

Bachelor Thesis Finance

Effect of Size on the January Effect

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Introduction

Roseff and Kinney (1976) were the first to study the influence of seasonalities to the stock returns and ground it with convincing and supportive evidence. They reported evidence of a so called “January effect” which includes that in January stock returns are abnormally high compared to the remaining other months. To be precise, they found that in the period from 1904 to 1974 the average return on an equally-weighted portfolio of the New York Stock Exchange in January was 3.47% compared to 0.42% in the eleven remaining months of the year.

These results are contrary to the paper by Fama (1970) in which the efficient stock market is discussed. A market is considered efficient if all available information from the past is fully reflected and if new information is processed immediately in prices. This suggests that stock prices and returns are unpredictable and take a random walk. Historical information cannot be used to predict future stock prices. In the paper are three tests to determine an efficient market discussed. The seasonal patterns of the January effect decline the fact there is an efficient market even in the case of the weakest form of testing. Investors know the opportunity of making high profits in the first month of the year. Because they incorporate this knowledge of the market in their strategies, the profits should be removed through arbitrage. This is not the case, because in recent years there was still a January effect found in the stock market. This is very interesting, since this would mean there are opportunities to make high profits without taking high risks. To predict which stock prices are going to increase, it is helpful to know where the January effect comes from.

Many researchers proposed hypotheses that could explain why there is a January effect in the stock market. Musto (1997) for example stated that fund managers shift their portfolio at disclosure dates to make them look more conservative and more successful. This is called the “Window dressing hypothesis”. There are also other hypotheses for explaining the January effect, like the tax-loss selling hypothesis (Reinganum, 1983), the parking-the-proceeds hypothesis (Ritter, 1989) and the gambling hypothesis (Doran, 2009).

Previous study from Banz (1981) suggests there is a negative relation between size and excess returns, also known as the size effect. In this paper there will be investigated what the effect from the size of a firm is on the January effect. This will be done by running various regressions. Data will be extracted from the website of the researchers Eugene Fama and Ken French. These data will include returns from portfolios based on size (market capitalization) from 1926 to 2011. The data include stock returns of firms listed on the NYSE, AMEX and NASDAQ. Furthermore market returns, risk-free rate and Fama and French-factors are included. The first regression will involve a CAPM specification that includes the market excess return. The second regression will be run with an enhanced model of the CAPM by Fama and French (1993) that incorporates size (SMB). The last regression comes from the paper of Keim (1983). This regression uses the months February until December as dummy variables to project the January effect.

Literature Review

Rozeff and Kinney (1976) caused the main breakthrough in the beliefs about the influence and importance of season anomalies. But seasonalities in the stock market have been a subject of study for almost a century. The Harvard Committee on Economic Research (1919) documented that their study, which included stock prices of the United Kingdom from January 1897 to January 1914, didn't have enough evidence that would support the existence of seasonal tendencies in the stock market. After this comprehensive study, Owens and Hardy (1925) also decided to investigate possible seasonality with included data up to 1925. Their results were conform to the results of the Harvard Committee. In the conclusion of the research they wrote: "Seasonal variations of security prices are impossible.... If a seasonal variation in stock prices did exist, general knowledge of its existence would put an end to it." This conclusion would have made any further investigation unnecessary and would have closed the topic of investigation.

But the research department of a brokerage firm based in New Orleans called Fenner and Beane (1939) thought different. In a study on security prices from 1924 to 1939 they reported an existence of bullish tendencies in stock prices in fourteen of the fifteen studied summers. This led to a new wave of investigations, from which the study of Wachtel (1942) was the most influential. He mapped the advances and declines of high yield stocks of the Dow Jones Industrial Stock Market from the third Saturday in December to the third Saturday in January and compared it with other months. He also made a chart in which the average value of the twenty highest yielding stock was compared to the Dow-Jones Industrial Average throughout the year. Wachtel came to the conclusion that there is significant evidence that supports bullish tendencies in the months December and January. As possible causes for this founding he already opted the tax-loss selling hypothesis and the gambling hypothesis. In later years the literature after his study has been broad and the January effect has been the most investigated seasonal anomaly. Evidence from D'Mello suggests that the January effect still exists in the stock market. In the further sections of this part of the research an extensive theoretical scope in the form of hypotheses and historical empirical findings are presented.

Window Dressing Hypothesis

Typically a money fund manager must disclose his portfolio at predetermined dates. Usually these dates are at the end of a quarter or at the yearend for accounting purposes. There are two options for the manager to choose from. The first option is to hold on to the portfolio he have had for the period and thereby ignoring the disclosure schedule. This would give a representative and unbiased image of the investment strategy followed by the manager. The second option is to shift from the portfolio he has hold for the most of the period to another portfolio that under represents the riskiness of the portfolio held on non-disclosure dates. Outsiders might see this portfolio as more strategic, more successful or more conservative. The portfolio shifting at disclosure dates is called window-dressing (Musto, 1997). This

strategy could explain the January effect, since managers repurchase the small risky stocks after the year end to increase risk and corresponding expected return.

There are good reasons to believe money managers would want to window-dress. As Grinblatt and Titman (1994) notice in their paper usually a benchmark portfolio is used for the evaluation of the performance of managed portfolio's. However, stock returns are noisy and therefore a really good investment strategy can flop because of a few unlucky stocks. So sponsors may check the portfolio held at disclosure dates. To make a good impression to these sponsors, managers want to window-dress their portfolio by buying winners and selling losers (Lakonishok et al.). Another reason is that outsiders have few other opportunities to collect information about a fund's riskiness, so this increases the value of the disclosed portfolio's. A last reason is that disclosed portfolio's are often used as a proxy for undisclosed portfolio's by academics (e.g. Chevalier and Ellison (1995), Sias and Starks (1997)).

Haugen and Lakonishok (1988) supported the window-dressing hypothesis with empirical results. Lakonishok et al. (1991) presented more results in support. They found that "in every quarter, funds sell poorly performing stocks disproportionately to their holdings, that is, they get rid of "mistakes". Moreover, the pace of dumping mistakes accelerates in the fourth quarter, consistent with the most common window-dressing strategy." Remarkably they came to the conclusion that the amount of losers purchased also rise in the fourth quarter. This would imply that sponsors might think buying losers might be a successful investment strategy since they could be undervalued.

Performance Hedging Hypothesis

The performance hedging hypothesis is another hypothesis given by Haugen and Lakonishok (1988). This hypothesis proposes that managers rebalance their portfolio throughout the year and that they lock in performance based compensation. Because managers are afraid of sharp declines in the portfolio value, they periodically sell of risky assets as the year progresses and purchase stocks of their benchmark, usually an index like the S&P 500. When the managers are evaluated on their performances, they reinvest in small risky securities in the beginning of the new year. Lee et al. (1998) were concerned about the manager evaluations at calendar year ends and the effect those evaluations may have on stock returns. Therefore they wanted to investigate whether the January effect is the result of window-dressing or the performance hedging. Using difference of means tests they came to results that suggest that if the January effect is the result of manager behavior, it is more likely that the effect is a consequence of performance hedging rather than window-dressing. This is an important conclusion for investors, since performance hedging locks in a superior performance and window-dressing comes with high unnecessary transaction costs.

Tax-Loss Selling Hypothesis

Reinganum (1983) proposed another hypothesis to give a reason for the abnormal stock returns in January. As stated before, the calendar year often coincides with the fiscal year of companies in various countries of the world. And since capital gains are taxed in a lot of these countries, there is a possibility of tax-loss selling. This can be achieved by selling stocks at the end of the year which have declined sharply in value for the last couple of months. The substantial loss that has been made by selling can be used as a tax shield to reduce taxes. If there are a lot of companies that sell last year's or months' loser stocks this will lead to a downward pressure on the stocks which will cause undervaluation. In the new year, investors want to exploit this undervaluation and this gives the abnormal returns.

In his research he used market capitalization and a measure called PTS, potential for tax-loss selling. The best way to calculate such a measure would include data for prices, volume and institutional holdings. But due to data constraints, only price data were available. Therefore Reinganum constructed the PTS measure by taking the price of the security at the second last day of the year and dividing it by the maximum price of the security in the last 6 months of the year. After computing the market capitalization and PTS of the securities he categorized them in ten groups of ten percent regarding market capitalization and in four groups based on tax-loss selling potential. This gave a total of forty subgroups for which he computed the returns for.

The results of his study contributed evidence to the tax-loss selling hypothesis, since he found that in the first days of January stocks with the greatest relative declines in value (lowest quartile) experience on average higher returns than firms in the upper quartile of the PTS measure. To be precise, on the first trading day in January the firms in the bottom quartile of portfolio MV1 (the 10% of the firms with the lowest market capitalization) average a daily return of more than 4.0 percent whereas the firms in the upper quartile earn slightly less than 0.4 percent. However, another finding of his research was that small firms least likely to be sold for tax reasons also had on average abnormal returns in January. As an explanation for this result he concluded that the tax-loss selling hypothesis could not explain the January effect completely. His conclusions may be questioned by the restrictions of his PTS measure.

More recent empirical study of D'Mello et al. (2003) resulted in new evidence with respect to the tax-loss selling hypothesis. The big difference between their study and the study of Reinganum (1983) is that they use intra-day transaction and quote information, which allows them to check for each trade if it is a buy or a sell and also to check whether an increase in trading activity comes from an increase in selling or an increase in buying. In combination with the potential tax-loss selling measure this gives them data to investigate the selling pressure around year end. The intra-day information also gives them the possibility to investigate the source of the trading activity. The average trading size is used to examine

where the trading activity comes from. An increase in the average trading size means there are more trades made by institutional investors and a decrease in trading size means there are more trades made by individual investors, since individuals normally own smaller funds. These new opportunities to investigate trading patterns also motivated them to study the influence of tax-loss selling on the January effect.

Their findings were in support of the tax-loss selling hypothesis. One of them is an abnormal increase in selling activity of stocks that have sharply declined in value, thus stocks with a high PTS measure, at the end of the year. This selling pressure goes away when turning in the new year. There is also an abnormal increase to be found in selling stocks that gained in value in the beginning of the year. These results strokes with the tax-loss selling hypothesis. But they also found an increase in buying activity in the first days of January, which agrees to the parking-the proceeds hypothesis by Ritter (1989) discussed further in this section. The average trading size of transactions decreases at the end of the year, which implies individual investors dominate before the turning of the year. Though the most important finding is that the tax-loss selling hypothesis is the primary explanation for the January effect in contrary to firm size or share price effects.

The role that the well-documented tax-loss selling hypothesis plays is not that clear. Several studies have tried to establish the hypothesis and to support it with enough strong evidence. However, not all evidence reported is conclusive and some studies even show results that contradict the tax-loss selling hypothesis. For example, Roll (1983) found a significant negative relation between last year's returns of a stock and the returns in the beginning of the new year. But this finding can also be the result of institutional window dressing. Brown et al. (1983) tested the tax-loss selling hypothesis in a different way. They studied the monthly returns in Australia, where the tax year-end is June 30 and where different tax rules apply to capital gains and losses. Important is that there is no 3000 Dollar limit to tax deduction like in the US. Therefore they stated a similar or even stronger January effect should be visible in the month July. The findings of their study are remarkable: abnormal returns in the period December-January and July-August, with the strongest in January and July. Reinganum and Shapiro (1987) investigated the United Kingdom's stock market. In the UK, the tax year-end is on April 4th. They found no seasonalities before 1965, but they found strong abnormal return seasonality in April and January since the introduction of capital gains in that year. This somewhat objects the tax-loss selling hypothesis, because of the presence of the strong return premiums in January. Research done by Van den Bergh and Wessels (1985) showed abnormal returns in January in the Dutch stock market. This would support the hypothesis, if it wasn't that capital gains realized by individuals are free of income tax in the Dutch tax code. Though it still might be supportive evidence, since foreign investors and institutions do have to pay taxes on capital gains. Furthermore, Jones et al. (1987) concluded that the January effect was present in the stock market even before the introducing of taxes on capital gains.

Parking-the-proceeds Hypothesis

Ritter (1988) proposed in his publication in the Journal of Finance the parking-the-proceeds hypothesis. This can be seen as a generalization of the tax-loss selling hypothesis. The parking-the-proceeds hypothesis states that the January effect is caused by the buying and selling behavior of individual investors. As in the tax-loss selling hypothesis, individual investors sell off loser stocks to realize a deductible tax loss. The money that these sales bring in will not be reinvested directly, but will be parked until the beginning of the new year. In January then, this money will be used to buy back small risky stocks. This buying pressure leads to an increase in the prices of small stocks.

The argumentation around the hypothesis involves 3 single steps. The first step requires that individual investors construct a portfolio more focused on low capitalization and low priced stocks. Empirical evidence from Blume and Friend (1986) and more recent Kumar (2009) suggests this is the case. This is important because individuals have incentives for tax-loss selling where institutional investors don't. The second step needs buying and selling pressure to have influence on stock prices. Studies by Lakonishok and Smidt (1984) and Rozeff (1986) provide evidence for this requirement. The third and last step involves the parking of the proceeds. Ritter (1988) himself found patterns that investors save their proceeds on their brokerage accounts for a couple of time and then reinvest it.

Gambling Hypothesis

Wachtel (1942) again was the first to mention the state of people's minds and the atmosphere around the turn of the year as possible causes of the January effect. As he states in his publication in The Journal of Business of the University of Chicago: "The general feeling of good fellowship and cheer existing throughout the Christmas holidays tends to last in the security markets through the beginning of January. Coupled with this idea might be a widespread hope that the new year will prove better than the old." But after his publication, there hasn't been much investigation with respect to this hypothesis for a long time. Financial economists contained that the gambling preferences of individuals had a significant influence in some financial decision making processes like buying insurances and lotteries (Friedman and Savage 1948; Markowitz 1952) and portfolio underdiversification (Statman, 2004). But none of the economists connected the gambling preferences to the January effect.

Thaler (1985) was one of the pioneers of behavioral finance and had important contributions to this field of economic research, especially gambling preferences of individuals. One of his findings was that multi-period financial decisions are usually evaluated in intertemporal mental accounts and that the time between two evaluation moments often is one year. A natural starting point of a new period is the beginning of a calendar year, and therefore the evaluation moment for decision makers is most of the times at the end of the year. The loads of information about companies' and stocks' performances that come available also make the end of the year a suitable evaluation moment. Another finding of Thaler and Johnson (1990)

was that individuals are likely to take more risk after experiencing outcomes and payoffs from earlier rounds of gambling. For example, when you are in a casino, you are more likely to put money on red or black in the popular casino game roulette if you have put money on red or black in a previous round - and therefore have lost or won money - than when you haven't engaged in a gambling round. These two findings combined leads to the statement that people are inclined to take more risk in the beginning of the new year. The increased risk taking leads to a price pressure and higher returns on lottery type stocks. This is called the gambling hypothesis.

The existence of seasonality in gambling activity has been proved. In the United States, the period between the Super Bowl final and Chinese New Year brings high profits for casinos in Las Vegas. The final is a very popular betting subject under sports fans and the typically traditional and high rolling Asians celebrate the New Year by throwing some money in the game. Gambling around New Year is big in countries like Greece and Turkey, where there is a real hype around the special New Year lottery. In New Zealand, people tend to engage in gambling activities during the Christmas holidays. (Doran, 2009)

Doran (2009) investigated this empirically. To test whether the gambling activities in casinos during the beginning of the year are higher, he studied the revenues from the casinos in Las Vegas, one of the biggest casino strips in the world. He found that in the period from 1997 untill 2007, a visitor gambles on average \$159.50 in January and \$140.32 in other months. This is a significant difference of \$19.18 or almost 14%. The result is not coming from a higher visitor level in January. His study turns out that there is little variation in the number of visitors per month. Therefore the higher average on gambling activity cannot be explained by seasonality in visitation. So it must be a result of an increased gambling mentality.

Evidence determines a higher gambling mentality of casino visitors in the month January, but this doesn't have to mean that investors in the stock market also experience a higher gambling mentality around the turn of the year. To check whether this is the case, he studied the prices of out-of-the-money call options and lottery-type stocks in the US and China. These two securities are viewed as the securities with the highest gambling features. On top of that, China is the ideal stock market to test this gambling hypothesis, since the Chinese New Year's Day does not take place on the same day as in most parts of the world. Spring Festival, the Chinese celebration day for the start of the new year based on the Lunar calendar, usually takes place between half January and half February. Also, taxes on capital gains do not have to be paid on the 1st of January. This gives the researcher the opportunity to distinguish the influences of different hypotheses. His findings show that the out-of-the-money call options and lottery-type stocks have abnormally high prices, returns and trading volume around the turn of the year in the US and China. These results cannot entirely be explained by the traditional hypotheses involving window-dressing and tax-loss selling. Also, as mentioned in the conclusion of his paper, the results follow the parking-the-proceeds hypothesis. But while Ritter (1988) could not come up with a motive for investors to park the proceeds, Doran (2009) suggest that investors save the money from selling their stocks at the end of the year to invest in lottery type stocks.

Methodology

Data

The portfolio returns based on size are extracted from the website of the researchers Eugene Fama and Ken French. Monthly returns from July 1926 until December 2011 are extracted. The portfolio's are based upon market capitalization and the total number of stocks are divided in deciles, quintiles and also in one portfolio consisting the 30% of the stocks with the lowest market capitalization, 30% of the stocks with the highest market capitalization and the 40% with the middle. Stocks included in the portfolios are all the stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ) for which equity data were available at the moment of construction of the portfolios. The portfolios are constructed at the end of each June using the June market equity and NYSE breakpoints.

The extracted data are divided into 12 different samples with respect to the months of the year for each ten size portfolios. For all of these groups, excess returns are calculated by subtracting the risk free rate from the monthly returns. Also, the excess returns of the smallest minus the largest size portfolios have been subtracted.

To use a Fama and French specification of the CAPM model on the regression run to determine the January Effect, three Fama/French factors are also extracted from the same website. The first factor is the Small-minus-big factor. The SMB factor is the average return on the three small portfolios minus the average return on the three big portfolios. This accounts for the spread in returns between small and large-sized firms, also known as the small-firm effect.

$$SMB = 1/3 (Small Value + Small Neutral + Small Growth) \\ - 1/3 (Big Value + Big Neutral + Big Growth).$$

The second factor obtained from the Fama and French site is the High-minus-low factor. The HML factor is the average return on the two value portfolios minus the average return on the two growth portfolios. HML accounts for the spread in returns between value and growth stocks. HML argues that companies with high book-to-market ratios (value stocks) outperform those with low ones (growth stocks).

$$HML = 1/2 (Small Value + Big Value) \\ - 1/2 (Small Growth + Big Growth)$$

The last Fama and French factor is one that already exists in the CAPM model, namely the excess return on the market. This factor is calculated by subtracting the risk-free rate by the market return. These are both extracted from the site. $R_m - R_f$, the excess return on the market, is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). The one-month Treasury bill rate is chosen because the returns are also monthly.

CAPM Model

Sharpe and Lintner's (1962) Capital Asset Pricing Model is a financial investment theory used to determine a required rate of return of a risky security investment. It is based on the Modern Portfolio Theory from Markowitz. It's a rather simple model to describe the relationship between risk and expected return. The general idea behind the model is that investors in a security need to be compensated in two ways: the time value of money and risk. The time value of money is represented in equation (1) by the risk-free rate. This compensates the investor for placing his money in an investment while the investor could have saved it on a bank account and could have gained interest. The beta is a risk measurement that accounts for the systematic risk. The premium the investor gets for his risk is given by multiplying the beta with the excess return on the market, which is given by subtracting the risk-free rate from the market return. Following the CAPM theory, only the systematic risk needs to be compensated to the investor, since this risk cannot be eliminated by portfolio diversification.

$$(1) \quad R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t} (R_{m,t} - r_{f,t}) + \varepsilon_{i,t}$$

In the equation the left hand side consists of $R_{i,t} - r_{f,t}$, the monthly stock excess returns. This is defined as the closing price in month t relative to the closing price in last month subtracted by the monthly risk-free rate. On the right hand side, the monthly market excess return is given by $R_{m,t} - r_{f,t}$. It is defined as the monthly closing price of the market index relative to the closing price in last month subtracted by the risk-free rate. The risk of the investor is represented by $\beta_{i,t}$. It is calculated by correlating the asset returns with the market returns. These two factors combined give the systematic risk premium for the investor. The $\alpha_{i,t}$ in the equations corresponds with the stock's performance relative to the market. If alpha is equal to zero, the stock return corresponds perfectly with the systematic risk. If alpha is positive or negative, the stock has respectively out- or underperformed relative to the market. The $\varepsilon_{i,t}$ stands for the measurement errors of the regression. In case of the existence of a January effect, there should be a significant abnormal return $\alpha_{j,t}$ for the January sample. If size has got a negative relation with the January effect, the abnormal returns in January should be higher for the decile with the smallest size than for the decile with the largest size.

Three Factor Model

Fama and French (1993) extended the CAPM by adding two other risk factors. This extension is build on a key observation that two classes of stocks outperform the market as a whole. The first class is small caps and the second class consists of stocks with a high book-value-to-price ratio, also known as value stocks. The two additional factors have been discussed in the previous section. The addition of the measurement of size to the CAPM gives the following equation.

$$(2) \quad R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t} (R_{m,t} - r_{f,t}) + s_{i,t}SMB_t + \varepsilon_{i,t}$$

In this regression, SMB_t stands for the size measurement SMB in the month t and $s_{i,t}$ stands for the slope of the spread in returns between small and large firms and therefore the impact of size on the excess returns. The regression will be used to check if the January effect is still there when controlling for the impact of size.

Equal Expected Excess Returns

To test the null hypothesis that all equal expected excess returns are the same for all months of the year, the third regression of Keim (1983) will be used for all ten size deciles. Dummy variables of all the months except January are included in this regression.

$$(3) \quad R_t - R_f = a_1 + a_2D_{2t} + a_3D_{3t} + \dots a_{12}D_{12t} + \varepsilon_{i,t}$$

In this regression, $R_t - R_f$ is the average monthly excess return in the month t for the specific size portfolio. The dummy variables, noted by D_{2t} , D_{3t} and further, point in which month the excess return was observed: the subscript equals to the number of the month (D_{2t} corresponds to February, D_{3t} to March). The excess return for January is given by a_1 , where the others a_2 to a_{12} account for the differences in the excess return of January and the excess returns of the respective months. If the excess returns of all the months are equal, then a_2 through a_{12} should be close to zero and the F-statistic of the regression test should be insignificant. If a_2 through a_{12} are significantly negative, then there is evidence for the existence of the January effect. That last statement is the case when the F-statistic is lower than 1,83 for a 95% significance level. If the F-statistic is higher, the dummy variables are joint significant.

Summary Statistics and Empirical Evidence

In table 1 the average excess returns per month are given for all ten size portfolios. The excess returns are calculated by subtracting the risk-free rate from the monthly portfolio returns. The highest average excess return of 7,56% is reported for the smallest size portfolio in the month January. The smallest size portfolio also has the lowest average excess return of -1,32% in the month October. Except for the months September and October all excess returns are positive. In the first five months of the year the excess returns decrease when the portfolio size increases. There is a negative relation between excess returns and size. In the last three months of the year the excess return increases when the portfolio size increases. There is a positive relation between excess return and size. The excess return of all deciles is the highest in the month January with a return of 3,11% and the lowest in the month September with a return of -0,91%. The difference between the smallest size portfolio and the largest size portfolio is the highest in the month January with a difference of 6,87 percent point and the lowest in the month October with -1,59 percent point.

Table 1

Average Excess Returns in percent of portfolios constructed from firms of each decile of size (measured by market capitalization) on the NYSE, AMEX and NASDAQ by Fama and French over the period 1926-2011.

Month	Smallest	2	3	4	5	6	7	8	9	Largest	All	Smallest-Largest
January	7,56	5,00	4,14	3,32	2,86	2,49	1,97	1,58	1,51	0,69	3,11	6,87
February	1,54	1,27	0,97	0,75	0,83	0,72	0,82	0,65	0,57	-0,04	0,81	1,58
March	0,31	0,38	0,54	0,64	0,60	0,59	0,60	0,63	0,48	0,41	0,52	-0,10
April	1,23	1,12	1,18	1,20	1,36	1,35	1,22	0,96	0,97	1,14	1,17	0,09
May	1,03	0,90	0,65	0,76	0,41	0,32	0,37	0,31	0,30	0,20	0,53	0,84
June	0,41	0,51	0,44	0,52	0,56	0,51	0,52	0,50	0,55	0,60	0,51	-0,19
July	1,77	1,35	1,37	1,21	1,10	1,23	1,15	1,20	1,16	1,28	1,28	0,49
August	0,86	0,98	1,16	1,11	1,39	1,23	1,18	1,31	1,07	0,86	1,12	0,00
September	-0,36	-0,97	-0,92	-0,72	-0,87	-0,97	-0,97	-1,20	-1,01	-1,10	-0,91	0,74
October	-1,32	-0,94	-0,73	-0,81	-0,76	-0,53	-0,42	-0,16	-0,07	0,27	-0,55	-1,59
November	0,53	1,19	1,37	1,25	1,47	1,57	1,45	1,62	1,23	1,15	1,28	-0,62
December	0,16	0,81	1,39	1,77	1,57	1,95	1,92	1,71	1,67	1,35	1,43	-1,19

The size measure SMB has an average of 0,24%. The highest observed SMB is 39,04% in the month May of 1933. The lowest observed SMB is -16,62% in March 2000. It has a median of 0,06%.

The market return has an average of 0,91%. The highest observed market return is 38,37% in the month April of 1933. The lowest observed market return is -29,01% in the month September of 1931. It has a median of 1,3%.

Table 2 contains the average monthly abnormal returns in percent of the size portfolios obtained by running a CAPM regression. Data from July 1926 to December 2011 obtained from the website of Fama and French are subject of the regression. Each year, the portfolios have been updated based on the market capitalizations of the stocks. This table gives a quick overview of the average abnormal returns per size portfolio per month. Also the significance level of the abnormal returns are included in the table. The smallest size portfolio has the highest average monthly abnormal return in January of 5,77%. It also has the lowest abnormal return of -1,89% in December. This sharp decrease conforms to the hypotheses from the literature review section. The significance levels of the abnormal returns are highest in January and February. This means that those abnormal returns are estimated most precise by the regression.

Table 2

Average monthly abnormal returns in percent of portfolios constructed from firms of each decile of size (measured by market capitalization) on the NYSE, AMEX and NASDAQ by Fama and French over the period 1926-2011. These abnormal returns are obtained by running a CAPM regression for each sample of months. Significance levels are under parentheses.

Month	Smallest	2	3	4	5	6	7	8	9	Largest
January	5,77 (0,000)	3,16 (0,000)	2,49 (0,000)	1,70 (0,000)	1,33 (0,000)	0,98 (0,002)	0,57 (0,009)	0,27 (0,099)	0,30 (0,039)	-0,47 (0,000)
February	1,23 (0,049)	0,96 (0,034)	0,68 (0,027)	0,48 (0,120)	0,55 (0,022)	0,45 (0,032)	0,57 (0,004)	0,41 (0,010)	0,33 (0,009)	-0,25 (0,012)
March	-0,18 (0,654)	-0,16 (0,668)	0,24 (0,945)	0,16 (0,588)	0,09 (0,741)	0,11 (0,571)	0,13 (0,529)	0,17 (0,262)	0,05 (0,683)	0,01 (0,909)
April	-0,19 (0,689)	-0,28 (0,457)	-0,17 (0,562)	-0,16 (0,591)	0,00 (0,991)	0,03 (0,900)	-0,05 (0,812)	-0,23 (0,170)	-0,23 (0,114)	0,18 (0,088)
May	0,62 (0,526)	0,53 (0,545)	0,28 (0,675)	0,43 (0,421)	0,09 (0,828)	0,03 (0,919)	0,09 (0,716)	0,06 (0,682)	0,06 (0,529)	0,00 (0,930)
June	-0,35 (0,436)	-0,20 (0,619)	-0,23 (0,440)	-0,07 (0,793)	-0,09 (0,677)	-0,12 (0,561)	-0,09 (0,557)	-0,11 (0,436)	-0,02 (0,835)	0,08 (0,325)
July	0,14 (0,767)	-0,30 (0,457)	-0,30 (0,402)	-0,36 (0,232)	-0,42 (0,104)	-0,30 (0,181)	-0,20 (0,260)	-0,20 (0,153)	-0,18 (0,062)	0,16 (0,054)
August	-1,00 (0,274)	-0,48 (0,356)	-0,30 (0,522)	-0,21 (0,550)	0,11 (0,708)	0,00 (0,985)	0,01 (0,954)	0,14 (0,431)	0,03 (0,780)	-0,19 (0,817)
September	1,42 (0,128)	0,67 (0,267)	0,52 (0,154)	0,72 (0,056)	0,47 (0,081)	0,37 (0,125)	0,29 (0,169)	0,01 (0,957)	0,18 (0,213)	-0,08 (0,344)
October	-1,25 (0,004)	-0,86 (0,014)	-0,65 (0,038)	-0,74 (0,014)	-0,69 (0,009)	-0,46 (0,042)	-0,34 (0,036)	-0,09 (0,513)	-0,01 (0,962)	0,33 (0,001)
November	-0,95 (0,150)	-0,35 (0,419)	-0,07 (0,839)	-0,09 (0,762)	0,15 (0,564)	0,24 (0,258)	0,13 (0,460)	0,37 (0,024)	0,03 (0,806)	0,02 (0,802)
December	-1,89 (0,002)	-1,27 (0,007)	-0,62 (0,108)	-0,11 (0,754)	-0,25 (0,389)	0,19 (0,458)	0,27 (0,200)	0,08 (0,619)	0,03 (0,850)	-0,08 (0,389)

In figure 1 the relation between abnormal return and firm size has been plotted for each month of the year during 1926 until 2011. There is a clear and significant difference of the negative slope of the January line (the darkest line on top) and the lines of the other months. Where the other months are all clustered around the null-point, the January line springs out, especially in the smaller size portfolios. Therefore, the size effect is more pronounced in January than in any other month. Remarkably, if you examine the figure closely - in combination with the table above - the first months of the year (January, February) have a positive result for the smallest size portfolio and their lines have a negative slope, whereas the last months of the year (October, November, December) have a negative result for the smallest size portfolio and have a slightly positive slope. This last finding is in accordance to the performance hedging hypothesis.

The line of the January average abnormal return is above all the lines of the other months from the smallest portfolio through the sixth size portfolio. For the larger portfolios, the January line is not on top. This means that the January effect is mostly a small firm phenomenon.

When observing the differences between size portfolios, the smallest size portfolio has a wide array of average abnormal returns. In January it has the highest abnormal return of all months, but in December it has the lowest abnormal of all (the light line that starts left in the bottom). To be precise, in January the average abnormal return of the smallest size portfolio is equal to 5,77%, where in December the average abnormal return equals -1,89%. The smallest size portfolio therefore has the highest variance of average abnormal returns. The ninth size portfolio has the lowest variance in abnormal returns. The returns of the months are all clustered together, and the difference between the highest average abnormal return in February (0,33) and the lowest return in April (-0,23) is only 0,56 percent points.

These results partly stroke with the results of Keim (1983). He also found high average abnormal returns for the smaller portfolios in the month January and a negative relation for abnormal returns and size for the month January. But as results from his research, he did report quite large negative abnormal returns for the larger portfolios in the month January, but in this research only the largest size portfolio has a small negative return in January. The clustering of the other months fits the results of Keim. But he found regardless of the clustering also a slightly negative slope of the all the clustered months. This is in contrary to the slightly positive slopes of the last months of the year that this research shows.

Some possible explanations can be given for the differences between the results of this research and Keim's. In his investigation the abnormal returns were extracted from the CRSP database and in this investigation, abnormal returns are acquired by running a CAPM regression. The CRSP database uses a Scholes-Williamson betas and the excess return of an equal-weighted control portfolio. The excess returns that are used in this research obtained from the website of Fama and French are on a value-weighted base. Another possible explanation is the time frame. Keim included data from 1963 to 1979. He also did not include NASDAQ stocks in his portfolios.

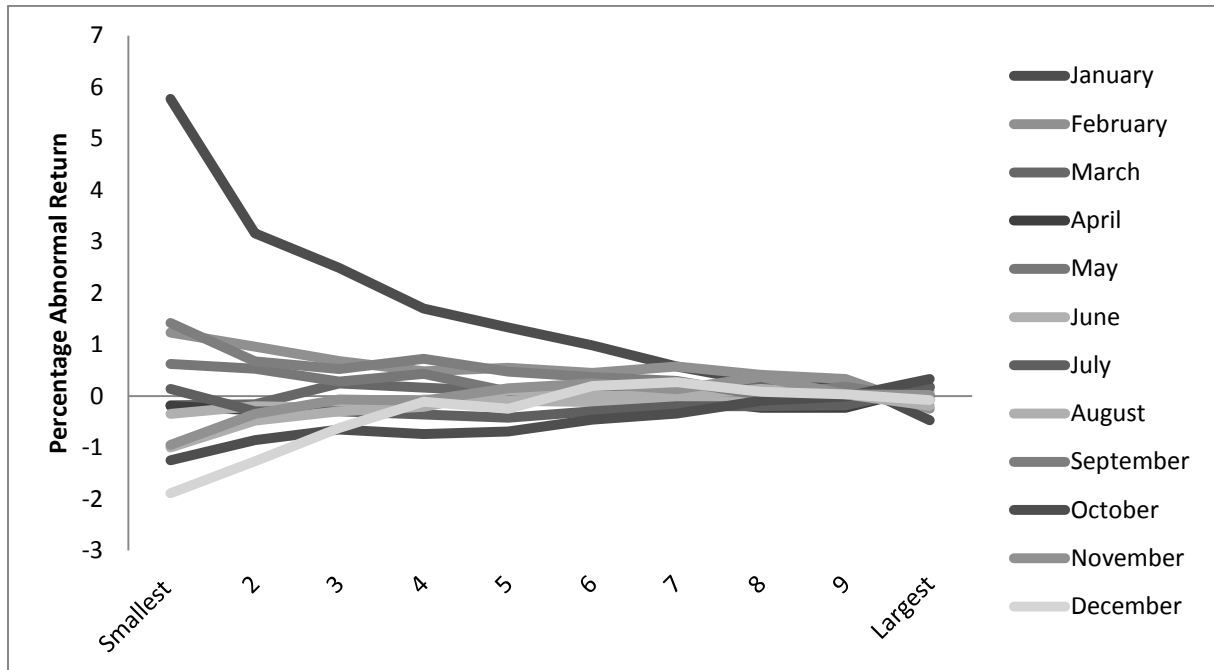


Figure 1: The relation between average monthly abnormal returns (in percent) and decile of market value for each month over the period 1926-2011. The ten market value portfolios are based on market capitalization of stocks from the NYSE, AMEX and NASDAQ and extracted from the website of French and Fama. The abnormal returns are calculated by running a CAPM regression.

Table 3 contains the average monthly abnormal returns in percent of the size portfolios obtained by running a CAPM regression controlled for size by using the SMB measure of Fama and French. Data from July 1926 to December 2011 obtained from the website of Fama and French are subject of the regression. Each year, the portfolios have been updated based on the market capitalizations of the stocks. This table gives a quick overview of the average abnormal returns per size portfolio per month. Also the significance level of the abnormal returns are included in the table. The smallest size portfolio has the highest average monthly abnormal return in January of 1,99%. It also has the lowest abnormal return of -1,49% in December. The significance levels of the abnormal returns are highest in December. This means that those abnormal returns are estimated most precise by the regression.

Table 3

Average monthly abnormal returns in percent controlled for size of portfolios constructed from firms of each decile of size (measured by market capitalization) on the NYSE, AMEX and NASDAQ by Fama and French over the period 1926-2011. These abnormal returns are obtained by running a CAPM regression controlled for size by using the SMB measure for each sample of months.*

Month	Smallest	2	3	4	5	6	7	8	9	Largest
January	1,99 (0,003)	0,28 (0,425)	0,27 (0,217)	-0,33 (0,191)	-0,26 (0,158)	-0,28 (0,270)	-0,23 (0,233)	-0,16 (0,350)	0,09 (0,590)	0,04 (0,568)
February	0,61 (0,266)	0,46 (0,223)	0,27 (0,233)	0,06 (0,788)	0,23 (0,193)	0,18 (0,261)	0,40 (0,025)	0,31 (0,043)	0,32 (0,001)	-0,15 (0,083)
March	-0,32 (0,170)	-0,30 (0,668)	-0,10 (0,567)	0,05 (0,709)	-0,01 (0,908)	0,05 (0,702)	0,08 (0,638)	0,14 (0,292)	0,04 (0,740)	0,05 (0,371)
April	0,17 (0,554)	0,03 (0,847)	0,07 (0,592)	0,06 (0,721)	0,15 (0,391)	0,14 (0,491)	0,05 (0,772)	-0,16 (0,290)	-0,20 (0,159)	0,10 (0,118)
May	0,01 (0,790)	-0,03 (0,916)	-0,16 (0,395)	0,07 (0,621)	-0,17 (0,258)	-0,13 (0,379)	-0,06 (0,669)	-0,01 (0,882)	0,06 (0,579)	0,03 (0,370)
June	-0,14 (0,606)	0,01 (0,852)	-0,09 (0,609)	0,05 (0,723)	0,01 (0,877)	-0,06 (0,712)	-0,04 (0,737)	-0,08 (0,586)	-0,02 (0,813)	0,04 (0,419)
July	0,48 (0,193)	0,09 (0,730)	-0,01 (0,812)	-0,04 (0,789)	-0,16 (0,304)	-0,14 (0,456)	-0,04 (0,774)	-0,12 (0,336)	-0,17 (0,090)	0,09 (0,142)
August	-0,52 (0,370)	-0,16 (0,456)	-0,02 (0,932)	0,01 (0,950)	0,30 (0,028)	0,13 (0,367)	0,10 (0,459)	0,20 (0,182)	0,06 (0,573)	-0,06 (0,247)
September	0,03 (0,926)	-0,30 (0,376)	-0,11 (0,498)	0,08 (0,647)	-0,01 (0,951)	0,00 (0,925)	-0,03 (0,809)	-0,13 (0,365)	0,07 (0,587)	0,03 (0,639)
October	-0,36 (0,204)	-0,12 (0,564)	0,05 (0,772)	-0,09 (0,607)	-0,10 (0,473)	-0,02 (0,888)	-0,08 (0,550)	0,10 (0,427)	0,04 (0,688)	0,12 (0,037)
November	-0,93 (0,048)	-0,34 (0,219)	-0,06 (0,734)	-0,08 (0,603)	0,15 (0,163)	0,24 (0,089)	0,14 (0,295)	0,38 (0,005)	0,03 (0,800)	0,02 (0,754)
December	-1,49 (0,000)	-0,92 (0,000)	-0,32 (0,084)	0,16 (0,328)	-0,03 (0,842)	0,33 (0,074)	0,40 (0,009)	0,15 (0,263)	0,06 (0,683)	-0,15 (0,016)

* Significance level of the constant of the regression is under parentheses.

Figure 2 plots the relationship between the average monthly abnormal returns controlled for size and size portfolios. The January line has the highest percentage abnormal return for the smallest portfolio. This return of 1,99% is clearly higher than all other returns. The smallest size portfolio also has the lowest abnormal return of -1,49%, namely in December, which is illustrated with the light grey line that starts in the bottom left corner. It is easy to see that the smallest portfolio has the widest variation of average abnormal returns per month. The second size portfolio also has a little spread between the months, but from the third portfolio all the abnormal returns are clustered. You would expect this since the unpredictability of stock returns that is used in asset pricing models. The slopes of the lines are quite flat from portfolio two through the largest.

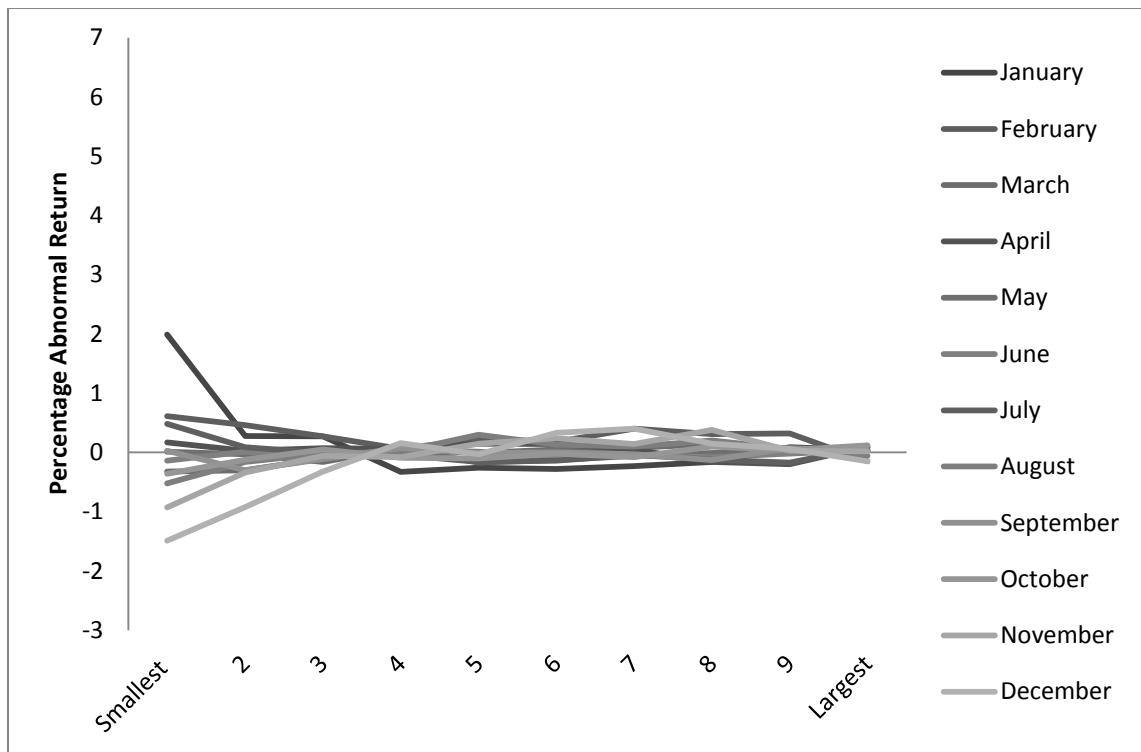


Figure 2: The relation between average monthly abnormal returns (in percent) controlled for size and decile of market value for each month over the period 1926-2011. The ten market value portfolios are based on market capitalization of stocks from the NYSE, AMEX and NASDAQ and extracted from the website of French and Fama. The abnormal returns are calculated by running an enhanced CAPM regression including SMB.

It is interesting to see that the January line is only significantly higher than the other months in case of the smallest portfolio and the line clusters already at the second size portfolio compared to figure 1 where it clustered at the seventh portfolio, since this implicitly gives a lot of information about the role of size in the January effect. From these two figures the conclusion can be drawn that size plays an important role in the January effect. Because when the abnormal returns are corrected for size, for January only the smallest portfolio shows significant higher abnormal returns. The average abnormal return for the smallest size portfolio has decreased from 5,77% to 1,99%, which is a decrease of 65,51%. Moreover, the January abnormal returns for the other portfolios sharply declined and are not higher anymore than the returns of other months. The significance levels of these abnormal returns declined besides that. So this regressions suggest that the January effect mostly comes from the size of a firm, but in the case of the smallest size portfolio, other characters of a firm play a role.

Table 4 contains the results of running the following regression:

$$R_t - R_f = a_1 + a_2 D_{2t} + a_3 D_{3t} + \dots a_{12} D_{12t} + \varepsilon_{i,t}$$

This regression can be used to test for the hypothesis that the mean excess returns of the size portfolios are constant. The regression can also be used to test if the size effect is apparent in all the months. Lastly the regression tests if there is a significant difference in the excess returns of the smallest and largest portfolio.

The highest average difference in excess returns between months is observed for the smallest size portfolio. This portfolio has an average excess return of 7,56% in January. Because all the a 's are negative, the average estimated excess returns of the other months are all significantly smaller. This is not only the case for the smallest size portfolio, but this is the case for all portfolios except for the largest portfolio. Hence the excess returns appear disproportionally large in the month January, especially for the smaller firms. The F-statistics of the smallest three portfolios all exceed the 95% significance level of 1,83. Further, the negative differences in excess returns measured decrease for any given month when the size portfolio increases. This is in support of the size effect. Finally, the estimates for differences in average excess returns denote that the examined size premium is positive and significant, since the F-statistic of 7,437 rejects the null hypothesis at all significance levels.

Table 4

Test of the month-to-month stability of the size effect using monthly excess returns in percent of portfolios constructed from firms of each decile of size (measured by market capitalization) on the NYSE, AMEX and NASDAQ by Fama and French over the period 1926-2011.*

Decile	a ₁	a ₂	a ₃	a ₄	a ₅	a ₆	a ₇	a ₈	a ₉	a ₁₀	a ₁₁	a ₁₂	R ²	F
Smallest	7,56 (6,93)	-6,02 (-3,90)	-7,25 (-4,70)	-6,33 (-4,10)	-6,53 (-4,23)	-7,45 (-4,63)	-5,80 (-3,77)	-6,70 (-4,35)	-7,92 (-5,15)	-8,88 (-5,77)	-7,03 (-4,57)	-7,40 (-4,81)	0,042	4,031
2	5,00 (5,20)	-3,74 (-2,75)	-4,62 (-3,40)	-3,89 (-2,86)	-4,10 (-3,01)	-4,49 (-3,30)	-3,66 (-2,69)	-4,02 (-2,96)	-5,98 (-4,40)	-5,95 (-4,38)	-3,82 (-2,81)	-4,19 (-3,09)	0,026	2,422
3	4,14 (4,69)	-3,17 (-2,54)	-3,60 (-2,88)	-2,96 (-2,37)	-3,49 (-2,79)	-3,69 (-2,96)	-2,77 (-2,22)	-2,98 (-2,39)	-5,06 (-4,07)	-4,87 (-3,91)	-2,77 (-2,22)	-2,75 (-2,21)	0,022	2,068
4	3,32 (4,06)	-2,57 (-2,22)	-2,68 (-2,32)	-2,13 (-1,84)	-2,57 (-2,22)	-2,80 (-2,42)	-2,11 (-1,83)	-2,22 (-1,92)	-4,04 (-3,51)	-4,13 (-3,58)	-2,07 (-1,80)	-1,55 (-1,35)	0,019	1,747
5	2,86 (3,64)	-2,03 (-1,83)	-2,26 (-2,04)	-1,49 (-1,35)	-2,45 (-2,21)	-2,30 (-2,07)	-1,76 (-1,59)	-1,47 (-1,33)	-3,72 (-3,36)	-3,62 (-3,27)	-1,39 (-1,25)	-1,29 (-1,16)	0,018	1,702
6	2,49 (3,32)	-1,77 (-1,67)	-1,89 (-1,79)	-1,13 (-1,07)	-2,16 (-2,04)	-1,98 (-1,87)	-1,26 (-1,19)	-1,26 (-1,19)	-3,45 (-3,27)	-3,02 (-2,86)	-0,92 (-0,87)	-0,54 (-0,51)	0,018	1,732
7	1,97 (2,78)	-1,15 (-1,14)	-1,38 (-1,37)	-0,76 (-0,75)	-1,60 (-1,59)	-1,46 (-1,45)	-0,82 (-0,82)	-0,79 (-0,79)	-2,95 (-2,94)	-2,39 (-2,39)	-0,52 (-0,52)	-0,06 (-0,06)	0,016	1,530
8	1,58 (2,35)	-0,93 (-0,98)	-0,96 (-1,01)	-0,63 (-0,66)	-1,27 (-1,34)	-1,09 (-1,14)	-0,38 (-0,40)	-0,27 (-0,29)	-2,78 (-2,93)	-1,75 (-1,84)	0,03 (0,03)	0,13 (0,13)	0,017	1,591
9	1,51 (2,35)	-0,94 (-1,04)	-1,04 (-1,14)	-0,54 (-0,60)	-1,21 (-1,33)	-0,97 (-1,06)	-0,36 (-0,39)	-0,44 (-0,49)	-2,52 (-2,79)	-1,59 (-1,75)	-0,28 (-0,31)	0,16 (-0,17)	0,014	1,354
Largest	0,69 (1,25)	-0,73 (-0,93)	-0,28 (-0,36)	0,45 (0,57)	-0,50 (-0,63)	-0,09 (-0,12)	0,58 (0,75)	0,17 (0,22)	-1,79 (-2,29)	-0,42 (-0,54)	0,46 (0,58)	0,66 (0,85)	0,017	1,575
Smallest - Largest	6,87 (8,64)	-5,29 (-4,71)	-6,97 (-6,20)	-6,78 (-6,03)	-6,03 (-5,37)	-7,05 (-6,28)	-6,38 (-5,69)	-6,87 (-6,13)	-6,13 (-5,47)	-8,46 (-7,55)	-7,49 (-6,69)	-8,06 (-7,19)	0,075	7,437

* The dummy variables represent the numbers of the month, e.g. a_1 equals January excess returns and a_2 through a_{12} account for the difference between the January excess return and the excess return of the specific month. T-statistics are under parentheses. R^2 measures the usefulness of the model and the F-statistic measures the joint significance of the dummy variables.

Summary and conclusion

The January effect has been extensively reviewed in the past. Based on the research of Keim (1983) this paper provides evidence with respect of the impact of firm size on the January effect by analyzing data of size portfolios from the NYSE, AMEX and NASDAQ from the period 1926 to 2011 that are extracted from the Fama and French website. Evidence obtained by running CAPM regressions suggests that the size effect is more pronounced in January than in any other month. Remarkably, in the last months of the year, the abnormal returns of the larger size portfolios are higher than the smaller size portfolios. This finding does not conform to the results of Keim, but it can be explained by performance hedging. The January effect is mostly a small cap phenomenon, since only the smaller portfolios perform better in January than in other months. When comparing the results of the CAPM regression with the results of a CAPM regression controlled for size by adding the SMB measure of French and Fama, abnormal returns in January decrease. The average abnormal return in January of the smallest size portfolio declined from 5,77% to 1,99%, which is a decline of 65,51%. The comparison of the regressions also suggest that the size effect plays an important role in the January effect. Finally, excess returns appear disproportionally large in the month January, especially for the smaller firms. A limitation to this study is the fact that the risk-free rate is given in only 2 decimals. This could bring some rounding errors. However the most important limitation is the use of monthly returns. Daily returns would give more precise information. Future research could try to explain the positive slope of the last months of the year illustrated in figure 1 and use daily returns to examine this closer around the turn of the year.

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