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“The Effect of Weather Conditions on IPO Performance”

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Abstract

A variety of studies have demonstrated over the past decade that environmental conditions, such as the weather and the Seasonal Affective Disorder (SAD), have a significant effect on the market behavior of listed stocks. The present study extends the empirical literature in this area by investigating for the first time the effect of weather on Initial Public Offering (IPO) performance using an extensive dataset from 6 countries (US, UK, Singapore, Malaysia, France and Australia) between 1982 and 1997. In order to control for known effects we use a number of control variables which reflect both financial data and behavioral conditions. Our results indicate that the weather has a statistically significant effect on the behavior of the IPO market. In particular, irregularly high cloudiness on a particular day is associated with lower levels of IPO underpricing. However, the short term volatility and stock performance the 5 days following the IPO, is not affected by cloudiness. In line with a previous study, SAD has also a significant effect on IPO underpricing. The new result here is that we find that this behavioral factor also affects short time IPO volatility.
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1. Introduction

Each year many companies decide to go public through which they have access to public equity which can provide funding for the company’s investment and operation plans. The majority of companies plan to open up to the capital market via an Initial Public Offering (IPOs) to potential investors. The area of IPOs has been of great interest to academics and professionals as it entails a number of anomalies. Most notably the underpricing of IPOs has been the main topic of interest in most researches. The conclusion to which most studies on IPO underpricing arrive is that the majority of IPOs are likely to be underpriced. The way in which one can observe whether underpricing in an IPO exists is by calculating the percentage change from the IPO offer price to the closing price of the first trading day. Consequently, if the percentage change is positive, then the issue has been underpriced and on the first trading day it attracts investors’ interest resulting in a closing price being higher than the offer price. On the other hand, should the percentage change be negative, means that the issue is overpriced and investors are willing to sell the issues they had previously subscribed for. To illustrate this theory, Logue (1973) and Ibbotson (1975) in their studies of the US markets documented an average underpricing of 19% which indicates that companies when going public via IPOs, leave a significant amount on the table. More specifically, theories developed so far suggest that underpricing is in essence an opportunity cost for the owners of the firm prior to its IPO. These theories suggest that an underpriced IPO essentially means that shares sold at a discount dilute the value of pre existing equity (Dolvin and Pyles (2007)). As a result most studies focused on the factors that cause or effect the level of underpricing, such as information asymmetry (Rock (1986)) and incentives provided by issuers (Loughran and Ritter (2004)).

More recently however, studies in the area of behavioural finance have examined whether mood fluctuations, and more specifically those incurred by weather conditions, can affect investors’ behaviour. Indeed many researchers have found a strong correlation between weather variables, such as cloud cover, temperature and Seasonal Affective Disorder (SAD), and the level of equity returns. The justification most of these researches give is that weather that affects the mood of the investors positively, make them have a more optimistic attitude towards the future performance of equities
and thus they are more likely to take long positions which in turn can lead to higher returns (Symeonidis et al. (2010)). Many researchers who have examined the effect of SAD in particular on the level of underpricing, have found that SAD can indeed affect the underpricing which supports our results as IPOs in fall and winter, seasons where SAD is observed, produced higher returns than those in spring and summer. Furthermore, when examining the SAD seasons alone, Dolvin and Pyles (2007) concluded that when compared to each other, underpricing tend to be higher in winter than in fall. This is consistent with our findings where, we found that winter issues have a higher level of underpricing with an average of 25.32 percent compared to fall with an average of 24.05 percent.

With the relationship between weather conditions and stock market returns being the centre of a number of researches, recent studies have examined the effect of weather conditions on stock and market volatility (Kamstra et al (2003)). Interestingly, Kamstra’s findings suggest that returns volatility does not vary significantly across fall and winter, and spring and summer time periods. Taking this into account, in this study we chose to measure volatility by using the standard deviation of the returns during the first five trading days since the listing date. In the IPO volatility literature, studies have been carried out in order to establish whether a correlation between underpricing and volatility exists. Indeed empirical research by Beatty and Ritter (1986) and Michaely and Shaw (1994) has shown that there is a relationship between the two. This theory further supports our findings where one can observe 2056 underpriced IPOs with a standard deviation of 3.23 and 3227 overpriced IPOs with a standard deviation of 2.57. However, even though literature so far examines the weather conditions effect on volatility, to the best of our knowledge there are no studies examining the effect of Seasonal Affective Disorder on IPO volatility.

The performance of IPOs has been an area of debate as the timing it seizes to be an IPO an becomes common stock is not widely accepted. Nevertheless, studies which have taken a different approach each to defining and measuring IPO performance, consider an IPO short term performance (closing prices of the 5 first trading days) to be the same with the level of underpricing (closing price of the first trading day). Regardless of this, we have chosen to differentiate between the two. This method was followed due to the fact that we examine performance and the effect weather conditions have on it. The
attribute these variables have is that they can have an impact on the performance of equity only for a short period of time. The results further support our choice of method as they indicate that although some IPOs might have positive initial returns, they are likely to underperform in the 5 consecutive days after that. In his research, Levis (1993) examined a sample of 712 IPOs listed in the London Stock Exchange from 1980 to 1988. He calculated three types of returns for his research. For this research it was necessary to examine the first day adjusted return, the first month adjusted return and long aftermarket return for 3 years. So what essentially Levis calculated is the level of underpricing, the short and long term performance. For the first day returns the average IPO return was 14.3 percent, result which is in essence is identical to the returns for the first month, which was consistent with Ritter’s (1991) findings (14.1 percent). The calculations for the three year returns the results showed a gradual decline starting with -11.38 percent in the first year and reaching -22.96 percent in the third year.

Despite previous studies which examined the effect of weather on investors’ mood and consequently on the returns of equities, we will examine the effect weather conditions such as cloud cover and Seasonal Affective Disorder have on the level of underpricing of the IPOs, short term performance and volatility of the stock price using data from the five days after the listing.
2. Literature Overview

2.1 Weather related literature

Research has shown that stock prices are affected to an extent by investors’ moods. Rosenthal et al (1984) developed a theory called ‘Seasonal Affective Disorder’ effect (SAD). SAD is a condition whereby the shortness in the length of day over fall and winter, can cause depression to people and make them less willing to take any risks. Stock market returns thus can be seasonally affected as investors can suffer from such a disorder. In their research, they examined the number of daylight hours in several countries and found this factor to be statistically significant in relation to the market returns. More specifically, once the days started to lengthen again, stock markets had increasing stock returns. Their study was designed to extend the psychology literature that linked the SAD effect to the length of the day, while at the same time extending the economics literature by relating economic factors to the returns of the stock market.

Prior to Kamstra et al, other researchers had examined the relation of market returns to the weather conditions. Saunders (1993), Hirshleifer and Shumway (2003) and Goetzman and Zhu (2005) found that there is a strong relation between the returns of stocks and the weather conditions of the city the stock market is in. Saunders (1993) examined the correlation between the weather in New York city and the NYSE index returns and found a strong relation between the two with the returns of the market being significantly lower on cloudy days. Hirshleifer and Shumway (2003) examined several markets from around the world and found that market returns on average tend to be higher on sunny days. Goetzmann and Zhu (2005) attempted to look at the stock returns-weather conditions using a different method. They examined a database comprised of individual trading accounts, from 5 big cities in the US, throughout the country in order to have the advantage of having different weather patterns. Their regressions lead them to two findings. The first finding confirms previous studies that in New York City, the cloud cover (SKC) affects the NYSE and returns are stock returns are higher in sunny days rather than in cloudy days. The second finding dealt with net buy in shares (NBS), buy-sell imbalance (BSI) and SKC. Their empirical results showed that both NBS and BSI were not affected by SKC.
Other researchers that applied Saunder’s methods in other countries such as Spain (Pardo and Valor (2003)), Germany (Kramer and Runde (1997)) and Turkey (Tufan and Hamarat (2004)) found no correlation between the returns of the market and weather conditions. As opposed to Kamstra’s et al research, Cao and Wei (2005) examined indices from 8 different countries throughout the world, from 1989 to 1999 and gathered 2252 observations. By using two methods already used by previous researchers, the 'bin test' used by Saunders (2003) and running regressions to determine the precise relation of temperature with stock returns while controlling other known anomalies method used by Kamstra et al (2003) and Hirshleifer and Shumway (2003). They found evidence of the SAD effect but no significant evidence of temperature effect. The only countries in which the temperature had an impact on stock returns were New Zealand and South Africa.

According to the Efficient Market Hypothesis (EMH), there is no weather impact on stock returns and volatility. However, other theories concerning behavioural finance argue that weather conditions can, to a certain extent, affect the volatility of the markets. Limpaphayom et al (2005) reported a positive relationship between wind and precipitation in the Chicago futures markets, and volatility. Evidence of this have also been provided by Dowling and Lucey (2008) who conducted a similar research with data from a number of countries around the world. Besides wind and precipitation, Dowling and Lucey also used geomagnetic storms, daylight savings time changes (DSTC) and the SAD and found a positive correlation with most of the indices under consideration. Additional empirical evidence of weather effect on volatility is presented by Kang et al (2009) who used a data sample of 2903 stocks in the Chinese stock market from 1996 to 2007. Mehra and Sah (2002) proposed a model where shifts in investor moods have a significant impact on the volatility of equity prices. Lee et al (2002) found that there is a negative correlation between market volatility and shifts in investors’ sentiment. Brown (1999) argues that the volatility of returns of closed–end funds increase with abnormal levels of investors’ sentiment. Kamstra et al (2003) came to an interesting conclusion, for all countries under consideration that the volatility in returns is not affected by seasonality.

Though not to a great extent, studies have shown that the weather can affect the trading volume of an IPO. Hirshleifer and Shumway (2003) argue that trading activity by investors is higher in sunny days and lower in cloudy days. On the same note,
Goetzmann and Zhu (2003) investigated the effect sky cover has on trading volume and do not support the view put forward by Hirshleifer and Shumway. They found that in five cities under investigation there is no significant difference in trading activity in sunny and cloudy days and in one city (Chicago) they found that in sunny days trading volume is lower than in cloudy days. Loughran and Schultz (2003) using a sample comprising of 25 US cities, found that blizzards have a significant impact on investors trading activity. Cities excluded from the sample are unaffected by blizzard conditions.

2.2 Not weather related literature

2.2.1 Underpricing

Over the years, a number of researchers have examined the phenomenon of IPO underpricing. Among the most important factors that cause IPO underpricing is the asymmetric information among the issuing firm, the underwriting institution and investors. The most widely-used asymmetric information model is presented by Rock (1986). In this study, Rock introduces the ‘Winner’s Curse’ whereby informed investors invest in underpriced IPOs, while uninformed investors subscribe to every IPO due to their inability to distinguish between underpriced and overpriced IPOs. As a result, underpriced IPOs are more likely to be oversubscribed. In attempting to enrich Rock’s findings, Beatty and Ritter (1986) argue that investment banks prefer IPOs to be underpriced since investors will refrain from cooperating with banks whose IPOs tend to generate low returns. Thus, investment banks drive new issues to underpricing. The ‘Winner’s Curse’ model has been used by a number of researchers and empirical evidence by Koh and Walter (1989), Levis (1990), Keloharju (1993) and Amihud, Hauser and Kirsh (2003) support Rock’s model.

Consequently, it can be argued that the greater the ex ante uncertainty, the greater the expected underpricing. The existing literature shows that ex ante uncertainty for IPOs is considerably lower in cases of: the underwriter is very highly esteemed on the market,

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a credible auditor is assigned with the task of providing an auditor’s opinion and the IPO is venture capital-backed\(^2\). On the other hand, Carter and Manaster (1990) found in their research that there is negative correlation between the underwriters’ reputation and underpricing. Due to the fact that ex ante uncertainty is difficult to be measured, researchers use a number of proxies as substitutes. Depending on company characteristics, the most commonly used proxies include the age of the company (Ritter (1984), Megginson and Weiss (1991)), the size of the company measured by sales (Ritter (1984)) and by the industry which the company operates in (Benveniste et al (2003)) . In order to determine the relationship between underpricing and ex ante uncertainty, many researchers (Wang, Chan and Gau (1992), Habib and Ljungqvist (1999), Jegadeesh et al (1993), Brennan & Franks (1997) and Jaitley and Sharma (2004)) have considered aftermarket volatility as a measure of uncertainty and some others, trading volume (Miller and Reilly (1987)).

Despite the factors affecting IPO undepricing mentioned above, there are cases where the underwriter and the issuing firm affect the underpricing of new issues. Underwriters in the US tend to underprice IPOs in order to avoid lawsuits (Logue (1973), Ibbotson (1975) and Tinic (1988)). The lawsuit avoidance hypothesis involves underwriters and issuing firm deliberately selling their stock at a discount in order to avoid lawsuits from existing shareholders who hold shares that may lose value in the post-IPO period. Opposed to this hypothesis are Drake and Vetsuypens (1993) who studied the underpricing by comparing the IPO year, offer size and underwriter reputation of 186 IPOs in the US and came to the conclusion that there is negative correlation between underpricing and sued firms. Loughran and Ritter (2002) examine the lawsuit avoidance from a different perspective. They found that even though there is a positive correlation between lagged index returns and underpricing, it is impossible to determine whether they can affect lawsuits.

Price stabilisation is another method underwriters use to affect underpricing. Price stabilisation is a technique where the underwriter repurchases shares of an IPO performing poorly in an attempt to stabilise its price (Lewellen (2003)). Price stabilisation has been examined by Hanley, Kumar and Seguin (1993) who argue that by stabilising the price, underwriters can increase the stock price temporarily and giving

overpriced offerings a deceptively higher value. Schultz and Zaman (1994) suggest that price stabilisation increases the stock price permanently due to the lack of tradable shares. Benveniste, Busaba and Wilhelm (1996) support the view that price stabilisation is offered mainly to unsophisticated investors and it is a commitment held by the underwriter to repurchase IPO shares at the offer price.

Another factor affecting underpricing is tax avoidance. In his research, Rydqvist (1997) found that prior to 1990 in Sweden, companies prefer to reward employees with stocks rather than high salaries due to the fact that employment income is more heavily taxed than capital gains. Taranto (2003) conducted a similar research in the US and came to the conclusion that even though the tax system is more complicated than in Sweden, it still offers tax advantages to employees and managers with stock options. For this reason companies prefer to have underpriced IPOs to allocate to employees.

Informational cascades can also arise in some IPO cases as presented by Welch (1992). In his research, Welch concluded that when informed investors are not satisfied with the offer price of the IPO shares, they will not be willing to subscribe. As a result, uninformed investors may be discouraged from subscribing as well. This gives early investors (informed) the market power to demand more underpricing, and this in turn can create positive cascades which may lead to uninformed investors eventually participating.

Welch (1989), Grinblatt and Hwang (1989) and Allen and Faulhaber (1989) have come up with a number of models which examine the fact that issuing firms underprice the IPO to appeal to the investors. This way companies can be distinguished in high quality and low quality firms, and investors in seasonal equity offering prefer high quality firms because they expect these firms to produce higher returns. Although such practices leave money on the table, the issuing firm expects a future seasonal equity offering to counterbalance the loss of the IPO.
2.2.2 Performance

The investigation of IPO performance has been conducted by a number of researchers throughout the last decades and various approaches have been incorporated to do so. It is worth mentioning the key researches that deal with IPO long-term underperformance. Ritter (1991) and Loughran and Ritter (1995) found significant IPO underperformance in the US. Ritter (1991) used 1526 US IPOs from 1975 to 1984 listed in the AMEX-NYSE and NASDAQ and documented that the IPOs underperformed the benchmark over a 3-year horizon. More specifically, he calculated the returns for two intervals: the first closing price of the IPO since its listing and a 3 year period after the initial listing. In order to assess the long term performance of IPOs he used two methods. The first method was cumulative adjusted returns (CAR) with monthly portfolio rebalancing and the second was method was the 3 year buy and hold returns. His results showed that although the average CAR had a slight increase in the first two months, by the end of the year period it had fallen to -29.3 percent. Using IPO data during the period from 1970 to 1990, Loughran and Ritter (1995) found that listing firms underperform when compared to non-listing firms. Many researchers have identified long-term underperformance in other markets such as Cai and Wei (1997) in the Tokyo stock exchange, who used a data sample of 180 IPOs listed between 1991 and 1992, Levis (1993) in the London stock exchange using a sample of 712 IPOs from 1980 to 1988, and Aggarwal, Leal and Hernandez (1993) who investigated the markets of Brazil, Mexico and Chile who witnessed market-adjusted returns of -47%, -19.6% and -23.7 respectively. There are some researchers however, whose results are not so clear. Wasserfallen and Wittleder (1994) and Ljungqvist (1997) examined the German IPOs and for the period 1961-1987 found that the IPOs did not underperform the FAZ index. While conducting a research on the same market during 1988-1990, Ljungqvist found that the IPOs underperformed the index and concluded that IPO long-term performance depends on the period under examination rather than a set of factors affecting each IPO. Loughran et al (1994) reported that IPOs do not underperform the Swedish stock exchange significantly. In an extraordinary case, Kiymaz (1997) found that industrial IPOs in the Turkish stock market for the period 1990-1995, have higher abnormal returns in the long run.
Ritter (1991) develops a hypothesis in an attempt to explain the IPO underperformance. The *Windows of Opportunity* is a hypothesis which states that companies going public take advantage of periods with good market conditions, when investors are optimistic and willing to overpay for equity. These IPOs are likely to have a low long-run performance. There is evidence by a number of researchers who support the windows of opportunity. Loughran et al (1994) found a negative relation between the number of IPOs and the market return the year after the issuance. Lerner (1994) using a sample of 350 venture capital-backed firms, for the period between 1978 and 1992, concluded that these firms go public when markets are performing well. In addition, Cai and Wei (1997) provide evidence for this hypothesis concerning the Japanese market.

Shiller (1990) first developed the argument of the *Impresario hypothesis* in order to explain the long run underperformance of IPOs. This hypothesis argues that underwriters underprice IPOs in order to attract investors. This hypothesis states that IPOs which are highly underpriced will consequently have low long-term returns. Empirical evidence of this hypothesis is also illustrated in the studies of Ritter (1991) and Levis (1993).

An additional hypothesis attempting to identify a source of long-term IPO underperformance is the *Divergence of Opinion hypothesis* (Miller (1977)). This hypothesis argues that optimistic investors will buy the IPO shares and in the long run the divergence of opinion between optimistic and pessimistic investors will become narrow thus decreasing the price. Evidence of this hypothesis has been presented by numerous authors confirming Miller’s results (Ritter (1991), Morris (1996), Bradley et al (2001) and Brav and Gompers (2003)).

However, there are various other factors that can affect the long-run performance of an IPO. In his research, Krigman et al (1999) observed that IPOs which are heavily flipped on the first day, underperform IPOs which are less flipped on the first trading day. They documented that in their sample, the hot IPOs flipping accounted for less than cold IPOs flipping in the first trading day. They concluded that if an IPO outperforms a size adjusted benchmark in the first trading day, it will continue to do so over the first year.
2.2.3 Post-IPO Volatility

The majority of IPOs are usually underpriced. Empirical researches have shown that underwriting companies find the process of fair pricing an IPO complicated. The pricing problem of an IPO can be explained by the extremely high initial returns and by the fact that ‘hot’ IPO markets have high variability in their initial returns. A theory developed by a number of researchers, states that when an underwriter prices an IPO, it should take into account the level of information asymmetry. Beatty and Ritter (1986) found that on average, when there is high information asymmetry about a company, it is more likely to be underpriced. There is empirical evidence that support this notion by many researchers (Michaely and Shaw (1994) and Sherman and Titman (2002)). Lowry et al (2010) stated that firms with higher uncertainty (high information asymmetry) have higher volatility in their initial returns. In their study, they came to the conclusion that small, young and technology firms have significantly higher initial return variability and are more underpriced. In another study, Xu and Malkeil (2003) stated that high volatility is linked to high trading activity by financial institutions. They also noted that stock volatility is occasionally related to the amount of a company’s shares owned by institutions.

2.2.4 Trading Volume

Empirical researchers have developed a number of theories concerning trading volume that originated in the field of behavioural finance. Odean (1998) and Gervais and Odean (2001) have developed a model to explain the changes in trading volume. The overconfidence hypothesis argues that investors normally falsely believe that the market-wide returns are due to their ability to pick the right stocks. This in turn makes investors more confident and such investors increase trading in forthcoming periods. Consequently, in periods of market-wide losses, investors’ overconfidence decreases thus reducing trading volume. Another hypothesis concerning trading volume has been developed by Shefrin and Statman (1985) called the disposition effect. They argue that emotions of pride and regret have a direct impact on trading. Pride is caused by the
realisation of gains and regret is caused by the realisation of losses. Thus, they state that investors sell securities that have gains in order to experience the feeling of pride and hold the securities that have losses in order to delay the feeling of regret. This direct effect of investors emotions to trading volume has also been examined by a number of researchers (Ferris, Haugen and Makhija (1988), Odean (1998) and Heath, Huddart and Lang (1999)).

However, Merton (1987) approaches the issue from another perspective. He argues that investors trade securities which they have heard of. When an IPO stock has high initial return and high initial trading volume, this will become more recognised by investors and as a result more investors will continue to invest in that particular security. This can lead to a high trading volume in the long run. Reese (1998) also argues that IPOs that have a high level of interest by investors, maintain a high trading volume due to the additional information made known about the company and reduced transaction costs. This is supported by the studies of Constantinides (1986) who argued that lower transaction costs can encourage higher trading volume.

Many researchers have examined the relationship between underpricing and trading volume. More specifically, Miller and Reilly (1987) and Schultz and Zaman (1994) reported a position correlation between underpricing (positive initial return) and high trading volume. More specifically, they argue that underpricing in IPOs occurs due to the uncertainty about the true value of the issues. Therefore, the main idea behind this theory is that the greater the investor’s uncertainty, the greater the trading volume.

Hanley (1993) notes that IPOs with a high interest by investors before the issue, priced above the mid-point of the initial price range, tend to be more underpriced than issues priced below the mid-point. Hanley also states that IPOs priced above the mid-point have continuously higher trading volume than IPOs priced below mid-point.

Finally, Goetzmann and Zhu (2002) conducted a research which, among others, examines the extent at which cloud cover (SKC) affects the level of trading volume. His empirical results show that trading volume is not significantly higher on sunny days rather than cloudy. In fact, in Chicago trading volume is actually lower in sunny days than in cloudy days. These results however are not consistent with the empirical results presented by Hirshleifer and Shumway (2002) who put forward some behavioural assumptions. Should these assumptions hold, the level of trading volume of individual
investors should be different on sunny and cloudy days. A similar study was conducted later on by Loughran and Schultz (2003) but instead of measuring the effect cloud cover had on trading volume, they used blizzards to determine if it affected equity trading volume. The empirical results showed that on the blizzard dates, trading volume of stocks decreased by 17% compared to the previous trading day.

**Hypotheses**

In our study we examine the IPO underpricing, return volatility and performance not by focusing on firm and offer characteristics as the majority previous researcher have done. We concentrate our study on psychological and behavioural factors that can affect the demand side, the investors. More specifically, we analyze a potential impact of two factors. The SAD and cloudiness or cloud cover. The SAD as was mentioned before is the psychological condition that causes depression and make investors more risk averse during fall and winter seasons, when the amount of daylight time is lower than the rest months of the year. The cloudiness is the how sunny or cloudy is one day. When the day is sunny people are in a good mood and they are more optimistic about the future prospects. We examine these effects using regressions based on cross sectional data at 7 stock exchanges all over the world from 1982 to 1996. We use two methods. One is a country by country regression and one joint test which contains the whole sample of the IPOs. In both methods we control for a number of non psychological factors.

Concerning underpricing, in our study we assume that investor who are affected by SAD are more risk averse hence less willing to buy stocks. According to Dovlin and Pyles (1997) issuers know that, so they adjust the offer price downwards which leads to higher underpricing during SAD months. In our study we find the majority of the IPOs to be overpriced and indeed the IPOs during the SAD period have tendency to be less overpriced than the non SAD period. To the best of our knowledge there are no previous studies which examine the effect of cloudiness on underpricing. We made an assumption that there is a negative correlation between cloud cover and underpricing because the investors are more optimistic in sunny days so they are more willing to buy stocks which leads to higher returns. We find a positive but not significant relation in
the country by country regression but in the pooled regression there is a significant effect (t-stat 2.08).

For the volatility we assume that there is a negative effect relation both between the SAD and the cloudiness. During SAD period and when the sky is cloudy investors are not in the mood for investing. People are pessimistic and unhappy and this leads to a less intense trading activity. Small trading volume usually drives stocks into small volatility. Our results, however, are not clear since there are mixed signs in the regressions. The coefficients are very close to zero and there are only a few significant. In addition the difference in stock volatility during the SAD period is almost equal to the stock volatility during the non SAD period.

The performance of the IPO has been studied by several authors. The short term performance, in IPO literature, is connected with the underpricing. The long term performance is measured with Cumulative Adjusted Returns (CAR) or the Buy and Hold Returns (BHAR) by the vast majority of the authors. In our study we examine the 5 days IPO performance measured by simple returns. Based on previous authors result we expect to find a negative relation between SAD effect and IPO performance. This means that the IPO performance during the SAD period will underperform the IPO performance the non SAD period. This is consistent with the studies of Rosenthal et al (1984), Kamstra et al (2003) and many others. Many researchers have also examined the effect of cloudiness in investors’ psychology. Saunders (1993) and Hirshleifer and Shumway (2003) are among the most popular and they have found a significantly negative relation between cloudiness and stock performance. Our assumption is that the short term performance is affected in a negative manner from cloudiness. We find that there is no significant effect of SAD but cloud cover, in some countries, can affect in a great extend the performance of the IPOs. However, in our sample, the IPOs during the SAD period are poorly performed in comparison to the issues in non-SAD period.

Concluded, we have a summary of the hypothesis that are going to be tested in this paper:

Hypothesis 1: There is a positive effect of SAD on IPO underpricing and there is a negative relation between cloud cover and underpricing.
Hypothesis 2: SAD as well as cloudiness has a negative impact on IPO return volatility.

Hypothesis 3: IPO are doing better during the non SAD period and the performance of the IPOs is also worse in cloudy days.

This paper is structured as follows: Section 1 is this section the Introduction; Section 2 is the previous literature related to our study; Section 3 describes the Data used for the regressions and outlines the methodology and the models used; Section 4 Contains the statistical analysis of the data and the discussion of the results; Section 5 documents the conclusion and the recommendations.
3. Data and Methodology

3.1 Data

The IPO data used for this research (companies, date of issuance, offering price, closing prices, index closing prices, trading volume, industry and gross proceeds) comes from Bloomberg Databases and includes the initial public offerings of common stock issued from January 1982 through December 1997 with no constraints regarding minimum offering price in order to be considered. Our data sample does not include Seasonal Equity Offerings (SEOs) and IPOs of closed-end funds, ADRs and REITS.

The sample used for this research consists of 5283 IPOs from seven markets throughout the world. The markets used are Singapore, Australia, France, Malaysia, UK and U.S.A. Table 1 depicts a summary of the different indices and the number of IPOs considered for each of them.

<table>
<thead>
<tr>
<th>Country</th>
<th>No of IPOs</th>
<th>Sample Timeframe</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>4240</td>
<td>1982-1997</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>413</td>
<td>1988-1997</td>
</tr>
<tr>
<td>Australia</td>
<td>158</td>
<td>1989-1997</td>
</tr>
<tr>
<td>Malaysia</td>
<td>229</td>
<td>1987-1997</td>
</tr>
<tr>
<td>France</td>
<td>144</td>
<td>1994-1997</td>
</tr>
</tbody>
</table>

Weather data were extracted from the International Surface Weather Observations (ISWO)\(^3\) of the National Climatic Data Center (NCDC). SKC is the cloud cover and is measured on a scale of 0 to 8, 0 being clear sky and 8 being overcast and is the average cloud cover from 6 am to 4 pm local time. The daily cloud cover is highly seasonal for every city under examination. Thus, we have used SKC which relates to the cloud cover which has been de-seasonalised by subtracting the weekly average from each observation. This ensures that our outcomes will not be affected by seasonal return patterns. The reason why fall and winter have been chosen is because medical research

\(^3\) The data were compiled by Symeonidis, Daskalakis and Markellos (2010)
have shown that Seasonal Affective Disorder is a condition which affects individuals in winter and fall due to the amount of daylight during these seasons (Mollin et al (1996) and Young et al (1997)). Furthermore, research by Kamstra et al (2003) has shown that SAD has a direct effect on the investors’ risk aversion. They demonstrated that investors suffering from SAD were more prone to switch from investing in a risky asset, to investing in a riskless asset. Finally, Dolvin and Pyles (2007) in their research found that SAD results in higher underpricing. This indicates that underpricing is higher in SAD months and when compared to previous studies they find no asymmetric effect.

3.1.1 Underpricing

By observing table 2 we can see that in the sample of IPOs we examine, the overpriced or these that have zero initial returns are by far more than the underpriced IPOs. More specifically, in a sample of 5283 IPOs, 3227 are over or fairly priced and 2056 are underpriced.

<table>
<thead>
<tr>
<th></th>
<th>Overpriced</th>
<th>Underpriced</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Issues</td>
<td>3227</td>
<td>2056</td>
<td>5283</td>
</tr>
<tr>
<td>Initial Returns</td>
<td>-41.92%</td>
<td>23.63%</td>
<td></td>
</tr>
<tr>
<td>Volatility</td>
<td>3.23%</td>
<td>2.57%</td>
<td>2.83%</td>
</tr>
<tr>
<td>5 Day Returns</td>
<td>0.03%</td>
<td>-0.24%</td>
<td>-0.08%</td>
</tr>
<tr>
<td>No of Non-SAD issues</td>
<td>1580</td>
<td>966</td>
<td>2546</td>
</tr>
<tr>
<td>Initial Returns</td>
<td>-42.46%</td>
<td>21.61%</td>
<td>-18.15%</td>
</tr>
<tr>
<td>Volatility</td>
<td>2.84%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Day Returns</td>
<td>46.47%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No of SAD Issues</td>
<td>1647</td>
<td>1090</td>
<td>2737</td>
</tr>
<tr>
<td>Initial Returns</td>
<td>-32.52%</td>
<td>24.87%</td>
<td>-9.66%</td>
</tr>
<tr>
<td>Volatility</td>
<td>2.75%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Day Returns</td>
<td>57.09%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No of Fall issues</td>
<td>1052</td>
<td>699</td>
<td>1751</td>
</tr>
<tr>
<td>Initial Returns</td>
<td>-28.41%</td>
<td>25.32%</td>
<td>-6.96%</td>
</tr>
<tr>
<td>No of Winter issues</td>
<td>593</td>
<td>391</td>
<td>984</td>
</tr>
<tr>
<td>Initial Returns</td>
<td>-39.88%</td>
<td>24.05%</td>
<td>-14.48%</td>
</tr>
</tbody>
</table>
Previous studies have shown that SAD might affect the IPOs and lead to higher underpricing. Thus, issues during fall and winter (21 September to 20 March in each year) have higher returns than the ones during spring and summer (Dolvin and Pyles (2007)). In our sample there are 2737 issues during the SAD period and 2546 during the non-SAD period. The IPOs in our sample agree with the findings of previous researchers in the sense that there is higher first day returns but the most issues were found to be overpriced. The IPOs have an initial average return of -9.66 percent in the SAD period and -18.15 percent initial return in the non-SAD period and this difference is significant at the 5 percent level. If we take a look only at the underpriced IPOs we see that there is the SAD effect in this sub-sample. The underpriced IPOs have an initial average return of 24.87 percent in the SAD period and 21.6 percent in non-SAD period.

In their study, Dolvin and Pyles (2007), make another interesting finding. They found that there is higher underpricing during winter season than in fall. As we can see in table 2 during winter there are 1751 issues with initial average return of -6.96 percent and in fall 984 issues which have average initial return -14.48 percent. If we examine only the underpriced IPOs we observe that the underpriced issues in winter have higher level of underpricing than the fall issues (25.32 percent in fall and 24.05 percent in winter).

3.1.2 Volatility

The second hypothesis is that the weather can affect the volatility of the IPO returns. We have chosen to measure volatility by the standard deviation of the returns. We estimate the standard deviation of the first five trading days after the listing date. Table 2 depicts the volatility of IPO returns during SAD and non-SAD period. If we see each country individually there is significant difference in some countries like Singapore (0.88 percent) and Australia (0.76 percent) where the returns have higher volatility in non-SAD period than in the SAD period. The results in our sample are mixed since there are some countries where the IPO returns are more volatile in the SAD period and others that have bigger variability in the non-SAD period. However, the variability of all countries together, if we see it as a whole, seems that is not affected by the SAD effect since the difference is slightly bigger during the SAD period (0.09 percent).
In the past many researchers has studied the relationship between underpricing and volatility (which exist due to the information asymmetry) and have stated that the more volatile an IPO is the more possible is to be underpriced (Beatty and Ritter (1986), Michaely and Shaw (1994)). Our study is consistent with these findings. Table 2 depicts that in our sample there are 2056 underpriced issues, of which the standard deviation is 3.23 percent and 3227 overpriced with standard deviation of 2.57. This happens also for the majority of the countries where the underpriced IPOs show higher variability in their returns than the overpriced.

3.1.3 Performance

In the bibliography short-term performance (performance of 5 days) is usually considered the same with the initial underpricing (first day returns) because there is small difference between the two measures. In our study, however, we treat performance differently from underpricing. This happens because we examine something unique, the weather effect, which can have an impact on the performance of a stock only for a very short time interval. In our sample the results are mixed. In the four countries the short term performance of the IPO is negative and only in the two is positive. The same phenomenon happens for the underpriced and the overpriced IPOs with the exception of Singapore which have different sign in the returns of under and overpriced IPOs. Previous studies Rossenthal et al (1994), Kamstra et al (2003) have shown the SAD effect has a negative impact on stock performance in the long run. IPOs in our sample do not agree with these studies since the IPO 5 day performance in SAD months is 57.09 percent whereas in the non SAD period is 46.47 percent. Previous authors have claimed that IPOs that have positive initial returns are more likely to be underperformed in a horizon of 3 years. We found our study to be consistent with this theory for the performance of 5 days period. The 5 day average returns of the underpriced IPOs is -0.24 percent and the average returns of the overpriced IPOs is 0.03 percent.
3.2 The models

3.2.1 Underpricing

The regression model that we will use in order to determine the SAD and SKC effect and estimate the coefficients is the model below.

\[ R_{i,t} - R_{m,t} = \alpha + \beta_1 DH_{i,t} + \beta_3 SKC_{i,t} + \beta_4 TECH_{i,t} + \beta_5 \text{Indexlag}_{m,t} + \beta_6 \text{Proceeds}_i + \epsilon_i \]

where the dependant variable is the initial underpricing. Proceeds is one control variable and is the natural logarithm of the gross proceeds amount (in million dollars), TECH is the technology dummy variable and Indexlag which is the second control variable and is the accumulative returns that the Index of each country had 15 days before the issue.

As already mentioned, we define the underpricing as the initial returns (returns of the first trading day) adjusted for market returns. The initial returns is the percentage difference from the offer price to the first trading day closing price. The indices for each particular country are the SES Index in Singapore\(^4\), the ASX Index in Australia, the CAC40 Index in France, the KLSE Index in Malaysia, the FTSE 100 Index in the UK and the S&P 500 Index in the U.S.A which contain all the stocks listing in each country. The formula used for the estimation of initial returns is depicted below.

\[
\text{Market Adjusted Initial Returns} = \frac{P_{t,i} - P_{of,i}}{P_{of,i}} - \frac{P_{t,m} - P_{t-1,m}}{P_{t-1,m}}
\]

Where the first division is the first day raw returns of the IPO and the second is the index raw returns of the country the company operates in at the day of the listing. More specifically:

\(P_{t,i}\) is the closing price of the first trading day of the firm \(i\)

\(P_{of,i}\) is the offer price of the IPO of the firm \(i\)

\(P_{t,m}\) is the closing price of the Index the first trading day of the IPO

\(^4\) In 1999 the SES index merged with the SIMEX (Singapore International Monetary Exchange) to form the SGX (Singapore Exchange) which has been the main Index of Singapore ever since.
$P_{t-1,m}$ is the closing price of the Index the day before the IPO

The variable SKC were defined previously. As far as the variable DH concerned has the opposite effect that SAD has. We would expect SAD to have a positive correlation with underpricing. Thus, the variable DH is expected to have a negative impact on first day returns. This expectation is based on the results of previous researches that have witnessed a positive relationship between underpricing and SAD (Dolvin and Pyles (2007)) and inverse relationship between temperature and stock market changes (Cao and Wei (2005)). Although Kamstra et al (2003) and Cao and Wei (2005) use daily data, Jacobsen and Marquering (2007) argue that using daily data is noisier as there they face problems of kurtosis and skewness. This research will also use daily data. There are no empirical findings of previous studies of the relation between SKC and underpricing.

Proceeds is the amount of capital raised in the IPO. Issues that raise a great amount of funds are usually less risky because they are large companies that are supported by many analysts. In addition in such big offerings, price manipulation is more difficult to occur because the bigger the issue is, the more investors will hold shares. Thus, we expect large offerings to be less underpriced and have lower long-term returns than smaller offerings. This view is supported by a number of researchers who demonstrate how issue size can affect underpricing (Beatty and Ritter (1986) and Ibbotson et al (1994)).

In our sample the large offerings are more overpriced than the small offerings. The initial average return of the big companies’ IPOs is -17.93 percent and the small companies’ initial average returns -5.92 percent. There is also a huge difference concerning the underpriced issues. In our sample the 15 percent of the large offerings are underpriced and the same time the small offerings are 35 percent underpriced. Our sample is also consistent with the findings of previous researchers, concerning the volatility and performance. In our case the big companies’ stock five days after the listing have less volatile returns and outperform small companies’ stocks.

High-technology companies usually have greater underpricing than others so we include the TECH dummy variable in our model in order to control this phenomenon. The TECH dummy takes the value of “1” if the company operates in technology industry and “0” in all other cases. Technological companies have more volatile earnings so this
makes them riskier. Since technological companies are riskier, we expect a higher underpricing and higher returns in the long-run than companies of other industries.

Our sample is consistent with this theory and the 649 high-technology IPOs are less overpriced than the non-technology ones. The initial average underpricing for the technology companies is -11.23 percent whereas the non-technology companies have initial average returns -17.69 percent. In addition form the high technology companies the 59 percent is underpriced and the 41 percent is overpriced. The sample of companies we examine is also consistent with the empirical evidence of previous studies that the high-technology companies have more volatile returns than the others. In our case the 5 day standard deviation for high-tech company stock is 3.66 percent and the non-technology companies’ standard deviation is 2.71.

Indexlag is the cumulative returns the specific Index of each country has 15 trading day prior to the listing date. We use this variable to identify market conditions shortly before the IPO. Previous studies have shown that market performance before the issuance has a positive relation with initial underpricing and post IPO performance (Ljungqvist (1997)). However our sample is not consistent with this theory. In the case when the Index had good performance before the listing date, the IPOs have higher level of overpricing than in the case when the Index of the specific country is badly performed.

3.2.2 Volatility

The model that we will use for the testing of the volatility is the same that we used for underpricing the only difference being that instead of having the initial underpricing as the dependent variable, we will use volatility.

\[ \text{VOL} (\sigma) = \alpha + \beta_1 \text{DH}_{i,t} + \beta_2 \text{SKC}_{i,t} + \beta_3 \text{TECH}_i + \beta_4 \text{Indexlag}_{m,t} + \beta_5 \text{Proceeds}_i + \varepsilon_i \]

VOL is the aftermarket volatility which is expressed as standard deviation. The standard deviation is estimated for the interval of the next five (5) day stock returns after the IPO of each company. The standard deviation is estimated with this formula

\[ \sigma (R_{j,t}) = \sqrt{\frac{\sum_{i=1}^{n} (R_{j,t} - \bar{R})^2}{n-1}} \]
Where $R_{j,t}$ is the simple daily returns of stock $i$ at time $t$ and $\bar{R}$ is the average daily returns of all IPOs.

In the regression model the dependant variable as already mentioned is the standard deviation of 5 days returns. The right hand side variables are the same with some differences in the way we take the values. DH is the average DH from the listing day to 5 days after the listing. The same happens for SKC variable where it is the average of 5 day values of SKC. The other three right hand side variables are the same. Proceeds variable is the natural logarithm of the gross proceeds amount, TECH is the technology dummy variable and Indexlag is the cumulative returns of the Index 15 days before the issue.

### 3.2.3 Performance

The model that we will use for the testing of the performance of the IPO is the same that we used for the volatility testing the only difference being that instead of having the standard deviation as the dependent variable, we will use simple returns.

$$R_{i,t} - R_{m,t} = \alpha + \beta_1 DH_{i,t} + \beta_2 SKC_{im,t} + \beta_3 TECH_i + \beta_4 Indexlag_{m,t} + \beta_5 Proceeds_i + \epsilon_i$$

In this regression model the dependant variable is the 5 days performance of the IPO. The right hand side variables are the same we used for the model of volatility. In the IPO literature, the researchers study the long term performance. Short term performance is the initial underpricing. In order to estimate the long term performance researchers have used cumulative adjusted returns (CAR) or Buy and Hold Adjusted Returns (BHAR). The time interval we examine the performance is very small so we are going to use the 5 day simple returns.

The performance of the IPO is measured by the 5 days simple returns adjusted for the market returns. In the 5 day returns we do not conclude the initial returns of the IPO.
3.3 Methodology

In section 4 we describe all the statistical results of testing the effect of SAD effect and cloudy weather on IPO underpricing in two parts. In the first part we do a country-by-country regression analysis on the model discussed above controlling for other variables, except for SKC and DH, which can have an impact on IPO underpricing. In order to see whether our results are driven by the weather conditions, it is important to control for other factors firm or issue related. Through the regression analysis we are attempting to have an estimation of the model’s coefficients and discover the statistical significance of these coefficients. The method that is going to be used for the estimation of the model’s coefficients is the Ordinary Least Squares (OLS) method. However, having a relatively small number of IPOs in some countries we do not expect the tests for some countries to have statistically significant coefficients. In the second part, in order to control for all the factors that affect the underpricing, we perform a pooled regression including all countries together. Performing this test will help us have more clear results of these effects because this is an across city and indices test. It is important at this point to mention that we have performed a cluster analysis for the countries that have more than one IPOs in the same date which results in having repeated values of SKC and DH variables and these dates gain more weight comparing to dates that have only one IPO. Performing the clustering test did not provide substantial difference in our results in any country. After testing our sample for White heteroskedasticity, we found heteroskedasticity to exist in the residuals both in the country-by-country analysis and in the pooled analysis. Thus, in order to overcome this problem the OLS coefficients are adjusted for White heteroskedasticity. We also performed a Ramsey Reset test with one fitted term in order to check the robustness of our model. All the probabilities are equal or bigger than 0.05 thus our model can be used since all the coefficients are not biased or inconsistent. In addition the residuals were also tested for normality with the Jarque-Bera test. All the probabilities are zero or smaller than 0.05 so we can safely say that the residuals follow the normal distribution. Finally, we check the data for the existence of multicollinearity. In order to do so we created the correlation matrices for all the dependent variables except the TECH dummy variable. As we can see in tables I-VIII the low correlation and probability values between each independent variable with the others, combined with the small adjusted R² of the OLS regression,
brings us to the conclusion that there is no multicollinearity between the independent variables.

We followed the same process for the other two models, where the dependent variables are the standard deviation of the returns and the stock performance 5 days after the listing. We also tested our sample for robustness, heteroskedasticity, normality and multicollinearity. The results were satisfactory and thus we did not have to make any changes in the sample, change or even omit one of the independent variables.
4. Empirical results

4.1 Underpricing

In the first part we perform a country-by-country regression analysis. It is important to note that due to the small number of IPOs in all the countries except the US and the UK our results are not 100 percent acceptable but they clearly can show us a tendency. In table 3 we can see all the OLS coefficients of this simple regression. The coefficients with asterisks are significant, in different percentage levels of significance. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively. As far as the deseasonalized sky cover (SKC) is concerned, it is clear that there is a positive relationship between SKC and underpricing. The majority of the coefficients on each country is positive and there are only two country coefficients that have negative value. This is not consistent with our hypothesis (H1). However, only the in the US there is significant impact of SKC on underpricing. We also added a one-day lagged variable of SKC in our model in order to investigate the previous day’s impact on investor’s mood but there is no significant difference. Although there is a positive relationship in the majority of the countries, this can hardly be acceptable due to the lack of statistical significance for the most countries.

As far as the DH variable is concerned, the results are quite similar to those we were expecting. By observing table 3 we can see that there is a clear negative relationship between DH and underpricing with the exception of Singapore and Malaysia where there is an insignificant and significant positive impact respectively. This is consistent with the hypothesis which claims that investors who have SAD, usually demand higher return to invest in a security. Thus, in fall and winter season, the period the SAD is observed, we would expect a high underpricing. In our sample the IPOs in the SAD period are found to be less overpriced than the issue in the non SAD period (-9.66 percent instead of -18.15 percent in the non SAD period).
Table 3  
Underpricing Regression and t-test results

This table displays country by country and pooled results of estimating a regression of underpricing on cloudiness (SKC), daylight hours (DH), Technology dummy (TECH) which takes the value of 1 for high technology companies and 0 in other cases, the natural logarithm of the amount of funds raised (PROCEEDS) and 15 day cumulative returns of the market (INDEXLAG). For each variable the first raw is the coefficient and the second raw is the t statistic. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively.

<table>
<thead>
<tr>
<th></th>
<th>AUS</th>
<th>FRA</th>
<th>MAL</th>
<th>SIN</th>
<th>UK</th>
<th>US</th>
<th>POOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>SKC</td>
<td>0.008</td>
<td>-0.003</td>
<td>-0.105</td>
<td>0.052</td>
<td>0.009</td>
<td>0.006***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>0.56</td>
<td>-0.30</td>
<td>-0.93</td>
<td>0.92</td>
<td>1.10</td>
<td>2.50</td>
<td>2.08</td>
</tr>
<tr>
<td>HD</td>
<td>-0.345</td>
<td>-0.024</td>
<td>9.497***</td>
<td>6.842</td>
<td>-0.063</td>
<td>-0.136***</td>
<td>-0.126***</td>
</tr>
<tr>
<td></td>
<td>-1.51</td>
<td>-0.34</td>
<td>2.67</td>
<td>0.48</td>
<td>-1.00</td>
<td>-3.64</td>
<td>-3.74</td>
</tr>
<tr>
<td>TECH</td>
<td>0.132</td>
<td>-0.046</td>
<td>-0.453***</td>
<td>-0.102</td>
<td>-0.089</td>
<td>0.054***</td>
<td>0.042**</td>
</tr>
<tr>
<td></td>
<td>1.49</td>
<td>-1.59</td>
<td>-3.80</td>
<td>-0.37</td>
<td>-1.38</td>
<td>2.66</td>
<td>2.13</td>
</tr>
<tr>
<td>PROCEEDS</td>
<td>-0.039</td>
<td>-0.002</td>
<td>-0.033</td>
<td>0.073</td>
<td>-0.039</td>
<td>-0.071</td>
<td>-0.042</td>
</tr>
<tr>
<td></td>
<td>-1.95</td>
<td>-0.13</td>
<td>-1.07</td>
<td>1.21</td>
<td>-4.60</td>
<td>-13.21</td>
<td>-8.79</td>
</tr>
<tr>
<td>INDEXLAG</td>
<td>1.409</td>
<td>-0.168</td>
<td>-2.135</td>
<td>3.999</td>
<td>2.474</td>
<td>0.034</td>
<td>0.461</td>
</tr>
<tr>
<td></td>
<td>0.42</td>
<td>-0.14</td>
<td>-1.18</td>
<td>0.87</td>
<td>1.72</td>
<td>0.05</td>
<td>0.76</td>
</tr>
<tr>
<td>C</td>
<td>0.261</td>
<td>-0.816</td>
<td>-9.496</td>
<td>-7.397</td>
<td>-0.002</td>
<td>0.235</td>
<td>0.096</td>
</tr>
<tr>
<td></td>
<td>0.99</td>
<td>-9.95</td>
<td>-2.66</td>
<td>-0.51</td>
<td>-0.03</td>
<td>5.48</td>
<td>2.47</td>
</tr>
<tr>
<td>R² Adjusted</td>
<td>0.04</td>
<td>0.01</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>N</td>
<td>158</td>
<td>144</td>
<td>229</td>
<td>99</td>
<td>413</td>
<td>4240</td>
<td>5255</td>
</tr>
</tbody>
</table>

The effect of the other control variables is more or less what we were expecting. More specifically it is more possible for an IPO to be underpriced (overpriced) if the company raises a small (large) amount of capital. Moreover, when the market is performing well, a few days before the listing date, there is a mixed possibility that the issue will be underpriced because the signs of the coefficients are mixed and only in the UK there is highly significant positive relation. In our sample, however, when the market had a positive performance before the IPO the average initial returns of the IPOs was -16.96 percent whereas if the market had experience a bad performance the average intial returns was -15.70 percent. Although previous studies have shown that high-technology companies are usually more underpriced than others in their listing to stock exchange, the results of our study are mixed. The two countries that the coefficient on TECH dummy is significant are USA (positive coefficient and highly significant) and Malaysia (where the impact of TECH variable is clearly negative and highly significant). In fact the technology companies experience a lower level of underpricing (-11.23 percent) from the non technology issues (-17.11 percent).
In the second part we use the entire dataset to determine the statistical significance of the model’s coefficients on variables. So we report the results of a pooled regression analysis and tests of significance (across cities and indices) in this section. The results are very close to the US results because the sample consists of about 70 percent of US observations. The coefficient on SKC is negative but very close to zero and the coefficient on DH variable is also negative and highly significant (t-statistic -2.37) which is different from the result of country-by-country regression. In addition, the results of t-test for the other variables are quite similar to those of individual country regressions.

In general there does not seem to be a significant difference with respect to firm characteristics (technological or not) but offer characteristics (large or small amount or capital raised) provide us a good explanation. Our hypothesis that we can expect higher initial returns in SAD months and in cloudy days seems to be right. However there is still space for improvement. The small adjusted R$^2$ of the OLS regressions reminds us that even though there are some significant relations between the dependent variable and the independent ones, we cannot consider the explanatory power of the independent variables to be trustworthy.

4.1.2 Volatility

In this section we use the standard deviation of 5 days returns in order to measure the variability of the stock. We study the variability for such a short time interval because we can assume that the weather and other psychological factors can affect the volatility of the returns only for a very short term horizon. The main thing that previous authors have examined is the relationship between underpricing and volatility. They argue that the underpriced IPO have more volatile returns. We find that the underpriced IPO have a 5 day return standard deviation of 3.23 percent whereas the overpriced 2.57 percent.

As mentioned in Section 2, volatility is usually related to the trading volume of a specific stock. The more intensive is the trading activity of a stock the more volatile its returns are going to be. Moreover, small and high technology companies have usually more volatile returns. This happens because these kind of companies have volatile returns not only throughout the year, but also throughout their life. This fact makes investors more uncertain about the specific stocks and this leads to a greater volatility.
The volatility of IPO in our sample is consistent with this theory since the technological IPOs have a standard deviation of 3.66 percent whereas the issues of non technological companies experience a standard deviation of 2.71 percent. In table 4 we can see all the OLS coefficients of this simple regression. The coefficients with asterisks are significant, in different percentage levels of significance. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively.

**Table 4**

Volatility Regression and t-test results

This table displays country by country and pooled results of estimating a regression of volatility on 5 days average cloudiness (SKC), 5 days average daylight hours (DH), Technology dummy (TECH) which takes the value of 1 for high technology companies and 0 in other cases, the natural logarithm of amount of funds raised (PROCEEDS) and 15 day cumulative returns of the market (INDEXLAG). For each variable the first raw is the coefficient and the second raw is the t statistic. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively.

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<td>-0.005**</td>
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<td>-0.002**</td>
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If we observe table 4 we can see the results of the simple and pooled regressions. In the simple country-by country regressions we see that the cloudiness does not affect the volatility of the returns. The investors’ activity seems not to be affected from the sunshine five days after the listing of the company since only in the regression of Malaysia the coefficient on SKC is significant. On the other hand, DH has a highly significant but slightly negative relation with the standard deviation. This means that in SAD period the volatility tends to be a little higher than in spring and summer. In our sample the IPOs during SAD period have a standard deviation of 2.84 percent and in the
non-SAD period 2.74 percent. In other words IPO stocks are about 10 basis points more volatile in SAD period.

Besides, the volatility is also affected from some firm specific factors such as the size or the industry in which operates. Table 4 also depicts the effect of gross proceeds and the TECH dummy variable as well. It is clear that the stock of a large company has a significantly lower volatility than the stock of a small company. In our sample the large companies have almost twice greater volatility from small companies and this is significant at the 1 percent level in 4 out of 6 countries. On the contrary, the fact that a company is technological does not have the results we expected. The coefficients on TECH dummy of all countries regressions are close to zero and only in the US the coefficient is highly significant at 5 percent level. The last control variable, the indexlag, is negatively related with the volatility in most countries but again is significant only in US. Thus we can say that the market condition before the issue does not affect the investors’ beliefs to a great extent.

The results of the pooled regression are also depicted in table 4 we observe that the OLS coefficients as well as the t-statistic are affected from the US regression values. In this regression we can see that cloudiness does not have significant effect on the volatility of returns. On the other hand, it is obvious that DH has statistically significant impact on volatility but it is substantial. Just like the USA, if we see the sample as whole we see that investors’ activity and psychology in the SAD period does not affect in a great extend the variability of the stocks.

In addition we have to observe the control variables of the regression. We see that all the most of the coefficients are statistically significant at 1 percent level but the coefficients are almost zero. The lowest coefficient in absolute value is 0.036 and the highest 0.084. The relation is what we expected. The high technology companies tend to have more volatile earnings and there is a negative relation between size and volatility. Smaller companies are likely to have more variability in their stocks.

In conclusion, we can safely say that volatility is not influenced by the cloudiness but can sometimes be affected by the SAD. The firm and offer specific characteristics can cause small changes but the condition of the market shortly before the listing keep investors unaffected. The main issue is that we have to consider the $R^2$ one more time. The small $R^2$, the smallest is 2.84 percent and the biggest 17.78 percent, cannot keep us
satisfied for explanatory ability of the dependent variables, coefficients and the t – tests. Having a greater sample or choosing control variables that can explain better the variability of the returns we can result in an improved $R^2$.

4.1.3 Short Term Performance

As mentioned in a previous section in IPO literature short term performance of about a week is usually the same with the initial returns. However, the weather and other psychological effects can be only for a very short time period. Thus we examine the effect of cloudiness and SAD for five trading days following the first trading day. For the regressions where we used as dependent variable the 5 days cumulative returns we have used the same left hand side variables that we used for the volatility regressions. Previous authors have found that underpriced IPOs usually underperform overpriced IPOs in the long run. The majority of IPOs in our sample are found to be underpriced. The performance of the underpriced IPOs is inferior to the performance of the overpriced IPOs for five out of six countries. In table 5 we can see all the OLS coefficients of this simple regression. The coefficients with asterisks are significant, in different percentage levels of significance. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively.

In table 5 we see the results of country by country regressions. In the SKC row are the coefficients of each country regression regarding SKC. We see that there is a very small positive effect in the majority of the countries but only in the UK regression the coefficient is significant in 10 percent level. The average of the coefficients on cloudiness is 0.0010, which shows that the difference in the returns when the sky is clear and when the sky is cloudy is 10 basis points. Put differently, in money terms is only 10 cents on a one hundred dollar stock. For the DH variable we have a positive relation with the stock returns in most of the countries but only the coefficient of Malaysia is significant in 5 percent level. However the SAD effect is more intense than the cloudiness since the average of the coefficients on DH is 0.1094.
Table 5. Performance Regression and t-test results

This table displays country by country and pooled results of estimating a regression of 5 days returns on 5 days average cloudiness (SKC), 5 days average daylight hours (DH), Technology dummy (TECH) which takes the value of 1 for high technology companies and 0 in other cases, the natural logarithm of amount of funds raised (PROCEEDS) and 15 day cumulative returns of the market (INDEXLAG). For each variable the first raw is the coefficient and the second raw is the t statistic. One, two or three asterisks denote the significance in 1%, 5% and 10% respectively.

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However, the coefficients on the control and dummy variable are mixed. We cannot have a clear picture of the effect of the TECH dummy because three coefficients on the dummy are positive and three are negative. In addition there is one highly, positively significant in Malaysia and one negatively significant in the UK at 5 percent level. Besides, the difference average of 5 days returns between the tech and the non tech IPOs is 4 basis points (-0.0025 technology stock and -0.0021 non technology). The same occurs for the Indexlag variable. The results have mixed signs but there are two extremely high positive coefficients in Australia and France but we see a significant effect on 1 percent level for France which is an indicator that the market condition before the listing date can have a big impact on next days’ performance. We find that the variable of gross proceeds has a slightly negative impact on IPO performance and this is significant in UK regression. The large issues have lower average returns of about 0.023 percent than the small issues.

If we take a look at the pooled regression results at table 5 we see that there is only one highly significant but zero coefficient on Proceeds variable. Both the coefficients on
SKC and DH are statistically insignificant and there is an effect close to zero. Moreover, all the coefficients slightly differ from zero. Thus we can note that there is neither a weather effect nor a psychology factor that can an impact on the 5 day performance. The only factor that seems to influence the stock returns is the size of the company which clearly indicates that large companies will have 6 basis points less cumulative returns than the small companies.

However, the problem is, in performance regressions as well, the small R squared. The values of R squared is from 0 to 4.96 percent which indicates that only a very small part of the variability of the returns can be explained by the right hand side variables. This means that we cannot be based on this model in order to form a portfolio of stocks for short term investment purposes.
5. Conclusion

IPOs represent an interesting part of the security market. Previous studies focus on firm and issue characteristics in order to find the factors that affect the behavior of an IPO. We examine it from a different perspective, focusing on psychological factors that affect peoples’ mood and behavior which consequently affects their trading activity. These factors are the SAD and the cloud cover. Psychological studies have found evidence that not only the SAD but cloudy weather is also related to downbeat mood of the people as well. This paper examines the relationship between the SAD effect, the cloudiness and the IPO returns in 6 different countries from 1982 to 1997. We examine the effect of these factors on undepricing, volatility and performance of an IPO after controlling for some firm or offer specific factors.

The primary conclusion of this study, concerning underpricing, is that there is a positive relationship between underpricing and cloudiness. This is not consistent with our expectations and what psychology studies have found. Our results show that investors are not negatively affected by cloud cover and they invest in IPOs no matter what the sky is cloudy or sunny. We also find that there is a positive relationship between SAD and underpricing but in the most countries but the statistical significance is low.

The second conclusion of this study, concerning volatility, is that the post IPO volatility is affected in a very small extent by cloudiness. The average coefficients we find are not, in absolute values, much more different from zero. This is normal because we examine the standard deviation of 5 days time interval. So we can result that it is possible that the investors mood may not be affected the volatility of an IPO returns in such a short period. However, SAD is found to have a positive relation with IPO volatility which in some cases is significant. In other words stocks have higher variability during SAD period which is also different from what we assumed in the second hypothesis.

The third and last conclusion is the results concerning performance. Hirshleifer and Shumway (2003) and some years before Saunders (1993) found a strong negative correlation between cloud cover and IPO performance using time series data on the long term horizon. We find an almost zero effect of cloudiness in the 5 day performance of
the IPOs. On the other hand there is a negative impact of SAD on the performance. This difference, however, is not significant in the most countries. This is consistent with our hypothesis as well as with the findings of previous authors’ studies concerning performance and weather effect.

Our study examines the impact of psychological situation of the investors on IPOs. However due to the lack of information of other weather variables it was impossible to test the implications of these factors. Other weather factors that have been used of other researchers that could be added in order to have a better picture of weather effect is precipitation, temperature, snowfall and many others. Temperature has been used by Chang et al (2005) who found a positive effect of temperature on stock performance and Symeonidis et al (2008) who witnessed a positive relationship between stock market volatility and temperature. Symeonidis et al (2008) also used precipitation in their model and they witnessed that the rainy days the volatility was bigger. On the other hand we could extend our model using other weather variables based not on psychological explanation but more rational. For example Loughran and Schultz (2004) found that the trading volume is significantly lower when there is a blizzard in the city due to the fact that investors go late to work because it takes time to shovel the snow. Those are from the weather variables perspective. We could also use a bigger sample of IPOs or other firm or offer specific variables and fundamental variables that could possibly explain better the left hand side variables of our models.

We don’t think that our study will help investors to invest in an IPO portfolio based on weather and season. It not possible to price a security thinking that its price is changes because of the weather conditions. The practical implications are not to direct investors to specific trading strategies but something else. Our results can help investors to avoid trading mistakes from mood leading trading activities. They will be aware that they are influenced by weather so they can make more rational trades and more fundamental based judgments. Besides when the situation of the economy is good everyone is happy and optimistic. When this changes people are becoming less willing to invest and they see future in a more pessimistic way than they should. The general idea which this paper is based is that the security prices do not fluctuate only because investors decide their trades based on previous prices and fundamentals but they are also influenced by their moods and emotions.
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Bilkent*
University working paper


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### Appendix

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France Correlation Matrix
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