Climate Risks and Economic Activity in France: Evidence from Media Coverage

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Abstract

This study investigates the impact of climate risks on economic activity in France. Using natural language processing methods on three major French newspapers (*Le Monde*, *Les Echos*, and *Le Figaro*) in 2000-2023, we construct a measure of climate risks that we disentangle into physical- and transition-risk components. Our findings highlight several transmission channels through which climate risks affect the economy: the business cycle channel, the precautionary savings channel, the inflation channel, and the banking/credit channel. Moreover, while we document the existence of heterogeneous responses to our measures of physical and transition risks, we find that the tone of media covering climate risks matters beyond the frequency of published articles. Our findings show that the media plays a crucial role in influencing public beliefs about climate change related issues.

Keywords: climate risks; natural language processing; local projections

JEL classification: E32; Q54; C32

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1 Introduction

The scarce but burgeoning literature on climate risks is consensual about their economic impact. For instance, risks related to climate change significantly affect macroeconomic and financial outcomes, such as output (Colacito et al. 2019), credit supply (Schüwer et al. 2018), prices (Ciccarelli and Marotta 2024), stock returns (Engle et al. 2020; Bolton and Kacperczyk 2021), and the behavior and perception of producers and consumers (Stroebel and Wurgler 2021; Choi et al. 2020). In the present study, we collect a novel dataset on climate risks in France using media coverage as a proxy to assess their effects on economic activity. We focus on France, given its central role in climate diplomacy as reflected in the hosting of the 2015 Paris Agreement,[1] and to provide evidence on the climate-risk impact at a country-specific level.

Two channels are emphasized in the literature to assert the effects of climate risks on the real economy and the financial system: the physical-risk and the transition-risk channels (Carney 2015). On the one hand, physical risks result from natural disasters stemming from or aggravated by climate change, such as droughts, storms, or floods. These disasters impact labor productivity and physical capital and result in supply-chain disruptions, which in turn, weigh on economic activity. The effects of disasters can also diffuse into the financial system through a reduction in the value of the assets pledged for loans, which increases the share of nonperforming loans in bank portfolios (Faiella and Malvolti 2020). On the other hand, transition risks result from the adjustment process to a decarbonized economy aimed at preventing or mitigating global warming. This implies a set of regulatory, technological, market, and reputational risks that may transform productive assets into stranded ones and may entail systemic risks for financial stability. Following this line of thought, McGlade and Ekins (2015) estimated that approximately one-third of the current oil reserves, half of the natural gas reserves and almost 90% of the coal reserves would become stranded assets if the 2015 Paris Agreement's targets were achieved.[2]

However, the question of how climate risks are measured is crucial to effectively assess

[1]The 2015 Paris Agreement granted France prominence on the international climate change agenda, and triggered a substantial surge in climate risk perception for all agents including households, firms, investors, and policymakers (Bolton and Kacperczyk 2021; Bua et al. 2022).

[2]See Sen and Von Schickfus (2020) for a more informative discussion on climate policies and stranded asset risks.

their impact. The latter can be gauged in many ways. First, carbon emissions or footprints, which are obtained from the Scope emissions, allow to evaluate the carbon emission profile of firms to assess their exposure with respect to climate risks (Capasso et al. 2020). Second, extreme weather events, such as heatwaves, heavy rainfalls or droughts, have been utilized as indicators of climate risks in the literature (Sheng et al. 2022). Third, measures of losses, such as income losses or fatalities owed to extreme weather-events, are used as proxies of climate risks (Eckstein et al. 2021). These indicators have a direct implication on the climate-risk dimension that is measured. For example, carbon emissions and footprints mainly reflect transition risks and ignore physical risks, while it is the opposite for extreme weather events and fatalities.

To overcome the limits of these measures, previous studies rely on text analysis based on the frequency and tone of keywords related to climate change in the media. The idea underlying this approach is that the general public has limited knowledge on climate change, hence, the latter tends to rely on newspapers as a source of information to update its beliefs (Shapiro et al. 2022). As an illustration, Bleda and Shackley (2008) disentangle climate change impacts into direct (impacts from weather events) and indirect signals (the interest of the media). While the direct signals are more difficult to recognise since the weather events that cause them are often perceived by agents as isolated rather than as indications of a climate change phenomenon, the indirect signals are easier to recognise since they are based on a more accessible and digestible form of information, i.e., news. They conclude that cognitive factors such as beliefs and media perceptions are a determinants factor in the willingness or reluctance of agents to adapt to anthropogenic climate change. More recently, Drews and Van den Bergh (2016) and Agneman et al. (2024) show that contextual factors such, as media coverage, significantly shape climate change knowledge, climate risk perception and the implementation of effective climate policies.

In this respect, we hypothesize that media coverage of climate risks can affect economic and financial variables through several channels. First, economic activity, proxied by GDP growth and the level of employment, can be negatively affected by the losses to capital stock and infrastructure due to the extreme climate events (Colacito et al. 2019), the *business cycle channel*. Hence, we include the Economic Sentiment Indicator (ESI), given that it reflects the business cycle, and the unemployment rate to account for labor market adjustments to climate change.[3] Second, to withstand climate risks, risk-adverse households might put more weight on future consumption and, thus, increase their current savings, the *precautionary savings channel*. To account for this, we include the Consumer Confidence Index (CCI), which provides an estimation of households' expected financial situation and their sentiment about the general economic situation, unemployment, and savings capacity.[4] Third, since climate risks have a significant and persistent effect on price levels (Schnabel 2022), the *inflation channel*, we include the Harmonized Index of Consumer Prices (HICP) as an aggregated proxy of price variations and sector indices for energy, food, and core prices. This distinction is crucial to identify the supply- or demand-side dimensions of climate shocks that may affect the energy and agricultural sectors (Ciccarelli and Marotta 2024). Finally, it is recognized that climate risks contribute to financial turbulence that may take the form of falling asset prices, losses for banks, and credit supply disruptions (Batten et al. 2020), the *banking/credit channel*. Banks are particularly exposed to climate change since they face default probabilities of firms exposed to physical or transition risks, which could lead to disruptions in the credit market. Following this line of thought, we include banks' equity returns and credit supply to households and (non)-financial companies to account for the potential tightening of financial conditions resulting from climate shocks.

While most studies dealing with climate risks either refer to the United States or to the euro area as a whole, little is known about the impact of climate risks on specific countries such as France, although the latter has played a central role in climate diplomacy since the 2015 Paris Agreement. Against this background, this study aims to fill this gap by constructing a media proxy for climate risks that reflects both physical and transition risks for France. Specifically, we seek to address three questions: (i) do risks related to climate change reported by the French media affect the economic sentiment of firms and consumers, the level of prices, banks, and credit conditions? (ii) Do topics related to physical and transition risks have a different impact on these variables? (iii) Does the tone of climate news reports matter for households, firms and financial market participants beyond the frequency of published articles?

[3] The ESI is produced by the European Commission to track GDP growth at the member-state level. The sectors covered by the ESI are industry (40%), services (30%), consumers (20%), retail (5%), and construction (5%).

[4] A rising CCI indicates an optimistic attitude of households over future economic developments, possibly resulting in a tendency to save less and consume more.

By doing so, we make several contributions to the literature. First, we use a novel dataset by collecting 16,109 newspaper articles about climate risks from three major French newspapers (*Les Echos*, *Le Figaro*, and *Le Monde*). Second, we use the correlated topic model (CTM) of Blei and Lafferty (2007) to construct two types of climate risk indices corresponding to physical and transition risks. Third, we quantify the impact of these indices on the sentiment of consumers and firms, the level of prices, and other key economic and financial variables using local projections à la Jordà (2005). Finally, we use a lexicon-based approach to capture the tone of climate-related news articles to check if the latter matters beyond the frequency of published articles.

Our results allow us to gain further insights into the various transmission channels of climate risks to the real economy and the financial sphere, and their mixed supply- or demand-side nature. In particular, we find that rising aggregate climate risks are transmitted to the French economy through multiple channels, namely, the *business cycle channel*, the *precautionary savings channel*, the *inflation channel*, and the *banking/credit transmission* channel. On the one hand, a higher climate risk index is associated with lower economic sentiment, lower employment, and lower consumer confidence, while the relationship is positive with the level of prices. On the other hand, we find that bank equity returns and credit supply decrease following an increase in climate risks, as reported by the media. In addition, our topic modeling analysis reveals a marked difference between sectors since (i) all macroeconomic and financial variables are more responsive to physical-risk disturbances except for energy prices and bank equity returns; (ii) physical (transition) risks exercise downward (upward) pressures on energy prices, which could be associated with negative demand (supply) shocks on the energy market; and (iii) the banking sector is subject to substantial transition risks stemming from its key role in funding the transition to a decarbonized economy. Finally, the lexicon-based media tone provides evidence that a positive media tone related to climate risks is associated with better economic conditions.

This study stands at the crossroads of several strands of literature. The first one uses natural language tools to construct climate-risk metrics. Bua et al. (2022) use a text-mining method on scientific texts to distinguish between transition and physical climate risks based on related vocabularies.[5] The authors find evidence of the presence of physical

[5]Keywords such as "ecosystems", "sea level", and "precipitation" are related to the physical risk topic, while keywords such as "hydrofluorocarbon", "bioenergy" and "greenhouse gas" are related to transition

and transition climate-risk premia in euro area equity markets, notably since 2015. Kölbel et al. (2022) train an AI-based algorithm to distinguish between transition and physical risks in annual company filings. They find that disclosing transition risks increases credit default swap spreads after the Paris Climate Agreement of 2015, while disclosing physical risks decreases the spreads. The second literature our study builds on uses media coverage to construct climate risk proxies to investigate their impact on financial variables. Engle et al. (2020) use the *Wall Street Journal* to develop a text-based measure of climate risk, the Climate-Change News Index. Faccini et al. (2023) use the latent Dirichlet allocation (LDA) method on Reuters climate-change news in 2000-2018 to split climate risks into four categories (natural disasters, global warming, U.S. climate policy, and international climate-change summits). The authors show that only the climate policy factor is priced in the U.S. stock market. Finally, Ardia et al. (2022) construct a Media Climate Change Concerns Index from major U.S. newspapers and newswires. They find that when the index increases, the stock prices of "green" firms increase while those of "brown" firms decrease.

While these two strands of the literature focus on the financial effects of text/media-based climate risks, our study also relates to the literature on the macroeconomic impact of climate related variables. Donadelli et al. (2017) show that a positive shock to U.S. temperature has an adverse effect on the growth rate of main macroeconomic aggregates including total factor productivity, output, and labor productivity. Ciccarelli and Marotta (2024) use a panel dataset for twenty-four OECD countries over the 1990–2019 time span and find that physical risks act as negative demand shocks while transition risks act as downward supply movements.[6][7] However, while none of these papers investigate the macroeconomic effects of media-based climate risk measures, we combine all these approaches by measuring different types of news-based climate risk proxies at the French country level to assess their effects on a large set of macroeconomic and financial variables. By doing so, we include variables which have rarely been considered in the literature, i.e., sentiments of firms and consumers, which allows us to better understand

risks.

[6] Ciccarelli and Marotta (2024) use the the OECD Environmental Policy Stringency index (EPSI) and the Green innovation index (the number of patents related to developments in environmental related technologies) to proxy for transition risks. The main proxies for physical risks refers to the Environmental degradation index (the cost of premature deaths from exposure to environment-related risks) and total greenhouse gases (GHG) emissions per unit of GDP (emission intensity).

[7] See also Burke et al. (2015) and Newell et al. (2021) on this "macroeconomic climate risk" literature.

the transmissions channels driving the relationship between climate risks and economic and financial variables.

The study is organized as follows. Section 2 measures the Climate Risk Index (CRI) and its impact on economic activity. Section 3 disentangles the aggregate risk index into its physical and transition components. Section 4 measures the tone of the (dis)aggregated risk measures. Section 5 provides further robustness tests and extensions. Finally, Section 6 concludes the analysis.

2 The Climate Risk Index

In this section, we first detail the data we collect and the methodology we use to construct the Climate Risk Index (CRI) for France. subsequently, we investigate how this index affects the economic sentiment of firms and consumers, the level of prices, and bank and credit conditions using Jordà (2005)'s local projections.

2.1 Climate Risks News Articles

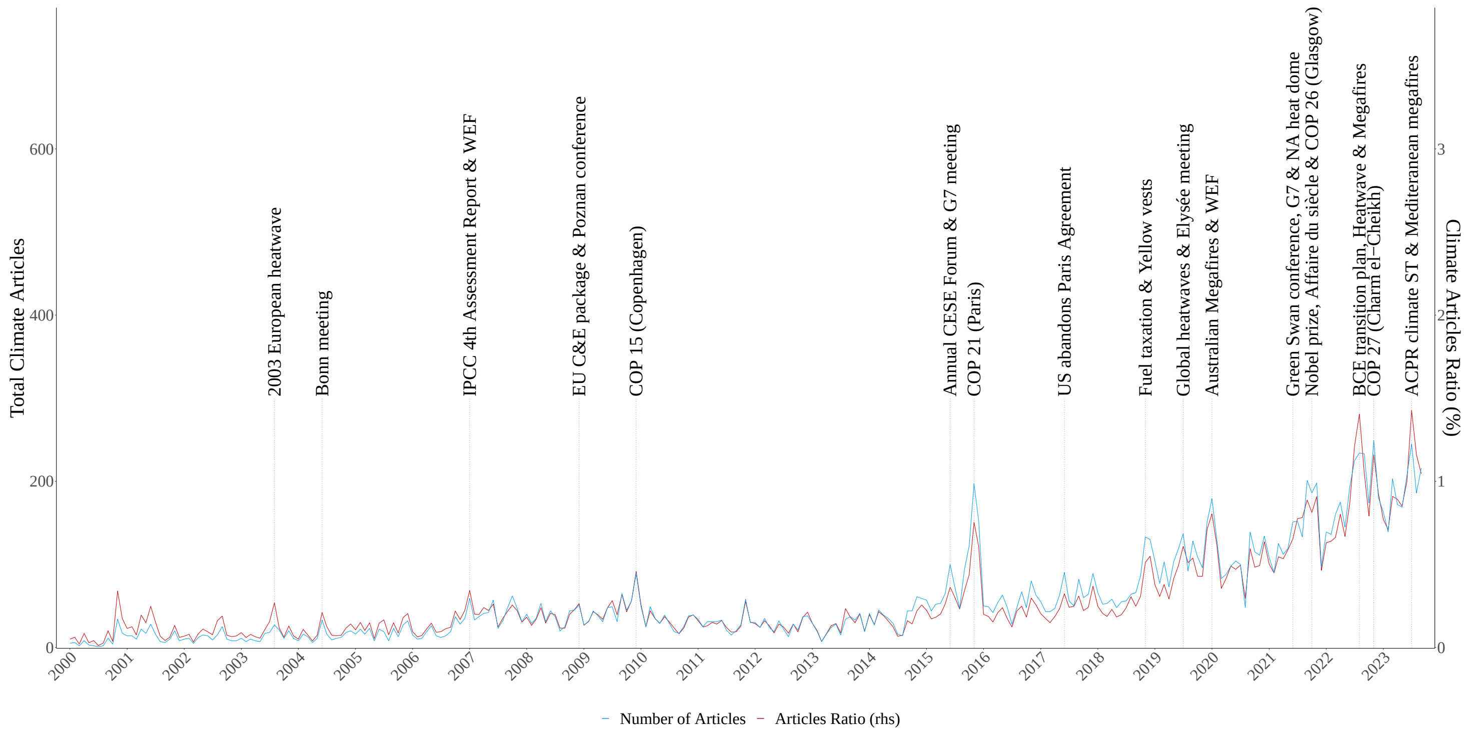
We construct monthly indices of climate change related risks based on newspaper coverage frequency. We restrict our sample analysis to three leading French newspapers: *Les Echos* (business), *Le Figaro* (center-right), and *Le Monde* (center-left) in January 2000 - September 2023. Our corpus includes news articles - belonging to digital and paper formats of each newspaper- that contain the terms {"risqu*"} and {"change*" or "réchauffe*" or "dérègle*" or "dérégle*"} with {"climat*" or "planète" or "planétaire" or "global"} included within the seven preceding or following words.[8] We consider all the inflected forms of a word (indicated by *); hence, they can be analysed as a single item, i.e., a lemma. For example, the lemma "réchauffe" indicates that we are also considering words such as "réchauffer" or "réchauffement".

The final corpus comprises 16,109 news articles after duplicate inspection and interpretability checking.[9] Figure 1 plots the total counts of climate-risk articles (blue curve).

[8]The English translation of our set of words is as follows: {"risk*"} and {"change*" or "warming*" or "disrupt*"}, preceded/followed in an interval of seven words by {"climat*" or "planet" or "planetary" or "global"}

[9]We refer the reader to Section 4 for a detailed discussion on the interpretability checking strategy.

Figure 1 Total count of climate risks articles in blue (left axis) and their share over total published articles in red (right axis).



A first noteworthy observation shows that concerns about climate risks have particularly increased since the 2015 Paris Agreement. This is consistent with Frondel et al. (2017) who show that extreme natural hazards imply strong media coverage. However, one might argue that this rising trend is simply due to the increase in total articles published by newspapers. To consider this additional dimension, we compute the ratio of climate-risk articles to the total number of published articles, which confirms the increasing tendency since 2015 (red curve). Figure 1 also highlights the aggregated nature of our index as it shows spikes around events related to physical and transition risks. The first category includes repeated heatwaves and megafires, while the second one could be associated with events such as the June 2017 Donald Trump's decision to withdraw from the Paris Agreement and the social unrests related to the introduction of fuel taxation in December 2018 (the yellow vests movement).

2.2 Effects of Climate Risks

2.2.1 Empirical Framework and identification strategy

We estimate the response of a set of financial and macroeconomic variables to an increase in the coverage of climate risks in the media at different horizons h using Jordà (2005)'s local projections in the period 2000M01-2023M09:

$$\Delta \ln(y_{t+h}) = \alpha^h + \beta^h CRI_t + \sum_{j=1}^{J} \psi_j^h L^{j-1} \ln(y_{t-1}^{\Delta}) + \sum_{j=1}^{J} \varphi_j^h L^{j-1} X_t + \varepsilon_t^h, \tag{1}$$

where $\Delta \ln(y_{t+h}) = \ln(y_{t+h}) - \ln(y_{t-1})$ is the monthly cumulative change in the response variable to a distant time horizon $h \in [\![1, h_{max}]\!]$ (h_{max}=24), and CRI_t the climate risk index. $\sum_{j=1}^{J} \psi_j^h L^{j-1} \ln(y_{t-1}^{\Delta})$ is a polynomial in the lag operator of the first differences of the dependent variable and $\sum_{j=1}^{J+1} \varphi_j^h L^{j-1} X_t$ a polynomial in the lag operator of a vector including a set of control variables. Standard errors are estimated with the Newey-West procedure to control for heteroskedasticity and serial correlation in the error term ε_t (Newey and West 1994). We set J to six to include the lags of the dependent and control variables.

To test the validity of the transmission channels, we consider two sets of dependent variables: the macroeconomic set and the financial set. The macroeconomic set contains the following variables: (i) the Economic Sentiment Indicator (ESI), (ii) the unemployment rate, (iii) the Consumer Confidence Index (CCI), (iv) the Harmonized Index of Consumer Prices (HICP), (v) the energy prices, (vi) the food prices, and (vii) the core prices. For the financial set, we include (i) banks' equity returns and (ii) aggregate credit supply to households, financial and non-financial companies. Finally, the set of control variables, X, comprises the French Economic Policy Uncertainty index (EPU) of Baker et al. (2016) to control for business cycle conditions,[10] and the French 10-year sovereign bond yield (i^{10y}) to control for financial conditions. The descriptions of the variables and the summary statistics are provided in Table A.1 and Table A.2 in Appendix A, respectively.

The identification scheme used in Equation (1) assumes the exogeneity of the CRI. This assumption is consistent with similar empirical frameworks using other climate-related proxies like Donadelli et al. (2017), Gallic and Vermandel (2020), Alessandri and Mumtaz (2021), Ciccarelli and Marotta (2024), amongst many others. Two arguments could be cited in favor of the climate exogeneity hypothesis. First, climate change is exogenous to macroeconomic shocks in the short term given that the alteration of global

[10] It is now well established in the literature that policy uncertainty shocks foreshadow deteriorations in macroeconomic outcomes. EPU innovations cause a peak drop in industrial production and a rise in the unemployment rate. This EPU countercyclical nature has been demonstrated for numerous countries. See Baker et al. (2016) and Istiak and Serletis (2018) for the French economy, for instance.

climate due to human economic activities is a long-term phenomenon that is very unlikely to have a measurable impact over a short horizon (Gallic and Vermandel 2020).[11] Second, the media-based proxy of climate risk is exogenous since it is driven by concerns related to salient climate events of physical and/or transition nature that heighten climate change discussion and news coverage (See Engle et al. 2020; Faccini et al. 2023). This is all the more true when looking at Figure 1, where the CRI spikes during climate events, such as major natural disasters and international summits, that pose substantial risks to the economy (like e.g., the introduction of a fuel tax).

2.2.2 Results

Figure 2 presents the cumulative impulse response functions (IRFs) of our variables of interest to an increase of one-standard deviation in the CRI. Since the aggregate CRI includes both the physical-risk and the transition-risk dimensions, our results are interpreted in light of these two elements. First, we find that following a one-standard deviation increase in the CRI, the ESI diminishes significantly by 4.5% one and a half year later. This drop in the ESI might be explained by the following factors: (i) the reduced productive capacity of the economy due to losses suffered by infrastructure following extreme climate events such as megafires, floods, and storms; (ii) a decline in the rate of productive capital accumulation; or (iii) the increase in costs of emission reduction, which reduces capital availability. Moreover, we observe that higher climate risks significantly increase unemployment by 0.4 percentage points (p.p.) two years later. This finding could be explained by the transition process to a low-carbon economy that might lead to job destruction in traditional emission-intensive sectors. Moreover, an additional channel through which higher climate risks affect the level of employment is the labor productivity channel, which states that labor supply declines because of the diminishing physical and cognitive performance of human capital (Park 2016).

Alongside these supply-side effects, climate risks also have significant demand-side impacts since the CCI falls by 3 p.p. one and a half year after a one-standard deviation increase in the CRI. This result highlights the *precautionary savings channel* through

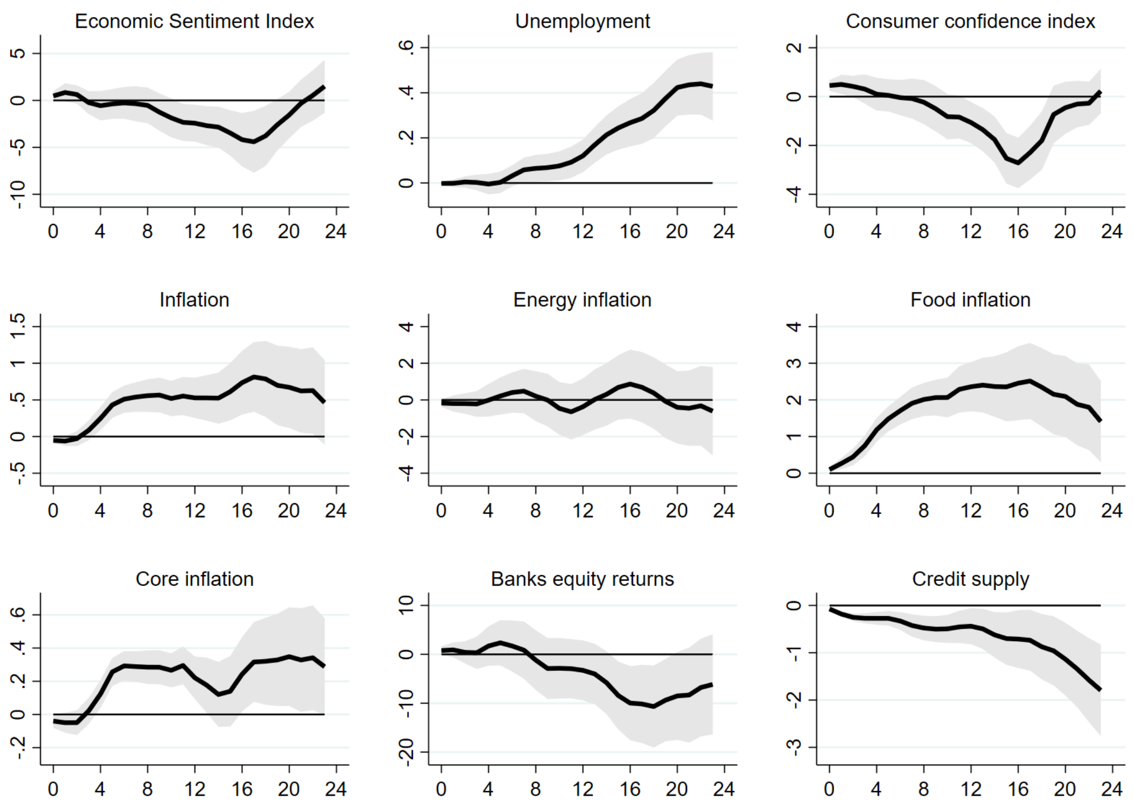
[11] This is contrary to the Integrated Assessment Models pioneered by Nordhaus (1991), that consider long time horizons and capture the nexus between temperatures and production through a quadratic damage function in order to provide an estimation of future costs of carbon emissions on output. However, this conception faces many criticism. See Millner (2013), Stern (2016) and Pindyck (2017) for a rich discussion on this point.

which heightened climate risks might raise the risk aversion of economic agents, leading to reduced (increased) consumption (saving) expectations of households. Hence, to the extent that the latter become more aware of higher climate vulnerability, their future consumption path change and precautionary savings are naturally playing the role of climate risk buffers.

Turning to the effects of climate risks on the level of prices, we observe a strong increase in the HICP following a one-standard deviation increase in the CRI. This result is consistent with the work of Schnabel (2022) and Breckenfelder et al. (2023),[12] and suggests that climate risks act like adverse productivity shocks that raise the marginal cost of production and cause inflationary pressures in the economy. However, representing climate risk effects on prices as a purely supply-side phenomenon is too simplistic, as extreme weather events might also lead to demand-side shocks. Therefore, Figure 2 depicts the disaggregated responses of the headline (energy and food) and core components of the HICP. At first glance, the impact of the aggregate CRI on energy inflation is ambiguous; however, the analysis provided thereafter will clear up this ambiguity as we demonstrate that the response of energy inflation depends on the overall balance between supply shocks (from transition risks) and demand shocks (from physical risks) related to climate risks. Food inflation, however, significantly increases, contributing positively to pressures on aggregated inflation. This might be explained by the harmful effects of (i) high temperatures on crop yield levels, (ii) insufficient rainfall on agricultural income, or (iii) climate-driven food and water insecurities and supply instability. Finally, core inflation jumped by approximately 0.3% in the sixth month following the increase in the CRI.

[12]For example, Schnabel (2022) distinguishes between (i) aggregate inflationary effects of climate change, that may be referred to as "climateflation", (ii) direct inflationary effects of a higher price of carbon energy, constituting "fossilflation", and (iii) the process of adjustment by firms away from carbon energy into non-carbon energy, or green investment, that may trigger "greenflation".

Figure 2 Cumulative IRFs for shocks in CRI



Notes: Solid black lines show impulse responses of a one standard deviation in the CRI. Gray-shaded areas indicate 68% confidence bands.

Regarding the effects on the financial variables, we observe that rising climate risks negatively impact bank equity returns. This adverse effect on bank stock performance might materialize *via* two channels. First, physical risks could result in large losses for firms and households and deteriorate their financial situation. On the one hand, if these losses are insured, insurance companies might experience a large distress that could negatively impact the balance sheets of banks (French et al. 2015). On the other hand, if these losses are not well insured, physical risks could reduce collateral value, which would increase the probability of loan default and adversely affect the balance sheet of banks (Batten et al. 2020, Faiella and Malvolti 2020). This is in line with Zhang et al. (2024), who show a positive association between climate risks and non-performing loans.

However, the effects of physical risks are mitigated in developed economies with sound financial regulation and supervision, where banks tend to have diversified asset portfolios. Therefore, the transition-risk dimension of the CRI is more likely to affect the soundness of the French banking sector. Specifically, transition risks such as a policy tightening of carbon emissions might imply losses in the value of carbon-intensive assets.[13] The transition to a low-carbon economy could therefore lead to acute drops in the stock prices of these assets and increase the volatility of fossil fuels and firms, which would ultimately threaten the resilience of the banking system. This finding is similar to Reinders et al. (2023) who find a significant decline in the market value of banks' assets following unexpected carbon tax shocks. Ultimately, distressed banks could reduce their credit supply to the sectors affected and non-affected by the transition or the physical risks to meet their regulatory capital ratio requirements. This is in line with our results, which reveal a significant diminution in aggregate credit supply including three different sectors (households, financial and nonfinancial companies) following a one-standard deviation increase in the CRI.

Overall, we provide evidence that rising climate risks are transmitted to the economy through several channels: the *business cycle channel*, the *precautionary savings channel*, the *inflation channel*, and the *banking/credit channel*. However, it is still unclear which of the two dimensions of the CRI is generating the largest effects on our variables of interest. Consequently, we delve into a second exercise where we disentangle between the physical and transition dimensions of the aggregated CRI using natural language processing tools.

3 Disentangling the Climate Risk Index

This section outlines our topic modeling strategy, which aims to differentiate the physical- and transition-risk dimensions of the CRI, and to assess their impact on our variables of interest.

3.1 The Correlated Topic Model

The aggregated nature of the CRI comprises a highly heterogeneous set of latent topics related to climate-change risks, such as threats to biodiversity, natural disasters, or climate policy shifts. This topic heterogeneity may often be reflected within a single article (see Figure B.1 in Appendix B for an illustration of this heterogeneity). To shed light on this variety of topics, we use the correlated topic model (CTM) of Blei and Lafferty

[13] In France, the oil and gas sectors accounted for 11.8% of the CAC40 index in July 2022 if we consider the cumulative capitalization ratio of Air Liquide, Engie, and TotalEnergies.

(2007), which extends the latent Dirichlet allocation (LDA) model of Blei, Ng, et al. (2003) by allowing correlation between the identified topics.

In the field of natural language processing, a corpus is a collection of D documents, with each document modeled as a string composed of w words. Equivalently, each document is represented by a set of K latent topics, with each topic being assigned a probability distribution over words. Each word in a document is assigned a probability that it belongs to a specific topic with regard to the distribution of topics across the document. The prevalence of a given word w in a given topic k is denoted $\phi_{w,k}$, with $\sum_{w=1}^{W} \phi_{w,k} = 1$. In addition, the CTM expresses the distribution of topics being present in a given document, or equivalently, the share of each document associated with a given topic. These shares are denoted by topic prevalence $\theta_{k,d}$, with $\sum_{k=1}^{K} \theta_{k,d} = 1$. The sum of these topic shares across a given time period reflects the intensity of the news coverage of a given topic over that period. Moreover, topic mixtures in the CTM are sampled following a logistic normal distribution that allows to capture the correlation of topics among documents through a covariance structure, contrary to the LDA, which relies on the less flexible Dirichlet distribution (Blei, Ng, et al. 2003; Roberts et al. 2016). A positive correlation between topics suggests that both topics are likely to be discussed within a document.

However, one of the most challenging steps in the characterization of the CTM is the determination of the optimal number of topics K to describe our corpus. We estimate a CTM for each $K \in [10, 15, 20, ..., 60]$. Subsequently, we use two criteria to assess the model outcomes: semantic coherence and exclusivity. Semantic coherence is maximized when the most probable words in a given topic frequently co-occur together in documents and correlates well with human judgment of topic quality (Mimno et al. 2011). Nevertheless, this metric is sensitive to the number of topics and the commonality of words composing the topics in a given language; hence, a corpus with a few topics composed of substantially common words would almost certainly reach high levels of coherence (Roberts et al. 2016). We thus complete this criterion with the exclusivity one, where high exclusivity means that high-probability words for a topic do not typically appear in other topics (Airoldi and Bischof 2016). Figure B.2 in Appendix B shows the coherence and exclusivity measures for a series of models with $K \in [10, 15, 20, ..., 60]$. We select the 25-topic model since this setting yields the most semantically coherent and exclusive outcomes.[14] In addition to these criteria, we perform a careful human inspection of model outcomes to determine the most meaningful topic clustering. Therefore, we vary the number of topics from 15 to 35 to inspect the results, and we find that a 24-topic model performs the best in terms of interpretability.[15]

3.2 Topic Summary and Correlation Analysis

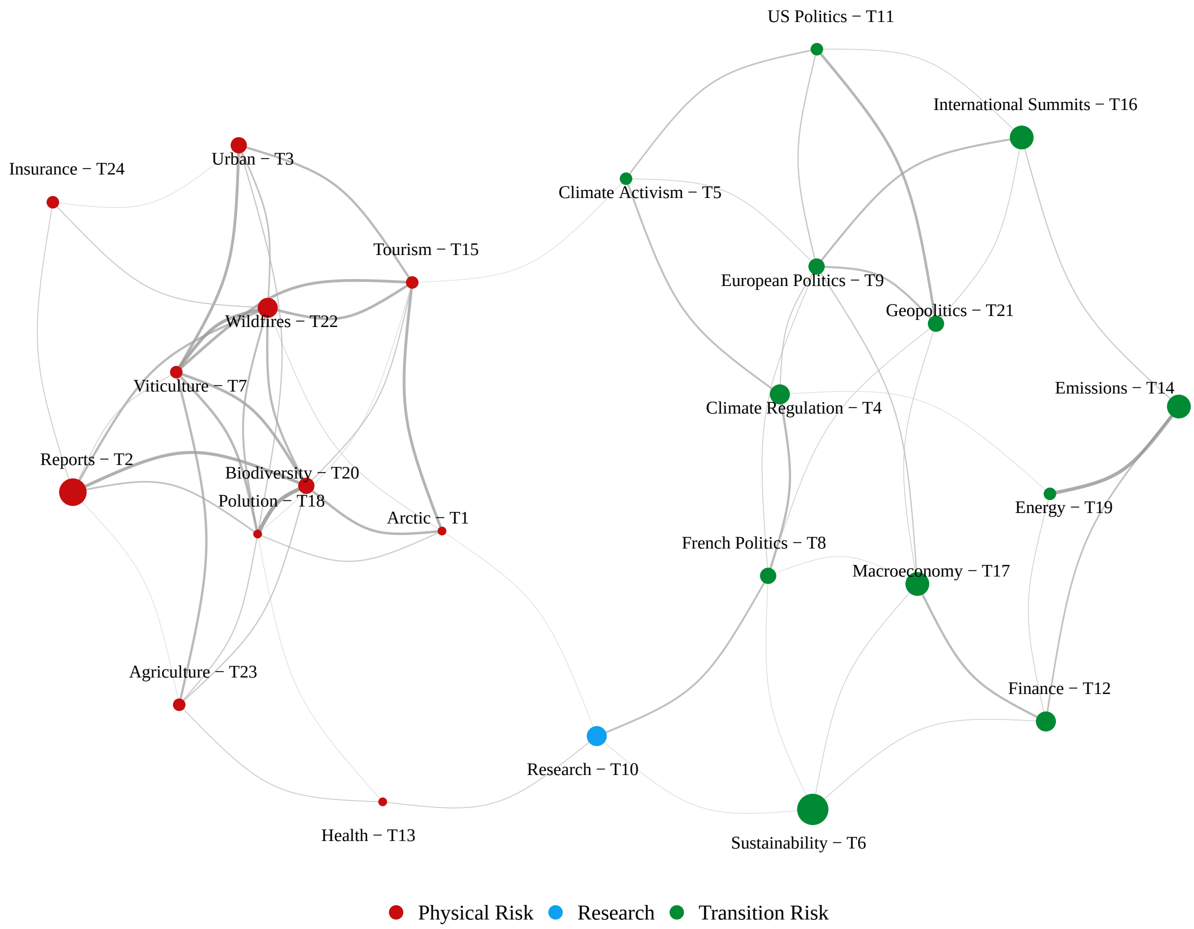
Figure 3 highlights the relationships between the different topics in our corpus. Each topic is represented by a node, whose size is proportional to the prevalence of the topic. The width of the edge between two nodes is proportional to the correlation between the two topics. Node/topic color denotes the theme to which they belong: green, red, and blue for Physical risks, Transition risks, and Research, respectively.

We distinguish transition risks arising from the process of adjustment toward a low-carbon and more circular economy from physical risks that could be categorized as either acute if they arise from extreme climate- and weather-related events (e.g., heatwaves, droughts, floods, wildfires and storms) or chronic if they arise from longer-term progressive shifts in climate and weather patterns (e.g., rising sea levels and average temperatures). Finally, a theme reporting the results of scientific research is connecting the two clusters. A closer examination reveals the intuitive nature of co-occurrence relationships among topics, e.g., *Energy* debates are highly related with *Emissions* ones in the Transition risks cluster, or the strong relationships between Agriculture, *Viticulture* and *Wildfires* topics in the Physical risks group.

[14] This number is consistent with the previous literature since Ardia et al. (2022) and Faccini et al. (2023) considered a 30-topic model and a 25-topic model, respectively.

[15] Blei (2012) pointed out that interpretability is a key objective in selecting the optimal topic model, and careful human inspection is the most common approach. In our case, we discard a topic about cinema (films and documentaries essentially) since it is not directly related to the scope of this study, ending up with 24 relevant topics.

Figure 3 Network of climate topic correlations



Notes: For readability, only Spearman correlations above 0.35 are displayed.

Table 1 classifies the 24 topics into three clusters that correspond to general themes related to climate risks. We use the correlation analysis above to group topics into clusters. The first and third columns show the label and the top five keywords for each topic, respectively.[16] The second column presents the unconditional prevalence of a topic that is obtained as the average of the topic prevalence across all news articles.[17] For each theme, we order first the most prevalent topic, and then topics follow in a decreasing order of prevalence.

[16]Top words are those that have the highest levels of joint frequency and exclusivity. That is, these words appear most frequently in one topic but least frequently in other topics. These top words discriminate one topic from the others. For the sake of brevity, we report in Table 1 the top five keywords. To facilitate the visualization of other keywords, we report in Figure B.4 word clouds for the two most prevalent topics per climate theme.

[17]The unconditional prevalence of a given theme is the sum of the unconditional prevalence of each topic within the theme, which is static.

Table 1
List of topics together with their unconditional prevalence and top five keywords in terms of probability

Topic	Prevalence θ	Top five keywords in term of probability ϕ
Theme 1: Transition risk	**57.48**	
Sustainability - T6	8.25	development, politics, economic, firms, environment
International Summits - T16	6.39	country, agreement, climate, Paris, development
Emissions - T14	6.21	emissions, carbon dioxide, gas, energy, oil
Macroeconomy - T17	5.78	crisis, country, growth, rate, economy
Finance - T12	5.35	firm, fund, investor, billion, group
Climate Regulation - T4	4.87	Macron, president, France, minister, government
Geopolitics - T21	4.05	China, country, war, U.S., Russia
European Politics - T9	3.70	Europe, European, E.U., Germany, commission
French Politics - T8	3.59	politics, world, France, country, Europe
Energy - T19	3.31	nuclear, energy, electricity, plant, France
U.S. politics - T11	3.22	Trump, U.S., president, Obama, American
Climate Activism - T5	2.70	justice, government, rights, militants, NGO
Theme 2: Physical risk	**37.64**	
Reports - T2	6.65	climate change, report, warming, country, IPCC
Wildfires - T22	5.40	fires, France, heat, south, weather
Biodiversity - T20	4.45	species, biodiversity, forests, sea, nature
Urban - T3	3.53	city, Paris, inhabitant, euros, project
Viticulture - T7	2.96	water, drought, wine, France, year
Agriculture - T23	2.69	agriculture, food, production, farmer, price
Insurance - T24	2.67	risk, insurance, disaster, billions, floods
Tourism - T15	2.52	year, meter, water, mountain, snow
Arctic - T1	2.40	arctic, earth, ice, north, year
Health - T13	2.30	health, Covid, virus, case, disease
Pollution - T18	2.03	pollution, health, air, environment, study
Theme 3: Research	**4.88**	
Research - T10	4.88	world, life, science, time, question

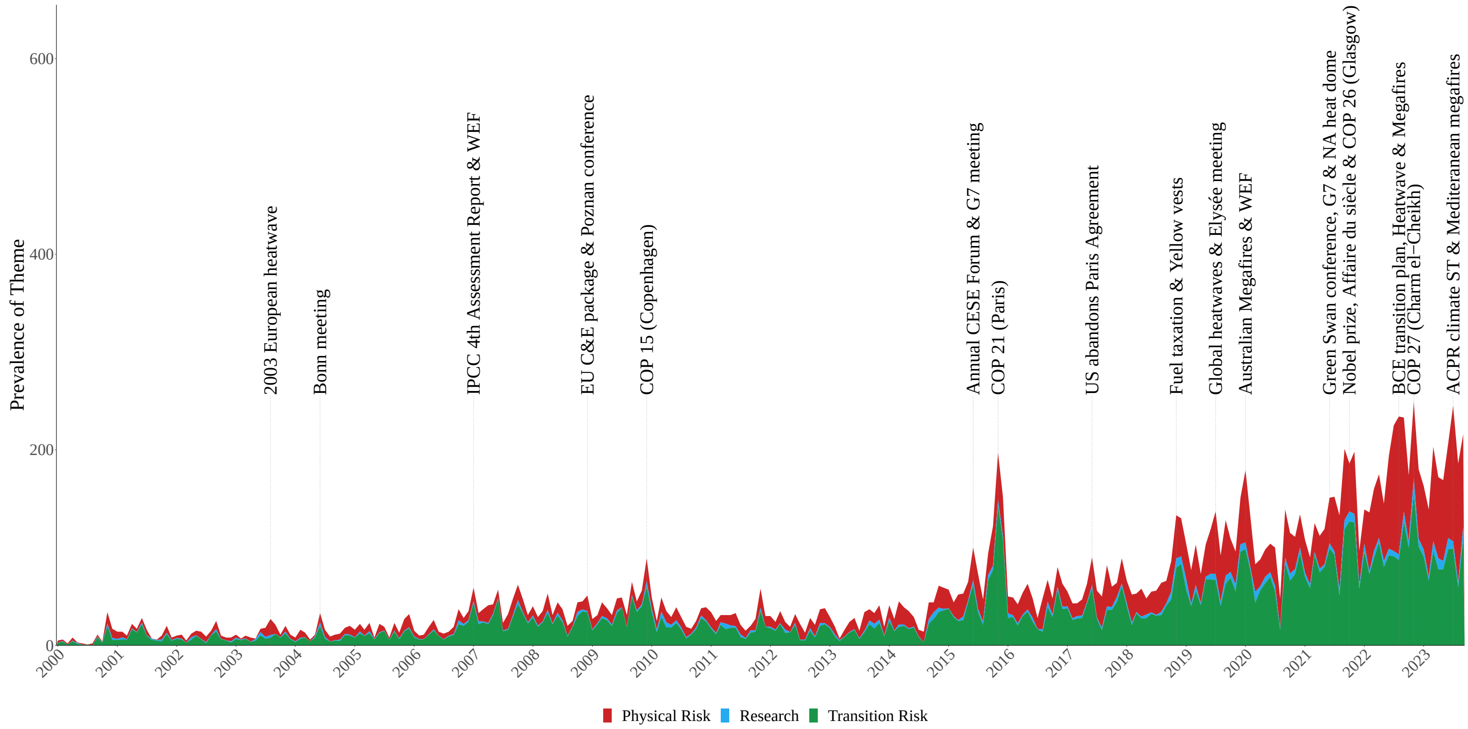
Notes: This table classifies the twenty-four topics into three clusters: transition risks, physical risks and research. The unconditional prevalence θ of a topic is obtained as the average of the topic prevalence across all news articles. For a theme, the unconditional prevalence is the sum of its topic prevalence. For each theme, we order first the most prevalent topic, and then topics follow in decreasing order of prevalence. Original French words are translated in English.

Table 1 shows that the most prevalent theme is transition risks ($\theta = 57.48\%$), whose topics, such as *Macroeconomy* and *Finance*, are related to the effects of transition risks on the real and financial spheres and how they could adapt to or mitigate those risks. While Topic 6 is associated with *Sustainability* requirements and policies, Topics 16 and 21 are about *International Summits* and *Geopolitics* events associated with climate change, such as the 2015 United Nations Climate-Change Conference (COP21) and the subsequent Paris Agreement. The second most prevalent theme is physical risks ($\theta = 37.64\%$), where topics such as *Reports* of governments, NGOs, and the Intergovernmental Panel on Climate Change are quoted (Topic 2). Other examples include the Topic 22, which is related to news about acute physical risks (mainly wildfires and heatwaves), or Topics 1 and 20, which describe chronic physical risks related to the Arctic region and biodiversity loss, respectively. The detrimental effects of climate change on *Agriculture* (Topic 23) and particularly on the *Viticulture* sector (Topic 7) are another important concern of French media that report news about farmers increasingly suffering from extreme weather events such as droughts, late frosts, hail, fires, or floods. Interestingly, service industries such as *Tourism* (Topic 15) and *Insurance* (Topic 24) can also be affected by physical risks, unlike the *financial sector* (Topic 12), which is more exposed to transition risks. The last theme, Research ($\theta = 4.88\%$), reflects news about the scientific research on the effects of global warming and climate change on the ecosystems and on how societies should face this complex challenge. Therefore, this theme is associated with both physical and transition risks.

The dynamic of media attention toward each of the three themes in 2000-2023 is displayed in Figure 4. We define a time series of "article-equivalents", which captures the number of articles discussing a specific topic for a given period. We then aggregate the number of article-equivalents by theme, which allows us to construct monthly theme indices, i.e., the Physical-Risk Index (PRI) and the Transition-Risk Index (TRI). The PRI share spike corresponds to events related to megafires in the Gironde department during summer 2022, while the TRI's highest shares are related to the different COPs 21, 26, and 27.[18]

[18] For more physical and transition events, see Figures B.5 and B.6 in Appendix B, where the PRI and the TRI are plotted separately.

Figure 4 Article Share by Climate Risk Themes

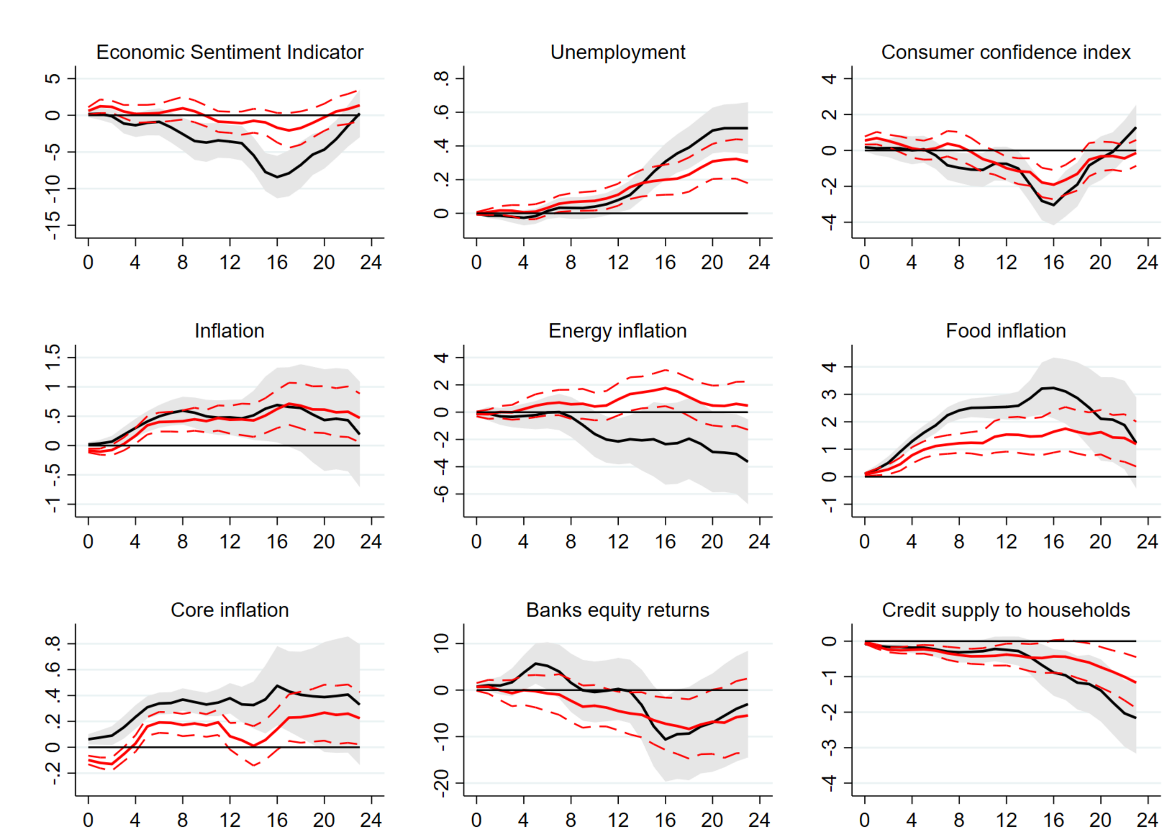


3.3 Impact of Disaggregated Climate Risk Indices

We re-estimate Equation (1) including successively the PRI and the TRI as independent variables. The cumulative responses of our variables of interest are displayed in Figure 5.

The comparative analysis between both types of risks yields three main findings. First, except for energy prices and bank equity returns, we observe that the responses of macroeconomic and financial variables to a one-standard deviation increase in the PRI are larger than the responses generated by a rise in the TRI. This is particularly the case for the ESI, for which the effect is muted following an increase in the TRI. This might be explained by the fact that shocks to environmental policies might stimulate private investment, which positively affects production in the short run but it has a less persistent effect over the long run. Second, regarding the *inflation channel*, the impact of both indexes on the HICP is roughly similar, however, the analysis of disaggregated prices allows to clears up the ambiguity highlighted previously on the effect of the aggregated CRI on energy prices. We find that that disaggregated climate-related risks have opposite effects on energy prices: physical (transition) risks put downward (upward) pressures on energy prices. While the negative effect induced by higher PRI could be explained by the fact that natural disasters reduce energy consumption and prices through drops in oil, renewable, and nuclear energy demands (Lee et al. 2021), the positive effect associated with higher TRI could be due to the restrictive environmental policies implemented as part of the transition process to a low-carbon economy. Finally, the IRFs of the financial variables suggest that banks' equity returns primarily react to rising transition risks, while credit supply react to transition risks and physical risks. The latter result can be explained by the direct exposure of households and nonfinancial firms to physical risks, which is not necessarily the case for banks given their diversified portfolios (Klomp 2014).

Figure 5 Cumulative IRFs for shocks in PRI and TRI



Notes: Solid black lines show impulse responses of a one standard deviation in the PRI. Solid red lines represent the corresponding IRFs of a one standard deviation in the TRI. Gray-shaded areas (red dashed lines) indicate 68% confidence bands.

4 Tone Analysis of Climate Risks News Articles

The analyses conducted in Section 3 and Section 4 rely on the (implicit) hypothesis that an increase in media coverage of climate risks is associated with higher climate risks. However, the coverage of climate events may also reflect good news stemming, for example, from the policies implemented such as the European climate law introduced in 2019. In this section, we check if the tone of the media coverage about climate risks matters beyond the frequency of the published articles. For that purpose, we follow a two-step procedure: (i) we use a dictionary-based approach to capture the tone conveyed in the newspaper articles covering climate risks and (ii) we investigate the effect of the climate-related media tone on our variables of interest.

4.1 Methodology

We use a lexicon-based approach, such as in Loughran and Mcdonald (2011) to measure the positive/negative tone of the newspaper articles covering climate risks. Specifically, we count the number of words with an acknowledged positive or negative tone according to the French Lexicoder Sentiment Dictionary (LSDFr), developed by Duval and Pétry (2016). The LSDFr contains 4155 words, of which 2870 (69%) are classified as negative and 1285 (31%) as positive. The tone measure for each newspaper article a is calculated as follows:

$$Tone_a = \frac{Pos_a - Neg_a}{Pos_a + Neg_a}; \tag{2}$$

where $Tone_a$ is a continuous variable comprised between -1 and 1 reflecting the tone of the newspaper article a, and Pos_a and Neg_a are the numbers of positive and negative words, respectively, used in the climate-related newspaper article. An increase (decrease) in $Tone_a$ reflects a shift in media coverage toward more positivity (negativity). We show below how the tone is computed for an excerpt of an article published in *Le Figaro* in 2015:

> "[...] *Le coût lié aux <u>catastrophes</u> naturelles est exponentiel. De 30 milliards de 1988 à 2007, il devraît avoisiner les 60 milliards les vingt années suivantes, selon la mission <u>risques</u> naturels de la FFSA. En cause un double phénomène : une densité plus **<u>forte</u>** de la population dans les zones les plus <u>exposées</u> – comme le Sud-Est, selon l'étude – mais aussi un changement climatique qui va doubler, selon les experts, « la fréquence des événements <u>extrêmes</u> ». Cette étude qui dresse une projection <u>inquiétante</u> de notre proche avenir doit être réactualisée avec des résultats communiqués dès novembre prochain.* [...]."

Source: Negroni, A., « Intempéries : la facture ne cesse de s'alourdir pour les assureurs », *Le Figaro*, 6 October 2015.

According to the LSDFr, there are five words conveying a negative tone (bold and underlined) and one word conveying a positive tone (italics and underlines). The tone of this excerpt is therefore equal to -0.67. We compute the monthly average tone of all newspaper articles published in month m as follows:

$$Tone_m = \frac{1}{N_m} \sum_{m=1}^{N_m} Tone_a; \tag{3}$$

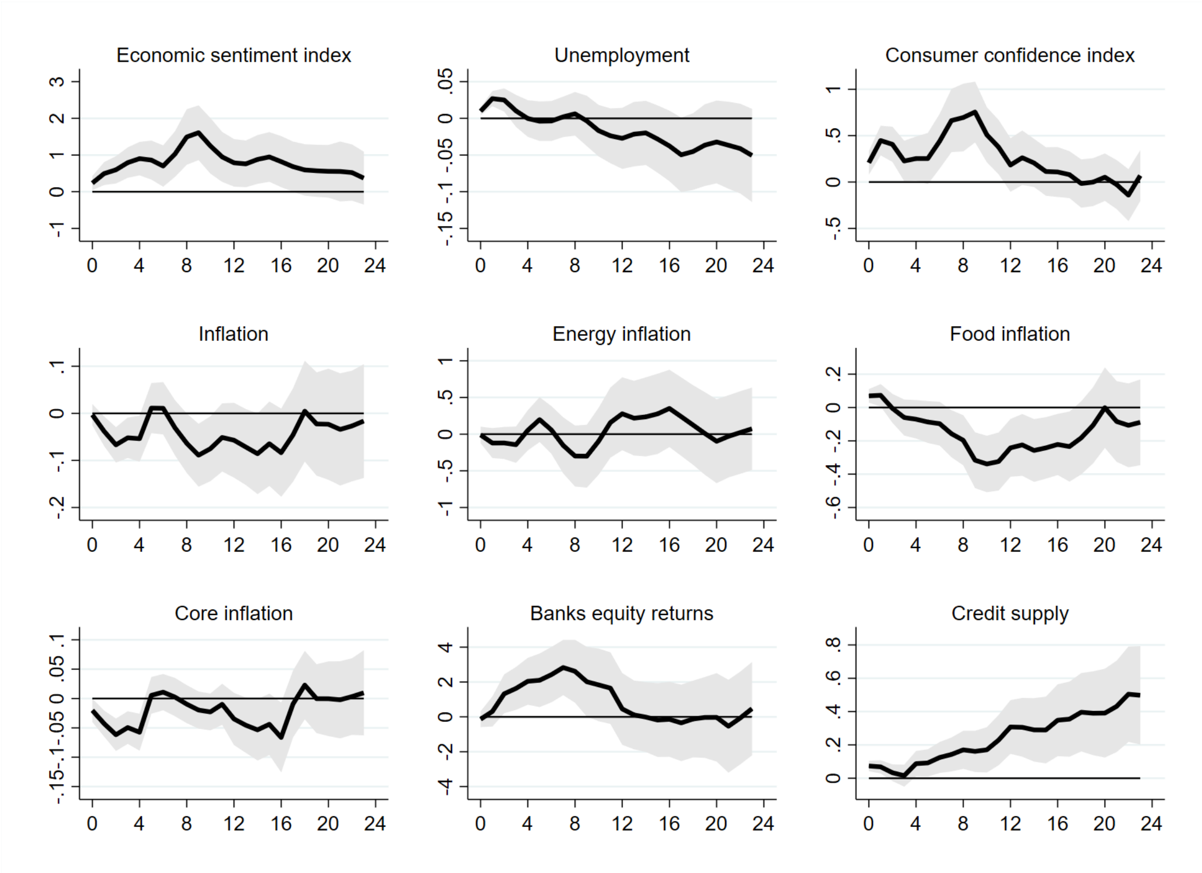
where $Tone_m$ is the average monthly tone of newspaper articles and N_m is the monthly number of articles. Figure B.7 suggests that the Climate Tone Index (CTI) tends to decrease after each major climate event. This shows that climate risk-related news articles primarily convey a negative tone., which is particularly the case for extreme physical events (see, e.g., the 2003 European heatwave and the Gironde department and Mediterranean megafires in 2022 and 2023, respectively).

4.2 Impact of Climate-Risk related Media Tone

We include our tone measure in Equation (1) as an independent variable to assess its effect on our variables of interest. The cumulative IRFs are displayed in Figure 6.

We find that the media tone regarding climate risks has a significant impact on the economy. In particular, a positive shift in media tone leads to better real economic conditions and an improvement in consumer confidence. On the financial market side, bank equity returns tend to significantly improve three months after an increase in the CTI. This effect can be linked to the increase in the volume of credit granted to the economy, as reflected in the response of the credit supply metrics to a more positive media tone.

Figure 6 Cumulative IRFs for shocks in CTI



Notes: Solid black lines show impulse responses of a one standard deviation in the CTI. Gray-shaded areas indicate 68% confidence bands.

5 Robustness

To test the robustness of our findings, we conduct several tests. First, we modify the selection strategy of the newspaper articles by changing the distance between the second and third groups of keywords within a range of 5-10 words. This has very little impact on the climate-risk measures and on the overall results. Second, since both concepts of risk and uncertainty might refer to related situations (see Baker et al. 2016), we extend the keywords by adding an uncertainty dimension, that is, we add words such as {"incertitude*" or "incertain*"}.[19] This new selection strategy adds approximately 1400 news articles, but with no significant change regarding the results. Third, we use alternative measures of climate risks. Specifically, we consider the ratio of climate-related articles to total published articles plotted in Figure 1, and the number of climate words per article

[19]In English: {"uncertainty*" or "uncertain*"}.

as proxies of the CRI (see Figure B.8). The two measures display a substantially similar pattern compared with the baseline one; hence, the results remain robust to these alternative measures. Finally, we use the Industrial Production Index instead of the economic sentiment index measure as a proxy for the business cycle. The impact is more short-lived following an increase in the CRI and the PRI, but considerably similar in response to an increase in the TRI.[20]

6 Conclusion

Using natural language processing methods on newspaper articles covering climate risks in 2000-2023, this study constructs an index of climate risks for France to assess its impact on economic activity. In doing so, we highlight several transmission channels through which climate risks affect economic activity in France: the *business cycle channel*, the *precautionary savings channel*, the *inflation channel*, and the *banking/credit* channel. Specifically, we find that higher climate risk, as proxied by media coverage, is associated with the following: (i) lower economic sentiment; (ii) higher unemployment rate; (iii) higher inflation; (iv) lower banks' returns; and (v) a lower credit supply to households and (non)-financial companies. Moreover, the decomposition of the aggregate climate risk index into its physical- and transition-risk components shows that all variables, except for energy prices and bank equity returns, are more affected by physical risks than transition risks. Finally, we find that the tone of media coverage of climate risks matters beyond the frequency of published articles. These results provide evidence that the media play a significant role in shaping the beliefs of households and market participants regarding issues related to climate change.

[20] To save some space, the results of the robustness tests are available from the authors upon request.

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A Description of Variables

Table A.1
Description of Variables

Variable	Label	Source	Description/Transformation
Estimated climate risk variables			
Climate Risk Index	CRI	Authors' calculation	Standardized total counts of climate risk articles from Europresse
Physical Risk Index	PRI	Authors' calculation	Standardized prevalence of physical risk articles
Transition Risk Index	TRI	Authors' calculation	Standardized prevalence of transition risk articles
Climate Tone Index	CTI	Authors' calculation	Standardized monthly average of sentiment scores over all articles
Macroeconomic block variables			
Economic sentiment index	ESI	European Commission	First differences of the natural logarithm of ESI, which is a weighted average of the balances of replies (difference between positive and negative replies) to selected questions addressed to firms covered by the E.U. Business and Consumer Surveys and to consumers. The ESI is scaled to a long-term mean of 100. Thus, values above 100 indicate above-average economic sentiment and vice versa.
Consumer confidence index	CCI	OECD data	First differences of CCI, which is based upon households' answers regarding future developments of their consumption and saving. An indicator above 100 signals a boost in the consumers' confidence towards the future economic situation, as a consequence of which they are less prone to save, and more inclined to increase consumption expenditures in the next twelve months. Values below 100 indicate the opposite situation. Long-term average = 100
Unemployment rate	Unemp	OECD data	First differences of Unemp
Harmonized Index of Consumer Prices	HICP		First differences of the natural logarithm of HICP; index 2015 = 100
Energy price index	EPI		First differences of the natural logarithm of EPI; index 2015 = 100
Food price index	FPI		First differences of the natural logarithm of FPI; index 2015 = 100
Core price index	CPI		First differences of the natural logarithm of CPI; index 2015 = 100
Financial block variables			
Banks equity returns	BANKSFR	Datastream	First differences of the natural logarithm of BANKSFR, constructed as a capitalisation weighted index encompassing all major listed French banks (BNP Paribas, Crédit Agricole, Société Générale, Caisses Régionales du Crédit Agricole Mutuel Nord de France, Île de France and Brie Picardie, and Crédit Foncier de Monaco)
Credit supply to households		Banque de France	First differences of the natural logarithm of lending by credit institutions to households and nonprofit institutions serving households (EURm)
Credit supply to non financial corporations		Banque de France	First differences of the natural logarithm of lending by credit institutions to private non financial companies (EURm)
Credit supply to financials		Banque de France	First differences of the natural logarithm of lending by credit institutions to private financial sector (EURm)
Control variables			
Economic Policy Uncertainty	EPU	www.policyuncertainty.com	
10-Year government bond yield	i^{10y}	ECB Data Portal	

Notes: All variables are of monthly frequency over the January 2000 to September 2023 time period.

Table A.2 Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Estimated climate risk variables				
Climate Risk Index (CRI)	56.52	54.46	1.00	249.00
Physical Risk Index (PRI)	21.28	24.10	0.17	140.99
Transition Risk Index (TRI)	32.49	30.69	0.19	155.31
Climate Tone Index (CTI)	-0.06	0.07	-0.34	0.10
Dependent macroeconomic variables				
Economic sentiment index (ESI)	99.87	9.87	62.50	121.50
Consumer confidence index (CCI)	99.42	1.43	96.70	102.64
Unemployment rate (Unemp)	8.90	0.92	7.00	10.50
Harmonized Index of Consumer Prices (HICP)	95.63	10.40	77.40	122.10
Energy price index (EPI)	95.54	23.28	63.15	161.94
Food price index (FPI)	97.00	11.61	76.11	133.62
Core price index (CPI)	95.91	7.55	81.61	112.60
Dependent financial variables				
Banks equity returns (BANKSFR)	675.09	409.03	208.20	1117.89
Control variables				
Economic Policy Uncertainty (EPU)	197.68	105.35	16.59	574.63
10-Year government bond yield (i^{10y})	2.63	1.73	-0.34	5.66

B CTM Characterization

Figure B.1 Example of newspaper article

Le Monde

Le Monde
Planète, samedi 10 juin 2023 960 mots, p. 7

Aussi paru dans 8 juin 2023 - Le Monde (site web)

Le réchauffement planétaire s'accroît à un rythme sans précédent

La quantité de gaz à effet de serre à ne pas dépasser pour limiter le réchauffement à 1,5 °C a été divisée par deux par rapport à la précédente estimation

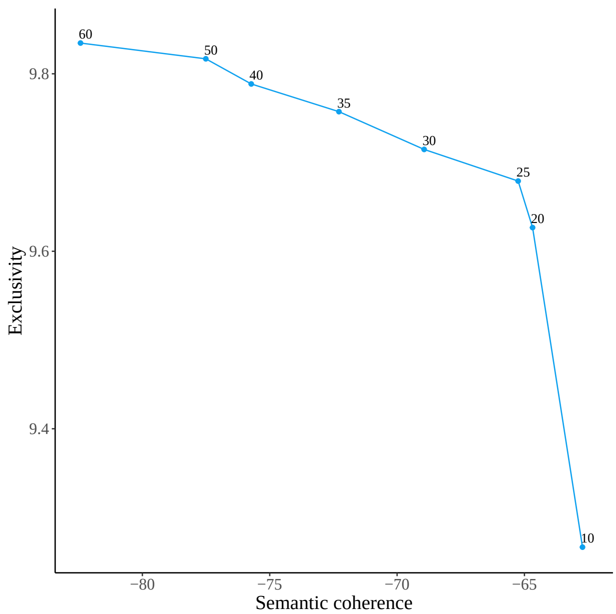
Audrey Garric

Le réchauffement climatique non seulement n'offre pas de répit, mais s'amplifie. Ce que chacun peut observer directement, qu'il s'agisse des vagues de chaleur en Asie ou des incendies immenses au Canada, est confirmé par une nouvelle étude scientifique publiée dans *Earth System Science Data*, jeudi 8 juin, par un groupe international d'une cinquantaine de scientifiques de renom.

Ces chercheurs mettent à jour les principaux indicateurs climatiques du rapport du groupe de travail 1 du Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC) paru en 2021, consacré aux bases physiques du changement climatique. *« Le rapport du GIEC, qui est publié tous les sept ans environ, méritait d'être mis à jour dans un contexte de climat qui change très rapidement et pour éclairer les négociations climatiques »* , explique Aurélien Ribes, chercheur au Centre national de recherches météorologiques et coauteur de l'étude.

Notes: Sentences highlighted in yellow indicate a general climate change topic, while sentences in red, green and light blue refer to physical risk, transition risk and research topics, respectively.

Figure B.2 Semantic coherence (horizontal axis) vs. Exclusivity (vertical axis) for various numbers of topics: K $\in \{10, 15, 20, ..., 60\}$



Notes: The 25-topic model is optimal as it yields the most semantically coherent and exclusive outcomes.

Figure B.3 List of Topics with Most Frequent Words

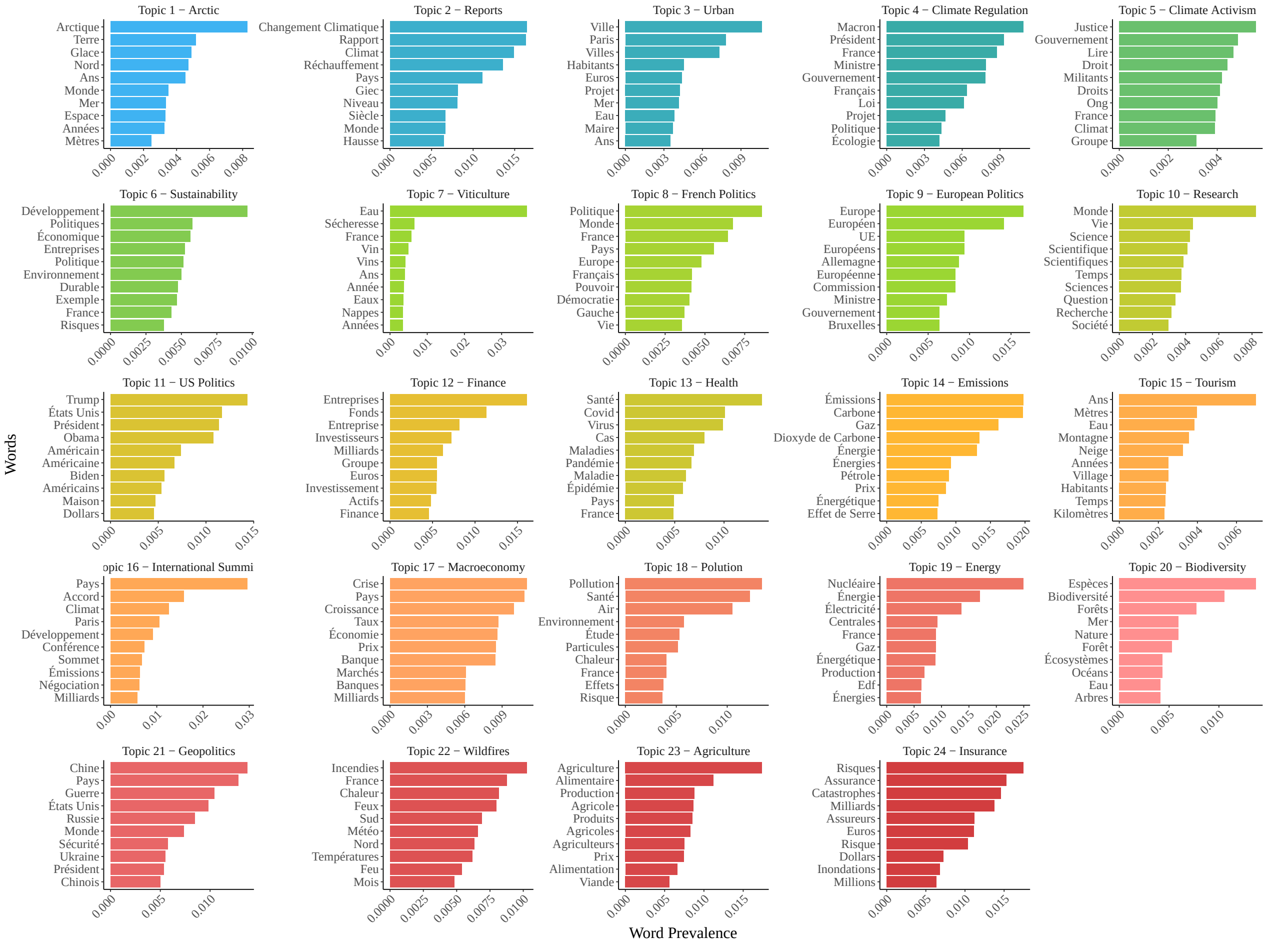
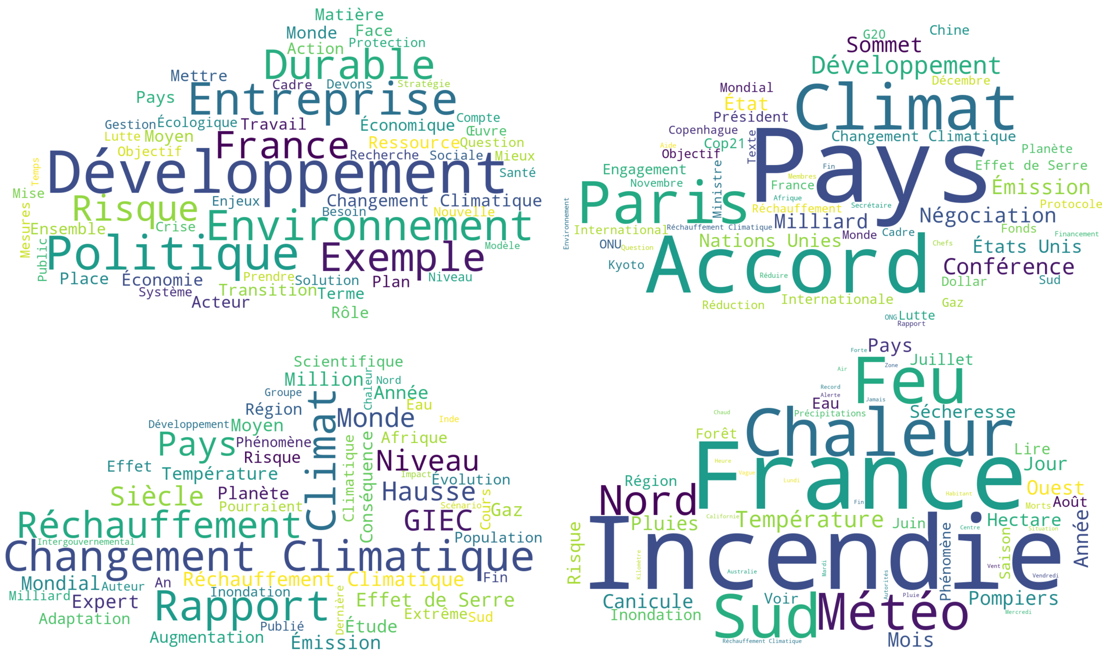


Figure B.4 Word clouds for the two most salient topics per climate theme



Note: The word clouds are defined in Table 1, including sustainability, international summits, reports and wildfires. Words in bigger fonts have the highest probability of occurrence ϕ in each topic.

Figure B.5 Physical Risk Index (PRI)

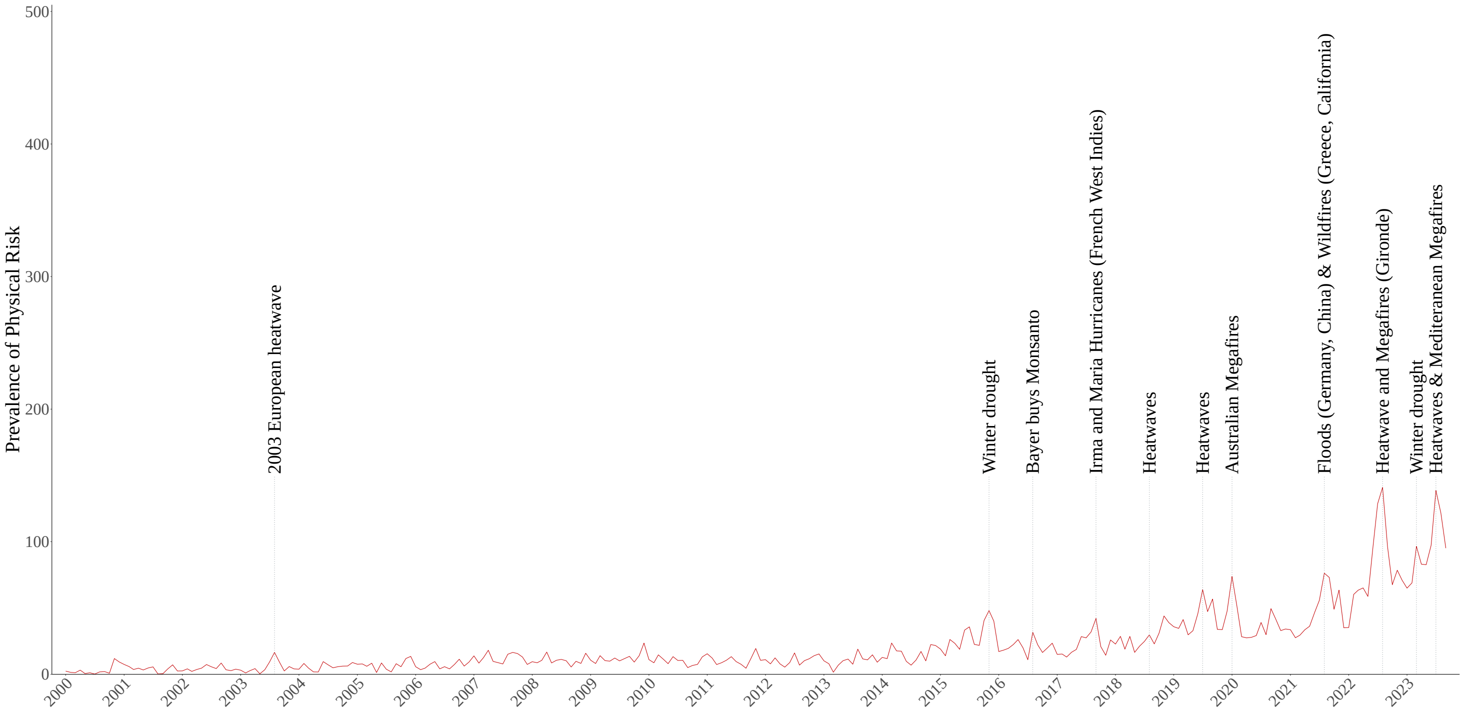


Figure B.6 Transition Risk Index (TRI)

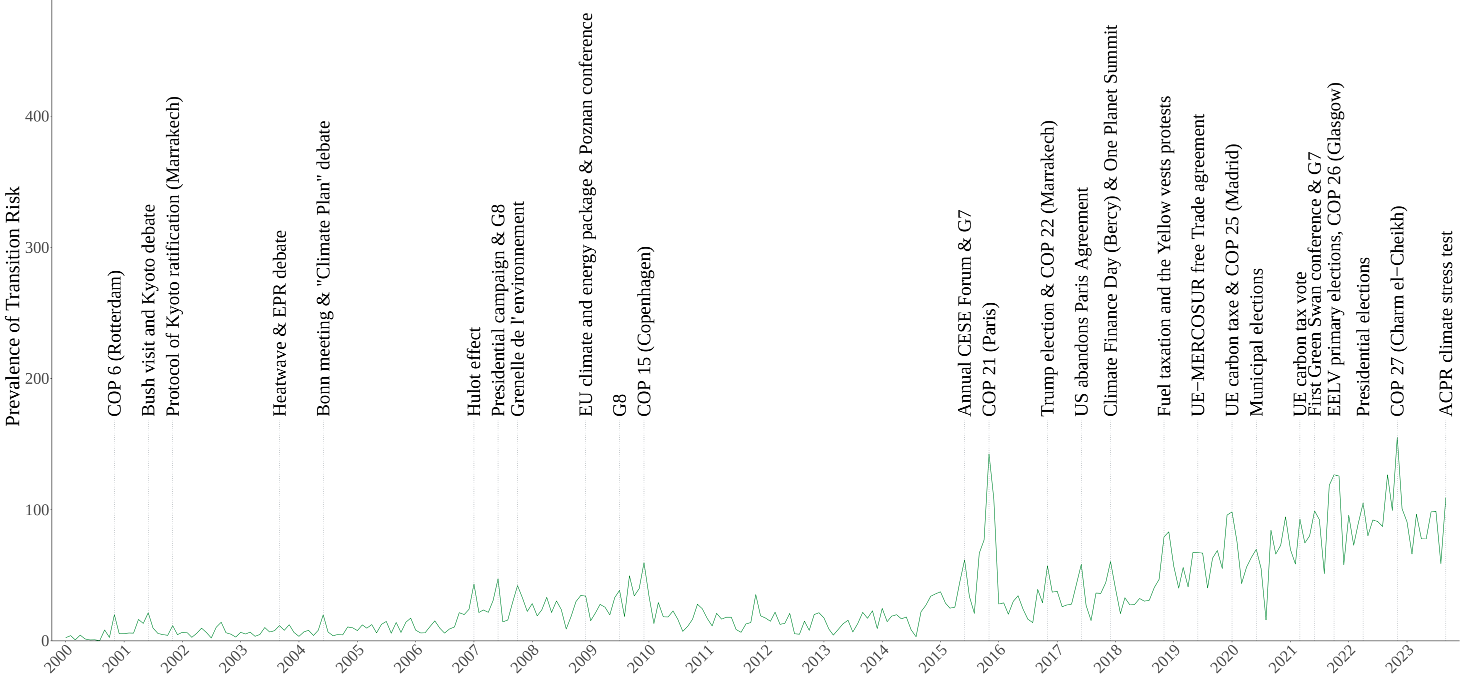


Figure B.7 Monthly Climate Tone Index (in blue) and its 12-month moving average (in red)

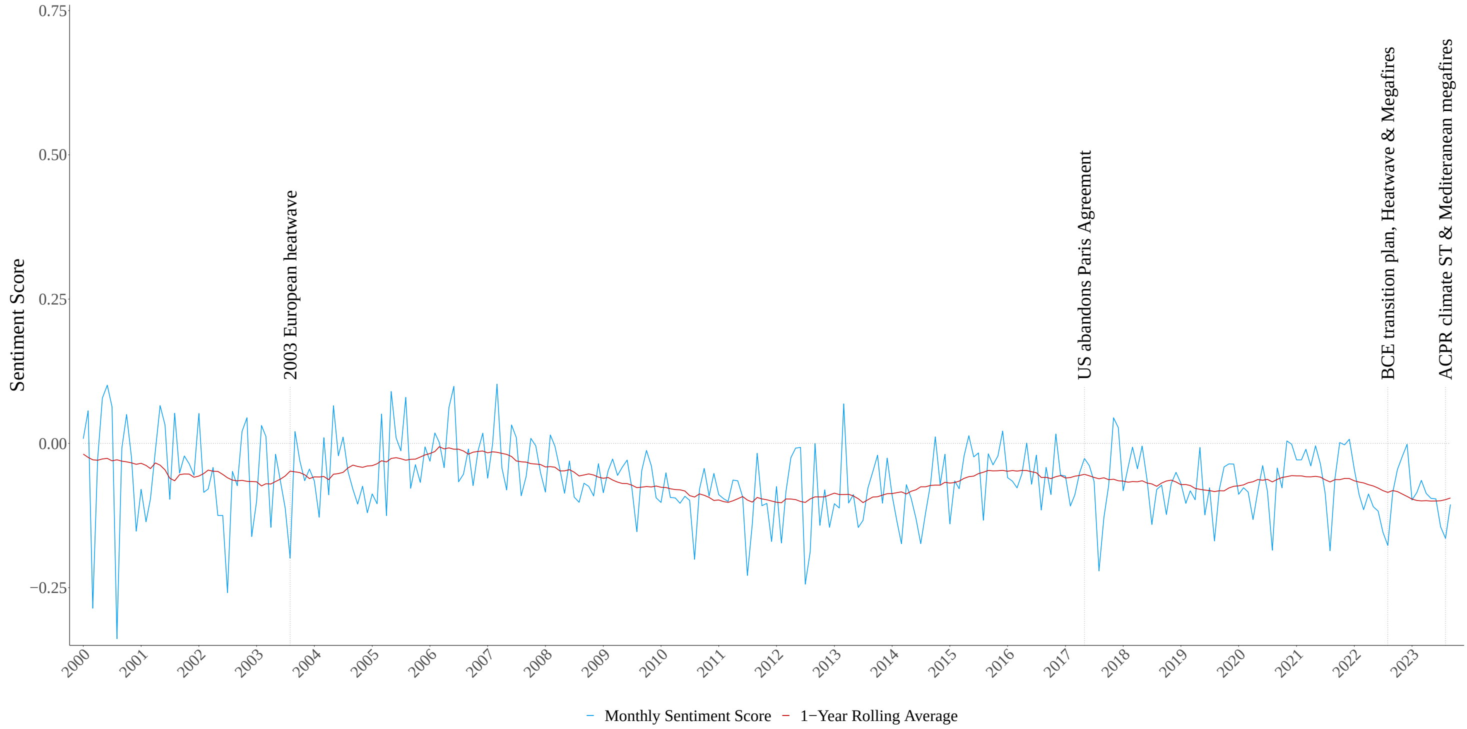


Figure B.8 Total Count of Climate-Related Words