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Is there still a weather anomaly? An investigation of stock and foreign exchange markets☆

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ABSTRACT

Since Saunders (1993), there has been ongoing research on whether the weather can affect asset prices. Our study of the impact of weather on stock and foreign exchange (henceforth *FX*) markets shows that the weather has no effect during 2002–2018, suggesting that any effect may have dissipated after discovery as practitioners have tried to use investment vehicles to exploit it. The results indicate that mood changes caused by the weather do not significantly affect *FX* and stock returns.

1. Introduction

Behavioral finance holds that security market prices are determined not only by their intrinsic values but also by investor psychology. Weather can affect investors' moods and thus their behavior in financial markets. For example, investors may be in a good (bad) mood when it is sunny (during thunderstorms), so they (do not) buy stocks (Daniel et al., 1998).

If the weather affects investor mood, resulting in stock price fluctuations, could the weather also affect the *FX* market? The exchange rate is affected by many factors, like inflation and interest rates. In the short term, it may be affected by events like Brexit. Will *FX* participants be affected by the weather in their trading decisions?

We investigate whether the weather affects *FX* markets. We select nine currencies: US Dollar (USD), Japanese Yen (JPY), Euro (EUR), Pound (GBP), Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), New Zealand Dollar (NZD) and Swedish Krona (SEK), respectively. We include eight currency pairs in our study, pairing the various currencies against USD and GBP, respectively. To compare the effects of the weather on the *FX* and stock markets, we also review US and UK stock indices. We find insufficient evidence that the weather can affect the stock and *FX* markets in the US and the UK. Although the weather can affect a person's mood, this does not mean that it can affect asset prices.

The next section reviews the relevant literature. Section 3 describes the weather and return data for the *FX* and stock markets. Section 4 details the methodology. Section 5 offers the results and Section 6 discusses their implications. The final section concludes.

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2. Related literature

2.1. Weather and behavioral finance

When the weather is favorable, people's cognitive processes are simplified (Isen, 2001) while increased humidity negatively affects staff performance, causing a loss of focus (Howarth and Hoffman, 1984). Exposure to extreme temperatures decreases ability to perform tasks (Pilcher et al., 2002) and willingness to help others (Cunningham, 1979).

Existing research on weather and financial markets is confined to stock markets. Saunders (1993) finds a negative relationship between cloud cover on Wall Street and New York Stock Exchange (NYSE) returns for a period of more than 50 years. Hirshleifer and Shumway (2003) (henceforth *HS*) find a positive correlation between sunshine and stock index returns for markets with low transaction costs. Extreme weather also affects stock markets. If a snowstorm occurs, investors spend more time commuting, and therefore have less time for stock trading. On blizzard days, trading volumes of listed companies in affected locations drop 17% (Loughran and Schultz, 2004).

MacAndrew (1993) argues that seasonal affective disorder (SAD) can change investors' risk attitude. He finds a positive correlation between stock market returns and daily hours of sunshine. Cao and Wei (2005) show that the returns of nine countries' stock indices are negatively correlated with temperature and this relationship is stronger in winter. Jacobsen and Marquering (2008) find that in 44 countries, seasons influence investment strategies by changing investors' moods.

Keef and Roush (2005) find that icy winds from Antarctica have a negative effect on daily returns on the New Zealand Stock Exchange. Dowling and Lucey (2005) show that precipitation plays a significant role in investors' decisions and offer evidence that the relationship between weather and equity returns is more pronounced in times of positive market performance. Using a large and globally diverse dataset, robust econometric approaches and deseasonalized and regular weather variables, Dowling and Lucey (2008) find that SAD and low temperatures have the strongest relationship with equity prices. This literature studies the effects of weather on stock markets; however, no study examines its effects on currency markets.

The *FX* transaction network is global and in 24-hour continuous operation except during weekends and major holidays. There may be difficulties in studying the effects of emotional variables on *FX* returns. For example, in trading the GBP/JPY, it is difficult to determine whether the weather in London or Tokyo has a greater effect. Saunders (1993) acknowledges that NYSE trading orders are from across the US. However, as local brokers in New York (henceforth *NY*) may influence stock pricing, the local weather in *NY* could be used as a proxy for the mood of market participants. Loughran and Schultz (2004) note that NYSE's trading orders come from across the US. Hence, they study the changes of stock returns of NASDAQ companies in relation to the weather of the company's registered location (represented by one of 25 US cities).

Since weather affects mood, our hypothesis is that it indirectly affects financial markets by influencing market participants' risk preferences. We choose markets in London and New York because the local investors in these financial centers play important roles in trading.

2.2. Foreign exchange market participants

To study whether *FX* market participants are affected by the weather when they trade, we need to discuss the institutional setting of the *FX* market and the main electronic trading venues.

The *FX* market is the largest financial market worldwide with a daily volume of USD5.1 trillion (BIS, 2016). Currencies are traded through the spot and derivatives markets. The players in the *FX* market include: central banks, commercial banks, investment managers, hedge funds, corporations and retail investors. The highest volume of currencies is traded in the interbank market. Commercial banks assist customers with *FX* transactions and conduct speculative trades for themselves. Central banks act in the *FX* market to stabilize, or increase the competitiveness of, their nations' economies. Investment managers and hedge funds comprise the second-largest group of *FX* market participants, after banks. Investment managers trade currencies for pension funds, foundations and endowments. Firms involved in importing and exporting conduct *FX* transactions to pay for goods and services and hedge exchange-rate risk.

Retail investors account for an extremely low share in *FX* trading. However, this share is growing rapidly due to emergence of electronic trading and the proliferating number of execution venues, which have lowered transaction costs and increased market liquidity. Most *FX* brokers operate from the UK. The Electronic Broking Services and Thomson Reuters Dealing are the two main competing trading exchanges and together connect more than 1000 banks (Cheng, 2007) while major banks provide their own trading systems.

The result of the different *FX* traders is a highly liquid global market with large transaction volumes and low transaction costs, creating the common perception that currency markets are extremely informationally efficient. However, the literature has documented currency anomalies or, in other words, investment strategies able to make systematic profits, such as 'carry trade' (Lustig and Verdelhan, 2007; Lustig et al., 2011), 'momentum' (Burnside et al., 2011; Menkhoff et al., 2012), 'value effect' (Asness et al., 2013; Menkhoff et al., 2016), and 'output gap' (Colacito et al., 2018). The literature has studied a number of currency anomalies but not the weather issue that is the focus of this study.

3. Sample and summary statistics

We select the world's nine most traded currencies by value according to BIS (2016): USD, EUR, JPY, GBP, AUD, CAD, CHF, NZD and SEK. We include eight currency pairs, pairing the various currencies against USD and GBP respectively. For stock index data in *NY*, we choose the Dow Jones Industrial Average (DJIA), NASDAQ, and S&P500. For London, we choose the FTSE100 and FTSE350.

We collect daily weather data from Bloomberg, 4078 observations from 02/01/2002 to 29/06/2018. We delete non-trading days in the weather data. To compare the effects of the weather on *NY* and London, we delete non-trading days on either of the two exchanges. All the data is in logarithmic returns. We subtract the lowest from the highest temperature to obtain the temperature difference. Extreme temperatures and temperature differences are used as independent variables. Keim (1983) argues that stock returns are seasonal. *HS* seasonally adjust their data, since seasonal patterns may affect the results. To ensure unbiased results, we follow the same data pre-processing protocol.

Overall, the weather in each of these cities has its distinct characteristics. *NY* has a higher (lower) temperature than London in summer (winter). London's wind and humidity are far greater than *NY's* all year. *NY*'s rainfall is greater than London's during the whole period. In spring (summer), except for London's highest (lowest) and average temperature, the other London and *NY* weather variables follow a normal distribution. In autumn in *NY*, although humidity is relatively low, its fluctuation is high. In Table 1, Panel A shows the correlations among the different UK and US stock indices and Panels B and C show the correlations respectively of the USD and GBP's exchange rates.

Table 1
This table provides descriptive statistics for stock return and *FX* rate data.

Panel A Correlation	DJIA	SP500	NASDAQ	FTSE 100	FTSE 350			
DJIA	100%							
SP500	97.89%	100%						
NASDAQ	90.04%	94.07%	100%					
FTSE100	56.81%	56.97%	51.89%	100%				
FTSE350	57.01%	57.26%	52.33%	99.76%	100%			
Panel B Correlation	**USD/JPY**	**USD/EUR**	**USD/GBP**	**USD/AUD**	**USD/CAD**	**USD/CHF**	**USD/NZD**	**USD/SEK**
USD/JPY	100%							
USD/EUR	29.74%	100%						
USD/GBP	15.13%	63.55%	100%					
USD/AUD	1.86%	56.56%	52.50%	100%				
USD/CAD	−0.61%	49.33%	46.01%	66.65%	100%			
USD/CHF	39.98%	71.48%	46.32%	35.93%	30.83%	100%		
USD/NZD	6.82%	54.48%	51.59%	82.49%	60.17%	36.16%	100%	
USD/SEK	16.46%	82.04%	58.07%	60.49%	53.90%	57.31%	56.76%	100%
Panel C Correlation	**GBP/USD**	**GBP/EUR**	**GBP/JPY**	**GBP/AUD**	**GBP/CAD**	**GBP/CHF**	**GBP/SEK**	**GBP/NZD**
GBP/USD	100%							
GBP/EUR	38.22%	100%						
GBP/JPY	61.26%	42.56%	100%					
GBP/AUD	21.80%	39.86%	7.30%	100%				
GBP/CAD	51.03%	42.46%	25.05%	57.75%	100%			
GBP/CHF	35.14%	66.32%	49.04%	21.43%	27.51%	100%		
GBP/SEK	21.65%	72.46%	20.48%	45.33%	42.39%	45.71%	100%	
GBP/NZD	20.14%	37.37%	11.84%	73.77%	48.69%	22.37%	39.33%	100%

4. Methodology

Following *HS* and Chang et al. (2008), we study the relationship between the stock and *FX* market returns against seven weather variables: wind speed (WIND), average temperature (TEMPMEAN), high temperature (HIGHTEMP), humidity (HUMI), low temperature (LOWTEMP), precipitation (PREC) and temperature difference (TEMPDIFFER), as follows:

$$return_i = \alpha_1 + \beta_{i,1}WIND_j + \beta_{i,2}TEMPMEAN_j + \beta_{i,3}HIGHTEMP_j + \beta_{i,4}HUMI_j + \beta_{i,5}LOWTEMP_j + \beta_{i,6}PREC_j + \beta_{i,7}TEMPDIFFER_j + \epsilon_i \tag{1}$$

where $i = US, UK$ and $j = NY, London$.

We use a Logit model to estimate the probability of the weather variables affecting the stock and *FX* returns, following *HS*. We distinguish two cases: (1) positive and (2) negative or zero returns, The Logit model is described as:

$$\mathrm{P}(r_i > 0) = \frac{e^{\gamma}}{1 + e^{\gamma}}$$
$$\text{where } \gamma = \gamma_1 WIND_j + \gamma_2 TEMPMEAN_j + \gamma_3 HIGHTEMP_j + \gamma_4 HUMI_j + \gamma_5 LOWTEMP_j + \gamma_6 PREC_j + \gamma_7 TEMPDIFFER_j. \tag{2}$$

When the returns are positive, the variable (r_i) takes a value of one, and zero otherwise.

In both models, the independent variables are *NY*'s (London's) weather variables, and the dependent variables are the US (DJIA, S&P500 and NASDAQ) or UK stock market returns (FTSE100 and FTSE350) and eight foreign currencies against the USD or GBP. The dummy variable, temperature difference, takes the value of one when the difference between the highest and the lowest temperature is greater than 10 degrees, and zero otherwise, to deal with multi-collinearity.

5. Empirical results

In Table 2, Columns (1)-(2) report the linear regression results of *NY* weather and the USD exchange rates with the *t*-value in brackets, adjusted to Newey-West standard errors. Only the CHF/USD is significantly related to the low and average temperatures (at 5%). A one-degree increase of the low (average) temperature will decrease (increase) the CHF/USD returns by 0.03% (0.04%).

We then move to the Logit model. From Columns (3)-(4) in Table 2, the γ coefficients of the low and average temperatures in *NY* for the NZD/USD returns are respectively -7.09% and 11.00% and they are significant at 5%. Hence, keeping all other variables constant, when the low or average temperature in *NY* increases by one degree, the probability of positive NZD/USD returns increases to $\exp(-0.071)/(1+\exp(-0.071)) = 48.23\%$ or $\exp(0.1100)/(1+\exp(0.1100)) = 52.75\%$ respectively. The other significant γ coefficient, 9.3% (Columns (3)-(4)) is of the average temperature in *NY* for the AUD/USD. When, the probability of positive AUD/USD returns increases to $\exp(0.093)/(1+\exp(0.093)) = 52.32\%$, the average *NY* temperature increases by one degree.

Columns (1)-(3) in Table 3 report the linear regression results of US stock indices and the weather in *NY*. All variables are insignificant. The correlation between precipitation and the US stock indices is insignificant, which conflicts with the findings of *HS*. The latter study the correlation between precipitation in 26 cities and the city's stock market returns, and find that precipitation is negatively correlated with the *NY* stock market. This difference with our results could be because we choose a different time period (2002–2018). Columns (4)-(6) in Table 3 show the Logit regression results of US stock indices. All but two γ coefficients are insignificant: the DJIA and *NY*'s precipitation, and the S&P500 and *NY*'s temperature difference. One unit increase in *NY*'s precipitation (temperature difference) increases the probability of positive returns for DJIA (S&P500) to 51.04% (45.81%).

We also run linear and Logit regressions of the weather in London with the GBP exchange rates and two UK stock indices respectively, shown in Tables 4 and 5. There is no significant correlation between the London weather and the GBP exchange rates or UK stock indices.

The exception is in two Logit regressions, between AUD/GBP and NZD/GBP returns with London wind speed and precipitation, respectively. The probability of positive AUD/GBP (NZD/GBP) returns increases to 49.69% (55.87%), corresponding to $\gamma = -0.0123$ ($\gamma = 0.236$) when the wind speed (precipitation) in London increases by one unit. This is consistent with the results of *HS*, in which London precipitation is unrelated to the UK stock market.

Table 2
New-York weather regressions and USD exchange rates.
Columns (1)-(2) display New York regression results of exchange rate returns on seven weather variables. Columns (3)-(4) display the New York Logit model results that relate the probability of positive daily USD *FX* return to seven weather variables. *N* is the sample size. The Logit model with the lowest Bayesian information criterion (BIC) is preferred.

Weather variables	(1) JPY USD	(2) EUR USD	(3) JPY USD	(4) EUR USD
NYK LOWTEMP	−0.0015	−0.0002*	−0.0547*	−0.0467
	(−1.5800)	(−1.9100)	(−1.8200)	(−1.5500)
NYK TEMPMEAN	0.0002	0.0002*	0.0857*	0.0632
	(1.5900)	(1.6700)	(1.8300)	(1.3500)
NYK HIGHTEMP	−0.0001	−0.0001	−0.0311	−0.0170
	(−1.1000)	(−1.0300)	(−1.4400)	(−0.7900)
NYK TEMPDIFFER	−0.0004	−0.0003	−0.1410*	−0.1030
	(−1.4900)	(−1.2500)	(−1.6800)	(−1.2300)
NYK WIND	−0.0000	−0.0000	−0.0082	−0.0027
	(−1.1700)	(−0.4600)	(−1.0300)	(−0.3400)
NYK HUMI	0.0000	0.0000	0.0010	0.0003
	(0.6200)	(0.4900)	(0.4900)	(0.1300)
NYK PREC	−0.0000	−0.0000	−0.0264	−0.0126
	(−0.8800)	(−0.7800)	(−1.4600)	(−0.7000)
_cons	−0.0004	−0.0004	−0.0295	−0.0449
	(−0.9400)	(−0.9500)	(−0.2400)	(−0.3600)
N	4077	4077	4077	4077
BIC	-	-	5975.3	5996.9
Weather variables	(1) GBP USD	(2) AUD USD	(3) GBP USD	(4) AUD USD
NYK LOWTEMP	−0.0001	−0.0002	−0.0279	−0.0586*
	(−0.8200)	(−1.2900)	(−0.9300)	(−1.9400)
NYK TEMPMEAN	0.0001	0.0003	0.0173	0.0933**

(*continued on next page*)

Table 2 (*continued*)

Weather variables	(1) JPY USD	(2) EUR USD	(3) JPY USD	(4) EUR USD
	(0.5200)	(1.2800)	(0.3700)	(1.9900)
NYK HIGHTEMP	−0.0000	−0.0001	0.0047	−0.0416*
	(−0.2500)	(−1.3300)	(0.2200)	(−1.9200)
NYK TEMPDIFFER	0.0000	0.0002	−0.0722	−0.0206
	(0.1100)	(0.5000)	(−0.8600)	(−0.2400)
NYK WIND	−0.0000	−0.0000	0.0014	−0.0127
	(−1.0300)	(−1.3700)	(0.1700)	(−1.6000)
NYK HUMI	0.0000	0.0000	0.0009	0.0013
	(1.2300)	(0.8700)	(0.4200)	(0.6100)
NYK PREC	0.0000	−0.0001	0.0117	−0.0315*
	(0.1100)	(−1.3300)	(0.6500)	(−1.7400)
_cons	−0.0004	0.0001	−0.0925	0.1040
	(−0.9400)	(0.1700)	(−0.7400)	(0.8200)
N	4077	4077	4077	4077
BIC	-	-	5998.6	5956.5

Weather variables	(1) CAD USD	(2) CHF USD	(3) CAD USD	(4) CHF USD
NYK LOWTEMP	−0.0002*	−0.0003**	−0.0232	−0.0466
	(−1.7100)	(−2.4300)	(−0.7700)	(−1.5500)
NYK TEMPMEAN	0.0002	0.0004**	0.0175	0.0614
	(1.4100)	(2.1700)	(0.3700)	(1.3200)
NYK HIGHTEMP	−0.0001	−0.0001	0.0001	−0.0130
	(−0.8300)	(−1.5400)	(0.0100)	(−0.6000)
NYK TEMPDIFFER	−0.0002	−0.0004	−0.1290	−0.0846
	(−0.9200)	(−1.2100)	(−1.5300)	(−1.0000)
NYK WIND	−0.0000	−0.0000	−0.0056	−0.0005
	(−1.0500)	(−0.9800)	(−0.7100)	(−0.0600)
NYK HUMI	0.0000	0.0000	0.0017	−0.0005
	(1.0300)	(0.6200)	(0.7900)	(−0.2400)
NYK PREC	−0.0000	−0.0001	0.0109	−0.0116
	(−0.3500)	(−1.3700)	(0.6000)	(−0.6400)
_cons	−0.0004	−0.0004	−0.0784	−0.0962
	(−1.1700)	(−0.7900)	(−0.6300)	(−0.7700)
N	4077	4077	4077	4077
BIC	-	-	5971.9	5977.1

Weather variables	(1) NZD USD	(2) SEK USD	(3) NZD USD	(4) SEK USD
NYK LOWTEMP	−0.0002*	−0.0001	−0.0709**	−0.0407
	(−1.7800)	(−1.0700)	(−2.3400)	(−1.3600)
NYK TEMPMEAN	0.0004*	0.0002	0.1100**	0.0624
	(1.7700)	(1.0900)	(2.3400)	(1.3400)
NYK HIGHTEMP	−0.0001	−0.0001	−0.0415**	−0.0239
	(−1.5200)	(−0.9300)	(−1.9100)	(−1.1100)
NYK TEMPDIFFER	0.0000	−0.0003	−0.1010	−0.1060
	(0.1200)	(−1.0500)	(−1.1800)	(−1.2600)
NYK WIND	−0.0000	−0.0000	−0.0055	−0.0021
	(−0.2400)	(−0.4300)	(−0.6900)	(−0.2700)
NYK HUMI	0.0000	0.0000	−0.0006	0.00103
	(0.6700)	(0.3800)	(−0.2600)	(0.4900)
NYK PREC	−0.0001	−0.0001	−0.0299*	−0.0160
	(−1.4100)	(−0.8100)	(−1.6500)	(−0.8900)
_cons	−0.0003	−0.0001	0.0147	−0.0280
	(−0.6400)	(−0.2200)	(0.1200)	(−0.2200)
N	4077	4077	4077	4077
BIC	-	-	5954.1	6008.3

Notes: The *t*-statistics of estimates are reported in parentheses. * significance at the 10% level, ** significance at the 5% level, *** significance at the 1% level.

Table 3
New York weather regressions and US stock indices.

Columns (1)-(3) display New York regression results of daily stock returns on seven weather variables. Columns (4)-(6) display the New York Logit model results that relate the probability of positive daily stock returns to seven weather variables. *N* is the sample size. BIC is the Bayesian information criterion; the Logit model with the lowest BIC is preferred.

Weather variables	(1) NASDAQ	(2) DJIA	(3) SP 500	(4) NASDAQ	(5) DJIA	(6) SP 500
NYK LOWTEMP	0.0000	0.0001	0.0001	−0.0102	0.0034	−0.0355
	(0.0900)	(0.3700)	(0.4200)	(−0.3400)	(0.1100)	(−1.1600)
NYK TEMPMEAN	−0.0000	−0.0001	−0.0001	−0.0016	−0.0377	0.0204
	(−0.0800)	(−0.4300)	(−0.4900)	(−0.0300)	(−0.7900)	(0.4300)
NYK HIGHTEMP	0.0000	0.0001	0.0001	0.0122	0.0326	0.0150
	(0.1500)	(0.3800)	(0.4800)	(0.5500)	(1.4800)	(0.6800)
NYK TEMPDIFFER	0.0002	0.0004	0.0003	−0.1360	−0.1600*	−0.1680**
	(0.3900)	(0.7100)	(0.5700)	(−1.6100)	(−1.9000)	(−1.9800)
NYK WIND	0.0000	0.0001	0.0001	0.0060	−0.00148	−0.0037
	(1.1700)	(1.1900)	(1.1800)	(0.7500)	(−0.1900)	(−0.4600)
NYK HUMI	0.0000	0.0000	0.0000	0.0022	0.0009	0.0017
	(0.4600)	(0.4000)	(0.3500)	(1.0500)	(0.4300)	(0.8000)
NYK PREC	0.0000	0.0000	0.0001	0.0277	0.0416**	0.0294
	(0.1300)	(0.3800)	(0.4400)	(1.5000)	(2.2500)	(1.5800)
_cons	−0.0003	−0.0001	−0.0001	−0.0068	0.0676	−0.0544
	(−0.4200)	(−0.0900)	(−0.1500)	(−0.0500)	(0.5400)	(−0.4300)
N	4077	4077	4077	4077	4077	4077
BIC				5939.0	5959.9	5937.5

Notes: The *t*-statistics of estimates are reported in parentheses. * significance at the 10% level, ** significance at the 5% level, *** significance at the 1% level.

Table 4
London weather regressions and GBP exchange rates.

Columns (1)-(2) display London regression results of daily exchange rate returns on seven weather variables. Columns (3)-(4) display the London Logit model results that relate the probability of a positive daily GBP *FX* return to seven weather variables. *N* is the sample size. The Logit model with the lowest Bayesian information criterion (BIC) is preferred.

Weather variables	(1) USD GBP	(2) EUR GBP	(3) USD GBP	(4) EUR GBP
LD TEMPMEAN	0.0073	0.0037	0.2180	−0.5370
	(1.1300)	(0.6600)	(0.0900)	(−0.2300)
LD LOWTEMP	−0.0036	−0.0019	−0.0986	0.2640
	(−1.1300)	(−0.6700)	(−0.0800)	(0.2200)
LD HIGHTEMP	−0.0036	−0.0018	−0.1130	0.2760
	(−1.1300)	(−0.6400)	(−0.1000)	(0.2300)
LD TEMPDIFF	0.0001	−0.0003	0.0597	−0.0545
	(0.2600)	(−1.1800)	(0.5300)	(−0.4800)
LD PREC	−0.0000	0.0004	−0.0040	0.0913
	(−0.1600)	(1.7100)	(−0.0400)	(1.0000)
LD HUMI	0.0000	−0.0000	0.0006	−0.0020
	(0.7500)	(−0.5200)	(0.1600)	(−0.5000)
LD WIND	−0.0000	−0.0000	−0.0008	−0.0075
	(−0.1100)	(−1.6100)	(−0.1300)	(−1.2700)
_cons	−0.0006	0.0006	0.0128	0.2750
	(−0.5000)	(0.5100)	(0.0300)	(0.6400)
N	4077	4077	4077	4077
BIC	-	-	5944.0	5999.1
Weather variables	**(1) JPY GBP**	**(2) AUD GBP**	**(3) JPY GBP**	**(4) AUD GBP**
LD TEMPMEAN	0.0080	0.0037	1.0540	0.5640
	(0.8600)	(0.5600)	(0.4500)	(0.2400)
LD LOWTEMP	−0.0040	−0.0020	−0.5230	−0.2950
	(−0.8600)	(−0.5900)	(−0.4400)	(−0.2500)
LD HIGHTEMP	−0.0040	−0.0018	−0.5220	−0.2760
	(−0.8600)	(−0.5300)	(−0.4400)	(−0.2300)
LD TEMPDIFF	0.0003	−0.0007*	0.1290	−0.1590
	(0.5600)	(−1.7600)	(1.1400)	(−1.4100)

(*continued on next page*)

Table 4 (*continued*)

Weather variables	(1) USD GBP	(2) EUR GBP	(3) USD GBP	(4) EUR GBP
LD PREC	0.0003	0.0004	0.0553	0.1610*
	(0.8000)	(1.4200)	(0.6000)	(1.7300)
LD HUMI	0.0000	−0.0000	0.0070*	−0.0050
	(1.2700)	(−0.6200)	(1.7300)	(−1.2600)
LD WIND	0.0000	−0.0000	0.0013	−0.0123**
	(0.0300)	(−0.8500)	(0.2200)	(−2.0800)
_cons	−0.0019	0.0009	−0.6520	0.7350*
	(−1.0600)	(0.6100)	(−1.5100)	(1.7100)
N	4077	4077	4077	4077
BIC	-	-	5947.1	5985.6

Weather variables	(1) CAD GBP	(2) CHF GBP	(3) CAD GBP	(4) CHF GBP
LD TEMPMEAN	0.0088	0.0067	−0.3840	2.4860
	(1.3100)	(1.1400)	(−0.1600)	(1.0500)
LD LOWTEMP	−0.0045	−0.0034	0.1690	−1.2410
	(−1.3200)	(−1.1700)	(0.1400)	(−1.0500)
LD HIGHTEMP	−0.0044	−0.0033	0.2110	−1.2390
	(−1.2900)	(− −1.1100)	(0.1800)	(−1.0500)
LD TEMPDIFF	−0.0004	−0.0004	−0.0669	−0.0293
	(−1.2000)	(−0.8100)	(−0.5900)	(−0.2600)
LD PREC	0.0001	0.0003	0.0797	0.1030
	(0.5200)	(1.0100)	(0.8700)	(1.1200)
LD HUMI	−0.0000	0.0000	−0.0025	−0.0033
	(−0.7800)	(0.4400)	(−0.6200)	(−0.8100)
LD WIND	−0.0000	−0.0000	−0.0051	−0.0053
	(−0.7000)	(−0.5400)	(−0.8600)	(−0.9000)
_cons	0.0009	−0.0009	0.2470	0.3140
	(0.6300)	(−0.4100)	(0.5700)	(0.7300)
N	4077	4077	4077	4077
BIC	-	-	5943.5	5941.3

Weather variables	(1) SEK GBP	(2) NZD GBP	(3) SEK GBP	(4) NZD GBP
LD TEMPMEAN	0.0054	0.0070	−0.0538	2.9290
	(0.8500)	(0.9200)	(−0.0200)	(1.2100)
LD LOWTEMP	−0.0027	− −0.0036	0.0367	−1.4740
	(−0.8400)	(−0.9500)	(0.0300)	(−1.2200)
LD HIGHTEMP	−0.0027	−0.0034	0.0126	−1.4560
	(−0.8500)	(−0.9000)	(0.0100)	(−1.2100)
LD TEMPDIFF	0.0000	−0.0005	0.0445	−0.0628
	(0.1300)	(−1.2800)	(0.3800)	(−0.5500)
LD PREC	0.0004	0.0006*	0.1560	0.2360**
	(1.2800)	(1.8800)	(1.6000)	(2.4900)
LD HUMI	−0.0000	−0.0000	−0.0042	−0.0039
	(−0.8500)	(−0.4200)	(−1.0000)	(−0.9600)
LD WIND	−0.0000	−0.0000	−0.0090	−0.0051
	(−0.9400)	(−0.5400)	(−1.4500)	(−0.8600)
_cons	0.0013	−0.0003	0.6830	0.4790
	(0.9500)	(0.2200)	(1.5000)	(1.1100)
N	4077	4077	4077	4077
BIC	-	-	5441.1	5900.3

Notes: The *t*-statistics of estimates are reported in parentheses. * significance at the 10% level, ** significance at the 5% level, *** significance at the 1% level.

Table 5
London weather regressions and UK stock indices.
Columns (1)-(2) display London regression results of daily stock returns on seven weather variables. Columns (3)-(4) display the London Logit model results that relate the probability of positive daily stock returns to seven weather variables. *N* is the sample size. The Logit model with the lowest Bayesian information criterion (BIC) is preferred.

Weather variables	(1) FTSE 350	(2) FTSE 100	(3) FTSE 350	(4) FTSE 100
LD TEMPMEAN	0.0041	0.0040	2.2210	2.9130
	(0.5400)	(0.5300)	(0.9400)	(1.2300)
LD LOWTEMP	−0.0019	−0.0018	−1.0810	−1.4270
	(−0.5100)	(−0.4900)	(−0.9100)	(−1.2000)
LD HIGHTEMP	−0.0021	−0.0021	−1.1270	−1.4770
	(−0.5700)	(−0.5600)	(−0.9500)	(−1.2400)
LD TEMPDIFF	−0.0006	−0.0005	−0.0559	−0.0801
	(−0.7700)	(−0.7000)	(−0.5000)	(−0.7100)
LD PREC	−0.0005	−0.0005	−0.0922	−0.1070
	(−1.0500)	(−0.9600)	(−1.0100)	(−1.1800)
LD HUMI	0.0000	0.0000	−0.0024	−0.0024
	(0.2000)	(0.1600)	(−0.6000)	(−0.5900)
LD WIND	−0.0000	−0.0000	−0.0069	−0.0073
	(−0.8900)	(−0.8800)	(−1.1600)	(−1.2400)
_cons	0.0012	0.0013	0.5810	0.6300
	(0.4900)	(0.5300)	(1.3500)	(1.4700)
N	4077	4077	4077	4077
BIC			5970.1	5978.2

Notes: The *t*-statistics of estimates are reported in parentheses. * significance at the 10% level, ** significance at the 5% level, *** significance at the 1% level.

6. Discussion

Some studies (e.g., *HS*), report that the weather affects the stock market. The literature has also documented many currency anomalies (e.g., Lustig and Verdelhan, 2007). Moreover, FX trading volume from retail investors has recently grown rapidly with the growth of electronic execution and proliferating execution venues, increasing market liquidity.

However, we find that the weather has little effect on stock and *FX* markets during 2002–2018. Our study is consistent with Dowling and Lucey's (2005) statement that "*Investor sentiment impact on decisions is not equivalent to emotional impact on asset pricing*".

One reason may be that, based on Saunders (1993), investors recognize the effects of weather and have tried to exploit it. It may be also because the weather anomaly has been absorbed by financial markets. The world's first weather derivative instrument was introduced in 1997 (Jeucken, 2004), and in 1999 the Chicago Mercantile Exchange introduced exchange-traded weather futures and options. Meanwhile, since 2000, electronic trading has become much more popular and the importance of local market participants (brokers and market makers) therefore diminished, though many trades still take place in *NY* and London while investors are geographically dispersed, from virtually everywhere.

7. Conclusions

We use seven weather variables, eight bilateral exchange rates and New York's and London's main stock indices. In 42 regressions (including the Logit and linear regressions), only nine out of 294 (42 regressions times seven coefficients per regression) coefficients are significant. Hence, the weather variables used for New York and London have no apparent impact on the stock and *FX* markets during 2002–2018.

As the economy is globalizing and investors increasingly dispersed, it is increasingly difficult to find significant relationships between weather and financial markets. Future research should study how the weather affects the economy and how firms can hedge weather risks.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2019.03.026.

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