Can variations in temperature explain the systemic risk of European firms?

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Received: date / Accepted: date

Abstract We employ a *ΔCoVaR* model in order to measure the potential impact of temperature fluctuations on systemic risk, considering all companies from the STOXX Europe 600 Index, which covers a wide range of industries for the period from 1/1/1990 to 29/12/2017. Furthermore, in this study, we decompose temperature into 3 factors; namely (i) trend, (ii) seasonality and (iii) anomaly. Findings suggest that, temperature has indeed a significant impact on systemic risk. In fact, we provide significant evidence of either positive or nonlinear temperature effects on financial markets, while the nonlinear relationship between temperature and systemic risk follows an inverted U-shaped curve. In addition, hot temperature shocks strongly increase systemic risk, while we do witness the opposite for cold shocks. Additional analysis shows that deviations of temperature by 1°C can increase the daily Value at Risk by up to 0.24 basis points. Overall, higher temperatures are highly detrimental for the financial system. Results remain robust under the different proxies that were employed to capture systemic risk or temperature.

Keywords Conditional Value at Risk · Systemic risk · Climate change · Temperature
JEL Classification C21 · C33 · G32 · Q54

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1 Introduction

Understanding the empirical relationship between climate change and financial markets is gaining much prominence within the recent climate - finance literature. Literature has shown that temperature is a risk factor that can erratically affect economic activity (Dell et al, 2014; IPCC, 2014). At the same time, the persistent trend of rising temperature has been spreading uncertainty to the whole financial system and thus it significantly contributes to systemic risk (e.g., Battiston et al, 2017). The systemic risk element of temperature has a twofold justification. First, variations of temperature can trigger a direct revaluation of climate sensitive assets. Particularly, equity losses can occur due to direct exposures to climate shocks such as natural catastrophes, changes in climate policy and increased energy costs (ESRB Advisory Scientific Committee, 2016). Second, firms that possess climate sensitive assets could affect the financial system given their high interconnection with other businesses, thereby increasing systemic risk indirectly (Battiston et al, 2017). For instance, on one hand, temperature could affect agricultural output (i.e., direct impact of temperature) (Schlenker and Roberts, 2009), while on the other, agricultural firms that experience abnormal losses due to weather conditions might subsequently transmit uncertainty to their counterparts or to other industries with which they trade (i.e., indirect impact of temperature) (Miranda and Glauber, 1997). Amid climate change, *radical uncertainty*[1] impedes the capacity of financial markets to operate efficiently. The reason is that investors' expectations about future environmental regulations and climate change events are highly disparate and therefore climate sensitive assets are impossible to be reevaluated instantaneously (Aglietta and Espagne, 2016; Karydas and Xepapadeas, 2019). Instead, what can be observed, historically, is investors' reaction on temperature changes. With these in mind, our overriding priority is to investigate whether systemic risk is conditioned on temperature changes. At the same time, we also address other noteworthy questions such as: Is climate uncertainty priced in financial markets? How much is the cost for the financial system? Do we have only losers or also gainers? What is the optimal temperature for the normal operation of financial markets?

As far as the motivation of our study is concerned, it should be noted that in this paper, we combine knowledge from (i) the effects of temperature on stock markets and (ii) the broader systemic risk literature. The first strand of the literature concentrates mainly on how temperature innovations influence stock market returns (e.g., Cao and Wei, 2005; Bansal and Ochoa, 2011; Novy-Marx, 2014; Donadelli et al, 2017b; Balvers et al, 2017). This strand has mainly identified that temperature has macroeconomic risk characteristics that affect stock market returns. A possible explanation has been given by labour productivity scholars. In particular, Hsiang (2010); Donadelli et al (2017b); Letta and Tol (2018) underscore that temperature and productivity are negatively related and this could potentially lead to financial turmoil, considering that their interaction might change the components of aggregate supply

[1] *Radical uncertainty hypothesis* has been described by Aglietta and Espagne (2016) and defined as collective prudential actions that minimise the probability of occurrence of unforeseen events due to high uncertainty. For instance, investors might be driven away from climate sensitive firms (selling climate sensitive stocks) because they anticipate unexpected climate events.

and demand. (ESRB Advisory Scientific Committee, 2016; Dafermos et al, 2017). In close relation to this, Weagley (2018) supports that extreme temperatures would increase the energy demand and consequently increase operational cost for firms. By contrast, Cao and Wei (2005) offers an alternative justification by claiming that temperature variations can affect financial behaviour as temperature has been found to cause psychological disturbances.

The second strand of the literature highlights the importance of systemic risk on the financial stability; especially during financial crises (e.g., crisis 2007-2009), when financial stability seems quite vulnerable to rises in systemic risk. Systemic risk does not only affect financial markets but it can also have severe consequences to the real economy (Galati and Moessner, 2013). For this reason, policymakers and researchers have developed analytic tools in order to measure and predict rises in systemic risk (e.g., Engle and Manganelli, 2004; White et al, 2015; Adrian and Brunnermeier, 2016). Accordingly, the main objective of these tools is to stress the equilibria generated by exogenous shocks. Empirical examples are abundant, for instance, Reboredo and Ugolini (2015) who study systemic risk dependency across European sovereign debt markets, Mensi et al (2017a) find that oil price volatility generates systemic risk to currencies and vice versa. Along a similar vein, de Mendonça and da Silva (2018) show that liquidity, profitability, leverage and interest rates have important role in triggering systemic risk fluctuations in the financial sector.

In this regard, to empirically examine whether temperature shocks affect systemic risk, we follow the Conditional Value at Risk (*CoVaR*) literature (Adrian and Brunnermeier, 2016). *CoVaR* is a systemic risk measure that is robust to spillover effects and distribution assumptions and is defined as the spread between the Value at Risk of the financial system and that of an institution under distress. The attractiveness of *CoVaR* lies in its ability to pinpoint the root of economic crises, while computationally can be easily facilitated through a quantile regression framework. The motivation of using *CoVaR* stems from the fact that some firms might be affected by climate change while others not. This method offers a unique potential to identify both an asset that has the highest risk exposure and the interconnectedness of this asset with other assets across the financial system. Given that temperature can directly trigger macroeconomic alterations (Dell et al, 2014), climate-sensitive firms inevitably absorb the initial shock emerging from these alterations and transmit it even further, generating spillovers to the whole economy. Hence, with the use of *CoVaR*, we can examine the Value at Risk dependency on temperature fluctuations.

Our study provides the following main contributions. First, while previous literature investigates whether temperature affects stock market returns (Cao and Wei, 2005; Bansal et al, 2016; Apergis and Gupta, 2017; Balvers et al, 2017), this is the first study, to the best of our knowledge, to empirically investigate if temperature has an impact on systemic risk. Our study is motivated by prior literature underlining the systemic element of climate change (Aglietta and Espagne, 2016; ESRB Advisory Scientific Committee, 2016; Battiston et al, 2017). Second, the study provides strong evidence from the European Union; an area highly committed to climate change mitigation. Contrary to existing literature that uses lower frequency data, we use 28 years of daily data that might directly account for both short-term and long-term temperature effects. That is, either quarterly or annual data cannot fully detect temperature variations because crucial information about temperature is cancelled out. Thus, *CoVaR* can measure the maximum daily losses attributed to changes in temperature. Finally, we decompose temperature as suggested by the climate change literature (Vecchio and Carbone, 2010; Ji et al, 2014) and thus we provide a more meaningful and articulate picture of temperature effects. More particularly, the decomposition employed in this study implies that we provide evidence about the unexpected temperature variations on the systemic risk of firms.

The main findings of the study indicate that, in a panel data sample of 600 firms for 7305 trading days in 17 different EU countries from 1/1/1990 to 29/12/2017, temperature has a prominent role in affecting the 99% daily and monthly *CoVaR*. In particular, we document that temperature has weak nonlinear effect on the financial markets. Moreover, we observe that temperature shocks contain a systemic risk factor that strongly increases the losses of the firms. What is more, cold shocks have negative contribution to systemic risk, while the effect of hot shocks appears to be positive. Alternative model specifications, such as different systemic risk and temperature shock proxies as well as lower frequency examination, establish the robustness of the results with some small variations across different industries. Particularly, in line with Balvers et al (2017), we demonstrate that manufacturing firms seem to be the ones mostly affected by temperature variations.

The findings of the study are very important to promote the climate- finance research. Scholars can monitor climate-sensitive firms that have spillover effects to the whole financial system. IPCC (2014) forecasts higher frequency and magnitude of extreme weather events and rising temperatures. For this reason, our study pinpoints a possible way of measuring the climate systemic impact of firms and thus to help the financial system to be equipped with adequate tools and knowledge in view of further climate change deterioration.

The remainder of the paper is structured as follows: Section 2 outlines the previous climate change - financial literature and states the hypotheses. Section 3 presents the data, the *CoVaR* methodology, the temperature components and the testable regressions. In section 4, results are reported. Section 5 summarises and concludes.

2 Literature Review and Hypotheses

2.1 Systemic Risk

We commence this section by presenting a brief review of the literature on systemic risk. Systemic risk can be defined as the increase in losses due to the spreading of financial distress across firms (Engle and Manganelli, 2004; Adrian and Brunnermeier, 2016). There is a large body of literature that proposes different methods in order to model systemic risk. Assessing systemic risk has been highlighted especially during financial crises (Galati and Moessner, 2013).

Value at Risk (*VaR*) is the most widespread measure of losses due to its simplicity. The *VaR* for any firm given can be written as:

$$Pr(X^i \leq VaRq^i) = q\%,$$

where X^i is the stock return losses of a firm i for which $VaRq^i$ is defined and $q\%$ is the quantile of the probability distribution, where the upper tail of the distribution denotes the highest financial losses. However, *VaR* is not sufficiently focused on systemic risk and this is because *VaR* is a sample of returns of a firm i at isolation. Thus, *VaR* neglects the spillover effects, which are responsible for spreading the risk. Another problematic setting in *VaR* calculation is that financial time-series are highly skewed, indicating that *VaR* underestimates or overestimates the actual risk. As described by Angelidis et al (2007), in order to forecast the risk accurately, *VaR* modelling needs to accommodate non-symmetrical fat tails.

Dealing with the skewness of returns, Giot and Laurent (2003) propose univariate and multivariate ARCH models based on skewed student distribution. Furthermore, Engle and Manganelli (2004) use a combination of quantile regressions with GARCH models in order to allow for relaxation of any distribution assumptions, but at the same time this method assumes that systemic risk has a short autoregressive memory. Similarly, White et al (2015) propose a method that utilizes vector autoregressive models simultaneously with the associated quantile of stock returns. This method is robust to outliers and tailors different variables in order to deal with the spillover effects.

The most recent contributions to *VaR* modelling emphasise the importance of spillover effects (e.g., Girardi and Tolga Ergün, 2013; Reboredo et al, 2016; Mensi et al, 2017b; Karimalis and Nomikos, 2018). In the influential study of Adrian and Brunnermeier (2016), the *VaR* of the whole financial sector is conditional on one particular firm under distress; this is known in the risk literature as *CoVaR*. *CoVaR* can be easily measured by quantile regressions. $\Delta CoVaR$ which is the main risk measure of this analysis, is the difference between the *CoVaR* of a firm under distress and the *CoVaR* of the median state of this firm. Adrian and Brunnermeier (2016) show that $\Delta CoVaR$ is a robust method, which captures the tail dependency of stock returns, and the sensitivity of $\Delta CoVaR$ can be tested by accommodating different micro and macro risk variables.

2.2 Temperature and Economy

We now move on to discuss why temperature is a macroeconomic risk factor. Rising global temperature can have an impact on the economy and activate macroeconomic alterations. Fankhauser and Tol (2005); Stern (2007); Du et al (2017); Colacito et al (2018) argues that climate change will have a direct effect on countries GDP due to the fact that they have to bear the consequences of extreme weather events, such as rainstorms, extreme temperatures and floods. Having quantified this effect, Horowitz (2009) documents that 1°C increase in average temperature would decrease the world GDP by 3.8%. Heal and Kriström (2002); Dell et al (2014); Donadelli et al (2017a); Arbex and Batu (2018) underline that temperature shocks are inevitably connected with agricultural outcome, health, tourism, productivity, energy consumption, research & development and to some extent the economic performance of firms. Schlenker and Roberts (2009) identify that temperature changes can have an impact on agricultural products because crop yields can thrive under certain circumstances. Their findings indicate that different temperature change scenarios can lead to decrease in the average crop yield from 30% to 82% by the end of the century. Moreover, Deschenes (2014) underscores that the direct recipient of climate change is humans and the main threat is whether humans will be able to adapt to the new environment or not. According to World Health Organization[2] (2016) the direct cost to health will be 2-4 billion USD annually by 2030 due to the increasing number of deaths caused by climate change. Letta and Tol (2018) find a strongly negative relationship between total factor productivity and temperature. Donadelli et al (2017b) support that temperature shifts have a long run negative effect on labour productivity. Hsiang (2010) finds that increasing temperature by 1°C can have negative effect of 2.4% on labour productivity. Similar finding is supported by Graff Zivin and Neidell (2014) who identify that a temperature rise reduces the hours worked in industries.

Besides, literature supports that temperature is a risk factor that affects the economy. Global warming can bring financial instability because it directly affects components of aggregated demand for energy (Dafermos et al, 2017; Weagley, 2018). Therefore, to some extent macroeconomic consequences are attributed to climate change, however the main challenge is to test if temperature risk is transmitted to financial markets.

2.3 Temperature and Financial Markets

Before turning to the empirical climate - finance literature, it is sequential to understand the link between stock price movements and temperature. This link can be summarised in four main points: (1) evidence from psychological literature shows that temperature affects investors' mood (Kamstra et al, 2003; Cao and Wei, 2005); (2) temperature acts as a reminder and increases investors' concerns about imminent de-carbonised policies (Karydas and Xepapadeas, 2019); (3) extreme temperatures would increase energy consumption and thus firms have to bear higher cost to maintain standard working conditions (Weagley, 2018) and (4) temperature shocks act as a systematic negative productivity shock, which in turn affect the stock valuations (Balvers et al, 2017; Donadelli et al, 2019).

A summary of the empirical literature is given by Table 1. In the seminal contributions of Kamstra et al (2003); Cao and Wei (2005), a stock market anomaly was observed; high temperature causes apathy towards financial markets while cold temperature is followed by higher risk-taking. Temperature-stock anomaly is also supported by Novy-Marx (2014) who states that the global warming can be used as a proxy because it has a significant role in predicting financial performance anomalies.

[INSERT TABLE 1 HERE]

Additionally, Bansal and Ochoa (2011) present that temperature is a source of aggregated risk and they identify a temperature beta in the stock market, which is the risk exposure of stocks to the temperature. They perform cross sectional regressions for different portfolios sorted by country and their results indicate that countries

[2] Retrieved from http://www.who.int/mediacentre/factsheets/fs266/en/

closer to Equator hold a strong and negative temperature risk premium but moving away from Equator the effect becomes positive. Negative beta is followed by higher stock returns, implying that there is a higher compensation for assets that are exposed to higher temperatures. Bansal et al (2016) add long-run temperature shifts in their analysis in order to separate the long from the short run effect of the temperature. They, overall, find that temperature risk has a negative effect on equity valuations. Similarly, Balvers et al (2017) examine the effect of temperature shocks on the cost of equity. By taking different portfolios and incorporating temperature shocks in asset pricing models, the authors identify that temperature is a risk factor that has significant and negative effect on firms' stock returns that operate in climate sensitive industries. Their findings suggest that 0.22% of the total cost of equity is attributed to temperature risk. Therefore, it can be argued that temperature is an aggregated risk factor that influences the stock returns depending on the geographical latitude (Bansal and Ochoa, 2011) and the industry (Balvers et al, 2017). Temperature negatively affects productivity and therefore the results are not surprising since productivity shocks play a crucial role in equity valuations (Garlappi and Song, 2016). In align with the theory of finance, temperature risk can be categorised as a risk factor that has a negative effect on equity evaluations (Chen and Wang, 2012).

2.4 Temperature Information

Before proceeding to state our hypotheses, it is important to investigate the different temperature proxies used in relevant analyses and the information content of temperature data.

There is a plethora of proxies about the temperature effects. While, Kamstra et al (2003) employ daily raw temperature data as predictive variable of stock returns, most of the studies use temperature anomaly. Temperature anomaly is defined either as the difference between the daily temperature and the average historic temperature, or as the innovations of temperature, when lower frequency data are examined (Cao and Wei, 2005; Novy-Marx, 2014; Bansal et al, 2016; Apergis and Gupta, 2017; Donadelli et al, 2017b, 2019). This method eliminates the seasonality of the raw temperature data but at the same time, it contains information about both the trend and temperature shocks. Temperature trend and shocks are two different components which is imperative to be separated; according to IPCC (2014), temperature trend follows a linear gradual increase and can be observed for the last 150 years, while temperature shocks are more extreme since about 1950. Dealing with the different temperature components, Balvers et al (2017) decompose the monthly temperature series and obtain temperature shocks. Even though, their paper estimates shocks through detrended analysis, they neglect to distinguish between cold and warm shocks as it was previously suggested by Cao and Wei (2005); Novy-Marx (2014). Temperature shocks can be either cold or hot and can have significantly different economic consequences (Dell et al, 2012).

Notwithstanding the use of lower frequency temperature data in the climate - economy literature (Hsiang, 2010; Dell et al, 2012; Du et al, 2017; Colacito et al, 2018), while climate - finance studies tends to use higher frequency data (Kamstra et al, 2003; Cao and Wei, 2005; Apergis and Gupta, 2017). This can be explained by the unavailability of higher frequency macroeconomic and, sometimes, temperature data (particularly in developing countries) as well as, there are conceptually different research objectives between economy and finance scholars.

To provide more insights about temperature information, we now turn our attention to climate change literature. Daily temperature records are characterized by nonlinearities. By using monthly or annual aggregated data, critical information could be missed and temporal resolution will be reduced (Vecchio and Carbone, 2010). For this reason, an empirical decomposition on daily data can provide us with meaningful information. As Vecchio and Carbone (2010) explain temperature contains three equally important components; (i) trend, (ii) seasonality and (iii) anomaly. Trend is usually referred as the gradually increase in the average temperature which is a linear function that can vary over time (Ji et al, 2014). Seasonality is an oscillatory factor with constant frequency (≈ 365 days) and it is probably the least important component in terms of the information contained. In contrast, the anomaly component corresponds to the temperature variation, which is the unexpected temperature deviations from the detrended and deseasonalized mean temperatures.

2.5 Hypotheses of the Study

According to Dell et al (2014), temperature can be seen as a macroeconomic risk variable, which can potentially affect not only different economies but also individual firms. We extend this concept and, particularly, the unedited research question we posit is whether and, if so, how systemic risk responds to temperature changes. For instance, assume that a highly leveraged firm experiences losses from unanticipated temperature changes. This may impair the firm's ability to meet its financial obligations, and pose a threat to the financial system as a whole (ESRB Advisory Scientific Committee, 2016). To put it differently, we ask whether a firm's losses that result from temperature changes can be causal of losses to other firms within the industry or the economy.

Synchronously, Horowitz (2009); Schlenker and Roberts (2009); Dell et al (2012, 2014); Aglietta and Espagne (2016); Du et al (2017) underline the importance of nonlinear temperature effects on different economic activities. Aggregate economic losses accelerate with increasing temperature; according to different scenarios an average temperature increase beyond 2°C would amplify economic losses, while temperature increase below this threshold does not seem to cause a sizeable reaction to the economy (IPCC, 2014). For a similar reason, if temperature has nonlinear effects on the economy, then higher temperatures should amplify investors' concerns about climate change. Therefore, in the remainder of this research, we explore a nonlinear relation between temperature changes and systemic risk.

Hypothesis 1: Temperature has asymmetric effects on systemic risk.

It should be recognized that the multifaceted information content of temperature change might hinder a direct identification of its effects on the economy and financial markets. Moreover, if information about temperature is regarded as a significant pricing factor of stocks, then stock prices, returns and losses should respond to unanticipated changes in temperature, rather than to trend or seasonality. Therefore, to ascertain whether the asymmetric temperature effects are driven by unanticipated changes to temperature, and to delve deeper into the temperature-systemic risk nexus, we decompose the temperature variable into trend, seasonality component and anomaly, as suggested by Vecchio and Carbone (2010); Balvers et al (2017). Temperature anomaly should lead to gradual devaluation of climate-sensitive assets (Bansal et al, 2016) and thus we expect the entire financial system to be affected. As Jacobsen and Marquering (2009) claim, raw temperature might be correlated with different seasonal patterns and thus results might be driven by seasonal unobserved characteristics. For this reason, similarly with Hypothesis 1, temperature anomaly should be an appropriate measure to account for the potential asymmetries.

Hypothesis 2: Temperature anomaly has asymmetric effects on systemic risk.

There is adequate literature to support that temperature shocks have an effect on the productivity of firms (see e.g., Hsiang, 2010; Graff Zivin and Neidell, 2014; Dafermos et al, 2017; Donadelli et al, 2017b). Productivity is depleted by temperature shocks; in turn, productivity shocks can explain a large variation in the cross section of stock returns (Garlappi and Song, 2016). To be more explicit, temperature shocks should generate concerns to investors about global warming and thus a positive impact of temperature shocks on systemic risk is expected.

It is worth noting that for its most part, the climate - finance literature does not distinguish between hot and cold temperature shocks. Yet, in practice, temperature shocks can either be positive (e.g. a heat wave) or negative (e.g., extremely low temperatures). Pilcher et al (2002) puts forward the argument that, on one hand, exposure to cold weather can negatively affect reasoning and memory tasks, while on the other, hot exposure reduces attentional and perceptual tasks. Therefore, considering these distinct effects on performance, it would be interesting to investigate whether temperature effects hold given that the present study proceeds with a disaggregation of temperature shocks into hot and cold.

Based on the above, there are two main competing views on how hot or cold shocks should influence systemic risk. The first view relates to energy consumption. Authors such as Weagley (2018) maintain that extreme temperature deviations are associated with higher risk taking in financial markets. Weagley (2018) argues that this connection is justified by the additional energy needed in order to cool or heat a particular place in the aftermath of a temperature shock, which can be regarded as an adverse shock to the demand for energy, and can be generally perceived as "bad" news by investors and traders. Therefore, continuous and extreme temperature shocks can increase the energy demand and, in turn, firms will have to factor, in their profit functions, higher long-term operational cost to maintain standard working conditions.

Hypothesis 3a: Hot and Cold temperature shocks should increase systemic risk.

The second view relates to the psychological literature. More particularly, Heal and Kriström (2002); Cao and Wei (2005) identify that extreme temperatures are connected not only with different levels of productivity but also with psychological effects. Particularly, Cao and Wei (2005) find that cold temperature causes aggression and high risk-taking, while hot temperature can affect the mood of investors by causing either aggression or apathy and thus, either high or no risk-taking. In general, aggressive investors will tend to engage in more risky investments. As a result, investors will submit more demand orders for risky stocks, which will lead to an increase (decrease) in stock prices and returns (losses). In turn, lower losses are associated with lower levels of systemic risk. Therefore, according with the psychological literature, hot and cold shocks should decrease systemic risk.

Hypothesis 3b: Hot and cold temperature shocks should decrease systemic risk.

3 Research design

3.1 Sample

The sample consists of 600 European firms that are included in STOXX 600 Index from the period 1/1/1990 to 29/12/2017. Firms are coming from 10 different industries from 17 different countries (see, Table 2). All the data are in daily frequency, making a strongly balanced panel of 4,383,000 firm-day observations. The mean temperature and the precipitation for all 17 different locations have been retrieved from the European Climate Assessment & Dataset (ECA&D)[3]. We match the firms' main market location with the closest weather station in order to extract the weather data (see, panel C in Table 2). The stock market returns are available at Datastream, while the macroeconomic data are collected from Federal Reserve Bank of St. Louis. We choose this period of examination for the subsequent two reasons. First, financial and weather daily data are scarce before this period. Second, the Intergovernmental Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC), that are the two most prominent actions against climate change, were established relatively to this period.

A critical issue is the frequency of the data. In the climate-economy literature, temperature is commonly approximated with low frequency data (monthly, quarterly, annually) (Colacito et al, 2018); this is because climate change is a long term phenomenon which systematically affects macroeconomic conditions (e.g. Dell et al, 2014). However, in the case of financial markets, the situation is different. Due to the technology advances, high frequency traders react instantly to relevant news (O'Hara, 2015). Another example that further stresses the debate between low and high frequency data, is that if one day of the month is very hot and another day is very cold, then the monthly aggregated result would be downward biased (Vecchio and Carbone, 2010). Therefore, the higher the frequency of data, the more precise results we obtain. Although, daily data are used is the main analysis, we also consider monthly

[3] https://www.ecad.eu/

data in order to test whether long-run temperature shifts can shape the perception of investors in the financial markets.

[INSERT TABLE 2 HERE]

3.2 *ΔCoVaR*

In this sub-section, we define systemic risk as the contribution of Value at Risk (VaR) of one firm to the Value at Risk of the industry, in which this firm operates. For example, how HSBC Bank PLC under distress can transmit instabilities to the whole financial sector in the EU. In this study, a firm under distress is reflected on the 99% of the losses distribution. This part of the distribution represents the highest daily expected losses, which can easily be computed through the traditional *VaR* method. An alternative procedure to control for *VaR*, which is robust to outliers, spillover effects and is directly associated with systemic risk, is proposed by Adrian and Brunnermeier (2016):

$$Pr(X^j|C(X^i) \leq CoVaR_q^{j|C(X^i)}) = q\%, \tag{1}$$

where X^j is industry return losses conditional on the losses of a particular firm i (X^i) at any part of the distribution (i.e. $q = 99\%$). $CoVaR^{j|C(X^i)}$ is the Value at Risk of the industry j conditional on some event $C(X^i)$ of institution i. *CoVaR* can be implicitly estimated by running the following quantile regression:

$$X_q^j = a_q^i + \beta_q^i X^i + u_q^i, \qquad q \in (0,1), \tag{2}$$

where the predictive values of X_q^j are the Value at Risk of financial system conditional on X^i. Therefore $CoVaR_q^i = \widehat{X}_q^j$ and $CoVaR_q^i$ is the *VaR* of j conditional on *VaR* of i at any q given. Additionally, to more effectively approximate systemic risk we use the *ΔCoVaR* measure, which is the change in *CoVaR* of institution i at $q = 99\%$ to its median state ($q = 50\%$). The median state of any institution can be estimated by running the Equation 2 at $q = 50\%$ and then saving its fitted values ($CoVaR_q^{j|VaR_{50}^i}$). In other words, we run Equation 2 twice at q=99% and at q=50%, and save the fitted values. Then, *ΔCoVaR* can be measured as shown in Equation 3:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{j|VaR_{50}^i}. \tag{3}$$

3.3 Temperature Decomposition

We focus on the short-term temperature variations related to the 28-year time-span of our sample. In order to extract the short behaviour of temperature, we consider time-series decomposition. In the traditional time-series decomposition, the data can be a product of three components as shown by Zarnowitz and Ozyildirim (2006):

$$Temp_t = Trend_t + Season_t + Anom_t, \tag{4}$$

where t denotes the time, $Temp$ is the time series of the raw temperature data, $Trend$ is the trend-cycle component, $Season$ is the seasonality and $Anom$ is the anomaly component. The frequency of the seasonality can be easily defined as a 365 day cycle by including all weekend temperatures and excluding the 29th of February when the year is leap. We repeat this procedure for the 17 different market locations over the 28 years of our sample period.

The trend-cycle component contains the long-term temperature characteristics and it corresponds to A persistent temperature increase. We are now able to remove the seasonality from the raw temperature data. Finally, anomaly is defined as the unexpected temperature variations for any given day of our sample. It is important to underline that superscript t is retained only if t corresponds to market calendar day.

3.4 Empirical Model

Having defined $\Delta CoVaR_q^i$ (hereafter, $\Delta CoVaR_{i,t}$), we are now in a position to examine if higher temperature can incite extreme losses of firms. Hence, we add a nonlinear setting in the following regression:

$$\begin{aligned}\Delta CoVaR_{i,t} = {} & \gamma_0 + \gamma_1 \Delta CoVaR_{i,t-1} + \gamma_2 Temp_{k,t} + \gamma_3 Temp_{k,t}^2 + \gamma_4 Preci_{k,t} + \gamma_5 Mon_t \\ & + \gamma_6 Jan_t + \gamma_7 TED_t + \gamma_8 Credit_t + \gamma_9 Mar.R_t + \gamma_{10} Vol_t + \gamma_{11} Yield_t + \\ & \gamma_{12} Size_{i,t} + \sum_{\phi}^{28} \delta * Year_\phi + \sum_{k}^{17} \theta * Country_k + \sum_{p}^{10} \lambda * Industry_p + \varepsilon_{i,t}, \end{aligned} \quad (5)$$

where, i and t denotes the firm and day respectively with $i = 1, \ldots,$ 600 and $t = 01/01/1990, \ldots,$ $29/12/2017$ (7305 trading days), k corresponds to the geographical market location with $k = 1, \ldots,$ 17, p is the industry with $p = 1, \ldots,$ 10 (see, Table 2 Panel A and B) and ϕ is the year with $\phi = 1990, \ldots,$ 2017. We add an autoregressive term of systemic risk ($\Delta CoVaR_{i,t-1}$) to account for the short memory of systemic risk. Following Apergis and Gupta (2017); Donadelli et al (2017b), we add precipitation ($Preci$) as an alternative weather proxy, which is measured as millimetres of water fallen at a particular site for any given day. We also use Monday dummy (Mon) and January dummy (Jan) in order to capture some seasonal effects (Zhang and Jacobsen, 2013; Apergis and Gupta, 2017). We then follow the finance literature and add some important determinants of systemic risk (White et al, 2015; Adrian and Brunnermeier, 2016). TED, which is defined as the difference between the 3 month LIBOR rate and Treasury bill rate, can capture the short term liquidity risk. $Credit$ is the spread between Moody's Baa corporate bond and the 10-year treasury bond. TED and $Credit$ are known to capture variations of stock returns. Market return ($Mar.R$) as the daily return of STOXX 600 Index. Equity volatility (Vol) is defined as the 22-day rolling standard deviation of the daily stock market return. $Yield$ presents the 10-year government bond yields for the European Union, which is available in monthly frequency. Finally, we include $Size$ which is defined as the logarithm of the last daily market value of each firm. Our model also includes year, country and industry dummies in order to absorb the remaining heterogeneity of systemic risk.

Equation 5 is tested with pooled OLS and it can provide an answer to Hypothesis 1. The standard errors are robust correcting for heteroskedasticity. Our model is free of multicollinearity according to the variance inflation factor (VIF) test and we also perform augmented Dickey-Fuller unit root test for all variables in order to observe the auto-correlation of our data[4].

To answer Hypothesis 2, $Temp$ and $Temp^2$ are substituted with (i) the $Trend$ to identify the deterministic process of the temperature data and (ii) the anomaly ($Anom$) and the squared value of anomaly ($Anom^2$) as stochastic temperature components.

$$\Delta CoVaR_{i,t} = \xi_0 + \xi_1 \Delta CoVaR_{i,t-1} + \xi_2 Trend_{k,t} + \xi_3 Anom_{k,t} + \xi_4 Anom^2_{k,t} + \mathbf{Z}'B + \varepsilon_{i,t}, \tag{6}$$

where $\mathbf{Z}$ is a vector that contains all of the remaining explanatory variables appearing in Equation 5.

Finally, answering Hypothesis 3 demands to incorporate hot and cold temperature shocks. We calculate positive and negative temperature shocks, in line with Weagley (2018). A simplified way to calculate these shocks is through the energy needed to cool or heat a place, which can be approximated similar to a standard temperature derivative contract. Such a contract would consider that for temperature more than 18°C, any workplace needs to be cooled, while the place needs to be heated if the temperature is less than 18°C. Based on this logic, the Chicago Mercantile Exchange trades weather derivative contracts around this threshold (65 Fahrenheit degrees) (Perez-Gonzalez and Yun, 2013; Elias et al, 2014).

$$\begin{aligned} CDD_{k,t} &= Max\{Temp_{k,t} - 18, 0\}, \\ HDD_{k,t} &= Max\{18 - Temp_{k,t}, 0\}, \end{aligned} \tag{7}$$

where CDD is the cooling degree day and HDD is the heating degree day. In other words, if CDD=0 then it indicates that this is a cold day, while if CDD>0 this day is hot. Therefore, in Equation 5, $Temp$ and $Temp^2$ are substituted with either CDD or HDD:

$$\Delta CoVaR_{i,t} = \psi_0 + \psi_1 \Delta CoVaR_{i,t-1} + (\psi_2 CDD_{k,t} \text{ or } \psi_3 HDD_{k,t}) + \mathbf{Z}'B + \varepsilon_{i,t}, \tag{8}$$

3.5 Descriptive Statistics

[INSERT TABLE 3 HERE]

Table 3 reports the descriptive statistics for the variables of the study. 99% $\Delta CoVaR$ takes values from 0.43% to 7% with higher values indicating higher systemic risk. $Temp$ variable represents the raw temperature data. The 600 firms of our sample experience an average temperature of 10.6°C. A more articulated picture of the variables of interest is shown in Figures 1 and 2, while a more detailed picture of the temperature components is shown in Figure 3. Interestingly, for the 28 years of our examination the temperature has increased by 0.6 °C (see, $Trend$ in Figure 3). Also,

[4] Non-stationary data are transformed into stationary by taking their first difference (D.).

Anom variable reports minimum value of -22.25 and maximum of 13.2, displaying the most extreme unexpected cold and hot temperatures respectively. In terms of the distribution, apart from the temperature variables that are very close to satisfy the normality conditions, the rest of the variables are not normally distributed. Furthermore, comparing the mean, 1st percentile (Q1) and 99th percentile (Q99), we can conclude that our analysis does not seem to have extreme outliers except from the market capitalization (*Size*), which is also a sign of the heterogeneity of our sample.

[INSERT FIGURE 1, FIGURE 2 AND FIGURE 3 HERE]

At a first glance, in line with our expectations, temperature seems to have a quadratic effect on systemic risk (Figure 4). In order to provide a clearer picture of the relationship, we proceed to examine each one of our Hypotheses.

[INSERT FIGURE 4 HERE]

4 Empirical Results

4.1 Regression Analysis

Table 4 reports the OLS regression results based on Equations 5 and 6, with dependent variable 99% $\Delta CoVaR$. The total number of observations reaches approximately 2.75 million while the R-squared is more than 20%. The economic interpretation of $\Delta CoVaR$ is similar to the interpretation of the correlation coefficients (Adrian and Brunnermeier, 2016). Most of the the control variables appear significant, with the January dummy, market return and market capitalization being the ones decreasing systemic risk, while precipitation, Monday dummy, TED, credit risk, volatility and yield are associated with higher $\Delta CoVaR$. However, the lagged $\Delta CoVaR$, precipitation and volatility do not affect the systemic risk. Column 1 indicates that higher temperature (*Temp*) is associated with higher systemic risk. Columns 2 provides direct support of Hypothesis 1, that temperature has nonlinear effect on systemic risk. The coefficients of both linear and squared terms of temperature are statistically significant with the former being positive while the latter is negative, indicating that temperature-risk relationship follows an inverted U-shaped curve. This finding confirms our expectations and thus we can conclude that temperature has positive and asymmetric effects on the daily losses of firms (Hypothesis 1).

[INSERT TABLE 4 HERE]

In columns 3-6 (Table 4), we add the decomposed temperature time series to test Hypothesis 2 (temperature anomaly). We consider three different specifications of temperature anomaly, (1) the temperature anomaly (*Anom*) from the decomposed temperature series, (2) the first difference of *Anom* ($D.Anom$= $Anom_{k,t}$-$Anom_{k,t-1}$) and (3) a relative measure of temperature which is the difference between the *Anom* and the average European anomaly ($EU.Anom = Anom - \Sigma_{k=1}^{K=17} Anom/K$) . In column 3, temperature anomaly seems to increase $\Delta CoVaR$ at 5% level of significance. Moving to column 4, we witness that temperature anomaly and systemic risk follow an inverted U-shaped curve. When testing for the innovations in temperature anomaly ($D.Anom$ and $D.Anom^2$ in column 5) and the average EU anomaly temperature ($EU.Anom$ and $EU.Anom^2$ in column 6), both seem to monotonically increase systemic risk of firms. This finding indicates that the temperature-risk relationship is both positive and nonlinear and thus there is a strong evidence to support that temperature variations can influence the perception of financial markets about climate change. Thus far, Hypothesis 2, that temperature anomaly has an asymmetric effect on systemic risk, can be partially supported.

[INSERT TABLE 5 HERE]

Spillover effects from a firm to the financial markets might need some time to be observed, similarly, temperature effects are commonly categorised as long-term phenomena. To ascertain whether the frequency of the data can potentially moderate the results, we aggregate daily data to a monthly frequency by taking the median values of every month. Table 5 reports the monthly estimations. Results are more positive compared to the daily data estimations (Table 4). Particularly, higher temperatures significantly increase systemic risk (columns 1 and 2), the shape of this relationship appears steeper and hence Hypothesis 1 is partially supported. Regarding Hypothesis 2, both *Anom* and $EU.Anom$ strongly increase systemic risk, as both level and quadratic terms are positive, while temperature innovations ($D.Anom$) seem to exhibit inverted U-shaped curve with the $\Delta CoVaR$. Surprisingly, when examined daily data, the relationship appeared both positive and asymmetric, while in monthly examination, the positive sign dominates. A possible explanation is that the temperature changes have adverse long-term aspects while in the short-term this effect is weaker.

[INSERT TABLE 6 HERE]

Furthermore, Table 6 presents the results on Hypothesis 3, regarding hot and cold temperature shocks. Columns 1 and 2 report the hot shock (*CDD*) and the cold shock (*HDD*) estimations, respectively. Columns 2 and 4 also test for nonlinear *CDD* and *HDD*. Our results suggest that hot shocks have linear and positive association with systemic risk, while the effect of cold shocks are strongly negative. Particularly, higher *CDD* and lower *HDD* tend to be associated with higher systemic risk. Taken together, the results indicate that high temperatures are detrimental for the financial system, but low temperatures are not. At the same time, there is not enough evidence to support nonlinear temperature shock effects. Additionally, there is a mixed evidence regarding the view which is the most appropriate to justify the temperature shock - systemic risk relationship; either energy consumption or psychological effects. Our findings indicate that the former is related to hot shocks, while the latter to the cold shocks. Particularly, hot shocks increase systemic risk, as stated in Hypothesis 3a, while cold shocks decrease systemic risk, in line with Hypothesis 3b.

[INSERT TABLE 7 HERE]

In order to provide evidence about the aggregated temperature shock effects, we transform our daily data into a monthly frequency. Table 7 reports estimations based on monthly data. It seems that the level coefficients for *CDD* and *HDD* remain positive and negative, respectively, in line with the daily examination. Surprisingly, the quadratic coefficients follow a different pattern than the one in the daily analysis. Hot shocks and systemic risk exhibit an inverted U-shaped curve, while cold shocks and systemic risk exhibit a U-shaped curve. Daily analysis clearly shows that temperature shocks have linear effect while monthly analysis demonstrates that this effect is asymmetric. It can be suggested that hot (cold) shocks are not adequately approximated, for instance if one day of the month is very hot while the other is very cold then the median effect is negligible (Vecchio and Carbone, 2010). Therefore, the results might be downward biased when lower frequency temperature shocks are examined.

Even though, extreme temperatures might be associated with higher energy consumption and thus one would expect a higher systemic risk, this is only true for the hot shocks. These findings can have a threefold explanation, in line with Cao and Wei (2005); Bansal et al (2016); Apergis et al (2016).

First, consistently with the energy-consumption-based view, hot weather is expected to increase demand and prices of electricity (Hypothesis 3a). In turn, high energy prices may increase operational costs of firms, and eventually these firms may incur losses. The results imply that an imminent increase in electricity prices can be considered by stock market investors and traders as ”bad” news. Subsequently, investors and traders tend to sell off stocks, which leads to a propagation of losses within and across the industries, which in turn destabilises the financial system. Thus, the results are supportive of Hypothesis 3a, but not Hypothesis 3b, which postulates a negative relation between hot shocks and systemic risk. However, if hot weather causes apathy among stock market traders and investors, they are likely not to engage in riskier investments. Even if hot temperature causes aggression, Griffitt and Veitch (1971) assert that such aggression can be causal of an increased antisocial behaviour, which is not necessarily consistent with individual risk-taking. On the contrary, it can even lead to increased pessimism about future stock prices and returns, which can further translate into heightened risk aversion (Lucey and Dowling, 2005). Risk-averting investors tend sell off riskier stocks, which trigger a collapse (rise) in stock prices and returns (losses). The ensuing losses can propagate within and across the industries, and give rise to higher levels of systemic risk.

Second, if the energy-consumption based view holds, cold shocks are expected to increase systemic risk. However, the results do not accord with Hypothesis 3a. Instead, they agree with the second view, which builds on investor psychology to predict a negative relation between cold temperature shocks and systemic risk (Hypothesis 3b). According to Cao and Wei (2005), lower temperatures are associated with increased risk-taking as investors become more aggressive. As a result, investors tend to buy risky assets. These purchases, in turn, drive up (down) stock prices and returns (losses), and are associated with a bull market stance. Therefore, the net effect on investors risk preferences depends upon the balance between concerns about increasing energy demand and/or other psychological factors. Arguably, the latter dominates the former, which manifests in a negative effect of HDD. This leads to lower losses from securities trading, which are transmitted within the industry, in which the firm operates, and across other industries of the economy.

Yet a third explanation, which caters to both hot and cold shocks, underscores the geographical location. In this regard, Bansal et al (2016) advocate that countries with hotter climate also perform poorly in terms of financial development and are not well equipped to deal with adverse shocks. Therefore, hot shocks might negatively affect countries such as Italy, Spain and Portugal as their financial markets are quite vulnerable to exogenous shocks (Engle et al, 2014). By contrast, cold shocks, occurring mainly in the northern Europe coincide with markets that have higher financial stability.

4.2 Portfolio Analysis

Climate change is a risk factor that should have more detrimental effect on industries such as Agriculture, Health Care and Manufacturing and less detrimental effect on Services (Schlenker and Roberts, 2009; Deschenes, 2014; Balvers et al, 2017). In order to test the sensitivity of the previous results, we construct industry portfolios. Ten portfolios are constructed in respect to Table 2 Panel A. Then, we run regressions separately for every portfolio to observe the temperature effects within each industry. According to Dell et al (2014); Balvers et al (2017), we expected to identify some variations of the results depending on how vulnerable the industry is to weather patterns. Table 8 presents the results for Hypotheses 1, 2 and 3. First, in column 1, temperature ($Temp$) coefficient is positive for 9 portfolios and in 6 of them is statistically significant, the squared term ($Temp^2$) is negative in 8/10 portfolios while it is only significant in 3 portfolios. The results illustrate that temperature asymmetrically affect the losses of Financials, Health Care and Oil & Gas portfolios, while 4 portfolios (Technology, Consumer Services, Telecommunications and Utilities) are unaffected and 3 portfolios (Consumer Goods, Industrials, Basic Materials) are linearly affected. Second, in order to test Hypothesis 2, we now pay attention to the coefficient of temperature anomaly ($Anom$ in column 2). As it is shown, on average, Consumer Goods, Oil & Gas and Basic Materials are significantly affected by the temperature anomaly; findings are in line with Balvers et al (2017) who underline the direct detrimental temperature effects on the manufacturing sector. Even though, we can partially support Hypothesis 1 about the nonlinear effect of temperature, we are unable to support the same for the temperature anomaly when examined at a sector level. Overall, results indicate that higher temperatures increase systemic risk.

[INSERT TABLE 8 HERE]

The importance of analysing very cold and hot temperatures has been also underlined by Luterbacher et al (2004), whose results show that extreme temperatures can affect the economy. In columns 3 and 4 in Table 8, regression results are reported based on Equation 8 for different industries, using 99% $\Delta CoVaR$ as dependent variable. This table provides further evidence regarding Hypothesis 3. In line with previous estimations, hot shocks (CDD) have significantly positive effects on different industries (4 out of 10 industries) while cold shocks (HDD) decrease systemic risk (5 out of 10 industries). On average, there is a robust evidence that Consumer Goods, Industrials, Basic Materials and Utilities are industries that are most vulnerable to hot shocks; in line with Dell et al (2014); Balvers et al (2017). While, Consumer goods, Oil & Gas, Industrials, Consumer Services and Basic Materials can benefit from lower temperatures. Results also show that temperature effects do not negatively affect industries such as Technology, Consumer Services and Telecommunications. This finding implies that temperature shocks can influence the investment climate, particularly when climate sensitive firms are considered. Therefore, institutional investors and traders make investment decisions based on two principles; (i) how sensitive to climate change industries are and (ii) cold weather is “good” news, while hot weather is ‘bad” news for the financial markets.

4.3 Robustness Checks

The degree of interconnection in stock returns can be seen as a proxy for return-spillover effects between a firm and the financial system (Billio et al, 2012). To corroborate our results, we use two additional dependent variables as measures of interconnectedness. First, we focus on the endogenous risk between firm and industry losses by taking the first principal component ($PC1$) (see more in Appendix A). Second, we compute the dynamic conditional covariance ($h^{j,i}$) in an endogenous system, constituted by losses of firm i and industry j (see more in Appendix B). Because $h^{j,i}$ already accounts for the dynamics in the model, the autoregressive variable is omitted. In addition, both variables account for a degree of volatility in the market and therefore volatility (Vol) variable is excluded in order to avoid any simultaneity problem.

[INSERT TABLE 9 HERE]

The results are reported in Table 9, columns 1-4 and columns 5-8 show the estimations for $PC1$ and $h^{j,i}$, respectively. In line with the previous estimations, $PC1$ appears to confirm Hypothesis 1 and reject Hypotheses 2; temperature and $PC1$ exhibit an inverted U-shaped curve ($Temp$ and $Temp^2$ coefficients are positive and negative respectively, in column 1); the effect of temperature anomaly on $PC1$ does not follow a nonlinear pattern, but this linearly increases (column 2). Regarding Hypothesis 3, hot shocks (CDD) increase the interconnection of the financial markets (column 3), but cold temperatures (HDD) seem to decrease this interconnection (column 4). In terms of $h^{j,i}$, the results appear qualitatively similar with the previous specifications. The conditional covariances between a firm and its industry are equally affected by temperature effects, importantly, the only difference with $PC1$ estimations, is that both raw temperature and temperature anomaly monotonically increase the firm-industry interconnection (see $h^{j,i}$ in columns 5 and 6).

4.4 Additional Results

In order to provide more plausible results, we consider the $\Delta^{€}CoVaR$ methodology. In Equations 5, 6 and 8, we remove $Size$ variable since it is used to compute the $\Delta^{€}CoVaR$, which in turn is our new alternative dependent variable. Therefore, $\Delta^{€}CoVaR_{i,t} = Size_{i,t} \times \Delta CoVaR_{i,t}$. The € sign denotes the change of the size of the firm in Euro amounts conditional on any variable. $Size$ is the market capitalization of any firm i at any day t and $\Delta CoVaR$ is defined as previously. We also consider both the 99% and 95% $\Delta^{€} CoVaR$ in order to measure a reasonable confidence interval of the losses. To attain stationarity, in line with Adrian and Brunnermeier (2016), we normalise the $\Delta^{€} CoVaR$ by the cross-sectional average market capitalization and our new measure is now expressed in basis points. In contrast with the $\Delta CoVaR$, the $\Delta^{€} CoVaR$ takes into account the size of every institution which is closely related to the "Too big to fail" suggestion, indicating that poor performance of large firms would have amplified negative consequences to the financial system.

[INSERT TABLE 10 HERE]

The results are reported in Table 10, where columns 1-4 use 99% $\Delta^{€} CoVaR$ and columns 5-8 use 95% $\Delta^{€} CoVaR$ as dependent variable. As shown, $\Delta^{€} CoVaR$ is substantially different from $\Delta CoVaR$. In column 1, $Temp$ is positive and significant at 1% but $Temp^2$ is insignificant. The $Temp$ coefficient of 0.147 implies that an increase in temperature by 1°C would increase $\Delta^{€} CoVaR$ by 0.147 basis points of daily market equity losses at the 99% quantile. In column 2, $Anom$ is positive and its squared term is negative, representing an inverted U-shaped curve, confirming Hypothesis 2. Regarding CDD and HDD, results illustrate that hot shocks increase and cold shocks decrease systemic risk (Hypothesis 3). Particularly, the impact of temperature shocks is estimated to cause daily losses ranging between -0.303 and 0.239 basis points. This findings show that temperature is priced in financial markets. Despite the relatively "small" effect, we can claim that information about climate change is appreciated by investors. Specifically, it can be implied that low temperatures are perceived as "good" news, while high temperatures as "bad" news for the financial market. Overall, results can be explained by the climate change uncertainty, expectations about increasing energy demand and by psychological factors. Hence, investors are highly uncertain about the probability distribution of future payoffs, since their future expectations are based on current weather events.

5 Discussion and Conclusions

The purpose of this paper is to examine if systemic risk is conditioned on temperature changes. Systemic risk is measured by making use of the $\Delta CoVaR$ methodology (Adrian and Brunnermeier, 2016), while temperature data is retrieved from the closest weather stations to the firms' main market locations. Using a sample of 600 European firms listed in STOXX 600 Index for 7305 trading days in 17 different financial markets, we find that temperature has a versatile effect on the losses of firms. To be more explicit, in line with existing climate change literature, we decompose the temperature series to (i) trend, (ii) seasonality and (iii), anomaly components. In turn, we make the following assumptions: (1) temperature has asymmetric effects on systemic risk, (2) similarly, temperature anomaly has nonlinear effects on systemic risk and (3) hot and cold shocks are detrimental (beneficial) for the financial system. On general principles, all of our hypotheses can be partially supported to some extent, under all different specifications; however, we do record certain deviations among industries.

Our results provide support to the argument that temperature affects systemic risk. Specifically, raw temperature data and temperature anomaly seem to either increase or exert nonlinear effect on systemic risk. We argue that these asymmetries can be explained on the basis of decomposed temperature factors. For instance, on the one hand we show, in line with the psychological literature, that cold temperature shocks significantly decrease the $\Delta CoVaR$, while, on the other, we have adequate evidence to support, in line with the energy consumption view, that hot shocks positively influence systemic risk. More importantly, the portfolio analysis demonstrates that the manufacturing sector is strongly influenced by temperature changes (Balvers et al, 2017), while Technology, Telecommunications and Consumer Services firms seem to be unaffected by the climate. Finally, a numerical example based on the alternative measure of systemic risk, that is $\Delta^{€}CoVaR$, suggests that 1°C temperature change can increase systemic risk by up to 0.24 basis points.

Our study is important for many different stakeholders, as it provides informed insights in connection with the impact of climate change. While proposing hedging strategies and adaptation mechanisms are rather challenging, this paper underscores that the examination of the climate-finance relationship should receive priority and be further promoted. In addition, given the sample market of our study, our findings are quite useful to European firms that operate in relatively developed and well-informed markets and have the capacity to protect themselves against climate change (e.g., by purchasing weather derivatives). An interesting avenue for future research, would be to investigate how financial markets react to temperature changes in developing countries (Dell et al, 2012).

In turn, our findings can have important research implications. Scholars can gauge the effect of climate change on the financial system. The intuition for using $\Delta CoVaR$ is its unique capability to identify, among others, systemic climate sensitive firms that could potentially affect the entire financial system. Therefore, future studies should also investigate particular characteristics of these firms. Our findings also suggest that temperature variations are priced in financial markets. This finding could be important for the asset pricing literature (Apergis and Gupta, 2017). It can be suggested that market participants fear the regulatory pressure rising from changes in climate patterns (Balvers et al, 2017); this can be an alternative channel that helps rationalise our results.

On a final note, the main limitation of this study is the assumption that temperature recorded on a firm's primary market location affects the activity and the performance of investors and employees, respectively; thus contributing to higher levels of risk. However, it is also true that firms are able to mitigate this impact by diversifying activities to different countries or even continents that are subject to very different weather patterns. In this regard, gathering temperature data from multiple business locations might help resolve this issue. In line with arguments mentioned above, our results do not apply to all the financial markets. EU is an area adherent to environmental regulations (e.g. emissions trading scheme) and thus investors might be highly driven by climate change effects. As Bansal and Ochoa (2011) assert, heterogeneous temperature effects depend on geographic location. For this reason, similar studies should be conducted about different areas of the world, such as the United States, in order to determine (and compare) the accuracy of our findings.

Acknowledgements

We are grateful to two anonymous referees for their constructive comments and suggestions that helped us to improve the scope and clarity of this research. We also thank Professor Badi Baltagi, Tobias Adrian, Simone Manganelli and Cristina Belles-Obrero, as well as seminar participants at University of Portsmouth and University of Sussex for their valuable suggestions and rewarding discussions. We would like to gratefully acknowledge the support of the University of Portsmouth, where this research was developed.

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A Appendix. PCA

The appendix bellow proposes the construction of a measure of connectedness with principal component analysis (PCA), methodologically similar to the study of Billio et al (2012).

Instead of running PCA among all institutions simultaneously, we focus on the causal spillovers (endogenous risk) between a firm and its industry; we repeat this procedure for all the firms in the sample (600). Particularly, the two variables of interest are the firm (X^i) and industry (X^j) losses. In the PCA, the number of variables, that join the system, should be equal to the number of extracted components, also variables should be correlated; in fact, the correlation between (X^i) and (X^j) is, on average, 48%. As shown below, the principal components are new variables that combine the returns of firm i with the returns of industry j:

$$\begin{aligned} PC1_t &= a_{1,1}X_t^i + a_{1,2}X_t^j \\ PC2_t &= a_{2,1}X_t^i + a_{2,2}X_t^j, \end{aligned} \tag{9}$$

where the weights a are chosen so that: (i) the components are uncorrelated and (ii) the first component accounts for the maximum possible variance of the set (OECD, 2008). The first component (PC1) is used as a measure of connectedness and it is our alternative dependent variable. PC1 satisfies the Kaiser criterion that components with more than 1 eigenvalue, make sense to be included in the analysis. In this instance, PC1 explains 74% of the variability between the returns of firms and their industries, with eigenvalue 1.48, while PC2 explains the remaining 26 % with eigenvalue 0.52.

B Appendix. DCC

Adrian and Brunnermeier (2016) build on a bivariate diagnonal VECH-GARCH to estimate the conditional covariance between the firm and industry's losses, an alternative dynamic systemic risk measure. Similarly, we employ a parsimonious DCC-GARCH(1,1) model to identify the dynamic conditional correlation and the conditional covariance between the firm and industry's returns; as proposed by Engle (2002):

$$\mathbf{X_t} = \phi_\mathbf{0} + \varphi \mathbf{X}_{t-1} + \varepsilon_\mathbf{t}, \qquad \varepsilon_\mathbf{t} = \mathbf{H}_t^{1/2}\mathbf{v}_t, \tag{10}$$

$\mathbf{X}_t \equiv (X_t^j, X_t^i)'$ is a vector of daily return losses of j industry and i firm, ε_t is a vector of random disturbance terms, $\mathbf{v_t}$ is a vector of normal, independent and identically distributed innovations, and $\mathbf{H_t}$ is the conditional variance and covariance matrix, defined as:

$$\mathbf{H}_t = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2} = \begin{pmatrix} h_t^{j,j} & h_t^{j,i} \\ h_t^{j,i} & h_t^{i,i} \end{pmatrix}, \tag{11}$$

where $h_t^{j,i}$, the conditional covariance, is another measure of interconnection between firm and industry. It is conceptually similar to the alternative dynamic approaches of Billio et al (2012); Adrian and Brunnermeier (2016). $\mathbf{D_t}$ is a diagonal matrix of conditional variances $[\mathbf{D}_t = diag(\sigma^{j2}_{t}),\ \sigma^{i2}_{t})]$ from the univariate GARCH(1,1), and $\mathbf{R_t}$ is the time-varying quasicorrelation matrix, which is calculated as:

$$\mathbf{R}_t = diag(\mathbf{Q}_t)^{-1/2}\mathbf{Q}_t diag(\mathbf{Q}_{,t})^{-1/2}, \tag{12}$$

$$\mathbf{Q}_t = (1-a-b)\bar{\mathbf{Q}} + a(\mathbf{u}_{t-1}\mathbf{u}^{'}_{t-1}) + b(\mathbf{Q}_{t-1}) \tag{13}$$

and $\mathbf{R}_t$ has the following form:

$$\mathbf{R}_t = \begin{pmatrix} 1 & \rho_t^{j,i} \\ \rho_t^{j,i} & 1 \end{pmatrix}, \tag{14}$$

where $\mathbf{u_t} = \mathbf{D_t^{-1/2}}\varepsilon_\mathbf{t}$ and $\mathbf{u_t}$ is used to estimate the parameters of the conditional correlation, $\mathbf{Q}_t$ is the time-varying covariance matrix of $\mathbf{u_t}$, $\bar{\mathbf{Q}}$ ($\bar{\mathbf{Q}} = E[\mathbf{u_t}\mathbf{u_t}^{'}]$) is the unconditional variance and covariance matrix of $\mathbf{u_t}$ and parameters a and b should be non-negative and less than unity in aggregate. The coefficients of conditional mean and conditional variance models are estimated by maximizing the log-likelihood function for any t observation as shown below:

$$l_t = -\frac{1}{2}\sum_{t=1}^{T}[klog(2\pi) + 2log(|\mathbf{D}_t|) + \varepsilon_\mathbf{t}^{'}\mathbf{D}_t^{-2}\varepsilon_\mathbf{t}] + -\frac{1}{2}\sum_{t=1}^{T}[log|\mathbf{R}_t| + \mathbf{u}_t^{'}\mathbf{R}_t^{-1}\mathbf{u}_t - \mathbf{u}_t^{'}\mathbf{u}_t] \tag{15}$$

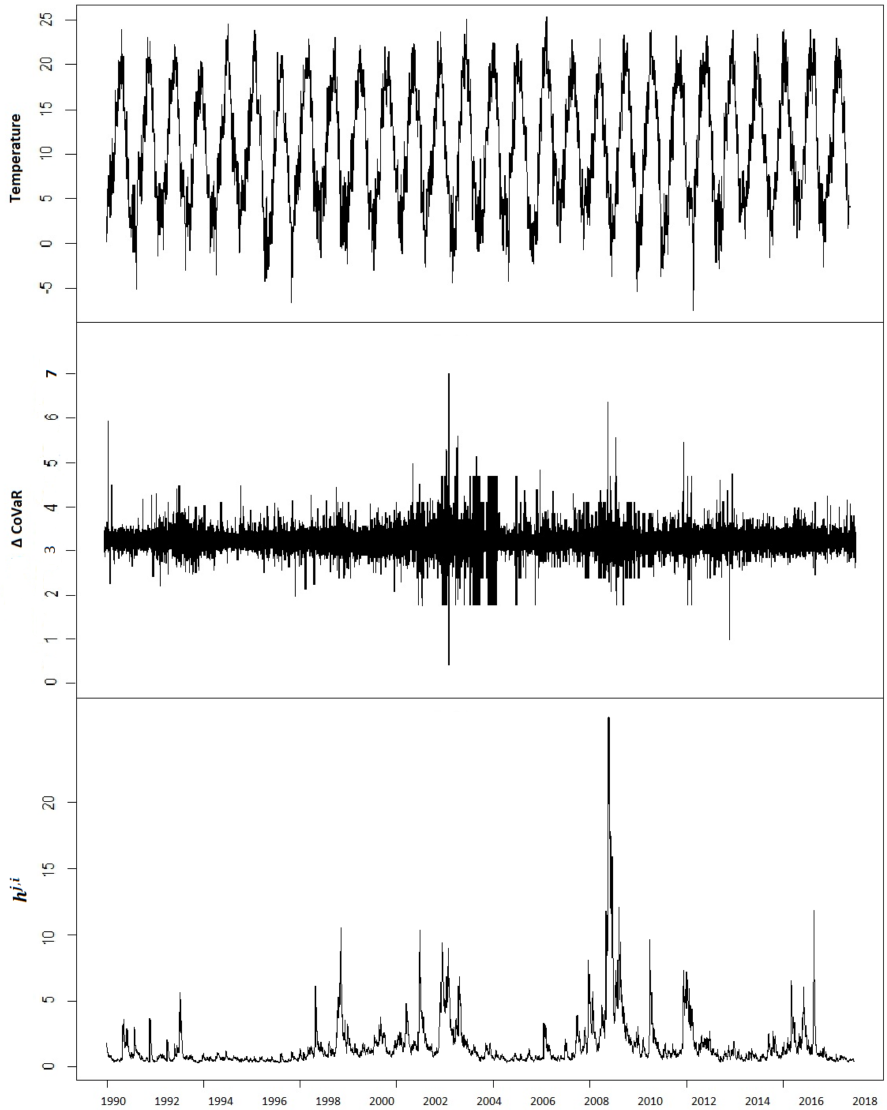

Fig. 1 Temperature, $\Delta CoVaR$ and interconnectedness. Temperature corresponds to the average raw temperature data as recorded by the 17 weather stations. 99% $\Delta CoVaR$ is the average $\Delta CoVaR$ of the 600 firms of our sample and $h^{j,i}$ is the average dynamic conditional covariance of our sample and is calculated as shown in Appendix B.

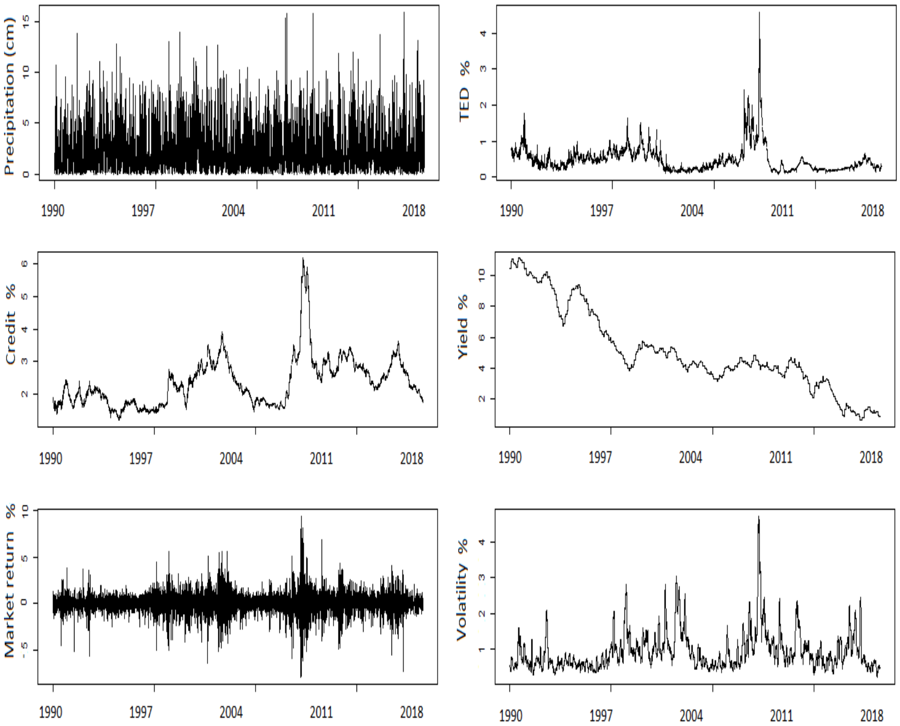

Fig. 2 Macro Variables.

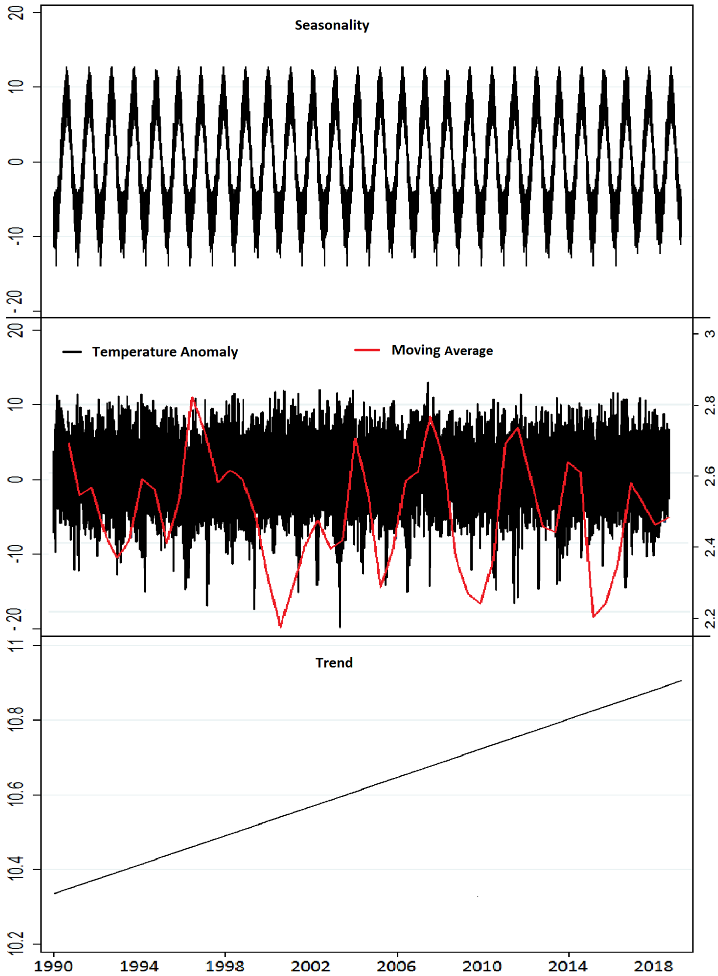

Fig. 3 Temperature series decomposition. The decomposition is based on Equation 4. The data used are the weighted temperature records as retrieved by the 17 weather stations. The moving average of temperature anomaly has been calculated as the 260-day rolling average of the absolute values of temperature anomaly; the right vertical axis scales the red line.

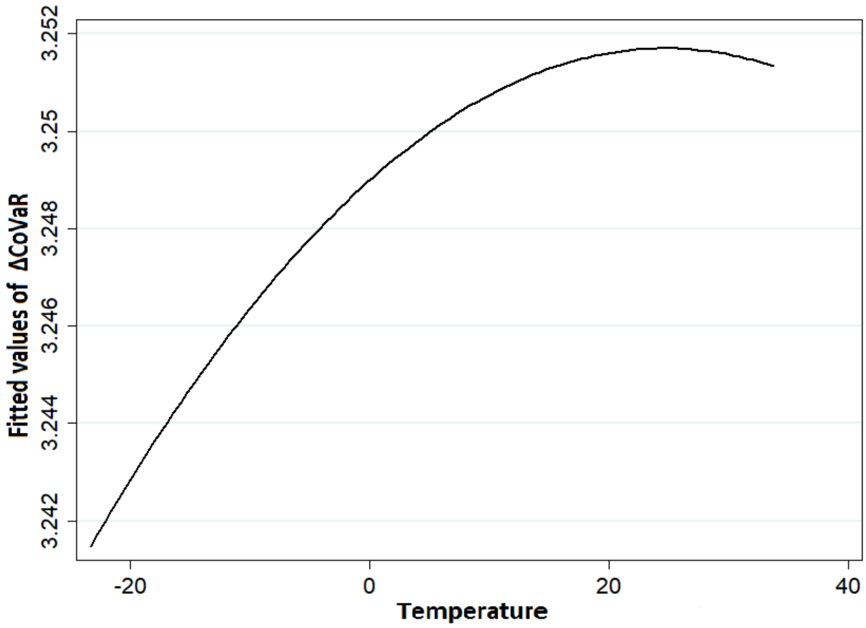

Fig. 4 99% *ΔCoVaR*-temperature. The line shows a quadratic regression between 99% *ΔCoVaR* and temperature with no other covariates. Our full sample is used for the calculations.

Table 1 Literature between stock returns and temperature

Authors	Method	Area	Period	Results
Kamstra et al. (2003)	OLS	US, Canada, Britain, Germany, Sweden, Australia, Japan New Zealand and South Africa	Daily data from January 4, 1928 to December 29, 2000	Higher temperature slightly increases stock returns for US, New Zealand and South Africa. Rest foreign stock market returns are unaffected by temperature
Cao and Wei (2005)	OLS	US, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan	Daily data from January 2, 1989 to December 31, 1999	Lower temperature leads to higher stock returns and higher temperature to both higher or lower stock returns
Bansal and Ochoa (2011)	OLS	38 countries and global temperature	Annual data from 1929 to 2009	Equity returns and temperature have high risk in countries closer to Equator while the risk is low in countries away from the Equator
Novy-Marx (2014)	OLS	New York	Monthly data from July 1973 to December 2012	Low and high temperatures have an abnormal predictive power of the financial markets.
Bansal et al. (2016)	OLS	US	Annual data from 1934 to 2014	Temperature has a negative effect on equity prices
Balvers et al. (2017)	OLS	US	Monthly data from April 1953 to May 2015	Temperature causes higher risk returns and higher cost of capital
Apergis and Gupta (2017)	GARCH	New York temperature and South African stock returns	Daily data from January 2, 1973 to December 31, 2015	New York temperature has a statistically significant negative effect on the stock returns in South Africa
Donadelli et al. (2017b)	VAR	US	Annual data from 1950 to 2015	High temperature increases the equity volatility and has negative correlation with market returns
Donadelli et al. (2019)	OLS	UK	Annual data from 1900 to 2015	Temperature volatility carries a positive risk premium in the equity market

Table 2 Industry, Country and Weather Stations

Panel A: Industry composition		
Industry	**Number of Firms**	**Percentage**
1. Consumer Goods	74	12.33
2. Financials	138	23
3. Health Care	49	8.17
4. Oil & Gas	20	3.33
5. Technology	28	4.67
6. Industrials	123	20.5
7. Consumer Services	71	11.83
8. Basic Material	47	7.83
9. Telecommunications	21	3.5
10. Utilities	29	4.83
Panel B: Country composition		
Country	**Number of Firms**	**Percentage**
1. Switzerland	51	8.5
2. United Kingdom	160	26.67
3. France	90	15
4. Netherlands	29	4.83
5. Belgium	15	2.5
6. Germany	75	12.5
7. Spain	29	4.83
8. Denmark	22	3.67
9. Norway	13	2.17
10. Italy	30	5
11. Sweden	44	7.33
12. Austria	7	1.17
13. Finland	17	2.83
14. Ireland	9	1.5
15. Czech Republic	2	0.33
16. Portugal	4	0.67
17. Luxembourg	3	0.5
Total	**600**	
Panel C: Weather Stations		
Country	**Market**	**Ecad ID and Station Name**
1. Switzerland	Zurich	244 ZUERICH/FLUNTERN
2. United Kingdom	London	1860 HEATHROW
3. France	Paris	38 PARIS - MONTSOURIS
4. Netherlands	Amsterdam	161 DE KOOY
5. Belgium	Brussels	944 BIERSET
6. Germany	Frankfurt	2761 M-FLUGHAFEN
7. Spain	Madrid	230 MADRID - RETIRO
8. Denmark	Copenhagen	116 KOEBENHAVN
9. Norway	Oslo	193 OSLO BLINDERN
10. Italy	Milan	242 LUGANO
11. Sweden	Stockholm	10 STOCKHOLM
12. Austria	Vienna	16 WIEN
13. Finland	Helsinki	28 HELSINKI KAISANIEMI
14. Ireland	Dublin	121 DUBLIN PHOENIX PARK
15. Czech Republic	Prague	27 PRAHA-KLEMENTINUM
16. Portugal	Lisbon	229 BADAJOZ
17. Luxembourg	Luxembourg	203 LUXEMBOURG AIRPORT

Note: Firms are allocated to industries according to the Industry Classification Benchmark (ICB). Ecad ID is the weather station identifier as listed in the www.ecad.eu database.

Table 3 Descriptive statistics and Auto-correlations

	mean	std	min	max	skew	kurt	Q1	Q99	unit root (p-value)
X^i	-0.00028	0.0233	-1.3437	1.7918	0.776	98.039	-0.061	0.060	0
X^j	0.00018	0.0127	-0.1486	0.1359	0.142	11.497	-0.0342	0.0373	0
99% $\Delta CoVaR$	3.251	0.046	0.434	7.007	0.749	97.458	3.123	3.377	0
99% $\Delta^{€} CoVaR$	39	72.2	0.001	1180	4.392	29.826	0.2337	364	1*
PC1	≈ 0	1.2162	-43.053	57.391	0.2957	20.5319	-3.2413	3.5099	0
$h^{j,i}$	0.0135	0.0213	0.000	0.9213	7.0469	88.826	0.0003	0.1033	0
Temp	10.622	6.984	-23.300	33.800	-0.093	2.810	-5.500	26.000	0
Trend	10.619	1.916	5.805	17.789	0.309	4.600	6.213	15.777	1*
Season	-0.006	5.845	-13.902	12.823	0.114	1.816	-9.918	10.982	0
Anom	-0.077	3.204	-22.254	13.209	-0.186	3.671	-8.179	7.352	0
CDD	0.4762	1.5367	0.000	15.8	4.063	21.3937	0.000	8.000	0
HDD	7.8538	6.2396	0.000	41.3	0.5313	2.6966	0.000	25.500	0
Preci	2.211	4.960	0.000	176.800	6.483	90.669	0.000	21.700	0
Mon	0.200	0.400	0.000	1.000	1.500	3.250	0.000	1.000	0
Jan	0.085	0.279	0.000	1.000	2.979	9.875	0.000	1.000	0
TED	0.0049	0.0037	0.0009	0.0458	3.301	22.354	0.00140	0.002	0
Credit	0.0237	0.00759	0.012	0.0616	1.623	7.673	0.0138	0.0557	1*
Mar.R	0.0002	0.011	-0.079	0.094	-0.245	9.050	-0.033	0.030	0
Vol	0.009	0.005	0.002	0.047	2.187	10.403	0.003	0.028	0
Yield	0.0508	0.0267	0.00613	0.1114	0.624	2.636	0.0077	0.11	1*
Size	12	22	0.001587	360	4.49295	31.1174	0.063009	110	0.99*

Notes: $\Delta^{€} CoVaR$ and Size are compressed to millions of Euro. Augmented Dickey-Fuller test is reported as unit root test. (*)Asterisk denotes that the panel is not stationary but the first difference is. X^i is the return losses of firm i and X^j is the industry losses. $\Delta CoVaR$ is calculated as shown in Equation 3. $\Delta^{€} CoVaR = Size$ x$\Delta CoVaR$. $PC1$ is calculated as shown in Appendix A and $h^{j,i}$ is calculated as shown in Appendix B. *Temp* is the raw temperature data. *Trend*, *Anom* and *Season* are the decomposed temperature series as shown in Equation 4. *CDD* is the cooling degree day. *HDD* is the heating degree day. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 4 Daily Data. Temperature on $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta CoVaR_{t-1} \times 10^4$	5.573	5.398	6.691	6.530	6.742	6.715
	(22.705)	(22.705)	(22.719)	(22.719)	(22.724)	(22.719)
Temp $\times 10^4$	0.423***	0.811***				
	(0.039)	(0.097)				
Temp^2 $\times 10^4$		-0.018***				
		(0.004)				
Anom $\times 10^4$			0.165**	0.131*		
			(0.079)	(0.079)		
Anom^2 $\times 10^4$				-0.050***		
				(0.015)		
D.Anom $\times 10^4$					0.100	
					(0.108)	
D.Anom^2 $\times 10^4$					0.071***	
					(0.017)	
EU.Anom $\times 10^4$						0.356***
						(0.118)
EU.Anom^2 $\times 10^4$						0.048
						(0.030)
D.Trend			-1.976*	-1.971*	-1.964*	
			(1.036)	(1.036)	(1.036)	
D.EU.Trend						-40.201**
						(18.690)
Preci $\times 10^4$	0.026	0.008	0.044	0.041	0.045	0.046
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Mon $\times 10^4$	8.498***	8.513***	10.702***	10.713***	10.653***	55.899**
	(0.654)	(0.654)	(1.314)	(1.314)	(1.314)	(22.101)
Jan $\times 10^4$	-3.437***	-2.866***	-6.677***	-6.418***	-6.701***	-6.774***
	(1.040)	(1.049)	(0.993)	(0.995)	(0.993)	(0.993)
TED $\times 10^4$	14.069***	13.902***	13.367***	13.297***	13.237***	13.288***
	(1.835)	(1.836)	(1.836)	(1.837)	(1.835)	(1.835)
D.Credit $\times 10^4$	93.159***	92.655***	96.399***	96.171***	97.049***	97.155***
	(11.636)	(11.636)	(11.638)	(11.638)	(11.638)	(11.639)
Mar.R	-1.822***	-1.822***	-1.823***	-1.823***	-1.823***	-1.823***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Vol	0.254	0.252	0.230	0.233	0.229	0.229
	(0.484)	(0.484)	(0.484)	(0.484)	(0.484)	(0.484)
D.Yield $\times 10^4$	8.772***	8.877***	7.765***	7.979***	7.666***	7.622***
	(1.473)	(1.474)	(1.469)	(1.471)	(1.468)	(1.468)
D.Size	-0.134***	-0.134***	-0.134***	-0.134***	-0.134***	-0.134***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Cons	3.248***	3.248***	3.248***	3.248***	3.248***	3.251***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Obs	2,754,821	2,754,821	2,750,000	2,750,000	2,749,118	2,750,000
R^2	20.82	20.82	20.83	20.83	20.83	20.83

Notes: The results are based on Equations 5 and 6. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *Temp* is the raw temperature data.*Anom* is the value of the temperature anomaly and *Trend* is the trend from the decomposed temperature series (Eq. 4). *EU.Anom* is difference between the *Anom* of the firm's market location and the average EU *Anom* as recorded by the 17 weather stations. *EU.Trend* is the average EU trend from the 17 market locations. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 5 Monthly Data. Temperature on $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta CoVaR_{t-1} \times 10^4$	69.839	60.482	163.430***	162.769***	168.675***	262.651***
	(45.063)	(45.056)	(44.311)	(44.296)	(44.869)	(45.326)
Temp $\times 10^4$	0.194***	0.015				
	(0.007)	(0.019)				
Temp^2 $\times 10^4$		0.008***				
		(0.001)				
Anom $\times 10^4$			1.702***	2.353***		
			(0.088)	(0.106)		
Anom^2 $\times 10^4$				0.587***		
				(0.042)		
D.Anom $\times 10^4$					0.588***	
					(0.110)	
D.Anom^2 $\times 10^4$					-1.998***	
					(0.199)	
EU.Anom $\times 10^4$						1.678***
						(0.107)
EU.Anom^2 $\times 10^4$						0.606***
						(0.0446)
D.Trend			1.175***	1.017***	1.188***	
			(0.078)	(0.079)	(0.0782)	
D.EU.Trend						0.005***
						(0.0002)
Preci $\times 10^4$	-0.026	-0.025	0.025	0.001	0.032	0.0022
	(0.022)	(0.022)	(0.022)	(0.022)	(0.0221)	(0.0222)
Jan $\times 10^4$	-2.801***	-3.086***	-4.603***	-4.233***	-5.173***	-2.861***
	(0.117)	(0.119)	(0.100)	(0.107)	(0.099)	(0.127)
TED $\times 10^4$	18.638***	21.196***	5.475***	8.199***	4.982***	16.912***
	(1.048)	(1.061)	(0.858)	(0.917)	(0.859)	(0.989)
D.Credit $\times 10^4$	0.139	0.138	-0.039	-0.013	-0.074	-0.247***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.0934)	(0.0934)
Mar.R	-0.966***	-0.966***	-1.058***	-1.035***	-1.082***	-1.030***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Vol $\times 10^4$	-66.855***	-64.236***	-52.824***	-52.162***	-54.412***	-31.811***
	(10.434)	(10.437)	(10.453)	(10.448)	(10.453)	(10.432)
D.Yield $\times 10^4$	0.398**	0.436**	0.513***	0.478***	0.555***	0.104
	(0.172)	(0.172)	(0.173)	(0.173)	(0.173)	(0.172)
D.Size $\times 10^4$	-0.183***	-0.184***	-0.181***	-0.181***	-0.181***	-0.178***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Cons	3.228***	3.231***	3.195***	3.196***	3.194***	3.166***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Obs	144,647	144,647	144,395	144,395	144,395	144,395
R^2	14.50	14.55	14.41	14.48	14.27	14.46

Notes: The results are based on Equations 5 and 6. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *Temp* is the raw temperature data.*Anom* is the value of the temperature anomaly and *Trend* is the trend from the decomposed temperature series (Eq. 4). *EU.Anom* is difference between the *Anom* of the firm's market location and the average EU *Anom* as recorded by the 17 weather stations. *EU.Trend* is the average EU trend from the 17 market locations. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 6 Daily Data. Temperature Shocks on $\Delta CoVaR$

	(1)	(2)	(3)	(4)
$\Delta CoVaR_{t-1} \times 10^4$	6.442	6.441	5.419	5.377
	(22.702)	(22.702)	(22.705)	(22.705)
CDD $\times 10^4$	0.277*	0.445		
	(0.162)	(0.402)		
CDD^2 $\times 10^4$		-0.023		
		(0.050)		
HDD $\times 10^4$			-0.510***	-0.280**
			(0.044)	(0.113)
HDD^2 $\times 10^4$				-0.012**
				(0.006)
Preci $\times 10^4$	0.043	0.043	0.018	0.011
	(0.051)	(0.051)	(0.051)	(0.051)
Mon $\times 10^4$	8.404***	8.404***	8.519***	8.518***
	(0.654)	(0.654)	(0.654)	(0.654)
Jan $\times 10^4$	-6.633***	-6.615***	-3.011***	-2.824***
	(0.995)	(0.996)	(1.045)	(1.049)
TED $\times 10^4$	13.311***	13.326***	14.078***	13.971***
	(1.835)	(1.835)	(1.835)	(1.836)
D.Credit $\times 10^4$	96.617***	96.587***	92.612***	92.548***
	(11.631)	(11.632)	(11.637)	(11.637)
Mar.R	-1.823***	-1.823***	-1.822***	-1.822***
	(0.003)	(0.003)	(0.003)	(0.003)
Vol	0.230	0.230	0.258	0.255
	(0.484)	(0.484)	(0.484)	(0.484)
D.Yield $\times 10^4$	7.763***	7.772***	8.847***	8.892***
	(1.468)	(1.468)	(1.473)	(1.473)
D.Size	-0.134***	-0.134***	-0.134***	-0.134***
	(0.009)	(0.009)	(0.009)	(0.009)
Cons	3.248***	3.248***	3.249***	3.249***
	(0.007)	(0.007)	(0.007)	(0.007)
Year	YES	YES	YES	YES
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Obs	2,754,821	2,754,821	2,754,821	2,754,821
R^2	20.82	20.82	20.82	20.82

Notes: The results are based on Equation 8. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *CDD* is the cooling degree day and *HDD* is the heating degree day. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 7 Monthly Data. Temperature Shocks on $\Delta CoVaR$

	(1)	(2)	(3)	(4)
$\Delta CoVaR_{t-1} \times 10^4$	132.992***	102.344**	77.896*	52.054
	(44.206)	(44.430)	(45.085)	(45.210)
CDD $\times 10^4$	0.742***	1.836***		
	(0.039)	(0.082)		
CDD^2 $\times 10^4$		-0.197***		
		(0.013)		
HDD $\times 10^4$			-0.202***	-0.493***
			(0.008)	(0.024)
HDD^2 $\times 10^4$				0.017***
				(0.001)
Preci $\times 10^4$	0.031	-0.030	-0.023	-0.034
	(0.022)	(0.022)	(0.022)	(0.022)
Jan $\times 10^4$	-4.335***	-4.032***	-2.832***	-3.079***
	(0.096)	(0.097)	(0.118)	(0.119)
TED $\times 10^4$	13.287***	17.324***	17.055***	21.865***
	(0.950)	(0.990)	(1.029)	(1.052)
D.Credit $\times 10^4$	-0.016	0.034	0.118	0.131
	(0.093)	(0.093)	(0.093)	(0.093)
Mar.R	-1.061***	-1.030***	-0.970***	-0.953***
	(0.010)	(0.010)	(0.010)	(0.010)
Vol $\times 10^4$	-55.033***	-54.570***	-66.309***	-62.733***
	(10.450)	(10.441)	(10.439)	(10.441)
D.Yield $\times 10^4$	0.333*	0.367**	0.368**	0.426**
	(0.173)	(0.173)	(0.172)	(0.172)
D.Size $\times 10^4$	-0.181***	-0.182***	-0.183***	-0.184***
	(0.021)	(0.021)	(0.021)	(0.021)
Cons	3.208***	3.218***	3.226***	3.234***
	(0.0144)	(0.0144)	(0.0147)	(0.0147)
Year	YES	YES	YES	YES
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Obs	144,647	144,647	144,647	144,647
R^2	14.33	14.49	14.44	14.54

Notes: The results are based on Equation 8. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *CDD* is the cooling degree day and *HDD* is the heating degree day. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 8 Industry Portfolios

	(1)		(2)		(3)	(4)		
Portfolio:	Temp $\times 10^4$	Temp$^2 \times 10^4$	Anom$\times 10^4$	Anom$^2 \times 10^4$	CDD$\times 10^4$	HDD$\times 10^4$	Obs $\approx$	$R^2 \approx$
Consumer	0.994***	-0.0125	0.389*	-0.0616	1.010*	-0.855***	355,000	16.4
Goods	(0.346)	(0.0138)	(0.228)	(0.0424)	(0.568)	(0.145)		
Financials	0.462**	-0.0209**	0.124	-0.0336	-0.314	-0.0391	647,000	26.5
	(0.193)	(0.0082)	(0.160)	(0.0306)	(0.408)	(0.0898)		
Health	0.793**	-0.0333**	0.245	0.0156	-0.447	-0.159	217,000	13.9
Care	(0.325)	(0.0146)	(0.264)	(0.0505)	(0.713)	(0.141)		
Oil &	1.901***	-0.0526**	1.950***	-0.0494	1.313	-0.670**	89,000	21.9
Gas	(0.575)	(0.0218)	(0.508)	(0.0939)	(1.010)	(0.297)		
Technology	0.681	-0.0237	-0.228	-0.0667	-2.521**	-0.325	131,000	20.8
	(0.508)	(0.0224)	(0.431)	(0.0075)	(1.170)	(0.251)		
Industrials	1.022***	-0.0117	-0.111	-0.101***	1.003**	-0.964***	609,000	20.3
	(0.186)	(0.0082)	(0.164)	(0.0302)	(0.450)	(0.093)		
Consumer	0.194	0.0069	-0.204	-0.0078	-0.036	-0.450***	289,000	21.2
Services	(0.315)	(0.0134)	(0.245)	(0.0488)	(0.713)	(0.142)		
Basic	1.160***	-0.0166	0.536*	0.0358	2.951***	-0.953***	205,500	23.8
Material	(0.317)	(0.0145)	(0.279)	(0.0489)	(0.821)	(0.162)		
Telecom-	-0.0283	-0.0152	-0.885*	-0.0196	-1.982*	0.274	85,500	22.5
munications	(0.456)	(0.0193)	(0.471)	(0.0819)	(1.1070)	(0.254)		
Utilities	0.152	0.0083	0.221	-0.0988	1.081*	-0.291	125,000	21.2
	(0.393)	(0.0137)	(0.312)	(0.0657)	(0.563)	(0.182)		

Notes: The results are based on Equations 5, 6 and 8. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. The rest of control variables are not reported here for brevity but are available upon request. *Temp* is the raw temperature data. *Anom* is the value of the temperature anomaly (Eq. 4). *CDD* is the cooling degree day and *HDD* is the heating degree day.

Table 9 Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PC1				$h^{j,i}$			
$PC1_{t-1}$	0.034***	0.034***	0.034***	0.034***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Temp $\times 10^4$	11.970***				0.0068			
	(1.762)				(0.022)			
Temp^2 $\times 10^4$	-0.243***				0.0097***			
	(0.074)				(0.001)			
Anom $\times 10^4$		2.493*				0.0769***		
		(1.373)				(0.020)		
Anom^2 $\times 10^4$		-0.066				0.0178***		
		(0.261)				(0.004)		
D.Trend		-59.507***				-0.3955		
		(17.471)				(0.251)		
CDD $\times 10^4$			11.290***				0.9115***	
			(3.534)				(0.041)	
HDD $\times 10^4$				-8.821***				-0.2032***
				(0.782)				(0.011)
Preci $\times 10^4$	0.418	0.782	0.845	0.437	0.0480***	0.0496***	0.0554***	0.0371***
	(0.994)	(0.907)	(0.909)	(0.908)	(0.014)	(0.014)	(0.014)	(0.014)
Mon $\times 10^4$	177.840***	150.711***	78.055***	81.909***	0.7011***	1.1148***	0.6583***	0.7077***
	(12.210)	(22.398)	(11.101)	(11.085)	(0.166)	(0.328)	(0.166)	(0.166)
Jan $\times 10^4$	-33.644*	-55.146***	-52.089***	-5.624	-5.3783***	-6.8406***	-6.2942***	-5.2399***
	(19.900)	(17.809)	(17.802)	(18.980)	(0.293)	(0.276)	(0.276)	(0.295)
TED $\times 10^4$	230.024***	-605.505***	-604.578***	-605.102***	69.8178***	69.4113***	69.5949***	69.6492***
	(34.211)	(30.931)	(30.931)	(31.080)	(2.589)	(2.590)	(2.593)	(2.590)
D.Credit $\times 10^4$	-1004.417***	-1188.799***	-1215.499***	-1277.928 ***	-12.9475***	-11.5103***	-11.7501***	-13.0831***
	(227.974)	(193.344)	(194.512)	(194.210)	(3.565)	(3.564)	(3.566)	(3.564)
Mar.R	-81.392***	-77.036***	-77.008***	-77.011***	0.0190***	0.0187***	0.0188***	0.0190***
	(0.070)	(0.063)	(0.064)	(0.063)	(0.001)	(0.001)	(0.001)	(0.001)
D.Yield $\times 10^4$	144.451***	354.094***	354.388***	370.934***	-48.6605***	-49.2141***	-48.8877***	-48.6811***
	(26.642)	(24.675)	(24.742)	(24.815)	(1.366)	(1.366)	(1.361)	(1.366)
D.Size	-2.164***	-1.986***	-1.988***	-1.968***	-0.0021***	-0.0021***	-0.0021***	-0.0021***
	(0.148)	(0.140)	(0.140)	(0.139)	(0.001)	(0.001)	(0.001)	(0.001)
Cons	-0.007	0.089***	0.084***	0.091***	-0.0070***	-0.0068***	-0.0069***	-0.0067***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2,673,025	2,696,545	2,673,025	2,673,025	2,630,428	2,626,327	2,630,428	2,630,428
R^2	57.83	57.92	57.83	57.83	44.96	44.95	44.96	44.96

Notes: The results are based on Equations 5, 6 and 8 by substituting $\Delta CoVaR$ with either PC1 or $h^{j,i}$. PC1 is the first principal component of industry and firm losses (see Appendix A) and $h^{j,i}$ is the dynamic conditional covariance between a firm and its industry (see Appendix B). Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *Temp* is the raw temperature data. *Anom* is the value of the temperature anomaly (Eq. 4) and *Trend* is the trend from the decomposed temperature series (Eq. 4). *CDD* is the cooling degree day and *HDD* is the heating degree day. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalization for every firm.

Table 10 OLS regressions on $\Delta^{€}CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	99% $\Delta^{€}CoVaR$				95% $\Delta^{€}CoVaR$			
$\Delta^{€}CoVaR_{t-1}$	-0.366***	-0.366***	-0.366***	-0.366***	-0.458***	-0.458***	-0.458***	-0.458***
	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.00590)	(0.00590)	(0.00590)	(0.00590)
Temp	0.147***				0.237***			
	(0.0490)				(0.0605)			
Temp^2	0.00284				0.00170			
	(0.00192)				(0.00235)			
Anom		0.190***				0.239***		
		(0.0301)				(0.0362)		
Anom^2		-0.0105**				-0.0148***		
		(0.00485)				(0.00573)		
D.Trend		9346.5***				9426.4**		
		(3492.8)				(3756.4)		
CDD			0.157**				0.160*	
			(0.0736)				(0.0906)	
HDD				-0.221***				-0.303***
				(0.0339)				(0.0410)
Preci	-0.0172	-0.0201	-0.0229	-0.0214	-0.0215	-0.0246	-0.0285*	-0.0258
	(0.0162)	(0.0161)	(0.0162)	(0.0161)	(0.0173)	(0.0172)	(0.0173)	(0.0172)
Mon	-0.493**	-1.557***	-0.507**	-0.485**	-0.652***	-1.722***	-0.671***	-0.642***
	(0.211)	(0.525)	(0.211)	(0.211)	(0.231)	(0.529)	(0.231)	(0.231)
Jan	0.783***	0.769**	0.783***	0.779**	0.238	0.219	0.239	0.234
	(0.304)	(0.304)	(0.304)	(0.304)	(0.356)	(0.356)	(0.356)	(0.356)
TED	-2.840***	-2.856***	-2.859***	-2.838***	-4.173***	-4.198***	-4.200***	-4.171***
	(0.455)	(0.455)	(0.455)	(0.455)	(0.570)	(0.570)	(0.570)	(0.570)
D.Credit	-57.66***	-57.75***	-57.68***	-57.68***	-73.46***	-73.57***	-73.48***	-73.47***
	(3.293)	(3.295)	(3.294)	(3.294)	(4.128)	(4.130)	(4.129)	(4.129)
Mar.R	-2045.8***	-2045.5***	-2045.5***	-2045.5***	-2835.2***	-2834.8***	-2834.7***	-2834.9***
	(10.48)	(10.49)	(10.48)	(10.48)	(12.81)	(12.81)	(12.81)	(12.81)
Vol	55.60**	55.04**	55.27**	55.66**	100.9***	100.1***	100.4***	100.9***
	(23.50)	(23.51)	(23.50)	(23.50)	(29.40)	(29.40)	(29.40)	(29.40)
D.Yield	-1.812***	-1.799***	-1.812***	-1.807***	-3.078***	-3.064***	-3.080***	-3.073***
	(0.454)	(0.454)	(0.454)	(0.454)	(0.493)	(0.493)	(0.493)	(0.493)
Cons	1.288**	0.539	1.317***	1.298***	1.189*	0.439	1.227**	1.199*
	(0.500)	(0.557)	(0.500)	(0.500)	(0.618)	(0.683)	(0.618)	(0.618)
Year	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2,753,672	2,748,810	2,753,672	2,753,672	2,753,672	2,748,810	2,753,672	2,753,672
R^2	15,72	15,71	15,72	15,72	24.34	24.33	24.34	24.34

Notes: The alternative dependent variable is either 99% $\Delta^{€}CoVaR$ or 95% $\Delta^{€}CoVaR$, where $\Delta^{€}CoVaR = Size$ x $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *Temp* is the raw temperature data. *Anom* is the value of the temperature anomaly (Eq. 4) and *Trend* is the trend from the decomposed temperature series (Eq. 4). *CDD* is the cooling degree day and *HDD* is the heating degree day. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond.