Journal of Business Research xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Understanding the economic effects of abnormal weather to mitigate the risk of business failures

Jean-Louis Bertrand*, Miia Parnaudeau

ESSCA School of Management, 1 rue Joseph Lakanal, 49003 Angers CEDEX 01 BP 40438, France

A R T I C L E I N F O

Keywords:
Weather risk
Adaptation
Business failure
Resilience

A B S T R A C T

Warm or cold, wet or dry, weather impacts almost every industry as 70% of businesses are exposed to unexpected variations that influence demand for goods and services. The financial losses caused by adverse weather that did not seem material enough to have an impact or to require being managed a decade ago, may now do so as the frequency and severity of abnormal weather have dramatically increased. A surge in investigating the contribution of weather to financial distress is also prompted by more reliable weather data, and the development of new risk mitigation tools. Drawing upon the UK's retail sectors for empirical evidence, this paper provides a methodology to determine the contribution of weather to sales and to structure financial products to reduce the consequences of adverse weather on expected cash-flows. Our results open new research opportunities for weather to be considered as an additional cause of business failure.

1. Introduction

A drop in sales and earnings may, at some point, reduce the ability of a business to meet its financial obligations, and create a state of financial distress, which is the step preceding business failure and reorganization (Gordon, 1971; Stiglitz, 1972). Most failures involve some interaction between external forces in the environment of the company, and the choices made by management to respond to them (Moulton, Thomas, & Pruett, 1996). In particular, the weather is an external factor of growing importance and consequence. Over the last two decades, as a result of climate change, the frequency and intensity of abnormal weather patterns and extreme weather events have significantly increased (WMO, 2013; IPCC, 2014). Today, weather risks, over which managers have no control, affect approximately 70% of companies worldwide (Hanley, 1999; Dutton, 2002; Larsen, 2006). Abnormal weather events act as environmental jolts (Amankwah-Amoah, Boso, & Antwi-Agyei, 2016) that disrupt the financial performance of companies operating in retail, consumer goods, apparel, transportation, utilities, food processing to name a few (Lazo, Lawson, Larsen, & Waidmann, 2011). In a more volatile environment, companies are more likely to exit the market, and the greater the uncertainty, the higher the exit rate (Anderson & Tushman, 2001).

The unusually warm winter temperatures across Europe in 2015–2016 illustrate the extent to which these weather-induced environmental jolts result in reduced consumer spending and lower sales of many consumer goods. Apparel sales were particularly affected (Gustafson, 2016), as these abnormal temperatures delayed the launching of the spring season at H & M (Milne, 2016), and triggered store closures and job cuts elsewhere (Swamynathan & Layne, 2016).

The repetition and accumulation of the effects of adverse weather events may prove especially harmful to retail companies, as they are particularly exposed to the vagaries of the weather, and display some of the highest failure rates (Everett & Watson, 1998; Amankwah-Amoah & Zhang, 2015). For example, Vivarte, the French fashion retailer, which reorganised its debt in 2013 because of lower sales caused by economic conditions made worse by adverse weather, was forced to again reset its financial expectations in the middle of 2016, mostly because of adverse weather in fall and spring. At the same time, competitor IKKS's debt was lowered further by S & P Global Ratings due to similar reasons (Ruckin, 2013; Fishta & Casiraghi, 2016). In 2014, Jardiland, the leading retailer of garden and pet products initially cut 20.8% of its workforce and avoided bankruptcy only by being recapitalized by a private equity fund, L-GAM Investments, after it experienced lower sales brought on by two consecutive abnormally cold and wet springs (Foucault, 2014).

Whilst the connection between weather and sales has long been acknowledged (Steele, 1951; Maunder, 1973), research to understand exactly how the weather impacts sales is scarce (Dell, Jones, & Olken, 2014). For years, limited access to reliable weather data across large geographical areas has reduced the ability and motivation of researchers to investigate the effects of weather on business activity. This is no longer true, as access to quality data is now almost unlimited

* Corresponding author.
E-mail addresses: jean-louis.bertrand@essca.fr (J.-L. Bertrand), miia.parnaudeau@essca.fr (M. Parnaudeau).

http://dx.doi.org/10.1016/j.jbusres.2017.09.016
Received 5 April 2017; Received in revised form 10 September 2017; Accepted 11 September 2017

through cloud-based platforms, ready to be used and combined with business data to take better decisions (IBM, 2015).

Further incentives to understand the exact contribution of weather to sales performance arise from the finance and insurance industries, as new index-based weather risk management tools to automatically compensate for both sales losses and increased costs caused by adverse weather are now available (Hershey & Breslin, 2015). Today, businesses are no longer compelled to cope with the weather but can respond to disruptive weather events.

Index-based weather hedging instruments offer features of interest to the majority of industries seeking protection against the financial consequences of adverse weather. However, industrial firms by and large have not widely used them to hedge weather risks (Huault & Weiss-Rainelli, 2011). Barriers to effective corporate risk management to reduce the likelihood of business failure include a lack of information about the nature, immediacy, and magnitude of the company's risk exposure. Companies also struggle with the inability to act on information concerning their risks, including concerns about potentially high costs of risk mitigation strategies such as premiums to hedge these risks (World Bank, 2013). A lack of knowledge and understanding on how external events can interact with the business is a key feature of business failure (Carter & Auken, 2006). Small businesses and start-ups are even more vulnerable to weather risks, as they hedge even less than large corporations (Judge, 2006; Collier, Haughwout, Kunreuther, Michel-Kerjan, & Stewart, 2016). Closing the information gap surrounding a company's exposure to weather risks will allow companies to proactively monitor their exposure and identify early warning signals of decline to prevent business collapse (Amankwah-Amoah et al., 2016). Therefore, we propose a methodology to determine the maximum potential loss resulting from the accumulation of weather risks. Further, using the case study of the effects of the weather on UK retail sectors, we illustrate how managers can take measures to mitigate their weather risk exposure.

Building from Maunder (1973) and Toeglhofer, Mestel, and Prettenthaler (2012), we test the relationship between abnormal weather and sales using weather-sensitivity models in which the only unknown explanatory variable is a weather variable (Pres, 2009). The weather variable of the model is used to determine the weather-driven historical sales loss probability distribution. It is also used to structure weather index-based financial instruments aimed at mitigating the risk of lost sales.

The next section sets out the definition of weather risks and defines the scope of the review. Following the methodology and empirical results, we provide an example of risk mitigation and outline directions for future research.

2. Literature review

Our research is related to three streams of the literature, namely, (i) weather and economics, (ii) business failure prediction, and (iii) weather risk management.

2.1. Weather and business activity

Weather affects production and consumption in a variety of activity sectors, most particularly agriculture, energy, food and beverages, tourism, transportation, entertainment, mining, apparel, construction and retail (Deschênes & Greenstone, 2007; Murray, Muro, Finn, & Popkowski, 2010; Mirasgedis, Georgopoulou, Sarafidis, Papagiannaki, & Lalas, 2014; Subak et al., 2000; Day, Chin, Sydnor, & Cherkauer, 2013; Fergus, 1999; Steinker & Hoberg, 2014).

Unlike many exogenous variables, the *normal* value of weather on any given day, in any given place, is known. It is the average value of weather observations, also called normal seasonal value, and meteorologists calculate it by averaging observation values such as temperature or precipitation of a given day over a 30-year period. The current calculation period for normal seasonal weather is 1981–2010 (as defined by the World Meteorological Organization). Consequently, since seasonal weather is known, businesses are able to plan for the seasonality of their activity and organise marketing and production accordingly, and so long as the weather remains normal, it does not disrupt sales.

The risk to which businesses are exposed to the weather is the risk that *abnormal* weather patterns develop and directly affect consumers' behavior in terms of what products they buy, where, and in what quantity, or how the weather indirectly affects the price of commodities through unexpected high or low yields (Maunder, 1973; Barsky & Miron, 1989). Weather risks can be catastrophic or non-catastrophic. Financial losses caused by catastrophic events such as hurricanes and tornadoes can easily be transferred using traditional insurance. They are not the focus of our analysis. Non-catastrophic weather risks stem from the accumulation of day-to-day deviations from *normal* weather. For example, above-normal temperatures in winter reduce demand for heating and adversely impact the revenues of energy companies (Huntington, 2007; Blázquez, Boogen, & Filippini, 2012), whilst below-normal precipitations decrease agricultural yields (Yu, Li, Xin, & Zhang, 2014) and drive sales of tourism and recreational activities higher (Martin, 2005). They refer to excessive levels of heat, cold, precipitation or wind (Corbally & Dang, 2002). In this paper, weather risk is defined as the extent to which adverse weather can cause financial losses (Clemmons, 2002).

Examining the weather risk of a business unit or sector can be complex. Whilst weather mostly affects the volume of activities and therefore the quantity of goods sold, there are situations where weather affects both volume and price. In some industries (e.g., the energy industry) the relationship between weather and sales is straightforward. However, in most cases too little knowledge is available. Thus, the identification of suitable weather variables or indexes is imperative to determine how weather impacts sales (Toeglhofer et al., 2012). This comprises selecting weather conditions in a list of weather variables for a specific time period and geographic area that may have an impact on a business' revenues or costs, and in establishing an empirical relationship between sales and weather. This defines the weather-sensitivity relationship, which provides the two parameters required to construct a financial product to protect against adverse weather: the weather index (which has the most significant impact on the business' financial results), and its multiplier effect on the business' financial loss defined in monetary units.

Many studies have established a relationship between sales and weather, but research on how to estimate the potential loss caused by adverse weather and how to mitigate them is scarce (Dell et al., 2014). The goal of modeling is usually to develop predictive models so that businesses can take corrective actions. A company like Tesco has used weather forecasts for years in an attempt to reduce costs and avoid wasting food (Werdigier, 2009). The use of short-term weather forecasts to improve demand forecast can prove effective to adapt marketing, promotion and staff costs only to the extent that weather forecasts are reliable, which in practice means less than a week (Steinker, Hoberg, & Thonemann, 2017).

When weather conditions are on average unfavourable over days, weeks or entire seasons, falling sales cause reduced cash-flows that have the potential to generate financial distress, especially if adverse weather conditions are sufficiently severe (Beaver, 1966). For all companies that order goods weeks or months in advance of the selling season, what is required is not a model to predict, but a weather-sensitivity model to determine the parameters necessary to structure a financial cover that compensates for reduced cash-flows, and that improves the financial stability of the company.

From a methodological point a view, the weather-sensitivity relationship is established through correlation or regression analysis. Steete's (1951) seminal work consisted of observing the sales of a department store in Iowa and performing a multiple regression analysis with sales as a dependent variable and whatever explanatory weather variables were needed to fully express the weather situation. Ten years later, Linden (1962) related sales of winter coats and average monthly temperatures in New-York. The simplest method known as Best/Worst approach was developed by Clemmons and Radulski (2002). The relationship is obtained by dividing the difference between best and worse annual sales and best and worse weather index observed over the analyzed years. The Analog approach focuses on anomalous weather events (e.g. the unusually hot summer in the UK in 1995) to evaluate the impact of future analog events on economic performance (Giles & Perry, 1998; Agnew & Thornes, 1995). More recent studies also used lagged dependent variables as explanatory variables in regression models (Agnew & Palutikof, 2006; Murray et al., 2010; Bahng & Kincade, 2012), or moved the discussion to analyzing the potential effects of abnormal weather on sales (Tran, 2016; Arunraj & Ahrens, 2016). Toeglhofer et al. (2012) and Bertrand, Brusset, and Fortin (2015) opened new avenues by proposing a method to provide both the potential loss caused by adverse weather and its probability of occurrence, by extending the concept of Value-at-Risk to weather risks. Value-at-Risk (VaR) is a financial measure of the exposure of asset returns to day to day volatility (Linsmaier & Pearson, 2000). By analogy, Weather-VaR is the maximum expected loss in sales caused by adverse weather over a given period of time for a given level of confidence.

2.2. Weather risk and financial distress

Financial distress is the situation that a business has certain kind of financial difficulties (Sun, Li, Huang, & He, 2014). Even though definitions of financial distress vary from insufficiency of resources to inability to fulfill its financial obligations (Walsh & Cunningham, 2016), they are based on the theoretical framework of cash flow. Beaver (1966) compares a business to a reservoir filled up with cash flows, made of inflows (sales) and outflows (operating expenses). Financial distress occurs when the reservoir starts to drain.

Financial Distress Prediction (FDP) is the core process of financial distress early warning (Sun et al., 2014; Amendola, Giordano, Parrella, & Restaino, 2017). Academic research on FDP has gone on for almost eighty years (Fitzpatrick, 1932), and has been dominated by financial ratio analysis (Almamy, J. Aston, & Leonard, 2016). Early works were based on univariate analysis, focusing on one ratio at a time, such as cash-flow to debt ratio (Beaver, 1966), until Altman (1968) questioned this approach and introduced multivariate analysis.

Cash flows and financial ratios have long been used as variables in the development of business failure prediction models (Casey & Bartczak, 1985; Gahlon & Vigeland, 1988; Gombola, Haskins, Ketz, & Williams, 1987). These models test the risk that a deterioration in cash flows may prevent businesses from meeting debt repayment obligations. The probability of failure increases with insufficient cash flows. From the perspective of theoretical analysis, financial distress has different degrees. Moderate financial distress may just be temporary cash flow difficulty, whilst serious financial distress is business failure or bankruptcy (Sun et al., 2014). From the perspective of empirical research however, mostly due to a lack of data availability, financial distress is often defined as a stage of liquidation or bankruptcy.

Financial distress however is a dynamic ongoing process, and is the result of abnormality of external factors that interact with business operations for a period of time, from days or months to years (Fig. 1). External factors, such as competitors, tax and legal environments, and environmental jolts are disruptive. Meyer (1982) describes environmental jolts as *transient perturbations whose occurrences are difficult to foresee and whose impacts on organisations are disruptive and potentially inimical*.

Schumpeter's view of creative destruction emphasizes the role of environmental jolts in their capacity to disrupt organisations. The effects of unexpected and sudden environmental changes have often been studied in the context of disruptions to economic systems and activities, but the focus has been limited to external factors such as competition, technology, innovation, tax or business cycles, and the development of corresponding risk or crisis adaptation mechanisms (Tushman & Anderson, 1986; Covin & Slevin, 1989; Poole & Van de Ven, 2004).

Following the integrative process framework of organisational failure proposed by Amankwah-Amoah et al. (2016), we argue that weather events act as hostile jolts (external factors) that have the potential to repeatedly cause a decline in sales, cash flows and profitability (stages of decline), and lead to organisational failure.

Dealing with unexpected changes in organisations' environments has been an ongoing challenge for organisational managers (Linnenluecke & Griffiths, 2010). Sudden changes have often been analyzed in the framework of disruptions to economic systems, and have resulted in calls for understanding and developing risk and crisis adaptation mechanisms (Kovoor-Misra, Zammuto, & Mitroff, 2000; Meyer, 1982) or the deployment of product, process, and organisational change innovations (Poole & Van de Ven, 2004). To the best of our knowledge, the role of abnormal weather as potential external factor likely to disrupt sales, reduce cash flows and generate financial distress, and the development of mitigating mechanisms have not been addressed.

Yet, empirical evidence shows that few environmental factors exhibit as much uncertainty and potential to generate large financial losses as severe weather events and climate variability associated with climate change (Barnett, 2001). In the UK, in 2015, two thirds of small businesses declared to have been negatively affected by weather over the previous three years (Federation of Small Businesses, 2015). Severe weather events caused disruption to people (customers and staff) and logistics (supply chain, utilities and transport). Whilst 93% of small businesses believe severe weather poses a risk to their businesses, half say they do not get information from any source about how to mitigate the consequences of severe weather. At the very beginning of 2016, Sports Direct, the UK's largest sporting retailer, operating roughly 670 stores worldwide issued a profit warning announcing that it expected to miss its target for underlying profits due to unexpectedly warm weather over the Christmas period. The warning sent shares falling 14%. In 2015, industry leaders released no less than 18 profit warnings directly attributed to abnormal weather. An unusually warm autumn in the UK led to retailers lamenting loss revenues in profit warnings, each causing shares to fall. Esprit, Boohoo, N Brown, SuperGroup and Shoe Zone all experienced well below forecast revenues.

According to the UK National Statistics (ONS), the retail sector has consistently exhibited the highest number of business failures between 2011 and 2015, accounting on average for 10% of the total number of failures. Even large companies declare that they have already started to feel the financial consequences of abnormal weather (Bloomberg, Paulson, & Steyer, 2014). The likely increase in frequency and intensity of weather events should encourage researchers to revisit theories of organisational adaptation in order to incorporate a wider perspective of organisational resiliency to impacts of severe weather events (Linnenluecke & Griffiths, 2010). Such research begins with investigating and understanding the extent to which abnormal weather affects business cash flows.

2.3. Mitigating non-catastrophic weather risks

For over two decades, policy makers have urged the financial sector to improve knowledge on weather-related risks, recognise them as a decision factor in business planning, lending and portfolio management, and develop efficient risk transfer products to deal with them (IPCC, 1990; UNEP-FI, 2006).

Over the same two decades, the number and the intensity of abnormal and severe weather events has risen. The Intergovernmental Panel on Climate Change forecasts that heat waves and severe rainfall

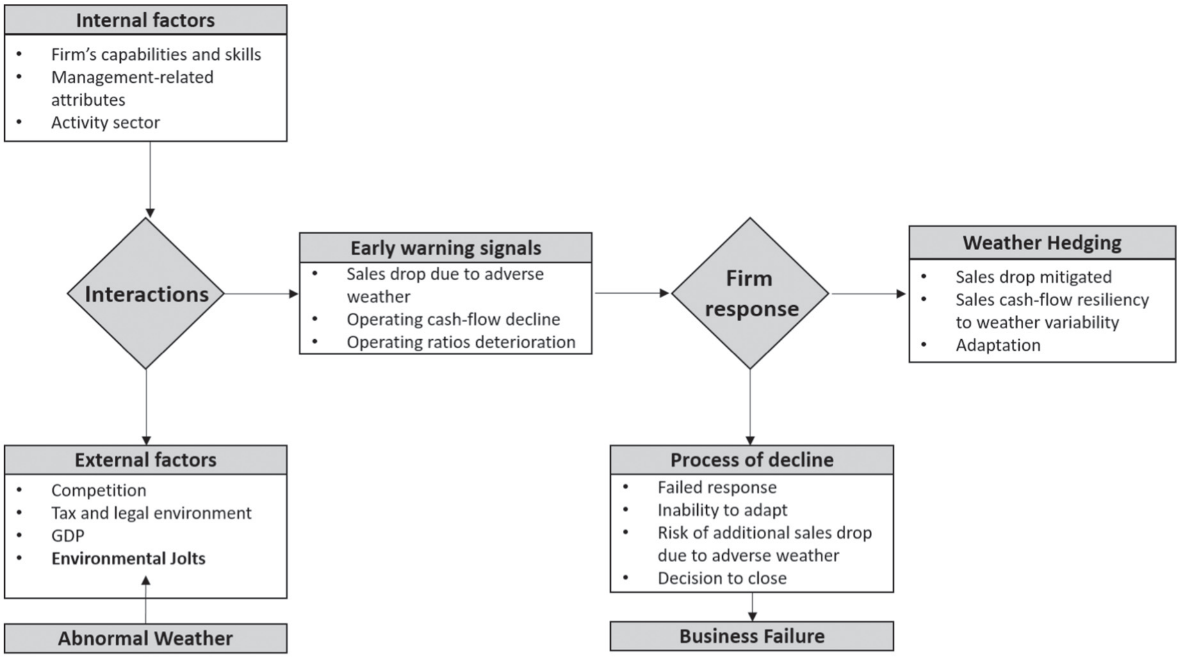

Fig. 1. Integrative process framework of business failure.
Source: Adapted from Amankwah-Amoah et al. (2016), and enclosed references

are likely to continue to increase in the 21st century (2013). In the United Kingdom, for instance, the standard deviation of temperature anomalies measured as the difference between observed and normal temperatures, has doubled since 2000. The standard deviation of weather variables is now at about similar levels as the volatility of other financial variables such as foreign exchange rates, interest rates and commodity prices, but the trend is up, which implies that weather risks have become environmental jolts that have the potential to disrupt the economic activity and generate business failures, and mitigating mechanisms must be considered and tested (Meyer, 1982).

Efficient risk management can only take place on the condition that the risks are perfectly defined (Merna & Al-Thani, 2011). Applied to weather risk management, this means identifying the weather parameters that have impacts on financial results, and understanding exactly how they affect these results. Once this is done, a business may determine if its exposure to weather is material, and if so, the extent to which it can withstand the financial losses incurred by the weather without hedging this risk. The success of coming up with the best hedge in most cases lies in the accuracy of the evaluation of the weather parameters (Pres, 2009).

Index-based weather risk management instruments were introduced in 1997 to automatically compensate the financial losses when the weather index exceeds a predefined level (Muller & Grandi, 2000). They work like any other traditional hedging instruments except that the index on which they are settled is a weather index. The index can be average temperature thresholds, rainfall levels, wind speeds or any combination of variables that represent the risk to which the business is exposed. The payment is triggered by and linked to the weather index, not the actual financial loss incurred by the business. The first weather hedging products were derivative instruments designed for the US energy market some 20 years ago to protect energy distribution companies from above-average winter temperatures resulting in lower sales and profits (Dischel, 2002). Standard contracts based on temperature were later launched on the Chicago Mercantile Exchange during the summer 1999 to address weather risks to a city or a region, and contracts based on snowfall, frost and rain were introduced several years after. However, most of weather hedge contracts continue to be bespoke contracts, and respond to the specific needs of each business situation (Jewson & Brix, 2005).

The details and usage rates of such instruments has remained largely confidential (Huault & Weiss-Rainelli, 2011). The cost of transacting has been traditionally high as many players existed along the supply chain between the potential client and the risk taker, each requiring fees and commissions (e.g. brokers, weather data providers, weather-sensitivity analysts, product structurers, lawyers, risk capacity providers and insurers if the product is packaged as an insurance instead a financial instrument).

Today, prompted by better access to free and reliable historical weather data, new companies (e.g. ClimateSecure or Speedwell) integrate all these functions in order to analyze clients' risks, structure and distribute products. Some have developed web-based underwriting and pricing platforms to provide easy access for businesses of any size to cover weather risks almost anywhere in the world, for any amount, for any period (Hershey & Breslin, 2015).

In addition, through the same platforms, the pricing of weather derivatives has become more transparent. The most common pricing technique is the *burn analysis*, which looks at how the financial hedges would have performed in previous years, and averages the payout to calculate the cost of the product (Jewson & Brix, 2005). Other pricing methods include simulating the value of the weather index at the expiry date of the product (e.g. Monte Carlo methods) or using more sophisticated stochastic models that replicate the weather index (Dorfleitner & Wimmer, 2010; Pirrong & Jermakyan, 2008; Cabrera, Odening, & Ritter, 2013). It is worth noting that, since the level of volatility of weather variables is at similar levels as the volatility of financial indexes, there is no reason for businesses to hedge financial risks and continue to bear weather risks (Pres, 2009).

2.4. Hypotheses

Drawing upon the UK retail sectors for empirical evidence, we formulate the following hypotheses:

1. Abnormal weather has an incidence on sales (cash inflows).
2. Each retail sector exhibits a different sensitivity to the same abnormal weather conditions.

3. A breakdown analysis per season provides a more accurate estimate of weather risks.
4. Abnormal weather has the potential to cause large sales losses (environmental jolts).
5. Tailor-made weather index-based financial products can reduce the risk of large losses (unexpected lower cash inflows) and the uncertainty on sales cash flows caused by abnormal weather.

3. Methodology and data

3.1. Methodology

The objective of the weather-sensitivity analysis is to determine the weather index that has the most impact on sales, to define how a unit change in the index affects sales, and to evaluate the maximum potential loss caused by adverse conditions. We follow the methodology presented in Bertrand and Parnaudeau (2017).

Step 1 of the methodology consists in testing *for each season* the correlation between the change in monthly sales year on year, and abnormal temperature, precipitation and humidity rate, to select the most influential weather variables. In step 2, the selected weather variables are used to estimate the empirical relationship between weather and sales, for each season, using the following model:

$$\Delta S_{m,s} = \alpha \Delta S_{m-1,s} + \beta W_{m,s} + c + \gamma GDP_{m,s} + \epsilon_{m,s} \tag{1}$$

$\Delta S_{m,s} = \frac{Sm,s - S_{m,s-12}}{S_{m,s-12}}$ is the monthly growth rate of sales (volumes) year-on-year for month m during season s, with s = (spring, summer, autumn, winter). The choice of the variable $\Delta S_{m-1,s}$ follows national statistics reporting and management practices that compare sales performance of a given month from one year to the other (Berry, 1987). The first month of spring, summer, autumn and winter are March, June, September and December respectively. $W_{m,s}$ is a weather variable that passed the correlation test in step 1. In each model, there is only one weather variable at a time, for which we test the significance. If more than one weather variable is significantly correlated with sales for a given retail category, we build as many models as the number of correlated weather variables. This way, we can measure the impact of each weather variable independently, and avoid potential over-fitting issues. $GDP_{m,s}$ accounts for the economic situation of the country. Finally, c is a constant and $\epsilon_{m,s}$ is the disturbance term.

The parameters of the models are estimated using the Generalized Methods of Moments following Blázquez et al. (2012). The relevance of our GMM estimates is verified using Sargan tests of over-identification. The verification of the normality of the residuals is done using Gaussian distribution tests. Our results showed that the assumption of a normal distribution for the residuals appears to be reasonable (histogram of frequencies, skewness and kurtosis coefficients). The independence between residuals has also been verified on the basis of the autocorrelations and partial autocorrelations between the residuals. The residuals were not significantly different from a white noise series. All our tests are performed using the R statistical programming environment. For comparison purpose, several SARMA estimations have been realized without making any breakdowns in the sample. Results are available in the Appendix (Table A.11).

In step 2, we keep the models that comply with all the tests. At this stage, we have selected for each weather-sensitive retail category and each season, the weather variable that impacts sales, and the extent to which it impacts them (the β coefficient of the model).

Step 3 consists in playing back observed historical weather of all available years (usually 30 years) in the models, to build the historical loss occurrence distributions and determine the potential maximum losses caused by adverse weather.

Table 1
UK retail sales stores (UK SIC 2007).

Retail sectors
Sporting equipment, games and toys
Textile, clothing and footwear
Textiles
Clothing
Footwear and leather goods
Alcoholic drinks, other beverages
Cosmetics and toilet articles
Medical and orthopaedic goods
Carpets, rugs, wall and floor coverings
Books, newspapers and stationery
Audio, music and video recordings
Household goods
Hardware, paints and glass
Furniture, lighting and household articles

3.2. Data: the UK retail industry

The retail industry is highly vulnerable to business failure (McGurr & DeVaney, 1998) and is believed to be one of the most exposed to the consequences of abnormal weather. In October 2014 for instance, the ONS explained that UK retail sales were down 0.7%, partly due to warmer than usual weather affecting sales of winter clothing. In April 2013, retail sales were down 1.3%. Again, the ONS attributed the drop in consumption to abnormal weather that impacted sales of garden furniture and barbecue food.

Retail sales data are collected from a sample of approximately 5000 retailers across Great Britain. The sample represents the whole retail sector and includes all large retailers and a representative sample of smaller businesses. The known retail industry population is approximately 200,000 businesses and whilst the sample represents 2.5% of this population in terms of number of businesses the sample covers approximately 93% of all known turnover in the retail industry.

We analyze the impact of abnormal weather on monthly retail sales for all retail categories and all four seasons, but for concision, we chose to present the most significant results and limit the categories to the list displayed in Table 1. Our data set covers the period January 1989–August 2015. Retail sales express volumes bought in a month.

Weather data is aggregated into variables for analysis, to a level which is consistent with the resolution of the economic data (Dell et al., 2014). Following Maunder (1973) and Parsons (2001), we aggregate weather at the national level using twelve weather stations spread across the UK, and a fixed set of population weights (Table A.10).

We use daily observations of temperature, precipitation and humidity rate. Humidity rate is the amount of water vapor in the air expressed as a percentage. It indicates the likelihood of precipitation, dew or fog. Humidity may result in consumer behaviors distinct from those caused by precipitation. Weather data is extracted from the National Oceanic and Atmospheric Administration GSOD database. The measure of abnormal weather in a given month is the average anomaly calculated as the average difference between the daily observed weather and its normal value.

4. Results

4.1. Influential weather variables

Table 2 provides correlations for each season for the retail categories we present. Within this list of categories, the highest number of significant correlations is observed for abnormal temperatures. Sales in sporting equipment, clothing, footwear and leather goods are all positively correlated to temperature anomalies in the spring season, which means that above-normal temperatures are associated with higher sales. In autumn, it is the opposite. Correlations are all negative: above-

Table 2
Extraction of correlations for selected retail categories.

	Temperature				Precipitation				Humidity			
	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter
Sporting equipment, games and toys	.45***		−.19*									
Textile, clothing and footwear	.58***		−.31***		−.45***	.24**			−.40***			
Textiles		−.29***	−.27***			.34***		.28**		.38***		
Clothing	.53***		−.26***	.22**	−.45***			.28**	−.37***			
Footwear and leather goods	.51***		−.24**	.23**	−.38***				−.38***			
Alcoholic drinks, other beverages		.32***	−.48***		−.22*				−.28***	−.29***		
Cosmetics and toilet articles			−.22***		−.19*	−.20**	−.26**	.20**	−.38***	−.21*		
Medical and orthopaedic goods												−.36***
Carpets, rugs, wall and floor coverings	−.19*									.30***		
Books, newspapers and stationary		−.33***							.20***	.27**		
Audio, music and video recordings		−.19*			.23**	.38***				.28**		
Household goods		−.32***	.26**	.28**		.46***		.24**		.29***	.24**	
Hardware, paints and glass	.49***		.24**	.27**	−.47***		−.27**	.23**	−.36***		.23**	
Furniture, lighting and household article	−.20*	−.45***	.33***	.33**	.28**	.48***		.27**		.42***	.33**	

*$p < 0.1$; **$p < 0.05$; ***$p < 0.001$.

normal temperatures are associated with lower sales. In the summer, when temperatures are warmer than normal, sales in beverages are higher whilst sales in cultural goods (books and music) and home furniture are weaker. This is consistent with both Maunder (1973) and with anecdotal evidence discussed in Section 1.

In spring, almost all retail categories exhibit a negative correlation between sales and precipitation, except for sales of music and household furniture: the sales of clothing, footwear, beverages, and cosmetics are all adversely affected by excess rain. In the summer however, abnormal rain is positively correlated to textiles, clothing and footwear, implying that excess rain drives more consumers to stores. Humidity rate provides very similar information to precipitation. It is interesting to note that the effects of excess humidity in the spring has a stronger correlation with the sales of beverages and cosmetics than rain. Also in the summer, humidity rate is positively correlated to the sales of books and carpets.

4.2. Weather-sensitivity per season

The weather variables selected in the previous section are used to model the relationship between sales and weather for spring, summer, autumn and winter. Examples of weather-sensitivity models that comply with Sargan and serial correlation in residuals tests presented in Tables 4–6 illustrate the incidence of weather on sales (Hypothesis 1). These tables display both models with and without *GDP*. In our case, the ultimate objective of modeling is to construct a financial protection against unfavourable weather conditions, for a given business in a given sector. This requires defining two parameters: type of weather exposure (one or more weather indices that have a crucial impact on financial results), and the sensitivity coefficient (β) that describes the size of possible losses. Pres (2009), who reviewed all available methods to determine weather-sensitivity models, stresses that *"usually in weather-risk estimating, only three categories of weather indices (air temperature, precipitation and wind speed) and one financial variable (sales volume, total income or total margin) are used"*. Hence, in the next sections, we will only use models without *GDP*.

In Table 4, we note that retail sectors exhibit very different sensitivities to the same weather variable (Hypothesis 2). In autumn for instance, a positive deviation of 1 °C increases sales of alcoholic drinks by more than 11%, whilst the same deviation in temperature causes sales of footwear to decrease by about 1%.

We broke down our analysis by season to avoid the *wash-out* effects discussed by Lazo et al. (2011) who concluded that the contribution of weather to the US economic activity was lower than expected. Table 3 is an illustration of this *wash-out* effect. A positive deviation of 1 °C in spring causes sales of footwear to increase by 3.238% and sales of clothing to increase by 1.648%. The same positive deviation of 1 °C in autumn causes sales to decrease by 3.067% and 1.133% respectively. This is easily explained because spring and autumn collections are different. Small pieces like tee-shirts and skirts sell more in warm springs, whilst larger garments such as jumpers and coats sell less in warm autumns.

Table 3
Wash-out effects in the case of footwear and clothing sales.

Sector	Season	$Temp_m$
Footwear	Spring	3.238***
Footwear	Autumn	−3.067***
Clothing	Spring	1.648***
Clothing	Autumn	−1.133***

Seasonal patterns are often addressed using SARMA models. The use of SARMA models for footwear and clothing sales (see Table A.11 in the Appendix) supports the presence of significant seasonal effects ($SAR(4) = 0.129^{***}$ and 0.270^{***} resp.) whilst the Breusch-Godfrey tests confirm the absence of serial correlations in the residuals. *GDP* holds a marginal significance, but abnormal temperature ($Temp_m$) is a strong explanatory variable for both categories, with a β of 1.945^{***} and 0.787^{***} respectively. The low intrinsic value of both coefficients reflects the *wash-out* effects. 2013 weather conditions in the UK illustrate our discussion. 2013 was almost a *normal* year, with an average temperature for the year 0.11 °C above normal. Using SARMA models, we estimate the contribution of weather to the sales of footwear and clothing to be +0.19% and 0.08% respectively (β * 0.11 °C), which does not reconcile with the type of weather effects experienced by retailers in 2013.

If we measure this effect using a breakdown analysis by season, the picture is very different. In 2013, spring was abnormally cold (−2.11 °C) and autumn was abnormally hot (+1.01°). Using β coefficients in Table 3, we calculate the cumulative impact of abnormal weather of −9.9% for footwear sales and 4.6% clothing sales, which is consistent with empirical evidence.

4.3. Estimation of sales losses caused by adverse weather

The weather-sensitivity model provides a business with the opportunity to understand how a change in weather conditions will affect sales of a given product in the considered season. To evaluate a weather risk exposure, a first approach consists in calculating the average and maximum losses caused by adverse weather, based on historical weather observations. We use 30 years of historical data to calculate *normal* weather.

Table 4
Extraction of models for which Temperature is an influential variable.

Sector	Season	ΔS_{m-1}	$Temp_m$	c	GDP	DW	Sargan
Books	Summer	0.391^{***}	-3.159^{***}	0.152		2.102	6.068*
Books	Summer	0.323^{***}	-3.003^{***}	0.324^{**}	-14.075^{***}	1.930	8.481*
Furniture	Summer	0.397^{***}	-2.424^{***}	0.084		2.058	15.760^{***}
Furniture	Summer	0.271^{***}	-1.939^{***}	-0.936^{***}	20.110^{***}	1.756	13.705^{**}
Household goods	Summer	0.380^{***}	-1.276^{***}	0.120		1.8107	15.036^{***}
Household goods	Summer	0.176^{**}	-1.142^{***}	-0.653^{***}	14.039^{***}	1.469	14.433^{***}
Textiles	Summer	0.241^{***}	-4.941^{***}	0.640^{***}		1.779	15.895^{***}
Textiles	Summer	0.274^{***}	-4.361^{***}	0.706^{***}	2.637	1.818	16.069^{***}
Alcoholic drinks	Autumn	0.067^{***}	11.445^{***}	2.433^{***}		1.600	13.421^{***}
Alcoholic drinks	Autumn	0.041^{***}	11.697^{***}	3.029^{***}	-26.761^{***}	1.625	13.793^{**}
Footwear	Autumn	0.077	-1.052^{***}	-0.111		1.453	8.909^{**}
Footwear	Autumn	0.228^{***}	-0.977^{***}	-0.539^{***}	7.758^{***}	1.783	14.687^{***}
Hardware	Winter	-0.028	0.767^{***}	0.765^{***}		1.492	13.094^{***}
Hardware	Winter	0.047^{***}	1.057^{***}	1.407^{***}	-15.869^{***}	1.581	13.979^{**}

Table 7 provides the average and the maximum deviations from normal weather for temperatures in the UK. The same information is provided for precipitation and humidity rate in the Appendix (Table A.12). If we consider the retail sector of alcoholic drinks in autumn, since β is equal to 11.445, the average deviation from normal sales in autumn is 5.3% (11.445 × 0.47 °C). We proceed in the same way to calculate the maximum loss. In the case of alcoholic drinks, since β is positive, adverse weather is a negative deviation. As a result, the maximum loss caused by adverse weather in autumn is 29.4% (11.445 × 2.45 °C). Given retail margins in this sector, this level of sales loss and shortage in cash inflows is an important disruption, likely to drive any retailer into financial distress (Hypothesis 4).

A second approach consists in estimating the probability of occurrence of sales losses, using a probabilistic distribution of abnormal weather. Based on the 30-year historical distribution of abnormal weather, a common practice consists of smoothing the historical distribution with a process called *kernel smoothing* (Brix, Jewson, & Ziehmann, 2002), whereby the probability density function (PDF) f of the index distribution taken at point x is given by

$$\hat{f}\,(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h}k\left(\frac{x-\bar{I}_i}{h}\right) \tag{2}$$

In this PDF, the degree of smoothing is determined by the bandwidth h. Whereas the choice of smoothing function is not critical, the bandwidth selection is important for the overall shape of the estimated distribution: the larger h, the more smoothing is obtained. The kernel PDF function is used to estimate the probability that a weather anomaly exceeds a certain threshold. The 5% threshold is often used to refer to severe abnormal weather, as it is only observed 5% of the time (Linsmaier & Pearson, 2000). A summary of these thresholds is provided in the Appendix for UK temperatures, precipitations and humidity rates (Table A.12).

The distribution is then used in the weather-sensitivity models to estimate the probability that a loss in sales caused by adverse weather exceeds a certain threshold. For instance, based on the distribution of UK abnormal temperatures in autumn, there is a 5% probability that negative temperature deviations exceed −1.81 °C. In the case of alcoholic drinks, this means that there is a 5% probability that the loss caused by adverse weather in autumn exceeds 20.7% of sales. Using the same distribution, the probability that the loss exceeds 10% of sales is 17%. It is important to note that, since abnormal weather in a given season is statistically independent from abnormal weather in an other season, the effects of abnormal weather on sales for the year are cumulative. In the retail of footwear, the maximum loss in sales caused by abnormally cold temperatures is 6.8% in spring (3.238 × −2.11 °C) and 7.5% in autumn (−3.067 × 2.45 °C). To conclude this section, we find that in many retail sectors, the maximum loss caused by adverse weather is a reduction in cash inflow that is material and large enough to disrupt many businesses (Hypothesis 4).

4.4. Mitigating the effects of non-catastrophic weather risks: case of the alcoholic and other beverage retail sector in autumn

In this section, we show how index-based weather financial instruments can be used to lower the risk of experiencing large losses in sales caused by adverse weather and reduce the high level of uncertainty on sales variance due to abnormal weather variability year on year (Hypothesis 5). Index-based weather products are mostly sold by insurance and reinsurance companies. A business can implement index-based weather instruments to follow three different hedging strategies. The first strategy consists in eliminating completely the consequences of abnormal weather. This is done with a *swap*. In a swap, there is no upfront payment. The business is compensated to offset the loss in margins in case of adverse weather. Conversely, the business gives up all potential additional margins due to favorable weather conditions. The second strategy consists in buying a protection against the consequences of adverse weather and keeping 100% of potential additional margins in case of favorable weather. This is called an *option*. Finally, the third strategy is a combination of options, called a *collar* or a tunnel. A collar protects the business against the consequences of adverse weather, just like an option, but the business gives up a portion of

Table 5
Extraction of models for which Precipitation is an influential variable.

Sector	Season	ΔS_{m-1}	$Precip_m$	c	GDP	DW	Sargan
Furniture	Summer	0.421^{***}	0.079^{***}	0.168		1.776	12.889^{***}
Furniture	Summer	0.322^{***}	0.054^{***}	-0.675^{***}	14.288^{***}	1.643	13.722^{***}
Cosmetics	Summer	0.186^{**}	-0.0385^{***}	0.122		3.744	14.352^{***}
Cosmetics	Summer	0.227^{**}	-0.040^{***}	-0.253*	6.475^{***}	1.824	13.149^{**}
Textiles	Summer	0.259^{***}	0.189^{***}	0.785^{***}		1.600	11.254^{**}
Textiles	Summer	0.284^{***}	0.184^{***}	1.382^{***}	-15.133^{***}	1.649	11.008^{**}
Textiles	Winter	0.626^{***}	0.153^{***}	0.428^{***}		2.417	13.362^{***}
Textiles	Winter	0.506^{***}	0.083^{***}	2.909^{***}	-39.048^{***}	2.291	14.082^{***}

Table 6
Extraction of models for which humidity rate is an influential variable.

Sector	Season	ΔS_{m-1}	Hr_m	c	GDP	DW	Sargan
Medical	Winter	0.420***	−1.162***	0.642***		2.170	11.441***
Medical	Winter	0.374***	−1.437***	1.354***	−22.500***	2.075	12.363**

Table 7
30 year statistics of UK abnormal temperatures.

	Spring	Summer	Autumn	Winter
Maximum positive deviation	3.04 °C	1.67 °C	2.45 °C	2.17 °C
Maximum negative deviation	− 2.11 °C	− 1.89 °C	− 2.57 °C	− 3.02 °C
Average deviation	0.47 °C	0.37 °C	0.47 °C	0.57 °C

potential additional margins in case of favorable weather. As a result, it is less expensive that the straightforward option strategy.

The cost of index-based weather instruments is the fair value to which a margin, called the *load factor*, is added by the insurance company. The fair value of the weather index-based instrument is calculated using a burn analysis. The burn analysis looks at how the instrument would have performed under all historical weather observations available. In the case of the retail of alcoholic drinks, we have 30 years of weather observations that we can use to evaluate the fair value of various instruments.

To illustrate this, we consider a business that has normal sales of £100 m and a profit margin of 10%. We consider three hedging strategies: a swap, an option that protects the business if adverse weather causes margins to drop by more than 10%, and a collar that protects the business if sales fall by more than 10% because of weather but limits additional margins to 10% in case of favorable weather.

Fig. 2 is a reconstruction of profits and losses caused by abnormal weather conditions observed over the last 30 years. In other words, the weather conditions observed in 1986 applied to our model would produce an additional sales of 3%. Weather conditions observed in 2007 would generate a loss of 21%. The maximum loss of 29% corresponds to the weather conditions observed in 2012.

Table 8 is the burn analysis and the reconstruction of cash flows under all available weather conditions observed between 1986 and 2014, for four possible strategies: no hedge, an option, a collar, and a swap. If the business does not hedge, the maximum loss is £2.9 million and the standard deviation is £1.3 million. With an option, the loss is capped at £1 million, and the standard deviation is reduced to £1.1 million. With a collar, the maximum loss is still £1 million, but the standard deviation is further reduced to £0.9 million. Finally, with a swap, there is no loss and by definition the standard deviation is equal to zero.

The cost of the option or the collar is the burn to which a load factor is added. The load factor is usually a fraction of σ, the standard deviation of the cash flows used to determine the burn (Jewson & Brix, 2005). Using 10% of σ as the load factor, the cost of the option works at to be £194 969 or 1.95% of the margin. Similarly, the cost of the collar is £82 872 or 0.83% of the margin.

The efficiency of various hedging strategies is demonstrated in Table 9 (Hypothesis 5). For a cost that represents 0.19% of sales, an option reduces the maximum loss in margins from 29% to 10%, and reduces the variability of margins by 17% from 13.44% to 11.16%. The collar reduces further the variability of margins by 34%, from 13.44% to 8.88%.

5. Conclusion

This study has important implications for business failure research as it brings into focus the importance of considering increasing non-

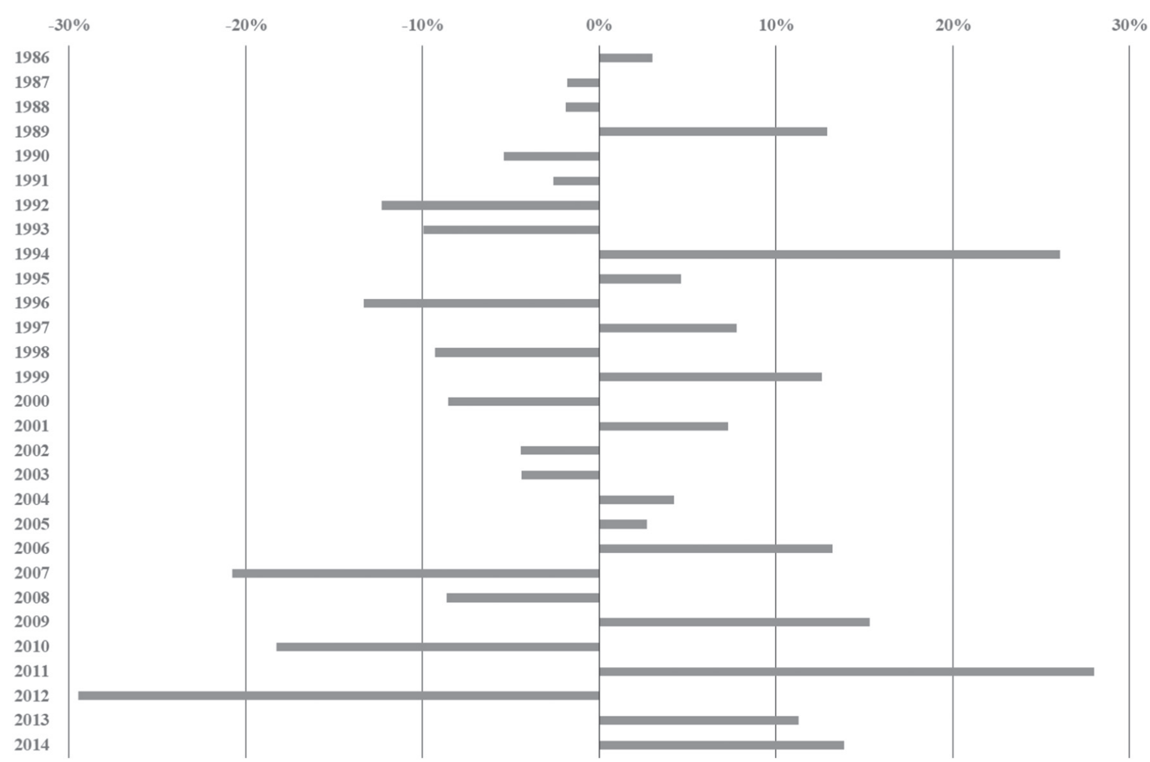

Fig. 2. Reconstruction of the contribution of weather conditions observed over the last 30 years (% of sales).

Table 8
Reconstructed net cash flows due to abnormal weather (in £); maximum loss in margin in bold.

Weather	No hedge	Option	Net cash-flow	Collar	Net cash-flow	Swap	Net cash-flow
1986	300 298	–	300 298	–	300 298	− 260 241	40 058
1987	− 182 532	–	− 182 532	–	− 182 532	222 589	40 058
1988	− 190 028	–	− 190 028	–	− 190 028	230 085	40 058
1989	1 287 402	–	1 287 402	− 87 402	1 200 000	− 1 247 344	40 058
1990	− 542 060	–	− 542 060	–	− 542 060	582 118	40 058
1991	− 259 383	–	− 259 383	–	− 259 383	299 441	40 058
1992	− 1 233 243	233 243	**− 1 000 000**	233 243	**− 1 000 000**	1 273 300	40 058
1993	− 994 460	–	− 994 460	–	− 994 460	1 034 517	40 058
1994	2 604 134	–	2 604 134	− 1 404 134	1 200 000	− 2 564 077	40 058
1995	460 248	–	460 248	–	460 248	− 420 190	40 058
1996	− 1 331 449	331 449	**− 1 000 000**	331 449	**− 1 000 000**	1 371 506	40 058
1997	776 381	–	776 381	–	776 381	− 736 323	40 058
1998	− 930 449	–	− 930 449	–	− 930 449	970 507	40 058
1999	1 257 773	–	1 257 773	− 57 773	1 200 000	− 1 217 715	40 058
2000	− 854 279	–	− 854 279	–	− 854 279	894 337	40 058
2001	729 245	–	729 245	–	729 245	− 689 187	40 058
2002	− 441 920	–	− 441 920	–	− 441 920	481 977	40 058
2003	− 439 863	–	− 439 863	–	− 439 863	479 920	40 058
2004	422 395	–	422 395	–	422 395	− 382 337	40 058
2005	270 015	–	270 015	–	270 015	− 229 957	40 058
2006	1 321 193	–	1 321 193	− 121 193	1 200 000	− 1 281 136	40 058
2007	− 2 077 200	1 077 200	**− 1 000 000**	1 077 200	**− 1 000 000**	2 117 258	40 058
2008	− 862 910	–	− 862 910	–	− 862 910	902 967	40 058
2009	1 529 291	–	1 529 291	− 329 291	1 200 000	− 1 489 233	40 058
2010	− 1 825 129	825 129	**− 1 000 000**	825 129	**− 1 000 000**	1 865 187	40 058
2011	2 800 100	–	2 800 100	− 1 600 100	1 200 000	− 2 760 043	40 058
2012	**− 2 946 624**	1 946 624	**− 1 000 000**	1 946 624	− 1 000 000	2 986 681	40 058
2013	1 127 970	–	1 127 970	–	1 127 970	− 1 087 912	40 058
2014	1 384 756	–	1 384 756	− 184 756	1 200 000	− 1 344 698	40 058
Burn		152 195		21 690		69	40 058
Std. dev.	1 343 604	427 746	1 116 449	611 827	887 981		0

Table 9
Efficiency of weather hedging in reducing maximum loss and cash-flow uncertainty.

	No Hedge	Option	Collar	Swap
Max. loss on margin cash flow (% of margin)	−29.47%	−10.00%	−10.00%	0.00%
Std. dev. on margin cash flow (% of margin)	13.44%	11.16%	8.88%	0.00%
Cost of hedging (% of margin)	–	1.95%	0.83%	0.00%
Cost of hedging (% of sales)	–	0.19%	0.08%	0.00%

catastrophic weather risks as a new environmental jolt that can generate financial losses and drops in cash inflows likely to precipitate business failure, especially in the case of small or new businesses.

We show that is now possible to establish a clear diagnosis of business exposure to weather. Using monthly UK retail sales, we identify each weather parameter that impacts sales in several retail categories, and show the extent to which, each season, adverse weather can cause significant sales losses and shortages of inflows.

We demonstrate that knowledge of weather risks makes it possible to structure simple weather index-based hedging instruments, to economically and efficiently reduce the risk of large financial losses caused by severe weather events, and decrease the volatility of future cash-flows exposed to weather. Today, weather risk management is still in its early days, and the majority of businesses do not hedge against weather risks, nor do they have an accurate view on how much is at risk. We contribute to raising awareness on the need for weather-sensitive businesses to make use of the methodology and weather data in order to get a clear picture of their exposure and implement operational or financial strategies to mitigate the financial impact of abnormal weather.

In using a simple method to apprehend concepts of short-term weather impacts, we are moving the discussions concerning climate change and its effects on the private sector within managerial boundaries. Whereas most studies that analyze the potential effects of climate change on the private sector address a time horizon that is too far out for managers and investors to be concerned, we provide retailers with a practical measure of their risk in the short-term, on a seasonal basis.

As climate variability is likely to continue to increase, we expect more research will be conducted to quantify the role of weather in contributing to business financial distress and business failure. We also anticipate growing interest from scholars and practitioners to evaluate the contribution of weather risk management to business sustainability.

Appendix A. Appendix

Table A.10
Weather stations and population weights.

Region	Station	USAF	Pop.	Weight (%)
Southeast	Odiham	37610	8 792 626	13,7
Greater London	London	37720	8 416 535	13,1
Northwest	Manchester	33340	7 103 260	11,1
Northeast	Boulmer	32400	2 610 481	4,1
East	Wattisham	35900	5 954 169	9,3

West Midlands	Birmingham	35900	5 674 712	8,9
Southwest	Plymouth	38270	5 377 595	8,4
Yorkshire and the Humber	Leeming	32570	5 337 710	8,3
East Midlands	Nottingham	33540	4 598 729	7,2
Scotland	Aberdeen	30910	5 327 700	8,3
Wales	Milford	36040	3 082 412	4,8
Northern Ireland	Belfast Aldergrove	39170	1 829 725	2,9
Total			64 105 654	100

Table A.11
SARMA models: extraction of results for temperature and precipitation (1989–2015).

Sector	ΔS_{m-1}	$Temp_m$	c	GDP	SAR(4)	MA(1)	Breush-Godfrey
Carpets	0.844***	2.422***	1.114	10.896	0.095*	−0.346***	23.46***
Hardware	0.796***	2.835***	0.937	−7.364	0.124**	−0.480***	46.063***
Textiles	0.439	0.873***	−0.082	3.763	0.254***	−0.332***	33.294***
Cosmetics	0.691***	1.580***	−0.391	12.118*	0.084***	−0.257	70.574***
Household goods	0.791***	0.621*	−0.244	12.151*	0.104**	−0.569***	10.373**
Footwear	0.583***	1.945***	−0.137	2.815	0.129***	−0.275*	64.527***
Clothing	0.418	0.787***	−0.0510	3.681	0.270***	−0.317	19.613***
Sector	ΔS_{m-1}	$Prcp_m$	c	GDP	SAR(4)	MA(1)	Breush-Godfrey
Audio	0.733***	0.061*	−0.794	36.116**	0.127***	−0.385***	11.496***
Books	0.789***	0.149***	1.723	−26.882*	0.093*	−0.479***	47.238***

Table A.12
Historical unseasonal weather statistics.

	Temperature	Precipitation	Humidity
Spring			
Maximum positive deviation	3.04	42.88	5.94
Maximum negative deviation	−2.11	−29.89	−3.99
Average positive deviation	0.50	6.80	0.95
Average negative deviation	−0.43	−7.10	−0.93
5% positive threshold	2.28	32.30	4.92
5% negative threshold	−1.36	−28.00	−3.44
Summer			
Maximum positive deviation	1.67	42.34	6.25
Maximum negative deviation	−1.89	−54.69	−8.36
Average positive deviation	0.37	8.64	1.34
Average negative deviation	−0.36	−9.28	−1.45
5% positive threshold	1.52	36.60	5.65
5% negative threshold	−1.37	−28.90	−6.37
Autumn			
Maximum positive deviation	2.45	60.18	3.43
Maximum negative deviation	−2.57	−54.26	−3.54
Average positive deviation	0.46	10.25	0.73
Average negative deviation	−0.47	−9.20	−0.64
5% positive threshold	2.28	41.30	2.63
5% negative threshold	−1.82	−42.10	−2.90
Winter			
Maximum positive deviation	2.17	50.35	3.99
Maximum negative deviation	−3.02	−61.8	−4.20
Average positive deviation	0.59	10.35	0.69
Average negative deviation	−0.55	−10.80	−0.70
5% positive threshold	2.08	46.90	3.19
5% negative threshold	−2.55	−39.2	−2.10

References

Agnew, M. D., & Palutikof, J. P. (2006). Impacts of short-term climate variability in the UK on demand for domestic and international tourism. *Climate Research, 31*(1), 109–120.

Agnew, M. D., & Thornes, J. E. (1995). The weather sensitivity of the UK food retail and distribution industry. *Meteorological Applications, 2*, 137–147.

Almamy, J., Aston J., J., & Leonard, N. (2016). An evaluation of Altman's z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the UK. *Journal of Corporate Finance, 36*, 278–285.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609.

Amankwah-Amoah, J., Boso, N., & Antwi-Agyei, I. (2016). The effects of business failure experience on successive entrepreneurial engagements: An evolutionary phase model. *Group and Organization Management,* 1–32.

Amankwah-Amoah, J., & Zhang, H. (2015). Business failure research: A review of the Chinese experience. *International Journal of Foresight and Innovation Policy, 10*, 180–197.

Amendola, A., Giordano, F., Parrella, M. L., & Restaino, M. (2017). Variable selection in high-dimensional regression: A nonparametric procedure for business failure prediction. *Applied Stochastic Models in Business and Industry, 33*(4), 355–368.

Anderson, P., & Tushman, M. (2001). Organizational environments and industry exit: The effects of uncertainty, munificence and complexity. *Industrial and Corporate Change, 10*, 675–711.

Arunraj, N. S., & Ahrens, D. (2016). Estimation of non-catastrophic weather impacts for retail industry. *International Journal of Retail and Distribution Management, 44*, 731–753.

Bahng, Y., & Kincade, D. (2012). The relationship between temperature and sales: Sales data analysis of a retailer of branded women's business wear. *International Journal of Retail and Distribution Management, 40*(6), 410–426.

World Bank. (2013). Risk and opportunity: Managing risk for development. *Technical report*. International Bank for Reconstruction and Development, Economic Research Report.

Barnett, J. (2001). Adapting to climate change in pacific island countries: The problem of uncertainty. *World Development, 29*, 977–993.

Barsky, R. B., & Miron, J. A. (1989). The seasonal cycle and the business cycle. *Journal of Political Economy, 97*(3), 503–534.

Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71–111.

Berry, D. (1987). A method to portray and analyze sales performance. *Industrial Marketing Management, 16*(2), 131–144.

Bertrand, J.-L., Brusset, X., & Fortin, M. (2015). Assessing and hedging the cost of unseasonal weather: Case of the apparel sector. *European Journal of Operational Research, 244*(1), 131–144.

Bertrand, J.-L., & Parnaudeau, M. (2017). No more blaming the weather: A retailer's approach to measuring and managing weather variability. *International Journal of Retail and Distribution Management, 45*(7/8), 730–761.

Blázquez, L., Boogen, N., & Filippini, M. (2012). Residential electricity demand in Spain: New empirical evidence using aggregate data. *Working Paper*.

Bloomberg, M. R., Paulson, H. M., & Steyer, T. F. (2014). Risky business: The economic risks of climate change in the United States. *Report*. Bloomberg.

Brix, A., Jewson, S., & Ziehmann, C. (2002). Climate risk and the weather market. *Weather derivative modelling and valuation: A statistical perspective* (pp. 126–150). London, United Kingdom: Risk Books.

Cabrera, B., Odening, M., & Ritter, M. (2013). Pricing rainfall futures at the CME. *The Journal of Banking and Finance, 37*, 4286–4298.

Carter, R., & Auken, H. V. (2006). Small firm bankruptcy. *Journal of Small Business, 44*, 493–512.

Casey, C. J., & Bartczak, N. J. (1985). Using operating cash flow data to predict financial distress: Some extensions. *Journal of Accounting Research, 23*, 384–401.

Clemmons, L. (2002). Weather risk management: Markets, products, and applications. In E. Banks (Ed.). *Introduction to weather risk management* (pp. 3–13). New York: Palgrave Macmillan.

Clemmons, L., & Radulski, D. (2002). Weather risk management: Markets, products, and applications. In E. Banks (Ed.). *The economics of weather* (pp. 25–58). New York: Palgrave Macmillan.

Collier, B., Haughwout, A., Kunreuther, H., Michel-Kerjan, E., & Stewart, M. (2016). Firms' management of infrequent shocks. *National Bureau of Economic Research, No. w22612*.

Corbally, M., & Dang, P. (2002). Weather risk management: Markets, products, and applications. In E. Banks (Ed.). *Underlying markets and indexes* (pp. 87–103). New York: Palgrave Macmillan.

Covin, J., & Slevin, D. (1989). Strategic management of small firms in hostile and benign environments. *Strategic Management Journal, 10*, 75–87.

Day, J., Chin, N., Sydnor, S., & Cherkauer, K. (2013). Weather, climate, and tourism performance: A quantitative analysis. *Tourism Management Perspectives, 5*, 51–56.

Dell, M., Jones, B., & Olken, B. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature, 52*, 740–798.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review, 97*(1), 354–385.

Dischel, R. S. (2002). Climate risk and the weather market. *Introduction to the weather market: Dawn to mid-morning* (pp. 3–24). London, United Kingdom: Risk Books.

Dorfleitner, G., & Wimmer, M. (2010). The pricing of temperature futures at the Chicago Mercantile Exchange. *The Journal of Banking and Finance, 34*, 1360–1370.

Dutton, J. (2002). Opportunities and priorities in a new era for weather and climate services. *Bulletin of American Meteorological Society, 83*(9), 1303–1311.

Everett, J., & Watson, J. (1998). Small business failure and external risk factors. *Small Business Economics, 11*, 371–390.

Federation of Small Businesses. (2015). Severe weather, a more resilient small business community. In A. Zeller (Ed.). *Economic research report.*. The Federation of Small Businesses, ER-1.

Fergus, J. (1999). Where, when, and by how much does abnormal weather affect housing construction? *Journal of Real Estate Finance and Economics, 18*, 63–87.

Fishta, E., & Casiraghi, L. (2016). *Vivarte in talks to reset loan covenant.* Bloomberg.

Fitzpatrick, P. (1932). A comparison of ratios of successful industrial enterprises with those of failed firms. *Certified Public Accountant. October, November and December* (pp. 598–605). .

Foucault, G. (2014). *L-GAM acquires Jardiland, the leading French garden and pet specialist.* Press release.

Gahlon, J. A., & Vigeland, R. L. (1988). Early warning signs of bankruptcy using cash flow analysis. *Journal of Commercial Bank Lending, 70*, 4–15.

Giles, A., & Perry, A. (1998). The use of a temporal analogue to investigate the possible impact of projected global warming on the UK tourist industry. *Tourism Management, 19*, 75–80.

Gombola, M. J., Haskins, M. E., Ketz, E. J., & Williams, D. D. (1987). Cash flow in financial prediction. *Financial Management, 16*, 55–65.

Gordon, M. (1971). Towards a theory of financial distress. *Journal of Finance, 26*, 347–356.

Gustafson, K. (2016). *A $500m hit and a bleak forecast for retail.* CNBC.

Hanley, M. (1999). Hedging the force of nature. *Risk Professional, July/August*, 21–25.

Hershey, L., & Breslin, E. (2015). *Meteo protect: Empowering the bottom line with weather modeling.* SAP Startup focus.

Huault, I., & Weiss-Rainelli, H. (2011). A market for weather risk? Conflicting metrics, attempts at compromise, and limits to commensuration. *Organization studies, 32*(10), 1395–1419.

Huntington, H. (2007). Industrial natural gas consumption in the united states: An empirical model for evaluating future trends. *Energy Economics, 29*, 743–759.

IBM.. (2015). Weather means business. *White paper.*. IBM Analytics.

IPCC.. (1990). Climate change: The IPCC scientific assessment. *Technical report.*. Cambridge, United Kingdom: IPCC.

IPCC.. (2014). Climate change 2014: Impacts, adaptation and vulnerability. *Report*. Intergovernmental Panel on Climate Change, IPCC.

Jewson, S., & Brix, A. (2005). *Weather derivative valuation: The meteorological, statistical, financial and mathematical foundations*. Cambridge University Press.

Judge, A. (2006). The determinants of foreign currency hedging by U.K. non-financial firms. *Multinational Finance Journal, 10*, 1–41.

Kovoor-Misra, S., Zammuto, R., & Mitroff, I. (2000). Crisis preparation in organizations–prescription versus reality. *Technological Forecasting and Social Change, 63*(1), 43–62.

Larsen, P. H. (2006). Estimating the sensitivity of U.S. economic sectors to weather. *Working Paper Cornel University, SSRN 900901*. Cornel University.

Lazo, J. K., Lawson, M., Larsen, P. H., & Waidmann, D. M. (2011). U.S. economic sensitivity to weather variability. *Bulletin of American Meteorological Society, 92*, 709–720.

Linden, F. (1962). Consumer markets: Merchandising weather. *The Conference Board Business Record, 19*(6), 15–16.

Linnenluecke, M. K., & Griffiths, A. (2010). Beyond adaptation: Resilience for business in light of climate change and weather extremes. *Business and Society, 49*, 477–511.

Linsmaier, T., & Pearson, D. (2000). Value at risk. *Financial Analysis Journal, 57*(2), 47–67.

Martin, M. (2005). Weather, climate and tourism a geographical perspective. *Annals of Tourism Research, 32*, 571–591.

Maunder, W. (1973). Weekly weather and economic activities on a national scale: An example using United States retail trade data. *Weather, 28*(1), 2–19.

McGurr, P., & DeVaney, S. (1998). Small business failure and external risk factors. *Journal of Business Research, 43*, 169–176.

Merna, T., & Al-Thani, F. F. (2011). *Corporate risk management*. John Wiley & Sons.

Meyer, A. (1982). Adapting to environmental jolts. *Administrative Science Quarterly,* 515–537.

Milne, R. (2016). Late spring chills H & M sales. *The Financial Times*.

Mirasgedis, S., Georgopoulou, E., Sarafidis, Y., Papagiannaki, K., & Lalas, D. (2014). The impact of climate change on the pattern of demand for bottled water and non-alcoholic beverages. *Business Strategy and the Environment, 23*(4), 272–288.

Moulton, M., Thomas, H., & Pruett, M. (1996). Business decline pathways: Environmental stress and organizational response. *Journal of Management, 22*, 571–595.

Muller, A., & Grandi, M. (2000). Weather derivatives: A risk management tool for weather-sensitive industries. *The Geneva Papers on Risk and Insurance. Issues and Practice,* (2), 273–287.

Murray, K., Muro, F. D., Finn, A., & Popkowski, L. P. (2010). The effect of weather on consumer spending. *Journal of Retailing and Consumer Services, 17*(6), 512–520.

Parsons, A. G. (2001). The association between daily weather and daily shopping patterns. *Australasian Marketing Journal, 9*, 78–84.

Pirrong, C., & Jermakyan, M. (2008). The price of power: The valuation of power and weather derivatives. *The Journal of Banking and Finance, 32*, 2520–2529.

Poole, M., & Van de Ven, A. (2004). Weather risk management: Markets, products, and applications. *Central issues in the study of change and innovation* (pp. 3–31). Oxford University Press.

Pres, J. (2009). Measuring non-catastrophic weather risks for businesses. *The Geneva Papers on Risk and Insurance Issues and Practice, 34*, 425–439.

Ruckin, C. (2013). *Vivarte in talks to reset loan covenant.* Reuters.

Steele, A. T. (1951). Weather's effect on sales of a department store. *Journal of Marketing, 15*, 436–443.

Steinker, S., & Hoberg, K. (2014). The influence of weather in online retailing - An empirical analysis. *Working paper.*.

Steinker, S., Hoberg, K., & Thonemann, U. (2017). The value of weather information for E-commerce operations. *Production and Operations Management*.

Stiglitz, J. (1972). Some aspects of the pure theory of corporate finance: Bankruptcies and takeovers. *The Bell Journal of Economics, 3*, 458–482.

Subak, S., Palutikof, J. P., Agnew, M. D., Watson, S. J., Bentham, C. G., Cannell, M. G. R., ... Woods, J. C. (2000). The impact of the anomalous weather of 1995 on the UK economy. *Climatic Change, 44*(1), 1–26.

Sun, J., Li, H., Huang, Q., & He, K. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems, 57*, 41–56.

Swamynathan, Y., & Layne, N. (2016). *Macy's to cut jobs, shut stores amid weak holiday sales.* Reuters.

Toeglhofer, C., Mestel, R., & Prettenthaler, F. (2012). Weather value at risk: On the measurement of non-catastrophic weather risk. *Weather, Climate, and Society, 4*(3), 190–199.

Tran, B. (2016). Blame it on the rain weather shocks and retail sale. *Working paper UC, San Diego*.

Tushman, M., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly, 31*, 439–465.

UNEP-FI.. (2006). Adaptation and vulnerability to climate change: The role of the finance sector. *technical report.*. United Nations Environment Programme Finance Initiative.

Walsh, G., & Cunningham, J. (2016). Business failure and entrepreneurship: Emergence, evolution and future research. *Foundations and Trends® in Entrepreneurship, 12*(3), 163–285.

Werdigier, J. (2009). Tesco, British grocer, uses weather to predict sales. *New York Times*.

WMO.. (2013). WMO statement on the status of the global climate in 2012. *Report 1108.*. World Meteorological Organization.

Yu, C., Li, C., Xin, Q., & Zhang, J. (2014). Dynamic assessment of the impact of drought on agricultural yield and scale-dependent return periods over large geographic regions. *Environmental Modelling and Software, 62*, 454–464.

Miia Parnaudeau is a full professor of finance at Essca School of Management (Essca), in Angers, France. She holds a PhD and a habilitation to direct research (HDR) in Economics. Her research topics include European and Chinese banking systems, Risk Management and Corporate Governance. She has been appointed as part of an international consortium that has been recruited by the European Space Agency and CGI-UK (Logica) to work on a study in Governance. She has published several scientific articles in Corporate Governance, Journal of Business Strategy, or Journal of Business Ethics.

Jean-Louis Bertrand is a full professor of finance at Essca School of Management (Essca), in Angers, France. He holds a PhD and an engineering degree. His research topics include Corporate Risk Management, Weather Risks and Weather derivatives. Prior to being a Professor, he worked in the banking sector as an account manager and a derivatives trader. He was also a treasurer where he managed foreign exchange and interest rate risks. He is a member of the Weather Risk Management Association and the French Treasurers Association. He has published books, book chapters, white papers and scientific articles mostly on weather risk management issues.