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Is it good to be bad or bad to be good?: Assessing the aggregate impact of abnormal weather on consumer spending[1]

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October 23, 2018

Abstract

Although the influence of exceptional weather on individual behaviour has already been acknowledged in finance, psychology, and marketing, the literature examining weather effects at more aggregate level is still limited. Further, there is a lot of anecdotal evidence that weather anomalies affect consumer spending and retail business. The main aim of this analysis is to investigate and quantify the effects of unusual weather in consumer spending at macro-level. Using aggregate retail sales data for Switzerland, our findings reveal that weather deviations from seasonal norms, especially, unusually high or low temperatures in a given month, do cause sizeable intertemporal shifts in consumer spending at country level. Furthermore, the effects of abnormal weather are found to differ across seasons, both with respect to sign and magnitude. In particular, our findings indicate that weather effects manifest mainly through the seasons change channel: weather conditions in line with the coming season boost the purchases early in the season.

JEL Classification: E21, E32, D12, C22

Keywords: Consumer spending, intertemporal shifts, retail sales, unusual weather

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There are not as many well-documented, quantified relationships between weather events and economically important activities as one would think existed.

McQuigg (1972)

Ideally, economic analysts would be able to look past the gyrations in the data that are caused by the weather. Unfortunately, this rarely seems to be the case. Most economists jump on the latest numbers and seem to lose sight of context.

Baker (2012)

1 Introduction

In the retail business, exceptional weather is often argued to have an impact on consumer spending. For example, in the UK, the unusually warm Autumn of 2014 was reported to be disastrous for the clothing and footwear stockists[1]. Such effects of abnormal weather typically manifest themselves as transitory shifts in consumer expenditure. Yet, formal support for this anecdotal evidence has hardly been found as the empirical literature on the impact of (abnormal) weather on consumer spending at aggregate level is still scarce. Obviously, usual weather effects can be easily quantified and removed by standard seasonal adjustment procedures. However, these procedures often struggle to appropriately accommodate the effects of weather anomalies, i.e., (very) untypical weather for a given season or month of the year, and may require non-conventional intervention in order to prevent distortions in the seasonal adjustment of the data of interest. In the light of the continuing dispute on climate change such weather anomalies are expected to occur more often (Beniston et al. (2007)) and to be more extreme (Jakob and Walland (2016); Siliverstovs et al. (2010)) than ever witnessed in the past and therefore require a special attention from researchers in order to evaluate their influence on consumer behaviour and eventually on the quality of macroeconomic data.

[1] http://www.weatherads.io/blog/2015/august/the-impact-of-weather-on-retail-sector-in-the-uk

Compared to the year 1972 when the quote in the first epigraph was made a substantial progress has been made in the marketing science on the interaction of weather conditions and consumer behaviour. Nevertheless, as our second epigraph with the more recently dated quote shows there is still a substantial scope for improving of understanding among economists on how weather deviations from its seasonal norms can influence the economy. It is crucial to disentangle if the observed changes are rather transitory (and possibly followed by a rebound in following month) or reflect genuine changes in underlying factors. Therefore, impacts caused by exceptional weather are relevant for business cycle analysis and monitoring current economic conditions as well as making projections in the future. Moreover, if abnormal weather affects retail sales, there could also be demand-led effects on inventories, production and employment, to mention but a few. In addition, the knowledge of weather impacts is also crucial for business planning and forecasting, especially for retailers.

Although the influence of extreme weather on consumer behaviour has already been acknowledged in finance, psychology, and marketing literature that relies on the micro-level data such as groups of individuals (Murray et al. (2010)), department stores (Linden (1962)), or specific products ((e.g. cars as in Busse et al., 2015)), the literature addressing this question at the macro-level is still limited. The probably first study examining the transitory effects of weather on economic activity is the paper of Maunder (1973). Using weekly non-seasonally adjusted data, his findings indicate that weather conditions can account for a moderate share of the short-term variation in retail trade sales in the US. Also Starr-McCluer (2000) studies the effects of weather on (nominal) retail sales in the US on monthly and quarterly basis. She finds unusual hot and cold weather (measured by cooling and heating days) to have a significant but rather small effect on monthly nominal retail trades. Furthermore, her results reveal that the effects tend to differ depending on the quarter (the periodic analysis is done only for quarterly data).

The main aim of our analysis is to investigate if weather anomalies lead to inter-temporal shifts in consumer spending at monthly frequency and to quantify the size of these effects at aggregate level using country-level data for Switzerland. We contribute to the existing literature in different ways. In relation to Maunder (1973) who considers only contemporaneous effects and uses only three years of data, we analyse longer time series and allow also for rebound impacts to get more reliable evidence. Compared to Starr-McCluer (2000) we use more precise weather measures using actual temperature instead of number of cooling or heating days only. More importantly, we conduct the periodic analysis on monthly level to be able to discover the exact nature of abnormal weather effects which tend to "wash out at a quarterly frequency" as noted by Starr-McCluer (2000). Murray et al. (2010), like most of the marketing literature, employ data of a particular store and specific product groups. Nevertheless, for statements of total (nation wide) impacts, aggregate sales data is required. Compared to the USA, Switzerland is a much smaller country and hence more homogeneous with respect to the weather conditions and their deviations from the seasonal norms. This allows us to more accurately capture unusual weather effects at a national level rather than in such a geographically and climatically diverse country as the USA. By analysing national weather indices in such big countries one runs a risk that the estimated impacts of anomalous weather may average out at this level of aggregation. As another contribution to the literature, we follow Boldin and Wright (2015) in quantifying the effects of abnormal weather on consumer spending by constructing counterfactual time series without these effects. We also test whether consumer under-/over-spending due to abnormal weather effects is exactly compensated in the following month, i.e. these effects tend to be short-lived or tend to persist in the long run. Last but not least, besides the listed empirical contributions we suggest a stylised theoretical model allowing for intertemporal shifts in consumer spending due to weather shocks.

Our main findings are following. We find that the impacts of weather anomalies on consumer spending are measurable also at the country level data, as the intertemporal shifts they cause are sizeable. Thus, unusual weather can explain a considerable share of the variability of seasonally-adjusted retail sales, especially in the non-food sector. We find that consumers react at most to exceptional temperatures and less to exceptional precipitation or sunshine. This implies that temperature is the most influential weather variable for explaining the intertemporal shifts in consumer spending. Furthermore, the effects of abnormal weather are found to differ across seasons, i.e., to be month-specific, both with respect to the sign and to the magnitude. In particular, our findings indicate that abnormal weather effects manifest mainly during season changes: exceptionally warm temperatures in early spring as well as unusually cold conditions in late summer and early autumn are generally associated with higher sales than usual. That is, weather conditions in line with the coming season induce consumer to make purchases earlier in the season. When addressing the question whether loss due to abnormal weather is permanent or it can be (fully) recovered at some point later when the weather is back to its climatic norm we test and successfully impose long-run restrictions that rule out permanent effects of weather shocks, i.e. what is over- or underspent in a given months due to a weather shock tends to be exactly compensated by counteraction in a month that follows.

The rest of the paper is structured as follows. The next section discusses the nexus between (abnormal) weather and consumer spending and describes a theoretical model formalising these considerations. Data used in our empirical analysis are described in Section 3. Section 4 presents our findings. Robustness of our results is verified in Section 5. The final section concludes.

2 Theoretical considerations

Already Linden (1962) noted that unusual weather conditions cause shifts in timing of purchases, generate purchases that might otherwise not occur or cause a permanent loss of demand. Yet, the channels of exceptional weather on retail sales are multiple. First, weather may affect consumers' mood and therefore their spending decisions as argued by Murray et al. (2010). The more sunlight, the better is the mood and the higher is the willingness to spend (more) money. We refer to this as *mood channel*. Second, weather conditions also affect the convenience of the shopping experience (sunny weather vs., heavy rain or snow) and thus, increase or decrease, respectively, the motivation for shopping (*convenience channel*). Furthermore, weather conditions can boost sales of weather related products such as air conditioners, umbrellas and snow shovels (*weather-related products*). Moreover, when season changes there is a need for different seasonal products such as apparel or leisure equipment. Unusual bad or good weather can shift sales peaks during the months when new seasonal products are launched (*seasons change channel*).

To formalize our arguments theoretically, we develop a stylized model of intertemporal consumption. In this model, in line with the discussion earlier, weather conditions directly affect consumption enjoyment i.e., the utility derived from consumption. Furthermore, we allow the importance of these weather conditions to vary across different seasons. Assuming an isoelastic utility function, this can be formalized as follows

$$U_t = \frac{C_t^{1-\gamma}}{1-\gamma} s_t^{\theta_m}, \tag{1}$$

where s_t stands for the weather state taking value 1 by average (normal) weather, θ_m indexes the importance of the weather state and $m = 1, \ldots, 12$ denotes the month in which t falls. s_t can be interpreted as a *taste-shifter*, a variable that shifts marginal utility. We assume life time utility to be additive so that

$$V_t = \sum_{i=0}^{T} \beta^i U_{t+i}, \quad 0 < \beta \leq 1, \tag{2}$$

where β is a time discount factor. The budget constraint is defined as

$$C_{t+1} = Y_{t+1} - A_{t+1} + (1 + r_{t+1}) A_t, \tag{3}$$

where Y is real income, r is the real interest rate and A is the end-of-period real value assets. Maximization of total utility yields

$$\frac{C_{t+1}^{-\gamma} s_{t+1}^{\theta_{m+1}}}{C_t^{-\gamma} s_t^{\theta_m}} = \frac{1}{\beta(1 + r_{t+1})}. \tag{4}$$

Taking logarithms and adding the disturbance gives us

$$\gamma \ln C_{t+1} + \ln s_{t+1}^{\theta_{m+1}} = \gamma \ln C_t + \ln s_t^{\theta_m} - \ln \left(\frac{1}{\beta(1 + r_{t+1})} + \epsilon_{t+1} \right). \tag{5}$$

We assume that the stochastic term is normally and identically distributed

$$\ln \left(\frac{1}{\beta(1 + r_{t+1})} + \epsilon_{t+1} \right) \sim N(\mu, \sigma^2).$$

Thus, we can use the properties of log-normal distributions to derive the following results:

$$E_t\left(\frac{1}{\beta(1+r_{t+1})}+\epsilon_{t+1}\right)=\exp(\mu+1/2\sigma^2)$$

and further,

$$\mu=\ln(1/\beta(1+r_{t+1}))-1/2\sigma^2.$$

Finally, we can write the equation (5) as

$$\ln C_{t+1}=\omega+\frac{\ln(1+r_{t+1})}{\gamma}+\ln C_t+\theta_m \ln s_t-\theta_{m+1}\ln s_{t+1}+u_{t+1}, \tag{6}$$

where

$$\omega_t=\frac{1}{\gamma}\ln(\beta+1/2\sigma^2).$$

Reordering the terms gives us the final specification:

$$\ln\frac{C_{t+1}}{C_t}=\omega+\frac{\ln(1+r_{t+1})}{\gamma}+\theta_m \ln s_t-\theta_{m+1}\ln s_{t+1}+u_{t+1}. \tag{7}$$

Equation (7) states that the growth in consumption depends on the time discount factor (β), the interest rate, the weather state of the current period as well as the weather state of the previous period and the forecast error. This implies that through intertemporal optimization unusual weather may cause shifts in consumption over time.

Often it is assumed that the utility does not depend only on the current consumption expenditure but also on the previous consumption level. A utility function with habit formation can be written as

$$U_t=\frac{1}{1-\gamma}\tilde{C_t}^{1-\gamma}s_t^{\theta_m}, \tag{8}$$

where $\tilde{C}_t=\frac{C_t}{C_{t-1}^{\phi}}$ and ϕ controls the importance of habit formation. Then, the maximization of total utility yields

$$\left(\frac{C_{t+1}}{C_t^{\phi}}\right)^{-\gamma}\frac{s_{t+1}^{\theta_{m+1}}}{C_t^{\phi}}=\left(\frac{C_t}{C_{t-1}^{\phi}}\right)^{-\gamma}\frac{s_t^{\theta_m}}{C_{t-1}^{\phi}}\frac{1}{\beta(1+r_t)}. \tag{9}$$

Under the same assumptions as earlier, we get

$$\ln\frac{C_{t+1}}{C_t} = \omega + \frac{\ln(1+r_{t+1})}{\gamma} + \theta_m \ln s_t + \theta_{m+1} \ln s_{t+1} + (1-\frac{1}{\gamma})\phi \ln\frac{C_t}{C_{t-1}}. \tag{10}$$

Now, the growth of consumption depends also on the growth rate of the previous period as well as weather conditions in the current and previous periods.

3 Data

For this analysis we employ three data sets: data on weather, retail sales and macroeconomic variables such as interest rates and inflation. The weather data for this paper comes from the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss). The various weather variables are available for numerous weather stations in Switzerland. The national values are defined as simple average of 12 specific weather stations[2]. Since we want to examine the effects of unusual weather, we construct our weather variables as deviations from the month-specific long-run mean following international standards[3]. First, we aggregate the data to the national level by averaging monthly observations across the 12 weather stations. Then the rolling 30-years mean for each month is computed. Finally, we define the deviations as the monthly value minus the (one-year) lagged rolling mean as follows:

$$W_t^m = w_t^m - \frac{1}{30}\sum_{t-31}^{t-1} w_t^m \tag{11}$$

where w_t^m denotes the value of the weather variable in month m. We repeat this for all the three weather variables we consider: homogenized monthly mean temperature (2 meters above the ground), homogenized monthly mean precipitation (in millimeters) and monthly mean duration of sunshine (in hours). The sample period of the weather variables runs from January 1980 to February 2017. These variables are plotted in Figure 1.

Since the national accounting data on consumer expenditure for Switzerland is available only

[2]Stations: BAS (Basel), BER (Bern), CHD (Château-d'Oex), CHM (Chaumont), DAV (Davos), ENG (Engelberg), GVE (Geneva-Cointrin), LUG (Lugano), SAE (Saentis), SIA (Segl-Maria), SIO (Sion), SMA (Zurich).

[3]See, Definition of World Meteorological Organization to Climatological Normals: www.wmo.int.

at quarterly frequency, we use the retail trade sales to proxy the consumer spending at monthly frequency. The data on retail trade sales in Switzerland is provided by the Swiss Federal Statistical Office (FSO). The indexes start on January 2002. The data are available for total retail trade (NOGA 47) and for the sub-branches. Our main series are the seasonally and calender effects adjusted retail sector without fuel (NOGA 47 without NOGA 473)[Total wo fuel], retail sales of food, beverages and tobacco (NOGA 4711 and 472) [Food] as well as retail sales of non-food (NOGA 4719, 474-479) [Non-Food]. Figure 2 shows the series over the sample period from January 2002 to December 2016.

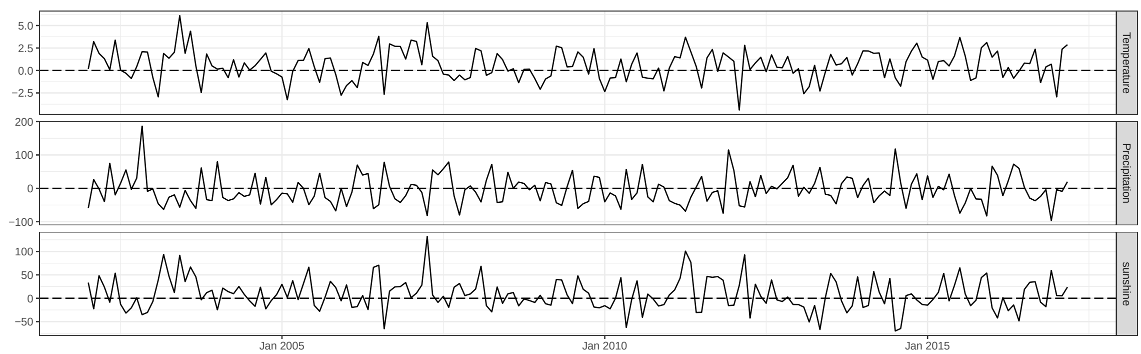

Figure 1: Weather variables - deviations from long-run rolling mean

The data on short-term nominal interest rates as well as CPI index were extracted from the SNB Dataportal for the same sample period (January 2002 - December 2016).

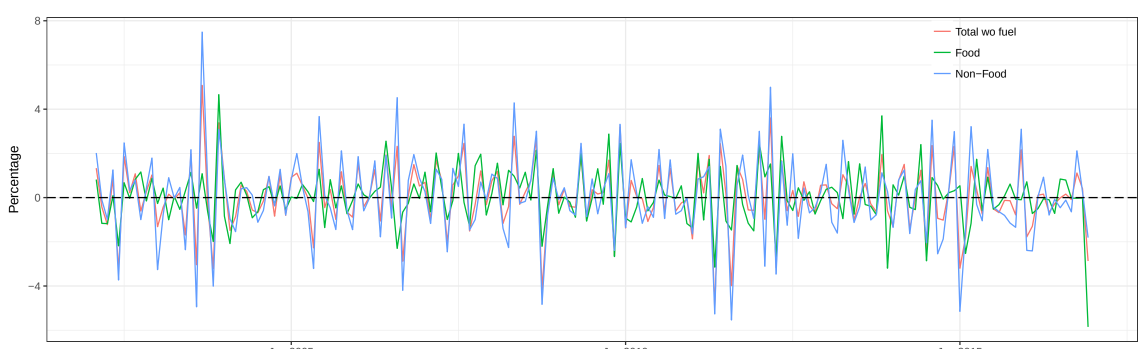

Figure 2: Nominal Retail sales (Month-to-Month growth rates)

4 Empirical analysis

In this section, we present our estimation results for several model specifications. In Section 4.1, we estimate our baseline model where we impose identical weather effects for all months. In Section 4.2, we relax this assumption and allow for month-specific or periodic weather effects. In Section 4.3, we test the null hypothesis that there are no long-run effects of abnormal weather on the level of consumption.

4.1 Baseline specification

To examine the short-term effects of unusual weather at aggregate level, we estimate various regression specifications derived from equation (7) of our theoretical model using the country-level data on retail sales. In the first step, we consider constant weather effects over the year i.e., assume that θ do not vary over different months:

$$\Delta C_t = \omega + \sum_{i=1}^{p} a_i \Delta C_{t-i} + \delta R_t + \sum_{l=0}^{1} \theta_l W_{t-l} + \epsilon_t, \tag{12}$$

where C_t is log nominal retail sales (index) at time t, p indicates the number of autoregressive lags, $R_t = \ln(1 + r_t)$ whereas r_t is the short-term interest rate and $\delta = 1/\gamma$ captures the elasticity of intertemporal substitution. $W_{t-l} = \{\text{Temp, Rain, Sun}\}$ is one of our weather variables and l denotes a lag. The model is estimated with OLS.

Coefficient estimates for this equation are reported in Table 1. In column (1), we do not include any weather variables so that we can later compare the results with this baseline specification. In column (2), we include the contemporaneous and lagged values of the temperature variable, in the third and fourth columns - those of the precipitation and the sunshine. In column (5), the estimation result of a model with all weather variables is presented.

Our estimation results suggest that when restricting the weather effects to be equal for all months of the year, there is a very limited evidence suggesting that abnormal weather influences retail sales in Switzerland. Almost all but one ($Temp_t$ in column (5)) weather variables are insignificant and the adjusted R^2 increases only marginally for models in columns (2) and (5) out of all models augmented with weather variables (columns (2)-(5)) as compared with our benchmark model in column (1) that excludes all weather variables.

Table 1: Average weather effects

	Dependent variable:				
	Nominal Retail turnover (dl)				
	(1)	(2)	(3)	(4)	(5)
Constant	0.041 (0.093)	0.050 (0.101)	0.036 (0.094)	0.027 (0.097)	0.037 (0.102)
Δc_{t-1}	-0.756^{***} (0.075)	-0.748^{***} (0.075)	-0.752^{***} (0.075)	-0.756^{***} (0.075)	-0.738^{***} (0.076)
Δc_{t-2}	-0.534^{***} (0.085)	-0.521^{***} (0.085)	-0.531^{***} (0.085)	-0.532^{***} (0.086)	-0.505^{***} (0.086)
Δc_{t-3}	-0.217^{***} (0.075)	-0.209^{***} (0.075)	-0.214^{***} (0.075)	-0.215^{***} (0.075)	-0.198^{***} (0.075)
R_t	0.452^{***} (0.119)	0.446^{***} (0.119)	0.454^{***} (0.120)	0.448^{***} (0.120)	0.425^{***} (0.122)
$Temp_t$		−0.081 (0.056)			-0.144^{**} (0.070)
$Temp_{t-1}$		0.066 (0.056)			0.082 (0.070)
$Rain_t$			−0.001 (0.002)		−0.0003 (0.003)
$Rain_{t-1}$			0.0002 (0.002)		0.001 (0.003)
Sun_t				0.001 (0.003)	0.005 (0.005)
Sun_{t-1}				0.001 (0.003)	0.001 (0.005)
Observations	176	176	176	176	176
R^2	0.389	0.399	0.390	0.390	0.409
Adjusted R^2	0.374	0.378	0.368	0.368	0.373

Notes: *p<0.1; **p<0.05; ***p<0.01
S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1+r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, $Rain_t$ is the precipitation variable and Sun_t is the sunshine variable.

4.2 Month-specific weather effects

Next, we examine if consumers are affected by weather anomalies differently at different seasons or months. Therefore, we allow the weather effects to differ periodically, i.e., θ may vary over the year:

$$\Delta C_t = \omega + \sum_{i=1}^{p} a_i \Delta C_{t-i} + \delta R_t + \sum_{l=0}^{1} \theta_{1,l} D^{Jan} W_{t-l} + \sum_{l=0}^{1} \theta_{2,l} D^{Feb} W_{t-l} + \cdots + \sum_{l=0}^{1} \theta_{12,l} D^{Dec} W_{t-l} + \epsilon_t \quad (13)$$

where $W_{t-l} = \{\text{Temp, Rain, Sun}\}$ is one of our weather variables and D^m a dummy variable taking value 1 in month m and zero otherwise. The standard OLS estimator is used.

Table 2: Month-specific effects of Temperature

	Dependent variable:	
	Nominal Retail turnover (dl)	
	(1)	(2)
Constant	0.041 (0.093)	0.033 (0.097)
Δc_{t-1}	-0.756^{***} (0.075)	-0.688^{***} (0.077)
Δc_{t-2}	-0.534^{***} (0.085)	-0.470^{***} (0.084)
Δc_{t-3}	-0.217^{***} (0.075)	-0.164^{**} (0.071)
R_t	0.452^{***} (0.119)	0.509^{***} (0.115)
$D^{Jan}Temp_t$		0.074 (0.187)
$D^{Feb}Temp_t$		0.028 (0.140)
$D^{Mar}Temp_t$		0.503^{**} (0.199)
$D^{Apr}Temp_t$		0.213 (0.139)
$D^{May}Temp_t$		0.068 (0.209)
$D^{Jun}Temp_t$		-0.315^{**} (0.145)
$D^{Jul}Temp_t$		0.197 (0.176)
$D^{Aug}Temp_t$		-0.615^{***} (0.156)
$D^{Sep}Temp_t$		-0.327^{*} (0.182)
$D^{Oct}Temp_t$		-0.697^{***} (0.214)
$D^{Nov}Temp_t$		-0.241 (0.162)
$D^{Dec}Temp_t$		0.195 (0.210)
$D^{Jan}Temp_{t-1}$		0.114 (0.202)
$D^{Feb}Temp_{t-1}$		-0.152 (0.192)
$D^{Mar}Temp_{t-1}$		-0.160 (0.119)
$D^{Apr}Temp_{t-1}$		-0.093 (0.206)
$D^{May}Temp_{t-1}$		-0.374^{**} (0.153)
$D^{Jun}Temp_{t-1}$		0.187 (0.207)
$D^{Jul}Temp_{t-1}$		-0.049 (0.146)
$D^{Aug}Temp_{t-1}$		0.271^{*} (0.157)
$D^{Sep}Temp_{t-1}$		0.461^{***} (0.163)
$D^{Oct}Temp_{t-1}$		0.416^{**} (0.198)
$D^{Nov}Temp_{t-1}$		0.157 (0.202)
$D^{Dec}Temp_{t-1}$		0.399^{**} (0.196)
Observations	176	176
R^2	0.389	0.608
Adjusted R^2	0.374	0.534
Residual Std. Error	1.190 (df = 171)	1.028 (df = 147)
F Statistic	27.188^{***} (df = 4; 171)	8.150^{***} (df = 28; 147)

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, D^m is a dummy variable for the month m.

The results for the temperature variable are presented in Table 2. Again, in the first column the estimated coefficients for the baseline model without weather variables are documented. The second column presents the results of the model with month-specific temperature effects. Numerous temperature coefficients turn out to be statistically significant, however, the sign and the magnitude of the coefficients differ greatly. The estimate for March is found to be positive indicating that unusual warm weather in March boost the retail sales. The coefficient on June temperature is, in turn, found to be negative implying that abnormal hot weather during the summer month exercises a dampening effect on the retail sales. From August to October the coefficients on the temperature dummies are negative and significant, with the October coefficient having the highest value. This finding implies that abnormal warm weather conditions during early autumn have negative impact on the retail sales hindering changes in the wardrobe and shifting the seasonal sales peaks later.[4]

Various coefficients on the lagged weather variables are also found to be significant. Again, depending on the month, the sign of the estimates differ. The coefficient $Temp_{t-1}^{May}$ tells us that the unusually warm weather in April has a negative effect on retail sales in May. On the other hand, the abnormally high temperatures in August, imply a positive rebound effect in September.

The estimated coefficients for temperature are also graphically illustrated in Figure 3 showing again temperature effects being positive in the first half of the year and become in general negative in the second half of the year. For the previous month's effect the picture is basically the opposite, the rebound effects being negative in first five months and turning positive from August on which is consistent with the rebound concept.

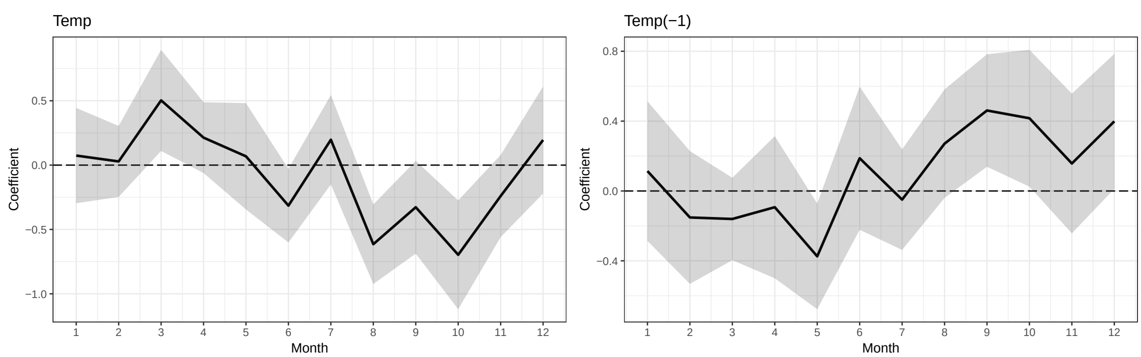

Figure 3: Month-specific coefficients of temperature variables (from Table 2 column 2)

Our results allow us to draw several conclusions regarding the relative importance of different channels through which abnormal weather is expected to affect consumer spending decisions. These findings do not support the mood channel since unusually good weather (warm, sunny, less rain) is found to have in some months positive and other months negative effects, if the mood effect would be the main channel we would expect the coefficients be always positive. Also the convenience

[4] We repeat the same analysis using precipitation and sunshine as weather variables. For the sake of brevity, the results are documented in Tables 5 and 6 in Appendix. These additional results are qualitatively in line with those from the model with temperature: abnormal nice weather (less rain or more sunshine, respectively) in spring months boost the sales of retailers, whereas it hinders the sales in early autumn. Though, there is not much of a strong statistical evidence supporting this finding as hardly any of the coefficients for rain and sunshine variables are significant.

channel does not find great support for similar reasons, bad weather seems to boost the sales in specific months. The weather-related products do not seem to play crucial role either since the impacts in winter or summer months are quantitatively small and not significant, except one. Yet, we find strong support for the seasons change effects. Abnormal high temperatures foster seasonal product sales in spring i.e., make new seasonal products more appealing. On the other hand, especially cold weather conditions lead to higher sales in late summer and early autumn. That is, weather conditions in line with the coming season induce consumers to make the purchases early in the season. This implies that in some months warm weather boost consumer spending, whereas in other months cold temperatures induce more sales.

All in all, abnormal weather is found to be able to explain considerable share of the variance of retail sales growth since the adjusted R^2 increases considerably. The other weather variables (precipitation and sunshine) seems to matter less as the adjusted R^2 hardly increases. Our findings suggest that there are positive effects of abnormal weather on the retail sales that can be realized equally well for unusually hot or cold days, depending on a season, or vice versa. Moreover, these effects are further reinforced because of rebound effects, i.e., what is over- or under-consumed in a given month tends to be caught up in the following month.

4.3 Long-run restrictions

In the previous section, we documented a rebound effect of the abnormal weather on retail sales. In this section, we test whether over- or under-consumption that take place in a given month tends to be exactly compensated in the following month such that there are no long-run effects brought by unusual weather on retail trade. In doing so, we follow Boldin and Wright (2015) (BW) and define monthly (dummy) variables such that they take 1 in a specific month (to capture the current weather effect) and -1 in the following month but for previous month's weather, i.e., equal size but opposite sign weather effect is imposed for the following month, and 0 otherwise. This implies that weather shocks cannot have permanent effects on the level of retail sales but will be followed by a bounce back in the following month or later through the autoregressive dynamics. One further advantage of testing and eventually correctly imposing these restrictions is that it allows us significantly reduce the number of parameters to be estimated in our regressions, thus mitigating the potential problem of overfitting.

The estimation results for total retail sales (without fuel), food and non-food sector are shown in Table 3. The likelihood ratio test indicates that we cannot reject these BW-restrictions, i.e., there is no sufficiently strong statistical evidence in favour of permanent weather effects. The findings in column (1) are similar to the earlier results that is we find a positive effect of excess temperatures in the early spring months, adverse effect in June and from August to November. In the other two columns we document the results for food and non-food sectors separately. The findings suggest that weather affects mainly the non-food sales, since the estimation results for non-food are similar but stronger than for total retail sales without fuel. For food, the temperature effects are not found to be significant in the first half of the year, but coefficients on weather variables from October to December are negative and significant, however smaller size than for non-food.

Table 3: Month-specific effects of Temperature with long-run restriction

	Dependent variable:		
	Total	Food	Non-Food
	(1)	(2)	(3)
Constant	0.035 (0.080)	0.079 (0.089)	−0.024 (0.102)
Δc_{t-1}	-0.602^{***} (0.069)		
Δc_{t-2}	-0.404^{***} (0.078)		
Δc_{t-3}	-0.123^{*} (0.068)		
Δc_{t-1}		-0.503^{***} (0.082)	
Δc_{t-2}		-0.263^{***} (0.090)	
Δc_{t-3}		−0.095 (0.084)	
Δc_{t-1}			-0.567^{***} (0.068)
Δc_{t-2}			-0.434^{***} (0.074)
Δc_{t-3}			-0.161^{**} (0.066)
R_t	0.390^{***} (0.104)	0.330^{***} (0.113)	0.454^{***} (0.131)
$D^{Jan}Temp_t$	0.181 (0.124)	−0.027 (0.143)	0.346^{**} (0.156)
$D^{Feb}Temp_t$	0.105 (0.088)	−0.018 (0.098)	0.211^{*} (0.111)
$D^{Mar}Temp_t$	0.353^{**} (0.143)	0.152 (0.158)	0.476^{***} (0.182)
$D^{Apr}Temp_t$	0.301^{***} (0.097)	0.170 (0.106)	0.272^{**} (0.122)
$D^{May}Temp_t$	−0.045 (0.137)	−0.022 (0.152)	−0.122 (0.174)
$D^{Jun}Temp_t$	-0.167^{*} (0.094)	0.014 (0.103)	-0.252^{**} (0.119)
$D^{Jul}Temp_t$	−0.094 (0.113)	0.180 (0.125)	−0.218 (0.143)
$D^{Aug}Temp_t$	-0.563^{***} (0.114)	−0.068 (0.121)	-0.833^{***} (0.147)
$D^{Sep}Temp_t$	-0.337^{**} (0.131)	−0.101 (0.144)	-0.549^{***} (0.166)
$D^{Oct}Temp_t$	-0.423^{***} (0.143)	-0.296^{*} (0.151)	-0.503^{***} (0.186)
$D^{Nov}Temp_t$	-0.375^{***} (0.116)	-0.301^{**} (0.129)	-0.419^{***} (0.145)
$D^{Dec}Temp_t$	0.093 (0.131)	-0.292^{**} (0.145)	0.293^{*} (0.167)
LR-test (p-value)	0.229	0.693	0.304
Observations	176	176	176
R^2	0.573	0.294	0.603
Adjusted R^2	0.530	0.223	0.563
Residual Std. Error (df = 159)	1.032	1.141	1.307
F Statistic (df = 16; 159)	13.325^{***}	4.146^{***}	15.104^{***}

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, D^m is a dummy variable taking 1 in month m and -1 in the following month but for the previous month's weather.

For some months the sign of the weather impact is the different for food and non-food sales indicating opposite effects. Yet, only for December, the coefficients for both product groups are significant. The unusually warm weather boost the non-food sales whereas it found have a negative effect on food sales.

Unlike Busse et al. (2015), we do not find evidence for projection bias since we find that unusual temperatures lead mainly to shifts in the purchase timing. Yet, we consider also very different product groups. Busse et al. (2015) examine car sales, that is, highly durable and specialized products, whereas we examine the retail sales (which do not include car sales) but include also many non-durable categories. It seems that in our case the abnormal temperatures supporting the coming season trigger consumer to make their purchases early in the season.

Also the increase in adjusted R^2 (compared to the models without weather variables) is the highest for the non-food retailers as shown in Table 4 implying that the unusual temperatures can capture considerable share of the volatility of retail sales. Altogether, abnormal weather seems to cause inter-temporal effects as consumers do shift their non-food purchases depending on the temperature conditions.

Table 4: Measuring explanatory power of weather variables: Incremental adjusted R^2

	Total	Food	Non-Food
Temperature	0.16	0.02	0.17
Precipitation	0.03	-0.00	0.02
Sunshine	0.06	0.07	-0.19

Note: Differences in adjusted R^2 between models with and without weather variables are reported for regressions presented in Table 3

To assess the quantitative meaning of these weather impacts, we firstly calculate the partial R^2 for the month-specific weather variables in order to single out those months that contribute the most to explaining variation in consumer spending in response to the weather deviations from its seasonal norms. The bars in Figure 4 tells us the proportion of variation explained by each month that cannot be explained by the other variables. The highest value is found for August indicating

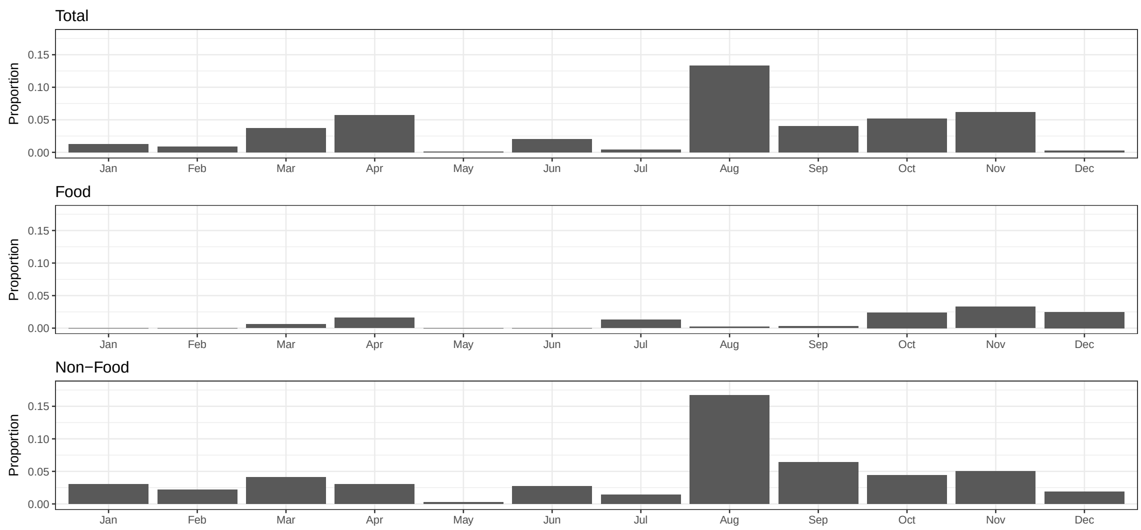

Figure 4: Partial R-squared
Note: Upper panel: Model in column (1) in Table 3, middle panel: column(2) in Table 3, lower panel: column (3) in Table 3

that the temperature in August can explain around 13 % of the variation in the total retail sales, for non-food even more than 15 % cannot be captured by the other variables.

Another way to quantify the weather impact is to define counterfactual series as in Boldin and Wright (2015). The counterfactual series are calculated by setting the weather indicators to zero but using the same residuals. The difference between the original series and the counterfactual series can then be interpreted as the weather effect. We make these calculations for the models in Table 3. As shown in Figure 5 the highest median absolute weather effects are found in August, September and November of size around 0.6-0.7 percentage points indicating that temperature anomalies can account for a noticeable change in the retail sales growth. The biggest (absolute) contribution of unusual temperature in September is as high as 2.5 percentage points. For almost half of the months is the median absolute temperature effect over 0.5 percentage points.

Again, it is obvious in Figure 5 that the non-food sector is influenced much more strongly by exceptional temperatures than the food retail sales. Here, the highest median effect is found for August and it counts for more than 1 percentage point, whereas the greatest impact of almost 4 percentage points is found for September. Altogether these findings imply that the influence of abnormal temperature on consumer spending at aggregate level is sizeable.

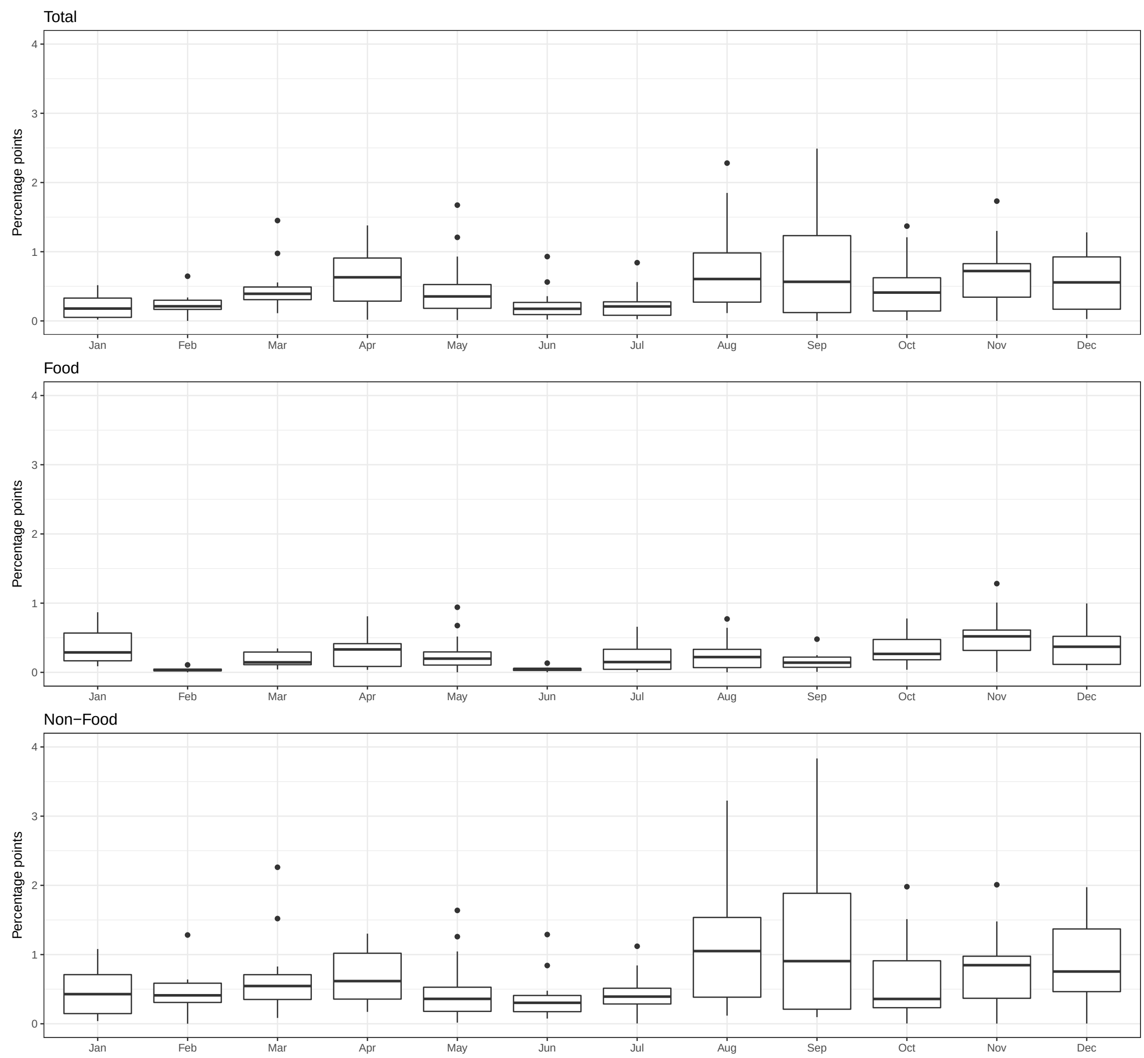

Figure 5: Absolute month-specific temperature effects
Note: Upper panel: Model in column (1) in Table 3, middle panel: column(2) in Table 3, lower panel: column (3) in Table 3)

5 Robustness

In order to verify the robustness of our results we estimated a number of alternative model specifications addressing the problem of over-fitting, definitions of dependent variable and different choices of weather and other explanatory variables.

From Table 2 one can infer that the number of estimated parameters is rather high compared to the number of observations, pointing out to the potential problem of overfitting. In order to address this issue we applied the variable selection procedure based on the LASSO (Least Absolute Shrinkage and Selection Operator) regression (**?**). The LASSO regression retains most relevant variables in the model while removing those with much less explanatory power. In Table 7 in Appendix we report the results of the re-estimated model with fewer variables as suggested by LASSO procedure. As seen, the main findings reported for the larger model still remain the same.

To examine if our results are sensitive to the definition of the dependent variable, we estimate also the main equations using real retail sales instead of nominal as well as year-to-year growth rates instead of month-to-month specification. Table 8 in Appendix provides the results for the specification in real terms. The outcomes are very much like those in Table 3 in Appendix. We again found the expected negative sign for the real short-term interest rates.

The impact of abnormal temperature is also found to be quite similar when the year-on-year growth rates of nominal retail sales are used instead of month-to-month changes (Table 9 in Appendix). In the third robustness check we control for unemployment rate to make sure that the results are not sensitive for labour market situation. The results are reported in Table 10 in Appendix. In column (1) the change in unemployment rate whereas in column (2) the level of unemployment rate is used. In both cases the findings concerning the weather effects do not change. Further, we also examine if including exchange rate affects the results. This is not the case as shown in Table 11 in Appendix.

6 Conclusions

Already Linden (1962) noted that unusual weather conditions cause shifts in timing of purchases, generate purchases that might otherwise not occur or cause a permanent loss of demand. Also in the business press, exceptional weather is often argued to have an impact on consumer spending and business activity in general, being one of the main causes for the transitory shifts. Yet, the formal evidence for the impact of weather anomalies on consumer expenditure at the macro-level is still limited.

In this paper, we contribute to the so far scarce literature by examining the influence of unusual weather conditions on consumer spending at aggregate level using country-level data for Switzerland. We develop a theoretical model based on consumer choice to illustrate how abnormal weather can affect the utility. Based on these theoretical considerations, we conduct a comprehensive periodic analysis.

Our empirical findings reveal that weather anomalies do cause substantial intertemporal shifts in consumer expenditure, measured by monthly retail sales, at aggregate level in Switzerland. Thus, they can explain a considerable share of the variability of seasonally-adjusted retail sales, especially in the non-food sector. We find that consumers react at most to exceptional temperatures, less to abnormal precipitation or sunshine, implying that temperature is the most influential weather variable for explaining volatility of retail sales. Furthermore, the effects of abnormal weather are found to differ across seasons i.e., to be month-specific, both the sign and the magnitude. In particular, our findings indicate that weather effects manifest mainly through the seasons change channel: exceptionally warm weather in spring tends to boost the sales (good to be good), whereas unusually cold conditions in late summer/early autumn are generally associated with higher sales (good to be bad). That is, weather conditions in line with the coming season induce consumers to make their purchases early in the season. In other words, depending on the season (or month) unusually good or bad weather may boost or delay consumer expenditures compared to periods with seasonally normal weather.

7 Appendix

Table 5: Month-specific effects of Rain

	Dependent variable:	
	Nominal Retail turnover (dl)	
	(1)	(2)
Constant	0.041 (0.093)	−0.023 (0.100)
Δc_{t-1}	-0.756^{***} (0.075)	-0.750^{***} (0.080)
Δc_{t-2}	-0.534^{***} (0.085)	-0.472^{***} (0.088)
Δc_{t-3}	-0.217^{***} (0.075)	-0.188^{**} (0.077)
R_t	0.452^{***} (0.119)	0.409^{***} (0.130)
Rain_t^{Jan}		0.014^{*} (0.008)
Rain_t^{Feb}		−0.003 (0.010)
Rain_t^{Mar}		−0.012 (0.009)
Rain_t^{Apr}		−0.009 (0.008)
Rain_t^{May}		−0.003 (0.007)
Rain_t^{Jun}		−0.002 (0.008)
Rain_t^{Jul}		−0.007 (0.007)
Rain_t^{Aug}		0.015^{**} (0.006)
Rain_t^{Sep}		−0.014 (0.010)
Rain_t^{Oct}		0.002 (0.008)
Rain_t^{Nov}		0.001 (0.005)
Rain_t^{Dec}		−0.004 (0.006)
Rain_{t-1}^{Jan}		0.008 (0.007)
Rain_{t-1}^{Feb}		−0.009 (0.008)
Rain_{t-1}^{Mar}		−0.005 (0.011)
Rain_{t-1}^{Apr}		0.003 (0.009)
Rain_{t-1}^{May}		0.014^{**} (0.007)
Rain_{t-1}^{Jun}		−0.008 (0.007)
Rain_{t-1}^{Jul}		−0.0003 (0.008)
Rain_{t-1}^{Aug}		0.003 (0.006)
Rain_{t-1}^{Sep}		−0.002 (0.006)
Rain_{t-1}^{Oct}		-0.017^{*} (0.010)
Rain_{t-1}^{Nov}		−0.003 (0.008)
Rain_{t-1}^{Dec}		0.006 (0.005)
Observations	176	176
R^2	0.389	0.495
Adjusted R^2	0.374	0.398
Residual Std. Error	1.190 (df = 171)	1.167 (df = 147)
F Statistic	27.188^{***} (df = 4; 171)	5.138^{***} (df = 28; 147)

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Rain_t$ is the precipitation variable, D^m is a dummy variable for the month m.

Table 6: Month-specific effects of Sunshine

	Dependent variable:	
	Nominal Retail turnover (dl)	
	(1)	(2)
Constant	0.041 (0.093)	0.003 (0.096)
Δc_{t-1}	-0.756^{***} (0.075)	-0.693^{***} (0.081)
Δc_{t-2}	-0.534^{***} (0.085)	-0.472^{***} (0.087)
Δc_{t-3}	-0.217^{***} (0.075)	-0.178^{**} (0.076)
R_t	0.452^{***} (0.119)	0.447^{***} (0.128)
Sun_t^{Jan}		-0.001 (0.018)
Sun_t^{Feb}		0.003 (0.011)
Sun_t^{Mar}		0.018^{**} (0.007)
Sun_t^{Apr}		0.011^{*} (0.006)
Sun_t^{May}		-0.005 (0.008)
Sun_t^{Jun}		-0.005 (0.007)
Sun_t^{Jul}		0.013 (0.008)
Sun_t^{Aug}		-0.024^{***} (0.007)
Sun_t^{Sep}		0.002 (0.013)
Sun_t^{Oct}		-0.013 (0.015)
Sun_t^{Nov}		-0.003 (0.016)
Sun_t^{Dec}		0.0001 (0.011)
Sun_{t-1}^{Jan}		0.008 (0.012)
Sun_{t-1}^{Feb}		0.021 (0.018)
Sun_{t-1}^{Mar}		-0.008 (0.012)
Sun_{t-1}^{Apr}		-0.004 (0.007)
Sun_{t-1}^{May}		-0.014^{**} (0.006)
Sun_{t-1}^{Jun}		0.002 (0.008)
Sun_{t-1}^{Jul}		-0.003 (0.007)
Sun_{t-1}^{Aug}		0.009 (0.008)
Sun_{t-1}^{Sep}		0.011 (0.008)
Sun_{t-1}^{Oct}		0.026^{*} (0.014)
Sun_{t-1}^{Nov}		-0.012 (0.016)
Sun_{t-1}^{Dec}		0.006 (0.014)
Observations	176	176
R^2	0.389	0.522
Adjusted R^2	0.374	0.431
Residual Std. Error	1.190 (df = 171)	1.135 (df = 147)
F Statistic	27.188^{***} (df = 4; 171)	5.726^{***} (df = 28; 147)

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, Sun_t is the sunshine variable, D^m is a dummy variable for the month m.

Table 7: Month-specific effects of Temperature - Lasso specification

	Dependent variable:
	Nominal Retail turnover (dl)
Constant	0.030 (0.092)
Δc_{t-1}	-0.602^{***} (0.064)
Δc_{t-2}	-0.338^{***} (0.064)
R_t	0.430^{***} (0.104)
$D^{Mar}Temp_t$	0.591^{***} (0.195)
$D^{Apr}Temp_t$	0.220 (0.135)
$D^{Jun}Temp_t$	-0.250^{*} (0.128)
$D^{Aug}Temp_t$	-0.628^{***} (0.156)
$D^{Sep}Temp_t$	-0.356^{*} (0.181)
$D^{Oct}Temp_t$	-0.646^{***} (0.211)
$D^{Nov}Temp_t$	-0.249 (0.161)
$D^{May}Temp_{t-1}$	-0.380^{***} (0.134)
$D^{Aug}Temp_{t-1}$	0.252 (0.157)
$D^{Sep}Temp_{t-1}$	0.531^{***} (0.159)
$D^{Oct}Temp_{t-1}$	0.465^{**} (0.197)
$D^{Nov}Temp_{t-1}$	0.178 (0.201)
$D^{Dec}Temp_{t-1}$	0.493^{***} (0.159)
Observations	176
R^2	0.577
Adjusted R^2	0.535
Residual Std. Error	1.026 (df = 159)
F Statistic	13.581^{***} (df = 16; 159)

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, D^m is a dummy variable for the month m.

Table 8: Month-specific effects of Temperature - Real retail sales

	Dependent variable:	
	Real Retail turnover (dl)	
	(1)	(2)
Constant	0.284*** (0.097)	0.245*** (0.084)
Δc_{t-1}	−0.741*** (0.076)	−0.596*** (0.070)
Δc_{t-2}	−0.493*** (0.088)	−0.372*** (0.079)
Δc_{t-3}	−0.171** (0.078)	−0.099 (0.070)
IntR_t	0.258* (0.152)	0.282** (0.133)
$\text{D}^{Jan}Temp_t$		0.175 (0.128)
$\text{D}^{Feb}Temp_t$		0.095 (0.091)
$\text{D}^{Mar}Temp_t$		0.367** (0.150)
$\text{D}^{Apr}Temp_t$		0.334*** (0.102)
$\text{D}^{May}Temp_t$		−0.059 (0.145)
$\text{D}^{Jun}Temp_t$		−0.146 (0.097)
$\text{D}^{Jul}Temp_t$		−0.069 (0.116)
$\text{D}^{Aug}Temp_t$		−0.559*** (0.117)
$\text{D}^{Sep}Temp_t$		−0.366*** (0.135)
$\text{D}^{Oct}Temp_t$		−0.413*** (0.149)
$\text{D}^{Nov}Temp_t$		−0.413*** (0.120)
$\text{D}^{Dec}Temp_t$		0.108 (0.135)
Observations	173	173
R^2	0.368	0.561
Adjusted R^2	0.352	0.516
Residual Std. Error	1.233 (df = 168)	1.066 (df = 156)
F Statistic	24.404*** (df = 4; 168)	12.452*** (df = 16; 156)

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

S.E. in parentheses. Dependent variable (Δc_t) is real retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, D^m is a dummy variable taking 1 in month m and -1 in the following month but for the previous month's weather.

Table 9: Month-specific effects of Temperature - year-on-year growth rates

	Dependent variable:	
	Nominal Retail turnover (yoy)	
	(1)	(2)
Constant	0.350^{**} (0.144)	0.305^{**} (0.140)
Δc_{t-1}	0.108 (0.077)	0.211^{***} (0.080)
Δc_{t-2}	0.146^{*} (0.076)	0.113 (0.078)
Δc_{t-3}	0.229^{***} (0.076)	0.224^{***} (0.076)
Δc_{t-12}	-0.185^{***} (0.063)	-0.170^{***} (0.063)
R_t	1.367^{***} (0.255)	1.220^{***} (0.250)
$D^{Jan}Temp_t$		0.016 (0.184)
$D^{Feb}Temp_t$		0.141 (0.136)
$D^{Mar}Temp_t$		0.602^{***} (0.223)
$D^{Apr}Temp_t$		0.301^{**} (0.142)
$D^{May}Temp_t$		0.201 (0.214)
$D^{Jun}Temp_t$		0.163 (0.252)
$D^{Jul}Temp_t$		-0.002 (0.172)
$D^{Aug}Temp_t$		-0.189 (0.213)
$D^{Sep}Temp_t$		-0.496^{**} (0.200)
$D^{Oct}Temp_t$		-0.419^{*} (0.235)
$D^{Nov}Temp_t$		-0.343^{*} (0.185)
$D^{Dec}Temp_t$		-0.241 (0.204)
Observations	156	156
R^2	0.589	0.648
Adjusted R^2	0.575	0.605
Residual Std. Error	1.553 (df = 150)	1.499 (df = 138)
F Statistic	43.005^{***} (df = 5; 150)	14.941^{***} (df = 17; 138)

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in year-on-year growth rates (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $Temp_t$ is the temperature variable, D^m is a dummy variable taking 1 in month m and -1 in the following month but for the previous month's weather.

Table 10: Month-specific effects of Temperature with unemployment rate

	Dependent variable:	
	Nominal Retail turnover (dl)	
	(1)	(2)
Constant	0.044 (0.082)	−0.660 (0.714)
Δc_{t-1}	-0.605^{***} (0.069)	-0.608^{***} (0.069)
Δc_{t-2}	-0.408^{***} (0.078)	-0.410^{***} (0.078)
Δc_{t-3}	-0.127^{*} (0.068)	-0.128^{*} (0.068)
R_t	0.384^{***} (0.104)	0.450^{***} (0.120)
Δu_t	−1.058 (1.567)	
u_t		0.228 (0.233)
$D^{Jan}Temp_t$	0.181 (0.124)	0.179 (0.124)
$D^{Feb}Temp_t$	0.103 (0.088)	0.104 (0.088)
$D^{Mar}Temp_t$	0.352^{**} (0.143)	0.351^{**} (0.143)
$D^{Apr}Temp_t$	0.298^{***} (0.097)	0.299^{***} (0.097)
$D^{May}Temp_t$	−0.054 (0.138)	−0.042 (0.138)
$D^{Jun}Temp_t$	-0.165^{*} (0.094)	-0.166^{*} (0.094)
$D^{Jul}Temp_t$	−0.093 (0.113)	−0.093 (0.113)
$D^{Aug}Temp_t$	-0.564^{***} (0.114)	-0.560^{***} (0.114)
$D^{Sep}Temp_t$	-0.334^{**} (0.131)	-0.336^{**} (0.131)
$D^{Oct}Temp_t$	-0.423^{***} (0.143)	-0.423^{***} (0.143)
$D^{Nov}Temp_t$	-0.376^{***} (0.116)	-0.374^{***} (0.116)
$D^{Dec}Temp_t$	0.091 (0.131)	0.091 (0.131)
Observations	176	176
R^2	0.574	0.575
Adjusted R^2	0.528	0.530
Residual Std. Error (df = 158)	1.033	1.032
F Statistic (df = 17; 158)	12.525^{***}	12.595^{***}

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, Δu_t is the change of unemployment rate, u_t is the unemployment rate, $Temp_t$ is the temperature variable, D^m is a dummy variable taking 1 in month m and -1 in the following month but for the previous month's weather.

Table 11: Month-specific effects of Temperature with exchange rate

	Dependent variable:	
	Nominal Retail turnover (dl)	
	(1)	(2)
Constant	0.053 (0.081)	−0.579 (1.087)
Δc_{t-1}	-0.591^{***} (0.069)	-0.604^{***} (0.069)
Δc_{t-2}	-0.395^{***} (0.077)	-0.407^{***} (0.078)
Δc_{t-3}	-0.130^{*} (0.068)	-0.125^{*} (0.068)
R_t	0.370^{***} (0.104)	0.294 (0.198)
$\Delta ExcR_t$	0.087 (0.055)	
$ExcR_t$		0.457 (0.806)
$D^{Jan}Temp_t$	0.165 (0.124)	0.181 (0.124)
$D^{Feb}Temp_t$	0.094 (0.087)	0.104 (0.088)
$D^{Mar}Temp_t$	0.362^{**} (0.142)	0.353^{**} (0.143)
$D^{Apr}Temp_t$	0.288^{***} (0.097)	0.300^{***} (0.097)
$D^{May}Temp_t$	−0.041 (0.137)	−0.045 (0.138)
$D^{Jun}Temp_t$	-0.166^{*} (0.093)	-0.166^{*} (0.094)
$D^{Jul}Temp_t$	−0.078 (0.113)	−0.093 (0.113)
$D^{Aug}Temp_t$	-0.545^{***} (0.114)	-0.561^{***} (0.114)
$D^{Sep}Temp_t$	-0.352^{***} (0.130)	-0.336^{**} (0.131)
$D^{Oct}Temp_t$	-0.434^{***} (0.143)	-0.424^{***} (0.143)
$D^{Nov}Temp_t$	-0.388^{***} (0.115)	-0.375^{***} (0.116)
$D^{Dec}Temp_t$	0.071 (0.131)	0.096 (0.131)
Observations	176	176
R^2	0.580	0.574
Adjusted R^2	0.534	0.528
Residual Std. Error (df = 158)	1.027	1.034
F Statistic (df = 17; 158)	12.814^{***}	12.507^{***}

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

S.E. in parentheses. Dependent variable (Δc_t) is nominal retail trade turnover in log differences (in percentage). Δc_{t-i} denote the lagged dependent variables, $R_t = ln(1 + r_t)$ whereas r_t is the short-term interest rate, $\Delta ExcR_t$ is the change of real exhange rate index, $ExcR_t$ is the real exhange rate index, $Temp_t$ is the temperature variable, D^m is a dummy variable taking 1 in month m and -1 in the following month but for the previous month's weather.

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