051	0.218	0.507*?	–0.027	–0.091	0.205	0.459*
		(0.058)	(0.065)	(0.082)		(0.054)	(0.116)	(0.172)		(0.064)	(0.112)	(0.169)
5	–0.082	–0.084	0.145*	0.484*	–0.121	–0.105*	0.445	0.541*	–0.074	–0.109	0.508*	0.385*
		(0.057)	(0.050)	(0.090)		(0.050)	(0.228)	(0.247)		(0.056)	(0.203)	(0.171)
Smallest	–0.091	–0.112	0.287	0.483*	–0.106	–0.151*	0.286	0.608*	–0.139	–0.147*	0.328*	0.385*
		(0.068)	(0.155)	(0.112)		(0.070)	(0.168)	(0.186)		(0.063)	(0.151)	(0.138)
Average	–0.032	–0.048	0.464	0.307	–0.054	–0.066	0.542	0.383	–0.052	–0.063	0.633	0.273
Industry portfolios												
Banking & Other Financial	–0.147	–0.212*	1.034*	0.758	–0.166	–0.353*	2.282	1.115	–0.178	–0.308*	0.938	0.173
		(0.100)	(0.489)	(0.543)		(0.086)	(1.543)	(1.096)		(0.082)	(0.521)	(0.097)
Forestry	0.029	0.002	0.687*	0.392	0.012	0.011	0.795*	0.457	0.006	0.041	1.684*	0.467
		(0.056)	(0.213)	(0.207)		(0.052)	(0.388)	(0.275)		(0.067)	(0.763)	(0.444)
Trade & Transport	0.020	0.008	0.407*	0.261*	–0.009	–0.007	0.408*	0.413*	0.011	0.037	0.698	0.315*
		(0.057)	(0.141)	(0.121)		(0.049)	(0.163)	(0.142)		(0.059)	(0.461)	(0.159)
Metal & Electronics	0.037	–0.006	0.644*	0.250	0.002	–0.011	0.828*	0.173	0.006	–0.035	1.617*	0.245
		(0.050)	(0.214)	(0.171)		(0.049)	(0.307)	(0.113)		(0.059)	(0.659)	(0.211)
Food Industry	0.038	0.039	0.890*	0.294	0.010	0.046	0.325	0.574*	0.007	–0.030	0.703	0.234
		(0.077)	(0.596)	(0.313)		(0.062)	(0.263)	(0.280)		(0.069)	(0.693)	(0.162)
Housing & Construction	–0.124	–0.123	0.796*	0.266	–0.155	–0.157	0.549	0.973	–0.155	–0.211*	0.308	0.505*
		(0.088)	(0.361)	(0.199)		(0.087)	(0.458)	(0.621)		(0.093)	(0.191)	(0.230)
Multi-Business	0.069	0.036	0.838*	0.035	0.038	0.059	0.727*	0.148	0.038	0.037	1.056*	0.117
		(0.046)	(0.205)	(0.031)		(0.044)	(0.183)	(0.087)		(0.065)	(0.453)	(0.077)
Average	–0.011	-0.043	0.757	0.322	–0.038	–0.059	0.845	0.550	–0.038	–0.067	1.001	0.294

and the beta. We also test whether the betas are constant using a Wald-test[23]. In addition, we report the average beta for all portfolios. Since the information variables are demeaned in the tests, the reported beta represents the average unconditional beta in February-December.

As expected, we find the relative proportion explained by the changing risk premia to account for most of the predictability similar to previous U.S. studies and Malkamäki (1993). On average the proportion explained by the premia is between 75–90 percent, whereas the predictable variation captured by the beta movements is practically zero (cf., from one to five percent in Ferson and Harvey, 1993). The results show, however, a sizable interaction effect between beta and risk premia, since the predictability attributable to the risk premia and to the beta usually does not sum one. The portfolios of smaller-sized companies seem to exhibit the highest positive interaction between beta and risk premium. This supports the idea of business cycle behavior in the stock returns. Interestingly, this can also be seen clearly in the banking industry portfolio. Intuitively, this could be caused by the banking sector crisis in Finland in the early 1990s.

Comparing the results for daily, weekly, and monthly return intervals, we can see that there are only subtle, albeit visible changes. On average, the contribution to the predictability coming from the risk premium seems to reach its peak in the weekly returns. The variation in the beta does not appear to get any higher explanative power in our system even over longer periods, which could be attributable to the low average market excess return during the sample period and to our selection of the information variables that are not related to firm-specific attributes.

Although the previous results show expectedly that the variation in betas is not as important as the variation in the risk premia for the return predictability, it does not mean that the variation is economically unimportant. The results from the Wald-test show similar to Ferson and Harvey (1993), that the hypothesis of constant betas can be rejected for more than half of the cases (20 out of 39) even using these interaction variables. Surprisingly, daily returns show the highest number of rejection of the constant beta hypothesis for size and industry portfolios (9 times out of 13).

We also analyze the differences in the betas over return intervals. Similar to Martikainen (1991), we find the betas to be bigger with the length of the return period. However, contrary to Handa, Kothari, and Wasley (1989) and Vaihekoski (1996, 1997), the difference in the betas of the size-ranked companies to do not widen when longer return intervals are used. This could be due to our sample period.[24]

4.4. Additional tests

In order to study the robustness of our results, we perform a few additional tests. The asset pricing model implies that after we have accounted for the risk, the residual should not be predictable using the conditioning information variables. The results from this test show that the adjusted R^2 is typically close to zero for all portfolios. This result is similar to Ferson and Harvey (1993). Thus, the results support the idea that most of the predictability is captured by the conditional asset pricing model. Furthermore, the results support the claim that the alpha (pricing error) is not predictable using these variables.

In addition, we test whether the relevance of the financial variables has increased after the decision to let the markka float after September 8, 1992. Since both foreign exchange and interest rates can be freely determined in floating currency regime, it implies *a priori* that

[23] See, e.g., Greene (1997) for description of the Wald-tests in the GMM framework.

[24] Sample period in this study is one year longer than in Vaihekoski (1996, 1997) and includes longer period of bull market. This can affect the magnitude of the betas, since there are some evidence that betas can be different in bear and bull markets (c.f., Pettengill, Sundaram, and Mathur, 1995). Since the sample period includes almost equal length of both, we tested whether beta differs in the first and the second part of the sample period using a dummy for both periods. Preliminary results show a clear difference in betas. In bull market, the gap between beta for small and the large size portfolios seems to widen more in daily returns, thus reducing the relative gap when longer return intervals are used.

Table 4.3: Decomposition of the predictable variation in the portfolio returns
The sources of the predictable variation in excess returns of six size and seven industry portfolios is studied by decomposing the predictability into the proportion of the variance explained by the predictability of changing risk premia and beta. Risk premium and beta are conditioned on the following demeaned variables: lagged equity market return, change in three-month Interbank interest rate, measures of the interest rate and exchange rate volatility, a measure of the interest rate term-structure, change in the trade-weighted FIM currency index, and a January dummy. Proportions are provided in the table with their standard errors in parentheses. Results are from an exactly identified GMM-system which is similar to that the system used in Table 4.2, except the last three conditions are replaced with the following ones (for risk premia):

$$u_{4it} = Z_{t-1}\kappa_i(Z_{t-1}\gamma) - \mu_{1i} \qquad u_{6it} = Z_{t-1}\gamma - \mu_3$$
$$u_{5it} = Z_{t-1}\kappa_i - \mu_{2i} \qquad u_{7it} = (u_{4it}^2)\Gamma_{1i} - \mu_{2i}^2 u_{6t}^2$$

and to calculate the proportion explained by the variation in the beta we replace the last condition with the following one:

$$u_{7it} = (u_{4it}^2)\Gamma_{1i} - \mu_{2i}^2 u_{6t}^2$$

In addition, we report a Wald-test statistic for the hypothesis that the conditional beta is constant over time (p-value in the parentheses) and the average unconditional beta in February-December. Sample sizes are 2510 daily, 521 weekly, and 120 monthly observations from January, 1987 to December, 1996.

Time Series	Daily returns				Weekly returns				Monthly returns			
	Risk Premia[a]	Beta[a]	Constant Beta[b]	Average Beta[b]	Risk PreMulti-mia[a]	Beta[a]	Constant Beta[b]	Average Beta[b]	Risk Premia[a]	Beta[a]	Constant Beta[b]	Average Beta[b]
Size portfolios												
Largest	0.985*	0.000	10.729	1.079	1.195*	0.000	34.718*	1.102	1.068*	0.000	15.772*	1.113
	(0.039)	(0.000)	(0.151)		(0.099)	(0.000)	(0.000)		(0.086)	(0.000)	(0.027)	
2	0.691*	0.000	67.014*	0.805	0.597*	0.000	46.869*	0.838	0.778*	0.000	54.276*	0.898
	(0.139)	(0.000)	(0.000)		(0.103)	(0.000)	(0.000)		(0.149)	(0.000)	(0.000)	
3	0.762*	0.000	29.380*	0.597	0.971*	0.000	12.739	0.735	0.871*	0.000v	8.05 1	0.807
	(0.127)	(0.001)	(0.000)		(0.153)	(0.000)	(0.079)		(0.212)	(0.000)	(0.328)	
4	0.770*	0.000	27.540*	0.437	0.849*	0.000	6.482	0.555	0.970*	0.000	12.921	0.581
	(0.129)	(0.001)	(0.000)		(0.162)	(0.000)	(0.555)		(0.322)	(0.002)	(0.074)	
5	0.823*	0.000	44.956*	0.428	1.082*	0.000v	12.752	0.614	0.699*	0.000	21.683*	0.684
	(0.107)	(0.001)	(0.000)		(0.182)	(0.000)	(0.078)		(0.149)	(0.001)	(0.003)	
Smallest	0.382*	0.000	9.411	0.322	0.466*	0.000v	15.425*	0.591	0.696*	0.000	11.905	0.601
	(0.186)	(0.001)	(0.224)		(0.200)	(0.001)	(0.031)		(0.233)	(0.001)	(0.104)	
Average	0.736	0.000			0.860	0.000			0.847	0.000		
Industry portfolios												
Banking & Other Financial	0.464*	0.000	19.486*	1.051	0.292*	0.000	72.094*	1.091	0.607*	0.000	22.603*	1.002
	(0.178)	(0.001)	(0.007)		(0.065)	(0.001)	(0.000)		(0.183)	(0.001)	(0.002)	
Forestry	0.902*	0.000	133.860*	0.976	1.088*	0.000	13.418	1.078	1.086*	0.000	20.119*	1.068
	(0.078)	(0.000)	(0.000)		(0.146)	(0.000)	(0.063)		(0.233)	(0.000)	(0.005)	
Trade & Transport	0.791*	0.000	18.422*	0.543	0.855*	0.000	10.182	0.626	1.984*	0.000	6.589	0.754
	(0.116)	(0.000)	(0.010)		(0.193)	(0.000)	(0.178)		(0.142)	(0.000)	(0.734)	
Metal & Electronics	0.961*	0.000	12.851	0.817	1.076*	0.000	14.298*	0.839	0.988*	0.000	5.405	1.028
	(0.146)	(0.000)	(0.076)		(0.187)	(0.000)	(0.046)		(0.157)	(0.000)	(0.611)	
Food Industry	0.712*	0.000	25.494*	0.453	1.092*	0.000	13.155	0.436	0.632*	0.000	7.861	0.415
	(0.168)	(0.000)	(0.001)		(0.436)	(0.001)	(0.068)		(0.291)	(0.000)	(0.345)	
Housing & Construction	0.786*	0.000	22.202*	0.767	0.852*	0.000	4.356	0.815	1.096*	0.000	4.156	0.891
	(0.130)	(0.001)	(0.002)		(0.243)	(0.000)	(0.738)		(0.323)	(0.000)	(0.762)	
Multi-Business	0.940*	0.000	13.657	1.056	1.152*	0.000	15.609*	1.171	0.944*	0.000	5.394	1.167
	(0.036)	(0.000)	(0.058)		(0.134)	(0.000)	(0.029)		(0.103)	(0.000)	(0.612)	
Average	0.794	0.000			0.915	0.000			0.905	0.000		

[a] Significant values (5 %) are marked with an asterisk (*).
[b] Unconditional beta in February-December.

their relevance increases as a general indicator of the economy. Using a separate dummy for post-fixed rate regime, we find that the change (not reported) in the VR1-ratio is not significant in most cases, though the direction of the change was typically towards VR1-ratio of one, but the movements are so subtle that we cannot draw any conclusions with respect to the variables or to the model.

5. Concluding Comments

This study has examined the short-term predictability of the Finnish stock portfolio returns using daily, weekly, and monthly return intervals and a selection of financial information variables. The results show that more than half of the observed statistical predictability can be explained for most of the portfolios using the conditional capital asset pricing model where the market-factor risk-premia and asset risk-sensitivity are allowed to vary over time.

Decomposing the sources of the predictability shows that the time-variation in the risk premia explains most of the predictability whereas the proportion of the predictability explained by the time-variation in the beta is expectedly very close to zero. However, the results show that there is a sizable positive interaction effect between the betas and the risk premia, especially for smaller companies. This may be related to the their correlation with the business cycles, but further analysis is needed.

Comparing the results for different return intervals shows only slight changes in the results. Consistent with the fact that short-term returns are mainly driven by their variance, the predictability of the returns seems to increase with the length of the interval, but so does the model's ability to explain the predictability. It would be interesting to study how the return interval affects the predictability in return volatility. A natural extension to this study would also be to examine how longer periods than the ones used in this study would affect the results, but it is left to future study.

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