What factors affect the Oslo Stock Exchange?

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Abstract

This paper analyzes return patterns and determinants at the Oslo Stock Exchange (OSE) in the period 1980–2006. We find that a three-factor model containing the market, a size factor and a liquidity factor provides a reasonable fit for the cross-section of Norwegian stock returns. As expected, oil prices significantly affect cash flows of most industry sectors at the OSE. Oil is, however, not a priced risk factor in the Norwegian stock market. As the case in many other countries, we find that macroeconomic variables affect stock prices, but since we find only weak evidence of these variables being priced in the market, the most reasonable channel for these effects is through company cash flows.

JEL codes: G12; E44
Key Words: Stock Market Valuation, Asset Pricing, Factor Models, Generalized Method of Moments

1 Introduction

In this paper we report results from an extensive empirical analysis of the Oslo Stock Exchange (OSE). The purpose of the analysis is to investigate whether the factors affecting the stock prices at the OSE can be explained using standard financial theory, and to what extent the results from other stock markets are also found in the Norwegian stock market.

The theoretical and empirical asset pricing literature is internationally very extensive. In spite of this there are few analyses that specifically study the Oslo Stock Exchange. The few extant studies are typically focused on the time series properties of

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aggregate market returns. By leaving out information about return differences across companies, and across time variation in company and sector weights, such analyses may give a misleading impression of the most important factors affecting the cross section of stock returns.[1]

The belief among participants in the Norwegian market seems to be that classical finance theory holds, for example that a company's market risk (beta) is important for the expected returns of a stock. There is, however, no in-depth test of whether the CAPM actually is able to price Norwegian stocks. Another "truth" among practitioners is that the OSE is driven by oil prices. Even if such a relationship seems probable, there is little empirical evidence to support this, and no clear understanding of how such a relationship is to be understood.

Knowledge of which risk factors are important for stock prices at the OSE, the magnitude of realized risk premia, and to what extent the cross-section of returns at the OSE is different from other stock markets is obviously of interest to investors on the exchange, and companies raising capital through the OSE. We find that both level and variation of risk premia at the OSE have been high. Internationally, newer research suggests that variation in risk premia, both over time and in the cross-section, can be used to predict economic cycles. Improved understanding of the Norwegian stock market is therefore also important for government work on financial stability and monetary policy.

1.1 Theories for pricing of equities

From investment theory we know that the value of a stock can be expressed as the present value of an uncertain future cash flow, where the discount factor is adjusted for risk. Similarly, the value of the OSE can be found as the present value of expected cash flows from all listed companies, discounted using a required rate of return reflecting the risk of the cash flows. Mathematically, this can be expressed as

$$P_0^M = \sum_{i=1}^{n} \sum_{t=0}^{\infty} E_t \left[\frac{D_{t+1}^i}{(1 + r_{t+1}^f + er_{t+1}^i)^t} \right] \tag{1}$$

[1]Estimation using aggregate market returns typically find what is important for the few largest companies/sectors in the market. This is particularly a problem when analyzing the Norwegian market, where a few companies account for a large part of the aggregate market value. Additionally one will not gain any understanding of factors affecting companies' earnings and risk in different sectors, and what factors affect all sectors.

where P_t^M is the value of the market at time t, i indexes company, and there are n companies listed on the exchange. D_t^i is the cash flow of company i at time t and r_t^f is the risk-free interest rate at time t. If r_t^i is the return of company i at time t, we define $er_t^i = (r_t^i - r_t^f)$ as the expected return in excess of the risk-free interest rate. This is the necessary compensation for the uncertainty of cash flows for company i, i.e. the risk premium. The present value formula shows that a factor which systematically affects the market return can do so through cash flows, risk-free interest rate, risk premia, or combinations of these. We typically distinguish between two channels: cash flow effects and risk premia. Cash flow effects influence future cash flows of a company, and therefore future dividends D_{t+1}^i. Risk premia will instead affect er_{t+1}^i. Risk premia are typically influenced by systematic risk factors, which are common to all companies. An understanding of which of these two channels causes stock price changes will be an important part of the following analysis. Is, for example, a positive covariability between the market index and oil prices due to oil prices being a systematic risk factor affecting the required return for all companies, or is the effect mainly caused by changes in expected cash flows of oil and oil related companies?

Theoretical valuation models attempt to explain *risk premia* in the market. Common to all models is the basic assumption of rational agents, and that prices (of equities and other financial assets) are determined by the degree of covariability between the return of the assets, and the marginal benefit of consumption. A company will typically do well in some states and bad in other states, something which varies over time. Valuation models say that consumers value companies doing well in states and times when they have low wealth (low consumption) and therefore high marginal evaluation of an increase in wealth (consumption). This will increase prices (and thereby decrease returns) of these companies. On the other hand, the prices of companies doing well in good states or good times will be driven downward. These kinds of effects will, according to theory, generate the observed risk premia in the market.

The best known valuation model is the capital asset pricing model (CAPM). The CAPM explains returns on stocks by how sensitive the company is to the return on a portfolio containing all wealth in the economy (the market portfolio). The CAPM is usually specified in an unconditional framework as

$$E[r_i] - r_f = (E[r_m] - r_f)\beta_m^i,$$

where $E[r_i] - r_f$ is the expected risk premium for company i, $E[r_m] - r_f$ is the expected risk premium for the market, and β^i_m measures the covariability between the return on stock i and the market portfolio.[2] If we set $er_i = E[r_i] - r_f$, and let $\lambda_m = E[r_m] - r_f$ be the *market risk premium*, we observe that the CAPM may also be expressed as

$$E[er_i] = \lambda_m \beta^i_m, \tag{2}$$

where $E[er_i]$ is the expected return on company i in excess of the risk-free rate, and λ_m is the risk premium of a unit market risk. The CAPM formalizes in a simple manner the idea that the expected return on an asset should be increasing with the risk of an asset.[3] The model is, however, based on very simplified assumptions, among them that the economy only lasts for one period. Currently it is therefore more common to use the intertemporal CAPM or the Arbitrage Pricing Theory (APT) as theoretical bases for estimation. Unconditionally, both the ICAPM and the APT can be expressed as

$$E[er_i] = \sum_j \lambda_j \beta^i_j, \tag{3}$$

where β^i_j is company i's exposure to risk factor j and λ_j the risk premium linked to factor j. The ICAPM is an expanded version of the CAPM where investors with longer investment horizons want to hedge future reinvestment risks.[4] This is modelled through state variables affecting investors' optimization problem over consumption and asset portfolios. State variables which predict market returns and changing investment opportunities are risk factors pricing companies. This is the extent to which the ICAPM specifies state variables; they are not linked directly to observable and measurable economic variables. Wealth/income is, however, an obvious candidate for a state variable. Assets covarying positively with wealth will in such a model have relatively low prices and high expected returns, because investors demand compensation for investing in assets with low returns in periods/states with low wealth (where the marginal utility of income is high). In addition there are variables or news which affect investors future consumption opportunities. Often suggested variables in such settings are GDP and

[2] In an unconditional framework one assumes that risk premia are constant over time.

[3] Investors demand risk compensation to invest in companies which fall in value at the same time as the market falls. The price of low-beta stocks increases and the price of high-beta stock decreases until the consumer's marginal utility of one unit of consumption is equalized across states.

[4] The following description of the ICAPM and APT are based on chapter 9 in Cochrane (2005), to which we refer for more details.

inflation.[5] The model was developed by Merton (1973). At the time there was little belief in the existence of variables capable of predicting returns. Accumulated empirical evidence in the following 30 years has, however, identified some predictability in stock returns. As a result the ICAPM has seen a renaissance in recent years.

The APT model was developed by Ross (1976). The model takes as a starting point empirical observations of stock price evolutions. In good times, when the market increases, most stocks also increase. Similarly, there are obvious common components of the stock evolution in an industry or sector. Ross shows how, from a purely statistical characterization of the realized stock return, and simple arbitrage arguments, one can show that expected returns will be characterized by a multi-factor model of the type specified in (3).

The difference between ICAPM and the APT model is primarily the motivation behind the chosen factors. In the APT one finds common factors through statistical analysis of realized returns, while in the ICAPM the focus is on state variables capable of describing the contingent distribution of future returns. The empirical implementation of both of these theoretical models will be the same; empirically it is therefore not important which model is used as a basis for the factors incorporated in the regressions.

In newer finance literature it is common to express all asset price models in a general framework typically expressed as

$$P_{i,t} = E_t \left[\mathbf{m}_{t+1} \mathbf{x}_{i,t+1}\right] \tag{4}$$

where $P_{i,t}$ is the price of an asset i at time t, $\mathbf{x}_{i,t+1}$ is the future cash flow from the asset, and $\mathbf{m}_{t+1}$ the marginal utility of wealth (also termed the intertemporal rate of substitution, the stochastic discount factor (SDF) or pricing kernel).

Different valuation models result in different specifications of $\mathbf{m}$. Independent of model, however, it is natural to interpret $\mathbf{m}$ as a countercyclical variable which is large in bad times and small in good times. As we will see this general framework is useful when interpreting relations between the stock market and macroeconomic variables. The framework in (4) is also the starting point for the currently most common way of empirically testing valuation models. Let us also remark that all of the models we have discussed earlier may be interpreted as special cases of this framework. If we, for

[5] In equilibrium all investors will invest in a portfolio of a risk-free asset, the market portfolio, and various "hedging portfolios" against variation in the state variables.

example, let $\mathbf{m}$ be a function of only the market portfolio, we are back in a CAPM world.[6]

1.2 Summary of main results

Our study is based on a data-set including all stocks listed on the Oslo Stock Exchange (OSE) in the period 1980 to 2006. In section 2 we survey some important characteristics of the development of the exchange through the period. In section 3 we first describe relations between stock returns and various empirical regularities also found in other stock markets, such as the size, book-to-market and momentum effects. We then proceed to construct risk factors using these effects and test the CAPM against various different empirically motivated multi-factor models. We also discuss different explanations of the empirical risk factors. Finally, we test different multi-factor models based on macro variables.

The main results from our analysis is that the return at the OSE can be explained reasonably well by a multi-factor model consisting of the market index, a size index, and a liquidity index. As expected, changes in the oil price affects the cash flows of most industry sectors at the exchange. Oil is however not a priced risk factor in the Norwegian market. As found in various other markets, there are few macrovariables priced in the market. We do however document a few significant risk premia for the variables inflation, money stock, industrial production and unemployment when we attempt to price portfolios sorted on size and liquidity. We find a significant relationship between most industry portfolios and the nominal variables inflation and money stock; portfolio returns fall with unexpected increases in inflation and increase with unexpected increases in money stock. Since we find little signs of these variables being priced in the market, it is reasonable to believe that the main effect on returns from these variables is through the companies' cash flows.

[6] All valuation models can be written in excess return form as $E[er_i] = -r_f cov(\mathbf{m}, er_i)$ where the specific valuation model (er_m in the CAPM version) is replaced by $\mathbf{m}$. The expression says the same as the CAPM, only with the opposite sign. Companies with a positive covariation with $\mathbf{m}$ (i.e. give high returns when consumers put a high value on consumption), have a lower expected return (higher price). In the same way the traditional discounted value expression in (1) can be written as

$$p_0^i = \sum_{t=0}^{\infty} E_t \left[\frac{D_{i,t+1}}{1 + r_f - r_f cov(\mathbf{m}, er_i)} \right]. \tag{5}$$

2 The Oslo Stock Exchange 1980-2006

Our analysis of the Norwegian equity market uses monthly returns for all stocks listed on the OSE in the period 1980–2006.[7] In this section we survey some of the important features of the development of the exchange in the period.

2.1 Organization of the market

The OSE has made a number of changes to its market structure in the period. In 1988 the earlier call auction was replaced with an electronic platform. The new system allowed for continuous trade throughout the day. The introduction of a new trading system (ASTS) in 1999 allowed for trade through the Internet. A number of specialized Internet brokers were established at the time. In 2000 the OSE joined the NOREX alliance, comprising all Nordic and Baltic exchanges.[8] The purpose of the alliance was to create a common Nordic/Baltic platform for the exchanges and market participants to compete as simply as possible. As part of the alliance the different NOREX exchanges have to some degree harmonized their regulations. All the major exchanges are using the same trading platform, allowing investors access to the Nordic investment universe from one trading terminal. The OSE moved to the common platform with the other NOREX exchanges in 2002 (SAXESS). Everyone wanting to trade stocks using SAXESS has to go through an authorized broker. Such authorized brokers are called exchange members (børsmedlem). The trading system gives the exchange members access to an electronic limit order book for each stock. Supply and demand for stocks is registered in the limit order book, and trades are executed automatically when price, volume, and other order characteristics coincide. SAXESS updates continuously all changes in the market and offers real-time distribution of information to the members. In 2006 the opening hours for the OSE were increased to match the international market for equities.

[7]Accounting, price and volume data are from the OSE data service (Oslo Børsinfomasjon (OBI)).

[8]The NOREX alliance comprises the exchanges in Oslo, Stockholm, Helsinki, Copenhagen, Reykjavik, Tallinn, Riga and Vilnius. Except for the OSE all the exchanges are owned by the OMX company.

2.2 Sectors

We use the GICS standard to group the companies on the OSE.[9] GICS contains 10 industry sectors. A company is put into a GICS category based on its most important business activity. The most important activity is usually decided based on sales. The ten major GICS industries are listed in table 1.

Table 1 The GICS standard

10	Energy and consumption
15	Materials/labor
20	Industrials
25	Consumer Discretionary
30	Consumer Staples
35	Health Care/liability
40	Financials
45	Information Technology (IT)
50	Telecommunication Services
55	Utilities

The energy sector comprises all the oil companies. The sector materials comprises such industries as chemicals, building materials, wrappings, mining, metals, paper and pulp. Utilities comprises companies in power, gas and water supplies as well as independent power producers and buyers.

2.3 Market size and activity

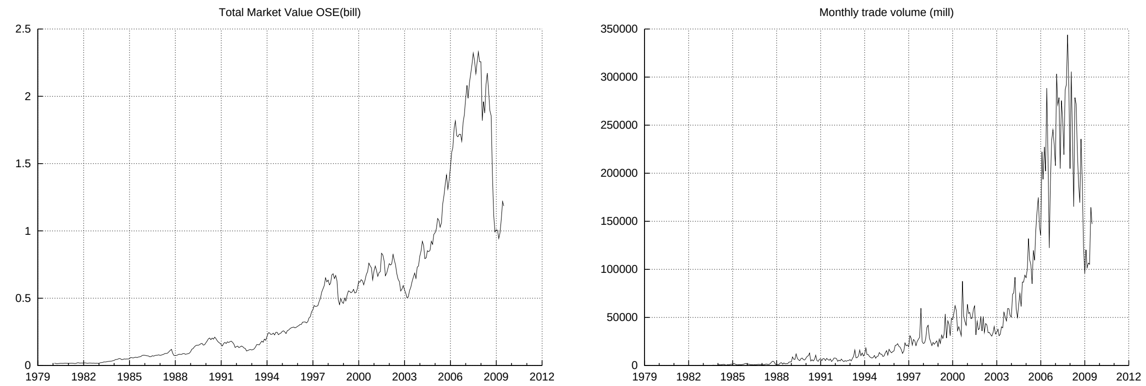
The OSE has been growing steadily over the period 1980–2006 both measured in trading volume and values. This is illustrated in figure 1, which shows the monthly development of respectively total trading volume and total market values for all listed companies. Tables 2 and 4 show the development of market sizes distributed on industry sectors, measured in respectively number of companies and market values.

In 1980 the 93 listed companies on the Oslo Stock Exchange had a total market value of NOK 16,500 million. At the end of 2006 the exchange had 253 listed companies and a total market value about NOK 1.95 billion. The average market value also increased in the period from 170 million in 1980 to 7,510 million in 2006. From 1998 to 2004 the number of listed companies fell from 269 to 207, mainly due to a reduction in the number of industrials. In 2002 the market weight of industrials fell from 23 % to 9 %.

[9]The GICS standard (Global Industry Classification Standard) was developed by Morgan Stanley Capital International (MSCI) and Standard & Poors (S&P). For companies that were delisted before 1997 there is no official OSE classification. We have therefore manually reconstructed the classification of these companies for the period 1980-97.

Figure 1 Total market value and trading volume - OSE 1980-2008

The figures show the development in activity at the OSE over the period 1980 to 2009:6 measured by monthly market values (left) and monthly total trading volume (right) for all listed companies



This was due to a reclassification of one large company, Norsk Hydro, from industry to energy.

Companies on the OSE are concentrated in a few sectors. Up to 1990 the two dominating sectors were Industrials and Financials. In terms of number of companies this pattern has changed over the last 15 years due to an increase in the IT sector and decrease in the industry sector. Looking instead at market weights for each industry sector this pattern is somewhat modified. We observe that the IT sector has a relatively low weight even though almost 20 % of the companies were in this sector in 2006. The energy sector has had a marked increase in market weights the last years, from 10 % in 2000 to 50 % in 2006. This is due to the listing of Statoil, the state oil company, and the reclassification of Norsk Hydro in 2002. Some sectors only comprise a few companies. Utilities and telecommunications were hardly present at the OSE until the mid-nineties.

A prominent characteristic of the OSE is that the exchange always has a few very large companies, companies that dominate the value of the exchange. To illustrate this we include figure 2, which shows the fractions of the value of the exchange in the largest companies. In 2006 the three large state-dominated companies Statoil, Norsk Hydro and Telenor accounted for more than 53 % of the total market value of the OSE.

In table 3 we show average market values for companies in the various sectors, for the whole period and for three subperiods. The industrial sector had the largest companies until the last subperiod, when the energy sector, dominated by oil companies, took over.

Table 2 The number of companies listed on the Oslo Stock Exchange for the period 1980-2006

The table shows the number of listed companies on the Oslo Stock Exchange over the period 1980 to 2006 distributed on industry sectors. Note that the table shows the number of companies and not securities. A number of companies have more than one security issued.

Year	Total	Industry sector (GICS)									
		10	15	20	25	30	35	40	45	50	55
1980	93	9	10	28	6	9	1	28	2	-	-
1981	96	9	11	28	7	9	1	29	2	-	-
1982	109	12	12	30	12	9	1	30	3	-	-
1983	120	12	11	36	13	9	2	31	6	-	-
1984	138	14	12	42	15	10	2	36	7	-	-
1985	158	17	12	48	18	11	2	37	13	-	-
1986	165	18	12	51	18	11	2	39	13	1	-
1987	159	20	12	47	15	9	2	39	13	2	-
1988	144	19	11	45	13	7	2	33	12	2	-
1989	141	17	11	44	11	7	2	37	12	-	-
1990	142	20	9	46	10	7	2	37	11	-	-
1991	131	21	9	45	9	5	2	30	10	-	-
1992	134	20	9	46	14	3	2	30	10	-	-
1993	145	19	9	55	17	4	2	29	10	-	-
1994	156	19	10	60	18	3	3	32	11	-	-
1995	173	20	11	63	21	2	3	39	14	-	-
1996	186	24	12	60	22	3	3	39	21	1	1
1997	226	37	13	71	25	5	5	39	29	1	1
1998	243	36	12	75	28	6	5	45	34	1	1
1999	245	33	11	72	28	6	6	47	39	2	1
2000	246	34	13	60	25	6	7	48	49	3	1
2001	231	36	9	57	22	8	7	45	44	2	1
2002	219	36	9	48	20	9	7	44	43	2	1
2003	209	37	8	41	21	8	8	42	40	2	2
2004	203	35	9	40	18	9	10	38	41	1	2
2005	237	53	9	42	17	13	11	43	46	1	2
2006	253	62	10	44	19	14	13	40	47	2	2

Figure 2 The largest companies on the Oslo Stock Exchange

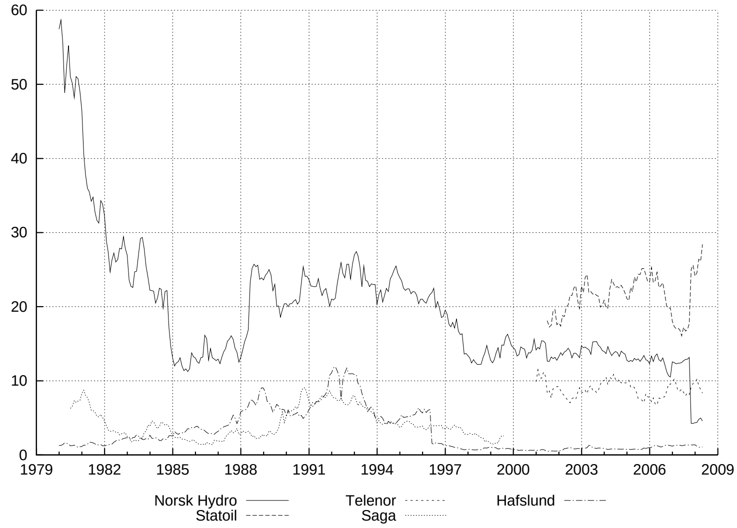


Table 3 Market value of companies in different industry sectors.

The table shows the average market value of companies within the different GICS sectors for the period 1980-2006 and three sub-periods; 1980-89, 1990-99 and 2000-2006.

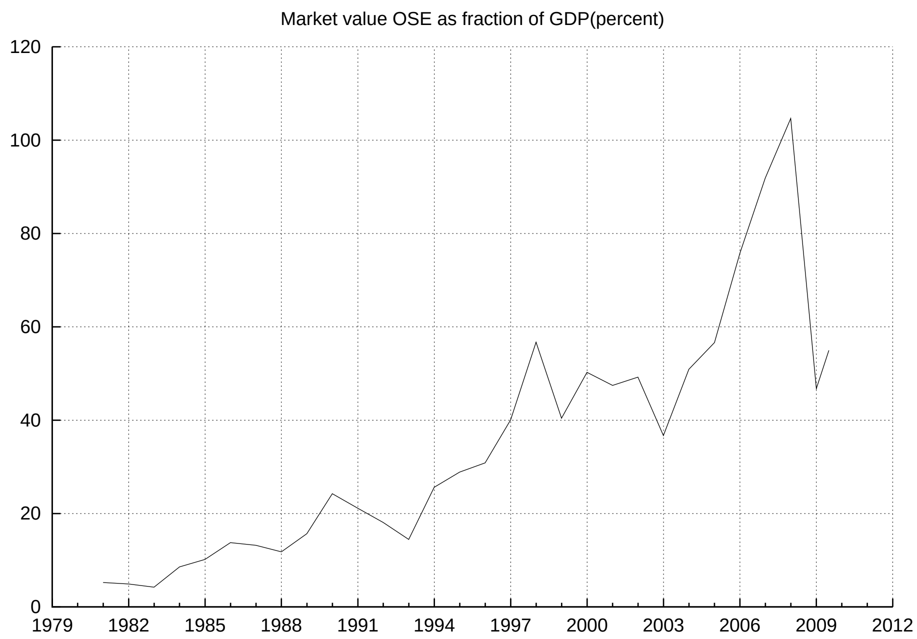
	Average market value for industries (bill. NOK)									
	10	15	20	25	30	35	40	45	50	55
Whole period										
1980-2006	20.75	6.99	31.46	6.15	7.49	5.65	17.52	5.36	2.86	0.38
Sub-periods										
1980-1989	9.88	10.43	39.39	4.06	6.92	4.08	21.86	6.60	0.04	0.00
1990-1999	19.36	5.99	35.94	7.43	8.85	7.11	15.57	3.82	0.79	0.39
2000-2006	38.26	3.51	13.73	7.29	6.37	5.80	14.10	5.78	9.84	0.93

From 1980 to 2006 the annual trading volume on the OSE increased from about NOK 370 million to about NOK 2.6 billion. In other words, currently one day of trading is larger that half a year of trading 26 years ago. The liquidity has also significantly improved. On average the number of trading days per stock has increased from 48 days in 1980 to 181 days in 2006.

Finally, to illustrate the importance of the OSE in the Norwegian economy we show in figure 3 the market value of all stocks on the exchange relative to annual Gross Domestic Product (GDP). In 1980 the market value of all stocks on the OSE was 5 % of annual GDP, a number which has increased to 90 % in 2006.

Figure 3 The market value of the Oslo Stock Exchange relative to GDP (percent)

The figure shows yearly development in the marketvalue of all companies listed on the Oslo Stock Exchange as a percent of GDP. The GDP figures are obtained from Statistics Norway (SSB).



2.4 Stock returns

As a final part of our descriptive analysis of the OSE we look at stock returns. Panel A in table 5 shows the average monthly return for industry portfolios, while panel B in the same table shows correlations between monthly returns of sector portfolios. In terms of average returns the IT and Energy sectors have been the most profitable over the period 1980–2006. The same sectors have also been the most risky, measured

Table 4 Market value of listed companies on the Oslo Stock Exchange for the period 1980-2006.

The table shows the total and average market value of companies listed on the Oslo Stock Exchange for the period 1980-2009:6. The table also shows the market capitalization weights for the 10 GICS industry sectors and the weight of the four largest companies during the period.

Year	Total	average	Market value weight in % for industry sector (GICS)									
	(bill. NOK)	(bill. NOK)	10	15	20	25	30	35	40	45	50	55
1980	16.5	0.17	11	9	58	1	2	1	18	1	-	-
1981	17.7	0.18	10	9	51	2	5	1	24	4	-	-
1982	17.0	0.15	8	8	39	3	5	2	28	6	-	-
1983	38.3	0.31	9	10	37	2	5	3	22	12	-	-
1984	51.5	0.36	9	11	31	4	7	3	23	12	-	-
1985	77.2	0.47	8	11	31	6	7	5	22	11	-	-
1986	77.7	0.45	7	11	34	8	10	4	24	10	0	-
1987	72.6	0.42	10	12	31	7	12	6	27	6	0	-
1988	102.2	0.65	10	10	43	5	8	9	15	3	0	-
1989	166.9	0.95	16	12	40	3	9	6	17	2	-	-
1990	156.3	0.84	21	8	40	3	10	7	16	2	-	-
1991	133.8	0.78	24	7	42	3	12	12	9	2	-	-
1992	115.1	0.68	19	6	41	5	15	12	9	2	-	-
1993	215.5	1.17	18	8	37	6	12	5	16	2	-	-
1994	254.3	1.30	16	8	41	6	6	5	18	1	-	-
1995	289.9	1.49	16	7	38	6	6	6	20	4	-	-
1996	404.5	1.96	24	5	36	6	7	3	18	5	1	1
1997	614.2	2.46	25	3	29	10	6	9	15	5	1	1
1998	460.9	1.71	15	4	27	15	6	7	18	5	2	1
1999	619.2	2.35	16	5	28	16	6	6	17	11	4	1
2000	701.9	2.71	10	5	27	10	8	8	17	11	13	1
2001	755.8	3.06	25	4	23	6	6	8	15	7	9	1
2002	562.8	2.49	43	4	9	6	7	8	15	4	9	1
2003	784.3	3.60	43	4	6	8	5	9	16	4	10	1
2004	986.9	4.77	43	3	10	9	6	8	14	4	10	1
2005	1456.8	6.07	53	3	11	6	6	0	11	4	8	1
2006	1952.7	7.51	50	2	10	5	6	0	11	6	10	1

by the standard deviation of the return. The returns of sector portfolios are highly correlated. The largest correlation we find for the energy and industry portfolios, with a correlation of 73 %.

Table 5 Historical returns for industry sectors (GICS)

Panel A shows the average equally weighted return for industry portfolios based on the GICS classification. For each portfolio, the table shows the first and last year for the return calculation, average monthly return (in percent), the standard deviation, the average number of companies in each portfolio and the number of months used in the calculation. Panel B shows the correlations between the monthly returns for the industry portfolios.

Panel A: Monthly return on industry portfolios

	First year	Last year	Mean return	Standard-deviation	Average companies	Number obs
Energy	1980	2007	2.53	9.74	19.6	336
Materials	1980	2007	1.93	8.62	7.6	336
Industrials	1980	2007	2.03	6.26	32.4	336
Consumer Discretionary	1980	2007	1.72	6.87	12.1	336
Consumer Staples	1980	2007	2.08	6.54	6.9	336
Health Care/liability	1980	2007	1.85	9.64	3.9	336
Financials	1980	2007	1.40	5.14	28.6	336
Information Technology	1980	2007	2.65	11.63	12.2	336
Telecommunication Services	1987	2007	1.12	11.46	1.3	152
Utilities	1996	2007	1.41	6.80	2.4	144

Panel B: Correlation between industry portfolios

	Energy	Materials	Industrials	Discr.	Staples	Health	Financ.	IT	Telecom
Materials	0.55								
Industrials	0.73	0.64							
Discr.	0.50	0.52	0.63						
Staples	0.55	0.52	0.59	0.52					
Health	0.39	0.36	0.45	0.40	0.35				
Finan.	0.62	0.58	0.68	0.62	0.59	0.35			
IT	0.53	0.36	0.49	0.47	0.46	0.47	0.45		
Telecom.	0.37	0.24	0.36	0.40	0.28	0.49	0.38	0.56	
Utilities	0.32	0.20	0.44	0.24	0.40	0.21	0.38	0.32	0.25

3 Empirical analysis of factors affecting returns

The first formalized model for pricing of financial assets was the Capital Asset Pricing Model (CAPM). The CAPM was developed by Sharpe (1964), Lintner (1965) and Mossin (1966) in the mid-sixties. By expanding the model to also account for reinvestment risk Merton (1973) extended the CAPM to the multi-factor model ICAPM. A few years later another multi-factor model (APT) was developed by Ross (1976). The CAPM was, however, the most used model for investigating risk and expected return till the beginning of the nineties.

During the eighties academics discovered a number of empirical regularities in stock returns which were not compatible with the CAPM. For example, one found that large companies on average had a lower return than small companies, even after adjusting for market risk. Since such observations were not compatible with the theory, they were termed "anomalies." In an important article Fama and French (1993) show that an empirically motivated multi-factor model, based on market risk and two of the anomalies had better explanatory power than the CAPM alone. In addition, one found in several empirical investigations support for predictability of stock returns on medium term horizons. Together these empirical results led to a renaissance of the multi-factor models developed in the seventies.

Estimation of multi-factor models can be grouped in two categories. One group constructs risk factors based on the anomalies relative to the CAPM. Such studies have met with considerable success in explaining stock returns, but they do not improve our identification and understanding of the underlying factors affecting returns. Some studies have, however, succeeded in relating the empirically motivated risk factors to underlying macroeconomic relations, such as business cycle and default risk. The other group investigates the link between realized stock returns and macroeconomic variables directly.

In this section we investigate what model specifications are best suited to explaining returns at the OSE from 1980 to 2006. We start by investigating the importance of anomalies in the Norwegian stock market by a few simple portfolio sorts. We then go through our chosen estimation methods, before presenting results for estimation of the CAPM on portfolios sorted by market risk, industries, and the various anomalies. We then present results from estimations of multi-factor models based on the empirically motivated risk factors, and summarize the literature which attempts to find the underlying factors behind the empirical factors. Finally, we present results from estimations using multi-factor models on macro variables.

3.1 Simple portfolio sorts based on CAPM anomalies

The three CAPM anomalies – firm size, book value relative to market value (B/M) and return momentum – were discovered in the US stock market. The anomalies have however shown remarkable persistence across markets and over time. A fourth characteristic often related to CAPM anomalies is liquidity. In this section we investigate, using portfolio sorts, whether these four characteristics also seem relevant for returns in the Norwegian market. In subsection 3.4 we perform a formal test of the relationship between CAPM anomalies and risk-adjusted returns. We also go through the literature attempting to explain why these characteristics are relevant for returns.

3.1.1 Company size

The size effect is an empirical regularity showing that investments in small companies on average have had a (risk-adjusted) return premium relative to investments in small companies. The size effect was first documented using US data 1936-1975 by Banz (1981). After Banz's study the size effect has been documented in similar studies in 17 other countries, which according to Dimson and Marsh (1999) make the size effect the most documented stock market anomaly in the world. The size effect has however turned out to be very sensitive to choice of time period. For most countries the effect was negative in the period 1980–2000, that is the twenty-year period after Banz's publication of his results. Over the short period from 2000 it has again become on average positive.

To investigate the size effect in Norway we use a portfolio sort method where we construct portfolios based on companies' market values at the end of the previous year. The portfolio compositions are fixed throughout the year, and re-balanced at the end of the year. Basing the portfolios on ex ante characteristics guarantees that this is an implementable trading strategy. Note however that the method does not adjust for risk differences.

Table 6 shows excess returns (returns in excess of the risk-free rate) for 10 portfolios sorted on size for the period 1980-2006. Portfolio 1 contains the smallest companies and portfolio 10 the largest companies. Table 6 shows a positive differential return in the period: The smallest companies have had the highest returns, and returns are falling almost monotonically with size. The period average differential return between a portfolio of the smallest companies and the largest companies has been more than 2% per month. We seem to have had a size effect also in the Norwegian stock market. An interesting observation is that the size effect seems to have been positive over a period when it was negative in other countries. In panel B of the table we observe that the differential return between small and large companies has been positive also for subperiods, but has fallen over time. The last column of the table shows the results for a test of whether the differential return between the two portfolios is significantly different from zero. For the last subperiod (2000-2006) we do not find support for a significant difference in the returns of small and large companies.

Table 6 Monthly excess returns for portfolios sorted on company value

Panel A shows the monthly percentage excess returns for 10 portfolios constructed based on market value. The results are for the whole sample period 1980-2006. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolio containing the 10% smallest firms (portfolio 1) and the 10% largest firms (portfolio 10) on the exchange for three sub-periods. The table also show t-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1980-2006

	Excess return					Number of stocks		
Portf.	Mean	(std.dev.)	min	median	max	min	median	max
1	2.66	(7.9)	-19.0	1.59	45.5	4	12	18
2	1.94	(7.1)	-18.8	1.77	31.1	3	12	18
3	1.08	(7.2)	-23.9	0.97	32.3	3	12	18
4	1.12	(7.2)	-24.6	1.10	26.1	3	12	18
5	1.42	(7.2)	-15.8	1.03	52.5	3	12	17
6	1.16	(6.7)	-30.4	1.15	26.9	4	13	18
7	0.87	(7.4)	-25.3	0.86	47.0	3	12	18
8	0.80	(7.0)	-24.9	0.95	18.8	3	12	18
9	0.69	(8.0)	-29.7	0.96	22.4	3	12	18
10	0.44	(7.1)	-30.2	0.70	24.2	3	12	17

Panel B: Sub-periods

	Small (Portf.1)	Large (Portf.10)	Diff.	t-test diff=0
1980-1989	8.14	1.80	6.34	4.48
1990-1999	4.51	1.50	3.01	3.66
2000-2006	2.44	1.96	0.48	0.92

3.1.2 Book value relative to market value

Another company characteristic which seems to give a systematic pattern in returns across companies is the relationship between book values and market values. Several studies, for example Rosenberg, Reid, and Lanstein (1984), Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994), find that companies with the highest book values relative to market values have systematically higher risk-adjusted returns than those with the lowest book value relative to market value.

To investigate whether there are any systematic return differences between companies based on differences in B/M ratios in the Norwegian stock market we construct portfolios in a similar manner to the size portfolios. Table 7 shows the results from this analysis. Portfolio 1 (10) contains the companies with the lowest (highest) B/M ratio. Portfolio 10 gives on average a (not risk-adjusted) excess return of 0.7 % per month compared with portfolio 1. It is substantially below the differences due to company size. Also note that the relationship between B/M and return is much less systematic than that due to size. In the table's panel B we show returns for the two extreme portfolios based on B/M for three subperiods. We see that the B/M effect has been dominating in the first part of the period, and the the return difference is not significant for the last two subperiods.

3.1.3 Momentum

Jegadeesh and Titman (1993) document that an investment strategy defined as buying stocks with high returns the last 3-12 months and selling companies with a low return over the same periods (buying winners and selling losers) give a risk-adjusted excess return.[10] The strategy, which is called momentum, was already known and commonly used by portfolio managers.[11]

Momentum strategies have also been shown to work outside the US. Rouwenhorst (1998) documents momentum strategies in 12 European stock markets over the period 1980–95, while Chan, Hameed, and Tong (2000) find support for momentum strategies in 23 international stock indices, of which 9 Asian, 11 European, two North-American and one South-African.[12]

[10] Jegadeesh and Titman (1993) use data from the US market over the period 1965 to 1989. Jegadeesh and Titman (2001b) show that momentum strategies also worked in the nineties.

[11] See Jegadeesh and Titman (2001a) for a survey of the American literature.

[12] Except for Austria, the analysis uses data from 1980-95.

Table 7 Monthly excess returns on portfolios sorted on B/M

Panel A shows the monthly percentage excess returns for 10 portfolios constructed based on Book to Market value (B/M). The results are for the whole sample period 1980-2006. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolio containing the 10% firms with the lowest B/M-value (portfolio 1) and the 10% of the firms with the highest B/M-value (portfolio 10) for three sub-periods. The table also show t-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1980-2006

	Excess return					Number of stocks		
Portf.	Mean	(std.dev.)	min	median	max	min	median	max
1	1.28	(9.5)	-26.6	0.46	63.4	4	11	18
2	1.21	(8.4)	-24.5	1.01	44.2	3	11	17
3	0.92	(7.1)	-24.6	0.83	23.8	4	11	18
4	0.41	(7.1)	-23.0	0.86	26.4	2	11	17
5	1.47	(7.0)	-26.9	1.25	22.8	4	11	17
6	1.35	(7.8)	-21.2	0.89	66.7	4	11	18
7	1.54	(7.5)	-22.6	1.59	45.8	3	11	17
8	1.51	(8.0)	-38.2	1.67	32.1	3	11	18
9	1.90	(7.3)	-22.4	1.71	26.3	4	11	17
10	1.99	(8.4)	-25.9	1.30	37.4	3	10	17

Panel B: Sub-periods

	Low B/M (Portf.1)	High B/M (Portf.10)	Diff. High-Low	t-test diff=0
1980-1989	2.65	4.82	2.167	2.14
1990-1999	2.89	3.33	0.434	0.47
2000-2006	2.51	4.34	1.829	1.82

Table 8 shows monthly returns of portfolios sorted on momentum in the Norwegian stock market. Portfolio 1 contains the stocks with the lowest return the previous 11 months, while portfolio 10 contains stocks with the highest return. The differential return between portfolio 10 and portfolio 1 was on average 0.44 % per month. The return differences are however not monotone in momentum. Also for subperiods we see in panel B little support for a significant momentum effect. The differential return also changes sign in the second sub-period.

Table 8 Monthly excess returns for portfolios based on momentum

Panel A shows the monthly percentage excess returns for 10 portfolios constructed based on momentum. The results are for the whole sample period 1980-2006. Momentum is defined as the return from January until the portfolios are re-balanced at the end of the year. Thus, portfolio 1 contains the firms with the lowest return the previous year, and portfolio 10 contains the firms with the highest previous year return. Panel B shows the average monthly return for the portfolio containing the 10% of the firms with the lowest previous year return (portfolio 1) and the 10% of the firms with the highest previous year return (portfolio 10) on the exchange for three sub-periods. The table also show t-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1980-2006

	Excess return					Number of stocks		
Portf.	Mean	(std.dev.)	min	median	max	min	median	max
1	1.40	(7.5)	-23.7	1.16	27.2	4	14	20
2	0.95	(6.8)	-28.7	1.08	21.5	3	13	20
3	0.85	(7.5)	-26.1	0.67	23.3	3	12	20
4	1.19	(8.7)	-28.2	0.40	37.9	2	11	19
5	1.24	(6.6)	-23.6	0.80	23.7	3	12	20
6	0.85	(6.2)	-19.7	0.69	26.1	3	12	20
7	1.18	(6.3)	-16.6	1.06	24.3	4	13	20
8	1.23	(6.2)	-23.8	0.54	20.4	3	13	20
9	1.44	(6.9)	-22.3	1.32	35.0	3	13	20
10	1.82	(7.6)	-23.0	1.45	31.7	3	13	20

Panel B: Sub-periods

	Low MOM (Portf.1)	High MOM (Portf.10)	Diff. High-Low	t-test diff=0
1980-1989	2.51	4.18	1.666	1.84
1990-1999	3.72	1.97	-1.756	-1.96
2000-2006	2.48	3.50	1.021	0.86

3.1.4 Liquidity (transaction costs)

One characteristic often related to CAPM anomalies is liquidity. Level and variation in companies' liquidity has been suggested as explanations of the size effect, B/M effect and momentum effect, see for example Acharya and Pedersen (2005), Liu (2006) and

Sadka (2006). These results suggest that the observed anomalies in returns both across companies and over time may be a result of unrealistic assumptions in the CAPM development of static and frictionless markets.[13]

A problem with the concept of liquidity is that it has several dimensions: a cost dimension (how much it costs to trade), a time dimension (how fast one can trade), and a quantity dimension (how much one can trade). This has led to a proliferation of liquidity measures in the literature, with little agreement about which to prefer.

Table 9 Monthly excess returns for portfolios sorted on relative bid-ask spread

Panel A shows the monthly percentage excess returns for 10 portfolios constructed based on the relative bid-ask spread as a proxy for liquidity. Portfolio 1 contains the most liquid firms with the lowest bid/ask spread, and portfolio 10 contains the least liquid firms. The results are for the whole sample period 1980-2006. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolio containing the 10% most liquid firms (portfolio 1) and the 10% least liquid firms (portfolio 10) for three sub-periods. The table also show t-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1980-2006

	Excess return					Number of stocks		
Portf.	Mean	(std.dev.)	min	median	max	min	median	max
1	0.56	(7.1)	-27.0	0.83	20.4	5	13	18
2	0.80	(7.3)	-28.7	1.18	20.6	4	12	18
3	1.14	(7.3)	-26.7	1.23	22.2	4	12	18
4	0.71	(6.7)	-25.6	1.47	22.8	4	12	18
5	0.99	(7.0)	-24.2	0.85	36.9	4	12	17
6	1.02	(6.9)	-21.1	0.81	29.9	4	12	18
7	1.38	(7.1)	-18.2	0.65	31.2	4	12	18
8	1.39	(7.5)	-21.9	0.86	37.2	4	12	18
9	2.15	(7.0)	-17.6	1.55	32.9	4	12	18
10	2.19	(7.8)	-21.3	0.97	39.0	4	12	17

Panel B: Sub-periods

	Low spread (Portf.1)	High spread (Portf.10)	Diff. High-Low	t-test diff=0
1980-1989	1.72	5.96	4.241	4.40
1990-1999	1.50	3.46	1.960	2.93
2000-2006	1.80	2.82	1.027	1.81

Table 9 shows the results of a portfolio sort based on relative spread. The relative spread is a much used measure of liquidity, and calculated as the difference between the closing bid and ask prices, relative to the midpoint price. Portfolio 1 contains the stocks with the lowest spread, i.e. the most liquid companies, while portfolio 10 contains companies with the biggest spread. The table shows that a portfolio of the

[13] Models which expand the CAPM with a liquidity factor (e.g. Acharya and Pedersen (2005) and Liu (2006)) have good explanatory power relative to observed CAPM anomalies.

least liquid stocks would in 1980-2006 have given excess returns of more than 1.5% per month. This result seems consistent across subperiods. In panel B the table shows that the portfolio of least liquid stocks has had a systematically higher return than the most liquid companies. Also note that the difference is not significant in the last subperiod.

To summarize the results of this subsection figure 4 illustrates the importance of the different anomalies. In each figure we compare three simple portfolio strategies (two extreme portfolios and the market portfolio). In each figure the extreme portfolios correspond to portfolio 1 and 10 in the preceding tables. The portfolios are value weighted using company market values. In figure 4(a) we show the accumulated return (without reinvestment) of a portfolio of the 10% smallest companies (grey line) and a portfolio of the 10% largest companies (broken line). These portfolios are reconstructed every year-end using company market values, and weights are kept constant through the year. In the figure the solid black line shows the accumulated return of the market index. Correspondingly, figure (b) shows results when we construct portfolios based on book to market values at the end of the year. Figure (c) shows the return of portfolios sorted on the previous year's return (momentum) and (d) shows results for portfolios based on relative spread (liquidity). Observe that in particular the size strategy (a) and liquidity strategy (d) give high excess returns relative to the market. Also the Book/Market strategy in (b) gives a positive excess return relative to the market, while the momentum strategy (c) does not give any excess return relative to the market. Figure 4 indicates that there is something special about particularly the size and liquidity portfolios which lead to excess returns. The excess return is however not adjusted for risk. In the next sections we will investigate whether there also is a risk-adjusted excess return related to the anomalies, and whether any such excess return can be explained by risk factors other than the market.

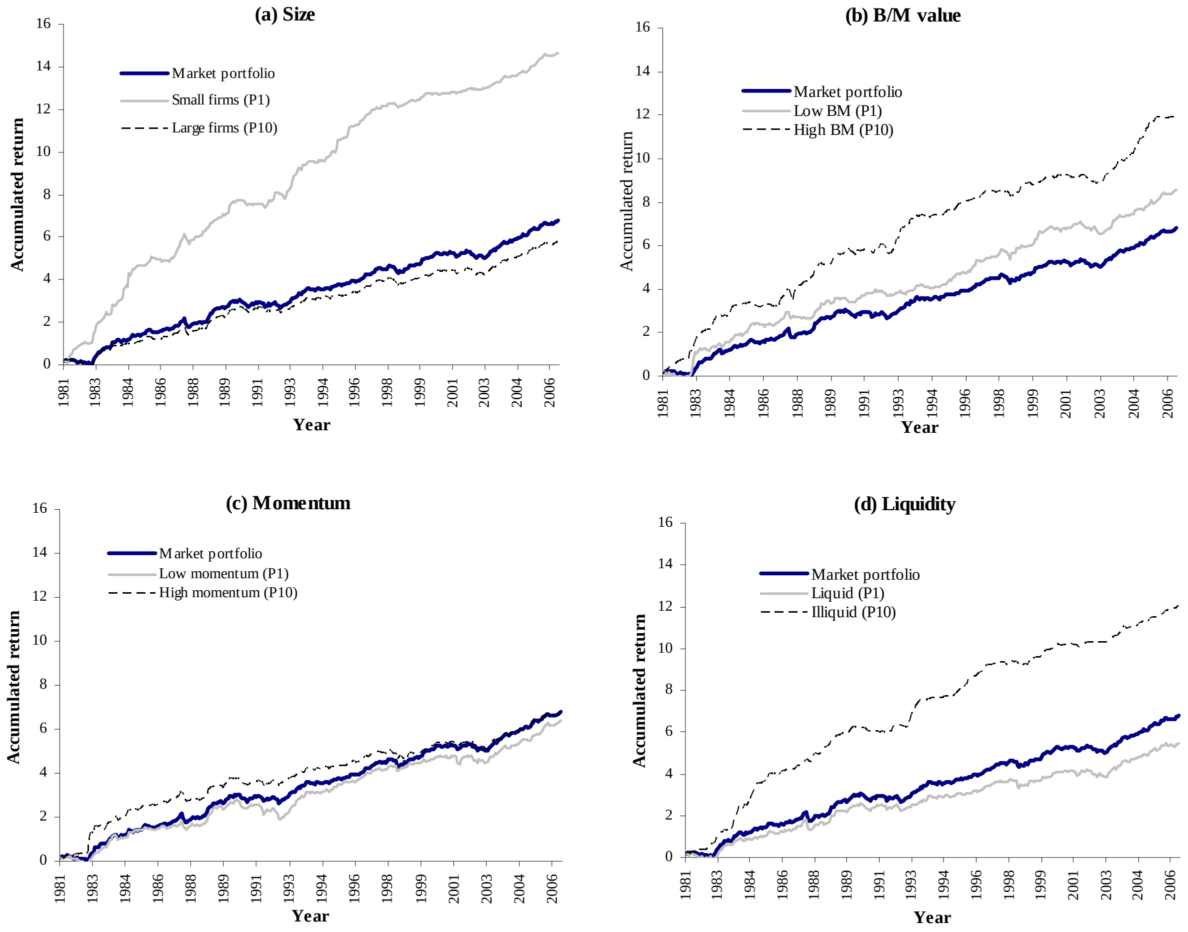
3.2 Method for estimation of factor models

In this subsection we give a short presentation of the methods of estimation used to test various valuation models. As mentioned in the introduction, in a theoretical factor model one will assume that the expected return for a stock in excess of the risk-free return in equilibrium can be expressed as

$$E[er^i] = \sum_j \lambda_j \beta_j^i \tag{6}$$

Figure 4 Portfolios based on various characteristics

The figures show the accumulated return (without reinvestment) for portfolios constructed at the beginning of each year based on (a) size, (b) book-to-market value (B/M), (c) momentum and (d) liquidity. In each figure we show the accumulated return for the two extreme portfolios for each characteristic in addition to the accumulated return on the value-weighted market portfolio. Note that the portfolio returns are not adjusted for market risk.



where $E[er^i]$ is expected excess return for stock i, $j \in \{1, .., J\}$ the number of factors affecting returns, β^i_j is the exposure to risk factor j for stock i and λ_j is the risk premium for risk factor j common to the whole market.

There are various methods for estimating risk premia for one or more factors, and testing whether a model can price a collection of assets. The traditional method uses two steps. The first step is the method developed by Black, Jensen, and Scholes (1972), time series regressions of the type

$$er^i_t = a^i + \sum_{j=1}^{J} \beta^i_j f_{jt} + \varepsilon^i_t \tag{7}$$

where er^i_t is the excess return for stock i, a^i a constant term, and β^i_j the estimated exposure to factor f_j of stock i. The estimated factor exposures measure the sensitivity of the return of an asset to movements in the respective factors. When a factor is expressed as a return series, for example as the return on a portfolio of large companies less the return on a portfolio of small companies, the factor model can be tested by testing the restriction that all the constant terms, a^i, equal zero. If this is rejected the model is rejected. If a factor model includes factors which are not return series, such as inflation or money stock, the analysis does not have such an interpretation.[14]

In this estimation we do not use the restriction of constant risk premia across assets. The next step in the the two-step procedure is therefore to estimate factor risk premia, and test whether the model is able to price stocks/portfolios correctly. Given the estimates from (7), the risk premium linked to factor j can be estimated by a cross-sectional regression

$$er^i = \lambda_0 + \sum_{j=1}^{J} \lambda_j \beta^i_j + \varepsilon^i \tag{8}$$

where λ_0 is a constant term, and λ_j is the risk premium of factor j. Finally, we will perform statistical tests on λ_j to investigate whether the risk premia of the various factors are significantly different from zero.

The traditional way of estimating (7) and (8) has been OLS. A problem with estimation of the model in two steps using OLS is the "generated regressors" problem,

[14] If one wishes to do such a test it is necessary to construct so-called "mimicking portfolios" representing the factors. A "mimicking portfolio" is a portfolio of stocks with similar properties to the factor. A couple of well known such mimicking portfolios are the Fama/French factors based on return representation of size and B/M.

that is that one does not account for the explanatory variables (β_i) in (8) having estimation errors. In newer literature it is becoming increasingly common to use the GMM (Generalized Method of Moments) method instead of this two-step procedure. By using GMM one can estimate (7) and (8) simultaneously, thereby accounting for the errors in variables problem. In addition, the GMM method is more robust to time series and distributional properties of the error terms.[15]

3.2.1 GMM estimation in a SDF setting

In newer empirical finance literature it is most common to do estimation by estimating the stochastic discount factor (*SDF* or $\mathbf{m}$) directly. SDF estimation will give estimates of the same risk premia as the above two-step procedure. The advantage of the SDF framework is that it is so general that it handles a number of different models. The framework is also particularly well suited in cases where the model contains factors which are not returns (such as macroeconomic variables). The SDF framework can incorporate such factors directly in the estimation, without the need for constructed "factor mimicking" portfolios. One problem with the direct SDF procedure is that it is less intuitive than the two-step procedure. The results from a SDF estimation also produce a bit less information.

The GMM method takes as its starting point a set of "moment conditions" derived from the underlying model to be estimated.[16] The general pricing relationship in equation (4) in the introduction gives us the necessary moment conditions to identify valuation models in the SDF framework. Rewriting it in returns form we have that

$$E\left[\mathbf{m}_t er_t^i\right] = 0 \tag{9}$$

This expression merely says that the risk-adjusted excess returns of all assets equal zero. It is necessary to put more structure on $\mathbf{m}$ to get a testable model. The SDF framework is hence very general as the specification of $\mathbf{m}$ depends on the valuation model employed. Since we in this study estimate and test unconditional linear factor

[15] If a model is estimated by OLS it is assumed that the error term is identically and independently distributed (iid). If the iid assumption is not valid, the OLS estimates will be biased with too low standard errors. GMM on the other hand will provide robust standard errors even in the non-iid case. In the special case of iid error term, the standard errors of the parameter estimates will be the same as in the case of OLS.

[16] The following is a short, intuitive summary of GMM estimation. For more detail we refer to Cochrane (2005).

models we assume $\mathbf{m}_t$ is a linear function of a set of risk factors and can be expressed as

$$m_t = c + \sum_{j=1}^{J} b_j f_{j,t} \tag{10}$$

where c is a constant, b_j the factor weight of risk factor f_j, and we have J risk factors.

In this study we will estimate all models in the SDF framework with the GMM method. In most cases we will also estimate factor exposures as in (6), since this gives us additional information about how the return of for example sector portfolios co-vary with different factors (β_j^i). GMM estimation proceeds by finding, for a given set of assets (stock/portfolio returns) with excess returns er_t^i and risk factors f_j, the factor weights b_j that makes the moment condition (9) equal to zero.[17] The GMM procedure in other words finds the values of factor weights which set the vector of moment conditions for all the portfolios (pricing errors) simultaneously closest to zero.

To evaluate the appropriateness of various factor models we use Hansen (1982)'s J-test. Suppose we have a cross-section of assets, and want to test a j-factor model. If $n > j$, which often is the case, the system is over-identified. The J test is used to test whether the over-identifying moment conditions are close to zero. In this case the J-test will say something about the size of the pricing errors from the factor model, and thereby how well the model fits the data.

A factor weight ($\mathbf{b}$) in (10) says something about how important the given factor is in pricing the portfolios, given the other factors. These factor weights should not be mistaken for the β estimates from (7). *After* having estimated $\mathbf{b}$ we calculate the risk premia λ as $\lambda_j = -var(f_j)b_j$. By testing whether the risk premia of the various factors equal zero, we can investigate whether a factor is priced. For factors which are returns (for example the market factor) λ gives a direct estimate of how much extra excess return one unit of extra exposure to the factor gives. For factors which are not return-based, one can not directly see from estimates of λ the implications for expected excess returns.

3.3 Capital Asset Pricing Model (CAPM)

The CAPM formalizes, in a simple way, the idea that the expected return on an asset should be higher the more risky the asset is. The model is based on very simplified

[17] In this estimation we need to force $\mathbf{m}$ to be different from zero, which is done by the normalization of the constant term (c in (10)) to equal one.

assumptions, where for example investors live for only one period, and have no other income. The model's assumptions lead to the only relevant risk for an asset being given by the asset's covariance with a value-weighted portfolio of all assets in the economy (the market portfolio). The CAPM can therefore be viewed as a special case of (6), where the market portfolio is the only relevant risk factor. To test the CAPM we need a proxy for the market portfolio.

What market portfolio to use in tests of the CAPM is much discussed in empirical finance. A well known article by Roll (1977) points out that the theoretically correct market portfolio, the portfolio of all assets in the economy, is unobservable, and a wrong proxy can give wrong conclusions. Even if this is acknowledged as a problem, newer literature has settled on using a wide stock market portfolio as a proxy for the market portfolio. It has also been found that for single country analyses one should use a broad market index for the market in question. For the Norwegian market a value weighted market portfolio will however mainly reflect the return of a few large companies (see table 4). We therefore estimate all specifications of models using both value and equally weighted market portfolios.

To reduce noise in estimation it is common to test factor models at the portfolio level. The CAPM predicts that companies with high market beta have high returns. To test this prediction it is sensible that the portfolio betas have a good cross-sectional distribution. It is therefore usual to sort portfolios using stock beta.[18] To investigate to what extent the CAPM prices stocks within the various industry sectors we also use industry sectors as a basis for portfolio sorts.

3.3.1 CAPM using a market index at the OSE

In this section we report results from estimating the CAPM where we use the market index at the OSE as a proxy for the market portfolio. Panel A in table 10 shows results from estimation of the CAPM for portfolios sorted on beta and industry. Both the beta and industry portfolios are value weighted. However, we find similar results for equally weighted portfolios. Note that we only have sufficient data for 7 of the 10 industry sectors. The calculations are based on monthly figures for the period 1982-2006.[19]

Columns two and three for each portfolio sort in panel A show estimated constant

[18]The beta portfolios are constructed at the end of each year and held constant through the following year. Market beta for each stock is estimated using returns data for the three previous years.

[19]We need a couple of years to estimate the momentum factor in table 12.

terms with accompanying p-values for each portfolio (industry sector). Constant terms significantly different from zero indicate a badly specified model. The last two columns in each portfolio sort show estimated market betas (β_i^1) and accompanying p values for each portfolio (industry) for an equally-weighted market portfolio. Estimated exposures using a value-weighted portfolio are not significantly different. Exposures are calculated using a time series regression as in (7). Panel B in the table shows the estimated risk premium, λ, for the market factor (equally weighted and value weighted) and the result of a J-test for for the explanatory power of the model.[20] A factor is said to be priced if λ is significantly different from zero. The J-test is based on the pricing errors of the model. A low p-value for this test suggests that the model should be rejected. The estimated risk premia are estimated using GMM in a SDF framework, as described in section 3.2.1.

Both models give significant betas for all portfolios. For the beta-sorted portfolios beta varies from 0.63 for portfolio 1 to 1.29 for portfolio 10. The betas of the industry portfolios also have a reasonable distribution, where the energy sector has the highest risk as measured by beta, and the financial sector the lowest beta. For the industry-sorted portfolios estimated risk premia are different from zero independently of whether we use an equally- or value-weighted market portfolio. For the beta-sorted portfolios only the equally weighted market portfolio results in a significant risk premium. None of the models has a constant term different from zero at the 1 % level. The models can neither be rejected based on the p-values of the J-tests. We find that the market portfolio is a priced risk factor, and that the CAPM is a reasonably well specified model for portfolios sorted on market risk and industry sector.

We then move to anomalies relative to the CAPM. Tables 11 and 12 show results of estimation of the CAPM on portfolios sorted on the various anomalies. All portfolio sorts in the tables are value weighted. Results for equally weighted portfolios sorts are similar.

Table 11 shows results from an estimation using size portfolios and an estimation using liquidity portfolios. We see that the beta estimates are significant for all portfolios in both models. The cross-sectional difference in estimated betas is however low. In spite of this we find that the market portfolio is a priced risk factor in all models with one exception: a value-weighted market portfolio and size-sorted portfolios. All size portfolios except the two containing the largest companies (portfolios 9 and 10) have

[20]see Hansen (1982).

Table 10 Estimation of the CAPM on portfolios sorted on market beta and industry sector

Panel A shows the results from estimating the CAPM as in equation (7) for portfolios sorted on market beta (i) and industry sectors (ii). Both the beta- and industry-portfolios are value weighted. For each set of portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The last two columns for each set of portfolios show the estimated market beta (β_i^1) and associated p-value. Panel B shows the risk-premia estimated in the SDF framework using GMM as described in section 3.2.1. The risk premium, λ, is estimated both using an equally-weighted (er_m^{ew}) and value-weighted (er_m^{vw}) market portfolio. A factor is said to be priced if λ is significantly different from zero. Panel B also reports the results of a J-test of the models. The J-test is based on the size of the pricing errors of the model. A low p-value indicates a rejection of the model.

Panel A: Exposure estimates

(i) Beta sorted portfolios					*(ii) Industry portfolios*				
Market risk	constant	p-value	β_i^1	p-value	Industry	constant	p-value	β_i	p-value
1 (low beta)	0.009	(0.02)	0.518	(0.00)	10 Energy	-0.001	(0.70)	1.103	(0.00)
2	0.004	(0.24)	0.472	(0.00)	15 Materials	-0.002	(0.43)	0.998	(0.00)
3	0.006	(0.12)	0.686	(0.00)	20 Industry	-0.003	(0.11)	1.062	(0.00)
4	0.002	(0.42)	0.705	(0.00)	25 Discretionary	0.005	(0.24)	0.903	(0.00)
5	-0.002	(0.50)	0.744	(0.00)	30 Staples	0.006	(0.06)	0.823	(0.00)
6	-0.005	(0.17)	1.010	(0.00)	40 Financials	-0.001	(0.65)	0.772	(0.00)
7	-0.004	(0.18)	0.939	(0.00)	45 IT	0.012	(0.07)	1.189	(0.00)
8	-0.006	(0.05)	0.947	(0.00)					
9	-0.001	(0.88)	1.196	(0.00)					
10	-0.001	(0.73)	1.207	(0.00)					

Panel B: Risk-premia estimates

(i) Beta sorted portfolios			*(ii) Industry portfolios*		
Factor	Risk premium	t-value	Factor	Risk premium	t-value
$\lambda[1](er_m^{ew})$	0.014	(2.70)	$\lambda[1](er_m^{ew})$	0.014	(2.97)
$\lambda[1](er_m^{vw})$	0.001	(1.92)	$\lambda[1](er_m^{vw})$	0.015	(3.07)
Chi Square test	J ($\chi^2(9)$)	p-value		J ($\chi^2(6)$)	p-value
er_m^{ew}	6.22	(0.51)	er_m^{ew}	5.57	(0.23)
er_m^{vw}	8.38	(0.30)	er_m^{vw}	4.80	(0.31)

Table 11 Estimation of the CAPM on portfolios sorted on size and relative spread

Panel A shows the results from estimating the CAPM as in equation 7 for portfolios sorted on size (i) and liquidity (ii). Firm size is measured as the market capitalization and liquidity is measured by the firms' relative spread. Both the size- and liquidity portfolios are value weighted. For each set of portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The two last columns for each set of portfolios show the estimated market beta (β_i^1) and associated p-value. Panel B shows the risk-premia estimated in the SDF framework using GMM as described in section 3.2.1. The risk premium, λ, is estimated both using an equally weighted (er_m^{ew}) and value-weighted (er_m^{vw}) market portfolio. A factor is said to be priced if λ is significantly different from zero. Panel B also reports the results of a J-test of the models. The J-test is based on the size of the pricing errors of the model. A low p-value indicates a rejection of the model.

Panel A: Exposure estimates

Size portfolios					*Liquidity portfolios*				
Size	constant	p-value	β_i^1	p-value	Liquidity	constant	p-value	β_i^1	p-value
1 (low MCAP)	0.037	(0.00)	0.674	(0.00)	1 (low spread)	-0.005	(0.00)	1.017	(0.00)
2	0.027	(0.00)	0.621	(0.00)	2	-0.002	(0.35)	1.020	(0.00)
3	0.010	(0.01)	0.851	(0.00)	3	0.001	(0.61)	1.087	(0.00)
4	0.015	(0.00)	0.827	(0.00)	4	0.003	(0.33)	1.001	(0.00)
5	0.014	(0.00)	0.792	(0.00)	5	0.003	(0.20)	0.869	(0.00)
6	0.013	(0.00)	0.875	(0.00)	6	0.004	(0.19)	0.895	(0.00)
7	0.008	(0.01)	0.871	(0.00)	7	0.005	(0.14)	0.905	(0.00)
8	0.007	(0.01)	0.931	(0.00)	8	0.013	(0.00)	0.787	(0.00)
9	0.001	(0.73)	1.035	(0.00)	9	0.016	(0.00)	0.752	(0.00)
10	-0.004	(0.00)	1.022	(0.00)	10	0.025	(0.00)	0.669	(0.00)

Panel B: Risk-premia estimates

Size portfolios			*Liquidity portfolios*		
Factor	Risk premium	t-value	Factor	Risk premium	t-value
$\lambda[1](er_m^{ew})$	0.026	(5.73)	$\lambda[1](er_m^{ew})$	0.026	(5.36)
$\lambda[1](er_m^{vw})$	0.008	(1.90)	$\lambda[1](er_m^{vw})$	0.018	(3.48)
Chi Square test	J ($\chi^2(9)$)	p-value		J ($\chi^2(6)$)	p-value
er_m^{ew}	20.01	(0.01)	er_m^{ew}	20.71	(0.00)
er_m^{vw}	26.87	(0.00)	er_m^{vw}	24.47	(0.00)

however constant terms significantly different from zero. The portfolios with lowest liquidity (as measured by relative spread) also have significant constant terms. Also note that the constant term is increasing in size and increasing liquidity (falling spread). The J-test is significantly different from zero at the 1 % level for both the size portfolios and the liquidity portfolios, suggesting that the pricing errors from the various models are large. The CAPM does not seem able to price neither size portfolios or the liquidity portfolios. This indicates a size effect in the Norwegian market, related to liquidity.

Table 12 shows results from estimations where we sort portfolios on book values/market values (B/M) and momentum. We find significant beta estimates, a nice spread in portfolio betas, and significant risk premia in both models. Portfolios with lowest B/M and highest B/M have constant terms significantly different from zero at respectively the 2 % and 1 % level. The model is also rejected by the p-value of the J-test. The momentum model is however not rejected by the p-value of the J-test. CAPM seems in other words to price momentum portfolios well. We therefore have only weak signs of momentum effects in the Norwegian equity market.

3.4 Multi-factor models based on empirically constructed factors

A common trait of the multi-factor models ICAPM and APT is that they do not identify what factors are important for returns. According to the ICAPM, stock returns will be driven by the market factor of the CAPM together with all factors (or state variables) important for the conditional distribution of future returns. In the APT model the common factors are estimated statistically using the returns on all assets in the market. To support the APT a significant factor should also be important for realized returns. This is not necessarily the case for an ICAPM factor. An advantage of the ICAPM model is the ability to apply theory to suggest candidate factors.

In table 11 we show that the market factor in the CAPM is unable to price portfolios sorted on size and liquidity. This is strong evidence that the CAPM is not sufficient to explain the Norwegian market. In the framework of a multi-factor model this can be explained by size and liquidity being risk factors for which investors demand compensation to be exposed to, but which are not expressed in the market portfolio. In this section we construct risk factors from the CAPM anomalies, and test to what extent this type of multi-factor model explains asset returns better in the Norwegian market,

Table 12 Estimation of the CAPM on portfolios sorted on B/M and momentum

Panel A shows the results from estimating the CAPM as in equation (7) for portfolios sorted on B/M-value (i) and momentum (ii). Both the size- and liquidity portfolios are value weighted. For each set of portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The two last columns for each set of portfolios show the estimated market beta (β_i^1) and associated p-value. Panel B shows the risk-premia estimated in the SDF framework using GMM as described in section 3.2.1. The risk premium, λ, is estimated both using an equally-weighted (er_m^{ew}) and value-weighted (er_m^{vw}) market portfolio. A factor is said to be priced if λ is significantly different from zero. Panel B also reports the results of a J-test of the models. The J-test is based on the size of the pricing errors of the model. A low p-value indicates a rejection of the model.

Panel A: Exposure estimates

B/M portfolios					*Momentum portfolios*				
B/M	constant	p-value	β^1	p-value	Momentum	constant	p-value	β^1	p-value
1 (low B/M)	0.006	(0.15)	0.964	(0.00)	1 (low momentum)	-0.001	(0.77)	0.973	(0.00)
2	0.004	(0.39)	0.902	(0.00)	2	0.001	(0.66)	0.966	(0.00)
3	-0.007	(0.03)	1.006	(0.00)	3	0.001	(0.86)	1.052	(0.00)
4	-0.003	(0.29)	0.988	(0.00)	4	-0.003	(0.54)	1.049	(0.00)
5	0.001	(0.66)	1.018	(0.00)	5	0.014	(0.00)	0.962	(0.00)
6	-0.001	(0.91)	1.042	(0.00)	6	-0.004	(0.25)	0.846	(0.00)
7	0.004	(0.21)	1.115	(0.00)	7	0.002	(0.47)	0.788	(0.00)
8	0.003	(0.32)	1.061	(0.00)	8	-0.001	(0.87)	1.012	(0.00)
9	0.005	(0.21)	1.173	(0.00)	9	0.003	(0.31)	0.907	(0.00)
10	0.017	(0.00)	0.992	(0.00)	10	0.004	(0.19)	1.026	(0.00)

Panel B: Risk-premia estimates

B/M portfolios			*Momentum portfolios*		
Factor	Risk premium	t-value	Factor	Risk premium	t-value
$\lambda[1](er_m^{ew})$	0.014	(3.04)	$\lambda[1](er_m^{ew})$	0.014	(2.96)
$\lambda[1](er_m^{vw})$	0.012	(2.62)	$\lambda[1](er_m^{vw})$	0.015	(3.13)
Chi Square test	J ($\chi^2(9)$)	p-value		J ($\chi^2(6)$)	p-value
er_m^{ew}	16.76	(0.02)	er_m^{ew}	11.24	(0.13)
er_m^{vw}	18.15	(0.01)	er_m^{vw}	10.84	(0.15)

relative to a single market factor. All risk factors are estimated using stocks at the Oslo Stock Exchange.

The three-factor model developed by Fama and French (1992, 1993) contains in addition to the market factor a factor HML ("high minus low") designed to measure the B/M effect, and a factor SMB ("small minus big") based on firm size. HML is a portfolio containing long positions in companies with high B/M and short positions in companies with low B/M. Similarly SMB is a portfolio of long positions in small companies and short positions in large companies. Both HML and SMB are constructed as zero investment portfolios. It is important to emphasize that these portfolios are constructed ex-ante using available information about characteristics of the companies at the time of construction. In other words they are implementable trading strategies.

Specifically, the factors are constructed as follows. First companies at the OSE are sorted into three B/M portfolios (H,M,L). Thereafter companies in each B/M portfolio are sorted into two size portfolios (S,B). Finally, HML and SMB are constructed from the size cross-sorted portfolios (SH,SM,SL,BH,BM,BL) in such a manner that they are zero investments:

$$\mathtt{HML} = \left(\frac{1}{2}\mathrm{SH} + \frac{1}{2}\mathrm{BH}\right) - \left(\frac{1}{2}\mathrm{SL} + \frac{1}{2}\mathrm{BL}\right) \tag{11}$$

$$\mathtt{SMB} = \left(\frac{1}{3}\mathrm{SH} + \frac{1}{3}\mathrm{SM} + \frac{1}{3}\mathrm{SL}\right) - \left(\frac{1}{3}\mathrm{BH} + \frac{1}{3}\mathrm{BM} + \frac{1}{3}\mathrm{BL}\right) \tag{12}$$

Carhart (1997) expands on the three-factor model by adding an additional factor (PR1YR) based on the momentum effect, identified by Jegadeesh and Titman (1993), in order to explain persistence in the returns of US mutual funds. PR1YR is constructed by sorting companies into 3 portfolios at the end of each month, based on the asset returns over the preceding 11 months. These portfolios are held constant through the month, before they are regrouped at the end of the month. The PR1YR risk factor is the difference between returns of portfolios 3 and 1. Another momentum factor much used in the literature is UMD ("Up minus Down"). The UMD factor is based on a cross-sort similar to the Fama and French factors. The main difference between UMD and PR1YR is that UMD attempts to correct for the size effect.

In table 13 we show results from an estimation of a four-factor model consisting of the Fama and French factors (Rm, SMB, HML) and the momentum factor (UMD). The table shows that four out of seven industry sectors have a significant exposure to the SMB factor, while two sectors have a significant exposure to the HML factor. Materials is the only sector exposed to both SMB and HML. As expected none of the industry portfolio has any significant exposure to the momentum factor. None of the estimated risk premia $\lambda[2]$, $\lambda[3]$ and $\lambda[4]$ are significantly different from zero. The preliminary conclusion based on the estimation of industry portfolios is therefore that the factors SMB, HML and UMD are not priced in the Norwegian market.

By sorting into portfolios based on industry sectors, rather than the characteristics the risk factors are based on, we are however reducing the possibility of identifying whether a factor is priced. This is also pointed out by Cochrane (2005), who argues that by looking at industry portfolios one seldom achieves sufficient cross-sectional differences in portfolio returns related to company characteristics to be able to tell whether a factor is priced. Other problems stem from some companies not being in the sample the whole period, and potentially a lot of noise in individual stock returns not related to pricing factors. Attempting to price portfolios instead of individual stocks solves all these three problems simultaneously. The cost is the need to construct portfolios in different manners to perform a comprehensive test of whether a factor is priced. We therefore sort portfolios based on size, B/M, liquidity, market beta and oil exposure, and re-estimate the four-factor model. Table 14 summarizes the estimates of the risk premia λ and the J-tests for four four-factor models estimated using various portfolio sorts. In the last two columns of the table we in addition show the results of a simple CAPM estimation of the portfolios.[21] The table shows that both SMB and HML are priced risk factors in cases where we sort portfolios on respectively size and B/M. Correspondingly we observe that the CAPM is rejected by the J-test in these cases. In none of the sorts is the four-factor model rejected by the J-test.

Many studies in the empirical finance literature find a positive relationship between liquidity and stock returns. This relationship, which is significant both statistically and economically, is found both at the company level and the aggregate level.[22] As we saw in table 11 the CAPM was rejected when we attempted to price portfolios sorted on liquidity, independently of whether we used an equally- or value-weighted market factor. In the same table we observed that the constant terms (excess portfolio returns) were increasing monotonically with illiquidity, and that the least liquid companies are the ones creating problems for the CAPM (significant constant terms for portfolios

[21]The estimation results for portfolio sensitivities are reported in an appendix in Næs, Skjeltorp, and Ødegaard (2007).

[22]Pastor and Stambaugh (2003) finds market liquidity to be a priced risk factor.

Table 13 A multi-factor model for the OSE – Industry portfolios

The table shows the estimation results of a four-factor model for the Oslo Stock Exchange. The model is estimated with industry portfolios as test assets. The portfolio exposures are estimated by OLS for each portfolio, i as

$$er_{i,t} = \alpha_i + \beta_i^1 er_m^{vw} + \beta_i^2 SMB_t + \beta_i^3 HML_t + \beta_i^4 UMD_t + \varepsilon_i, t$$

The risk premia for the four factors are estimated using GMM to solve the system,

$$m = \mathbf{b}'\mathbf{f} = 1 + b_1 f_1 + b_2 f_2 + b_3 f_3 + b_4 f_4 \quad \text{s.t.} \quad E(m\mathbf{r}) = 0$$

where m is the stochastic discount factor (SDF) and $f_1 = er_m$ is the excess return on the market. We estimate the model both using equally and value-weighted market excess returns. Furthermore, f_2 is the SMB factor return, f_3 the HML factor return and f_4 the UMD factor return. b_1, b_2, b_3 and b_4 are the weights (loadings) on the respective factors. The return of the test portfolios in $\mathbf{r}$ are value weighted. $\lambda[k]$ is the factor risk premia for factor k. Significant risk premia indicate that the respective risk factor is priced and can be expressed as $\lambda_j = -var(f_j)b_j$. At the end of the table we report the results of a J-test of the models. The J-test is based on the size of the pricing errors of the model. A low p-value indicates a rejection of the model.

Industry	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	$\beta[4]$	p-value
10 Energy	-0.001	(0.95)	1.090	(0.00)	-0.495	(0.00)	0.034	(0.58)	0.066	(0.33)
15 Materials	-0.003	(0.72)	1.035	(0.00)	-0.342	(0.00)	0.231	(0.00)	-0.017	(0.79)
20 Industrials	0.000	(0.98)	0.964	(0.00)	-0.486	(0.00)	0.010	(0.87)	0.079	(0.06)
25 Discretionary	0.004	(0.50)	1.105	(0.00)	0.035	(0.76)	-0.025	(0.78)	-0.097	(0.22)
30 Staples	0.005	(0.41)	0.835	(0.00)	-0.326	(0.00)	-0.106	(0.17)	0.099	(0.09)
40 Financials	-0.000	(0.92)	0.879	(0.00)	-0.100	(0.23)	0.090	(0.08)	-0.074	(0.10)
45 IT	0.004	(0.50)	1.420	(0.00)	-0.300	(0.06)	-0.676	(0.00)	0.012	(0.93)

Risk premia	R_m^{ew}		R_m^{vw}	
Factor	premium	t-value	premium	t-value
$\lambda[1]$ (er_m)	0.015	(2.33)	0.015	(2.61)
$\lambda[2]$ (SMB)	0.004	(0.36)	0.008	(0.63)
$\lambda[3]$ (HML)	-0.001	(-0.07)	-0.002	(-0.19)
$\lambda[4]$ (UMD)	0.030	(0.92)	0.032	(0.97)
Chi Square test	J ($\chi^2(3)$)	p-value	J ($\chi^2(3)$)	p-value
	1.83	(0.18)	1.59	(0.21)

Table 14 Asset pricing tests for different test assets

The table shows the GMM risk-premia estimates for the market factor ($\lambda[1]$), the Fama and French size ($\lambda[2]$) and value ($\lambda[3]$) factors and the momentum factor ($\lambda[4]$) with the associated J-test for different types of test assets/portfolios. The last two columns show the risk premium estimate from a one-factor CAPM model. The models are estimated for seven different sets of test assets constructed from various firm characteristics (industry sector, size, B/M, momentum liquidity, market-beta and oil exposure). All the test portfolio groups consist of 10 portfolios except in the case of industry portfolios where we only use 7 portfolios.
For each set of test assets, we estimate a model of the form,

$$m = \mathbf{b}'\mathbf{f} = 1 + b_1 f_1 + b_2 f_2 + b_3 f_3 + b_4 f_4 \quad \text{s.t.} \quad E(m\mathbf{r}) = 0$$

where m is the stochastic discount factor (SDF) and $f_1 = er_m$ is the excess return on the market. We estimate the models using value-weighted market excess returns. Furthermore, f_2 is the SMB factor return, f_3 the HML factor return and f_4 the UMD factor return. b_1, b_2, b_3 and b_4 are the weights (loadings) on the respective factors. The return of the test portfolios in $\mathbf{r}$ are value weighted. $\lambda[k]$ is the factor risk premia for factor k. Significant risk premia indicate that the respective risk factor is priced and can be expressed as $\lambda_j = -var(f_j)b_j$. Below each risk-premia estimate is the t-value.

	Fama/French + momentum (UMD)					**CAPM**	
Portfolio sort	er_m^{ew} $\lambda[1]$	SMB $\lambda[2]$	HML $\lambda[3]$	UMD $\lambda[4]$	J ($\chi^2(6)$) p-value	er_m^{ew} $\lambda[1]$	J ($\chi^2(9)$) p-value
Industry (vw)	**0.015**	0.004	-0.001	0.030	1.83	**0.014**	5.57
t-value	2.33	0.36	-0.07	0.92	0.18	2.97	0.23
Size (vw)	**0.018**	**0.012**	-0.009	-0.015	4.64	**0.026**	**20.01**
t-value	4.00	3.28	-0.47	-0.58	0.33	5.73	0.01
B/M value (vw)	**0.014**	0.004	**0.023**	0.003	3.48	**0.014**	**16.76**
t-value	2.16	0.30	2.91	0.12	0.48	3.04	0.02
Momentum (vw)	**0.013**	-0.008	0.026	-0.027	6.73	**0.014**	11.24
t-value	2.03	-0.96	1.24	-1.09	0.15	2.96	0.13
Liquidity (vw)	**0.022**	0.018	0.061	-0.042	1.53	**0.018**	**24.47**
t-value	2.57	1.330	0.887	-0.446	0.82	5.36	0.00
Marketbeta (vw)	**0.016**	0.008	0.005	-0.002	1.31	**0.014**	6.22
t-value	2.93	1.13	0.28	-0.13	0.86	2.70	0.51
Oil exposure (vw)	**0.022**	0.011	0.035	-0.013	0.66	**0.015**	3.89
t-value	2.34	0.72	0.72	-0.45	0.96	3.17	0.79

8-10). A potential explanation of this is that stocks in small companies are less liquid than stocks of large companies. In other words, liquidity and size effects could be two sides of the same coin. If that is the case the size factor (SMB) should help us price the liquidity portfolios. Table 14 shows however that the SMB factor is not helpful in pricing the liquidity-sorted portfolios.[23]

To investigate whether liquidity is a priced risk factor in the Norwegian market we construct a separate liquidity factor (LIQ) and estimate various model specifications using this factor.[24] Panel A in table 15 shows detailed results of a two-factor model with the market portfolio and the LIQ factor, estimated on liquidity-sorted portfolios. We see that exposure to the LIQ factors gives a significant risk premium independently of whether we use an equally- or value-weighted market factor. The model is also not rejected. From the constant term in the exposure regressions we observe that the model still has problems pricing portfolios 8, 9 and 10. A potential reason for this is that there may also be a SMB risk in these portfolios, which LIQ is not able to capture. To investigate this possibility we estimate a model using the market portfolio, SMB and LIQ. The results of this estimation are reported in panel B in table 15. Adding the SMB factor, only portfolio 10 is not priced correctly. The estimates of the risk premia now do not give a significant premium to the LIQ factor. An important reason for this is that LIQ and SMB are highly correlated, as shown in table 16. In other words they are capturing a lot of the same effects. Potentially, a model where we replace LIQ with a liquidity factor constructed to be less correlated with SMB could give a significant risk premium for liquidity.

3.5 What can explain empirically motivated factors?

A test showing that stock returns can be explained by risk factors constructed from CAPM anomalies does not give any understanding of the underlying sources of these effects. There is however a large literature on this topic. Vassalou (2003) groups the explanations of the empirically motivated risk factors in four main groups:

[23] The J-test does not reject the model, but we know that the market portfolio alone is not enough to price these portfolios. While SMB, HML and UMD do not give us a significant risk premium, a reduced model (with only the market portfolio) will not be correctly specified.

[24] The liquidity factor is constructed as follows: We first sort stocks into three portfolios based on average relative spread the previous month. We calculate returns holding these portfolios constant throughout the month. Difference returns are calculated as the difference between the return of the least liquid portfolio and the most liquid portfolio.

Table 15 Liquidity factor

Panel A shows the results from estimating a two-factor model consisting of market risk (er_m^{vw}) and liquidity risk (LIQ). The model is estimated on a set of portfolios with increasing illiquidity (increasing relative spread), such that portfolio 1 contains the most liquid firms (with the lowest relative spread), and portfolio 10 contains the least liquid firms (with the highest relative spread). Panel B shows the results from estimating a three-factor model adding the SMB factor to the model estimated in Panel A.

Panel A: Liquidity factor - Liquidity sorted portfolios

	a		er_m^{vw}		LIQ	
1 (low spread)	-0.0041	(0.00)	0.9745	(0.00)	-0.1708	(0.00)
2	-0.0011	(0.61)	0.9924	(0.00)	-0.1121	(0.02)
3	0.0010	(0.72)	1.1000	(0.00)	0.0519	(0.39)
4	0.0020	(0.50)	1.0279	(0.00)	0.1085	(0.09)
5	0.0025	(0.30)	0.8868	(0.00)	0.0708	(0.18)
6	0.0016	(0.57)	0.9625	(0.00)	0.2738	(0.00)
7	0.0017	(0.59)	1.0084	(0.00)	0.4174	(0.00)
8	0.0077	(0.04)	0.9462	(0.00)	0.6414	(0.00)
9	0.0082	(0.02)	0.9766	(0.00)	0.9065	(0.00)
10	0.0203	(0.00)	0.8194	(0.00)	0.6079	(0.00)

Risk premia	er_m^{ew}		er_m^{vw}	
Factor	premium	t-value	premium	t-value
$\lambda[1]$ (er_m)	0.022	(4.69)	0.019	(3.50)
$\lambda[2]$ (LIQ)	0.015	(2.48)	0.017	(2.81)
Chi Square test	J ($\chi^2(8)$)	p-value	J ($\chi^2(8)$)	p-value
	8.71	(0.19)	9.26	(0.16)

Panel B: The liquidity and size factors - Liquidity sorted portfolios

	a		er_m^{vw}		LIQ		SMB	
1 (low spread)	-0.0022	(0.11)	0.9610	(0.00)	-0.0637	(0.06)	-0.1556	(0.00)
2	-0.0013	(0.55)	0.9990	(0.00)	-0.1611	(0.00)	0.0831	(0.11)
3	0.0002	(0.95)	1.0950	(0.00)	-0.0070	(0.92)	0.0291	(0.68)
4	0.0013	(0.69)	1.0454	(0.00)	0.0823	(0.28)	0.0807	(0.28)
5	-0.0008	(0.72)	0.9366	(0.00)	-0.0732	(0.21)	0.3321	(0.00)
6	-0.0006	(0.82)	1.0191	(0.00)	0.2209	(0.00)	0.2157	(0.00)
7	-0.0008	(0.79)	1.0060	(0.00)	0.1994	(0.01)	0.2289	(0.00)
8	0.0021	(0.49)	0.9467	(0.00)	0.3971	(0.00)	0.2473	(0.00)
9	0.0019	(0.58)	1.0532	(0.00)	0.5976	(0.00)	0.6019	(0.00)
10	0.0136	(0.00)	0.8562	(0.00)	0.1603	(0.05)	0.5863	(0.00)

Risk premia	R_m^{ew}		R_m^{vw}	
Factor	premium	t-value	premium	t-value
$\lambda[1]$ (er_m)	0.019	(3.94)	0.012	(2.16)
$\lambda[2]$ (SMB)	0.023	(3.31)	0.023	(3.30)
$\lambda[3]$ (LIQ)	0.003	(0.40)	0.002	(0.24)
Chi Square test	J ($\chi^2(7)$)	p-value	J ($\chi^2(7)$)	p-value
	7.47	(0.19)	7.74	(0.17)

Table 16 Factor correlations - 1980-2006

The table shows the correlations between the monthly returns of the SMB, HML, the two momentum factors (PR1YR and UMD) and the liquidity factor (LIQ) for the period 1980-2006.

	SMB	HML	PR1YR	UMD
HML	-0.23			
PR1YR	0.11	0.01		
UMD	0.11	-0.06	**0.78**	
LIQ	**0.51**	-0.03	-0.07	-0.10

- Risk-based explanations. The factors are proxying for a risk rational investors demand compensation for, for example ICAPM state variables.
- Explanations based on irrational behavior. This group of explanations focuses mainly on B/M and momentum effects.
- Studies showing that the results are period–and/or market dependent. For example the size effects seem to have disappeared in many countries in the period from 1980 to 2000.
- "Data mining." A large number of hypotheses about a single data-set is tested by searching through a large number of combinations of variables looking for (possibly spurious) correlations.

3.5.1 Risk-based explanations

Fama and French (1992, 1993, 1995, 1996, 1998) argue for HML and SMB as state variables describing changes in investors' investment opportunities. If this is the case the factors must be related to fundamental risks in the economy. Fama and French find empirical support for this view. Dimson and Marsh (1999) find empirical support for the view that difference in return between small and large companies is due to differences in industry sectors. Liew and Vassalou (2000) find that both HML and SMB are related to future GDP growth. Vassalou (2003) also finds a model that includes the market factor and news about future GDP growth that prices stocks similar to the Fama and French model. The hypothesis that the factors proxy for state variables can thus not be rejected. High returns for small companies with high B/M value is in that case compensation for business cycle related risks. Vassalou and Xing (2004) find that B/M effects and size effects only are present in portfolios of companies with high business cycle risks, and that the SMB factor is more default-related information than HML.

Risk-based explanations of momentum rely on "earlier winners" being more risky than "earlier losers," or that the compensation for certain risk types is time varying and autocorrelated. Jegadeesh and Titman (2001b) use the three-factor model of Fama and French to investigate whether momentum can have a risk-based explanation.[25] In spite of losers being more sensitive to SMB and HML factors than winners, a Fama-French model can not explain momentum profits. Carhart (1997) constructs a risk factor based on the momentum effect of Jegadeesh and Titman (1993) and shows that it can explain abnormal returns of mutual funds. By constructing a variable "Corporate Innovation" (CI), Vassalou and Apeljinou (2003) argue for a risk-based explanation of the Carhart factor. CI is the fraction of a company's change in gross profit margin not due to changes in capital or employment. A significant reduction in CI is viewed as negative. Investors will therefore require risk compensation for companies sensitive to CI. Vassalou and Apeljinou find that momentum strategies only are profitable when winners are companies with high CI. CI-based strategies are however profitable independent of whether past asset returns have been high or low. With these results as a backdrop Vassalou and Apeljinou argue that the autocorrelation in return that momentum strategies rely on is due to information flows about and price adjustments to the CI-variable.

3.5.2 Other explanations

Some explanations of the size effect rely on agency theory. Maug and Naik (1996) argue that mutual fund managers have no incentives to buy small companies because they are not included in benchmark portfolios, while Arbel and Strebel (1983) argue that little information about small companies makes them difficult investment objects. Empirical studies however show that the size effect has been negative in many countries over long periods, which is difficult to reconcile with this type of explanation.

A number of studies find support for companies with high B/M being systematically mispriced (LaPorta, Lakonishok, Shleifer, and Vishny (1997) and Skinner and Sloan (2000)). Investors underestimate future earnings for companies with high B/M and overestimate future earnings for companies with low B/M. In an efficient market this type of mispricing should disappear, but Shleifer and Vishny (1997) point out that

[25] The study uses data for the US stock market in the period 1965–1998.

arbitrage activity may be both costly and risky in such settings. Ali, Hwang, and Trombleya (2003) find empirical support for this view: Companies with high B/M have a significantly higher unsystematic risk and also higher transaction costs than companies with low B/M.

A large fraction of the momentum literature argues that momentum effects are signs of market inefficiencies and irrational behavior. Such models are as a rule based on the assumption that the momentum effect is due to autocorrelated returns. Some models assume that autocorrelation is due to investors under-reacting to information, while other models assume that autocorrelation is due to delayed overreaction, for example due to strategies such as buying winners and selling losers. A newer study by Grinblatt and Han (2005) argue for the momentum effect being caused by investors tending to keep losers too long, and selling winners too early. This effect, which Shefrin and Statman (1985) term "the disposition effect" has been observed both in experimental and in real financial markets, for equities, futures, options and real estate. Grinblatt and Han (2005) find strong support for a "disposition" effect using data for the NYSE and AMEX stocks in the period 1962-1996.

3.6 Multi-factor models based on macro variables

As a point of departure it seems reasonable to look for risk factors among macroeconomic variables. There are reasons to believe that changes in macroeconomic variables may affect many companies' cash flows at the same time. There are also reasons to believe they can affect market risk premia and the risk-free rate. The macroeconomic conditions are in addition important for the number and types of available investment projects. Results from many years of empirical work on US data has however only delivered weak evidence that changes in macroeconomic variables affect returns in the stock market.

There are several reasons why it may be difficult to establish an empirical relationship between stock returns and variation in macroeconomic variables even if such a relationship exists. Firstly, it is difficult to find data capturing variation in macroeconomic relations in a precise manner. As we discussed in section 3.5, there are reasons to believe that the empirically motivated factors SMB and HML have good explanatory power just because they are high frequent representations of the underlying macro variables. Secondly, it is perfectly reasonable that the stock market is a leading indicator for the macroeconomy rather than the opposite. Prices in the stock market are based on expectations. This means that much information is reflected in stock prices before they are captured in available macro variables.

In this section we first discuss what macro variables are reasonable to think of as important for the stock market. Thereafter we estimate various factor models based on these variables.

3.6.1 Relevant macro variables

In section 3.4 we used empirical regularities as a motivation for constructing returns-based risk factors. When we want to identify factors which are not returns-based it is convenient to start with the general pricing model

$$P_i = E[mx_i].$$

All valuation models identify one particular m as a function of observable variables and model parameters. Independent of model there are three sources of variation in prices and returns: Predictable variation in expected returns due to time variation in the stochastic discount factor (m) – that is, variations in the relationship between the marginal utility of wealth from t to $t+1$ or from one state to another – shocks to m and shocks to expected cash flows (x). In other words, all variables which have information about (expected or unexpected) variation in investors' marginal utility of wealth can be factor candidates. In addition, variables which can give unexpected changes in expected cash flows. One and the same variable may of course affect both marginal utility and cash flows.

To capture variation in returns due to shocks to m or x we need estimates of unexpected changes in the variables. It is unexpected changes in variables which lead market participants to change their portfolios and thereby equilibrium prices. Looking at innovations may therefore increase the probability of identifying risk premia related to shocks in the various variables. To estimate the unexpected changes in a variable we assume changes in a variable are driven by a first order autoregressive model.

In the case of Norway, oil prices is an obvious factor candidate, which can potentially influence the stock market both through m and x. Since the energy sector is so important for the Norwegian economy we treat the relationship between the stock market and oil price in a separate section. Variables which can capture the business cycle should be particularly suited to capturing variation in m. Typical business cycle variables used in the literature are dividend as a fraction of price (dividend yield), credit spread, and term spread, see Chen, Roll, and Ross (1986) and Fama (1990). In Norway we unfortunately do not have long time series of credit spreads. We therefore only consider *dividend yield* and *term spread*.[26] Unexpected changes in term spread may influence cash flow through effects of firms' financing alternatives. *Industrial production* represents both business cycles and investment and can therefore influence both m and x. Other real economic variables possibly linked to unexpected changes in expected cash flows are *unemployment*, *consumption*, *imports* and *exports*. *Inflation* is often argued to be a state variable in the ICAPM literature. Changes in inflation expectations may influence future investment opportunities through effects on the real interest rate. Inflation shocks may also lead to changes in nominal interest rates. Changes in *money stock* is important for the liquidity of the financial markets. If we disregard any inflation-driving effect, increased liquidity may influence the discount factor through the interest rate. Table 17 shows correlations between the returns-based risk factors(SMB, HML, LIQ), macro variables and average D/P for the market. The correlations are based on monthly figures for the period 1980-2006.

Table 17 Correlations between market and macro variables

The table shows the correlations between the returns on the SMB, HML, LIQ factors and changes in various macro variables. Correlations that are significant at the 5% level are indicated in bold in gray boxes.

	HML	SMB	LIQ	dKPI	dKPI JAE	dM2	dIND PROD	dKON SUM	dARB LEDIG	dOP	dTerm
HML	1.00										
SMB	**-0.23**	1.00									
LIQ	-0.03	**0.51**	1.00								
dKPI	0.02	0.07	0.00	1.00							
dKPIJAE	**0.11**	-0.01	-0.06	**0.42**	1.00						
dM2	-0.01	0.02	0.03	0.08	0.03	1.00					
dINDPROD	-0.08	-0.01	-0.03	-0.02	0.06	0.01	1.00				
dKONSUM	0.01	0.06	0.07	**-0.12**	-0.07	0.00	0.07	1.00			
dARBLEDIG	0.04	-0.07	0.01	0.08	-0.06	0.05	0.02	0.02	1.00		
dOP	0.03	-0.01	0.06	-0.05	**-0.12**	-0.01	-0.10	-0.04	0.06	1.00	
dTerm	0.07	0.07	0.06	-0.02	0.07	0.02	**0.13**	0.02	0.09	-0.05	1.00
DP market	**-0.12**	**0.13**	**0.12**	0.02	-0.04	-0.07	-0.07	0.01	0.02	**-0.20**	-0.02

It is important to emphasize the difference between beta exposure and risk premia. The estimated betas show the relationship (over time) between changes (or innovations) in a variable, and realized return. If a variable has a significant risk premium this means

[26]The term spread is calculated as the difference in yield of a 10-year government bond and a three month government bill.

that it is priced in equilibrium, and that the variable is important for pricing (in the cross section) all the portfolios used in the estimation.

3.6.2 Oil price

Table 18 shows the correlation between oil price changes and stock returns at the OSE compared to correlations between oil price changes and returns for the MSCI indices for the World, Europe, and North America. Unlike stock markets in the rest of the world, which has a tendency to fall when the oil price increases, both the equally-weighted and value-weighted market portfolios at the OSE are positively correlated with oil price changes (both in NOK and USD). In countries with large oil reserves one will expect a positive relationship between oil prices and the stock market, particularly so when the national oil companies are among the largest on the national exchange. This is particularly relevant for the OSE, where several of the largest companies are oil-related. This is consistent with the observation that the value-weighted market index is more correlated with oil price changes than the equally-weighted over the period 1980–2006. Looking at the last 15 years there is no big difference in the correlations between the indices.

Table 18 Correlations between the stock market and oil prices

The correlation between the change in the oil-price (in NOK and USD) and the market return on the OSE, the return on the MSCI World index, Europe index and North-America index for the period 1980-2006 and for two sub-periods.

		Oslo Stock Exchange		MSCI		
	OP_{USD}	er_m^{vw}	er_m^{ew}	World	Europe	North Am.
Period 1980-2006						
OP_{NOK}	0.962	0.156	0.125	-0.129	-0.139	-0.117
OP_{USD}	1.000	0.123	0.096	-0.146	-0.183	-0.126
Period 1980-1990						
OP_{NOK}	0.969	0.175	0.098	-0.120	-0.162	-0.054
OP_{USD}	1.000	0.157	0.081	-0.125	-0.172	-0.072
Period 1991-2006						
OP_{NOK}	0.956	0.143	0.146	-0.134	-0.120	-0.169
OP_{USD}	1.000	0.097	0.109	-0.160	-0.189	-0.170

The observed correlations in table 18 can not be interpreted as oil price being a systematic risk factor for all the companies in the market. Results from empirical studies of the relationship between oil price and stock return are mixed, but most studies reject the notion that oil is a priced risk factor.

The oil price may affect the stock market both through m and x. The oil price could be an ICAPM state variable which generates hedge demand among investors. Even if the oil price may be such a business cycle indicator, other variables may be better candidates for capturing business cycle variation. On the other hand, the oil price is observed at higher frequency than most other business cycle variables. Finally, oil price may be important because oil is a direct or indirect production input for many companies. Thus unexpected increases in the oil price may lead to a reduction in future expected cash flows for these companies. At the same time, an increase in volatility of oil prices may increase the risk of cash flows for these companies, which may affect costs of capital (the discount factor). Oil companies will have an opposite cash flow effect from increases in oil prices. The effect of increases in volatility of oil prices will however be comparable to other companies, since this also will increase the uncertainty of cash flows to oil companies. The oil price sensitivity of the various industries will also depend on to what degree the companies hedge against oil price risk.

Table 19 shows to what extent the returns of various industry portfolios covary with changes in the oil price. Since oil is traded in dollars we use the (log) change in the oil price in USD to isolate oil price variation from currency variation. The table shows that Energy, Material, Consumer Discretionary and Consumer Staples have significant exposures to oil price changes. As expected, the energy sector has positive exposure to oil price changes, while the other three sectors have negative exposures. The industry sector has a positive, but not significant exposure. We would have expected this to be negative and significant. The main reason for this is one company, Norsk Hydro. This is a company which was classified as an industrial until 2002. In terms of value it was the largest company in the industrial sector. Much of its business is oil related, however. When we re-estimate the the model using equally weighted industry portfolios the dominance of Hydro is reduced, and the industry portfolio has a negative (but not significant) exposure to oil price changes.[27]

The results in table 19 show that oil price changes have a significant effect on returns in many industry sectors. The next step is to investigate whether the oil price is a priced risk factor. We do this test by investigating whether oil prices are significant factors

[27] These results are not reported. They are available on request.

Table 19 Oil price exposures for value-weighted industry portfolios

The table shows the estimated exposure for the different industry sectors to the market return (er_m^{vw}) and the oil price changes in USD (dOP). P-values for the the exposure estimates are shown in parenthesis to the right of each estimate. Exposures in bold indicate significance at the 5% level. The model estimated for each industry index is,

$$er_{i,t} = \hat{a}_i + \hat{\beta}_{1,i} er_m^{vw} + \hat{\beta}_{2,i} dOP$$

	$\hat{a}$		$\hat{\beta}_{1,i}[er_m^{vw}]$		$\hat{\beta}_{2,i}[dOP]$		R^2
10 Energy	-0.003	(0.19)	**1.106**	(0.00)	**0.131**	(0.00)	0.74
15 Materials	-0.003	(0.33)	**1.066**	(0.00)	**-0.115**	(0.00)	0.63
20 Industrials	-0.002	(0.29)	**1.034**	(0.00)	0.021	(0.29)	0.82
25 Discretionary	0.003	(0.49)	**1.004**	(0.00)	**-0.190**	(0.00)	0.44
30 Staples	0.004	(0.15)	**0.866**	(0.00)	**-0.074**	(0.03)	0.52
40 Financials	-0.002	(0.41)	**0.826**	(0.00)	-0.053	(0.06)	0.59
45 IT	0.000	(0.93)	**1.247**	(0.00)	-0.095	(0.14)	0.39

in the pricing kernel m. Table 20 shows results from tests of three different pricing kernels: A two-factor model containing the market factor and oil price, a CAPM version where the market factor is orthogonalized against the oil price, and a two-factor model using the orthogonalized market factor and oil prices. Models are tested on three different portfolio sorts: Industry, size and oil exposure. The oil exposure portfolios are constructed as follows: At the end of each year we estimate a regression for each stock with stock return on the left-hand side and oil price changes on the right-hand side. Based on the estimated oil exposures the companies are sorted into 10 portfolios. Thereafter the portfolios are held constant throughout the year, before we re-estimate exposures and resort the portfolios at the end of the year. By sorting based on oil exposure we maximize the distribution of returns due to oil prices. This increases the possibility of finding that oil prices are priced risk factors. Panel (a) in the table shows results from tests using equally weighted market returns, while panel (b) shows results of tests using value-weighted market returns.

The table shows that the estimated risk premia for oil, $\lambda[2]$, are not significant in any of the model specifications. This shows that the oil price gives no information about expected returns for any of the portfolios. In other words, we find no support for the hypothesis that oil prices are systematic risk factors in the Norwegian market. Significant beta estimates of exposure for most industry portfolios however indicate that oil prices are important for many companies' cash flows.

Table 20 Is oil price a priced risk factor?

The table shows the GMM estimates of the risk premia associated with the log changes in the oil price in USD. for different types of test portfolios, both with equally weighted (er_m^{ew} and value-weighted (er_m^{vw}) excess market returns. For $er_m^{ew}|dOP$ and $er_m^{ew}|dOP$, the excess return on the market is orthogonalized against the oil price changes. The models are estimated for industry portfolios, size portfolios and portfolios constructed based on firms' (rolling) exposure to oil price changes. The return on the portfolios are value-weighted. For each specification, we estimate two-factor models with the equally weighted market factor (er_m^{ew}) and the oil price change. The system estimated by GMM is,

$$m = \mathbf{b}'\mathbf{f} = 1 + b_1 f_1 + b_2 f_2 \quad \text{s.t.} \quad E(m\mathbf{r}) = 0$$

where m is the stochastic discount factor (SDF), f_1 is the excess return on the market (equally weighted/value weighted and orthogonalized against oil price changes) and f_2 is the log change in the oil price, b_1 and b_2 are the factor loadings to the market factor and oil factor respectively. The return on the test portfolios in $\mathbf{r}$ are value weighted. The risk premia for the market factor is $\lambda[1]$ and for the oil price is $\lambda[2]$. The risk premia tell us whether we can say that the factor is priced and can be expressed as $\lambda = -E(ff')b$. below the risk premia estimates are the t-values to the parameter estimates. Numbers in bold indicate significance at the 5% level. For the J-test we report the p-value.

	Industry portf.			**Size portf.**			**Oil portf.**		
	er_m	dOP	*J-stat*	er_m	dOP	*J-stat*	er_m	dOP	*J-stat*
	$\lambda[1]$	$\lambda[2]$	*(p-value)*	$\lambda[1]$	$\lambda[2]$	*(p-value)*	$\lambda[1]$	$\lambda[2]$	*(p-value)*
(a) EW market									
er_m^{ew}, dOP	**0.014**	-0.007	4.56	**0.023**	0.015	**19.22**	**0.015**	0.001	3.87
	2.72	-0.87	0.21	5.18	1.73	0.00	3.13	0.08	0.69
er_m^{ew}|dOP	**0.015**	-	5.15	**0.028**	-	**19.59**	**0.015**	-	3.68
	2.98	-	0.27	5.66	-	0.01	3.10	-	0.82
er_m^{ew}|dOP, dOP	**0.017**	-0.007	4.62	**0.016**	0.015	**19.03**	**0.015**	0.001	3.68
	2.89	-0.88	0.20	3.01	1.75	0.00	2.86	0.11	0.72
(b) VW market									
er_m^{vw}, dOP	**0.015**	-0.012	2.50	**0.009**	0.013	**25.86**	**0.013**	-0.005	4.99
	2.76	-1.37	0.48	2.26	1.47	0.00	2.75	-0.65	0.54
er_m^{vw}|dOP	**0.016**	-	4.04	0.008	-	**26.85**	**0.014**	-	5.39
	3.12	-	0.40	1.74	-	0.00	2.85	-	0.61
er_m^{vw}|dOP, dOP	**0.020**	-0.012	2.52	0.003	0.013	**25.86**	**0.015**	-0.005	4.80
	3.02	-1.38	0.47	0.55	1.47	0.00	2.52	-0.64	0.57

3.6.3 Other macro variables

In this section we report results from tests of what importance macro variables other than oil have for the pricing of stocks in the Norwegian market. Table 21 shows results of pricing tests based on term spread and average D/P for the market.[28] Both term spread and D/P are stationary variables. We also test the variables in first differences together with innovations in the variables. Both variables are tested in a two-factor setting where the other factor is the market return (value weighted). The models are tested on five different portfolio sorts: industry, size, B/M, momentum and liquidity. In the table highlighted numbers are significant at the 5% level. Significant risk premia for the variables D/P and term-spread are also indicated by a grey box.

The table shows that both term spread and D/P have significant risk premia when we sort portfolios on size or liquidity. Small and illiquid companies are most exposed in bad times. It is therefore natural that these portfolios give the best possibility for isolating the risk premia of term spread and D/P, if these variables are related to business cycle variation.

The risk premium for the term spread is positive, while the risk premium for D/P is negative. A high term spread can be interpreted to mean that the participants in the market expect increased future inflation. Companies with a positive covariance with term spread have in such cases high returns in good times. A positive risk premium is then consistent with investors demanding a compensation to invest in companies which have a high return when the marginal utility of consumption is low (and vice versa, low return when the marginal utility of consumption is high). A negative risk premium for D/P means that a company has lower expected returns the higher exposure it has to D/P. D/P is usually interpreted as a business cycle variable, which is high in bad times and low in good times. A company with high covariance with D/P will in other words give relatively high returns in bad times, when investors marginal utility is high. Investors will therefore value companies the higher their covariance (low negative covariance) with D/P. One interpretation of our results is that both term spread and D/P are ICAPM state variables, which contain information about future investment opportunities.

Table 22 shows to what degree returns in various industries covary with changes and

[28] The D/P series for Norway should be interpreted carefully, since dividend payments in Norway are much affected by tax motives. For example, in 1989 70% of the companies at the OSE did not pay dividends, a number falling to 50% in 1991 and 30% in 1995.

Table 21 Term spread and D/P as risk factors

The table shows the GMM estimates for the risk premia associated with two variables that in the literature have been found to predict expected returns. Both the term-spread and D/P are stationary variables, but we also use the change in the variables. In addition, we use innovations (unexpected change) in the variables denoted by UE(·). For each variable we test a two-factor model with the excess return on the value-weighted market portfolio (er_m^{vw}) and the respective variables for five different sets of portfolios (industry, size, B/M, momentum and liquidity). The models estimated by GMM are,

$$m = \mathbf{b}'\mathbf{f} = 1 + b_1 f_1 + b_2 f_2 \quad \text{s.t.} \quad E(m\mathbf{r}) = 0$$

where m is the stochastic discount factor, $f_1 = er_m^{vw}$ the excess return on the value weighted market portfolio and f_2 the log change in the respective variable in the first column of the table, b_1 and b_2 are the estimated factor loadings. The return on the test-portfolios in $\mathbf{r}$ are value weighted. The risk premium to the market factor is $\lambda[1]$ and to the second factor $\lambda[2]$. The risk premium associated with a factor tells us whether a factor is priced and can be expressed as $\lambda = -E(ff')b$. Below each risk-premium estimate is the associated t-value. Numbers in bold indicate significance at the 5% level. Significant risk premia associated with the term-spread and D/P are in grey boxes.

	Industry (vw)		Size(vw)		B/M value(vw)		Momentum (vw)		Liquidity (vw)	
	er_m^{ew}	f2	er_m^{ew}	f2	er_m^{ew}	f2	er_m^{ew}	f2	er_m^{ew}	f2
	$\lambda[1]$	$\lambda[2]$	$\lambda[1]$	$\lambda[2]$	$\lambda[1]$	$\lambda[2]$	$\lambda[1]$	$\lambda[2]$	$\lambda[1]$	$\lambda[2]$
Term spread:										
Term	**0.015**	-1.218	0.009	**3.728**	0.009	0.653	**0.014**	0.718	**0.017**	0.605
	2.95	-1.20	1.35	2.13	1.81	0.50	2.88	0.83	3.18	0.94
UE(Term)	**0.016**	0.508	0.008	0.034	**0.012**	0.164	**0.015**	0.034	**0.018**	**0.598**
	3.19	0.50	1.90	0.12	2.49	0.55	3.10	0.12	3.42	2.16
dTerm	**0.014**	-0.334	0.009	1.081	**0.013**	2.106	**0.014**	0.680	**0.016**	1.386
	2.91	-0.65	1.95	1.55	1.98	1.96	2.89	1.18	2.67	1.86
UE(dTerm)	**0.015**	-0.325	**0.011**	**1.567**	**0.012**	0.245	**0.015**	0.848	**0.019**	0.299
	2.97	-0.26	2.39	2.02	2.47	0.36	3.17	0.90	3.59	0.39
Dividend yield:										
DP market	**0.014**	0.426	**0.013**	**-1.147**	0.014	1.550	**0.015**	-0.028	**0.021**	**-0.056**
	2.53	0.55	1.98	-2.01	1.59	1.36	3.05	-0.12	2.41	-2.76
UE(DP market)	**0.015**	-0.010	0.008	0.041	**0.013**	0.015	**0.014**	-0.010	**0.015**	**-0.118**
	2.94	-0.21	1.88	0.72	2.70	0.48	2.57	-0.19	1.93	-3.28
dDP market	**0.016**	-0.014	**0.016**	**-0.031**	**0.011**	-0.015	**0.015**	-0.011	**0.018**	0.463
	2.99	-1.02	2.51	-2.50	2.11	-1.46	2.88	-0.80	3.07	1.43
UE(dDP market)	**0.015**	-0.001	**0.017**	**-0.103**	**0.013**	-0.053	**0.015**	-0.001	**0.016**	0.064
	3.06	-0.03	2.51	-2.88	2.27	-1.65	3.08	-0.07	3.14	1.38

Table 22 Industry exposure to macro factors

The table shows the estimated exposures for the industry portfolios with respect to the change and unexpected change in various macro variables. Since the unexpected changes in the variables are highly correlated with the total change in the variables, we estimate one model with the total change in the variables and one model with the unexpected change. The last two columns in the table show the sensitivities of the return on the equally weighted and value-weighted market portfolio to the various macro variables. The model estimated for each portfolio (i) and macro factor (f_k) is,

$$r_{i,t} = \hat{a}_i + \sum_{k,i} \hat{\beta}_{k,i} f_{k,t}$$

In the table we only report $\hat{\beta}_{k,i}$ for each model. Numbers in bold indicate significance at the 10% level or better. The last line shows the R^2 for the models when we look at the total change in the variables.

	Industry portfolios							Market portf.	
	Energy	Materials	Industrials	Cons. Discret.	Cons. Staples	Financials	IT	ew	vw
Real variables:									
INDPROD	0.278	0.038	-0.170	0.168	0.225	0.074	0.422	0.064	0.054
UE(INDPROD)	**-0.145**	-0.096	**-0.115**	-0.045	-0.041	-0.027	-0.054	-0.054	**-0.086**
KONSUM	-0.777	-0.606	-0.346	0.414	-0.665	-0.281	**-1.683**	-0.206	-0.450
UE(KONSUM)	0.170	-0.003	0.007	-0.106	0.081	0.079	-0.172	0.044	0.061
ARBLEDIG	0.138	-0.029	0.248	-0.047	-0.265	-0.139	0.397	0.006	0.097
UE(ARBLEDIG)	**0.165**	0.286	0.476	0.518	0.192	0.533	0.043	0.593	0.286
IMPORT	0.143	0.046	0.101	-0.026	-0.006	0.080	0.300	0.057	0.094
UE(IMPORT)	-0.026	-0.007	-0.018	0.011	0.004	-0.011	-0.066	-0.011	-0.019
EKSPORT	0.049	0.043	0.020	0.112	0.060	-0.053	0.117	0.035	0.012
UE(EKSPORT)	0.000	-0.011	0.012	0.001	-0.017	-0.008	-0.010	-0.006	0.005
Nominal variables:									
KPI	**-5.451**	-1.833	**-4.727**	-3.530	-1.210	**-5.520**	**-10.440**	**-3.761**	**-4.245**
UE(KPI)	-2.267	**-3.205**	**-3.920**	**-4.423**	-2.591	**-2.540**	0.168	**-2.081**	**-2.564**
KPIJAE*	**-6.489**	0.164	-2.323	-0.186	1.299	-4.460	**-9.810**	-3.625	-3.198
UE(KPIJAE)*	-2.674	**-4.595**	**-6.080**	**-6.850**	-1.924	-2.860	-2.746	**-2.866**	**-3.646**
M2	**1.617**	**1.004**	**1.029**	**1.592**	0.669	0.461	**1.528**	**1.351**	**1.089**
UE(M2)	-0.227	-0.203	-0.054	-0.166	-0.045	-0.025	0.129	-0.082	-0.109
R^2	0.047	0.015	0.030	0.028	0.018	0.020	0.050	0.048	0.034

* Since dKPI and dKPIJAE (and the innovations in these variables) are highly correlated (77%), we estimate the models with KPI og UE(KPI). The estimates for dKPIJAE and UE(KPIJAE) are from models estimated without dKIP og UE(KPI).

innovations in various macro variables. The table also shows the covariability between the market indices (value and equally weighted) and the macro variables. In the table the variables are split into real economic and nominal variables. For each industry sector and each macro variable we present estimates from two regression models: One where we estimate the relationship between industry returns and the total change in the macro variable, and one where we estimate the relationship between the industry returns and unexpected changes in the macro variable.

As in other work in this literature we find that mainly nominal macro variables are related to stock returns. For most industry portfolios we find a significant relationship between industry returns and the variables money stock and inflation. As expected, the relationship between inflation and return is negative, while the relationship between return and money stock is positive. For inflation it is mainly the estimated innovations which are significant. For money stock it is changes which are found relevant, not innovations. Among the other non-nominal variables we only find five significant exposures: innovation in industry production affects returns in the energy and industry sectors; innovation in unemployment affects returns in the energy sector, and changes in consumption affects returns in the IT sector. It should be pointed out that the total explanatory power of the macro variables is very low (R^2 varies from 1.5 % for the materials sector to five % for the IT sector).

To investigate whether any of the macro variables have a risk premium we estimate, for each macro variable, a two-factor model where one factor is the market, and the other factor is one of the respective macro variables. Table 23 shows results from tests of the risk premia of the various macro variables.[29] The main impression from the estimation is that very few risk premia are significant. It is also worth pointing out that we (with one exception) only find significant risk premia in cases where we sort portfolios on size or liquidity. These portfolios are as mentioned best suited to identify risk premia related to business cycle variation (small and illiquid companies are most exposed in bad times).

Several of the estimated risk premia can be explained from theoretical considerations:

- Innovation in unemployment has a significantly negative risk premium when we sort on size and liquidity. Companies with a positive covariability with shocks

[29] Appendix F of Næs et al. (2007) shows results for corresponding tests without the market portfolio as a factor.

to unemployment in other words have lower risk premia and expected returns than companies which don't covary (or covary negatively) with this variable. Since unemployment is high in recessions, companies which give higher returns when unemployment increases will be attractive to investors. The price of such companies will therefore increase, with the effect of lowering risk premia.

- Both changes to and innovations in money stock are priced in portfolios sorted on size. Innovation in money stock is also priced when we sort on liquidity. The estimated risk premium related to money stock is positive. Money stock is increasing in good times. Companies with positive covariability with money stock will therefore give relatively high returns in good times. A positive risk premium indicates that investors demand compensation for holding stocks with this property.

- Changes in the CPI has a significantly positive risk premium when we sort on liquidity. This result can be explained by inflation being a state variable which says something about future investment opportunities. Companies that covary positively with the CPI will give relative high returns in good times, when prices (and hence inflation) increase. Investors will therefore demand compensation for holding such companies.

Other risk premia are however more difficult to explain. Changes in industrial production have a significantly negative risk premium when we sort on liquidity, something it is hard to find an intuitive explanation for. Correspondingly a negative risk premium for innovation in inflation when we sort on momentum is hard to explain.

4 Can we differentiate cash flow effects and risk premia?

We showed in the introduction that stock returns can be decomposed in two parts: (expectations about) cash flow, and risk compensation. An interesting question is whether price variation is due to new information about future cash flows, or due to shocks or time variation in risk premia. Empirically it is difficult to differentiate the two components, since neither expected cash flow nor risk premia are observable. The results from a so far small empirical literature on the topic do not go in a single direction.

Table 23 Macro variables as risk factors

Part (a) of the tables shows GMM estimates for the risk premia associated with different real macroeconomic variables, and part (b) shows the estimates for nominal variables. For each variable we look both at the log change and the innovation (unexpected change) in the variable, denoted as UE(·). For each macro variable we estimate and test a two-factor model containing the excess return on the value weighted market portfolio (er_m^{vw}) and the respective macro-variable named in the first column. Each model is estimated for five different types of portfolios/test assets (industry, size, B/M, momentum and liquidity). The system estimated by GMM is,

$$m = \mathbf{b}'\mathbf{f} = 1 + b_1 f_1 + b_2 f_2 \quad \text{s.t.} \quad E(m\mathbf{r}) = 0$$

where m is the stochastic discount factor, $f_1 = er_m^{vw}$ the excess return on the value weighted market portfolio and f_2 represents the log change (or innovation) in a macro variable, b_1 and b_2 are the factor loadings. The return on the test-portfolios in $\mathbf{r}$ are value weighted. The risk premium estimate of the market factor is $\lambda[1]$ and the macro variable is $\lambda[2]$. The risk premium tells us whether the factor is priced and can be expressed as $\lambda = -E(ff')b$. T-values associated with the risk premia estimates are shown below the estimated risk premia. Numbers in bold indicate significance at the 5% level. Significant risk premia estimates for the macro variables are in grey boxes.

(a) Real macro variables

	Industry (vw)		Size(vw)		B/M value(vw)		Momentum (vw)		Liquidity (vw)	
Macro variable	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$
INDPROD	**0.015**	0.009	**0.012**	0.014	**0.012**	0.000	**0.017**	-0.019	0.013	**-0.033**
	3.05	0.82	2.58	1.87	2.53	-0.06	2.65	-1.81	1.79	-2.05
UE(INDPROD)	**0.014**	0.020	**0.009**	0.010	**0.012**	-0.016	**0.017**	-0.046	**0.019**	-0.042
	2.84	0.41	2.09	0.39	2.52	-0.61	3.05	-1.11	3.30	-1.34
KONSUM	**0.015**	-0.001	0.009	0.017	**0.012**	0.002	**0.013**	-0.002	**0.020**	0.017
	3.06	-0.19	1.14	1.75	2.47	0.37	2.79	-0.67	2.20	1.82
UE(KONSUM)	**0.015**	0.007	0.008	-0.003	**0.010**	-0.012	**0.015**	0.023	**0.019**	0.004
	2.95	0.46	1.88	-0.39	2.37	-1.61	2.55	1.64	3.49	0.54
ARBLEDIG	**0.016**	-0.010	**0.017**	-0.015	**0.016**	0.012	**0.016**	-0.004	**0.018**	0.002
	2.42	-1.27	2.35	-0.79	3.06	1.71	3.03	-0.85	3.57	0.34
UE(ARBLEDIG)	**0.013**	0.027	**0.012**	**-0.032**	**0.013**	0.020	**0.015**	-0.016	**0.019**	**-0.063**
	2.40	1.22	2.20	-2.71	2.63	1.15	2.87	-1.40	2.21	-2.93
IMPORT	**0.015**	-0.034	**0.018**	-0.066	**0.014**	-0.065	**0.015**	-0.002	**0.015**	0.527
	2.72	-1.30	2.58	-1.28	2.16	-1.72	3.10	-0.07	2.69	0.93
UE(IMPORT)	**0.014**	0.097	**0.010**	0.067	**0.012**	0.035	**0.014**	0.038	**0.017**	-0.034
	2.64	1.08	2.24	0.84	2.61	0.60	2.83	0.35	3.36	-0.27
EKSPORT	**0.015**	-0.005	0.008	-0.008	**0.013**	0.032	**0.015**	-0.009	**0.018**	0.030
	3.04	-0.23	1.81	-0.47	2.57	1.29	3.01	-0.50	3.40	1.60
UE(EKSPORT)	**0.015**	0.055	0.008	-0.015	**0.012**	-0.026	**0.014**	0.018	**0.030**	-0.485
	2.93	0.64	1.85	-0.31	2.50	-0.59	2.89	0.22	2.68	-1.47

(b) Nominal macrovariables

	Industry (vw)		Size (vw)		B/M value (vw)		Momentum (vw)		Liquidity (vw)	
Macro variable	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$	er_m^{vw} $\lambda[1]$	Macro $\lambda[2]$
KPI	**0.015**	0.118	0.008	0.000	**0.015**	0.001	**0.016**	-0.001	**0.025**	**0.001**
	2.63	0.61	1.90	-0.22	2.07	1.75	3.06	-1.31	3.65	2.02
UE(KPI)	**0.015**	-0.001	0.009	0.003	**0.012**	-0.002	**0.016**	**-0.002**	**0.025**	-0.004
	3.01	-0.77	1.64	1.63	2.23	-1.48	2.80	-2.20	3.48	-1.48
KPIJAE	**0.016**	7.302	0.005	-0.002	**0.016**	0.001	**0.014**	0.000	**0.015**	-0.001
	2.85	0.91	0.92	-1.79	2.67	1.61	2.91	-1.13	2.87	-0.99
UE(KPIJAE)	**0.015**	0.000	**0.017**	0.002	**0.013**	-0.001	**0.015**	**-0.002**	**0.026**	-0.005
	3.02	-0.06	2.71	1.52	2.62	-1.29	2.89	-2.03	2.96	-1.57
M2	**0.014**	1.276	**0.011**	**0.011**	**0.012**	0.004	**0.013**	0.008	**0.018**	0.008
	2.75	0.94	2.05	2.17	2.57	0.87	2.59	1.29	3.10	1.92
UE(M2)	**0.015**	-0.013	0.015	**0.069**	**0.013**	0.022	**0.015**	-0.005	**0.019**	**0.023**
	2.88	-0.79	1.45	1.97	2.24	1.58	3.17	-0.52	3.03	2.00

Using forecasts of companies' expected cash flows, gathered from the I/B/E/S database, Chen and Zhao (2007) solve for the risk premium in equation (1). They can thus investigate to what degree the risk premia vary over time, or whether changes in cash flow expectations are the most important component explaining price changes over time. Chen and Zhao (2007) find that changes in cash flows are more important (59%) than changes in discount factors (41%) in explaining price changes at aggregated, portfolio and company level. They also find that the relative importance of shocks to cash flow expectations increase with the time horizon. On the other hand, Campbell and Vuolteenaho (2003) find support for changes in discount factors generating substantially more variation in monthly returns than changes in cash flow expectations.

When we work within an unconditional model setting we are implicitly assuming in our analysis that risk premia (expected returns) are constant over time. One can also think of our estimates as long-term risk premia, that is estimates of expected return (independent of time and horizon) on investments with a given exposure to one or more risk factors. Since we do not take into account that risk premia may vary over time, it is difficult in our analysis to have strong opinions about the relative contributions of expected cash flow and risk premia in our results.[30] For some factors we can however say something about the likelihood that price changes are due to shocks to cash flow expectations or changes in risk premia for the factors. The reason why can easily be explained in the setting of the two-step estimation method described in section 3.2. This type of estimation can give two types of significant results:

1. The individual test portfolios have significant exposures to a risk factor in step 1 of the estimation, but these exposures to *not* explain differences in average returns across portfolios in step 2 of the estimation.

2. Exposures are significant in step 1 of the estimation. In addition to differences in exposures we have differences in average returns across portfolios (step 2).

In cases where we get results of type 1 this means we do not find support for risk factors being priced in spite of shocks to the factor affecting prices of assets over time. In other words the factor is not important for discounting expected cash flows. Shocks to the

[30]In a conditional framework one attempts to capture variation in expected return (around a long term risk premia) due to the state of the economy and investors' risk aversion. A conditional framework is therefore better suited to distinguish between price variation due to changes in discount factors and price variation due to shocks to expected cash flows.

factor will however change cash flow expectations. If we start with the present value formula in expression (1), this means that shocks to the factor influence expectations of future cash flow in the numerator, but not the risk premia in the denominator.[31] Results of type 2 indicate that the factor is priced, that is differences in expected returns across stocks can be linked to differences in exposure to the factor. In such cases it is difficult to differentiate cash flow effects from risk premia since the factor effects both numerator and denominator in equation (1).

4.1 Cash flow effects in the Norwegian market

4.1.1 Oil price

Given the importance of oil in the Norwegian economy, and the widespread view that the OSE is oil driven, one would expect the oil price to be an important explanatory factor for prices at the OSE. We do find that changes in the oil price affects stock prices. We do not, however, find that the oil price is a priced risk factor. In other words we have a result described as type 1 above. How is this to be interpreted? When we test whether a factor is priced in the market we are testing whether there are differences across sectors and stocks in how changes in the factor impact the marginal evaluations of future cash flows of market participants. There is no sign of such effects of the oil price. A possible explanation of this is that the oil price affects all sectors in the Norwegian economy in the same way, such that we find no differences in the cross-section of stocks at the exchange. This is hard to believe. Even if oil affects many industry sectors at the OSE, some sectors should be relatively unaffected by the oil price. A more believable explanation is that oil is not a systematic risk factor. In such a case we can conclude that oil prices affect companies at the OSE directly through changes in expected cash flows, but the *cost of capital* across companies is not affected by oil prices.

4.1.2 Other macro variables

In theory shocks to all macro variables f are proxies for shocks to investors' marginal utility represented by $\mathbf{m}$. If we find a result of type 1 above – that is that the variable explains time variation in companies' returns, but not realized returns in the cross-

[31] There is however a possibility that a factor which is not priced in an unconditional framework may be priced in a conditional framework.

section of companies – we may assume that the variable is relevant because it leads to revisions in investors expectations about future cash flows.

From the results in table 22 and table 23 we observe that few macro variables have a significant risk premium. The significant risk premia are also less robust to changes in the portfolios we want to price. Effects on the stock market from innovations in macro-variables seem therefore mainly due to changes in cash flow expectations.[32] Changes and innovations in real economic variables seem to have minimal effects also on the cash flow expectations. Inflation and money stock, on the other hand, influences most industry sectors. We should however be aware that the macro variables explain a very little part of the total variations in returns. The percentage explained by regressions (R^2) varies from 1.5% to 5% for the various industry portfolios. For the equally weighted (ew) and the value-weighted (vw) market index the macro-variables explain respectively 4.8% and 3.4% of the total variation.

5 Summary

In this paper we document an extensive empirical study of stock pricing at the Oslo Stock Exchange. We have looked at what factors systematically affect the exchange, using methods of analysis where these factors are allowed to affect different assets differently (cross-sectional analysis). An important goal of the work has been to see whether asset pricing results from other countries carry over to the Norwegian stock market. Such an extensive empirical analysis of the Oslo Stock Exchange has to our knowledge not been done before. The view in the market seems to be that classical financial theoretical results are relevant for the Norwegian market, for example that a company's beta is important for the expected return of the company. Up to now it has however not been tested whether the CAPM is actually suited to price Norwegian stocks. Another "truth" commonly argued is that the OSE is driven by oil. Even if such a statement seems reasonable, there is little empirical data to support it, and in any case how such a statement is to be understood. Knowledge about what drives equity prices in a market needs both long time series and advanced statistical pricing tests. Our study satisfies both of these criteria.

In the introduction we show that factors affecting stock prices can be split into two:

[32] An alternative explanation may be that the variables have risk premia that change with the business cycle, something that would require a conditional framework to identify.

(expectations about) cash flow, and risk compensation. An important goal of our work has been to identify what systematic factors actually demand risk compensation. The results of our analysis are important because such factors can be used to set required returns for investments, and evaluate a stock's contribution to a portfolio. In our analysis we investigate whether those factors typically used internationally for such purposes; the local stock market, and the empirically motivated Fama French factors related to firm size, book values, and momentum, also are relevant in the Norwegian setting. Our results show that in addition to the local market, empirically motivated factors linked to firm size and stock liquidity seem to be factors demanding risk compensation at the OSE. However, the other two empirically motivated "Fama French" factors, B/M and momentum, do not seem relevant in the Norwegian setting.

In addition to the empirically motivated factors we investigate whether directly observable macro factors, which it is reasonable to think are related to the evolution of the market, are priced in the cross-section of stock returns. We have particularly investigated how oil prices affect the OSE. Given the importance of oil for the Norwegian economy, and recurring arguments in the domestic media that the OSE is driven by oil, one would think oil prices were important for the Norwegian stock market. But some care is needed in how this question is asked. As expected we find that changes in oil prices are linked to changes in stock prices. When we test whether oil prices are a systematic risk factor for the OSE, we find a negative result.

We also consider other macro factors for the Norwegian economy, such as money stock, investments, consumption, etc, without finding any significant relationships. Such results are typical for most economies, and suggest that the stock market is a leading indicator for the macro economy rather than the other way around.

Finally, some potential problems and weaknesses of our analysis should be pointed out. Some of these weaknesses can be evaluated by expanding the analysis. Others we can do little about.

There is little we can do about the data used in the analysis. We have, as mentioned, used data for the OSE in the period 1980 to 2006. In a macroeconomic context this may seem like a short period, also compared with other countries, where one typically has stock market data over longer periods. On the other hand, it is not a given that a longer history for the OSE would have been particularly fruitful. It is first in the period after 1980 that the exchange's value has become substantial. In 1980 the value of the OSE as a fraction of GDP was only 5 %, a number which has increased to over

90 % in 2006.

Several of our methods could be improved. All our analyses are done using unconditional models, where the estimated relationships are presumed to be be independent of the state of the economy. In an expanded analysis, where one uses methods contingent on the state of the economy, one could possibly identify relationships varying with the business cycle. There are also methods which more directly estimate the type of time variation we investigate, such as GARCH models. We have in our analysis used relatively simple methods to model expectations of macro variables. This gives considerable noise in our estimated innovations. There is clearly a potential for using more advanced methods for estimation of expectations. In this context we can also point to the possibility of using factor analysis to extract more precise information from macro variables. When we attempt to investigate whether there is a risk premium related to macro variables, we identify variables which proxy for some underlying variable $\mathbf{m}$. It may be the case that each of these proxies contains some component of the "true" $\mathbf{m}$, but there is too much noise in each variable to be able to find a precise enough estimate of $\mathbf{m}$. A factor analysis would extract one or several factors which best capture the covariability in a larger collection of variables. In such a way we can extract a few variables which potentially may be better proxies for the underlying variation (business cycle) than the individual variables. Such factors could be the basis of an expanded analysis of whether time variation in macro variables is important for the relative pricing of stocks.

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