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The weather and stock returns

Bachelor thesis

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Abstract

This thesis examines a behavioral finance topic, the effect of weather on stock returns. The research was performed with the aim to verify formerly published results of various weather variables like sunshine, precipitation or temperature influencing stock markets. For the analysis Ordinary Least Squares regressions were implemented to investigate the relationships of stock returns and weather variables proposed in the previous literature as well as other market efficiency effects, a Monday and a January effect. In addition, GARCH model was carried out to check the influence of weather conditions on stock return volatility. Data used for the analysis consists of 24 emerging and 23 developed markets worldwide in the period 2006–2017. The results are not in support of the theory of weather affecting market trading which corresponds to the market efficiency theory. There seems to be no difference between the developed and emerging countries, not even countries' land area plays a role. However, in the thesis repeatedly appears significant evidence of the presence of the Monday effect.

Keywords

Behavioral finance, Weather effect, Market efficiency, Anomaly, GARCH

Abstrakt

Tato práce zkoumá téma behaviorálních financí, efekt počasí na akciové výnosy. Výzkum byl proveden za účelem ověření dříve publikovaných výsledků o vlivu různých proměnných počasí jako slunečního svitu, srážek nebo teploty na akciové trhy. Analýza k odhalení vztahů mezi akciovými výnosy a proměnnými počasí navrženými v předešlé literatuře, stejně tak jako dalšími efekty tržní efektivity, pondělním a lednovým efektem, byla provedena regresí pomocí metody nejmenších čtverců. Dále byl použit GARCH model ke zjištění vlivu klimatických podmínek na volatilitu akciových výnosů. Data použitá pro analýzu obsahují 24 rozvojových a 23 vyspělých trhů z celého světa v období 2006–2017. Výsledky nepodporují teorii, že počasí ovlivňuje obchodování na trhu, což koresponduje s teorií efektivního trhu. Nezdá se, že by byl rozdíl mezi vyspělými a rozvojovými státy, nehraje roli ani rozloha státu. Nicméně, v práci se opakovaně vyskytuje evidence o přítomnosti pondělního efektu.

Klíčová slova

Behaviorální finance, Efekt počasí, Efektivita trhu, Anomálie, GARCH

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, 4 January 2019

Signature

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Bachelor Thesis Proposal

author	Patrik Černý
supervisor	PhDr. Jiří Kukačka, Ph.D.
proposed topic	Effect of weather on stock returns

Motivation

In recent years, researchers came up with many behavioral finance theories, which contradict the typical efficient market approach. One of those theories, suggested by Saunders (1993), is the influence of weather on the stock market. So far, various theses have concluded that the only weather factor that has any significant effect on the market, of course, when we omit obvious events as natural catastrophes, is sunshine. It corresponds to the idea from the field of psychology, that people's mood is influenced by sun which can imply a possible change of their behavior. Closely related to sunshine is also Seasonal Affective Disorder (SAD), condition that affects people during the season with fewer hours of daylight, which was found to have an important effect on stock market returns by Kamstra, Kramer and Levi (2003). It is clear, that it does not make much sense to study the impact of weather on huge stock exchanges where the traders are from all over the world and thus confront very different weather conditions, which is discussed by Loughran and Schultz (2004). On the other hand, the less important (in global impact) stock exchanges in smaller countries, where most traders are domestic and the weather conditions are more or less the same in the whole area, could bring interesting results.

This thesis will focus on developed and emerging markets according to MSCI classification and will compare the weather effect on each of them.

Preliminary working hypotheses:

1. There is no evidence of impact of sunshine on stock returns.
(Saunders, 1993)

2. Sunshine does not cause higher returns.
Hirshleifer and Shumway (2003)

3. SAD does not influence returns. Kamstra, Kramer and Levi (2003)

4. The effect is not more significant in emerging markets.

5. The effect is not more significant in countries with small land area.
Loughran and Schultz (2004)

Contribution

The purpose of this thesis is to give an updated research of the weather effect on stock returns by following the present literature and expanding the research to larger amount of markets with focus on emerging markets. The contribution will be a comparison of the weather effect between emerging and developed markets and the results could clarify larger presence of market inefficiency in the markets which are emerging opposite to the ones that are considered already developed. Findings of the thesis, the weather effect, could serve as another variable to consider when trading on a stock market.

Methodology

Data about weather will be retrieved from "National Centers for Environmental Information", which has been the source of most papers dealing with the same topic. Data contains hourly information about cloud cover, temperature, precipitation, etc. Cloud cover will be used as a proxy variable for sunshine. Financial data will be obtained from Thomsom Reuters Eikon.

The analysis will follow the approach suggested by Hirshleifer and Shumway (2003), with later followed improvements, e.g. including dummy variables for January and Monday effects (Goetzmann & Zhu, 2005) and adding a SAD variable (Kamstra et al., 2003). Preliminarily, the econometric regression should look like:

$$R_t = \beta_0 + \beta_1 SKC_t + \beta_2 SAD_t + \beta_3 R_{t-1} + \beta_4 Temp_t + \beta_5 Prec_t + \delta_1 M_t + \delta_2 J_t + \varepsilon_t \tag{1}$$

where SKC stands for sky cover (cloudiness), SAD for seasonal affective disorder, R for returns, R_{t-1} for lagged returns, $Temp$ for temperature, $Prec$ for the amount of precipitation, M and J are dummy variables for Monday and January respectively, with values 1 if Monday or January, 0 otherwise. In the final work, the model may slightly differ.

Outline

1. Introduction
2. Literature review
3. Data description
4. Methodology
5. Discussion and results
6. Conclusion

Core literature

Chang, T., Nieh, C. C., Yang, M. J., & Yang, T. Y. (2006). Are stock market returns related to the weather effects? Empirical evidence from Taiwan. *Physica A: Statistical Mechanics and its Applications, 364*, 343-354.

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Chapter 1

Introduction

Behavioral finance is a branch of a popular field of behavioral economics which focuses on stock market anomalies based on psychology theories. The aim of behavioral finance is to identify and explain why people make certain investment decisions. The assumption of efficient market hypothesis is that market agents behave rationally but as it is well known, humans do not make decisions necessarily leading to the optimal level of benefit but according to their actual mood, feelings or beliefs. This thesis is dedicated to one of the behavioral finance topics, a weather effect. Weather conditions may influence people's mood (Denissen, Butalid, Penke & Van Aken, 2008) and even their actual behavior (Cunningham, 1979).

The topic of weather in behavioral finances was introduced by Saunders (1993). He rejected the null hypothesis of no influence of weather on stock prices which supports the presumption of security market being partially irrational. The paper claims that on one hand the weather influences brokers that are physically present at the exchange, on the other hand there is also an indirect impact on security traders via good news, possibly released by weather influenced journalists.

Saunders tried to include in his model many weather variables like temperature, humidity, precipitation, wind and cloud cover, of which only cloud cover turned out to appear significant. The final published model considered a lagged return, January effect, Monday effect and cloud cover. In this paper Monday effect was found with lower or negative returns on Monday, but much less negative on sunny Mondays.

Time period Saunders used is 1927–1989. Looking at this time period it is clear that since then the form of trading has drastically changed and it has become much easier to buy stocks worldwide and thus not experience the weather conditions in close distance to the stock exchange. However, due to Home equity bias introduced by French and Poterba (1991) explaining the tendency to buy domestic stocks rather than foreign ones and even preferring stocks of local domestic companies (Coval & Moskowitz, 1999; Grinblatt & Keloharju, 2001) one can expect that traders could still experience weather present close to the stock exchange or the company head quarter. In the past, trading decisions were done by humans, so it was reasonable to expect the market not to be absolutely rationally efficient and contain certain market anomalies. However, with the entry of algorithmic trading, which nowadays represents most of the market trading volume (Boehmer, Fong & Wu, 2015), the presence of weather effect becomes questionable.

The aim of this thesis is to provide an updated research of the weather effect on stock returns by following the present literature and expanding the research to larger amount of markets with focus on the difference between emerging and developed markets. The structure of the thesis is as follows: Chapter 2 provides an insight into literature concerning weather effects, Chapter 3 shortly describes the used data, Chapter 4 introduces employed methodology, Chapter 5 presents the results and the conclusion of the findings of the thesis is situated in Chapter 6.

Chapter 2

Literature review

2.1 First articles

Saunders (1993) has been an inspiration for many following studies, trying either to confirm found effects or to reject the hypothesis of any weather influence. Hirshleifer and Shumway (2003) found the effect of sunshine to be statistically significant at 5% level, Akhtari (2011) and Goetzmann, Kim, Kumar and Wang (2014) even at 1% level. What is convenient about all the papers following the topic is their source of weather data. Except for Krämer and Runde (1997), Tufan and Hamarat (2004), T. Chang, Nieh, Yang and Yang (2006) and Kang, Jiang, Lee and Yoon (2010) concentrating on only one country, all used data provided by National Oceanic and Atmospheric Administration (NOAA).

The first well known articles reacting to Saunders (1993) were Krämer and Runde (1997) and Hirshleifer and Shumway (2003). Krämer and Runde (1997) concluded that the short-term stock returns are not influenced by local weather. Hirshleifer and Shumway (2003) brought exactly the opposite result, and in consistence with Saunders, the sunshine and daily stock returns found to be strongly positively correlated, at 5% level.

Krämer and Runde (1997) basically replicated Saunders' method but instead of NYSE data they used stock index DAX situated in Frankfurt in Germany. During their data period 1960–1990 no electronic trading system was used yet and thus if there was any effect it should be present in their results. Especially because they used German stocks and German market agents are much less geographically dispersed in comparison to the US which means Frankfurt weather is quite a good proxy also for the weather in other German cities like Munich, Dusseldorf, etc. (Krämer & Runde, 1997).

Hirshleifer and Shumway (2003) decided to perform the analysis on panel data consisting of 26 stock exchanges internationally in the period 1982–1997. The only weather condition related to the returns appeared to be sunshine, the others like humidity or rain were found to be unrelated. To get rid of the seasonal effect, because cloudiness which is used as a sunshine proxy changes according to the yearly season — e.g. in the climate of Central Europe there are more clouds in the sky in Autumn than in other seasons, they deseasonlized the data with respect to the expected level of cloudiness for each day of the year in the dataset. The main idea of the article was that sun influences traders' mood during a trading day and the influenced persons incorrectly consider their good mood to be present due to the economic situation and not the weather conditions.

2.2 Frequently included weather related variables

2.2.1 Cloud cover

Cloud cover works as a proxy variable for sunshine. As it is the main common weather condition the researches were interested in, since there is a psychological theory behind it, all of the authors included it in their studies. The weather can be considered to be "good" or "bad" according to the amount of sunshine a person experience and thus sunshine, or rather cloud cover, could be taken as the main indicator of the mood of the weather. Bad weather usually means heavy rains, hails or storms, all of which is accompanied by the presence of clouds. Bassi, Colacito and Fulghieri (2013) investigated the impact of cloud cover on human's risk aversion and provided experimental evidence of a strong effect, being less averse during the good weather and more during the bad one.

The weather datasets were mainly obtained at NOAA. Their database contains worldwide data and offer a range of cloud cover from 0 to 10. A few authors decided to group these eleven dummy variables into less groups in order to easier define "good" and "bad" weather and thus be able to easier interpret the results (S.-C. Chang, Chen, Chou & Lin, 2008; Kang et al., 2010; Saunders, 1993).

One of the issues of cloud data is deciding where is the border line between good and bad weather in coverage percentage. Saunders (1993) compared mainly two groups, 0–20% cloud coverage with 100% cloud coverage and concluded that there is a significant effect on the stock returns. However, Trombley (1997) argued that Saunders' procedure of comparing these two groups was the only possibility to get significant results. Any other two groups were not so delightful, he claimed there was even no significant difference between 0% and 100% groups.

2.2.2 Precipitation

Cloud cover and rain are very related to each other and data about rain are easily available, it is generally a part of the weather datasets, thus precipitation was also quite often included in the model. Nevertheless, the effect of rain normally appeared to be inferior (Hirshleifer & Shumway, 2003; Loughran & Schultz, 2004; Saunders, 1993). It could also be due to multicollinearity between rain and cloud cover. 85% of all rain occurs on 100% cloud cover days (Saunders, 1993). Research of Dowling and Lucey (2005) and Sheikh, Shah and Mahmood (2017), performing their analysis on Irish and Indian markets respectively, did find the effect of precipitation significant together also with daylight saving time changes and lunar phases in the first case, with seasonal affective disorder and temperature in the second one.

2.2.3 Humidity

Humidity was not commonly included in the model, and if it was, the effect did not tend to be significant (Dowling & Lucey, 2005; Shim, Kim, Kim & Ryu, 2015). In certain articles humidity served as a helping indicator to decide whether the weather is considered good or bad. Krämer and Runde (1997) defined bad weather as a combination of 100% cloud cover and humidity between 70% and 90%. Kang et al. (2010) divided humidity to low and high and also combined it with the cloud cover variable.

2.2.4 Lunar phases

Beliefs that the moon influences human behavior are old thousands of years. Besides the legends around the world, moon cycles used to be an important factor for calendars and there are still Holidays, like Easter or Passover, which date of celebration still depends on the moon (Dichev & Janes, 2003).

Dichev and Janes (2003) found an effect of lunar cycle in stock returns. The returns in 15 days around new moon were twice as high as the returns in the other 15 days, thus the days around full moon. Their results were consistent while performing the analysis on major indexes in 25 countries over the previous 30 years.

Despite the research mentioned above, the moon phase variable was not commonly included by other researchers. Nevertheless, some of the following articles contained the moon variable. Some of them (Goetzmann & Zhu, 2005) did not find any effect, whereas others (Dowling & Lucey, 2005) did. Sheikh et al. (2017) also detected the effect, however not on Stock returns but rather on volatility.

2.2.5 SAD

Seasonal affective disorder (SAD) introduced by Rosenthal et al. (1984) is a condition affecting people due to fewer hours of daylight. SAD is supposed to have an influence on people's behavior and risk perception linked to stock returns. The idea to include this variable in an econometric model got first Kamstra et al. (2003). SAD effect in their article appeared to be significant and strong and thus they basically established a trend to include SAD in the model analyzing the impact of weather conditions on stock returns, since many of their research followers (Apergis, Gabrielsen & Smales, 2016; Dowling & Lucey, 2005, 2008; Goetzmann et al., 2014; Kelly & Meschke, 2010; Sheikh et al., 2017; Symeonidis, Daskalakis & Markellos, 2010) did include this variable.

The most used method of including SAD throughout the articles was the one proposed by Kamstra et al. (2003), calculating the number of hours of daylight during days in fall and winter using countries' latitude and thus the declination angle of the sun. Sheikh et al. (2017) did not calculate the variable using countries' latitudes and instead downloaded the data about night lengths from U.S Naval Observatory website.

SAD effect could be so substantial that if a pro-SAD strategy of investment was implemented for twenty years between 1980 and 2000 and a reallocation of the investment was done two times a year at fall and spring equinox, moving the money from Sweden to Australia according to the presence of fall and winter would have lead to a gain of 7.9 percent higher than would be a strategy of allocating the investment equally between Sweden and Australia, claimed Kamstra et al. (2003).

2.2.6 Other variables

Among other variables used in the literature there is temperature, which no article found to be of any influence, with an exception of the market in Taiwan (T. Chang et al., 2006) and other South Asian countries (Sheikh et al., 2017). Dowling and Lucey (2005) included in their study geomagnetic storms and Friday 13th. Even though these variables, together with lunar phases, sound a little bit over the line, Dowling and Lucey (2005) claimed they were argued to be psychologically important. Nevertheless, neither Friday 13th nor geomagnetic storms showed any significance. Not even their second study showed significance and after grouping mood proxy factors they also failed to show the effect of lunar phases (Dowling & Lucey, 2008).

2.3 Used data

Data used in related works consisted always of two different groups of data, namely weather data and financial data.

2.3.1 Weather data

Saunders (1993) began a trend to obtain climatological data from the National Climatic Data Center, which was lately renamed to NOAA. NOAA database includes weather data from meteorological stations over the whole world, not only the US, and the data is available through their websites. The wide offer and simplicity of the obtainment were surely the main reasons why this source was used the most in the related literature.

Saunders (1993) divided his data of New York weather into two periods (1927–1960 and 1960–1989). The data were divided due to the change of the weather observation point. Akhtari (2011) also focused only on New York in 1948–2010, and thus used only the second weather observatory that was suggested by Saunders (1993). Hirshleifer and Shumway (2003) used the same source for 26 different places in 1982–1997, the same data can be found also in the paper of Symeonidis et al. (2010). Loughran and Schultz (2004) used also almost the same cycle (1984–1997), however, they did not focus on international markets but on the location of the NASDAQ listed company's headquarters in the US. Although Dowling and Lucey (2005) did not obtain their meteorological data from NOAA but from Irish meteorological organization Met Eireann, they at least used NOAA to get access to geomagnetic data. Goetzmann and Zhu (2005) and Goetzmann et al. (2014) focused like Loughran and Schultz (2004) on different cities in the US, using NOAA data for 1991–1996 and 1999–2010 respectively. NOAA database contains hourly intervals, which made possible for S.-C. Chang et al. (2008) to focus on intraday trading in 1994–2004. Kelly and Meschke (2010) did not use the same period for each out of the used 36 countries, the oldest data was used according to the match of the weather and the finance data. Thus the beginning for each country lied somewhere between 1948 and 1996 with the end in 2008. Even Sheikh et al. (2017) performing their analysis only on South Asian's markets took advantage of NOAA database records for the years 2000–2012.

Other authors usually focused on only one country and thus did not have the incentive to obtain data from an international database with consistent form of the data, because local databases were good enough for their purposes. Krämer and Runde (1997) used data from Frankfurt airport, Tufan and Hamarat (2004) from Turkish State Meteorological Service database, Dowling and Lucey (2005) from the Irish national meteorological organization Met Eireann, T. Chang et al. (2006) from Central Weather Bureau of Taiwan, Kang et al. (2010) from China Meteorological Administration, Ødegaard (2014) from Norwegian Meteorological Service, Shim et al. (2015) from Climate Data Service System Korea. Nevertheless, there were also exceptions. Kamstra et al. (2003) performed their analysis on 8 different countries and also did not obtain their data from NOAA, but from Lamont-Doherty Earth Observatory of Columbia University. The other exception is Apergis et al. (2016) using Accuweather.com as the source of their weather data.

2.3.2 Financial data

Concerning the financial data, the most common source by far was Datastream (Apergis et al., 2016; Dowling & Lucey, 2005; Hirshleifer & Shumway, 2003; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Kim, 2017; Sariannidis, Giannarakis & Partalidou, 2016). In other cases the data was obtained either directly from respective stock exchange database (Krämer & Runde, 1997; Ødegaard, 2014; Saunders, 1993; Sheikh et al., 2017; Tufan & Hamarat, 2004), from a university database (S.-C. Chang et al., 2008; Goetzmann et al., 2014; Loughran & Schultz, 2004), or from a database of a private company (Goetzmann et al., 2014; Goetzmann & Zhu, 2005).

2.4 Effects

2.4.1 Effect found

The effects found in the literature differ from article to article due to the usage of various econometric methods and completely different data, meaning different amount of markets, different time periods and different included variables. That is the reason why it is complicated to come to a clear opinion. Often even the articles come to uncertain conclusions, because a slight change of defining the variables leads to a very different result. Thus the whole topic is frequently criticized for data mining (Kim, 2017; Krämer & Runde, 1997).

Papers by Saunders (1993), Hirshleifer and Shumway (2003), T. Chang et al. (2006), Symeonidis et al. (2010), Akhtari (2011), Goetzmann et al. (2014) concluded that cloud cover positively influences the returns with the statistical significance of at least 10% (T. Chang et al., 2006), usually the significance is at 5% or even 1% level. Shim et al. (2015) found cloud cover to be significant only before the financial crises in 2007. S.-C. Chang et al. (2008), who focused on intraday trading, also found the effect of cloud cover on stock returns. However, the effect was significantly different from zero, at 1% level, only during the first 15 minutes of the trading day.

Weather temperature was found statistically significant at 10% level in Taiwan (T. Chang et al., 2006) and at 5% level in Shanghai (Kang et al., 2010). In the first case both extreme temperatures, the high one and the low one, had an influence, whereas in the second one the significance was present only at the low temperatures.

Both Shim et al. (2015) and Sariannidis et al. (2016) who were looking for effect of weather on price volatility found wind to negatively influence it at 10% significance level. Sariannidis et al. (2016) performing their study considering socially responsible companies claimed that increased wind speed is crucial for dilution of pollution and responsible investors feel safe and optimistic which makes prices more stable.

Dowling and Lucey (2005) found rain to negatively influence equity returns on Irish market at 10% level. The conclusion of Sheikh et al. (2017) also claimed that rain is a significant factor on Indian market, however, the regression tables included in their article do not appear so clear.

SAD was found to be a significant factor considering both returns and price volatility. The effect on return was found to be negative, according to the psychological literature, and significant at 10% to 1% percent level according to the latitude, the more to the north or to the south the bigger and more significant the effect (Kamstra et al., 2003). These claims are also consistent with Dowling and Lucey (2008), who came to the same conclusions. Sheikh et al. (2017) found SAD to positively influence the returns in Indian markets, but as mentioned before, their conclusions were rather indecisive. Moreover, India is situated quite close to the equator and thus the SAD there should not have too much influence, since the daylight time is quite similar during the whole year.

Results about weather effects differ a lot in the papers, but interesting is that almost every author who included Monday effect in his model (Akhtari, 2011; S.-C. Chang et al., 2008; Dowling & Lucey, 2005; Goetzmann et al., 2014; Goetzmann & Zhu, 2005; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Krämer & Runde, 1997; Saunders, 1993) confirmed its presence with high significance.

2.4.2 Effect rejected

Most of the studies trying to find a weather condition influencing stock exchange behavior usually found one. Nevertheless, Trombley (1997) who replicated analysis of Saunders (1993) claimed that the relationship between weather and stocks was not as clear and strong as previously thought and that there might be no effect at all. Krämer and Runde (1997) performed the same procedure as Saunders (1993) on German data and they also came to the conclusion that stock returns are not affected by the local weather.

Loughran and Schultz (2004) who were analyzing localized trading behavior according to the companies' headquarters also did not find any relation between local cloud cover and stock returns. The only influence they found was that a snow storm in the city where the trading company is based lowers its trading volume during the day of the storm and also the following day by 17 % and 15% respectively.

Kelly and Meschke (2010) found no significance and criticized the economic definition of SAD. They cited three different psychology studies, Smoski et al. (2008), Clark, Iversen and Goodwin (2001) and Raghunathan and Pham (1999) who had detected a negative, neutral and a positive tendency, respectively, towards risk when being depressed. Anyway, most of the psychology studies, according to Kamstra et al. (2003), who introduced SAD to behavioral finance, agreed that depressions are related rather to the risk averseness.

Apergis et al. (2016) tried to explain the weather influence on stock exchange not to be direct via human's mood but rather by the change of energy prices, concretely change in prices of oil, natural gas or coal. However, the included results show every variable to be statistically significant at 10% level.

2.4.3 Criticism

According to Kim (2017) there is a huge problem with basically all the studies dealing with the weather topic in behavioral finance. All the papers adopted the traditionally used "p-value" as the indicator of statistical significance, even though it should be adjusted to the sample size. He pointed out that many authors adopted massive sample sizes which produce spurious statistical significance and argued that the conclusions are severely biased towards Type I error. To reach the balance between the probabilities of Type I and Type II error it would be reasonable to "adjust the level of significance as a decreasing function of sample size" (Kim, 2017, p. 6). As an alternative to p-value criterion he suggested to use Bayesian method of significance testing.

To prove that it is easy to reach p-value significance by using large enough data sample, he examined the effect of sun spots under the same research design as Hirshleifer and Shumway (2003). When performing the regression on a sample of 7,345 data inputs, the effect was negligible with no significance and a tiny R^2. After expanding the sample to 44,070 and more entries the effect stayed still small, but the significance at 5% level was reached, even though the goodness of fit did not get bigger, thus it is reasonable to expect that sun spots do not have any influence and the significance was obtained only by using too much data and a wrong method to justify the effect. When using alternative criteria, the statistical significance based on p-value could not be confirmed (Kim, 2017).

2.4.4 Methodology of previous papers

The estimation of parameters in previous studies was mainly done by ordinary least squares method (OLS). Kamstra et al. (2003) did not rely on OLS only and performed their analysis also using Maximum-likelihood method in order to be able to compare the results and GARCH model to control for heteroskedasticity. The results were very similar and even though the effects were a little smaller in magnitude, they still appeared economically important. Hirshleifer and Shumway (2003) and Loughran and Schultz (2004) used Logit regressions and tried to predict whether the return would be positive or negative. Dowling and Lucey (2005) performed their analysis using OLS but to deal with non-normality in the financial data they reanalyzed their data under least absolute deviation (LAD) and trimmed leas squares (TLS), however, their findings stayed qualitatively the same. In later studies it became common to perform the analysis using GARCH model (T. Chang et al., 2006; Dowling & Lucey, 2008; Kang et al., 2010; Sariannidis et al., 2016; Sheikh et al., 2017; Shim et al., 2015; Symeonidis et al., 2010).

It could seem like the early studies using simpler econometric analysis could have found more untrue effects than the latter ones adopting more advanced methods. However, according to the literature it is not the case and it is not so easy to decide which methods lead to confirmation of the weather influence more. There are early articles using simple OLS which rejected the effect of weather (Krämer & Runde, 1997), and there are quite new articles using GARCH model who found the effect of weather very significant (Symeonidis et al., 2010).

Chapter 3

Data

There are two types of data used in the thesis, similarly to previous studies. Weather data and financial data. The thesis focuses on the difference between emerging and developed markets according to Morgan Stanley Capital International All Country World Index (MSCI ACWI) classification (https://www.msci.com/acwi). The MSCI ACWI index consists of 24 emerging markets and 23 developed markets. The analyzed period is 2006–2017. The upper bound of the time interval was chosen in order to bring updated findings and the lower bound was determined by the availability of data from weather stations.

3.1 Financial data

Data of stock exchange close prices was obtained from Thomson Reuters Eikon using Datastream. The local stock indices were chosen correspondingly to their importance according to Thomson Reuters database. Local trading hours were found either on Wikipedia or on websites of the Stock Exchanges, if the information on Wikipedia was missing. Latitudes of all the cities were gathered on latitude.to.

To get rid of the trend in the development of prices the stock log-returns were calculated as

$$Return_t = log(Close\ price_t) - log(Close\ price_{t-1}) \tag{3.1}$$

Table 3.1: Emerging markets data

	City	Index	NOAA data	Trading hours (local time)	GMT	Latitude	Land area (sq. km)	First day	Last day	Number of days
Brazil	Sao Paulo	.BVSP	Guarulhos	09:30 - 18:00	-3	-23.54°	8358 K	03. 01. 2006	28. 09. 2017	2,102
Chile	Santiago	.SPCLXIPSA	Benitez	09:30 - 16:00	-4	-33.44°	744 K	03. 01. 2006	29. 09. 2017	2,651
Colombia	Bogota	.COLCAP	Eldorado	09:30 - 16:00	-5	4.65°	1039 K	17. 01. 2008	29. 09. 2017	1,873
Mexico	Mexico City	.MXX	Benito Juarez	09:30 - 16:00	-5	19.25°	1944 K	03. 01. 2006	15. 09. 2017	2,306
Peru	Lima	.SPBLPGPT	Jorge Chavez	09:00 - 16:00	-5	-12.05°	1280 K	03. 01. 2006	19. 11. 2015	2,293
Czech Republic	Praha	.PX	Ruzyne	09:15 - 16:00	1	50.08°	77 K	03. 01. 2006	29. 09. 2017	2,935
Egypt	Cairo	.EGX30	Cairo	10:30 - 14:30	2	30.04°	995 K	03. 01. 2006	27. 09. 2017	2,233
Greece	Athens	.ATF	Eleftherios	10:00 - 17:20	2	37.98°	131 K	03. 01. 2006	07. 07. 2014	1,649
Hungary	Budapest	.BUX	Ferihegy	09:00 - 16:30	1	47.5°	90 K	03. 01. 2006	19. 09. 2017	1,570
Poland	Warsaw	.WIG	Okecie	09:00 - 16:20	1	52.23°	304 K	03. 01. 2006	29. 09. 2017	2,927
Qatar	Doha	.QSI	Doha	09:30 - 13:15	3	25.29°	12 K	03. 01. 2006	25. 09. 2017	2,470
Russia	Moscow	.IMOEX	Sheremetyevo	10:30 - 19:00	3	55.76°	16378 K	12. 01. 2006	04. 09. 2017	1,558
South Africa	Johannesburg	.JALSH	South Africa	09:00 - 17:00	2	-26.2°	1214 K	04. 01. 2006	29. 09. 2017	2,640
Turkey	Istanbul	.XUTUM	Ataturk	09:30 - 17:30	2	41.01°	770 K	03. 01. 2006	29. 09. 2017	2,911
United Arab Emirates	Abu Dhabi	.ADI	Abu Dhabi	11:45 - 17:00	4	24.45°	84 K	03. 01. 2006	01. 10. 2017	2,519
China	Shanghai	.SSEC	Pudong	09:30 - 15:00	8	31.23°	9326 K	05. 01. 2006	29. 09. 2017	1,902
India	Mumbai	.BSESN	Chhatrapati	09:00 - 15:30	5:30	19.08°	2973 K	03. 01. 2006	29. 09. 2017	2,901
Indonesia	Jakarta	.JKSE	Soekarno	09:30 - 16:00	7	-6.18°	1812 K	03. 01. 2006	29. 09. 2017	2,786
South Korea	Seoul	.KS11	Gimpo	08:00 - 15:00	9	37.57°	97 K	09. 01. 2006	25. 09. 2017	1,932
Malaysia	Kuala Lumpur	.KLSE	Kuala Lumpur	09:00 - 17:00	8	3.16°	329 K	06. 07. 2006	29. 09. 2017	2,736
Pakistan	Karachi	.KSE	Jinnah	09:30 - 15:30	5	24.86°	771 K	04. 01. 2006	29. 09. 2017	2,893
Philippines	Philippines	.PSI	Ninoy	09:30 - 12:10	8	12.88°	298 K	03. 01. 2006	27. 09. 2017	2,065
Taiwan	Taipei	.TWII	Sungshan	09:00 - 14:00	8	25.03°	32 K	03. 01. 2006	22. 01. 2015	1,801
Thailand	Bangkok	.SETI	Bangkok	09:30 - 14:30	7	13.76°	511 K	04. 01. 2006	28. 09. 2017	2,614

Table 3.2: Developed markets data

	City	Index	NOAA data	Trading hours (local time)	GMT	Latitude	Land area (sq. km)	First day	Last day	Number of days
Canada	Toronto	.GSPTSE	Toronto city centre	9:30 - 16:00	-5	43.65323°	9094 K	04. 01. 2006	29. 09. 2017	2,811
United States	New York	.SPX	John F Kennedy international airport	9:30 - 16:00	-5	40.71278°	9148 K	04. 01. 2006	29. 09. 2017	2,937
Austria	Vienna	.ATX	Schwechat	8:55 - 17:35	1	48.20817°	82 K	03. 01. 2006	29. 09. 2017	2,888
Belgium	Brussels	.BFX	Brussels Natl	9:00 - 17:30	1	50.85034°	30 K	03. 01. 2006	29. 09. 2017	2,989
Denmark	Copenhagen	.OMXC20	Kastrup	9:00 - 17:00	1	55.6761°	42 K	03. 01. 2006	29. 09. 2017	2,923
Finland	Helsinki	.OMXH25	Vantaa	9:00 - 17:30	1	60.16986°	304 K	03. 01. 2006	29. 09. 2017	2,933
France	Paris	.FCHI	Charles de Gaule	9:00 - 17:30	1	48.85661°	550 K	03. 01. 2006	29. 09. 2017	2,984
Germany	Frankfurt	.GDAXI	Frankfurt main	8:00 - 20:00	1	50.11092°	349 K	03. 01. 2006	28. 09. 2017	1,544
Ireland	Dublin	.ISEQ	Dublin	8:00 - 16:30	0	53.34981°	69 K	04. 01. 2006	29. 09. 2017	2,963
Israel	Tel Aviv	.TA35	Ben Gurion	9:00 - 17:30	2	32.09291°	20 K	02. 01. 2006	01. 10. 2017	2,846
Italy	Milan	.FTITLMS	Malpensa	9:00 - 17:35	1	45.4642°	294 K	03. 01. 2006	29. 09. 2017	2,932
Netherlands	Amsterdam	.AEX	Schiphol	9:00 - 17:40	1	52.36798°	34 K	03. 01. 2006	29. 09. 2017	2,989
Norway	Oslo	.OBX	Oslo Blindern	9:00 - 16:30	1	59.91387°	304 K	03. 01. 2006	29. 09. 2017	2,909
Portugal	Lisbon	.PSI20	Lisboa	9:00 - 17:30	1	38.72225°	91 K	05. 01. 2006	22. 08. 2017	1,656
Spain	Madrid	.IBEX	Barajas	9:00 - 17:30	1	40.41678°	499 K	03. 01. 2006	29. 09. 2017	2,973
Sweden	Stockholm	.OMXS30	Stockholm	9:00 - 17:30	1	59.32932°	410 K	01. 03. 2010	29. 09. 2017	1,831
Switzerland	Zurich	.SSMI	Zurich	9:00 - 17:30	1	47.37689°	40 K	04. 01. 2006	29. 09. 2017	2,923
United Kingdom	London	.FTSE	Heathrow	8:00 - 16:30	0	51.50735°	242 K	04. 01. 2006	29. 09. 2017	2,180
Australia	Sydney	.AXJO	Sydney Intl	10:00 - 16:00	10	-33.86882°	7682 K	04. 01. 2006	29. 09. 2017	2,893
Hong Kong	Hong Kong	.HSI	Hong Kong Intl	9:30 - 16:00	8	22.3192°	1 K	04. 01. 2006	29. 09. 2017	2,794
Japan	Tokyo	.N225E	Tokyo Intl	9:00 - 15:00	9	35.68949°	364 K	05. 01. 2006	20. 09. 2017	1,795
New Zealand	Wellington	.NZ50	Wellington Intl	10:00 - 17:00	12	-41.28646°	265 K	05. 01. 2006	28. 09. 2017	2,138
Singapore	Singapore	.STI	Singapore Changi Intl	9:00 - 17:00	8	1.35538°	0.7 K	04. 01. 2006	29. 09. 2017	2,928

The issue of this representation of stock markets is that not every company traded is included, stock indices consist rather of stocks considered being of high quality, and so the reflection of the true market situation is not perfect.

3.2 Weather data

Weather data was obtained from NOAA database. NOAA is a large scientific agency, run under United States Department of Commerce, with the aim of observing conditions of the oceans, and the atmosphere. Although their weather stations are situated in the U.S., they possess and offer data from weather stations worldwide. The advantage of using this database is that the data should be reliable and comparable among different countries, since the form of data is consistent.

NOAA data used in this thesis consists of hourly records of weather conditions at certain weather stations. There are many variables included, like wind direction and speed, sky cover, type of clouds, visibility, temperature, air pressure and precipitation. Out of these variables the thesis inspires by previous literature and focuses on variables based on claimed influence on human sentiment. Thus the most important should appear sky cover, precipitation and temperature.

3.2.1 Sky cover

Sky cover used to be recorded in numbers from 0 (clear) to 10 (overcast) (Hirshleifer & Shumway, 2003), nowadays they do not use this scale anymore and offer only 4 dummy variables, explained as 0 = "clear", 1/8 to 4/8 = "scattered", 5/8 to 7/8 = "broken" and 8 = "overcast". In the data there are only expressions "CLR", "SCT", "BKN" and "OVC", the number values are not included, which means the division is not as precise as in the previous literature. On the other hand there is no need to create intervals for defining good and bad weather as they did in the past (S.-C. Chang et al., 2008; Kang et al., 2010; Saunders, 1993), because it has already been done by the weather station. We can consider "clear" and "scattered" as a good weather and the remaining, "broken" and "overcast" as a bad one.

To be able to include in the model the variable Sky cover to see the effect of sunshine on stock returns, the middle values of the intervals were assigned to the sky situation (CLR = 0, SCT = 0.3125, BKN = 0.75, OVC = 1), then the whole trading day was summed and averaged. After this procedure it is possible to either match the final result with the original intervals and explore the effect using dummy variables or leave it as numbers and analyze the overall effect of sunshine. By trading day is meant the period Trading

Hours as seen in Tables 3.1 and 3.2 plus one hour preceding the opening in the morning.

3.2.2 Precipitation

Precipitation appears in the data sets in three possible columns. Either as the amount of rain in last hour (PCP01), last six hours (PCP06) or preceding 24 hours (PCP24). The intention was to use the last hour variable to be the most precise, unfortunately the data among weather stations is not consistent and some of them include only PCP01, some of them only PCP06. PCP24 is almost always missing. None of the previous works mentioned missing precipitation data, even though most of them were using the same database. In order not to have too much missing data, both PCP01 and PCP06 are used, always according to availability of data. Nevertheless, for a few countries no precipitation data is included.

3.2.3 Temperature

The variable temperature shows the air temperature of every registered hour in degrees of Fahrenheit. There is no missing data among the countries. Like with previous variables, also temperature was averaged for every trading day in order to include it into the model.

3.3 Other variables

3.3.1 SAD

Seasonal affective disorder (SAD) was calculated according to the approach described by Kamstra et al. (2003). SAD is defined as

$$SAD_t = \begin{cases} H - 12 & \text{for t being a day in fall or winter} \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

where H_t is the number of hours of the day in day t. H_t is calculated as follows

$$H_t = \begin{cases} 24 - 7.72 \cdot arccos\left[-tan\left(\frac{2\pi\delta}{360}\right) tan(\lambda_t)\right] & \text{in the Northern Hemisphere} \\ 7.72 \cdot arccos\left[-tan\left(\frac{2\pi\delta}{360}\right) tan(\lambda_t)\right] & \text{in the Southern Hemisphere} \end{cases} \tag{3.3}$$

δ stands for latitude of a city where the stock exchange is located and λ_t the declination angle of the sun and is calculated as

$$\lambda_t = 0.4102 \cdot sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right] \tag{3.4}$$

where $julian_t$ stands for a day of the year, meaning that January 1st is number 1, January 2nd 2, etc.

Fall

A fall dummy is included in order to be able to differentiate between fall and winter SAD effect (Kamstra et al., 2003).

$$Fall_t = \begin{cases} 1 & \text{for t being a day in fall} \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

Fall is defined as a period between 23rd September and 21st December in the Northern Hemisphere or between 21st March and 21st June in the Southern Hemisphere.

3.3.2 Monday and January effects

Previous studies also often included well known seasonal effects like Monday and January effects and found them significant (Akhtari, 2011; S.-C. Chang et al., 2008; Dowling & Lucey, 2005; Goetzmann et al., 2014; Goetzmann & Zhu, 2005; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Krämer & Runde, 1997; Saunders, 1993). Because of previous results it seems to be reasonable to include also these variables in an econometric model, because their significance implies their place among the explanatory variables of market returns. They are included simply as dummy variables, meaning:

$$Monday_t = \begin{cases} 1 & \text{for day}_t \text{ being a Monday} \\ 0 & \text{for the other days} \end{cases} \tag{3.6}$$

$$January_t = \begin{cases} 1 & \text{for day}_t \text{ being in January} \\ 0 & \text{for the other days} \end{cases} \tag{3.7}$$

Chapter 4

Methodology

4.1 Ordinary Least Squares

Following the Section 2.4.4 Ordinary Least Squares (OLS) method is used in the thesis. In the thesis the following model is used to analyze the effect of mood affecting variables on Stock Returns:

$$R_t = \beta_0 + \beta_1 SKC_t + \beta_2 SAD_t + \beta_3 Fall_t + \beta_4 Temp + \beta_5 Prec + D_1 M_t + D_2 J_t + e_t \tag{4.1}$$

where R stands for returns, SKC for sky cover (cloudiness), SAD for seasonal affective disorder, $Fall$ is a dummy variable with value 1 for autumn and 0 otherwise, $Temp$ stands for temperature, $Prec$ for the amount of precipitation, R_{t-1}, which is not included for every market, thus does not figure in the equation above, for lagged returns, M and J are dummy variables for Monday and January respectively, with values 1 if Monday or January, 0 otherwise, e_t stands for an error term.

The Benefit of using OLS is the easy interpretation of the results and its simplicity, the disadvantage is necessity of conditions which must hold, specified in detail in Wooldridge (2015). The tests used for verifying the OLS assumptions are described in Section 4.3.

4.1.1 AIC

Akaike information criterion (AIC) is one of the econometric tools for a model selection. It compares the quality of a model relatively to the quality of other models using AIC estimator. By quality it is meant the optimum of the trade off between model's goodness of fit and it's simplicity. The AIC estimator is defined as

$$AIC = -2log(\hat{\mathcal{L}}) + 2K \tag{4.2}$$

where $\hat{\mathcal{L}}$ is the maximum value of log likelihood of the model, K is a bias-correction term and stands for the number of estimable parameters (Burnham & Anderson, 2003). Chosen is then the model, for which AIC is the lowest.

4.2 GARCH model

Generalized autoregressive conditional heteroskedasticity model (GARCH), introduced by Bollerslev (1986) is an instrument to investigate volatility of time series by analyzing the size of errors and its time development. GARCH predicts the variance for day t using a weighted average of the long-run variance, the forecast made in previous period and the new information that was not available when previous forecast was made, captured by the most recent squared residual.

Autoregressive integrated moving average model (ARIMA) needs to be fit for the dependent variable to obtain ARIMA estimated residuals in order to be able to estimate GARCH. Already the performed OLS described in previous section is autoregressive, but considers also other explanatory variables, which is not desired in this case, thus for the purpose of modeling GARCH, ARIMA model was performed automatically by the used software.

Following Kang et al. (2010), GARCH(1,1) which is used in the thesis is defined as

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{4.3}$$

where h_t stands for squared estimated residuals from the ARIMA model, $u_t = \sqrt{h_t z_t}$, $u_t \sim N(0, h_t)$ and z_t is an independent identically distributed random variable. The assumptions which must hold are $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$. In the equation α_0 expresses a weighted average of long term variance, α_1 a weighted average of a new information and β_1 a weighted average of the predicted variance. GARCH(1,1) is stationary if the sum of α_0, α_1 and β_1 is smaller than 1.

Because the aim of this thesis is to look for the influence of other variables on stock returns, the standard GARCH equation has been extended with four mood weather variables in the following form

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \theta_1 W_{SAD_{t-1}} + \theta_2 W_{SKC_{t-1}} + \theta_2 W_{Temp_{t-1}} + \theta_4 W_{PCP_{t-1}} \tag{4.4}$$

where W_{SAD} stands for seasonal affective disorder, W_{SKC} for sky cover, W_{Temp} for temperature and W_{PCP} for precipitation. In order to make the effects strong, some of the variables were transformed into dummy variables. Sky cover was assigned values 1, 0 and -1 for cloudiness being 0-0.25%, 0.25-0.75% and 0.75-100% respectively, inspired by Saunders (1993). Precipitation was assigned 0 for not a raining day and 1 for a raining day and temperature was assigned 1 for the temperature exceeding the average temperature for the month in day t and stayed 0 otherwise.

4.3 Statistical tests

When dealing with time series it is important to check the data for trends which could influence the regression and by that make any found correlation spurious. In the thesis there were performed Augmented Dickey-Fuller test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to test for stationarity of the time series data. To verify assumptions of OLS, Breuch-Godfrey test and Ljung-Box test were performed to test for autocorrelation and Breusch Pagan test to test for homoskedasticity.

4.3.1 Augmented Dickey Fuller test

Augmented Dickey-Fuller test serves as an indicator of a unit root present in a time series. Augmented Dickey-Fuller test is an extended version of Dickey-Fuller test defined as

$$\Delta y_t = \alpha + \theta y_{t-1} + e_t \tag{4.5}$$

where Δy_t is a change in the dependent variable and the null hypothesis is $H_0 : \theta = 0$ against the alternative $H_1 : \theta < 0$ if $t_{\hat{\theta}} < c$, where c stands for a critical value according to a table of asymptotic critical values for unit roots and $t_{\hat{\theta}}$ is the t statistic for θ.

Augmented Dickey-Fuller test includes p lags of Δy_t, allowing dynamics in the variable. The used regression in this case is

$$\Delta y_t \text{ on } y_{t-1}, \Delta y_{t-1}, ..., \Delta y_{t-p} \tag{4.6}$$

The addition of lagged changes should detect any serial correlation in Δy_t (Wooldridge, 2015).

4.3.2 KPSS test

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is a useful complement of Dickey-Fuller test because of the opposite hypothesis. The null hypothesis in this test is stationarity of the data with the alternative of non-stationarity. The test is based on a linear regression which decomposes the series into a determenistic trend ξ a random walk r_t and a stationary error ε_t

$$y_t = \xi t + r_t + \varepsilon_t \tag{4.7}$$

where the random walk $r_t = r_{t-1} + u_t$ and u_t are iid. The statistic used is one-sided LM statistic (Kwiatkowski, Phillips, Schmidt & Shin, 1992).

4.3.3 Breusch-Godfrey test

Breusch-Godfrey test is a test for autocorrelation in the error terms of the regression. After running the original OLS y_t on $x_{t1}, ..., x_{tk}$, the residuals $\hat{u}_t$

are regressed on the lagged residuals $\hat{u}_{t-1}, ...\hat{u}_{t-q}$. To reject or not to reject the null hypothesis of autocorrelation, Lagrange multiplier (LM) statistic is used. It is defined as

$$LM = (n - q)R^2_{\hat{u}} \tag{4.8}$$

where $R^2_{\hat{u}}$ is R-squared from the regression of residuals on lagged residuals. Under the null hypothesis $LM \sim \chi^2_q$ (Wooldridge, 2015).

4.3.4 Ljung-Box test

Ljung-Box test is a test for autocorrelation of the disturbances. It is defined as

$$Q = T(T+2)\sum_{j=1}^{P} \frac{r_j^2}{T-j} \tag{4.9}$$

where $r_j = (\Sigma_{t=j+1}^{T} e_t e_{t-j})/(\Sigma_{t=1}^{T} e_t^2)$, P stays for number of lags and Q refers to critical values in χ^2 table with P degrees of freedom (Greene, 2003). The null hypothesis of the test is independent distribution of the data against the alternative of no independence, in other words a presence of a serial correlation.

4.3.5 B-P test

Breusch-Pagan test is a test for homoskedasticity. It is used to find out whether it is necessary to replace standard errors by heteroskedasticity robust standard errors. The residuals $\hat{u}_t$ are obtained from the OLS regression and the following equation is considered

$$\hat{u}_t^2 = \delta_0 + \delta_1 x_{t1} + ... + \delta_k x_{tk} + \nu_t \tag{4.10}$$

with the null hypothesis H_0: $\delta_0 = ... = \delta_k = 0$ and assuming ν_t to be iid. If the null hypothesis of homoskedasticity is rejected, heteroskedasticity robust standard errors can be used to correct the bias in the standard errors, when evaluating the effects in the OLS regression.

Chapter 5

Results

The software used for the analysis was mainly R, GARCH models were performed in Gretl and tables were created by using R package Stargazer (Hlavac, 2015).

5.1 OLS

First of all, because of dealing with time series, the tests for stationarity were necessary to run. The variable Returns was tested for presence of a unit root using Augmented Dickey-Fuller test. P-values for all the markets were smaller than 0.01, meaning that the null hypothesis of a unit root in the data could be rejected. To be sure that all the data is stationary and thus not leading to spurious correlations, also KPSS test was used, because its null hypothesis is the opposite of the one of Dickey-Fuller test, which means they complement each other. Most of the markets show a p-value of KPSS test larger than 0.1 and so the null hypothesis of stationarity cannot be rejected. In three countries (Ireland, Peru and United Arab Emirates) the p-value is small, but at 1% level of significance the null hypothesis still cannot be rejected. The results of the tests are reported in Tables 6.1 and 6.2.

For testing autocorrelation, Breusch-Godfrey test was used. When the model 4.1 was showing marks of autocorrelation, lags of the dependent variables were included and the model was tested again. Using a test level of a significance of 1%, among all the markets serial correlation can be rejected after including 0 to 2 lagged dependent variables in the regression.

Breusch-Pagan test was used to test the data for heteroskedasticity. Testing at 10% level of significance, the null hypothesis of homoskedasticity was rejected among all the markets. To deal with heteroskedasticity in order not to have biased OLS estimators, heteroskedasticity robust standard errors were adopted. The results of the regressions can be seen in Tables 6.3 and 6.4.

In Tables 5.1 and 5.2 there are reported summaries of the models. In the tables the numbers of significant explanatory variables at different levels of significance are cumulative, the variables significant at 5% level are also reported among the variables significant at 10% level and variables significant at 1% level are reported in all the levels. Further the effects are reported according to the sign of the estimated coefficients, either positive or negative. SKC stands for sky cover, Temp for temperature, PCP for precipitation, SAD for the lack of daylight hours during the time between the autumn and the spring equinoxes, Fall and Jan express whether the day is in autumn and in January respectively and Mon stays for the day being a Monday. lag1 and lag2 are returns lagged by 1 and 2 days respectively.

Table 5.1: OLS; Emerging

Emerging	**SKC**		**Temp**		**PCP**		**SAD**		**Fall**		**Mon**		**Jan**		**lag1**		**lag2**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	13	11	10	14	9	8	20	4	8	16	5	19	5	19	13	0	0	1
Significant at 10%	1	0	0	0	4	3	3	0	2	2	1	9	1	1	12	0	0	1
Significant at 5%	0	0	0	0	1	2	2	0	1	1	1	5	0	1	12	0	0	0
Significant at 1%	0	0	0	0	1	1	0	0	0	0	0	3	0	0	9	0	0	0

Table 5.2: OLS; Developed

Developed	**SKC**		**Temp**		**PCP**		**SAD**		**Fall**		**Mon**		**Jan**		**lag1**		**lag2**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	9	13	6	16	11	7	20	2	6	16	2	20	1	21	2	1	0	1
Significant at 10%	2	4	1	4	1	2	2	0	0	0	0	4	0	5	2	1	0	1
Significant at 5%	1	2	0	2	1	1	1	0	0	0	0	4	0	1	1	1	0	0
Significant at 1%	0	0	0	0	1	1	0	0	0	0	0	2	0	0	0	1	0	0

The only variable that is significant in many markets is a Monday dummy.

It stays consistent having a negative influence on index returns across almost all the markets as stated by previous works (Akhtari, 2011; S.-C. Chang et al., 2008; Dowling & Lucey, 2005; Goetzmann et al., 2014; Goetzmann & Zhu, 2005; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Krämer & Runde, 1997; Saunders, 1993). It occurs to be significant at 10% level among 9 emerging and 4 developed markets, although in China it is significant at 5% level in the opposite direction. The other consistent variables according to their sign are January dummy and SAD, but their significance is not that strong. SAD acts according to the suggestions of Kamstra et al. (2003), having a positive sign, whereas January, being mostly negative does not to previous research (Rosol, 2016). The significance of SAD variable, however, does not correspond to the original theory of Kamstra et al. (2003). It is supposed to influence human behavior stronger the further from the Equator, but the analysis produced exactly the opposite results. Among emerging markets it has been found significant only in countries situated quite close to the Equator in comparison to the others (Peru, China and Taiwan). Among developed markets the significance corresponds to the theory by being significant in Ireland, consistently with the findings of Dowling and Lucey (2005), but Ireland is the only northern market with any effect found. Cloudiness, temperature and precipitation do not show any effect since their estimators are mostly not significant and if they are, the effect is both positive and negative.

5.2 Model selection using AIC

Because different weather factors could influence the stock returns in each market differently, Akaike information criterion, described in Section 4.1.1, was implemented for each market separately to find out which models fit different markets the best. The variables used are the same as in Section 5.1, expanded by lagged returns up to number ten. For each market separately models with all the combinations of the variables were evaluated and the one with lowest AIC was chosen. The results are demonstrated in Tables

6.5 and 6.6.

Table 5.3: Model AIC; Emerging

Emerging	**SKC**		**Temp**		**PCP**		**SAD**		**Mon**		**Jan**		**lag 1**		**lag (2-6)**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	1	0	0	1	3	0	4	0	1	12	1	2	16	0	0	5
Significant at 10%	1	0	0	0	2	0	1	0	1	10	1	0	14	0	0	3
Significant at 5%	0	0	0	0	0	0	0	0	1	5	0	0	14	0	0	1
Significant at 1%	0	0	0	0	0	0	0	0	0	3	0	0	9	0	0	0

Table 5.4: Model AIC; Developed

Developed	**SKC**		**Temp**		**PCP**		**SAD**		**Mon**		**Jan**		**lag 1**		**lag (2-5)**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	2	5	1	7	2	2	1	0	0	6	0	1	3	1	1	4
Significant at 10%	2	3	1	5	1	1	0	0	0	4	0	1	2	1	0	2
Significant at 5%	1	2	0	1	0	0	0	0	0	4	0	0	1	1	0	2
Significant at 1%	0	0	0	0	0	0	0	0	0	2	0	0	1	1	0	0

Summarized results are displayed in Tables 5.3 and 5.4. The idea of the summary tables is the same as described in previous section. In this case however, it is worth to notice that in the row *Overall* are counts of individual variables that were included by the automatic process of choosing the best model according to AIC. It means, for example, that Sky cover appears only in one model among emerging markets and seven times among developed markets, as can be seen in the table.

Similarly to the model in Section 5.1, only the dummy variable Monday is statistically significant, again mainly among emerging markets. The other consistent and very significant variable is the return of the previous day, being included in 16 emerging market models and being negative in all of them and in 14 of them significant at 5% level. Returns of previous days do not appear to be very important as explanatory variables. Among developed markets there is also a visible effect of temperature, but the occurrence is rather rare. The presence of lagged returns corresponds to the model in Section 5.1, where the autocorrelation of returns was dealt with by including lagged variables according to the results of Breusch-Godfrey test. Because of presence of heteroskedasticity, also in these model standard robust errors were used.

5.3 Replication of previous models

The results in previous section did not reject the hypothesis of no evidence of impact of weather variables on stock returns, which is in contradiction with the conclusions of the previous studies. Due to this fact, in this section there are replicated approaches of papers which have published significant results, in order to find out, if their models fit the data better or not.

5.3.1 Simple OLS with SKC and lagged return

Following the original idea of Saunders (1993) and his followers Hirshleifer and Shumway (2003) and (Akhtari, 2011) who worked with a similar model, the following regression was run,

$$R_t = \alpha + \beta_1 SKC_t + \beta_2 M_t + \beta_3 J_t + \beta_4 R_{t-1} + \epsilon_t \tag{5.1}$$

where R_t is defined as a return of the index for day t, SKC_t is a dummy variable for the average cloud cover in day t (being 1 for cloud cover between 0 and 0.25%, 0 for 0.25 to 0.75% and -1 for 0.75% to 1), M_t stands for a dummy variable for Monday, J_t for a dummy variably for January, R_{t-1} is a lagged return to control for the price movement dependence and ϵ_t is the error term. The results are reported in Tables 6.7 and 6.8 for emerging markets and developed markets respectively. In contradiction to their conclusion, which was a negative influence of cloudiness on index returns, the obtained results do not show any relation. From short summary of the results in tables 5.5 and 5.6 it is possible to conclude that when defining the model this way, sky cover has no relationship with stock returns at all. Among emerging markets there is absolutely no significance, among developed countries there is one estimate with 10% significance and one with 5% significance. Not even the sign of the estimators holds, the results are divided approximately in two halves between a positive and a negative sign. Omitting the lagged return variable as performed by Hirshleifer and Shumway (2003) does not create any difference.

Again, as confirmed by many previous papers (Akhtari, 2011; S.-C. Chang et al., 2008; Dowling & Lucey, 2005; Goetzmann et al., 2014; Goetzmann & Zhu, 2005; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Krämer & Runde, 1997; Saunders, 1993), Monday has a significant influence on stock returns which is consistent in both market groups, having always a negative effect among developed markets, in five of them significant and almost always a negative effect among emerging markets with nine of them significant. Again, the only significant positive effect of Monday is in China.

Even though the estimated coefficients of January effect are consistent in their sign, the significance of January effect in this data sample is not present. It tends to have mainly a negative direction and appears to be negatively significant only in Qatar, but also positively significant in Greece.

Interestingly the lagged return variable have almost always a positive influence among emerging markets, in 13 cases also significant, whereas among developed markets the division between positive and negative is even, also considering the significance.

Table 5.5: Replication of Saunders (1993); Emerging

Emerging	**SKC**		**Monday**		**January**		**Lagged Return**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	13	11	4	20	5	19	22	2
Significant at 10%	0	0	1	9	1	1	13	0
Significant at 5%	0	0	1	8	0	0	12	0
Significant at 1%	0	0	0	4	0	0	12	0

The reason for so different results from the previous works might be that Saunders (1993) and Akhtari (2011) concentrated only on one market and that is the New York stock exchange. The other issue of these two papers is the inclusion of large number of observations, reaching almost up to 10 000 in the research of Saunders (1993) and over 15 500 in the research of Akhtari (2011) as criticized by Kim (2017). Hirshleifer and Shumway

Table 5.6: Replication of Saunders (1993); Developed

Developed	**SKC**		**Monday**		**January**		**Lagged Return**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	11	11	0	21	2	20	11	11
Significant at 10%	1	1	0	5	0	0	6	7
Significant at 5%	1	0	0	4	0	0	4	5
Significant at 1%	0	0	0	2	0	0	2	1

(2003) performed their analysis on 26 stock exchanges internationally and the significance of city by city results was scarce, similarly to those reported in Tables 6.7 and 6.8. After running a pooled regression, simply done by running the former OLS model with concatenated data for all the indexes, they obtained a significantly negative effect of cloudiness. Number of observations in this case was over 92 000. This procedure does not seem like a correct one, because when merging different time series, the trend is lost because of the jumps at the points of the connection. Even when replicating this approach, the effect of sky cover in used data is negligible (Table 6.9). The only effects which stay significant are Monday and lagged return, in this case positive in both groups. Also it is worth to notice that all the R^2, which are supposed to serve as a goodness of fit of the model are really tiny, explaining less than 1% of the change in the dependent variable.

5.3.2 GARCH model

Many studies (T. Chang et al., 2006; Dowling & Lucey, 2008; Kamstra et al., 2003; Kang et al., 2010; Sariannidis et al., 2016; Sheikh et al., 2017; Shim et al., 2015; Symeonidis et al., 2010) did not use OLS to find relationships between stock returns and weather variables, but implemented GARCH model in order to discover the influence of weather variables on the volatility of returns. Because the results of previous models in the thesis did not find any direct effect of weather variables on stock returns, maybe the weather could influence the stock returns volatility of the used data.

GARCH model was run as described in section 4.2 and the results are displayed in Tables 6.11 and 6.13

Table 5.7: GARCH; Emerging

Emerging	**SAD**		**SKC**		**Temp**		**PCP**		α_0		α_1		β_1	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	13	8	10	11	5	16	7	8	21	0	21	0	21	0
Significant at 10%	1	1	0	0	2	6	0	2	20	0	15	0	18	0
Significant at 5%	1	0	0	0	0	5	0	0	20	0	15	0	18	0
Significant at 1%	0	0	0	0	0	1	0	0	10	0	15	0	18	0

Table 5.8: GARCH; Developed

Developed	**SAD**		**SKC**		**Temp**		**PCP**		α_0		α_1		β_1	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	19	2	12	9	7	14	7	11	21	0	21	0	21	0
Significant at 10%	4	0	3	1	0	0	2	1	21	0	19	0	19	0
Significant at 5%	1	0	1	0	0	0	1	1	19	0	19	0	19	0
Significant at 1%	0	0	0	0	0	0	1	1	18	0	19	0	19	0

In the summary results in Tables 5.7 and 5.8 it is possible to see that the volatility is very well explained by all the standard GARCH variables - long term variance with the reported coefficient α_0, actual period variance or new information with the coefficient α_1 and the predicted variance with the coefficient β_1. These variables are significant mainly at 1% level and among almost all the markets. There are of course exceptions. The long term variance does not seem to effect the volatility only in China, in all the other markets the effect is strong. The best explanation of the volatility seems to be the predicted variance, where the estimation of β_1 ranges between 0.7 and 0.9 with significance at 1% level among all the markets except for Hungary, Russia and United Arab Emirates among the emerging ones and Japan and New Zealand among the developed ones. The new information does not show any effect in Brazil, Hungary, Russia, United Arab Emirates, China and South Korea among emerging markets and Germany and Japan among the developed ones. The long term variance is significant among all the markets, but its estimated value of α_0 is always very close to zero.

The added weather variables (SAD, sky cover, temperature and precipitation) do not show statistical significance. The only weather variable which shows statistical significance in more markets is the dummy variable of Temperature, but only among emerging markets and only in six of them. The other variables appear to be significant very rarely and with low significance.

In general it is possible to conclude that GARCH model explains the volatility of the returns quite well itself, but any added variables seem to be negligible. T. Chang et al. (2006) who performed their analysis on Taiwan market found all the weather variables they included (sky cover, temperature and humidity) highly significant. Out of these variables this thesis does not work with humidity. The results of this thesis are in consensus with their finding of highly significant effect of temperature on Taiwan stock exchange volatility of returns, but the results of sky cover do not appear to be very important. The results are also in contradiction with the findings of Dowling and Lucey (2008), who reported a significant effect of SAD variable, mainly in markets which should experience big changes in daylight. From the results in tables 6.11 and 6.13 it can be seen that although in some countries the effect is found, it does not correspond to the theory of larger effects in countries situated very north in the Northern Hemisphere or very south in the Southern Hemisphere. Among emerging markets the effect was found only in Colombia, where the change is absolutely negligible and in Chile. Among developed markets the effect was found in Ireland, Switzerland, Australia and New Zealand, which does correspond to the theory, but the significance is small (10%) and the effect in northern markets like Norway, Sweden, Finland or Canada, where the effect should be the strongest, is missing.

5.4 Monday effect

The thesis was focused on the effect of weather on stock returns and could not confirm the conclusions of previous research (Akhtari, 2011; T. Chang et al., 2006; Goetzmann et al., 2014; Hirshleifer & Shumway, 2003; Saunders, 1993; Symeonidis et al., 2010), but as a side effect, another behavioral finance effect stands out in the regressions. That is a Monday effect, also known as a Weekend effect.

The Monday effect was included in the model as a well known anomaly of the market inefficiency. It has been already a part of models in many previous studies (Akhtari, 2011; Apergis et al., 2016; S.-C. Chang et al., 2008; Dowling & Lucey, 2005, 2008; Frühwirth & Sögner, 2015; Goetzmann et al., 2014; Goetzmann & Zhu, 2005; Kamstra et al., 2003; Kang et al., 2010; Kelly & Meschke, 2010; Krämer & Runde, 1997; Saunders, 1993; Sheikh et al., 2017; Tufan & Hamarat, 2004) and many of them reported its significance, usually negative.

The expected returns on Mondays should be either the same as on any other day (Rosol, 2016) or it should be three times the expected return for the other days of the week because it represents also weekend days, when no trades are happening (French, 1980). The idea of the second hypothesis is that a trader should be rewarded for the two additional days of investment, when the money is not liquid and could have been invested somewhere else in the meantime.

Table 5.9: Monday in previous models

Emerging/Developed	**OLS (E)**		**OLS (D)**		**AIC (E)**		**AIC (D)**		**Saunders (E)**		**Saunders (D)**	
Estimates of β_j	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
Overall	5	19	2	20	1	12	0	6	4	20	0	21
Significant at 10%	1	9	0	4	1	10	0	4	1	9	0	5
Significant at 5%	1	5	0	4	1	5	0	4	1	8	0	4
Significant at 1%	0	3	0	2	0	3	0	2	0	4	0	2

In all the regressions run, in the OLS model 5.1, in the models where variables were excluded according to Akaike information criterion 5.2 and also in the OLS replication of Saunders (1993) 5.3.1, the effect of Monday stands out being very significant and almost always negative. The summary of the performance of the Monday effect in the mentioned models is reported in Table 5.9, (E) and (D) stand for emerging markets and developed markets respectively. In the OLS model 5.1, Monday was negatively significant at least at 10% level in 13 markets and negative in 39 out of 46, when selecting the models according to Akaike information criterion, Monday was included 19 times, out of that in 14 cases the effect was significantly negative at least at 10% and once significantly positive at 5% level. When replicating Saunders (1993), the effect of Monday was negative in 41 markets out of 46, in 14 of them significant at at least 10% level and once significantly positive at 5% level. The findings are in consensus with the work of French (1980) who introduced the topic of this market anomaly and with most of the previous studies focusing on weather effect but including also the Monday effect in their models.

Chapter 6

Conclusion

The effect of weather variables influencing humans' mood and thus indirectly causing inefficiency in stock markets is an interesting theory. Stock markets are supposed to be efficient and unpredictable (Malkiel & Fama, 1970), presence of weather effects would mean a contradiction with markets being efficient and reflecting only the available economic information. The argumentation of previous studies of weather influencing mood of traders either directly by experiencing it themselves or indirectly by reading news written by journalists influenced by the local weather (Saunders, 1993) sounds reasonable, because it is based on a psychological theory (Howarth & Hoffman, 1984). Weather might influence humans' mood, but traders' performance should not be dependent on their current state of mind. Regulation of emotions is a necessary aspect in trading and high performing traders do not seem to be affected by their emotions, contrarily less expert traders sometimes do act according to their actual mood (Fenton-O'Creevy, Soane, Nicholson & Willman, 2011).

The findings of the thesis do not reject the hypothesis of no influence of weather on stock returns. After performing the OLS method described in Section 4.1 it turned out that the expected weather effects do not convincingly appear in the used data. In the used data, sky cover, which serves as a proxy for sunshine, in contradiction to the papers of Saunders (1993), Hirshleifer and Shumway (2003), Akhtari (2011) and Goetzmann et al. (2014) does not show reliable evidence of impact of sunshine on stock returns. Among a few markets there is a certain effect found, but at 1% level of significance the null hypothesis of it being zero cannot be rejected. Similarly the effects of temperature and precipitation do not appear to be of any significance. The sign of estimated coefficients of all three variables is evenly divided between a positive and a negative one and only scarcely there is an effect found and at 1% level of significance it is possible to conclude that the effects are simply not there. Seasonal affective disorder (SAD) shows consistence in being positive, but again the equality to zero can be rejected only at 5% level of significance, and the effect does not correspond to the theory of Hirshleifer and Shumway (2003) by not being present among the markets where the effect should be the strongest, in countries experiencing the largest changes in daylight throughout the year.

Due to Home equity bias (French & Poterba, 1991) the weather could be expected to influence the stock exchanges rather in markets with a small land area. Based on this hypothesis the largest effects should be in Qatar, Taiwan and the Czech Republic among emerging markets and in Singapore, Hong Kong and Israel among developed ones. Especially in Singapore and Hong Kong would be the effect expected, since the land area of these countries is only 678 and 1073 squared kilometers respectively. According to the Tables 6.3 and 6.4 the effect found in the smaller countries is not of any difference to the one found in large countries. Not even the comparison between emerging and developed markets brings any interesting outcomes. The significance of the variables does not appear to be present by any rule and seems to arise in the data either by randomness or it depends on each market separately and cannot be clustered. The results of the replication of the model suggested by Saunders (1993) do not show any difference.

Analysis of the stock return volatility using GARCH model also does not show the weather variables to have a significant effect, which means that the conclusions of T. Chang et al. (2006), Dowling and Lucey (2008), Kang et al. (2010), Symeonidis et al. (2010) and Sheikh et al. (2017) cannot be confirmed. Even though some of the weather variables appear significant in some markets, there is no visible pattern across the whole data sample.

Inspired by previous literature, there were also included seasonal effects, a Monday effect (also called a Weekend effect) and a January effect. Interestingly the Monday effect stands out in the results, being consistently negative and often significant, in consensus with French (1980) and many studies focusing on weather and stock returns. The results are in contradiction with both the calendar time hypothesis, according to which the returns on Monday should be three times larger than on other days in order to reward the holder for owning the stocks on non-trading days and trading time hypothesis, according to which the returns should not differ from the other days, because they are generated only during active trading. In this case there were indeed more occurrences of the Monday effect among emerging than among developed markets. The January effect also appears to be consistent in having a negative influence of the returns, which is in contradiction with the expected return according to previous research (Rosol, 2016; Thaler, 1987) but in this case the significance is not as frequent as in the case of the Monday effect. The frequency of significance is also reversed, being more frequently significant among developed than among emerging markets.

There are a few possible reasons why the analysis did not provide results corresponding to early studies of weather influencing stock markets. Previous researchers could have suffered from a confirmation bias and brought positive results after performing data mining with the aim to report outcomes which were in line with their beliefs (Nickerson, 1998). The other reason could be the involvement of two long time periods and by that making the t-test too powerful and finding the significance where there is none due to the tiny size of the effects and large data samples (Cohen, 1992; Kim, 2017). It is also possible that the effects in previous studies were observable, whereas in the data used in this study they were not.

The contribution of this thesis is the performance of the analysis on up to date data following the existing literature and expanding the research to a larger amount of markets with focus on the difference between emerging and developed markets. Most of the previous work focused on only one country and this thesis might be the first one trying to reveal different effects between emerging markets and developed markets due to the general belief of developed markets being more efficient and thus not being as easily influenced by weather factor as emerging markets. Future research should concentrate on different market anomalies than the weather ones, since they do not appear as a solid factor to influence the market and even in the previous studies where the effect was found significant, its magnitude was so little it probably could not be used as an information for trading due to transaction costs.

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Appendix A

On the following pages there are tables with the results of the statistical tests of the data and with the results of performed models, as described in Chapter 4. The results are discussed in Chapter 5.

Table 6.1: Statistical tests; Emerging

	ADF stat.	ADF p-value	No unit root	KPSS stat.	KPSS p-value	Stationarity	B-G stat.	B-G p-value	Serial corr.	B-G stat.1	B-G p-value1	Serial corr.1	B-G stat.2	B-G p-value2	Serial corr.2	BP stat.	BP p-value	Homos
Brazil	-12.991	< 0.01	1	0.174	> 0.1	1	2.217	0.136	0	0.139	0.709	-	0.247	0.619	-	21.464	0.002	0
Chile	-12.971	< 0.01	1	0.258	> 0.1	1	57.719	0	1	0.600	0.439	0	4.178	0.041	-	16.891	0.010	0
Colombia	-11.934	< 0.01	1	0.196	> 0.1	1	3.831	0.050	0	3.611	0.057	-	9.130	0.003	-	39.259	0.00000	0
Mexico	-12.283	< 0.01	1	0.113	> 0.1	1	10.268	0.001	1	2.345	0.126	0	0.859	0.354	-	44.322	0.00000	0
Peru	-12.051	< 0.01	1	0.615	0.0212422148814131	0	56.293	0	1	0.863	0.353	0	0.917	0.338	-	11.125	0.085	0
Czech Republic	-13.716	< 0.01	1	0.079	> 0.1	1	8.528	0.003	1	16.539	0.00005	1	3.141	0.076	0	27.407	0.0001	0
Egypt	-11.661	< 0.01	1	0.114	> 0.1	1	71.880	0	1	0.150	0.699	0	0.641	0.423	-	13.124	0.041	0
Greece	-10.995	< 0.01	1	0.206	> 0.1	1	1.896	0.168	0	4.896	0.027	-	1.618	0.203	-	12.174	0.058	0
Hungary	-11.057	< 0.01	1	0.072	> 0.1	1	15.253	0.0001	1	8.172	0.004	1	1.760	0.185	0	22.976	0.001	0
Poland	-13.067	< 0.01	1	0.085	> 0.1	1	23.130	0.00000	1	4.310	0.038	0	1.613	0.204	-	18.337	0.005	0
Qatar	-12.315	< 0.01	1	0.178	> 0.1	1	60.204	0	1	3.479	0.062	0	3.759	0.053	-	29.788	0.00004	0
Russia	-11.494	< 0.01	1	0.068	> 0.1	1	0.185	0.667	0	0.010	0.921	-	4.785	0.029	-	12.973	0.043	0
South Africa	-14.289	< 0.01	1	0.049	> 0.1	1	0.038	0.845	0	2.660	0.103	-	1.012	0.314	-	17.177	0.009	0
Turkey	-13.146	< 0.01	1	0.051	> 0.1	1	1.374	0.241	0	1.213	0.271	-	0.061	0.805	-	14.468	0.025	0
United Arab Emirates	-11.952	< 0.01	1	0.674	0.0159525487267537	0	107.037	0	1	4.677	0.031	0	0.087	0.768	-	42.965	0.00000	0
China	-10.860	< 0.01	1	0.315	> 0.1	1	0.002	0.964	0	0.117	0.732	-	0.865	0.352	-	33.719	0.00001	0
India	-12.744	< 0.01	1	0.052	> 0.1	1	13.366	0.0003	1	2.422	0.120	0	0.613	0.434	-	17.978	0.006	0
Indonesia	-12.629	< 0.01	1	0.147	> 0.1	1	19.417	0.00001	1	1.299	0.254	0	0.114	0.736	-	25.293	0.0003	0
South Korea	-12.693	< 0.01	1	0.049	> 0.1	1	0.035	0.852	0	0.744	0.388	-	0.750	0.387	-	46.966	0.00000	0
Malaysia	-13.136	< 0.01	1	0.191	> 0.1	1	38.264	0	1	1.101	0.294	0	1.714	0.190	-	35.741	0.00000	0
Pakistan	-12.323	< 0.01	1	0.183	> 0.1	1	78.012	0	1	2.505	0.114	0	0.390	0.532	-	31.612	0.00002	0
Philippines	-12.050	< 0.01	1	0.098	> 0.1	1	21.126	0.00000	1	0.189	0.664	0	5.254	0.022	-	17.451	0.008	0
Taiwan	-10.823	< 0.01	1	0.077	> 0.1	1	5.788	0.016	0	1.011	0.315	-	3.493	0.062	-	8.579	0.199	1
Thailand	-11.781	< 0.01	1	0.090	> 0.1	1	0.697	0.404	0	0.896	0.344	-	0.183	0.669	-	43.003	0.00000	0

Table 6.2: Statistical tests; Developed

	ADF stat.	ADF p-value	No unit root	KPSS stat.	KPSS p-value	Stationarity	B-G stat.	B-G p-value	Serial corr.	B-G stat.1	B-G p-value1	Serial corr.1	B-G stat.2	B-G p-value2	Serial corr.2	BP stat.	BP p-value	Homos
Canada	-14.614	< 0.01	1	0.039	> 0.1	1	5.135	0.023	0	4.127	0.042	-	0.040	0.842	-	64.425	0	0
United States	-15.020	< 0.01	1	0.184	> 0.1	1	30.628	0.00000	1	9.857	0.002	1	2.806	0.094	0	44.601	0.00000	0
Austria	-13.526	< 0.01	1	0.174	> 0.1	1	11.935	0.001	1	1.506	0.220	0	3.305	0.069	-	38.833	0.00000	0
Belgium	-14.803	< 0.01	1	0.248	> 0.1	1	3.496	0.062	0	0.047	0.828	-	6.723	0.010	-	37.986	0.00000	0
Finland	-14.538	< 0.01	1	0.133	> 0.1	1	1.205	0.272	0	0.052	0.820	-	1.513	0.219	-	25.686	0.0003	0
France	-15.456	< 0.01	1	0.121	> 0.1	1	4.485	0.034	0	4.337	0.037	-	4.072	0.044	-	33.456	0.00001	0
Germany	-11.633	< 0.01	1	0.046	> 0.1	1	0.186	0.666	0	0.716	0.397	-	0.213	0.645	-	13.047	0.042	0
Ireland	-15.184	< 0.01	1	0.535	0.0338847465612064	0	5.342	0.021	0	0.449	0.503	-	2.478	0.115	-	32.039	0.00002	0
Israel	-14.306	< 0.01	1	0.059	> 0.1	1	0.163	0.686	0	0.093	0.760	-	0.330	0.566	-	20.961	0.002	0
Italy	-14.353	< 0.01	1	0.186	> 0.1	1	1.302	0.254	0	0.616	0.433	-	0.433	0.511	-	21.218	0.002	0
Netherlands	-14.595	< 0.01	1	0.182	> 0.1	1	0.043	0.836	0	1.083	0.298	-	3.917	0.048	-	50.048	0	0
Norway	-13.545	< 0.01	1	0.055	> 0.1	1	2.762	0.097	0	4.532	0.033	-	2.151	0.142	-	47.139	0.00000	0
Portugal	-11.626	< 0.01	1	0.153	> 0.1	1	3.612	0.057	0	0.104	0.747	-	0.738	0.390	-	27.109	0.0001	0
Spain	-14.968	< 0.01	1	0.060	> 0.1	1	1.127	0.289	0	1.219	0.270	-	2.055	0.152	-	12.205	0.058	0
Sweden	-12.620	< 0.01	1	0.047	> 0.1	1	6.514	0.011	0	5.059	0.025	-	4.974	0.026	-	17.001	0.009	0
Switzerland	-15.541	< 0.01	1	0.126	> 0.1	1	3.738	0.053	0	8.997	0.003	-	1.577	0.209	-	25.679	0.0003	0
United Kingdom	-13.524	< 0.01	1	0.055	> 0.1	1	4.651	0.031	0	11.526	0.001	-	13.146	0.0003	-	33.479	0.00001	0
Australia	-14.630	< 0.01	1	0.054	> 0.1	1	3.866	0.049	0	0.552	0.457	-	0.991	0.320	-	14.114	0.028	0
Hong Kong	-13.502	< 0.01	1	0.073	> 0.1	1	1.555	0.212	0	0.972	0.324	-	3.013	0.083	-	47.171	0.00000	0
Japan	-11.227	< 0.01	1	0.260	> 0.1	1	4.306	0.038	0	1.183	0.277	-	0.251	0.616	-	29.511	0.00005	0
New Zealand	-12.755	< 0.01	1	0.065	> 0.1	1	12.716	0.0004	1	1.142	0.285	0	2.035	0.154	-	19.736	0.003	0
Singapore	-12.939	< 0.01	1	0.075	> 0.1	1	1.085	0.298	0	0.593	0.441	-	0.017	0.898	-	62.327	0	0

Table 6.3: OLS with robust SE; Emerging

	Dependent variable:											
	`Brazil Returns`	`Chile Returns`	`Colombia Returns`	`Mexico Returns`	`Peru Returns`	`Czech Republic Returns`	`Egypt Returns`	`Greece Returns`	`Hungary Returns`	`Poland Returns`	`Qatar Returns`	`Russia Returns`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SKC	0.0005	0.0004*	0.0002	0.00003	-0.00001	0.0001	0.0003	-0.001	0.0002	-0.0001	-0.00005	-0.001
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.001)
TEMP	0.0001	-0.00004	-0.0001	0.00004	-0.0001	-0.00002	-0.00000	-0.0001	-0.0001	0.00000	0.00002	-0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.00003)	(0.0001)	(0.0001)
PCP		-0.001	-0.003***	0.002	-0.165****	-0.006*	0.046			0.007*	0.031	
		(0.003)	(0.001)	(0.003)	(0.064)	(0.003)	(0.046)			(0.004)	(0.021)	
SAD	0.001	0.0004	-0.001	0.0004	0.003*	0.0003	0.001	0.0001	0.0002	-0.00003	0.0005	0.001
	(0.001)	(0.0003)	(0.005)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.001)	(0.0005)	(0.0002)	(0.001)	(0.0004)
Fall	0.0003	0.001*	-0.0005	0.0001	0.002***	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Monday	-0.001	-0.001*	-0.002***	-0.0003	-0.002*	0.0002	-0.003****	-0.003*	0.002	0.0003	-0.0002	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
January	-0.0002	0.001	-0.0004	-0.002	0.00002	-0.001	-0.0003	0.003	0.0003	-0.0005	-0.002	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
lag1		0.148****		0.066***	0.157****	0.058	0.180****			0.089****	0.156****	
		(0.041)		(0.032)	(0.050)	(0.050)	(0.035)			(0.024)	(0.044)	
lag2						-0.082*						
						(0.049)						
Constant	0.001	0.001*	0.001****	0.0004	0.001	-0.0001	0.001	-0.001	-0.001	0.0003	0.0004	-0.0004
	(0.001)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0004)	(0.001)
F Statistic	0.981 (df = 6; 2095)	3.372*** (df = 8; 2641)	1.88* (df = 7; 1865)	1.063 (df = 8; 2296)	3.674*** (df = 8; 2283)	1.193 (df = 9; 2923)	5.139*** (df = 8; 2223)	1.481 (df = 6; 1642)	0.707 (df = 6; 1563)	2.542*** (df = 8; 2917)	2.293** (df = 8; 2460)	0.673 (df = 6; 1551)
Observations	2,102	2,650	1,873	2,305	2,292	2,933	2,232	1,649	1,570	2,926	2,469	1,558
R^2	0.002	0.026	0.005	0.006	0.029	0.011	0.037	0.006	0.003	0.009	0.027	0.002
Adjusted R^2	-0.001	0.023	0.001	0.003	0.026	0.008	0.034	0.002	-0.001	0.007	0.024	-0.002
Residual Std. Error	0.018 (df = 2095)	0.010 (df = 2641)	0.011 (df = 1865)	0.013 (df = 2296)	0.017 (df = 2283)	0.014 (df = 2923)	0.018 (df = 2223)	0.024 (df = 1642)	0.018 (df = 1563)	0.013 (df = 2917)	0.014 (df = 2460)	0.025 (df = 1551)

	Dependent variable:											
	`South Africa Returns`	`Turkey Returns`	`United Arab Emirates Returns`	`China Returns`	`India Returns`	`Indonesia Returns`	`South Korea Returns`	`Malaysia Returns`	`Pakistan Returns`	`Philippines Returns`	`Taiwan Returns`	`Thailand Returns`
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
SKC	0.0001	0.0001	0.00002	0.0003	-0.00003	-0.0001	-0.0002	0.001	-0.0003	-0.0001	-0.001	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.002)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
TEMP	0.00004	-0.00003	0.00003	0.0001	-0.0001	0.0002	0.00000	-0.00001	-0.00004	-0.0001	-0.0001	0.0001
	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
PCP	-0.00003	-0.0004			0.002	0.002*		-0.0003	0.001****	-0.002	0.001	0.007*
	(0.001)	(0.005)			(0.001)	(0.001)		(0.001)	(0.0001)	(0.003)	(0.005)	(0.004)
SAD	0.001	0.00004	0.0003	0.002***	0.00003	0.003	0.0002	-0.004	-0.001	0.001	0.002***	0.001
	(0.0005)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Fall	0.0004	-0.001	-0.001	-0.001	-0.001	0.001	-0.001	0.0002	0.001	-0.001	-0.002***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Monday	-0.0001	0.0003	-0.001	0.002***	-0.0001	-0.002****	-0.001	-0.001***	-0.003****	-0.001	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
January	-0.0004	-0.0004	-0.001	-0.003	-0.001	-0.001	-0.002	-0.0002	0.002*	-0.001	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
lag1			0.207****		0.068***	0.083***		0.117****	0.163****	0.102****		
			(0.043)		(0.030)	(0.034)		(0.038)	(0.031)	(0.032)		
lag2												
Constant	0.001*	0.001	0.0002	-0.0003	0.001***	0.001****	0.001	0.0003*	0.001****	0.001*	0.0004	0.001****
	(0.0004)	(0.0004)	(0.0003)	(0.001)	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
F Statistic	0.397 (df = 7; 2632)	0.343 (df = 7; 2903)	3.987*** (df = 7; 2510)	2.182** (df = 6; 1895)	1.446 (df = 8; 2891)	2.578*** (df = 8; 2776)	0.748 (df = 6; 1925)	2.143** (df = 8; 2726)	21.252*** (df = 8; 2883)	1.579 (df = 8; 2055)	1.72 (df = 7; 1793)	1.423 (df = 7; 2606)
Observations	2,640	2,911	2,518	1,902	2,900	2,785	1,932	2,735	2,892	2,064	1,801	2,614
R^2	0.001	0.001	0.045	0.007	0.007	0.014	0.002	0.017	0.039	0.012	0.006	0.004
Adjusted R^2	-0.002	-0.002	0.042	0.004	0.004	0.011	-0.001	0.014	0.036	0.008	0.002	0.002
Residual Std. Error	0.013 (df = 2632)	0.016 (df = 2903)	0.011 (df = 2510)	0.017 (df = 1895)	0.015 (df = 2891)	0.014 (df = 2776)	0.014 (df = 1925)	0.007 (df = 2726)	0.012 (df = 2883)	0.014 (df = 2055)	0.014 (df = 1793)	0.013 (df = 2606)

Note: *p<0.1; ***p<0.05; ****p<0.01

Table 6.4: OLS with robust SE; Developed

Dependent variable:

	`Canada Returns`	`United States Returns`	`Austria Returns`	`Belgium Returns`	`Finland Returns`	`France Returns`	`Germany Returns`	`Ireland Returns`	`Israel Returns`	`Italy Returns`	`Netherlands Returns`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SKC	-0.0001	-0.0001	0.00001	0.0001	0.001*	-0.001*	0.0004	-0.00004	-0.001**	0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
TEMP	-0.00001	-0.00003	-0.00000	-0.00005	-0.00001	-0.0001*	0.00001	-0.0001	0.00000	-0.00000	-0.0001**
	(0.00003)	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00004)	(0.00004)	(0.0001)	(0.00004)	(0.0001)	(0.00004)
PCP	0.002	0.002	-0.0005	0.003	-0.596***	0.004		0.001	0.001	-0.0001	0.001
	(0.003)	(0.001)	(0.004)	(0.004)	(0.060)	(0.003)		(0.001)	(0.002)	(0.001)	(0.002)
SAD	0.0004	0.0004	0.0004	0.0003	0.0003	0.0002	0.00002	0.001**	-0.0001	0.00003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0002)
Fall	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.001	-0.002	0.0003	-0.0002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monday	-0.002***	-0.001	-0.001	-0.001	-0.001	-0.001	-0.0005	-0.002**	0.0004	-0.002***	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)
January	-0.001	-0.002**	-0.001	-0.001	-0.001	-0.001	-0.0004	-0.002*	-0.001	-0.0003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
lag1		-0.110***	0.065*								
		(0.034)	(0.034)								
lag2		-0.069									
		(0.046)									
Constant	0.0004	0.0005	0.0002	0.0002	0.0002	0.0002	0.0004	0.0001	0.0002	0.0004	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
F Statistic	1.572 (df = 7; 2803)	1.924** (df = 9; 2925)	0.809 (df = 8; 2878)	0.906 (df = 7; 2981)	24.257*** (df = 7; 2925)	1.459 (df = 7; 2976)	0.409 (df = 6; 1537)	2.304** (df = 7; 2955)	1.315 (df = 7; 2838)	1.122 (df = 7; 2924)	1.212 (df = 7; 2981)
Observations	2,811	2,935	2,887	2,989	2,933	2,984	1,544	2,963	2,846	2,932	2,989
R^2	0.005	0.018	0.006	0.002	0.003	0.003	0.002	0.005	0.003	0.003	0.003
Adjusted R^2	0.002	0.015	0.003	0.00001	0.0003	0.001	-0.002	0.002	0.001	0.001	0.0004
Residual Std. Error	0.012 (df = 2803)	0.012 (df = 2925)	0.016 (df = 2878)	0.013 (df = 2981)	0.015 (df = 2925)	0.014 (df = 2976)	0.014 (df = 1537)	0.015 (df = 2955)	0.011 (df = 2838)	0.016 (df = 2924)	0.014 (df = 2981)

	`Norway Returns`	`Portugal Returns`	`Spain Returns`	`Sweden Returns`	`Switzerland Returns`	`United Kingdom Returns`	`Australia Returns`	`Hong Kong Returns`	`Japan Returns`	`New Zealand Returns`	`Singapore Returns`
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
SKC	-0.0002	-0.0005	-0.0001	0.0003	-0.001**	0.0001	0.001**	0.0001	-0.001*	-0.0001	-0.0003
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0001)	(0.0005)
TEMP	-0.0001	-0.00001	0.00000	0.00001	-0.0001**	-0.0001*	0.0001*	-0.00002	-0.0001	-0.00004	0.0001
	(0.00004)	(0.0001)	(0.0001)	(0.00004)	(0.00003)	(0.00005)	(0.00004)	(0.0001)	(0.0001)	(0.00004)	(0.0001)
PCP	0.006		0.0003	0.175***	-0.001	-0.001	-0.004*	0.001			-0.001
	(0.006)		(0.005)	(0.039)	(0.003)	(0.004)	(0.002)	(0.001)			(0.001)
SAD	0.0003	0.0002	-0.0001	0.0001	0.0001	0.0002	0.0003	0.0001	0.001*	0.0002	0.003
	(0.0002)	(0.0005)	(0.0004)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.001)	(0.001)	(0.0001)	(0.006)
Fall	-0.002	-0.0003	0.0003	0.001	-0.0004	-0.001	0.0002	-0.001	-0.002	0.0002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0003)	(0.001)
Monday	-0.001	-0.0001	-0.002**	-0.001	-0.0003	-0.0002	0.00001	-0.0001	-0.001	-0.0002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)
January	-0.003*	-0.001	-0.001	-0.001	-0.001	-0.002*	-0.001	-0.001	-0.003*	0.00005	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.0004)	(0.001)
lag1										0.077**	
										(0.030)	
lag2											
Constant	0.0005	-0.0002	0.0004	0.0001	0.0002	0.0001	0.0003	0.0004	0.0001	0.001***	0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0005)	(0.0002)	(0.0003)
F Statistic	1.24 (df = 7; 2901)	0.312 (df = 6; 1649)	0.952 (df = 7; 2965)	5.421*** (df = 7; 1823)	1.354 (df = 7; 2915)	0.899 (df = 7; 2172)	1.702 (df = 7; 2885)	0.766 (df = 7; 2786)	1.391 (df = 6; 1788)	1.667 (df = 7; 2129)	1.13 (df = 7; 2920)
Observations	2,909	1,656	2,973	1,831	2,923	2,180	2,893	2,794	1,795	2,137	2,928
R^2	0.003	0.001	0.002	0.003	0.003	0.003	0.004	0.001	0.005	0.008	0.003
Adjusted R^2	0.0001	-0.003	0.00005	-0.001	0.001	-0.001	0.001	-0.001	0.002	0.005	0.001
Residual Std. Error	0.017 (df = 2901)	0.013 (df = 1649)	0.015 (df = 2965)	0.012 (df = 1823)	0.012 (df = 2915)	0.013 (df = 2172)	0.011 (df = 2885)	0.016 (df = 2786)	0.017 (df = 1788)	0.006 (df = 2129)	0.011 (df = 2920)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.5: AIC model selection; Emerging

Dependent variable:

	\`Brazil Returns\`	\`Chile Returns\`	\`Colombia Returns\`	\`Mexico Returns\`	\`Peru Returns\`	\`Czech Republic Returns\`	\`Egypt Returns\`	\`Greece Returns\`	\`Hungary Returns\`	\`Poland Returns\`	\`Qatar Returns\`	\`Russia Returns\`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SAD	0.001											0.0004
	(0.001)											(0.0003)
lag6			-0.010									
			(0.040)									
lag2						-0.082^{*}			-0.088^{*}	-0.050^{**}		
						(0.049)			(0.046)	(0.025)		
PCP										0.007^{*}		
										(0.004)		
lag1		0.150^{***}	0.048	0.067^{**}	0.160^{***}	0.059	0.182^{***}		0.108^{**}	0.093^{***}	0.157^{***}	
		(0.041)	(0.059)	(0.032)	(0.050)	(0.050)	(0.035)		(0.050)	(0.024)	(0.044)	
lag3			-0.043									
			(0.040)									
Monday		-0.001^{*}	-0.001^{**}		-0.002^{*}		-0.003^{***}	-0.003^{*}				
		(0.001)	(0.001)		(0.001)		(0.001)	(0.002)				
SKC		0.0003^{*}										
		(0.0002)										
January				-0.001				0.003^{*}			-0.002	
				(0.001)				(0.002)			(0.001)	
TEMP												
Constant	0.001	0.0005^{**}	0.001^{**}	0.0005^{*}	0.001^{*}	-0.0001	0.001	-0.001	-0.0004	0.0002	0.0002	-0.001
	(0.001)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.001)	(0.0005)	(0.0002)	(0.0003)	(0.001)
F Statistic	1.789 (df = 1; 2100)	6.894*** (df = 3; 2646)	1.799 (df = 4; 1862)	3.455** (df = 2; 2302)	5.556*** (df = 2; 2289)	2.115 (df = 2; 2930)	18.753*** (df = 2; 2229)	3.037** (df = 2; 1646)	3.531** (df = 2; 1565)	6.919*** (df = 3; 2921)	6.991*** (df = 2; 2466)	1.651 (df = 1; 1556)
Observations	2,102	2,650	1,867	2,305	2,292	2,933	2,232	1,649	1,568	2,925	2,469	1,558
R^2	0.001	0.025	0.007	0.006	0.026	0.010	0.036	0.004	0.018	0.011	0.026	0.001
Adjusted R^2	0.0003	0.024	0.005	0.005	0.026	0.009	0.035	0.003	0.016	0.010	0.025	0.0002
Residual Std. Error	0.018 (df = 2100)	0.010 (df = 2646)	0.011 (df = 1862)	0.013 (df = 2302)	0.017 (df = 2289)	0.014 (df = 2930)	0.018 (df = 2229)	0.024 (df = 1646)	0.018 (df = 1565)	0.013 (df = 2921)	0.014 (df = 2466)	0.025 (df = 1556)

	\`South Africa Returns\`	\`Turkey Returns\`	\`United Arab Emirates Returns\`	\`China Returns\`	\`India Returns\`	\`Indonesia Returns\`	\`South Korea Returns\`	\`Malaysia Returns\`	\`Pakistan Returns\`	\`Philippines Returns\`	\`Taiwan Returns\`	\`Thailand Returns\`
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
SAD	0.0005			0.001^{*}								
	(0.0004)			(0.001)								
lag6												
lag2												
PCP					0.002^{*}	0.001						
					(0.001)	(0.001)						
lag1			0.208^{***}		0.069^{**}	0.084^{**}		0.118^{***}	0.164^{***}	0.103^{***}	0.064^{**}	
			(0.043)		(0.030)	(0.034)		(0.038)	(0.031)	(0.032)	(0.030)	
lag3												
Monday				0.002^{**}		-0.002^{***}	-0.001	-0.001^{**}	-0.003^{***}	-0.001		-0.001^{*}
				(0.001)		(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)		(0.001)
SKC												
January												
TEMP		-0.00004										
		(0.00005)										
Constant	0.001^{*}	0.0004	-0.0001	-0.0003	0.0004	0.001^{***}	0.0003	0.0004^{**}	0.001^{***}	0.001^{**}	0.0001	0.001^{*}
	(0.0003)	(0.0003)	(0.0002)	(0.001)	(0.0003)	(0.0003)	(0.0004)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
F Statistic	1.086 (df = 1; 2638)	0.632 (df = 1; 2909)	23.429*** (df = 1; 2516)	3.605** (df = 2; 1899)	4.352** (df = 2; 2897)	5.642*** (df = 3; 2781)	1.358 (df = 1; 1930)	6.782*** (df = 2; 2732)	28.632*** (df = 2; 2889)	5.645*** (df = 2; 2061)	4.679** (df = 1; 1798)	3.268* (df = 1; 2612)
Observations	2,640	2,911	2,518	1,902	2,900	2,785	1,932	2,735	2,892	2,064	1,800	2,614
R^2	0.0004	0.0002	0.043	0.004	0.006	0.012	0.001	0.016	0.037	0.011	0.004	0.002
Adjusted R^2	0.00004	-0.0001	0.043	0.003	0.005	0.011	0.0002	0.015	0.036	0.010	0.004	0.001
Residual Std. Error	0.013 (df = 2638)	0.016 (df = 2909)	0.011 (df = 2516)	0.017 (df = 1899)	0.015 (df = 2897)	0.014 (df = 2781)	0.014 (df = 1930)	0.007 (df = 2732)	0.012 (df = 2889)	0.014 (df = 2061)	0.014 (df = 1798)	0.013 (df = 2612)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.6: AIC model selection; Developed

	Dependent variable:																					
	`Canada Returns`	`United States Returns`	`Austria Returns`	`Belgium Returns`	`Finland Returns`	`France Returns`	`Germany Returns`	`Ireland Returns`	`Israel Returns`	`Italy Returns`	`Netherlands Returns`	`Norway Returns`	`Portugal Returns`	`Spain Returns`	`Sweden Returns`	`Switzerland Returns`	`United Kingdom Returns`	`Australia Returns`	`Hong Kong Returns`	`Japan Returns`	`New Zealand Returns`	`Singapore Returns`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Monday	-0.002***		-0.001					-0.002**		-0.002***				-0.002**								-0.001
	(0.001)		(0.001)					(0.001)		(0.001)				(0.001)								(0.001)
lag1		-0.108***	0.066*													0.041					0.079***	
		(0.034)	(0.034)													(0.040)					(0.030)	
lag5																-0.095**						
																(0.037)						
lag3																-0.041						
																(0.036)						
lag4																0.040						
																(0.034)						
lag2		-0.068														-0.080**						
		(0.046)														(0.038)						
PCP		0.002																-0.004*	0.001*			-0.001
		(0.001)																(0.002)	(0.001)			(0.001)
TEMP				-0.0001		-0.0001*		-0.0001*			-0.0001**	-0.0001				-0.0001*	-0.0001*	0.0001*				
				(0.00003)		(0.00004)		(0.0001)			(0.00004)	(0.00004)				(0.00003)	(0.00005)	(0.00004)				
SKC					0.001*	-0.0005*	0.0004		-0.001**				-0.0005			-0.001**		0.001**		-0.001*		
					(0.0003)	(0.0003)	(0.0004)		(0.0002)				(0.0004)			(0.0002)		(0.0002)		(0.0004)		
January									-0.001*													
									(0.001)													
SAD															0.0002							
															(0.0001)							
Constant	0.0004*	0.0003	0.0002	0.00004	0.0002	0.00005	0.001	0.0003	0.0003	0.0003	0.0001	0.0003	-0.0001	0.0003	0.00001	0.0001	0.00000	0.00001	0.0001	-0.00005	0.0005***	0.0003
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0004)	(0.0001)	(0.0002)
F Statistic	7.142*** (df = 1; 2809)	3.957*** (df = 3; 2931)	2.541* (df = 2; 2884)	2.383 (df = 1; 2987)	3.697* (df = 1; 2931)	3.084** (df = 2; 2981)	0.847 (df = 1; 1542)	4.184** (df = 2; 2960)	4.329** (df = 2; 2843)	7.533*** (df = 1; 2930)	5.848** (df = 1; 2987)	2.416 (df = 1; 2907)	1.219 (df = 1; 1654)	5.308** (df = 1; 2971)	2.129 (df = 1; 1829)	3.246*** (df = 7; 2910)	3.184* (df = 1; 2178)	3.097** (df = 3; 2889)	3.34* (df = 1; 2792)	3.06* (df = 1; 1793)	6.881*** (df = 1; 2135)	2.438* (df = 2; 2925)
Observations	2,811	2,935	2,887	2,989	2,933	2,984	1,544	2,963	2,846	2,932	2,989	2,909	1,656	2,973	1,831	2,918	2,180	2,893	2,794	1,795	2,137	2,928
R^2	0.003	0.016	0.005	0.001	0.001	0.002	0.001	0.003	0.003	0.003	0.002	0.001	0.001	0.002	0.001	0.022	0.001	0.003	0.001	0.002	0.006	0.002
Adjusted R^2	0.003	0.015	0.004	0.0004	0.001	0.001	-0.0001	0.002	0.002	0.003	0.002	0.0004	0.00000	0.002	0.0004	0.019	0.001	0.002	0.0002	0.001	0.006	0.001
Residual Std. Error	0.012 (df = 2809)	0.012 (df = 2931)	0.016 (df = 2884)	0.013 (df = 2987)	0.015 (df = 2931)	0.014 (df = 2981)	0.013 (df = 1542)	0.015 (df = 2960)	0.011 (df = 2843)	0.016 (df = 2930)	0.014 (df = 2987)	0.017 (df = 2907)	0.013 (df = 1654)	0.015 (df = 2971)	0.012 (df = 1829)	0.011 (df = 2910)	0.013 (df = 2178)	0.011 (df = 2889)	0.016 (df = 2792)	0.017 (df = 1793)	0.006 (df = 2135)	0.011 (df = 2925)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.7: Emerging markets - replication of Saunders (1993)

Dependent variable:

	`Brazil Returns`	`Chile Returns`	`Colombia Returns`	`Mexico Returns`	`Peru Returns`	`Czech Republic Returns`	`Egypt Returns`	`Greece Returns`	`Hungary Returns`	`Poland Returns`	`Qatar Returns`	`Russia Returns`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SKCint	-0.001	-0.0004	0.00004	0.0002	0.001	-0.0001	-0.001	0.001	-0.001	-0.0002	0.0002	0.001
	(0.001)	(0.0003)	(0.0005)	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.002)	(0.001)	(0.0004)	(0.0005)	(0.001)
Monday	-0.001	-0.001**	-0.002***	-0.0003	-0.002*	0.0001	-0.003***	-0.003**	0.002	0.0003	-0.0002	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
January	-0.0001	0.001	-0.0002	-0.001	-0.0002	-0.0004	0.001	0.003*	0.001	-0.0004	-0.002	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
lag1	-0.032	0.149***	0.044*	0.067***	0.158***	0.054***	0.181***	0.033	0.098***	0.090***	0.157***	-0.010
	(0.022)	(0.019)	(0.023)	(0.021)	(0.021)	(0.018)	(0.021)	(0.025)	(0.025)	(0.018)	(0.020)	(0.025)
Constant	0.0004	0.001**	0.001**	0.001	0.001**	-0.0001	0.001	-0.001	-0.001	0.0001	0.0001	0.001
	(0.0005)	(0.0002)	(0.0003)	(0.0003)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0004)	(0.001)
Observations	2,101	2,650	1,872	2,305	2,292	2,934	2,232	1,648	1,569	2,926	2,469	1,557
R^2	0.002	0.025	0.006	0.006	0.027	0.003	0.036	0.005	0.012	0.008	0.026	0.001
Adjusted R^2	0.0004	0.023	0.003	0.004	0.025	0.002	0.035	0.003	0.009	0.007	0.025	-0.002
Residual Std. Error	0.018 (df = 2096)	0.010 (df = 2645)	0.011 (df = 1867)	0.013 (df = 2300)	0.017 (df = 2287)	0.015 (df = 2929)	0.018 (df = 2227)	0.024 (df = 1643)	0.018 (df = 1564)	0.013 (df = 2921)	0.014 (df = 2464)	0.025 (df = 1552)
F Statistic	1.193 (df = 4; 2096)	16.699*** (df = 4; 2645)	2.592** (df = 4; 1867)	3.339*** (df = 4; 2300)	15.963*** (df = 4; 2287)	2.243* (df = 4; 2929)	21.072*** (df = 4; 2227)	2.256* (df = 4; 1643)	4.753*** (df = 4; 1564)	6.084*** (df = 4; 2921)	16.599*** (df = 4; 2464)	0.323 (df = 4; 1552)

	`South Africa Returns`	`Turkey Returns`	`United Arab Emirates Returns`	`China Returns`	`India Returns`	`Indonesia Returns`	`South Korea Returns`	`Malaysia Returns`	`Pakistan Returns`	`Philippines Returns`	`Taiwan Returns`	`Thailand Returns`
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
SKCint	-0.0004	-0.0001	0.00005	-0.0005	-0.00001	0.00002	0.0003	-0.001	0.0004	0.0002	0.0002	-0.0001
	(0.0004)	(0.0004)	(0.0005)	(0.001)	(0.0003)	(0.0004)	(0.0004)	(0.002)	(0.0003)	(0.001)	(0.001)	(0.0004)
Monday	-0.0001	0.0004	-0.001	0.002**	-0.0001	-0.002***	-0.001	-0.001**	-0.003***	-0.001	-0.001	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
January	-0.0004	-0.0002	-0.0001	-0.0001	-0.001	-0.001	-0.001	-0.0003	0.001	-0.0003	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
lag1	0.004	0.022	0.208***	0.002	0.069***	0.084***	0.004	0.118***	0.164***	0.103***	0.063***	0.019
	(0.019)	(0.019)	(0.020)	(0.023)	(0.019)	(0.019)	(0.023)	(0.019)	(0.018)	(0.022)	(0.024)	(0.020)
Constant	0.0005*	0.0003	0.00001	0.0004	0.001	0.001***	0.0003	-0.001	0.001***	0.001*	0.0004	0.001
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.002)	(0.0003)	(0.0004)	(0.0005)	(0.0004)
Observations	2,639	2,910	2,518	1,901	2,900	2,785	1,931	2,735	2,892	2,064	1,800	2,613
R^2	0.0003	0.001	0.044	0.003	0.005	0.011	0.001	0.016	0.038	0.011	0.005	0.002
Adjusted R^2	-0.001	-0.001	0.042	0.001	0.004	0.010	-0.001	0.015	0.036	0.010	0.003	0.001
Residual Std. Error	0.013 (df = 2634)	0.016 (df = 2905)	0.011 (df = 2513)	0.017 (df = 1896)	0.015 (df = 2895)	0.014 (df = 2780)	0.014 (df = 1926)	0.007 (df = 2730)	0.012 (df = 2887)	0.014 (df = 2059)	0.014 (df = 1795)	0.013 (df = 2608)
F Statistic	0.221 (df = 4; 2634)	0.426 (df = 4; 2905)	28.711*** (df = 4; 2513)	1.653 (df = 4; 1896)	3.709*** (df = 4; 2895)	7.990*** (df = 4; 2780)	0.652 (df = 4; 1926)	11.291*** (df = 4; 2730)	28.353*** (df = 4; 2887)	5.976*** (df = 4; 2059)	2.358* (df = 4; 1795)	1.591 (df = 4; 2608)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.8: Developed markets - replication of Saunders (1993)

	Dependent variable:																					
	\`Canada Returns\`	\`United States Returns\`	\`Austria Returns\`	\`Belgium Returns\`	\`Finland Returns\`	\`France Returns\`	\`Germany Returns\`	\`Ireland Returns\`	\`Israel Returns\`	\`Italy Returns\`	\`Netherlands Returns\`	\`Norway Returns\`	\`Portugal Returns\`	\`Spain Returns\`	\`Sweden Returns\`	\`Switzerland Returns\`	\`United Kingdom Returns\`	\`Australia Returns\`	\`Hong Kong Returns\`	\`Japan Returns\`	\`New Zealand Returns\`	\`Singapore Returns\`
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
SKCint	0.00001	-0.00005	0.0001	-0.001	-0.001*	0.001	-0.001	-0.0002	0.0005	-0.0001	-0.0001	0.00004	0.0002	0.0002	-0.001	0.001	-0.0005	-0.0001	-0.0002	0.002**	0.0001	0.0003
	(0.0003)	(0.0004)	(0.001)	(0.0005)	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.001)	(0.0002)	(0.0004)
Monday	-0.002***	-0.001	-0.001	-0.001	-0.001	-0.001	-0.0005	-0.002**	0.0003	-0.002***	-0.0003	-0.001	-0.0001	-0.002**	-0.001	-0.0003	-0.0001	-0.00002	-0.0001	-0.001	-0.0002	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)
January	-0.0002	-0.001	-0.0001	-0.00005	-0.0003	-0.001	-0.001	-0.00002	-0.001	-0.0002	-0.0005	-0.001	-0.0001	-0.001	0.0003	-0.001	-0.001	-0.001	-0.001	-0.001	0.0002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
lag1	-0.040**	-0.102***	0.066***	0.036**	0.022	-0.039**	0.012	0.046**	0.009	-0.021	-0.003	-0.029	0.047*	0.020	-0.056**	0.036*	-0.044**	-0.035*	-0.023	-0.046*	0.078***	0.021
	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.026)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.025)	(0.018)	(0.023)	(0.018)	(0.021)	(0.019)	(0.019)	(0.024)	(0.022)	(0.018)
Constant	0.0004	0.0005	0.0002	0.00005	0.0001	0.0005	0.001	0.0002	0.0001	0.0004	0.0002	0.001	-0.0001	0.0004	-0.00004	0.0004	0.0002	0.00004	0.0002	0.001	0.0005***	0.001
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.001)	(0.0002)	(0.0004)
Observations	2,810	2,936	2,887	2,988	2,932	2,983	1,543	2,962	2,845	2,931	2,988	2,908	1,655	2,972	1,830	2,922	2,179	2,892	2,793	1,794	2,137	2,927
R^2	0.005	0.011	0.005	0.002	0.002	0.003	0.001	0.004	0.002	0.004	0.0002	0.001	0.002	0.003	0.005	0.003	0.003	0.002	0.001	0.006	0.007	0.002
Adjusted R^2	0.003	0.010	0.004	0.001	0.001	0.001	-0.001	0.003	0.0004	0.002	-0.001	0.0001	-0.0002	0.001	0.003	0.001	0.001	0.0002	-0.001	0.004	0.005	0.0004
Residual Std. Error	0.012 (df = 2805)	0.012 (df = 2931)	0.016 (df = 2882)	0.013 (df = 2983)	0.015 (df = 2927)	0.014 (df = 2978)	0.014 (df = 1538)	0.015 (df = 2957)	0.011 (df = 2840)	0.016 (df = 2926)	0.014 (df = 2983)	0.017 (df = 2903)	0.013 (df = 1650)	0.015 (df = 2967)	0.012 (df = 1825)	0.012 (df = 2917)	0.013 (df = 2174)	0.011 (df = 2887)	0.016 (df = 2788)	0.017 (df = 1789)	0.006 (df = 2132)	0.011 (df = 2922)
F Statistic	3.431*** (df = 4; 2805)	8.440*** (df = 4; 2931)	3.714*** (df = 4; 2882)	1.662 (df = 4; 2983)	1.502 (df = 4; 2927)	2.003* (df = 4; 2978)	0.457 (df = 4; 1538)	2.960** (df = 4; 2957)	1.296 (df = 4; 2840)	2.618** (df = 4; 2926)	0.142 (df = 4; 2983)	1.084 (df = 4; 2903)	0.932 (df = 4; 1650)	2.049* (df = 4; 2967)	2.346* (df = 4; 1825)	1.871 (df = 4; 2917)	1.674 (df = 4; 2174)	1.133 (df = 4; 2887)	0.647 (df = 4; 2788)	2.715** (df = 4; 1789)	3.496*** (df = 4; 2132)	1.328 (df = 4; 2922)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.9: Pooled regression as performed by Hirshleifer and Shumway (2003)

	Dependent variable:	
	`Returns Developed`	`Returns Emerging`
	(1)	(2)
SKC	0.00000	-0.00000
	(0.0001)	(0.0001)
Monday	-0.001***	-0.001***
	(0.0002)	(0.0002)
January	-0.0001	-0.0002
	(0.0002)	(0.0002)
lag1	0.072***	0.070***
	(0.004)	(0.004)
Constant	0.0004***	0.0004***
	(0.0001)	(0.0001)
Observations	51,830	56,243
R^2	0.006	0.005
Adjusted R^2	0.005	0.005
Residual Std. Error	0.015 (df = 51825)	0.015 (df = 56238)
F Statistic	71.801*** (df = 4; 51825)	74.246*** (df = 4; 56238)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.10: GARCH; Emerging 1/2

	Brazil	Chile	Colombia	Mexico	Peru	Czech Republic	Egypt	Hungary	Poland	Russia	South Africa
const	-0.000962941	0.001162905	0.003249719	0.001710528	0.001933559	0.002305916	0.003330099	0.001175837	0.002182459	0.000526936	0.001495958
	(0.001415)	(0.000696)*	(0.000826)***	(0.000866)**	(0.001042)*	(0.000939)**	(0.001392)**	(0.001489)	(0.000924)**	(0.001676)	(0.000884)*
SAD	0.000579184	0.000417736	-0.005855564	1.78e-05	0.001729473	-5.3e-05	0.000100072	-7.53e-05	-0.000105921	0.000115513	0.000490117
	(0.000664)	(0.000193)**	(0.003446)*	(0.000544)	(0.001124)	(0.000133)	(0.000491)	(0.000259)	(0.000122)	(0.000265)	(0.00036)
SKCint	-0.000238299	3.95e-07	-0.000449275	9.09e-05	-0.000104543	-0.000278411	-0.000131501	-0.000651668	-0.000234656	-0.000165779	7.67e-05
	(0.000436)	(0.000196)	(0.000359)	(0.00031)	(0.000458)	(0.000298)	(0.000543)	(0.000493)	(0.000322)	(0.000492)	(0.000378)
dTEMP	0.001837513	-0.00023577	-0.002645029	-0.001314048	-0.001089325	-0.001946822	-0.002527474	-0.0010451	-0.001738375	-0.000444164	-0.000655575
	(0.001469)	(0.000708)	(0.000815)***	(0.000776)*	(0.001052)	(0.000894)**	(0.001274)**	(0.001355)	(0.000874)**	(0.001507)	(0.000901)
dPCP		0.001026731	-0.001683312	7.43e-05	-0.003454276	-0.000818701	0.001909677		-0.00035479		-0.000460184
		(0.000937)	(0.000862)*	(0.000912)	(0.00311)	(0.000491)*	(0.003024)		(0.000496)		(0.000647)
alpha(0)	7.2e-06	2.89e-06	5.7e-06	2.06e-06	9.96e-06	3.54e-06	1.15e-05	9.41e-06	1.5e-06	5.71e-06	2.22e-06
	(2e-06)***	(1e-06)***	(3e-06)**	(1e-06)***	(3e-06)***	(1e-06)***	(5e-06)**	(3e-06)***	(0)***	(2e-06)**	(1e-06)***
alpha(1)	0.086209422	0.15662237	0.152762738	0.092180544	0.233942611	0.143273065	0.162278802	0.125375704	0.071244267	0.108864328	0.096769645
	(0.01697)	(0.024231)***	(0.039852)***	(0.017151)***	(0.044985)***	(0.017856)***	(0.029836)***	(0.025556)	(0.010322)***	(0.024586)	(0.01323)***
beta(1)	0.88933719	0.818122115	0.797718388	0.89609373	0.742444308	0.840888364	0.812129267	0.843076896	0.919873245	0.880565503	0.889041511
	(0.021212)***	(0.026543)***	(0.058809)***	(0.017774)***	(0.048124)***	(0.016909)***	(0.040972)***	(0.029966)	(0.010423)***	(0.024042)	(0.014135)***

Table 6.11: GARCH; Emerging 2/2

Turkey	United Arab Emirates	China	India	Indonesia	South Korea	Malaysia	Pakistan	Philippines	Taiwan
0.000723941	0.000338589	0.001201156	0.00114299	0.000615906	0.001225218	0.000180598	-0.000822227	-0.00046546	0.002448435
(0.001341)	(0.001359)	(0.001769)	(0.001077)	(0.000978)	(0.001031)	(0.001969)	(0.001198)	(0.001355)	(0.000976)**
-1.45e-05	0.000398845	0.000435083	-0.000914177	0.003341742	-0.00031836	-0.002859966	0.000418237	0.000663897	6.23e-05
(0.000274)	(0.000616)	(0.000546)	(0.000606)	(0.002066)	(0.00027)	(0.00216)	(0.000472)	(0.000937)	(0.000506)
-0.000141956	1.64e-05	-0.000564942	0.000433837	0.000199635	1.31e-05	-0.001046892	0.00010584	0.000158685	0.000366973
(0.000385)	(0.000384)	(0.000448)	(0.000263)*	(0.000291)	(0.000281)	(0.001885)	(0.000292)	(0.000524)	(0.000461)
0.000466815	-0.000186604	-0.000554916	-0.000349942	0.000289966	-0.000742507	-0.000848138	0.001879741	0.001436762	-0.001795498
(0.001267)	(0.001272)	(0.001615)	(0.001023)	(0.00099)	(0.00096)	(0.00057)	(0.001165)	(0.001279)	(0.000864)**
-0.000816514			0.001164027	0.000645188		-0.000451607	-0.000881847	0.000184822	8.56e-05
(0.000861)			(0.00079)	(0.000505)		(0.000371)	(0.00245)	(0.000852)	(0.001522)
8.95e-06	3.44e-06	1.57e-06	1.59e-06	2.89e-06	1.14e-06	9.89e-07	6.08e-06	5.58e-06	2.32e-06
(4e-06)**	(1e-06)**	(1e-06)	(1e-06)**	(1e-06)**	(0)**	(0)***	(2e-06)***	(2e-06)**	(1e-06)**
0.105147519	0.220859143	0.067984224	0.084281705	0.125336052	0.078607891	0.135448117	0.162716172	0.185311782	0.076066987
(0.027386)***	(0.045033)	(0.013107)	(0.014167)***	(0.024249)***	(0.013124)	(0.027081)***	(0.023261)***	(0.033345)***	(0.015984)***
0.862424894	0.773183285	0.929092082	0.909596244	0.864811597	0.915732532	0.852748368	0.797459623	0.803371726	0.911654182
(0.035911)***	(0.043628)	(0.013778)***	(0.014911)***	(0.0259)***	(0.01332)***	(0.025567)***	(0.026391)***	(0.03491)***	(0.017654)***

Table 6.12: GARCH; Developed 1/2

	Canada	United States	Austria	Belgium	Finland	France	Germany	Ireland	Israel	Italy	Netherlands
const	-9.57e-05	0.000647609	0.001408794	-0.000286898	0.000602944	-0.000614529	0.002328902	0.000501915	-0.000897118	-0.000125793	0.001393517
	(0.00078)	(0.000727)	(0.001208)	(0.000978)	(0.001076)	(0.001105)	(0.001109)**	(0.000916)	(0.000851)	(0.001271)	(0.000895)
SAD	0.000135054	0.000172937	0.000200493	0.000138117	0.000142071	0.000180383	-4.07e-06	0.000288693	8.7e-05	5.86e-05	3.22e-05
	(0.00013)	(0.000134)	(0.000168)	(0.000114)	(0.000102)	(0.000147)	(0.000187)	(0.000112)**	(0.00021)	(0.000185)	(0.000109)
SKCint	-0.000159783	0.000509943	2.14e-05	-0.000222554	-0.000163204	9.71e-05	-0.000108282	-0.000352863	0.000453254	0.000143874	-0.000198772
	(0.000195)	(0.000302)*	(0.000416)	(0.000326)	(0.000331)	(0.000336)	(0.000499)	(0.00039)	(0.00028)	(0.000306)	(0.000262)
dTEMP	0.000302471	-5.46e-05	-0.000983142	0.000588596	-0.000283968	0.001156153	-0.001509364	-0.000343009	0.001189884	0.000364525	-0.000999629
	(0.000743)	(0.000699)	(0.001151)	(0.000937)	(0.001024)	(0.001044)	(0.001)	(0.000873)	(0.000821)	(0.001201)	(0.000849)
dPCP	-1.35e-05	0.00032282	-0.000289296	0.000342711	-0.012659821	-0.000500744		-0.000377037	-0.000121942	0.00076256	0.000255283
	(0.000415)	(0.000412)	(0.000655)	(0.000471)	(0.00049)***	(0.000564)		(0.000485)	(0.00079)	(0.000709)	(0.000438)
alpha(0)	9.98e-07	2.31e-06	4.77e-06	3.73e-06	2.75e-06	3.43e-06	3.69e-06	3.36e-06	1.44e-06	2.78e-06	2.23e-06
	(0)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)*	(1e-06)**	(1e-06)***
alpha(1)	0.084841727	0.115038477	0.11388136	0.11998718	0.098645791	0.11353149	0.09459865	0.118478997	0.083427257	0.104832493	0.110594052
	(0.013984)***	(0.01628)***	(0.018251)***	(0.020784)***	(0.016025)***	(0.020273)***	(0.019602)	(0.016869)***	(0.026706)***	(0.016966)***	(0.017182)***
beta(1)	0.905446224	0.864928513	0.867379713	0.856273988	0.890451064	0.872520228	0.884979504	0.867956859	0.904378736	0.888461751	0.877437472
	(0.015548)***	(0.016816)***	(0.019502)***	(0.024932)***	(0.01616)***	(0.02041)***	(0.023005)***	(0.017414)***	(0.029995)***	(0.016071)***	(0.017659)***

Table 6.13: GARCH; Developed 2/2

Norway	Spain	Sweden	Switzerland	United Kingdom	Australia	Hong Kong	Japan	New Zealand	Singapore
0.002026526	9.47e-05	0.000922681	-0.000684874	0.001726438	0.000882039	0.001722448	0.002599258	0.001233894	0.001270159
(0.001145)*	(0.001323)	(0.000903)	(0.001073)	(0.000997)*	(0.000706)	(0.001312)	(0.001404)*	(0.000556)**	(0.000823)
4.3e-05	0.00010469	8.61e-05	0.00024955	4.4e-05	0.00036321	-0.000621822	0.000109605	0.000228951	0.00129524
(9.2e-05)	(0.000237)	(9.1e-05)	(0.000147)*	(0.000134)	(0.000218)*	(0.000508)	(0.000349)	(0.000118)*	(0.003115)
0.000227094	0.00016145	-0.000867387	0.000293164	-0.000131122	-0.000353891	0.000178761	0.000941887	9.12e-05	0.000649231
(0.000397)	(0.000391)	(0.000448)*	(0.000284)	(0.000331)	(0.000302)	(0.000355)	(0.000504)*	(0.000199)	(0.000314)**
-0.001280055	0.000294937	-0.001100401	0.000940806	-0.001369788	-0.000425951	-0.000990288	-0.00198522	-0.000498114	-0.000356443
(0.001089)	(0.001267)	(0.000859)	(0.001051)	(0.000933)	(0.000714)	(0.00126)	(0.001287)	(0.000574)	(0.000808)
-0.0001245	0.00056989	0.00740599	0.000947645	-0.000222933	-0.000105471	-6.75e-05			-0.000437295
(0.001028)	(0.000875)	(0.000326)***	(0.000535)*	(0.000512)	(0.000453)	(0.000568)			(0.000328)
2.77e-06	4.5e-06	2.73e-06	3.48e-06	2.38e-06	1.65e-06	1.88e-06	6.57e-06	1.3e-06	8.24e-07
(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(1e-06)***	(2e-06)***	(1e-06)*	(0)***
0.106417762	0.111867845	0.096463017	0.139662991	0.102892687	0.089614235	0.07628329	0.12547621	0.061106552	0.096545892
(0.015523)***	(0.019951)***	(0.020644)***	(0.02117)***	(0.018226)***	(0.015885)***	(0.011221)***	(0.025384)	(0.019037)***	(0.012282)***
0.882880628	0.8728418	0.884843694	0.834309907	0.881738877	0.896926221	0.914432438	0.847795722	0.902279819	0.898113134
(0.016441)***	(0.01803)***	(0.023248)***	(0.022064)***	(0.019946)***	(0.017709)***	(0.012052)***	(0.026742)	(0.038413)	(0.011619)***