Length of days and stock returns

Investigating the effect of the length of days on stock returns in 24 countries.

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ABSTRACT

This thesis examines the effect of the length of days on stock returns in 24 countries spread over the Northern and Southern Hemisphere. It should be seen as an extension to the research conducted by Kamstra et al. (2003). I do not find a clear, market wide effect of the length of days on stock returns, neither is it stronger pronounced in countries that have larger deviation in lengths of days. The effect of the length of days does not differ much in summer or winter and can be both positive and negative. This research shows that temperature can have an effect on stock returns, but contradictory to the expectations (Hirshleifer & Shumway, 2003), this effect is often negative.

Table of Contents

List of tables and figures

1. Introduction

One of the things that are certain is the length of days throughout the year. Each year the length of days follows the same pattern, it becomes shorter in summer and fall, and longer again in part of winter and spring. This pattern is not only known in advance, it can be exactly calculated for each location. There are neither irregularities nor surprises in it. This thesis will focus on the length of days and try to define its effect on stock returns.

From the traditional finance point of view, the length of days should not be of any influence on the returns of a stock market. The efficient market hypothesis (especially the strong form) leaves no room for irregularities in stock prices due to factors that have nothing to do with the underlying assets of a company or the market it operates in (Malkiel, 2003). Behavioural finance loosens the assumptions of the traditional finance paradigm and from that point of view, there can be an explanation how the length of days can influence the stock returns.

There are many psychological effects that people experience throughout the year that have to do with, among others, the length of days. Winter blues is one of the most familiar ones. People are more sad, depressed, and show higher levels of anxiety during winter (Rosenthal, et al., 1984). Existing literature also shows that people are happier and more optimistic when the temperature is better and the days are longer (Cunningham, 1979). It seems that the length of days influences people's their feelings and temper. Combining this with research showing that people experience higher subjective probabilities for positive events when they are happier (Wright & Bower, 1992), it is possible that the length of days explains part of the stock returns.

Similarly to Kamstra et al. (2003), this study is conducted to see whether the length of days has any influence on stock returns. Where the effects of many seasonal anomalies have been declining over the past decades due to, among others, internet trading it will be interesting to see if there still is an effect of the length of days on stock returns. If this study finds an effect of the length of days on stock returns, it simultaneously shows a violation of the efficient market hypothesis in its semi-strong form. If this is the case, there must be trading strategies that generate excess returns based on an easy measure. The length of days does not require technical or fundamental analysis, an investor can earn money by selecting the right indices based on the geographical location. If an effect of the length of days on stock returns exists, it is a violation of the efficient market hypothesis.

Following the methodology of Kamstra et al. (2003), this thesis tries to find what effect the length of days has on stock returns. When the length of days can have an effect on mood, the same might be true for the weather. Hirshleifer and Shumway (2003) wrote a paper specifically to test for the weather effects on stock returns. Similarly to Kamstra et al., I will take the temperature into account.

One of the points of interest in this study is whether the effect (if existing) of length of days on stock returns is more pronounced in countries that lie further away from the equator than those that are closer to the equator. If an effect exists, it should be more pronounced in countries that lie further away from the equator. First of all, it should be more pronounced since there is more deviation in those countries (the difference between the shortest and longest day in Kenya is much smaller than the difference in Norway). Secondly, it should proportionally be a bigger effect since the explanation lies within investor mood caused by differences in the length of days. If there is more deviation in the length of days, the mood should also be more influenced and the effect on stock returns should therefore be stronger.

Altogether, this thesis tries to define the relationship between the length of days and stock returns in a variety of countries spread over the Northern and Southern Hemispheres. Together with factors as temperature and common other stock drivers (seasonal anomalies, lagged returns, etcetera), a clear view of the effect of the length of days must be given. The research question is the following:

What is the influence of the length of days on stock returns?

The remainder of this paper is structured as follows: I start with the section literature review, which shows the theoretical basis for this research and the hypotheses that will be tested. The next section describes the data used in this thesis, followed by the methodology used to provide statistical evidence showing any possible effects of the length of days on stock returns. The results found are presented after the methodology, the discussion and conclusion are the final parts.

2. Literature Review

This section describes the theoretical framework on which the current research is based. It describes the efficient market hypothesis and the views of traditional finance, the deviations from the efficient market hypothesis and the explanations suggested by behavioural economic theories. From there, a theoretical basis will be established on which I will elaborate. It will show the results found by other researchers on the same or similar topics and derive hypotheses from the described theories.

2.1 Efficient market hypothesis and traditional finance

2.1.1 Efficient market hypothesis

For a long time the efficient market hypothesis has been the standard in traditional finance. Ever since the efficient market hypothesis was described, there has been research on the strength of this hypothesis and anomalies on the expectations that it brings. The efficient market hypothesis states that all available information is incorporated in the stock prices at all time. The only reason for a change in the stock price should be a change in the value of the underlying assets (Malkiel, 2003).

Traditional finance makes a distinction between the weak, semi-strong and strong form of the efficient market hypothesis. The strong form of the efficient market hypothesis states that all available public and private information is reflected in the stock prices at all times. Changes in stock prices can occur if the fundamentals of a company change, or an event occurs that influences the business and performance of the company. If the strong form of the efficient market hypothesis holds, both technical and fundamental analysis can not help an investor generate higher returns from trading on the stock market than holding a random portfolio of stocks with comparable risk would (Malkiel, 2003).

The length of days is public information, since the pattern is the same each year and it is relatively easy to calculate the length of any day at a certain location.

The semi-strong form of the efficient market hypothesis loosens the assumptions of the strong form. In the semi-strong form, all publicly available information is incorporated in the stock prices at all time. If any new information becomes public, the market should react immediately. Traders cannot benefit from publicly available information and neither technical nor fundamental analysis can help an investor gain excess returns.

The third form of the efficient market hypothesis is the weak form. In this form, the market is efficient in a way that it reflects the market information. The stock prices are not be influenced by past returns and the returns are independent. Technical analysis cannot predict the stock prices. The semi-strong form of the efficient market hypothesis captures the weak form, and the strong form captures the semi-strong form and thereby the weak form as well.

Nobel laureate Eugene Fama (1970) described the efficient market hypothesis as "a good first (and second) approximation for reality". A story that sort of explains the efficient market hypothesis tells about a finance professor and a student who walk across the street where there is a $100 bill on the ground. When the student stops to pick it up, the professor tells him not to bother; "If it really would be a $100 bill, it would not be on the ground". Technically speaking, it is possible that there are excess returns for grasps, but the market should react immediately in order to correct for this gap. In no way there should be room for structural opportunities to beat the market. Reoccurring events with excess returns are therefore immediately a violation of the efficient market hypothesis.

2.1.2 Rationality and expected utility

In the traditional view of finance, there is no place for irrational drivers of stock prices, the expectation is that agents are rational and maximize expected utility at all times. Traditional finance often follows the assumptions of transitivity, completeness, continuity, and independence, made by Von Neumann and

Morgenstern (1944) in order to be able to treat agents as rational. Those rational agents are, in traditional finance, expected to maximize their expected utility. An agent builds his decision only upon his utility payoff and is fully rational.

Related to the rational agents who maximize expected utility is Bayesian decision making. This theory states that agents assign probabilities to the occurrence of an event based on prior information and past experiences about this event (Harsanyi, 1978). Given their utility payoff, and the assigned probabilities, agents are able to make a decision that will maximize their expected utility.

Many of the financial models assume rational investors. However, multiple papers show that there are deviations from the efficient market hypothesis. Participants on the financial markets often violate the assumptions, they either make decisions that are not in line with maximizing expected utility or are not rational. Where it has been the industry standard, and certainly fits in many ways, mistakes are definitely made on the market causing the efficient market hypothesis to fail in certain circumstances

2.2 Investor behaviour and deviations from the efficient market

Common drivers of the mistakes on the market are described in the behavioural finance literature. Compared to traditional finance, behavioural finance elaborates more on the psychology of the individual investor and loosens the assumption of expected utility maximizing rational agents. Behavioural finance tries to explain many anomalies in the stock market and deviations from the efficient market hypothesis via investor behaviour and beliefs.

A term often heard in behavioural finance is bounded rationality. Simon (1979) suggests that agents, due to limited time or capabilities, are only rational to some extent; they are bounded rational. Kahneman (2003) elaborates on Simon's view on rational agents. He states that multiple persisting anomalies that could not completely be explained by traditional finance are (partly) explained by investor behaviour and bounded rationality. There is, for example, the paper of Barberis, Shleifer and Wurgler (2005), who connect comovement of share prices in indices to the sentiment of noise traders. Shefrin and Statman (1984) use prospect theory (Kahneman and Tversky (1979) describe a model where the losses and gains do not have the same value to a decision maker. They experience a larger negative effect from a loss than a positive effect from a similar gain and base their decision on this matter) with its loss aversion and mental accounting to suggest an explanation for the preference of investors for cash dividends instead of capital gains, even though the two result in exactly the same change in wealth (if taxes are left out of the equation[1]). Benartzi and Thaler (1995) describe the equity premium puzzle and try to explain it with loss aversion.

Other violations of the efficient market hypothesis are, among other, the abnormal returns of companies that change their names into something with ".com". During the internet bubble at the beginning of this century, Cooper, Dimitrov, and Rau (2001) found that stocks of companies that changed their name into something with .com generated on average 53% cumulated abnormal returns in the five days around the announcement of the change of their name. For the ten days surrounding this date they found 74% abnormal returns. Since there is no change in the fundamentals of the company whatsoever, the efficient market hypothesis suggests that there should be no excess returns at all. The authors show that the rise in stock value is permanent and that there is no "punishment" in the post-event period. It seems that merely the association with the Internet is enough to cause investors to expect higher returns[2].

Another deviation from the efficient market hypothesis and its rational agents is the influence of sport events on stock returns. Edmans, Garcia, and Norli (2007) find evidence of market losses after countries losing sport matches in a set of 39

[1] Shefrin and Statman show that the preference for cash dividends instead of capital gains even holds when they correct for taxes.

[2] It is possible that part of the excess returns are generated because the stock is in the media and grabbed the attention of the investors (Fang & Peress, 2009), which causes an overreaction around the announcement date. This still would not be a rational explanation of the excess returns.

countries. The authors point to investor sentiment as basis for the losses on the market. Again, those returns are abnormal from the view of traditional finance because there is no change in the fundamentals of the markets if a country loses a sport match. The excess returns seem to be caused completely by investor mood.

Most explanations explored via the behavioural finance approach are built on psychology, but even if there is a psychological explanation for an anomaly it is still a violation of the efficient market hypothesis. This is only the tip of the iceberg, there are many more anomalies that which explanation lies within investors' behaviour.

2.3 Seasonal anomalies

There are many papers that describe anomalies based on seasonality, this means that a deviation from the efficient market hypothesis happens on regular moments throughout the year. French (1980) described the Monday effect in his paper, it states that the returns on a Monday are significantly lower than on the other four days of the week. A possible explanation for this effect could be the bad news hypothesis, which says that it takes longer for bad news to incorporate in the stock prices and therefore is more pronounced after a weekend (when there was time for the news to sink in). Both the existence of the Monday effect and the possible explanation are violations of the efficient market hypothesis.

Reinganum (1983) describes another seasonal anomaly, he shows that the returns in January are much higher than in other months of the year. Tax loss selling probably causes the anomaly. The losses on stocks are tax deductible, and therefore often happen shortly before the end of a tax year. Investors start buying stocks again in the beginning of the new tax year giving the market a boost. Both anomalies are included in this research as explanatory variables.

2.4 Geography based anomalies

There are anomalies on the stock market that have a geographical basis. Yuan, Zheng, and Zhu (2006), show that there is a return difference of 3 to 5% between the days around the full moon and those around the new moon. The efficient market hypothesis predicts that there should not be any differences in returns based on this cycle because the lunar cycle is exactly the same every 29.5 days, and known in advance. Contrary to the expectations, Yuan, Zheng, and Zhu show that excess returns still exist. The anomaly might be explained by behaviour. Research in the direction of the influence of the lunar cycle on behaviour is ambiguous. Lieber and Sherin (1972) show a relationship between homicides and the lunar cycle. If mood is affected by the lunar cycle, it can influence the stock markets. Wilkinson et al. (1997), however, find that there is no significant relationship between the lunar cycle and mood. Both views show that there is at most a psychological, but certainly not a rational, explanation for the deviations from the efficient market hypothesis.

Another violation of the efficient market hypothesis is described by Saunders (1993), who show that there exists a correlation between the stock returns in New York and the local weather. According to the efficient market hypothesis and rational agents, weather should not have any effects on the stock returns[3]. Hirshleifer and Shumway (2003) elaborate on the research of Saunders. They find that sunshine indeed has a significant effect on daily returns. The returns of the market on sunny days are notably higher than that they are on cloudy or rainy days. The effects are not strong enough to make money out of this anomaly, especially not when the transaction costs are taken into account. The strategy based on weather is a frequent trading strategy, which has to be reconsidered with every change of weather.

The research of Cao and Wei (2005) contradicts the results found by Hirshleifer and Shumway. They find a negative correlation between temperature and stock returns and hypothesize that the cause is a higher level of aggression when the temperature is low. This higher level of aggression, according to Cao and Wei,

[3] With the minor exception for companies that have a business that is depends on weather factors. Since those companies are in a strong minority, it should not have a significant effect on the stock market as a whole.

causes more risk taking behaviour on the stock market and thereby higher stock returns. The flaw in their reasoning is that both higher (Baron & Ransberger, 1978) and lower temperature (Howarth & Hoffman, 1984) can cause more aggression. Baron and Ransberger even find that it reaches a peak at a certain temperature and then decreases when the temperature rises more. Even though there are studies that point to a negative relationship between temperature and stock returns, the reasoning of Hirshleifer and Shumway (2003) and Kamstra et al. (2003) for a positive relationship seems stronger.

The existence on itself however, is a violation of the strong form of the efficient market hypothesis. The explanations for the effects of weather effects lie in investor mood. Cunningham (1979) found in the late seventies that sunshine and temperature have a significant positive influence on self-reported mood, that participants gave higher tips when the weather was better, and that the willingness to assist the interviewer was higher. "Happy" people, according to Wright and Bower (1992), report higher subjective probabilities (their perception of the probability that something happens) for positive events than "neutral" or "sad" people. They furthermore report lower subjective probabilities for negative events. If people believe that the probabilities for positive events are higher and the probabilities for negative events are lower, they have a lower threshold to buy stocks and can thereby give the market a boost. Sunshine can therefore give the market a positive boost through investors' mood.

2.5 Stock returns and the length of days

The same reasoning can be followed when investigating the effect of the length of days, and thus the amount of daylight an investor is exposed to, on stock returns. Kamstra, Kramer and Levi (2003) study the influence of the length of days on the stock returns in twelve markets. Correcting for weather, tax loss selling, and calendar anomalies they find that there is a positive correlation between the length of nights and the stock market returns. This means that the stock returns are rising in the period that the days are shorter. Kamstra et al. connect their results to mood via the Seasonal Affective Disorder (SAD).

Rosenthal et al. introduce the Seasonal Affective, according to them, SAD is a disorder that is strongly associated with the seasons and causes sadness and anxiety as well as decreased physical activity and worse quality of sleep. Altogether, SAD is connected to more depressions during the winter. Rosenthal et al. find that exposing people to bright artificial light can decrease SAD and its depressions (Rosenthal, et al., 1984). This psychological paper does not go into the effects of these depressions on stock returns, but rather focuses on the health-consequences and possible cures.

Kamstra et al. (2003) connect the papers of Rosenthal et al. (1984), Cunningham (1979), and Wright and Bower (1992) and try to find the relationship between the length of days (expressed as a SAD factor) and stock returns. They find a significant influence of SAD in eleven out of twelve investigated markets, among them the S&P500 and NASDAQ. The SAD-effects at the Southern Hemisphere persist six months later than they do at the Northern Hemisphere. This is caused by the difference in length of days between the Northern and Southern Hemisphere. The length of days for two countries equally far from the equator on the Northern and Southern Hemisphere are the similar but six months apart. Kamstra et al. find the same pattern for the SAD-effects. A limitation to the research of Kamstra et al. is that they consequently speak of SAD-effects, as if the differences in stock returns are caused by the seasonal affective disorder, while the data used in their research are the returns of indices. Those indices represent all traders who traded stocks that are included in this index, not necessarily people who are diagnosed with SAD. Yet, there is a psychological explanation for the effects of mood on stock returns. It is possible that the investors of those markets suffer from a worse mood in winter than they would do in summer, without them actually experiencing the other effects of SAD. Because Kamstra et al. measure SAD via the hours of night-time they still are able to make assumptions about the influence of the length of days on stock returns. They find that a trading strategy based on SAD, long in the fall and winter of Sweden and later long in the fall and winter of Australia, yields 7,9% per annum more than a neutral strategy that has 50% allocated to both markets throughout the whole year. Kamstra et al. make the switch at the spring and fall equinoxes, where the length of the nights is equally long. Using this method, the year is split into two equal parts. The days in one part are longer than average, and the days in the other part are shorter than average.

Palinkas and Houseal (2000) investigate people who spend a winter at Antarctica (on the Southern Hemisphere). They find that people on Antarctica experience the highest levels of depression and anxiety during March, April, May, and July, which corresponds with September, October, November, and January in the Northern Hemisphere. When the lengths of days are prolonging again, from the 21st of December onwards, the levels of anxiety and depression should decrease and the stock markets should therefore, according to Cunningham, Wrigth and Bower, have positive returns. The argument of Kamstra et al. for the higher returns during winter is that the investors shun risky assets and rebalance their portfolio towards safer assets. This argument seems to be a contradiction with the theory explained by Cunningham, Wright and Bower.

Contrary to Kamstra et al. (2003), the expectations in this paper are that the length of days should have a positive influence on stock returns. A portfolio that goes long in summer and short in winter should in theory realize higher returns than a balanced long portfolio due to the longer days. This thesis will form portfolios that go long in summer and short in winter to show the economic relevance of the effect of the length of days on stock returns. The regressions will show the statistical influence. The statistical influence and economical influence can sometimes differ. A statistical difference can often be found even if it is very small. The economic effect of this statistical significant effect can then be negligible.

SAD does not only exist in countries that have strong differences in the length of days throughout the year. According to Rosenthal (2014), part of the population of Florida experiences effects of SAD. Since Florida lies on a latitude between approximately 25 and 30 degrees, and the deviation in length of days and temperature is relatively low, effects of SAD should also be lower. Since SAD also exists in the countries closer to the equator, it is possible that the difference in returns is driven by this psychological phenomenon. If I find that there is an effect in the countries that lie further away from the equator but not in countries that lie closer to the equator, SAD cannot be the cause anymore. In that case, the effect must be driven by the length of days. This research will not focus on SAD but will purely use the length of days.

Many violations of the efficient market hypothesis, and the signs of other behaviour than rationality are shown in this section. Some of the anomalies can be used in the advantage of this research. The difficulty with examining anomalies on stock indices is that it is easy to trade on a different market, or in a different country, than where a trader actually is. This could cause spurious results when regressing the latitude of a city on the returns of its market. If there is, for example, an investor in Sweden trading a stock on the stock market of Sydney, the latitudes do not coincide whatsoever.

This problem is mitigated if we assume that the home bias still is present on stock markets. French and Poterba (1991) describe the home bias and find that investors keep a large amount (94% for US investors at the time) of their shares in domestic stocks. Later on, Levy and Levy (2013) found that the home bias has not significantly changed in the past 15 years. Large part of a market's trades are done domestically. Coval and Moskowitz (1999) find similar results, they even state that significant part of an investors' portfolio is held in companies that have their headquarters close to that investors' place of residence. Those papers give reason to believe that most of the trades on a market are executed domestically, and that large part of the trades that are done abroad are still done in the countries close to this market. This is a crucial assumption in this research, since trades from traders from abroad must not influence the returns of a market index too much.

2.6 Hypotheses

Altogether, the expectation that follows from the results and psychological explanations of reviewed literature is that the length of days has a positive influence on stock returns. Considering the view of traditional finance, there should not be any excess returns based on the length of days, since the length of days is known in advance and should therefore already be incorporated in the stock prices. Finding any abnormal returns that can be traced back to the length of days is a violation of the semi-strong form of the efficient market hypothesis, but might be explained in a psychological way via mood. This research can be seen as an extension to that of Kamstra et al. (2003), with newer data and more indices that are being tested. Furthermore, countries closer to the equator will be added in order to see whether the seasonal deviations also exist in countries that do not experience large differences in length of days. The same methodology will be used in the regressions and a factor is added in order to correct for a general market trend.

In order to find what the influence of the length of days on stock returns is, the following hypotheses will be explored.

> *H_1: The length of days in a country is positively correlated with its stock returns.*

> *H_2: The effect of the length of days on stock returns is stronger in countries that have larger deviation in length of days.*

> *H_3: A trading strategy based on the length of days will generate positive excess returns.*

> *H_4: Anomalies based on seasonality explain part of the returns when added to a regression with the length of days.*

3. Data

This section describes the data used in this thesis and the alterations that I made in order to be able to use this data.

3.1 Price indices and daily returns

The data from the 24 countries is collected via Datastream. For all countries, the price indices of a broad market have been selected. The price index captures all gains and losses and adjusts for capital changes. The daily returns of those indices are calculated for all countries as change in percentage between the close value of one day and the previous day. If the returns for a Monday are calculated, the close value of the previous Friday is used. Time spans are chosen for the indices so that there is daily data available for all countries. If there are zeroes in the dataset due to a closed market, they are reported as missing values.

As Table 1 shows on the following page, there are some extreme values in this dataset, for example the -53,10% return on one day in Argentina and the 110,68% jump of the market in China. The length of days or the temperature do not cause those returns. To exclude the too extreme values, all values that deviate more than 5 times the standard deviation from the average are deleted from the dataset and reported as missing value as well. In this way the outliers cannot cause spurious results, but the largest part of the dataset is still included in the regressions[4]. The values that should be excluded are calculated via the averages and standard deviations of the original dataset, including the values that are later excluded. The averages and standard deviations reported in Table 1 are the averages and standard deviations of the datasets in which the extreme values are excluded. In order to see what kinds of outliers are found, the reported highest and lowest values of the daily returns are the values that are

[4] For example, only eleven values in Mexico are excluded from the dataset on a total of 7043 observations

excluded. The data retrieved are the stock returns from as early as possible, but not earlier than 1980, to the 1st of January 2015.

Country	Start Date	Minimum	Maximum	Return (avg)	Volatility
Argentina	19-10-1989	-53,10%	33,67%	0,096%	2,55%
Australia	29-05-1992	-8,33%	5,94%	0,029%	0,91%
Brazil	01-11-1994	-14,12%	32,49%	0.056%	1,86%
Canada	01-01-1980	-11,32%	9,82%	0,036%	0,89%
Chile	02-01-1987	-11,58%	9,48%	0,063%	0,82%
China	02-01-1992	-16,83%	110,68%	0,017%	2,09%
France	09-07-1987	-9,64%	11,18%	0,021%	1,33%
Germany	01-01-1980	-12,81%	11,40%	0,043%	1,29%
India	02-01-1991	-13,34%	16,22%	0,069%	1,54%
Indonesia	01-07-1996	-16,69%	17,43%	0,079%	1,91%
Japan	01-01-1980	-14,90%	14,15%	0,022%	1,31%
Kenya	11-01-1990	-38,86%	62,83%	0,029%	0,82%
Malaysia	01-01-1980	-21,46%	23,14%	0,037%	1,16%
Mexico	04-01-1988	-13,34%	12,92%	0,093%	1,46%
The Netherlands	03-01-1983	-12,00%	11,83%	0,036%	1,25%
New Zealand	29-12-2000	-5,11%	5,99%	0,018%	0,70%
Norway	02-01-1980	-21,10%	12,12%	0,043%	1,38%
Peru	14-02-2005	-15,21%	13,91%	0,059%	1,74%
South Africa	30-06-1995	-11,92%	7,71%	0.062%	1,18%
Sweden	02-01-1986	-8,17%	11,65%	0,042%	1,42%
Switzerland	30-06-1988	-10,52%	11,39%	0,028%	1,09%
Thailand	01-01-1980	-14,84%	12,02%	0,035%	1,38%
United Kingdom	02-01-1984	-12,22%	9,84%	0,033%	1,04%
United States	01-01-1980	-20,41%	11,58%	0,046%	1,03%

Table 1 shows the descriptive statistic of the used dataset. Minimum and Maximum show the lowest and highest realized returns on one day per country in percentages, Return (avg) shows the average daily return calculated over the entire dataset. The end date is for all countries the first of January 2015,

In order to be able to assume that traders on a market have approximately the same amount of daylight as the city where the market is located has, cities are selected that either lie around the centre of the country or lie in the area where the largest part of that countries inhabitants live. For example, I selected Santiago, which lies approximately in the middle of Chile. It lies at latitude -33 where the most northern part of the country lies at -17 and the most southern part at -54. In the metropolitan area of Santiago live around seven million people on a total of eighteen million (World Population Review, 2015), and it is safe to say that the largest part of the economic activity takes place in this city. If this is the case, most of the trades done on this market will probably be executed by traders that experience approximately the same length of days as the traders on the exact geographical location of the market do.

3.2 MSCI World

To take the comovement[5] of a country with the general stock market into account, the price index of MSCI World is added to the regression. It consists of daily data and captures a variety of stocks and bonds. It thereby represents the world's financial market. The data of the MSCI World index is downloaded from the 1st of January 1980 until the 31st of December 2014. This factor is added because an event in a particular country can influence the stock markets of other countries. If those countries have different geographic locations, the length of days in those countries can vary. If the returns in a country are influenced by an event in another country with another length of day, the results might be influenced by this comovement.

3.3 Temperature

The weather data is collected from the National Centers for Environmental Information. The downloaded data is the weather from the cities in which the markets are located. If there was no data available from the city itself, a close match is selected on basis of location. If the data from the closest match or the city itself is incomplete, more weather stations are added and the average of those stations is taken. In this way, a dataset that is as complete as possible on a daily basis on a time period that is as long as possible is generated[6]. The weather

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[5] Among others, Anthony Richards (1995) showed that a country's stock market often moves with the world market.

[6] Even though using additional weather stations expands the data, it is still incomplete in some countries. The weather data for Mexico, for example, only reaches to 1999. Regressions including the weather therefore only run until 1999 for this particular country.

data that are downloaded are the daily minimum and maximum temperatures per weather station. In the regressions, the average of the daily high and daily low is used. Since this research does not use intraday information about trading nor the weather, this seems the most precise way. As reported in Table 2, temperatures are precise to one tenth of a degree and are expressed as degrees Celsius.

Country	Latitude	Average daily Temperature	Hottest day	Coldest day
Argentina	-35	18,9	36,0	2,6
Australia	-33	17,8	35,7	5,6
Brazil	-23	23,0	31,0	6,6
Canada	43	8,7	32,0	-23,8
Chile	-33	13,4	24,2	-5,0
China	31	17,1	35,6	-4,6
France	48	12,5	29,9	-11,4
Germany	50	10,6	30,0	-13,6
India	18	26,4	34,3	15,7
Indonesia	-6	28,0	31,3	23,6
Japan	35	16,4	42,9	-1,0
Kenya	-1	24,2	33,5	14,5
Malaysia	3	27,7	30,8	23,3
Mexico	19	17,4	25,4	2,6
The Netherlands	52	10,3	26,7	-12,1
New Zealand	-41	12,9	23,7	2,0
Norway	60	6,8	25,7	-21,8
Peru	-12	20,1	30,3	1,0
South Africa	-26	18,4	32,9	7,0
Sweden	59	6,9	26,7	-24,1
Switzerland	46	10,7	28,6	-14,1
Thailand	14	29,2	34,2	19,0
United Kingdom	52	10,0	24,6	-6,8
United States	41	13,0	34,5	-15,9

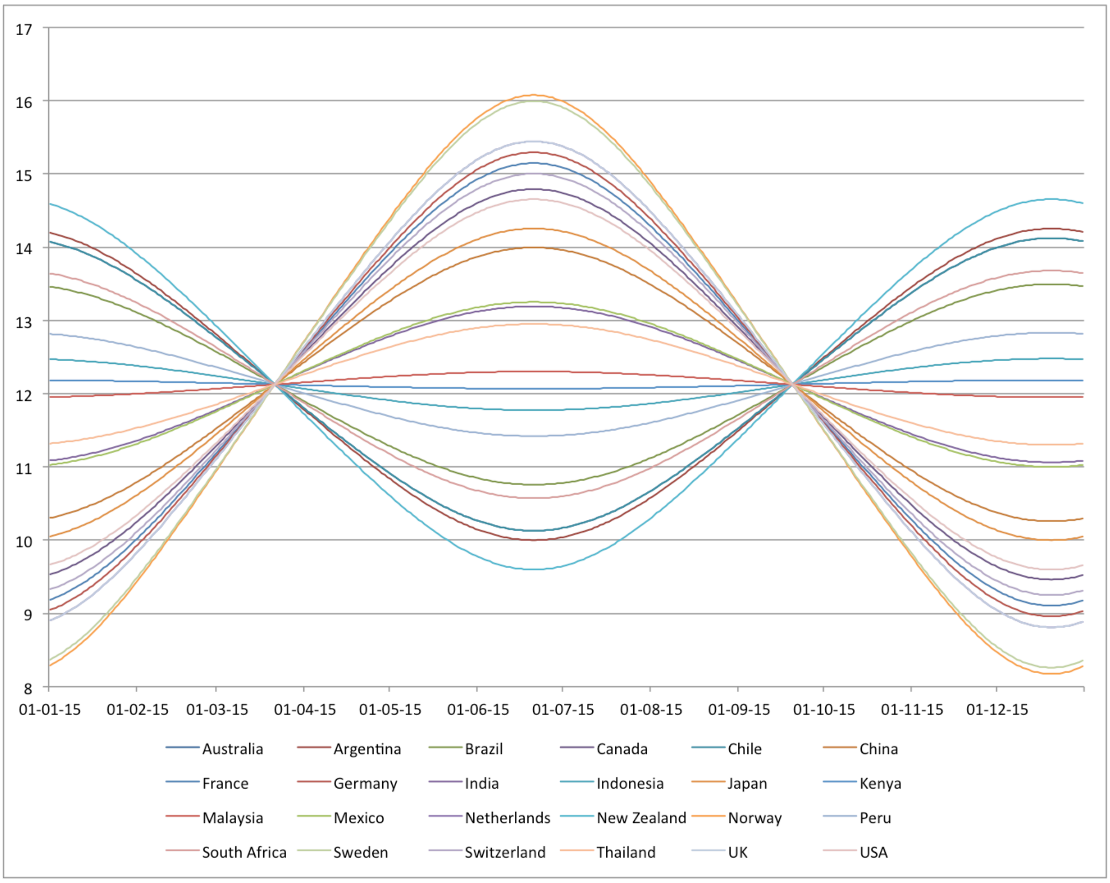
Table 2 shows the average daily temperature, calculated as the average of the daily high and the daily low temperature, the hottest day, the coldest day, and the latitude (rounded to the nearest degree) of the city in which the countries' financial markets are located in.

3.4 Length of days

The length of days is calculated via the following formula:

$$LengthOfDay_{i,j} = 7.72 * \cos^{-1}(-\tan\left(\frac{2\pi * Latitude_i}{360}\right)\tan 0.4102 - \sin\left(\frac{2\pi(j - 80.25)}{365}\right))$$

Where *i* represents the country, j is a number that corresponds to a date; the first of January is 1, the second is 2, up until 31st of December as day 365 (or 366 in leap years, the 365 in the denominator of the last part of the formula will then be 366 as well). The formula is suggested by Kamstra et al. (2003) and calculates the exact length of days in hours. The latitude that is used is the latitude of the city where the market is situated. For example, when testing on the returns of the AEX, the latitude of Amsterdam (52, rounded to the nearest degree) are used to provide the hours of daylight on a particular day.



Graph 1 shows the length of days of the countries in this dataset expressed as hours between sunrise and sunset in the year 2015. The length of days is similar in other years except for a small deviation in a leap year.

The measure that is used in the regression is similar to the method that Kamstra et al. use, with the difference that Kamstra et al. use the length of nights. Another difference is that they normalize the hours per night, they subtract the average night from the regression. I decided to use the full length of day to make interpretation easier. When calculating a prediction for a particular day, one can use the full length of day immediately and does not have to adjust it to length of days and de-normalize it first. As shown in Graph 1 on the previous page, the length of days varies strongly throughout the year in the selected countries. This is a requisite in this research because it allows testing whether the effect is stronger in countries that lie further away from the equator than in countries that lie closer to the equator.

3.5 Dummy variables

In order to control for effects of anomalies on stock returns, this research will use multiple dummy variables. This means that variables that either take the value one or zero are added to the regression. Those variables are able to show possible differences in returns in different seasons or on particular days (see, among others, the section 'Monday dummy')

3.5.1 Fall dummy

A fall dummy is constructed for both the Northern and Southern Hemisphere. This dummy takes the value one when a day is in the fall, and zero otherwise. Fall is defined, as in Kamstra et al. (2003), as the days between the 21st of September and the 20th of December on the Northern Hemisphere and between the 21st of March and the 20th of June on the Southern Hemisphere. This dummy is added to the regression in order to test whether a day in fall has significant lower returns than a similar day in the year (a day with similar amount of daylight, temperature etcetera). The fall dummy is added in Kamstra et al. to allow for an asymmetric effect, where the returns in fall are more extreme than they are in winter (following the findings of Palinkas and Houseal (2000)).

3.5.2 Monday dummy

In order to control for effects of the Monday-effect, a dummy is constructed that takes the value one if the returns of that day are from a Monday and zero otherwise. Adding this dummy to the regression makes sure that the effect is not (partly) driven by the Monday effect and simultaneously shows whether there is an abnormal return on Mondays.

3.5.3 Tax loss dummy

Similar to the dummy for the Monday-effect, a dummy is constructed to correct for tax loss selling[7]. The dummy for the tax loss effect is equal to one on the first five days as well as the last two days of a tax year. The end dates for tax years in the respective countries are retrieved from the website of KPMG. The end date is December 31st for Argentina, Brazil, Canada, Chile, China, France, Germany, Indonesia, Japan, Kenya, Malaysia, Mexico, the Netherlands, Norway, Peru, Sweden, Switzerland, Thailand, and the United States of America. The tax year ends in Australia at June 30th, in India and New Zealand at the 31st of March, in South Africa at the last day of February, the 28th or 29th, depending on whether it is a leap year or not, and the 5th of April in the United Kingdom. The tax-loss dummy when the tax year ends at the 31st of December is thus equal to one on the 30th and 31st of December, as well as the 1st until the 5th of January.

[7] Similarly to the Monday effect dummy, the Tax loss dummy is added to correct for spurious seasonal effects. Especially the Tax loss dummy could be an important factor since the tax-year for most countries follows the calendar year and ends in December, when the length of days is almost at its minimum.

4. Methodology

This section describes the methodology used in this thesis. It discusses among others the regressions, specifications, Gauss-Markov conditions, and the way this research investigates the economic effect of the length of days on stock returns.

4.1 Main model

This thesis will test whether there is an effect of the length of days on stock returns via least squares regressions. A single regression is used for each country separately. This method is used in order to be able to vary the length of days, tax loss dummy, fall dummy, and temperature per country. The main regression of this research is the following:

$$R_{i,t} = c + \beta_{1,i} * R_{i,t-1} + \beta_{2,i} * R_{i,t-2} + \beta_{3,i} * LengthOfDay_{i,t} + \beta_{4,i} * Temperature_{i,t} + \beta_{5,i} * Fall_i + \beta_{6,i} * Monday + \beta_{7,i} * Tax\ loss\ Selling_i + \beta_{8,i} * MSCI_t + \varepsilon_i \qquad (1)$$

In regression (1), i represents a particular country and t represents a particular day. An analysis of the $\beta_{3,i}$ will show whether there is an effect of the length of days on stock returns. If the beta is significantly different from zero, it shows that the corresponding variable has an effect on the stock returns. The betas are considered significantly different from zero if they deviate from zero at the 10% level. Significant at the 5% level will be indicated with ** above the value in the tables, significant at the 1% level will be indicated with ***. Results that deviate from zero at the 10% level (marginally significant) will be indicated in the tables with $^+$.

4.2 Lagged returns

In stock returns it is quite common that the returns follow a short sentiment trend. When the sentiment in the market is positive, and the returns of a certain day are positive, it is likely that the returns of the following days will be positive as well. Lehmann (1990), among others, found that the stocks often follow a short trend, and then reverse afterwards. In order to correct for those effects, the lagged returns of the previous two trading days are added to the regression. For example, when investigating the returns of a Thursday, the returns of the Wednesday and Tuesday before this Thursday are used as explanatory variables. The returns that are used in this regression are the returns of the previous trading day, that means that for a Monday, the one day lagged return is the return of the previous Friday and the two day lagged return is the return of the previous Thursday. When calculating the two day lagged returns, the lagged return of a Tuesday is the previous Friday.

4.3 Gauss-Markov conditions

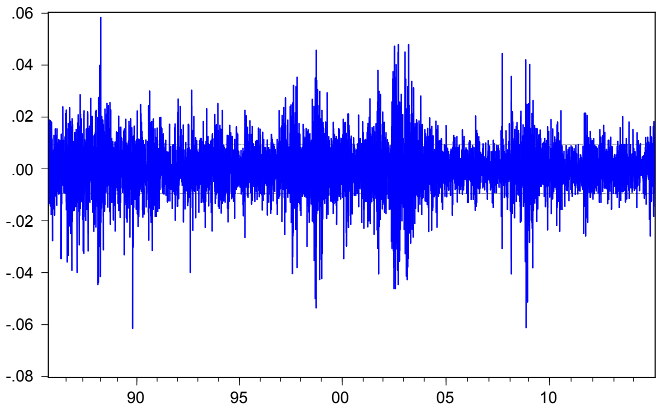
In a least squares regression, the residuals (the deviation of the actual value from the expected value, the part that is not explained by the regression) need to meet the conditions set by the Gauss-Markov theorem. This theorem states that the error terms should have an equal variance over time (homoskedastic), be uncorrelated, normally distributed, and expected to be zero (Verbeek, 2008). Tests are performed for each regression in order to see whether the linear estimator is unbiased.

4.3.1 Heteroskedasticity

For each regression the White test (1980) is performed in order to test for heteroskedasticity in the error terms. Heteroskedasticity in the error terms can cause problems with the interpretation of the betas, since the standard errors cannot be fully trusted any more. If heteroskedasticity is detected in one of the regressions, the regression is repeated with use of the White (1980) standard errors in order to still be able to interpret the results. An example of a typical[8] residual plot in this thesis is given in Graph 2 on the following page. This figure shows the residuals for the regression (1), which includes the length of days and temperature for the entire year in the Netherlands. This residual plot shows that

[8] This section shows only one of the residual graphs and residual distributions. The other distributions and residual plots are similar.

there are certain periods, especially around 2003 and 2009, where the residuals have a higher variance than in other time frames.



Graph 2 shows the residuals of regression (1), which includes the length of days and temperature, when in runs over the entire year for the Netherlands from 1985 until 2015.

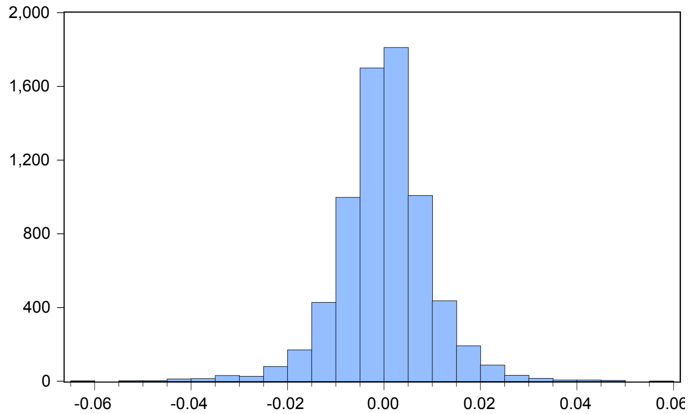
4.3.2 Serial correlation

To test for serial correlation between the residuals the Lagrange Multiplier (LM) test is conducted. Similarly to heteroskedasticity, serial correlation causes problems with the interpretation of the betas. As is common when investigating stock returns, serial correlation is often found in this sample. To solve this problem, a regression in which heteroskedasticity is detected is repeated with use of the Newey-West (1987) standard errors. These standard errors correct for both serial correlation and heteroskedasticity. With use of the Newey-West standard errors, the interpretation of the betas via the standard errors is valid again.

4.3.3 Normal distribution and average

As is often the case in economic models (Huber, 1981), the Jarque-Bera (1980) tests show that the residuals are not normally distributed in most of the regressions. Since the size of the datasets is large, typically between 3000 and 8000 observations per regression, the Central Limit Theorem (Dudley, 1999) states that the error terms can be assumed as normal distributed. Again, an example is given of a typical residual distribution. The residuals of the

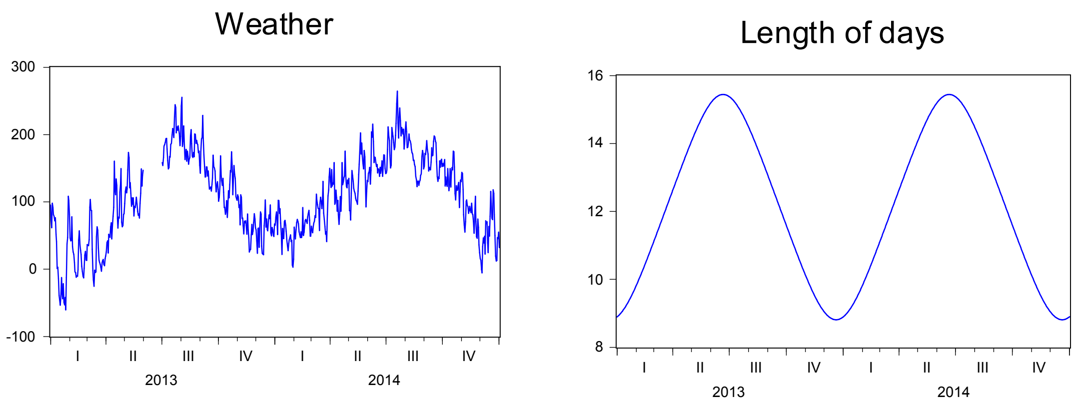
Netherlands are given. As reported in Graph 3 on the next page, a large part of the residuals lies between -0.01 and 0.01, with approximately equal tails to both sides. This regression captures 7061 observations, which is by far enough to assume normality via the Central Limit Theorem. The average of the residuals is zero in all regressions. Together with the White or Newey-West standard errors, all steps that prevent regressions from suffering from those Gauss-Markov violations are taken.



Graph 3 shows distribution of the residuals of regression (1), including weather, temperature and the dummy variables, and run for the entire year for the Netherlands

4.4 Multicollinearity

Because both the length of days and the temperature are caused for a large part (length of days entirely) by the predetermined position of the earth towards the sun, the correlation between the two variables is high. This can be seen in Graph



Graph 4 shows the temperature and length of days in the Netherlands for 2013 and 2014, it shows that the two variables follows the same pattern, which can cause multicollinearity problems

4, which shows the weather and length of days in the Netherlands in 2013 and 2014. For each country, the correlation between temperature and the length of days is calculated. As Table 3 reports, this correlation typically lies between 0.6 and 0.8. For some countries, Indonesia, Kenya, Peru, and Thailand, the correlation between the length of days and the temperature is close to zero or even negative. This probably has to do with the fact that those countries lie close to the equator and have limited variation in length of days (see Graph 1 and Table 2). Those countries still have seasons and deviations in average temperature that do not correspond with the change in length of days, the correlation is therefore very low. A high correlation between two variables can be problematic since it can increase standard errors, which can become unreliable (Verbeek, 2008). In order to check whether multicollinearity is a problem in this research, two actions have been taken. First, the Variation Inflation Factors are reviewed for each regression. Since some of those factors were high, especially for the factor length of days, multicollinearity can be a problem between the factors length of days and temperature.

Country	ρ	Country	ρ	Country	ρ
Argentina	0,708	India	0,613	Norway	0,801
Australia	0,728	Indonesia	-0,098	Peru	0,123
Brazil	0,468	Japan	0,722	South Africa	0,670
Canada	0,755	Kenya	0,338	United States	0,739
Chile	0,688	Malaysia	0,493	United Kingdom	0,716
China	0,761	Mexico	0,695	Thailand	0,110
France	0,749	The Netherlands	0,714	Sweden	0,755
Germany	0,779	New Zealand	0,673	Switzerland	0,795

Table 3 shows the correlation between a country its length of days and its temperature.

In order to take this problem into account, three different regressions are used. First including both length of days and temperature (regression (1)), then it excludes temperature (regression (2)) and last it excludes length of days (regression (3)). In this way it can be examined whether the significance of the betas changes when another factor is excluded from the model. The regressions used are, together with regression (1), the following:

$R_{i,t} =$
$c + \beta_{1,i} * R_{i,t-1} + \beta_{2,i} * R_{i,t-2} + \beta_{3,i} * LengthOfDay_{i,t} + \beta_{4,i} * Dummy_{Fall,i} +$
$\beta_{5,i} * Dummy_{Monday} + \beta_{6,i} * Dummy_{TaxLoss\ Selling,i} + \beta_{7,i} * MSCI_t + \varepsilon_i$ (2)

And:

$R_{i,t} =$
$c + \beta_{1,i} * R_{i,t-1} + \beta_{2,i} * R_{i,t-2} + \beta_{3,i} * Temperature_{i,t} + \beta_{4,i} * Dummy_{Fall,i} +$
$\beta_{5,i} * Dummy_{Monday} + \beta_{6,i} * Dummy_{TaxLoss\ Selling,i} + \beta_{7,i} * MSCI_t + \varepsilon_i$ (3)

The results from those regressions compared to regression (1) will show whether multicollinearity indeed was a problem. If there are large differences between the significance of outcomes, regression (1) will probably have suffered from multicollinearity. Even if that is the case, regression (2) and (3) will not be influenced by this multicollinearity and can provide reliable results.

4.5 Different effect for different countries

To study whether the effect of the length of days on stock returns in a certain country is stronger than in another country the confidence intervals of the betas will be compared. If the $\beta_{3,i}$ for a country is higher than the $\beta_{3,i}$ of another country, and their confidence intervals do not overlap, there is statistical evidence that the effect is stronger in the first country than in the second. This might be the case when, for example, Sweden and Kenya are compared. Kenya lies close to the equator and therefore has small deviation in length of days throughout the year (see Graph 1), whilst Sweden lies far up North and its nights are almost twice as long in winter as they are in summer. The expectation is that if an effect is present for the length of days, it is more pronounced in a country that has more deviation throughout the year, first because there is more deviation, which leads linear to a larger effect, and second because the larger deviation in length of days can influence mood more and thereby leads to a larger proportional effect.

4.6 Seasonal differences

The regression will run in three ways to test whether there is a difference between summer and winter or over the entire year. It runs separately for winter, summer, and the entire year. Winter is defined as the period that the nights are longer than on average. This is the period from the autumn equinox to the spring equinox in each country. Summer is the period from the spring equinox to the autumn equinox. The autumn equinox in the Northern Hemisphere is the spring equinox in the Southern. Two dummy variables are created in order to be able to run the regressions, one dummy which takes the value one when a day falls within the period defined as winter, and zero otherwise, and one dummy which takes the value one when a day falls in the period defined as summer and zero otherwise. The regression runs under the restriction that the dummy winter or summer takes the value one. There is no restriction if the regression runs for the entire year there. The dummies are not added to the regression but are solely used as a restriction.

This methodology is used to compare the results found in this paper to the ones found by Kamstra et al. (2003) and test whether the possible effect of the length of days on stock returns is the same in winter as it is in the summer or throughout the entire year. If this is the case, the effect cannot be attributed to the Seasonal Affective Disorder, but must have some other ground. Furthermore, it provides the possibility to investigate whether the effect is equally strong in the winter as in the summer or that there are differences throughout the year.

4.7 Difference between 1980-1999 and 2000-2015

An important assumption in this research is that traders that live in approximately the same area as the market is located are responsible for the largest part of the trades that occur on that market. It is possible, however, that the trades occurring later on in the dataset are more influenced by traders who trade online. As explained in the literature review, this can cause problems with the results found in this thesis. In order to test whether it influences the results found in this research, regression (1) runs for the periods 1980-1999 and 2000-

2015. These frames are chosen because Internet trading occurred more often in the latter period than it did in the earlier. Furthermore, it has as advantage that the earlier period overlaps with the timeframe Kamstra et al. (2003) use.

4.8 Monetary measurement

To show the effect of the length of days on stock returns in a monetary way, the returns of a simple strategy based on the length of days are calculated. The strategy is built upon the assumptions derived from previous literature. Following the findings of Bower and Wright (1992) and Cunningham (1979) (see the literature review), I expect that the returns in summer are higher than in winter. The strategy goes long in the summer, which is defined as the period between the spring and autumn equinoxes, and short in winter. Those time frames are selected because the length of days is longer than it is on average between the spring and autumn equinoxes (see Graph 1). If an effect exists, it should be most pronounced in this period. Another way of portfolio building is picking a market on the Northern Hemisphere and one in the Southern Hemisphere and go long in one and short in the other. Because the two markets have opposing seasons, a long position is taken in the Northern market during summer in the Northern Hemisphere. Simultaneously, a short position is taken in winter in the Southern Hemisphere. As the seasons change, this strategy is reversed. The results of this self-financing strategy are compared to a benchmark. A long position in both markets for the entire year is chosen as benchmark. The benchmark for the strategy that only invests in one country is a long position in that country's market for the entire year. For simplification, trading costs are not taken into account. Since trading on this strategy only needs two moments of portfolio rebalancing (assuming no extreme events that force investors to liquidate their positions), the costs of implementing this strategy should be low. If the strategies based on the length of days generate more returns than its benchmarks, it shows that the effect of the length of days is not only statistically significant, but also economically significant.

4.8.1 Theoretical returns

Similar to Kamstra et al. (2003), the theoretical returns are calculated by multiplying the beta that describes the influence of the length of days on stock returns with the excess hours of daylight per day. The excess hours of daylight are the hours at a day that are different from the average for the entire year. The average length of a day for each country is equal to its equinox. This is twelve hours, seven minutes and 36 seconds. For each country, the exact length per day of the year is known, the length of the average day is subtracted from this value in order to calculate the excess. The excess hours per day are multiplied with the beta to estimate the theoretical excess return on a day that is shorter or longer than the average. Via discrete compounding on a daily basis, these returns can then be annualized. In order to keep the results as clean as possible, weekends are kept out of the equation. The estimated returns are based on a year with approximately 260 trading days, 130 in summer and 130 in winter. Those returns are the theoretical returns because they are based on the statistical estimation of the effect of the length of days on stock returns.

4.8.2 Realized returns

The realized returns are calculated via the average returns of winters and summers. The returns of a countries market are split into summers and winters and the average total return per season (summer or winter) is calculated. The median of the average season returns is taken in order to control for extreme[9] summers or winters that can influence the averages. Taking the median of the averages should also correct for the effects of an unusual warm summer or other extraordinary events. The returns are calculated as if an investor went short in winter and long in summer.

[9] For example the 111,92% return in the winter of 1991 in Argentina or the 55,6% loss in the summer of 1998 in Thailand.

4.8.3 Benchmark

The benchmarks are calculated in the same way as the realized returns, the average returns per year are calculated for each country, and the median of those averages is taken.

5. Results

This section describes the results found in this thesis and compares them to the results found in previous literature and the expectations.

5.1 Length of days

This research finds ambiguous results concerning the influence of the length of days on stock returns. As shown in Table 4 on the following pages, there are few countries that experience abnormal returns caused by the length of days. An effect of the length of days on stock returns is found when regressing over the entire year for Canada, China, France, Indonesia and the United States of America in regression (2), which ignores the temperature, and for Kenya when temperature is included (regression (1)). The results in Kenya and the United States of America are only marginally significant. There are excess returns between -0.055% per extra hour of daylight (in China) and 0.006% per extra hour of daylight (in Kenya), which leads to more questions, since the direction of the excess returns is not consistent. A general statement concerning the influence of the length of days cannot be made. In some cases, the influence of the length of days is positive, in others the influence is negative. However, in most countries I do not find any relationship between the length of days and stock returns.

Solid statements about the entire dataset cannot be made here, since most betas did not statistically differ from zero. When comparing the results with the results found by Kamstra et al. (2003), differences are found. Where Kamstra et al. find an effect of the length of days on stock returns on eleven out of twelve markets, I find an effect in six out of 24 countries. Either there exist differences in the dataset and method of measurement, or the results are not significant any more but used to be in the time that Kamstra et al. performed their research.

Argentina	Length of days (1)	Temperature (1)	Length of days (2)	Temperature (3)
Summer	0,015	-0,001	-0,006	-0,001
Winter	0,002+	-0,002+	0,096	-0,001
Entire Year	0,045	-0,002+	-0,005	-0,001
Australia				
Summer	0,000	-0,002	-0,052	0,000
Winter	0,019	0,000	0,010	0,000
Entire Year	0,008	0,000	-0,004	0,000
Brazil				
Summer	0,071	0,000	0,051	0,000
Winter	0,020	0,000	0,040	0,000
Entire Year	-0,001	0,000	-0,002	0,000
Canada				
Summer	0,015	0,000	0,025**	0,000**[10]
Winter	-0,018	0,000	-0,030**	0,000**
Entire Year	-0,009	0,000	-0,009**	0,000+
Chile				
Summer	0,000	0,007	0,003	0,000
Winter	-0,033	0,000	-0,030	0,000
Entire Year	-0,001	0,000	-0,002	0,000
China				
Summer	-0,007	-0,001	-0,061	-0,001
Winter	-0,081	0,001	-0,043	0,000
Entire Year	-0,024	0,000	-0,055**	-0,001**
France				
Summer	-0,022	0,000	-0,022	0,000
Winter	-0,016	0,000	-0,011	0,000
Entire Year	-0,019	0,000	-0,014**	0,000+
Germany				
Summer	0,023	0,000	0,014	0,000
Winter	-0,034+	0,001	-0,002	0,000
Entire Year	-0,002	0,000	-0,025	0,000
India				
Summer	-0,026	-0,001	-0,036	-0,001
Winter	0,003**	0,003	-0,002**	0,000
Entire Year	-0,016	0,000	-0,010	0,000
Indonesia				
Summer	0,004	0,001	0,003	0,009
Winter	-0,005	0,006	-0,002	0,006
Entire Year	0,002	0,003	0,002**	0,003
Japan				
Summer	0,014	0,000	-0,020	0,000
Winter	0,037	-0,001**	-0,003	-0,001+
Entire Year	0,004	0,000	-0,012	0,000**
Kenya				
Summer	0,016+	-0,001	0,017+	-0,001
Winter	-0,007	0,000	-0,011	0,000
Entire Year	0,006+	-0,001	0,003	0,000

[10] A 0,000 value that is significant shows that the reported value is statistically significant (at a smaller value than 0,000) while it is not economically significant.

Malaysia	Length of days (1)	Temperature (1)	Length of days (2)	Temperature (3)
Summer	0,031	-0,004	0,028	0,003
Winter	-0,006	-0,001	-0,006+	-0,003
Entire Year	-0,069	-0,003	-0,001	-0,003+
Mexico				
Summer	-0,037	0,003	0,004	0,003
Winter	0,098	-0,002	-0,036	-0,001
Entire Year	-0,002	0,001	-0,004	-0,001
The Netherlands				
Summer	0,022	0,001	0,021	0,000
Winter	-0,035+	0,001+	-0,019	0,000
Entire Year	-0,008	0,000	-0,004	0,000
New Zealand				
Summer	-0,010	-0,001	-0,013	-0,001
Winter	-0,022	0,002**	0,011	0,001**
Entire Year	-0,007	0,000	0,000	0,000
Norway				
Summer	-0,006	0,000	-0,001	0,000
Winter	-0,014	0,000	-0,014	0,000
Entire Year	-0,009	0,000	-0,006	0,000
Peru				
Summer	-0,051	0,0017	-0,097	0,002
Winter	0,002	-0,001	0,002	-0,001
Entire Year	-0,009	0,000	-0,015	0,000
South Africa				
Summer	-0,017	0,000	-0,014	0,000
Winter	-0,014	0,000	-0,016	0,000
Entire Year	0,010	0,000	0,010	0,000
Sweden				
Summer	0,032+	0,000	0,024+	0,000
Winter	0,003	0,000	-0,001	0,000
Entire Year	0,004	0,000	0,004	0,000
Switzerland				
Summer	0,006	-0,001+	-0,007	0,000
Winter	0,002	0,000	-0,010	0,000
Entire Year	0,012	0,000+	-0,003	0,000
Thailand				
Summer	-0,009	-0,002	-0,008	-0,002
Winter	-0,047	-0,002	-0,049	-0,002
Entire Year	-0,013	-0,002+	-0,012	-0,002+
United Kingdom				
Summer	-0,003	0,001**	0,006	0,001**
Winter	0,011	-0,001	-0,003	0,000
Entire Year	-0,008	0,000	-0,006	0,000
United States				
Summer	0,004	0,000	0,008	0,000
Winter	-0,008	0,000	-0,019	0,000
Entire Year	-0,005	0,000	-0,010+	0,000+

Table 4 shows the statistical effect of one hour of extra dayligth on stock returns and of one tenth of a degree higher temperature on stock returns in regressions (1), (2), and (3) in summer, winter, and over the entire year. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

In order to test whether the results of this research match the results found by Kamstra et al., tests have been conducted if there exist differences between the periods 1980-1999 and 2000-2015. Very few differences have been found between those periods. As shown in Table 5, there only exists a difference between the first period and the latter in Australia, Kenya, and Norway. In all three cases, an effect of the length of days on stock returns was found in the first period, and it did not exist in the latter period. The effect of the length of days on stock returns in Australia and Norway is statistically spoken only marginally significant. The 1.285% excess returns for Kenya seem very high, but when kept in mind that this is the effect per extra hour of daylight, and that Kenya's shortest day is only seven minutes shorter than its longest day, the effect is small when calculating the effects.

Due to the limited changes there is no solid statistical evidence found in this dataset that the influence of the length of days on stock returns differs in the period 1980-1999 from the period 2000-2015.

Country	1980-1999	2000-2015	Country	1980-1999	2000-2015
Argentina	0,044	0,050	Malaysia	-0,196	-0,136
Australia	0,039+	-0,012	Mexico	-0,002	
Brazil	-0,144	0,032	The Netherlands	-0,010	-0,004
Canada	-0,005	-0,013	New Zealand		-0,007
Chile	0,010	-0,012	Norway	-0,023+	-0,001
China	0,020	-0,051	Peru		-0,009
France	-0,024	-0,001	South Africa	0,037	0,008
Germany	-0,003	0,006	Sweden	0,008	-0,003
India	-0,069	0,010	Switzerland	0,022	-0,003
Indonesia		0,002	Thailand	0,038	-0,029
Japan	0,015	-0,021	United Kingdom	-0,012	-0,005
Kenya	1,285***	0,135	United States	-0,001	-0,008

Table 5 shows the influence of the length of days on stock returns in the time periods 1980-1999 and 2000-2015 in percentages, missing values in the table exist because for some countries there was no data available before or after 2000 when the weather is taken into account. The reported data are the betas for the influence of the length of days on stock returns when all variables and dummies are included in the regression and the regression runs over the entire year. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

As said before, when comparing the results found in this study with the results found by Kamstra et al. (2003), there are not many similarities. Table 6 reports the theoretical annualized returns caused by the length of days next to the annualized returns due to SAD found by Kamstra et al. when regression (1) is limited to the years 1980-1999 and only runs in winter (similar to the approach of Kamstra et al. (2003)). The only country where it seems that similar results are found as in Kamstra et al. (2003) is Germany. The returns are similar (8,2% and 7,3%) but significant in Kamstra et al. and not in this study. The returns are calculated as if an investor is going long in winter to make the numbers comparable to the results from Kamstra et al. The table does not report the value for New Zealand of this research, since this research does not use data for New Zealand from before 2000. None of the effects of the length of days on stock returns were significantly different from zero in this regression, which means that there is no statistical evidence found in this thesis that supports the theory that the length of days has an effect in any of these countries in the period up to 2000.

Country	Kamstra et al. (2003)	Current research
Australia	5,7%	2,8%
Canada	13,2%***	1,9%
Germany	8,2%+	7,3%
Japan	6,9%+	-3,6%
New Zealand	10,5%**	
South Africa	17,5%+	-6,0%[11]
Sweden	13,5%**	3,1%
United Kingdom	10,3%**	-0,8%
United States	9,2%***	0,3%

Table 6 reports the findings of Kamstra et al. (2003) and the ones of this study. It reports the annualized effect of trading on the length of days in the way that Kamstra et al. did; long in winter. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

[11] The regression for South Africa consists of only 176 observations because the only data that is available starts at the first of January 1999. It is possible that only one winter with 176 observations is not enough to draw a solid conclusion.

5.2 Temperature

Among others, Kamstra et al. (2003) and Hirshleifer and Shumway (2003) found significant effects of weather factors on stock returns. I find ambiguous effects of the influence of temperature on stock returns[12]. As Table 4 shows, there are significant results for Argentina and Switzerland in regression (1), and for Canada, China, France, Japan, Malaysia, Thailand, and the United States of America in regression (3), which excludes the length of days when the regression runs over the entire year. The results in Switzerland, Canada, and the United States of America are only statistically significant but economically negligible. The effect of one tenth of a degree higher temperature is less than 0,000%. The results found in Argentina, Canada, France, Malaysia, Switzerland, Thailand and the United States of America are only marginally significant. The influence of the temperature factor lies between -0.003% (Malaysia) and 0,001% per tenth degree Celsius average temperature (China). The influence of the temperature on stock returns is only positive in China, where the literature suggests that the temperature should have a positive influence on stock returns. However, when controlling for tax loss selling and Monday effects, the temperature has a negative influence on stock returns in eight of the 24 countries and a positive influence in China.

5.3 Difference between summer, winter, and the entire year

The regressions ran in this research are tested in three ways; separately for winter and summer, and for the entire year. I found some differences between the three. Tables 4, 7, 8, and 9 show that the results for the influence of the length of days and temperature do not differ much between summer, winter, and the entire year.

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[12] Important to keep in mind is that this research was not specifically designed to find the effects of weather factors on stock returns, it is therefore possible that the variable temperature could be partly explained by, for example, the amount of sunshine, precipitation or cloud coverage.

As can be seen in Table 4 and 7, in Argentina, Germany, India, Malaysia and the Netherlands an effect of the length of days on stock returns is found in winter, but not in summer or over the entire year, China, France, Indonesia, and the United States of America experience an effect when tested over the entire year, but not in summer or winter separately, Kenya over the entire year and in the summer, but not when tested in winter separately, and Sweden in summer, but not in winter or over the entire year. There is an effect in Canada when tested for summer separately, winter separately, and over the entire year.

Country	Summer	Winter	Entire year
Argentina	-	+	-
Canada	**	**	**
China	-	-	**
France	-	-	**
Germany	-	**	-
India	-	**	-
Indonesia	-	-	+
Kenya	+	-	+
Malaysia	-	+	-
The Netherlands	-	+	-
Sweden	+	-	-
United States	-	-	+

Table 7 shows the significance of the factor length of days per part of the year. Significance is reported when regression (1) or (2) shows significant results. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

It seems to be that if there exist differences between winter and summer, a country is more likely to experience the influence of the length of days on stock returns in winter than in summer. However, for the most countries there does not exist any difference between testing over the entire year, summer, and winter.

	Length of days (1)	Temperature (1)	Length of days (2)	Temperature (3)
Summer	2	2	3	3
Winter	3	3	3	3
Entire Year	1	2	5	7

Table 8 shows the amount of significant results found in the regressions. The second column shows the number of countries in which an effect of the length of days is present in regression (1), the third column reports the number of countries where temperature has a significant influence in regression (1). The fourth and fifth column report the significance for those factors when ran separately, regression (2) and (3).

For the effect of temperature on stock returns, I find differences in ten countries. As Table 9 on the next page reports, the effect is present in winter and over the entire year, but not when tested for summer separately in Argentina and Japan. For China, France, Malaysia, Thailand, and the United States of America the effect persists over the entire year, but not when tested for winter or summer separately. Temperature only has an effect on stock returns in winter, but not over the entire year or in summer in New Zealand. It is present in summer and over the entire year in Switzerland, but not when tested separately in winter and only found in summer, but not when tested over the entire year or separately in winter, for the United Kingdom. For thirteen countries, there is no effect of temperature on stock returns found in the regressions. In Canada, it is present over the entire year, when tested for summer separately, and when tested for winter separately.

	Summer	Winter	Entire Year
Argentina	-	+	+
China	-	-	***
France	-	-	+
Canada	***	***	+
Japan	-	**	***
Malaysia	-	-	+
New Zealand	-	**	-
Switzerland	+	-	+
Thailand	-	-	+
United Kingdom	**	-	-
United States of America	-	-	+

Table 9 reports the influence of temperature on the stock returns per season. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

5.4 Monetary measurement – Theoretical versus realized

5.4.1 Theoretical returns of the trading strategy

Table 10 reports the results of a trading strategy that goes long in summer and short in winter. As shown in the table, the theoretical effect of trading on the length of days generates money in seventeen out of 24 countries (if we ignore trading costs) and loses money in the other seven countries. The returns, however, are only marginal statistically different from zero in Kenya[13]. The economic effect in Kenya seems to be negligible since trading on the length of days only yields 0,05% per year and will probably be diminished by trading costs. Comparing the significant effect in Kenya with the insignificant effects in France (9.07%), China (7.23%) or Norway (5.74%) shows a contradiction in the results. However, it is possible that the small effects, close to zero and not significant, in countries that lie further away from the equator are larger when summed up because there is more deviation in the length of days. The beta found is the influence of an extra hour of daylight on the stock returns. Since Kenya has only seven minutes of deviation between the shortest and the longest day, the

[13] This table uses the results of regression (1).

effects are slim. Norway, for example, has differences up to seven hours and 54 minutes in length of days. In the countries that lie further away from the equator, small hourly effects can have a large impact when compounded. As said before, there are seven countries that have theoretical losses when this trading strategy is applied but none of those losses are statistically significant. The only significant win is only statistically significant and economically negligible.

Country	Theoretical	Realized	Benchmark
Argentina	-15,40%	7,97%	26,56%
Australia	-2,54%	4,47%	10,04%
Brazil	0,22%	6,24%	1,15%
Canada	3,74%	-5,02%	7,42%
Chile	0,21%	-0,31%	12,32%
China	7,23%	-2,29%	3,12%
France	9,07%	-1,98%	11,31%
Germany	1,10%	-2,81%	12,86%
India	2,81%	-1,32%	16,00%
Indonesia	-0,11%	-1,13%	14,93%
Japan	-0,12%	-4,55%	7,12%
Kenya	0,05%$^{+}$	-0,66%	2,17%
Malaysia	1,97%	-1,83%	8,13%
Mexico	0,42%	-4,34%	20,97%
The Netherlands	4,24%	-6,19%	11,54%
New Zealand	2,67%	5,67%	10,67%
Norway	5,74%	-1,75%	8,07%
Peru	1,04%	-8,25%	17,03%
South Africa	-2,51%	3,80%	15,37%
Sweden	-2,48%	-5,31%	16,94%
Switzerland	-5,49%	-4,87%	14,29%
Thailand	1,74%	-1,98%	8,88%
United Kingdom	3,98%	-2,84%	11,63%
United States	2,14%	-4,26%	12,78%

Table 10 reports the theoretical and realized returns of trading on a strategy that goes long in summer and short in winter and the benchmark, which goes long in the countries market for one year. + stands for significant at the 10% level.

5.4.2 Realized returns of the trading strategy

The third column of Table 10 reports the results of the same trading strategy, but uses the median of the average returns of a countries entire year. As shown, the realized returns would have generated losses in fifteen out of 24 cases, and wins in nine countries. Overall, the returns vary between -7,21% (Malaysia) and 8,27% (South Africa). The realized returns are higher than the theoretical returns in eight countries, with the largest difference in Argentina (+7,97% instead of -15,40%). In the other sixteen countries, the realized returns are lower than the theoretical returns. The largest difference is found in France, where the theoretical returns would be 9,07% and the realized returns -1,98%.

Even though the previous paragraphs speak of wins and losses, the theoretical returns underperform the benchmark in 23 of the 24 countries. The theoretical returns of the trading strategy would only in China yield more return than the benchmark did (7,23% versus 3,12%), but the theoretical returns in China were not significantly different from zero. The realized returns also underperform the benchmark in 23 countries. The only country in which an investor who is following the strategy would generate more returns than the benchmark is Brazil (6,24% versus 1,15%). It seems that the trading strategy based on the length of days does not work as well as expected. Even if the strategy is reversed (short in summer, long in winter) the benchmark performs consistently better.

Portfolios that go long in the summer of a northern country and simultaneously short in the winter of a southern market, and reverse in winter also do not outperform their benchmarks (50/50 long in both markets for the entire year). The portfolio China-South Africa generates 1,51% returns versus 9,25% on its benchmark, Norway-Australia has positive returns of 2,72% versus the benchmark its return of 9,06%. A portfolio including the Netherlands and New Zealand loses 0,52%, where the benchmark would win 11,11%, and the portfolio with the United States of America and Chile loses 4,57%, where the benchmark would win 12,55%.

The results found show that trading on the effect of the length of days on stock returns in only one country provides excess returns, but those returns are economically negligible. 23 of the 24 countries' realized returns of the trading strategy underperform the benchmark, where the four portfolios that follow a strategy that simultaneously trades on two markets all underperform their benchmark.

5.5 Fall, Monday, and Tax loss effects

In order to see whether there are any excess returns in fall, on Mondays, or due to tax-loss selling[14], multiple dummy variables are added to the regression. Table 11 shows the results found in regression (1), ran over the entire year. Table 11 is a summary of Table A1 in the Appendix. Table A1 shows the results of Table 11, but also reports the coefficients found in summer and winter separately.

5.5.1 Fall

As Table 11 shows, there only exist excess returns in fall in three countries. In Canada and Norway, a day in fall is expected to have lower returns than a similar day (concerning weather, length of day, weekday, etcetera) that is not in fall. The effect is positive in Indonesia. The effects in Canada and Indonesia are only marginally significant. For the other 21 countries, this research does not find excess returns in fall. In general, it seems that days in fall do not have significantly lower returns than other days. The effects found are slim, the largest deviation is found in Indonesia, where the predictions for a day in fall are 0.15% higher than a similar day not in fall.

5.5.2 Monday

This research finds significant result for a Monday effect in eleven countries. In Argentina, Canada, Chile, Indonesia, Kenya, Malaysia, Mexico, Peru, and Thailand, the returns on a Monday are significantly lower than on another day of the week. In South Africa and the United States of America, the effect is positive. The effects in Canada and Kenya are only marginally significant. The traditional Monday effect predicts that returns on a Monday are lower than on the other days of the

[14] Important to keep in mind in this paragraph is that this research is not specifically designed to capture these effects. It is therefore possible that the results found for the effects are partly driven by other factors, which might not have been taken into account here.

week. The findings in South Africa and the United States of America are therefore unexpected. In the other thirteen countries, no excess returns due to the Monday effect are found. Argentina and Mexico show the strongest effect in percentage terms for the Monday effect. The predictions for Monday are in these countries 0,34% lower than they are for the other weekdays.

5.5.3 Tax loss effects

Table 11 shows that in seven countries tax loss-selling effects are found. All seven countries follow the expectation that the effect is positive. Australia (marginally significant), Chile, Indonesia, Kenya, Malaysia, New Zealand, and the United States of America show positive significant results. The strongest effect is found in Indonesia, where a day around the end of the tax year is predicted to have 0,59% excess returns.

Country	Fall	Monday	Taxloss
Argentina	-0,009	-0,342***	-0,035
Australia	-0,005	0,006	0,131+
Brazil	-0,153	-0,151	-0,318
Canada	-0,037+	-0,035+	0,127
Chile	0,001	-0,160***	0,210**
China	-0,154	-0,085	0,036
France	-0,070	-0,085	-0,138
Germany	-0,012	0,016	0,076
India	0,017	-0,041	-0,098
Indonesia	0,148+	-0,200**	0,589**
Japan	-0,028	-0,029	0,037
Kenya	0,040	-0,046+	0,227**
Malaysia	-0,002	-0,257***	0,324**
Mexico	0,006	-0,340***	0,093
The Netherlands	-0,028	-0,003	0,034
New Zealand	-0,026	-0,025	0,165**
Norway	-0,094**	-0,022	0,069
Peru	-0,040	-0,175**	0,153
South Africa	-0,003	0,095**	-0,088
Sweden	-0,037	0,010	0,012
Switzerland	0,014	-0,020	-0,016
Thailand	-0,058	-0,309***	0,434**
United Kingdom	-0,013	-0,018	0,022
United States	0,001	0,034**	-0,103

Table 11 shows the expected excess returns in percentages if a day is in Fall, a Monday or one of the days around the end of the Tax year. + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.

5.5.4 Differences throughout the year

Ambiguous results have been found concerning changes throughout the year for the significance of the Fall, Monday and Taxloss effects. In eight countries, differences in significance are found for different seasons. As Tables 12 and Table A1 (appendix) show, it seems that there can be differences for the three effects between the seasons, but it does not give reason to believe that there is a particular pattern. The tax loss effect did not significantly change between the seasons in any of the countries[15].

	Summer	Winter	Entire Year
Argentina		Monday	
Canada			Fall
China	Monday	Fall	
Indonesia			Fall
Kenya			Monday
South Africa			Monday
United Kingdom		Monday	
United States	Monday		Monday

Table 12 shows the effects that differ in different seasons. If an effect is reported under one of the columns, it means that this effect is significant in that season but not in the other seasons.

5.6 Overview

The results of this research show effects of length of days and temperature on stock returns in some cases, but over the most part the results were ambiguous or insignificant. I have to reject the first hypothesis of this research: "*The length of days in a country are positively correlated with its stock returns*". For six countries this research could find an effect of the length of days on stock returns when testing over the entire year. In two of those countries the effect was only marginally significant. Furthermore, the direction of those results was both positive and negative. I find no statistical support for the second hypothesis: *"The effect of the length of days on stock returns is stronger in countries that have larger deviation in length of days"*. Since only six countries experience an effect of the

[15] Tax loss selling is per country only added to the regressions for the entire year and for either summer or winter because it only occurs in one of those seasons.

length of days on stock returns, it is not possible to make a solid assumption concerning the strength of the effect in different countries. The theoretical returns caused by the length of days (stated in Table 9) cannot provide an insight about the strength in countries closer to, or further away from, the equator because there was only one country where the trading strategy yielded returns that are significantly different from zero. The third hypothesis: *"A trading strategy based on the length of days will generate positive excess returns"* can be rejected. Even though the theoretical returns can be positive, the benchmark outperforms the theoretical portfolio in 23 out of 24 countries. The realized returns of following the strategies also lead to underperforming the benchmark in 23 countries. The more sophisticated strategy, simultaneously going long and short in a Northern and Southern market, leads to lower returns than investing in a 50/50 long portfolio in all four cases. I do find statistical support for the last hypothesis: "*Anomalies based on seasonality explain part of the returns when added to a regression with the length of days"*. The Monday effect is found in eleven countries and the tax loss effect in seven. The fall effect is present in only three out of 24 countries. Temperature is found to be significant in eight countries. Contradictory to what one would expect after reading the existing literature, the effect is negative in seven of these eight countries. Concerning the change in seasons, tables 4, 7, 8, and 9 show that there do not seem to be many differences between the seasons. There are slightly more significant results when tested over the entire year, but there does not seem to be a particular pattern. Overall, the results found do not provide solid statistical evidence for the existence of an effect of the length of days on stock returns.

6. Discussion

This section will discuss the research conducted in this thesis. It will give recommendations for further research and show the possible limitations to this study.

6.1 Difference between current research and Kamstra et al. (2003)

Even though I use a similar approach as Kamstra et al. (2003) to study the effect of the length of days on stock returns, I do not find similar results. As Table 6 shows, there are eight countries that Kamstra et al. and the current research both examine in the period before 2000. In order to compare my results with theirs, I have adjusted my approach as much as possible to make it comparable. Where Kamstra et al. find an effect of the length of days in seven of those countries (only marginally significant in three of them), I do not find an effect in any of those countries.

There are multiple possible explanations for the differences between their research and mine. First, Kamstra et al. include more weather factors, which might capture another part of the returns. Second and most important, they test on most markets on a different time period than I did. For example, Kamstra et al. and I both test on the S&P500, but their dataset starts in 1928. It is possible that a large part of their results is driven by the period 1928-1980, and the effect later on disappeared. In order to see whether the effect indeed diminished over time, further research should investigate a longer period of time and test for different effects in different time frames. However, for some countries, for example the UK, the time period is almost exactly the same. Different results in their dataset then must be due to the slightly different research approach.

6.2 Seasonalize or normalize variables

A possible interesting addition to this research is seasonalize or normalize the factor describing the weather. If the temperatures are seasonalized, only the surprise in temperature is regressed on the stock returns. Seasonalized temperatures would be the temperature that exceeds the average of, for example, a month. If the average temperature in July is 25 degrees Celsius for a country, and a value of 31 degrees is found for a particular day, the seasonalized value is then six degrees. The downside of using a seasonalized temperature variable is that the research only can find whether the surprise in temperature is of influence on stock returns, and not if average higher temperatures cause higher stock returns. The upside is that it will probably decrease the possible multicollinearity problems caused by the correlation between the length of days and the temperature. Table 8 shows that the results in this thesis are probably not influenced by multicollinearity. When the regressions ran without one of the correlated factors, the results were similar.

6.3 Adding more weather variables

Due to multiple limitations, this study only uses the temperature to capture the weather. Since other research found that people report higher subjective probabilities when there is more sunshine (Cunningham, 1979), it would be interesting to add a variable like sunshine or cloud coverage to the regressions. Another weather variable that might be of influence is the amount of precipitation on a particular day. The downside of adding more weather variables is that it might result in more multicollinearity problems. Higher temperature will be associated with higher temperature and cloud coverage, and more precipitation will probably be correlated with higher precipitation.

Because the weather is added to the regressions, the time frames in some countries became narrower. For example in Mexico, the original dataset captured the period from January 1988 until 2015 but the temperature variable was only available until 1999. It would be better if the dataset is more complete with longer periods to test on. Using more weather variables might give a more complete picture of how the stock returns are influenced by the weather. It is possible that more weather factors, and seasonalizing temperature, can bring the results of this thesis closer to the results found by Kamstra et al. (2003) and Hirshleifer and Shumway (2003).

6.4 Differences within countries

This thesis studies the effects of the length of days on stock returns per country. It is possible that there are differences within a country. Chile, for example, has large differences in length of days between the northern and southern part. However, most markets are located in cities that lie either in the area where the largest part of the population lives, in a part of the country that experiences around the average of deviations in length of days.

6.5 Investor mood

This thesis only makes assumptions about the mood of investors derived from previous research. It tests on the entire market and therefore tests on all investors. It would be interesting to see whether the mood of investors can indeed cause excess returns. A study that uses individual investors with known mood and trades could tell more about the relationship between mood and stock returns. It is possible that the length of days is of significant effect on stock returns via this mood. This is the psychological reasoning described by Cunningham (1979) and Wright and Bower (1992) from which the hypotheses used in this thesis are derived. A study focussed on those factors could provide more insights of how investors behave when they are in a certain mood and could therefore be an interesting addition in the field of behavioural finance.

7. Conclusion

This thesis investigated the effect of the length of days on stock returns. Other than in Kamstra et al. (2003), there is no clear evidence that gives reason to believe that there is a market wide effect present in the countries that I have studied. The stock returns in most of the countries seem unaffected by the length of days.

There are some effects of the length of days on stock returns, but the direction is not always as expected. Over the entire year, the only country with excess returns is Kenya in regression (1). Canada, China, Indonesia, France, and the United States of America experience an effect when tested in regression (2), which excludes temperature. The other countries do not show any statistical evidence. When tested for winter or summer separately, six other countries had experienced effects, but the effects for China, France, Indonesia and the United States of America disappeared. Most results found are only marginally significant. Where Kamstra et al. (2003) found statistical and consistent proof in eleven out of twelve markets, this research does not find the same results. Even when the period is adjusted to the period in which Kamstra et al. did their research, I do not find similar results.

Concerning the influence of temperature on stock returns, I found a significant effect in seven countries: Argentina, France, Canada, Malaysia, Japan, Thailand, and the United States of America. This is unexpected since the previous behavioural and psychological literature points to the opposite. The results in Canada, Japan, and the United States of America are only statistically significant but economically negligible. Only in China there is a positive relationship. For the other thirteen, there does not exist any relationship between temperature and the stock returns.

For both the effect of the length of days on stock returns and the effect of temperature on stock returns some differences are found throughout the year.

The influence of the length of days changes in eleven countries in over the seasons, but there does not seem to be a pattern. It is present over the entire year in six countries, in winter for six countries and in summer for three countries. For temperature, changes are found in ten countries. For temperature, the effect is most often present when tested over the entire year but not when tested for the seasons separately. This pattern is found in eight countries. For most countries, however, there are no significant results or changes throughout the year. I therefore find no clear indication that an effect might be more present in one season or another.

My results give no reason to believe that there is a solid, market wide effect of the length of days on stock returns. The limited number of significant results shows that the effect on stock returns is minimal. The returns of portfolios formed on basis of the length of days are consistently underperforming their benchmarks and are therefore a bad recommendation for investors.

The effects found in eleven countries on Monday show a violation of the efficient market hypothesis in its semi-strong form. The existence and persistence of the Monday effect can be explained by behavioural economics, for example by the bad news hypothesis, but the traditional finance paradigm does not leave room for those excess returns. An effect of the length of days on stock returns would have implied a violation from the efficient market hypothesis in the semi-strong form. In some of the cases (marginally) statistical evidence for the existence of this effect is found. I therefore cannot conclude that people violate the semi-strong form of the efficient market hypothesis by letting their trades be influenced by the length of days. I assume that the stock market as a whole is mainly unaffected by this effect.

It will be interesting to see what further research finds concerning the influence of the length of days and temperature on stock returns. Further research may show whether the effect of the length of days on stock returns indeed has disappeared (as this research indicates) or that a different methodology finds unambiguous results following the expectations derived from psychological and behavioural finance literature. This would indicate a violation of the efficient market hypothesis in its strong and semi-strong form, which is not found in this thesis. The results might have been different if more weather variables were added, but the variety of regressions ran in this research give reason to believe that the results are robust. Comparing my results to the results of Kamstra et al. (2003) suggests that the effect of the length of days on stock returns has disappeared, but further specified research on different time frames is the only way to know for sure.

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9. Appendix

Argentina	Fall	Monday	Tax loss
Summer		-0,168	-0,137
Winter	-0,002	-0,498***	
Entire Year	-0,009	-0,342***	-0,035
Australia	Fall	Monday	Tax loss
Summer		-0,006	
Winter	-0,002	0,003	0,138^{+}
Entire Year	-0,005	0,006	0,131^{+}
Brazil	Fall	Monday	Tax loss
Summer		-0,020	-0,329
Winter	-0,163	-0,265^{+}	
Entire Year	-0,153	-0,152	-0,319
Canada	Fall	Monday	Tax loss
Summer		-0,082***	
Winter	-0,019	0,003	0,121
Entire Year	-0,037^{+}	-0,035^{+}	0,127
Chile	Fall	Monday	Tax loss
Summer		-0,152***	0,197**
Winter	0,008	-0,169***	
Entire Year	0,010	-0,160***	0,210**
China	Fall	Monday	Tax loss
Summer		-0,222**	
Winter	-0,270**	0,068	0,010
Entire Year	-0,154	-0,085	0,036
France	Fall	Monday	Tax loss
Summer		-0,016	
Winter	-0,071	-0,152***	-0,134
Entire Year	-0,070	-0,085	-0,138
Germany	Fall	Monday	Tax loss
Summer		0,006	
Winter	-0,045	0,027	0,047
Entire Year	-0,012	0,016	0,076

India	Fall	Monday	Tax loss
Summer		-0,095	-0,120
Winter	0,009	0,020	
Entire Year	0,017	-0,041	-0,098
Indonesia	Fall	Monday	Tax loss
Summer		-0,153	0,551^{+}
Winter	0,139	-0,248***	
Entire Year	0,149^{+}	-0,200**	0,589**
Japan	Fall	Monday	Tax loss
Summer		-0,023	
Winter	0,055	-0,037	0,086
Entire Year	-0,028	-0,029	0,037
Kenya	Fall	Monday	Tax loss
Summer		-0,043	0,193^{+}
Winter	0,040	-0,049	
Entire Year	0,040	-0,046^{+}	0,227**
Malaysia	Fall	Monday	Tax loss
Summer		-0,274***	
Winter	0,006	-0,239***	0,305**
Entire Year	-0,002	-0,257***	0,324**
Mexico	Fall	Monday	Tax loss
Summer		-0,232**	
Winter	0,014	-0,451***	0,088
Entire Year	0,006	-0,340***	0,093
The Netherlands	Fall	Monday	Tax loss
Summer		0,022	
Winter	-0,056	-0,026	-0,006
Entire Year	-0,028	-0,003	0,034
New Zealand	Fall	Monday	Tax loss
Summer		-0,052	
Winter	-0,061	0,000	0,146^{+}
Entire Year	-0,026	-0,025	0,165**

Norway	Fall	Monday	Tax loss
Summer		0,024	
Winter	-0,089**	-0,063	0,062
Entire Year	-0,094**	-0,022	0,069
Peru	**Fall**	**Monday**	**Tax loss**
Summer		-0,219**	0,169
Winter	-0,043	-0,140+	
Entire Year	-0,040	-0,175**	0,153
South Africa	**Fall**	**Monday**	**Tax loss**
Summer		0,085	-0,104
Winter	-0,005	0,099	
Entire Year	-0,003	0,095**	-0,088
Sweden	**Fall**	**Monday**	**Tax loss**
Summer		0,033	
Winter	-0,072	-0,010	0,090
Entire Year	-0,037	0,010	0,012
Switzerland	**Fall**	**Monday**	**Tax loss**
Summer		0,010	
Winter	0,017	-0,046	-0,027
Entire Year	0,014	-0,020	-0,016
Thailand	**Fall**	**Monday**	**Tax loss**
Summer		-0,253***	
Winter	-0,054	-0,360***	0,426**
Entire Year	-0,058	-0,309***	0,434**
United Kingdom	**Fall**	**Monday**	**Tax loss**
Summer		0,040	0,070
Winter	0,002	-0,062+	
Entire Year	-0,013	-0,018	0,022
United States	**Fall**	**Monday**	**Tax loss**
Summer		0,051**	
Winter	0,013	0,016	-0,110
Entire Year	0,001	0,034**	-0,103

Table A1 shows the influence of the Fall, Monday, and Tax loss dummy in percentages in Summer, Winter, and over the entire year found in regression (1). + stands for marginally significant (significant at the 10% level), ** for significant at the 5% level, and *** for significant at the 1% level.