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NTNU
Norwegian University of
Science and Technology
Faculty of Economics and Management
Department of Economics

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The January Effect at Oslo Stock Exchange

Examining the presence and causes for the January effect in Norway, from 1980 to 2019

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Trondheim, Spring 2021

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Preface

This paper concludes our master program in Economics at the Norwegian University of Technology and Science, written by Tina Ulriksen Tørmoen and Benjamin Vigdel. We would like to thank our supervisor Costanza Biavaschi for guiding us through the process of writing this paper and providing valuable feedback. Also, we would like to thank Amanda Njøten and Rannei Skjermo Telstad for proofreading. Last, we would like to thank each other for mutual support through all the ups and downs, while having sufficient room for disagreement and for not taking ourselves too seriously.

All views and statements in this thesis are our own, and cannot be assigned to NTNU. The authors of this paper take full responsibility for any errors that may follow.

Norwegian University of Science and Technology

Trondheim, June 2021

Abstract

In this paper we first test for the January effect on Oslo Stock Exchange over the period 1980 to 2019 using a GARCH estimation. Next, we use a rolling window estimation to consider the evolution over time in the January premium. Finally, we use this variation over time to test several hypotheses on what influences the January effect. In our sample we find a January premium. However, this effect diminishes continually over the sample period, and vanishes by the end of it. We prove that the January premium is positively related to a momentum premium factor, contrary to what we expected, and to a liquidity premium factor. Further, the January effect is more likely to occur during periods with a high positive production gap and high growth rate. Finally, we show that the January effect is partly caused by a misspecification of risk in the estimation procedure, due to monthly variation in skewness and kurtosis, meaning previous research may overestimate the January premium.

Sammendrag

I denne artikkelen tester vi først for januareffekten på Oslo Børs over perioden 1980 til 2019 med en GARCH estimering. Videre, ved bruk av estimering med et rullerende vindu, betrakter vi evolusjonen av januareffekten over tid. Til slutt bruker vi denne variasjonen over tid til å teste hypoteser for hva som påvirker januareffekten. I datasettet vårt finner vi en januarpremie, imidlertid reduseres effekten kontinuerlig over tid og forsvinner innen slutten av datasettet. Vi beviser at januareffekten er positivt relatert til en momentum faktor, i motsetning til våre forventninger, og en likviditets premium faktor. Videre har januareffekten større sannsynlighet for å være tilstede i perioder med høyt produksjonsgap og høy vekstrate. Til slutt beviser vi at januareffekten er delvis begrunnet med feilspesifisering av risiko, grunnet variasjon i skjevhet og kurtose, som betyr at tidligere forskning kan ha overvurdert januarpremien.

Keywords – January effect, GARCH, Fama and French

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1 Introduction

In this paper we examine the January effect on Oslo Stock Exchange over the period from 1980 to 2019. The January effect is a known anomaly and calendar effect where stocks have a higher return rate in the month of January. The January effect has important implications for the efficient market hypothesis which implies excessive return is not realistic. Efficiency is important for ease of investing and is good for attracting funding from investors. Further, a January effect can be exploited by traders for profit making. For this group of participants it will also be important to know how stable the effect is, and in what periods the January effect is more likely to occur, as well as how other known factors influences the January effect.

We start the analysis by first testing for the presence of a January effect over the period 1980 to 2019, on Oslo Stock Exchange (OSE) using a GJR-GARCH specification. Second, we use a rolling window estimation to study the evolution of the January effect over the period. Finally, we use the variation over time in the January effect to test several hypotheses of what influences the January premiums, in a logit setup as in Chatzitzisi et al. (2019). This includes testing for how the Fama and French, and other pricing factors influence the January premiums, whether or not the business cycle influence the premiums, and finally, if there is misspecification in risk due to monthly variation in higher moments about the mean, skewness and kurtosis.

Our results show that there has been a January effect at the OSE, however, it had a downward trend over the sample period, and was fully arbitraged away by approximately 2005 for the value weighted index and by approximately 2015 for the equally weighted index. Overweighting small-cap stocks extends the presence of the January effect, indicating and confirming it is a small-cap phenomenon.

Furthermore, we find that the significant differences between January and the other months are positively influenced by two pricing factors for liquidity risk premium and a momentum premium factor. The positive effect of the momentum premium is contrary to what has been suggested in the literature. We also find that the business cycle influences the January effect, as well as evidence of misspecification of risk, meaning previous research may overestimate the January Effect.

Section 2 gives a brief overview of the central literature for our research, section 3 presents the data, 4 discuss our hypotheses and estimation procedures. The results are presented in section 5, and are followed by a brief discussion in section 6. Finally, the conclusion is presented in section 7.

2 Calendar Anomalies

Research on the January effect goes back as far as Wachtel (1942), who finds that the stocks that gained value in January outnumbered the ones that lost value, over the period from 1927 to 1942. Furthermore, the magnitude of these rises where more positive compared to the rest of the year. The study provides some evidence, but lacks statistical tests. The interest in the anomaly stayed low until a seminal paper by Rozeff and Kinney Jr (1976) who finds a January effect on the New York Stock Exchange in the period from 1904 through 1974 using parametric and non-parametric estimation methods.

Gultekin and Gultekin (1983) puts the January effect in an international perspective and studies 17 major countries, including Norway. The indices are monthly, value-weighted returns for the period 1959-1979. With a non-parametric Kruskal-Wallis test the authors find seasonality in 13 of the 17 countries. Norway had seasonality with a January premium.

Giovanis (2016) tests for the January effect using modern GARCH specifications in 55 stock markets during different time periods. Norway is tested from 2001:2 to 2009:2 using a GJR-GARCH specification on the Oslo All Share Index (OSEAX). Giovanis finds no January effect in Norway nor most other countries. Only 7 of the 55 markets has a January effect. Giovanis data sample is very short for Norway and does not specifically test if January is significantly different from the other months for these countries, only if the monthly dummies, twelve in total, are significantly different from zero. As stocks tend to rise, we would expect all months to have a positive value and should be represented by a constant in the regression model. Excluding the January dummy from the estimation would allow easy hypothesis testing for difference between January and the other months. In the first part of our paper we also use GJR-GARCH, but only with 11 dummies and a constant, and a much longer sample, as well as other indices.

These results indicate that the January effect has subsided over time in most countries, including Norway. However, it is still unclear if there was a January effect during 1980-2000, and if so, what are the causes for the January premiums and why are they not arbitraged away. Roll (1983) suggests the January anomaly is preserved by high transaction costs. This is especially relevant for small, infrequently traded stocks and stocks with a high bid-ask spread relative to the stock price.

Theories for the January premiums. Wachtel (1942) explains that tax-loss selling may cause the January effect, as investors sell at the end of the year, to gain tax benefits, and then buy back the same stocks in early January. Depressed stocks are more likely candidates for tax-loss selling than other candidates, and therefore have the highest likelihood of having a January premium. According to financial theory, dividends should depress share prices by as much as the size of the dividend. Based on this, Wachtel claims that high-yield stocks are, on an objective selection, the best large groups of stocks, exceptionally subject to tax-loss selling. Furthermore, he is able to show that the January effect is more likely to be present in high-yield stocks versus low-yield or no-yield stocks. Dividends depends to a large degree on the business cycle, implying the January effect has a business cycle component through dividend payments. This has yet to be formally tested.

The tax-loss selling hypothesis has received further support in the literature. Using a data set that contains variations in a few tax codes, Dai (2003) finds significant evidence of the tax-loss selling hypothesis on OSE, and that the January effect is strongly related to the size of previous capital loss, the tax rate and the interest rate. However, tax-loss selling cannot single-handedly explain the January effect. Grinblatt and Keloharju (2000) collect a unique data set containing individual trading orders in the Finnish stock market. They document that investors not only realize losses more than gain towards the end of the year, but also repurchase the same stock recently sold to establish new cost bases, strongly supporting the argument that trading activities around the turn of the year are highly motivated by tax reasons (Dai (2003)).

Anomaly or correlation? In research on stock market anomalies it is important to determine if a new anomaly is in reality a correlation with a different, more established anomaly. Haug and Hirschey (2006) finds strong January returns in U.S. to be consistently positively related to the Fama and French factors, SMB[1] and HML[2], and negatively related to the momentum factor, UMD[3]. See the Appendix A1.2 for further information on the factors used in this paper. The negative influence of the momentum confirms that the January returns are highest for stocks with negative returns in the prior period. This is consistent with the tax-loss selling explanation. The authors do not run any statistical tests to check if these factors determine the statistical difference between January and other months, but simply show that there is a higher January return premium in these portfolios. It is possible that this is simply a correlation between two anomalies, and that the pricing factors does not actually cause the January effect.

Hidden risk factors. Aggarwal and Schatzberg (1997) determine that the day of the week effect is partly caused by difference in the higher moments about the mean, skewness and kurtosis. These are hidden risk factors in a model that only accounts for the return and variation of return. Hence they suggest that further research on the day of the week effect should account for these moments to avoid misspecification of risk. The influence of these moments on the January effect has not been researched yet, and therefore, there is a need for investigation to avoid misspecification.

Identification. Using a clever new setup, Chatzitzisi et al. (2019) performs a rolling window GARCH to test for day of the week effects in the US market. The regression windows from this test are used as a new data sample, which the authors use in a logit setup to test hypotheses for what causes the weekly effect. The paper reveals that recessions and uncertainty have explanatory power for the day of the week effect whereas trading volume does not. This identification strategy is easily implemented for our purpose, the January effect. We will test for various hypotheses including overlap with the Fama-French factors and other known pricing factors, as well as the effect of GDP on the premiums and finally for hidden risk factors.

[1] "Small minus big" is the premium on return that small companies receive, compared to larger ones.

[2] "High minus low" is the premium on high book value companies vs. low book value companies. Meaning how value stocks outperform growth stocks.

[3] Measures the premium on momentum in stocks. The portfolio is long previous 12 months winners and short previous 12 months losers.

3 Data

In our paper two sources of data are used. The first one is various data compiled by Professor Bernt Arne Ødegaard.[4] Data from this source include two indices made with stocks on Oslo Stock Exchange (OSE) as well as pricing factors, including the Fama and French (1998) factors, with a momentum factor and Næs et al. (2009) liquidity factor ranging from 1980:1 to 2019:12 with daily observations. Ødegaard replicates the pricing factors using his own data from the Oslo Stock Exchange. The second source is Statistics Norway, which provides quarterly GDP data in Norway for the period under investigation. With this data we generate a variable with first differenced log growth rate and a variable with output gap measured as a size of the total economy.

Both stock-indices captures the whole, broad market with one index being value weighted (VW) and the other being equally weighted (EW). See Appendix A1.1 for further explanation between EW and VW. These indices are chosen over popular indices, such as the main OSEBX index, because those indices are not available for the earlier part of the period under investigation. In addition, using the two VW and EW indices with the same underlying firms, allow us to make inferences about firm-size effects.

Ødegaard's data comes from the Oslo Stock Exchange and are based on daily observations of end of the day bid and ask prices, as well as last traded price. There may be some problems with using all stocks on the exchange, as the purpose of the indices are to show an accurate picture of the market. For this reason Ødegaard excludes stocks with fewer than 20 trading days for a year, equity in companies where a share costs less than NOK 10 and also companies with a lower market value than NOK 1 million. The indices are constructed in a way that dividends are reinvested in the whole index and included in returns. For our stock indices, simple returns[5] are used, as it is the most accurate way to measure returns. For additional information about the indices we refer to Ødegaard (2020).

[4] Downloaded from his website https://ba-odegaard.no/financial_data/index.html Last retrieved February 2021

[5] Simple returns are defined by $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$ where R_t is the return at time t and P_t is the price of the index at time t.

3.1 Descriptive Statistics

Table 3.1 show that the average daily return is 0.10892 % and 0.0978 % for the equally weighted and value weighted index, respectively. Both indices exhibits negative skewness, meaning that the left tail is fatter than the right, while the main probability mass is centered on the right side. The indices are also leptokurtic with fat tails, narrow shoulders and peaked top at the center. This is shown in the charts in figure A1.1 in the Appendix.

As expected, the null-hypothesis of a unit root is strongly rejected with the Phillips-Perron test, since our time series are returns from financial series. We use this test as it is not vulnerable to shifts and structural breaks.

Visual analysis of the return time series in figure A1.2 in the Appendix confirms periods of high volatility that is somewhat persistent. This is volatility clustering. We also test for ARCH effects in the residuals more formally; The LM-test rejects the null hypothesis of no auto-regressive conditional heteroskedasticity (ARCH) effect with a 1% significance level. For this reason, models described in section 4.1 will include terms that correct for the heterogeneous nature of the process.

Descriptive statistics, whole sample, Jan 1980 - Dec 2019		
	EW	*VW*
Obs.	10033	10033
Mean	0.0010892	0.000978
Std. dev.	0.0090011	0.0126389
Skewness	−0.6584621	−0.4081361
Kurtosis	20.22842	14.32535
Phillips-Perron	−85.59***	−91.038***
White noise Q-test	362.8642***	155.7350***
LM test for ARCH effects	1863.924***	1030.839***
*** = p<0.01		

Table 3.1: Descriptive Statistics

4 Hypotheses and Research Design

In this paper, we test for a significant difference between the January return and the return of other months. We use the whole, 1. and 2. half of the sample of 10,033 daily observations to estimate time constant monthly coefficients. This is done using GARCH, as explained in section 4.1. We proceed to use a rolling-window estimation method to make inferences about the evolution of the January effect over the sample. Finally, we use the variation over time to test our hypotheses in a logit setup, as explained in section 4.2. The hypotheses are outlined in detail in section 4.3.

4.1 GARCH Models

As we are investigating if there is a significant difference between January and other months, we rely on having correctly estimated standard errors. Before assessing the presence and causes of a January effect, it is therefore essential to account for the statistical assumptions of potential estimation procedures. One of the known Gauss-Markov assumptions for linear regression, is homoskedasticity. Violation of this particular assumption causes misleading standard error estimates and makes inference of significance impossible.

Another important point can be observed from figure A1.2 which shows that volatility occurs in bursts where there is persistence in shocks of high volatility, causing us to go through periods of high or low volatility. This is known as volatility clustering. In addition, leverage effects cause asymmetries in variance from shocks of different magnitude. As a negative price shock hits a stock the firm's debt-to-equity ratio increases which is a risk factor that will increase volatility in the future.

Both time series, EW and VW, exhibit autoregressive conditional heteroskedasticity (ARCH) effects. This is shown in Appendix A2.1. This means that we have a violation of the homoskedasticity assumption. For these reasons, we specify our models as asymmetric GJR-GARCH(1,1) with slight differences in the mean processes.

$$R_{EW,t} = \beta_1 + \beta_2 Feb + ...\beta_{12} Dec + \gamma_1 R_{t-1} + \gamma_2 R_{t-2} + \gamma_3 R_{t-3} + \epsilon_t \tag{4.1}$$

$$R_{VW,t} = \beta_1 + \beta_2 Feb + ...\beta_{12} Dec + \gamma_1 R_{t-1} + \epsilon_t \tag{4.2}$$

Model 4.1 and 4.2 includes AR(3) and AR(1) processes, respectively, to allow for serial correlation. We found these two specifications to fit the data the best. The volatility process is the same for both indices and is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{4.3}$$

See Appendix A2.2-3 for further details on our model selection.

4.2 Logit Framework

While our baseline analysis in section 4.1 estimates constant effects, we move on to study the evolution of the January premiums. We adapt the procedure from Chatzitzisi et al. (2019), where rolling window GARCH is used to test various hypotheses in a logit framework for the day of the week effect. In a rolling regression, a sample is divided into subsamples and several regressions are performed over the whole sample. We test several windows, but prefer a window of 1250 periods, roughly five years and a step size of 50, because this produces sufficient variation in both the outcome variables and control variables which we use for hypothesis testing, while still generating a large enough sample size to allow us to use the logit framework. The first regression uses the period from 1 to 1250 (Jan 3, 1980 to Dec 19, 1984) , the next one from 51 to 1300 (Mar 12, 1980 to Mar 6, 1985) and so on, until it reaches the end. The rolling GARCH regression will produce 177 rows of different beta coefficients for each month.

In our analysis, we will examine whether the existence of the January effect can be explained by various factors. The dependent variables are based on the significance of the coefficients for the monthly values in the rolling regression windows. To further clarify, for each month, dummy variables are generated, indicating the presence or absence of the significant difference between January and other months:

$$psigMonth_{it} = \begin{cases} 1 & \text{if p-value} < 0.1 \\ 0 & \text{otherwise} \end{cases} \tag{4.4}$$

where month i is February through December, and t is a specific row or window in the rolling window results. This means that if a particular month within a rolling regression window is significantly different from January at the 10% level, the dummy variable for this particular row and month will be unity, and zero otherwise. In the logit estimation setup, we will utilize each of these columns of dummy variables as the dependent variables to test our hypotheses.

In a logit model we attempt to model how different control variables affects the chance of an outcome variable being unity. In general, we have

$$P_i = Pr(Y_i = 1) = F(\beta_1 + \beta_2 x_{2i} + ... + \beta_k x_{ki} + u_i) \tag{4.5}$$

which is bounded between zero and one. To overcome this issue it is common to use the logistic distribution given by

$$F(w) = \frac{e^w}{1 + e^w} \tag{4.6}$$

which results in the logit model. Due to the nonlinear nature of F, there is no straight forward way of interpreting the beta coefficients in the logit estimation, and we have to use derivation to consider the effects.

Note that the control variables must be adjusted to accommodate the windows in the rolling regression data set. We do this by averaging the controls over each window. Meaning, for instance, we get a LIQ factor for the first window covering the period 1 to 1250 and so forth.

4.3 Hypotheses

Using the rolling window results, we test for several hypotheses about the causes of the January effect:

- **Hypothesis 1:** The January effect is a correlation with a multi-factor model including Fama and French factors with momentum and liquidity premium factors, meaning the January effect does not exist on its own.
- **Hypothesis 2:** In periods with high GDP growth and a positive production gap, the January effect is more likely to occur. This is caused by higher dividend payouts from firms during said periods.

- **Hypothesis 3:** The January effect is caused by hidden risk-factors caused by monthly variation in the higher moments about the mean, skewness and kurtosis.

5 Results

In this section we will first present results for the GARCH estimation of the January effect in section 5.1. Then we consider the evolution over time in the January effect in section 5.2. Finally, we present results from the logit regressions for hypotheses testing in section 5.3.

5.1 Estimation of the January Effect

Table 5.1 show the differences between the month of January, the constant, and the 11 other months for the EW index. For the full sample, all months exhibit significantly lower return compared to January. The reduction in return compared to January's 0.00255 daily return rate is on average 50 %, meaning January returns as much as two normal months.

In the second column, for the first half of the sample, we find a much larger January effect, that is even more significant. All months are at least just as significant as in the first column, and a few months, are more significant. The economic magnitude in the difference between January and other months are also larger. Now the returns for the other 11 months are on average 67 % lower compared to the daily return in January, meaning January returns as much as three average months.

The third column in table 5.1 show a convergence between the months from the first 20 years to the last 20 years. The constant is only half of what it was previously and only a few of the months are significantly different from the constant. The months that are significant have a 50 % reduction in returns compared to January.

In table 5.2 we report results for the VW index. The first column covers the whole sample of 40 years. The constant for this index is much lower compared to EW. In addition, only a few of the months are significantly different from January. Further, 6 of the 11 other months are significant with an average reduction in returns of 63 % compared to January. 5 of the months are insignificant, which is unique for the VW index.

Table 5.1: Model estimation, whole and half sample

	EW, full		EW, 1. half		EW, 2. half	
EW						
Feb	-0.000843**	(-2.32)	-0.00195***	(-3.30)	-0.000130	(-0.30)
Mar	-0.00147***	(-3.99)	-0.00236***	(-3.99)	-0.000932**	(-2.08)
Apr	-0.000635*	(-1.72)	-0.00146**	(-2.48)	-0.000164	(-0.36)
May	-0.00120***	(-3.16)	-0.00225***	(-3.70)	-0.000521	(-1.13)
Jun	-0.00222***	(-6.15)	-0.00353***	(-6.20)	-0.00118***	(-2.61)
Jul	-0.00123***	(-3.51)	-0.00207***	(-3.70)	-0.000796*	(-1.84)
Aug	-0.00182***	(-5.15)	-0.00295***	(-5.13)	-0.00106**	(-2.50)
Sept	-0.00196***	(-5.43)	-0.00343***	(-5.89)	-0.000941**	(-2.14)
Oct	-0.00150***	(-4.10)	-0.00263***	(-4.49)	-0.000708	(-1.59)
Nov	-0.00136***	(-3.73)	-0.00240***	(-4.06)	-0.000666	(-1.53)
Dec	-0.000638*	(-1.70)	-0.00206***	(-3.42)	0.000272	(0.60)
Constant	0.00255***	(9.72)	0.00366***	(8.32)	0.00181***	(5.95)
ARMA						
L.ar	0.118***	(11.13)	0.194***	(13.10)	0.0414***	(2.69)
L2.ar	0.0486***	(4.62)	0.0484***	(3.20)	0.0376**	(2.56)
L3.ar	0.0190*	(1.85)	0.00838	(0.58)	0.0242*	(1.68)
ARCH						
L.arch	0.226***	(15.08)	0.236***	(10.13)	0.209***	(11.31)
L.tarch	-0.128***	(-8.33)	-0.101***	(-4.04)	-0.160***	(-8.42)
L.garch	0.794***	(70.14)	0.769***	(44.62)	0.821***	(56.62)
Constant	0.00000323***	(10.39)	0.00000405***	(7.62)	0.00000268***	(7.67)
Observations	10033		5016		5017	

t statistics in parentheses

Distribution: Student's t-distribution

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Considering the second column of the table 5.2, we see the same pattern which we noted for table 5.1 with much more extreme values for the first half of the sample. The constant is much larger and only 3 months are insignificant. The significance levels of the significant months are also higher or at least as high as before, for all significant months. The reduction in average return in the significant months are 76 % compared to January, meaning January returns as much as four other normal significantly different months.

In the third column we discover a complete convergence between January and the other months. No month is significantly different from January. In addition, the constant has a much lower value, with a lower significance level than before.

Table 5.2: Model estimation, whole and half sample

	VW, full		VW 1. half		VW, 2. half	
VW						
Feb	-0.000603	(-1.23)	-0.00195***	(-2.61)	0.000455	(0.72)
Mar	-0.000932**	(-1.96)	-0.00176**	(-2.42)	-0.000315	(-0.52)
Apr	0.000616	(1.28)	0.0000345	(0.05)	0.000720	(1.16)
May	-0.000830*	(-1.67)	-0.00207***	(-2.75)	0.000185	(0.29)
Jun	-0.00155***	(-3.25)	-0.00281***	(-3.90)	-0.000292	(-0.47)
Jul	-0.000357	(-0.78)	-0.00111	(-1.60)	-0.000106	(-0.17)
Aug	-0.000933**	(-2.00)	-0.00174**	(-2.43)	-0.000319	(-0.53)
Sept	-0.00110**	(-2.27)	-0.00262***	(-3.53)	0.000236	(0.39)
Oct	-0.000426	(-0.90)	-0.00154**	(-2.11)	0.000426	(0.70)
Nov	-0.00104**	(-2.15)	-0.00199***	(-2.68)	-0.000344	(-0.56)
Dec	-0.000143	(-0.29)	-0.00111	(-1.52)	0.000362	(0.57)
Constant	0.00170***	(4.98)	0.00271***	(5.08)	0.000884**	(2.07)
ARMA						
L.ar	0.0952***	(9.14)	0.192***	(13.38)	0.0000831	(0.01)
ARCH						
L.arch	0.187***	(14.92)	0.216***	(9.72)	0.167***	(12.03)
L.tarch	-0.122***	(-9.43)	-0.116***	(-4.99)	-0.139***	(-9.60)
L.garch	0.844***	(91.42)	0.792***	(45.78)	0.878***	(89.00)
Constant	0.00000433***	(9.35)	0.00000671***	(7.16)	0.00000314***	(6.79)
Observations	10033		5016		5017	

t statistics in parentheses
Distribution: Student's t distribution'
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conclusion. We find a significant difference between January and other months, where January has a higher return than other months for both the EW and VW indices.

The effect is more significant and economically meaningful during the first half of the sample, compared to the second half. For the VW there is no January effect at all during the second half, but it is still there to some degree for the EW. During the first half of the sample the EW index is most significant and with largest differences in return, compared to the VW index. With these results we can confirm that the January effect is to a large extent a small-cap effect, as the January effect becomes more significant when we weight the same small companies more heavily.

5.2 Rolling Window Estimation

In this section we consider the evolution of the January effect over time, to determine if it has remained stable or changed over time. In figure 5.1 we observe the evolution of the January effect over the 40 year period for the EW index. The first window, in the upper, left, corner, is the constant effect for January. The other remaining windows are the difference between the constant and the other 11 months of the year. We see a number of interesting effects here. First, the constant for January started out positive, but shows a downward trending behavior. At the end of the sample, the constant was still positive. Second, all other 11 months start out negative, but show an upward trend where they tend towards zero. Lastly, about year 1992, there was a temporary reversal in these trends, where the constant became more positive and the other 11 months more negative. We are unable to explain the reason for this.

In figure 5.2 we observe some interesting effects for the VW index. First, the constant for January started out positive and as for the EW index, it tends towards zero, a level it reaches approximately in year 2004. Second, all 11 other months start out negative and ends higher than where it started. Thirdly, the same reversals observed around year 1992 in the EW index happened in the VW index. Finally, the trends are less obvious for the VW index than for the EW index. A few windows, for instance February, July and August were mostly flat during the sample. Also the economic magnitudes are lower in absolute value than for the EW index.

Conclusion. The January effect has not been constant over the sample. It has evolved over time in both directions. However the main trend is a convergence between the month of January and the other months. The January effect is a small-cap effect, because the trends in the VW index is less clear than for EW. Furthermore the January effect has disappeared for the EW index by the end of the sample, while it was completely gone by early 2000's for the VW index. With the variation in the levels of the January effect over time, it is possible to test for its causes in a regression model.

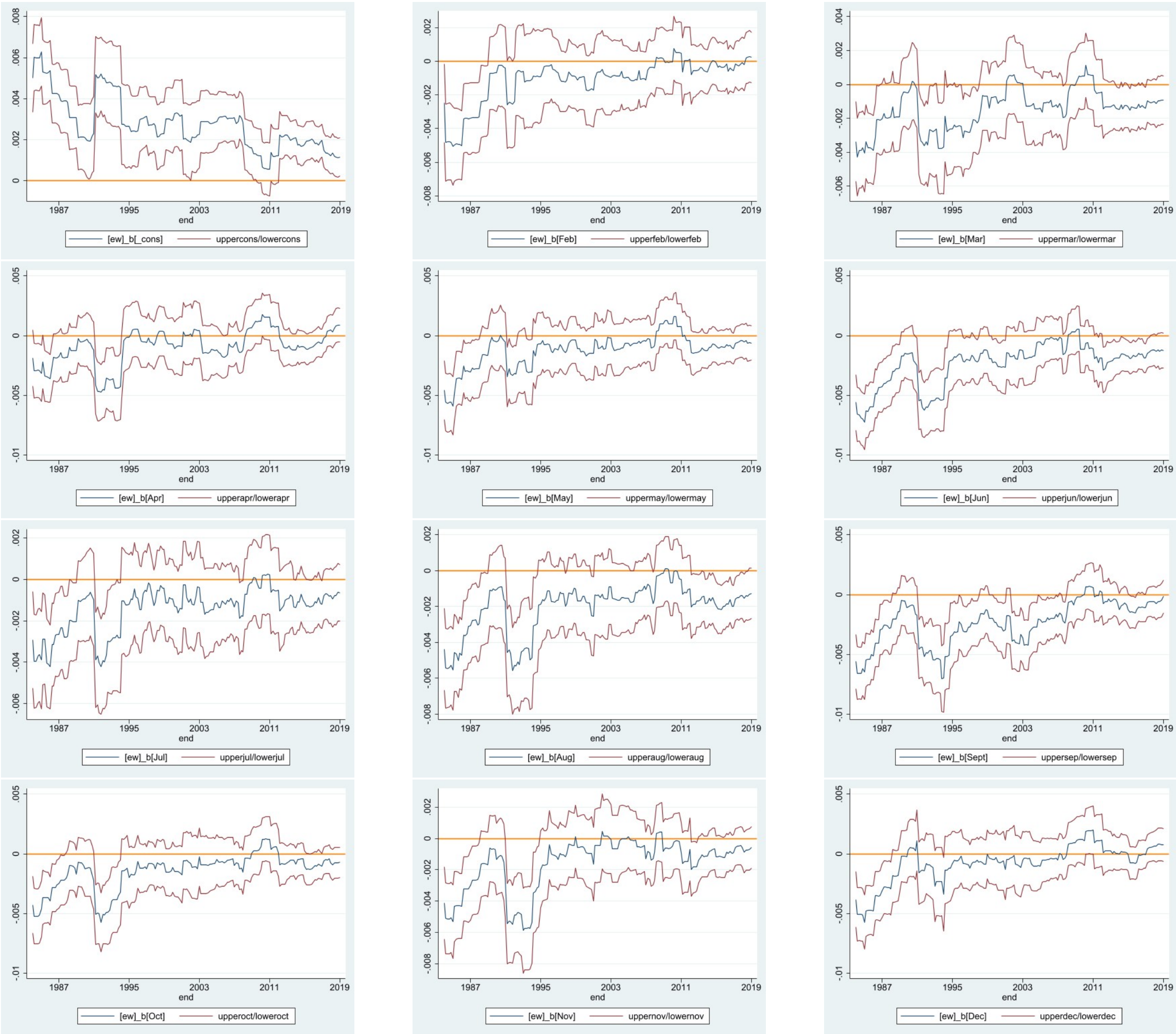

Figure 5.1: EW rolling estimated monthly beta coefficients

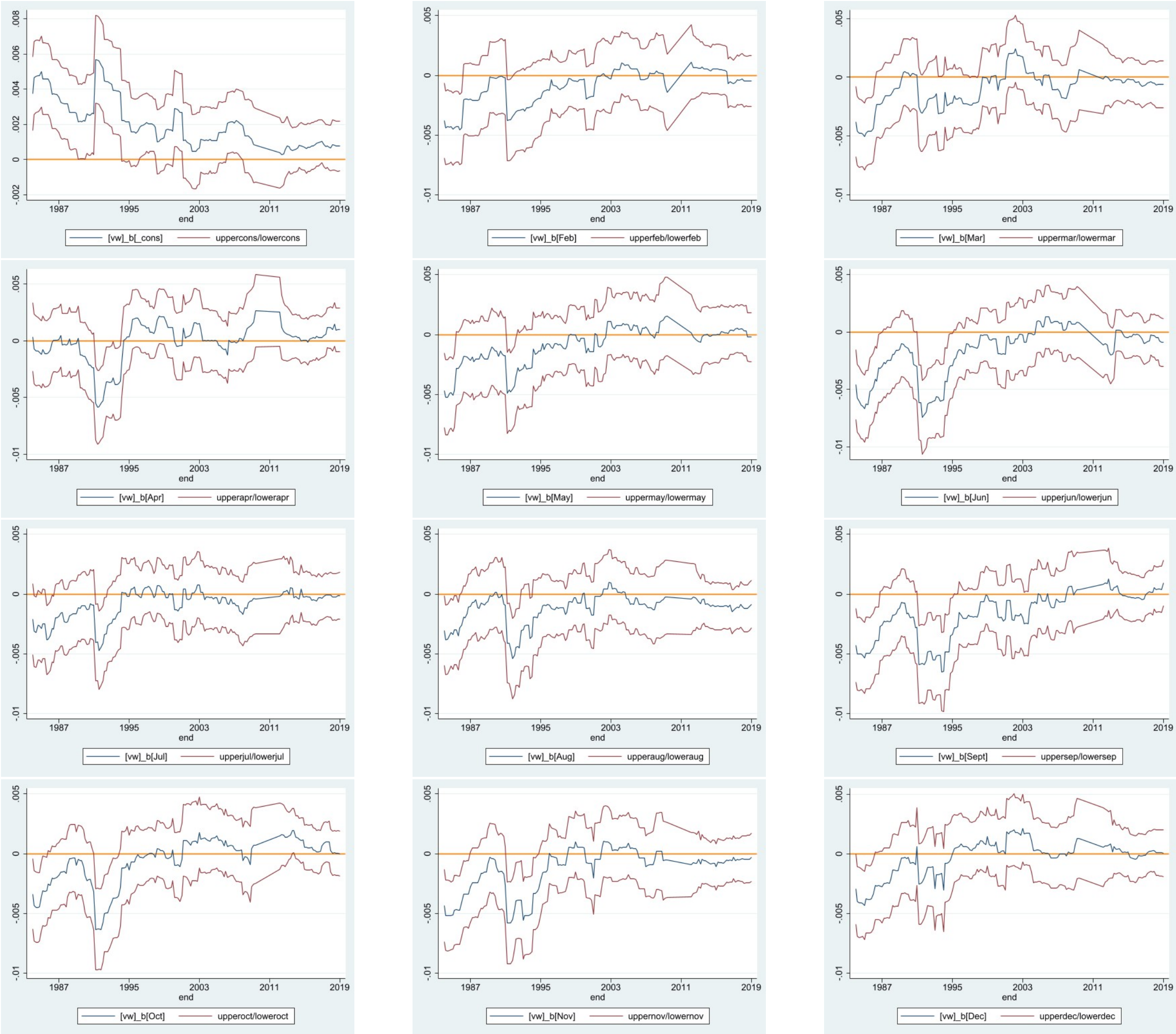

Figure 5.2: VW rolling estimated monthly beta coefficients

5.3 The Causes for the January Effect

As explained in section 4.2, we use the results from rolling window regressions as a new data set, and create dummies that equals unity if a month, February through December, is significantly different from January, during the specific window. The window is 1250 periods, roughly 5 years, with a step size of 50. We get a total of 177 different windows, which equals the sample size N. In table A3.1 in the Appendix, we find the share of N in which the dummy variables gets a unity value. Some months have zero unity values, which makes them unusable in a logit regression. More variation in the outcome variable will produce more reliable results. We will be more able to explain the January effect using the EW index, as it has a higher share of unity dummy variables. Several of the VW index dummies are zero, otherwise the samples have 2-5 % unity dummies with the exception of June, which has 14 % unity dummies. We believe several of the months in the EW index will produce reliable results. These months are June, August, September and November. We may be able to draw inference from other months as well for the EW index, but for the VW index only June and perhaps April, September and October have sufficient variation for meaningful inference.

Using a logit model with 3 groups of controls, a multi-factor model with the Fama-French factors with momentum and liquidity premium factors, GDP variables and higher moments about the mean, we estimate the drivers behind the January effect, measured by the outcome variables $psig\_Month_{it}$. These are the dummy variables that equals unity if a month i is significantly different from January in a specific window (see section 4.2 and eq. 4.4).

EW Index Logit Results. We start our investigation with a group-wise analysis, where we measure the significance of the variables according to the groups in table 5.3. We do this by a likelihood ratio test, controlling for each of the groups together and noting the likelihood ratio test statistics. We find that the four pricing factors are significant in all months, usually at a 1 % level. The GDP factors are the most significant group with a 1 % significance in all months. The skewness and kurtosis are the least significant of our variables, however they are still have 8 months with a significant explanatory power, several of which at a 1 % level.

Groupwise Likelihood Ratio Tests			
Month	PF	GDP	Skew/Kurt
Feb	65***	43.05***	65.34***
Mar	52.93***	29.37***	13.56***
Apr	11.45**	23.32***	3.15
May	58.86***	58.86***	58.86***
Jun	91.11**	71.21***	4.72
Jul	16.78***	13.11***	10.58**
Aug	67.31*	34.78***	26.1***
Sept	75.42***	27.78***	27.69***
Oct	51.86***	35.01***	16.12***
Nov	82.66***	37.09***	7.2
Dec	35.02***	35.96***	8*

***=p<0.01,**=p<0.05,*=p<0.1

Table 5.3: EW, likelihood ratio tests for logit results. Groups of controls, PF, GDP and Skew/kurt.

We proceed to the individual significance levels. Regression tables with the logit results can be seen in Appendix A3. The results show that there is a lot of bias in the models, which does not include all controls, meaning there is correlation between the control variables. For several months we are unable to control for all factors in one single regression model, because for these months we only get as result that the controls entirely explains the dependent variable with an R^2 of 1.0. This makes Stata unable to report results for these regressions. Further, these results must be biased as it is unlikely that all of the January effect is explained entirely by these controls. For these reasons we report a selected few months that are particularly interesting and reliable. These results are reported in table 5.4.

Among the four pricing factors, the two Fama-French factors, SMB and HML, are only significant in 1 month each, at a 10 % level. This provides some indication of a possible explanation for the January effect, but not to a large extent. The momentum factor, UMD, significantly explain the difference between January and 3 other months. The significance levels are at a high level, 1 % for two months and 5 % for the last. All of the significant coefficients are positive and have roughly the same economic magnitude, which makes this factor reliable. The liquidity premium factor, LIQ, is the most significant of the pricing factors, and significantly explains the difference between January and 4 other months. The coefficients are all positive and have roughly the same magnitude, which makes this control reliable.

We proceed with GDP controls, and out of these two, the production gap, PGap, is the most significant. The growth rate significantly explains difference between January and two other months. The production gap is significant in all months. All coefficients are positive and within the same economic range and results in having reliable controls.

We only consider the skewness and kurtosis controls as a group, as each month controls for skewness and kurtosis in both the said month and the constant for January, causing our controls to work together.

Table 5.4: EW Several Months, Logit

	psig_Jun01	psig_Jul01	psig_Aug01	psig_Sept01	psig_Oct01
main					
SMB	11921.5	-21427.7	-8169.1	280.0	23639.0*
	(1.36)	(-1.52)	(-1.46)	(0.05)	(1.65)
HML	1576.2	9716.0	-2905.9	-6911.6*	8118.8
	(0.44)	(1.08)	(-0.95)	(-1.80)	(0.80)
UMD	19693.5***	14877.6**	9638.1***	-2567.4	19714.5
	(2.76)	(2.02)	(2.71)	(-0.87)	(1.60)
LIQ	19756.2*	33752.5*	15324.9***	17296.7***	10469.0
	(1.77)	(1.95)	(3.12)	(2.75)	(0.79)
DlogGDP	770.1	515.7	609.3**	1670.2***	444.5
	(0.97)	(0.69)	(2.06)	(2.87)	(0.70)
PGap	307.1***	244.8*	57.82*	96.37***	721.5***
	(3.12)	(1.79)	(1.81)	(2.59)	(2.64)
Skewness/kurtosis	No	Yes	Yes	Yes	Yes
_cons	-98.38***	-116.2**	-43.10***	-54.06***	-130.9**
	(-2.77)	(-2.07)	(-3.14)	(-3.69)	(-2.45)
N	176	176	176	176	176
pseudo R^2	0.869	0.630	0.673	0.757	0.814
LR	154.9	37.06	96.87	139.0	94.56
p	7.08e-31	0.0000552	2.30e-16	6.62e-25	6.65e-16

t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

SMB is the average return on three small-cap portfolios minus the average return on three large-cap portfolios. HML is the average return on two value-stock portfolios minus the average return on two growth-stock portfolios. UMD is a momentum factor, up minus down, and is the average return on the two high-prior-return portfolios minus the average of the returns on the two low-prior-return portfolios.
LIQ is a liquidity factor explained as the difference between the closing bid and ask prices, relative to the midpoint price. DlogGDP is the first differenced log growth rate in GDP. PGap is the production gap measured as a share of the total economy.
Skewness/kurtosis measures these moments in the base month January and the month we use as the dependent variable, meaning they include 4 variables in each regression.

VW Index Logit Results. We proceed as earlier, with a group wise analysis first, and refer to table 5.5. For the months we are able to run regressions on (months with unity dummy variables for significance), all factors are significant, with an exception for April. The significance levels are usually at 1 % level.

As for individual significance, it is difficult to draw any conclusions for the VW index. When controlling for all groups of controls, there is few significant controls. For this reason we don't report any results, but refer the interested reader to Appendix A3.

Groupwise Likelihood Ratio Tests			
Month	PF	GDP	Skew/Kurt
Feb	.	.	.
Mar	14.48***	7.46**	8.72*
Apr	3.67	0.65	2.08
May	.	.	.
Jun	70.73***	32.91***	18.94***
Jul	.	.	.
Aug	.	.	.
Sept	17.22***	12.56***	24.95***
Oct	17.08***	12.79***	29.07***
Nov	45.47***	40.81***	36.20***
Dec	.	.	.

***=p<0.01,**=p<0.05,*=p<0.1

Table 5.5: VW, likelihood ratio tests for logit results. Groups of controls.

Conclusion. We find evidence that all groups of controls can explain the January effects in both EW and VW indices. There is high correlation between our controls. Therefore we should only rely on the regressions where we are able to control for all variables. There is a small-cap effect in the explanatory variables, meaning some of the variables can only explain why the small firms have a January effect. These variables are in particular the LIQ (liquidity premium) pricing factor and the UMD (momentum factor), which has good explanatory power in the EW index. Also the GDP variables has more explanatory power for small firms. They are highly significant for the EW, but only partly meaningful to the VW. The risk factors measured by higher moments about the mean are significant for both the EW and VW indices.

6 Discussion

Previously we found evidence of omitted variable bias, when excluding some of the control factors. From table 6.1 we find evidence of correlation, especially between the four pricing factors. This will make identification very difficult as it will be unclear what factor actually explains the January effect, *ceteris paribus*. This correlation warrants lowering our demands for significance levels, and taking a 10 % level as decent.

Table 6.1: Cross-correlation table

Variables	SMB	HML	UMD	LIQ	Dlog GPA	PGap
SMB	1.000					
HML	0.323	1.000				
UMD	-0.699	0.137	1.000			
LIQ	0.822	0.176	-0.825	1.000		
Dlog GPA	0.094	0.506	0.245	-0.080	1.000	
PGap	-0.132	0.012	-0.145	0.212	0.317	1.000

Hypothesis 1: We find good evidence that the pricing factors influence the January effect. As a group they are almost always significant for both indices, with some exceptions, see tables 5.3 and 5.5. As for individual significance, the factors UMD for momentum and LIQ for liquidity premium are the most important controls, see table 5.4. These are positively correlated to the January effect. This is as expected for the liquidity factor, as some of the January effect is caused by little liquidity and high costs of trading, such as a high bid-ask spread. The results on the momentum factor is contrary to Haug and Hirschey (2006) and shows that a high premium on momentum portfolios cause the negative difference between January and other months. Further, we are unable to prove an effect from the other two Fama-French factors HML and SMB, unlike Haug and Hirschey (2006). Hypothesis one confirm, and explains the small-cap claim, because the confirmation of hypothesis 1 is much less clear in the VW index.

Hypothesis 2: We can confirm the second hypothesis, however there seems to be a small-cap effect here as well to some extent. The January effect is more likely to be present in times with a high positive output gap, and to a lesser extent with a higher than normal growth rate. In these particular states dividend payouts from firms will be much higher than typical, causing some firms to have a depressed stock price after being noted ex. dividend. This points towards the tax-loss selling hypothesis.

Hypothesis 3: We confirm the hypothesis of misspecification of risk and conclude that the higher moments about the mean, skewness and kurtosis are hidden risk factors, which we are unable to capture in our GARCH model. Differences between risk levels in different months will cause variation in returns.

Small-cap anomaly: We find evidence of a small-cap effect in the explanatory power of the January effect. Both the LIQ factor and the momentum factor, UMD, seems to cause the January effect in the EW index, but not to the same extent in the VW. The VW index has less variation over time in the January effect than the EW index, making it far more difficult to explain the effect in the VW index. In the regressions where we are able to control for all four groups of controls, we achieve high explanatory power ranging from a pseudo R^2 of 0.6 to 0.9. In the regressions where we are unable to regress on all groups of controls we get a pseudo R^2 of 1.0 which is erroneous and probably due to having low variation in the outcome variable. We still conclude that our four groups of factors are able to explain most of the January effect on their own.

To our knowledge there is no research that has considered the January effect accounting for full, direct and hidden, transaction costs. We believe this may be a next step in the literature. This will require considerable effort in creating a data set with all stocks and their (estimated) transaction costs at different times.

7 Conclusion

We find that there existed a January effect at the Oslo Stock Exchange for the period 1980 to 2019 for both EW and VW indices. Over the sample, the premium decreases steadily and disappears entirely by year 2000 for the VW index. For the EW index, the premium is gone by the end of the sample. The premium is economically larger and more significant for the EW index, confirming that the premium is a small-cap effect.

Using results from a rolling window regression, we test various hypotheses in a clever logit setup. We find that a momentum factor, UMD and a liquidity premium factor, LIQ, significantly and positively explain the difference between January and the other months. The liquidity is lower for small firms, causing higher transaction costs for traders. As liquidity has increased with improved technology and a larger market, transaction costs have been lowered over the sample period. This has made arbitraging the January effect easier. The evolution of the January effect over the 40 year sample should closely follow full trading costs. We are unable to explain why UMD is positively related to the January effect, as we would expect it to have a negative relationship due to tax-loss selling at the end of the year. Further we find a business cycle effect in the explanation of the January effect, which is probably due to higher dividends during periods with a positive production outgap and rapid growth. Finally, we find evidence of misspecification in previous models, as these does not account for the higher moments about the mean, skewness and kurtosis.

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Appendix

A1 Data

A1.1 Equally weighted and value weighted indices

An equally weighted market index is a way of assessing the return of the market by putting an equal amount of weight to each stock-company. This produces an average return for the companies. This is the same as an implicit portfolio strategy where the same amount of capital is invested in each stock. This is in contrast to value-weighting or market-value-weighting where investments are in proportion to outstanding value. In an equally weighted index the small companies get the same investment amount as the large companies and hence in the equally weighted index the small caps are over represented. Comparing the two indices may tell something about how large cap returns compares with small caps.

A1.2 Pricing factors

The Fama-French benchmark factors are SMB and HML which summarize the performance of small-cap stocks relative to large-cap stocks and the performance of value stocks relative to the performance of growth stocks. Haug and Hirschey (2006)

SMB, or small minus big. The difference between the return on portfolios of small stocks and the return on portfolios of large stocks.

$$SMB = \frac{1}{3}(SH + SM + SL) - \frac{1}{3}(BH + BM + BL)$$

HML, or high minus low. The difference between the return on a portfolio of stocks with high book to market equity and stocks with low book-to-high equity. Value stocks tend to outperform growth stocks.

$$HML = \frac{1}{2}(SH + BH) - \frac{1}{2}(SL + BL)$$

The factors are constructed as follows. Companies at the OSE are sorted into three book-to-market portfolios (H, M, L). Meaning high-, medium- or neutral- and low- book to market ratios. Thereafter companies in each book-to-market portfolios are sorted into two size portfolios (S,B), small and big. Last, both SMB and HML are constructed as zero investment portfolios from the size cross-sorted portfolios. Meaning HML containing long positions in companies with high book-to-market ratios and short positions in companies with low book-to-market ratios. Likewise SMB is a portfolio of long positions in small companies and short positions in large companies.

The Carhart four-factor model is an extension of the Fama and French (1993) model and add the momentum effect PR1YR, documented by Jegadeesh and Titman (1993).

UMD, (Up minus Down), is another momentum factor introduced by Kenneth R. French and an alternative to the Carharts PR1YR factor. This momentum is much used in the literature and we choose to use UMD.

The momentum is the average of the returns on two high-prior-return portfolios minus the average of the returns on two low-prior-return portfolios. The two portfolios are divided in big and small firms.

$$UMD = \frac{1}{2}(SH + BH) - \frac{1}{2}(SL + BL)$$

UMD is constructed from six value-weighted portfolios by using independent sorts on size and prior return. The six portfolios are formed monthly and include NYSE, AMEX and NASDAQ stocks. Prior return is measured from prior 2-month to prior 12-month. The median NYSE market equity is the monthly size breakpoint. The breakpoints for the low and high prior-return portfolios are at the 30th and 70th NYSE percentiles respectively.

Until know the risk according to liquidity is left unexplained and in response we incorporate an additional factor to the multi-factor model with a liquidity factor, LIQ. A much used measure of liquidity is the relative spread from a portfolio. The factor is explained as the difference between the closing bid and ask prices, relative to the midpoint price. Næs et al. (2009)

The liquidity factor is estimated on liquidity-sorted portfolios and constructed more specifically as follows: First, stocks are sorted into three portfolios based on average relative spread the previous month. Second calculating 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. (Næs et al. (2009))

A1.3 Descriptive statistics

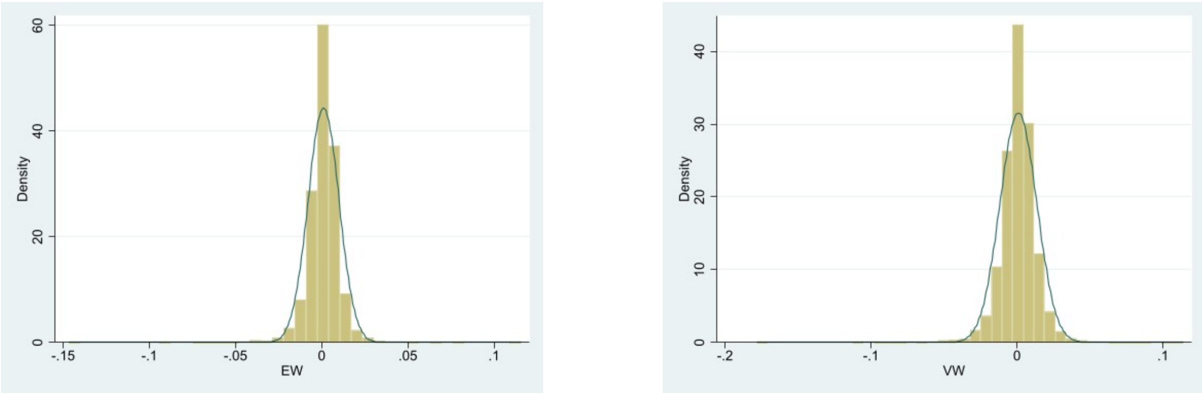

Figure A1.1: Daily return distribution for the two indices with normal distribution line.

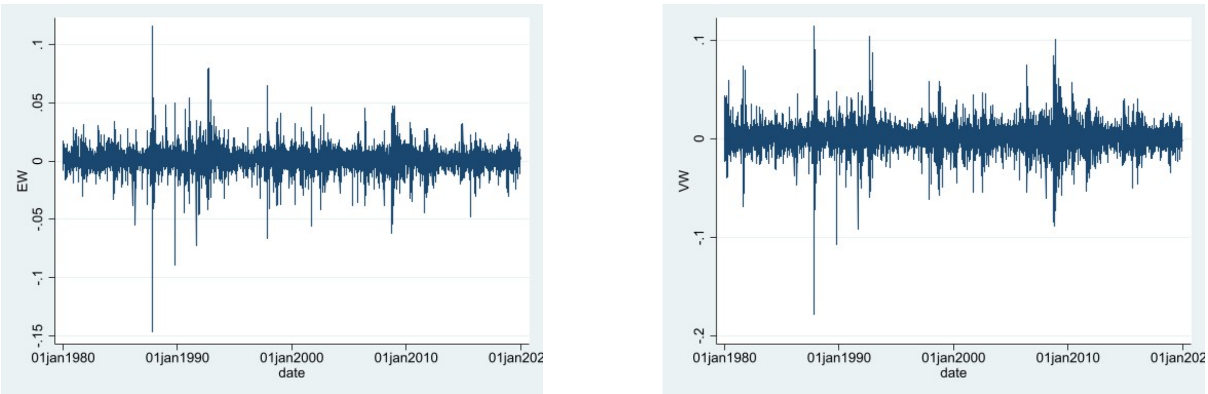

Figure A1.2: Daily return rate.

A2 Methodology

A2.1 ARCH-test

To test for ARCH effects we first ran one estimation for each of the two indices using OLS:

$$y_t = \beta_1 Jan + \beta_2 Feb + ... + \beta_{12} Dec + u_t \tag{.1}$$

Skewness and kurtosis by month				
	EW		VW	
	Skewness	Kurtosis	Skewness	Kurtosis
Jan	-0.1605327	7.314798	-0.3032937	5.487273
Feb	-0.1345795	4.823918	-0.0715351	4.905967
Mar	-0.1252861	4.605015	0.0016825	5.249588
Apr	-0.6780329	8.900516	-0.018038	5.196581
May	-0.5601633	6.992305	0.2680305	7.784539
Jun	-0.2502098	5.577842	-0.3392784	6.129845
Jul	-0.4604334	7.783407	-0.0802019	5.569493
Aug	-0.5153505	17.3449	-0.216901	13.68392
Sept	0.1739663	13.57142	-0.262492	8.875726
Oct	-1.602012	31.96688	-1.403539	20.73672
Nov	-0.4463028	8.808368	0.0235001	13.66118
Dec	0.1377666	6.725838	0.3673881	13.28756

Table A1.1: Monthly variation in skewness and kurtosis

Where Jan, Feb,..., Dec are dummy variables that equals unity if the observation falls within the specific month. We keep the residuals of these regressions and square them, and regress them on q of their own lags to test for ARCH of order q, meaning we run the regression:

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \gamma_2 \hat{u}_{t-2}^2 + ... + \gamma_q \hat{u}_{t-q}^2 + v_t \tag{.2}$$

From this estimation we receive an R^2 which we multiply by total number of observations, 10033 for our data set, which gives a test statistics which is distributed as $\chi^2(q)$. This will be equal to using an F-test to test if all the γ coefficients on the lagged residuals are significantly different from zero. If the test statistics are sufficiently high we disregard the null hypothesis of no ARCH effects. For our two indices we reject no ARCH effects at 1% level.

A2.2 ARCH class of models

Different forms of modeling of heteroskedastic time series processes with volatility clustering are employed in the literature. Engle (1982) suggests an ARCH(1) model,

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{.3}$$

where σ_t^2 is the volatility of a time series at time t and u_{t-1}^2 is a lagged squared residual term of the time series. This volatility process is only the second part of a complete ARCH process, as we also need an equation for the mean process that can practically take any form, for instance with dummy variables for each month. The model is called an ARCH(1) because it contains one auto-regressive lag of the residual, but it could also be extended to include several lags and thus be an ARCH(q).

Bollerslev (1986) extended the ARCH model with what he called generalized ARCH (GARCH) models. The model adds another term to the ARCH model which is an autoregressive lag of the variance. The GARCH(1,1) appears like:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{.4}$$

The GARCH model has become very popular in finance and is preferred over ARCH for various reasons. Several extensions of the GARCH has been published and in our thesis we make use of asymmetric GARCH models using the GJR-GARCH form. Asymmetries in GARCH allows for larger impact on volatility from a negative shock than from a positive shock. This is important in finance to account for so called **leverage effects**. As an indebted company gets a negative shock in its asset price their equity cause to be significantly smaller and the debt-to-equity ratio rise. This is a measure of risk that should be one of the drivers behind the volatility of a company.

The GJR-GARCH is a simple way to account for asymmetries and just add another term to the already known GARCH model. The volatility may be represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{.5}$$

where I_{t-} is a dummy equal to one if the residual of the model u_{t-1} is negative.

A2.3 Selection

We select appropriate models by minimizing information criteria, AIC and SBIC, which is given by:

$$AIC = ln(\hat{\sigma}^2) + \frac{2k}{T} \tag{.6}$$

$$SBIC = ln(\hat{\sigma}^2) + \frac{k}{T}\, ln\, T \tag{.7}$$

where $\hat{\sigma}^2$ is the residual variance and k equals to the total numbers of parameters estimated. These two equations balance a trade-off between a lower residual variance with a less parsimonious model, i.e. additional parameters. We note that SBIC penalizes additional parameters more than AIC.

Several models are tested, including plain symmetric GARCH models, asymmetric GJR- and E-GARCH, with or without GARCH-in-mean, students t-distribution and generalized normal distribution, GED and different specifications of auto-regressive terms in the mean process. The optimal models are GJR-GARCH(1,1) with t-distribution and an AR(3) process in the mean process for the equally weighted index and a similar model, except we use AR(1) instead of AR(3) in the value weighted index. We include lagged returns in the mean process as AR(1) or AR(3) processes to allow for autocorrelation in the return series.

Note that our data set contain several breaks for instance every weekend and holidays. Using a GARCH on a data set with many gaps will produce misleading results. We avoid this potential issue by generating a new variable that simply numbers each observation. We use this variable to keep track of time.

A3 Logit results

	EW	VW
Feb	6%	0%
Mar	5%	2%
Apr	5%	4%
May	4%	0%
Jun	20%	14%
Jul	4%	0%
Aug	14%	0%
Sept	22%	5%
Oct	10%	4%
Nov	15%	3%
Dec	10%	0%

Table A3.1: Share of significant monthly beta coefficients in the rolling window regressions at p<0.1 level.

This shows the share of unity values for the dummy variables $psig\_Month_i$. We are unable to use months with 0% significant coefficients in a logit regression as there is no variance in the outcome variables. Months with few significant rows will give unreliable estimates.

Table A3.2: EW February, Logit

	psig_Feb01	psig_Feb01	psig_Feb01
psig_Feb01			
SMB	439.8		
	(0.07)		
HML	32827.5**		
	(2.22)		
UMD	9686.5**		
	(2.01)		
LIQ	-8930.1		
	(-1.47)		
DlogGDP		814.7***	
		(3.09)	
PGap		93.68**	
		(2.16)	
Jan_kurt			-1.589
			(-0.81)
Jan_Skew			-12.57
			(-1.15)
Feb_Kurt			-6.476**
			(-2.11)
Feb_Skew			30.05*
			(1.69)
_cons	-24.06**	-29.67***	20.38
	(-2.56)	(-2.62)	(1.44)
N	176	176	176
pseudo R^2	0.847	0.561	0.851
LR	65.00	43.05	65.34
p	2.57e-13	4.49e-10	2.18e-13

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.3: EW March, Logit

	psig_Mar01	psig_Mar01	psig_Mar01
psig_Mar01			
SMB	-1016.2		
	(-0.11)		
HML	38148.1**		
	(2.06)		
UMD	10061.9		
	(1.05)		
LIQ	-12378.9		
	(-1.58)		
DlogGDP		580.0***	
		(3.02)	
PGap		62.89*	
		(1.90)	
Jan_kurt			-0.383
			(-0.96)
Jan_Skew			-2.539*
			(-1.84)
Mar_kurt			-1.771**
			(-2.50)
Mar_skew			3.525**
			(2.34)
_cons	-25.51**	-21.14**	4.983
	(-2.14)	(-2.54)	(1.48)
N	176	176	176
pseudo R^2	0.813	0.451	0.208
LR	52.93	29.37	13.56
p	8.83e-11	0.000000420	0.00885

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.4: EW April, Logit

	psig_Apr01	psig_Apr01	psig_Apr01
psig_Apr01			
SMB	-7931.3**	5300.5	-1782.4
	(-2.14)	(1.01)	(-0.16)
HML	-624.2	-5687.9*	-883.7
	(-0.41)	(-1.76)	(-0.09)
UMD	-61.47	2561.0	-1444.5
	(-0.03)	(0.68)	(-0.25)
LIQ	4337.7*	-3040.3	-5880.1
	(1.86)	(-0.76)	(-0.88)
DlogGDP		-343.5	-1384.9*
		(-0.85)	(-1.65)
PGap		162.7**	346.4**
		(2.57)	(2.22)
Jan_kurt			0.302
			(0.45)
Jan_Skew			-7.512*
			(-1.88)
Apr_kurt			0.328
			(0.58)
Apr_skew			5.966
			(1.36)
_cons	-3.492**	-27.53***	-47.27**
	(-2.08)	(-2.73)	(-2.01)
N	176	176	176
pseudo R^2	0.176	0.444	0.676
LR	11.45	28.89	43.97
p	0.0219	0.0000640	0.00000333

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.5: EW June, Logit

	psig_Jun01	psig_Jun01	psig_Jun01
psig_Jun01			
SMB	-10623.5***	10806.4	-14129.7***
	(-4.23)	(1.23)	(-3.72)
HML	1404.0	5196.5	-1287.9
	(1.26)	(0.66)	(-0.56)
UMD	9080.8***	25974.6*	6199.7**
	(3.71)	(1.78)	(2.02)
LIQ	12459.5***	22693.3*	15272.8***
	(4.87)	(1.76)	(4.52)
PR1YR		-4390.1	
		(-0.52)	
DlogGDP		991.2	
		(1.09)	
PGap		349.8**	
		(2.52)	
Jan_kurt			0.377
			(1.44)
Jan_Skew			-1.521
			(-1.16)
Jun_kurt			0.765
			(1.21)
Jun_skew			-3.203*
			(-1.90)
_cons	-12.13***	-113.7**	-18.71***
	(-4.74)	(-2.30)	(-3.93)
N	176	176	176
pseudo R^2	0.511	0.870	0.640
LR	91.11	155.2	114.2
p	7.66e-19	3.29e-30	5.30e-21

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.6: EW July, Logit

	psig_Jul01	psig_Jul01	psig_Jul01
psig_Jul01			
SMB	-4811.9	-895.9	-21427.7
	(-1.44)	(-0.16)	(-1.52)
HML	1094.2	1031.5	9716.0
	(0.55)	(0.29)	(1.08)
UMD	2859.9	8052.4**	14877.6**
	(1.62)	(2.04)	(2.02)
LIQ	4678.0**	5733.4	33752.5*
	(2.53)	(1.43)	(1.95)
DlogGDP		-291.7	515.7
		(-0.97)	(0.69)
PGap		63.90*	244.8*
		(1.81)	(1.79)
Jan_kurt			0.503
			(0.25)
Jan_Skew			-5.081
			(-0.54)
Jul_kurt			2.236*
			(1.93)
Jul_skew			-4.029
			(-1.55)
_cons	-7.110***	-20.45**	-116.2**
	(-4.41)	(-2.33)	(-2.07)
N	176	176	176
pseudo R^2	0.285	0.413	0.630
LR	16.78	24.33	37.06
p	0.00213	0.000454	0.0000552

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.7: EW August, Logit

	psig_Aug01	psig_Aug01	psig_Aug01
psig_Aug01			
SMB	-10364.7***	-5075.3	-8169.1
	(-3.53)	(-1.33)	(-1.46)
HML	344.3	-1645.0	-2905.9
	(0.30)	(-1.04)	(-0.95)
UMD	8877.2***	8661.0***	9638.1***
	(3.62)	(3.52)	(2.71)
LIQ	11419.2***	8476.3***	15324.9***
	(4.29)	(2.92)	(3.12)
DlogGDP		34.41	609.3**
		(0.22)	(2.06)
PGap		30.59*	57.82*
		(1.71)	(1.81)
Jan_kurt			0.169
			(0.32)
Jan_Skew			-4.985*
			(-1.88)
Aug_kurt			0.858***
			(2.83)
Aug_skew			-0.963
			(-1.20)
_cons	-11.40***	-15.57***	-43.10***
	(-4.56)	(-4.55)	(-3.14)
N	176	176	176
pseudo R^2	0.468	0.510	0.673
LR	67.31	73.40	96.87
p	8.40e-14	8.19e-14	2.30e-16

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.8: EW September, Logit

	psig_Sept01	psig_Sept01	psig_Sept01
psig_Sept01			
SMB	-3237.8**	2601.6	280.0
	(-2.31)	(0.61)	(0.05)
HML	1760.8	1567.5	-6911.6*
	(1.62)	(0.73)	(-1.80)
UMD	3052.0**	2055.5	-2567.4
	(2.25)	(1.06)	(-0.87)
LIQ	5984.8***	13599.7***	17296.7***
	(5.05)	(2.79)	(2.75)
DlogGDP		1382.8***	1670.2***
		(3.04)	(2.87)
PGap		110.7***	96.37***
		(3.41)	(2.59)
Jan_kurt			0.266
			(0.70)
Jan_Skew			-4.648**
			(-2.19)
Sept_kurt			-0.166
			(-0.53)
Sept_skew			-0.353
			(-0.14)
_cons	-7.601***	-53.25***	-54.06***
	(-5.13)	(-3.83)	(-3.69)
N	176	176	176
pseudo R^2	0.411	0.706	0.757
LR	75.42	129.7	139.0
p	1.63e-15	1.51e-25	6.62e-25

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.9: EW October, Logit

	psig_Oct01	psig_Oct01	psig_Oct01
psig_Oct01			
SMB	-10463.7***	-3587.8	23639.0*
	(-3.08)	(-0.66)	(1.65)
HML	380.4	285.5	8118.8
	(0.27)	(0.07)	(0.80)
UMD	5391.8***	7341.2**	19714.5
	(2.78)	(2.01)	(1.60)
LIQ	9589.4***	12939.4**	10469.0
	(3.95)	(2.07)	(0.79)
DlogGDP		550.4**	444.5
		(2.10)	(0.70)
PGap		217.4**	721.5***
		(2.05)	(2.64)
Jan_kurt			-4.161**
			(-2.16)
Jan_Skew			-0.933
			(-0.15)
Oct_kurt			-1.321**
			(-2.03)
Oct_skew			-3.182
			(-1.16)
_cons	-9.053***	-63.60**	-130.9**
	(-4.54)	(-2.24)	(-2.45)
N	176	176	176
pseudo R^2	0.446	0.626	0.814
LR	51.86	72.70	94.56
p	1.48e-10	1.14e-13	6.65e-16

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.10: EW November, Logit

	psig_Nov01	psig_Nov01	psig_Nov01
psig_Nov01			
SMB	-11099.7***	-6470.4	-15985.4***
	(-2.99)	(-0.66)	(-3.22)
HML	-1110.7	1965.5	-1301.5
	(-0.77)	(0.29)	(-0.76)
UMD	10028.7***	12728.2***	8539.1***
	(3.56)	(2.68)	(2.81)
LIQ	13557.8***	27123.0*	15808.7***
	(4.04)	(1.94)	(4.27)
DlogGDP		1102.8	
		(1.48)	
PGap		272.4**	
		(1.97)	
Jan_kurt			-0.254
			(-0.77)
Jan_Skew			-1.560
			(-0.86)
Nov_kurt			-0.903*
			(-1.91)
Nov_skew			-3.104
			(-1.04)
_cons	-13.49***	-95.77**	-7.898*
	(-4.46)	(-2.09)	(-1.93)
N	176	176	176
pseudo R^2	0.561	0.814	0.620
LR	82.66	120.0	91.37
p	4.75e-17	1.64e-23	2.45e-16

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.11: EW December, Logit

	psig_Dec01	psig_Dec01	psig_Dec01
psig_Dec01			
SMB	-3484.8*	-2121.0	-2746.7
	(-1.82)	(-0.78)	(-0.76)
HML	2346.3	-155.6	1583.7
	(1.55)	(-0.08)	(0.51)
UMD	3843.2***	5204.6**	3600.5
	(2.83)	(2.27)	(1.40)
LIQ	2237.5	1340.4	-789.4
	(1.59)	(0.93)	(-0.30)
DlogGDP		102.0	166.9
		(0.93)	(1.19)
PGap		35.35*	24.95
		(1.83)	(1.11)
Jan_kurt			0.444*
			(1.84)
Jan_Skew			1.355
			(1.59)
Dec_kurt			-0.444
			(-1.05)
Dec_skew			0.924
			(0.69)
_cons	-5.386***	-11.84***	-9.113*
	(-4.66)	(-2.96)	(-1.76)
N	176	176	176
pseudo R^2	0.313	0.409	0.480
LR	35.02	45.72	53.65
p	0.000000459	3.37e-08	5.63e-08

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.12: VW March, Logit

	psig_Mar01	psig_Mar01	psig_Mar01
psig_Mar01			
SMB	12107.6	28241.1	67940.5
	(1.49)	(1.32)	(1.44)
HML	-2984.8	-3416.7	-16440.9
	(-0.70)	(-0.72)	(-0.89)
UMD	11344.7*	16894.5	36573.6*
	(1.83)	(1.38)	(1.68)
LIQ	4561.1	4033.3	5383.8
	(1.55)	(1.24)	(0.37)
DlogGDP		-1.164	605.1
		(-0.00)	(0.40)
PGap		84.03	101.5
		(0.95)	(0.57)
Jan_kurt			-5.040
			(-0.74)
Jan_Skew			-3.651
			(-0.47)
Mar_kurt			-2.178
			(-0.55)
Mar_skew			8.744
			(1.01)
_cons	-22.64**	-49.82	-71.67
	(-2.11)	(-1.40)	(-1.30)
N	176	176	176
pseudo R^2	0.477	0.526	0.696
LR	14.48	15.97	21.14
p	0.00591	0.0139	0.0201

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.13: VW April, Logit

	psig_Apr01	psig_Apr01	psig_Apr01
psig_Apr01			
SMB	1384.1	1608.3	1857.2
	(0.69)	(0.47)	(0.14)
HML	-2225.4	-2077.8	-7140.1
	(-1.24)	(-1.09)	(-1.16)
UMD	-1515.1	-1810.5	-23571.6*
	(-0.60)	(-0.66)	(-1.72)
LIQ	-1109.1	-1436.8	-16150.7
	(-0.68)	(-0.53)	(-1.53)
DlogGDP		-43.51	-542.1
		(-0.24)	(-0.85)
PGap		-0.654	364.9**
		(-0.04)	(2.00)
Jan_kurt			-0.564
			(-0.57)
Jan_Skew			-55.54**
			(-2.13)
Apr_kurt			8.081**
			(1.99)
Apr_skew			38.01**
			(2.10)
_cons	-2.073	-1.407	-93.77*
	(-1.06)	(-0.50)	(-1.94)
N	176	176	176
pseudo R^2	0.062	0.065	0.705
LR	3.667	3.801	41.47
p	0.453	0.704	0.00000931

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.14: VW June, Logit

	psig_Jun01	psig_Jun01	psig_Jun01
psig_Jun01			
SMB	-8353.3***	8889.7	-50327.6*
	(-2.60)	(1.09)	(-1.84)
HML	-2290.7	-3944.4	-5634.2
	(-1.52)	(-0.63)	(-0.79)
UMD	6587.5***	14724.8**	34847.7
	(3.35)	(2.56)	(1.59)
LIQ	9862.7***	20232.5**	51623.7*
	(4.32)	(2.24)	(1.85)
DlogGDP		564.0	
		(1.32)	
PGap		395.4**	
		(2.24)	
Jan_kurt			-6.874
			(-1.60)
Jan_Skew			-60.91*
			(-1.70)
Jun_kurt			-7.003
			(-1.24)
Jun_skew			12.26
			(1.44)
_cons	-9.758***	-112.2**	-4.647
	(-5.05)	(-2.29)	(-0.60)
N	176	176	176
pseudo R^2	0.518	0.846	0.888
LR	70.73	115.5	121.2
p	1.59e-14	1.44e-22	1.85e-22

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.15: VW September, Logit

	psig_Sept01	psig_Sept01	psig_Sept01
psig_Sept01			
SMB	-8795.6*	-901.4	-8404.1
	(-1.94)	(-0.15)	(-0.63)
HML	-84.09	-585.7	11171.7
	(-0.04)	(-0.15)	(0.81)
UMD	1969.4	2648.0	-154.6
	(1.13)	(0.92)	(-0.03)
LIQ	6803.3***	4934.3	6833.2
	(2.60)	(1.14)	(0.89)
DlogGDP		146.5	-1033.7
		(0.58)	(-1.33)
PGap		82.78	148.9
		(1.54)	(1.54)
Jan_kurt			-7.855*
			(-1.73)
Jan_Skew			-4.356
			(-0.66)
Sept_kurt			0.411
			(0.79)
Sept_skew			-2.733
			(-1.02)
_cons	-6.698***	-25.14*	0.414
	(-3.80)	(-1.82)	(0.03)
N	176	176	176
pseudo R^2	0.264	0.379	0.667
LR	17.22	24.69	43.44
p	0.00176	0.000390	0.00000414

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.16: VW October, Logit

	psig_Oct01	psig_Oct01	psig_Oct01
psig_Oct01			
SMB	-12698.3**	-6469.2	
	(-2.36)	(-1.09)	
HML	-1190.1	-3337.5	
	(-0.72)	(-1.33)	
UMD	-1603.0	-1368.6	
	(-0.56)	(-0.39)	
LIQ	5635.0*	1831.1	
	(1.70)	(0.46)	
DlogGDP		-84.57	
		(-0.25)	
PGap		56.53	
		(1.46)	
Jan_kurt			-5.162**
			(-2.50)
Jan_Skew			-2.605
			(-0.66)
Oct_kurt			0.300*
			(1.94)
Oct_skew			-0.231
			(-0.32)
_cons	-2.740	-10.28*	12.09*
	(-1.22)	(-1.80)	(1.87)
N	176	176	176
pseudo R^2	0.290	0.355	0.467
LR	17.08	20.89	27.50
p	0.00186	0.00192	0.0000157

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$