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From Climate Chat to Climate Shock: Non-Linear Impacts of Transition Risk in Energy CDS Markets

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ABSTRACT

It is still unclear to what extent transition risks are being internalized by financial investors. In this paper, we provide a novel investigation of the impact of media-based measures of transition risks on the credit risk of energy companies, as measured by their credit default swaps (CDS) indices. We include both European and North American markets in the 2010–2020 period. Using linear and non-linear local projections, we find that a transition risk shock affects CDS indices only when combined with tangible physical climate-related impacts. We also find evidence of non-linear cross-border effects, with North American energy companies particularly affected by European dynamics. We suggest that the public reaction in the wake of severe climate-related disasters, which might push policymakers to adopt more decisive climate action, contributes to making the transition-related debate salient in the eyes of credit market actors.

JEL Classification: C32, C58, G12, Q43, Q54

1 | Introduction

The threat of runaway climate change calls for a rapid process of decarbonization (IPCC 2023). Unless carbon capture and storage and other net-zero technologies become economically viable at scale soon, mitigating climate change will involve moving away from the use of fossil resources (oil, gas, and coal) and carbon-intensive production processes. This, in turn, will likely affect the economic prospects of firms in the fossil sector, as well as all firms using fossil-intensive intermediate inputs.[1]

How large are these "transition risks," and to what extent have they been internalized by financial investors? An expanding literature has been trying to address these challenging questions in recent years, often focusing on the impact of some transition risk measure (usually emission intensity) on the price of financial assets (e.g., Antoniuk and Leirvik 2024; Bauer et al. 2022; Bolton and Kacperczyk 2021, 2023; Cortez et al. 2022; El Ouadghiri et al. 2021; Hsu et al. 2023; Ilhan et al. 2021; Monasterolo and De Angelis 2020; Peillex et al. 2021; Ramelli et al. 2021).[2] A parallel strand of literature has instead been developing media-based climate-related risk measures, that is, indices of the quantity and/or nature of the news provided by popular media outlets on climate change and the low-carbon transition (Ardia et al. 2023; Bessec and Fouquau 2021, 2022; Bua et al. 2024; Engle and Campos-Martins 2020; Faccini et al. 2023; Kapfhammer et al. 2020; Meinerding et al. 2022). These indices can offer a measure of perceived aggregate transition risks, assuming the

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news reaches financial investment decision-makers, and they have indeed been found to affect the relative valuation of dirty and clean companies. However, to the best of our knowledge, no study connecting media-based transition risk measures and *credit* risk currently exists.

Studying energy firms' credit risk in light of transition risks is crucial due to the sector's central role in both economic activity and carbon emission generation. Energy companies, especially fossil-intensive ones, are highly exposed to regulatory, market, and reputational risks tied to the shift toward low-carbon economies. As governments and investors increase their focus on sustainability, energy firms face significant potential impacts from policies aimed at curbing greenhouse gas emissions, technological advancements in renewable energy, and shifting consumer preferences. Thus, the importance of this research lies not only in understanding the direct impact on energy firms but also in capturing broader implications for financial markets, risk management, and policy effectiveness in the face of transition-related uncertainties.

In this paper, we contribute to this stream of research by studying how credit default swaps (CDS) of firms in energy sectors react to shocks in transition risk perceptions.[3] The price of CDS—that is, the price at which two parties are willing to exchange the risk of a borrower—gives us an indication of how high the perceived risk of default is: if a firm is perceived to be at higher (lower) risk of default, the market price of the CDS contract will be higher (lower). We employ linear and non-linear local projections (Jordà 2005; Ramey and Zubairy 2018; Jordà and Taylor 2024) to study how CDS indices reacted to shocks in transition risk perceptions in both North America and Europe, as measured by two recent novel media-based measures (Ardia et al. 2023; Bua et al. 2024), in the 2010–2020 period.[4]

We find that the media debate related to transition risks (e.g., the unexpected implementation of a climate policy) is not sufficient per se to have a significant effect on credit risk, as measured by the CDS indices of energy companies, in either of the two regions. The effect becomes significant only when transition risk perceptions are coupled together with climate-related physical impacts (droughts, extreme temperatures, floods, glacial lake outbursts, landslides, storms, and wildfires). This effect is visible in both North America and Europe, suggesting a limited internalization of transition risks so far. In both jurisdictions, a transition risk shock becomes salient to the attention of financial decision-makers only in the concurrent occurrence of major physical "disasters," The wave of commotion following damaging events might trigger in investors the perception that the implementation of transition-friendly measures has become more likely. We control for and exclude the possibility that the effect is driven by disasters themselves: it is mainly the interaction between the two that matters.

Our work builds upon and connects three main streams of research. First, we closely relate to a recent wave of research studying the impact of climate-related dimensions on financial dynamics with the help of media-based attention indices. More specifically, we employ the indices developed by Ardia et al. (2023) and Bua et al. (2024), presented more in detail in Section 2.3. Among the other indices proposed by the literature, these are the only ones available at a daily frequency and for the whole time period we consider.[5] Most of the contributions in this field have been focusing on the impact of media attention concerning either climate change or the low-carbon transition (or both) on stock prices. The general conclusion is that there is indeed a significant negative impact on the relative valuation of firms more exposed to climate-related risks compared to the ones less exposed. When focusing on transition risks, this suggests that "dirtier" firms (usually identified as the ones with the largest carbon footprints) are penalized when the media attention on transition-related topics, such as the introduction of climate policies, is higher. Recent evidence from the bond market by Bats et al. (2024) confirms this pattern, finding a significant physical risk premium of 34 basis points in euro-area corporate bonds, though with smaller effects for transition risks. None of these papers has looked at other types of financial assets, such as CDS, as we do in this paper.

Second, we connect to the literature focusing on the links between CDS and sustainability. Blasberg et al. (2022) construct a novel measure of transition risk through firms carbon emission intensity data and show that this factor is a relevant driver of CDS spreads. Barth et al. (2022) and Christ et al. (2022) focus on ESG ratings as a proxy of a firm's sustainability, and find that better environmental ratings are related to lower CDS spreads. Kölbel et al. (2022) investigate the relationship between the cost of default protection and a measure of transition risk based on corporate disclosure, finding that higher exposure to transition risks increases CDS spreads. Likewise, Carbone et al. (2021) consider climate disclosure practices and prospective emission reduction targets in addition to firms' emission intensity as factors that may influence credit risk. However, none of the papers above has connected CDS dynamics to media-based measures of transition risks.

Finally, we build upon the stream of research studying the impact of disasters on economic and financial dynamics. Huynh and Xia (2021) and Bourdeau-Brien and Kryzanowski (2017) examine the exposure of firms to natural disasters. The former finds a positive correlation with its future stock and bond returns, while the latter reports mixed results regarding the direction of the impact of catastrophes. Worthington and Valadkhani (2004) assess the influence of natural disasters on the Australian equity market, analyzing different types of disasters and concluding that bushfires, cyclones, and earthquakes exert significant effects on market returns, whereas storms and floods have a lesser impact. Furthermore, these effects were more pronounced on the event date, followed by some subsequent adjustments. Lastly, Pagnottoni et al. (2022) explore international contagion effects, studying the repercussions of natural disaster shocks on stock market indexes in Europe, Asia, and America. They find that climate-related disasters in Europe have a negative impact on stock market indexes, even affecting geographically distant countries.

The remainder of the paper is structured as follows. In Section 2, we illustrate the econometric approach based on linear and non-linear local projection methods and describe the data used in the analysis. Section 3 presents and discusses our results. Section 4 concludes. Robustness checks and additional analyses are reported in Appendix A.

2 | Methods and Data

This section discusses the methods and data employed in our analysis. Section 2.1 presents our econometric strategy based on local projections. Sections 2.2, 2.3, and 2.4 discuss financial, transition risk, and climate-related disaster data, respectively. Finally, Section 2.5 presents our control variables.

2.1 | Local Projections

The local projection (LP) method (Jordà 2005) allows the estimation of dynamic impulse responses by estimating a series of univariate regressions for each horizon h for each variable. In particular, the linear model is defined as follows:

$$y_{t+h} = \alpha_h + \beta_h x_t + \Psi_h(L) z_{t-1} + \epsilon_{t+h} \quad , \quad \text{for } h = 0,1,2, \ldots \quad (1)$$

where y_t is the variable of interest, x_t is the identified shock, z_t is a vector of control variables (including the lags of the dependent variable and the lags of the shock), and $\Psi(L)$ is a polynomial in the lag operator. It is important to note that the shock of interest in the analysis—severe climate-related disasters—can be considered as exogenous. This exogeneity allows us to avoid the need for external instruments and the Local Projection Instrumental Variables (LP-IV) approach proposed by Stock and Watson (2018). Since the coefficient β_h provides the response of y at time $t+h$ to the shock at time t, impulse response functions are obtained as a sequence of the $\beta_h' s$ estimated for each horizon $h = 0,1,2, \ldots$. This method is a recent alternative to the traditional structural VAR (SVAR) modeling approach to construct the impulse response functions. Local projections rely on single-equation methods, making them particularly suitable for analyses involving nonlinearities or state-dependence (Jordà and Taylor 2024), which is crucial for our study. Plagborg-Møller and Wolf (2021) prove a general equivalence of the local projection and SVAR impulse response function estimations when the number of lags used as controls is sufficiently large.[6]

Ramey and Zubairy (2018) show that the LP method can be easily adapted to capturing non-linearities in the responses by estimating a set of state-dependent regressions for each horizon h as follows:

$$\begin{aligned} y_{t+h} &= \left(1 - I_{t-1}\right)\left[\alpha_{0,h} + \beta_{0,h} x_t + \Psi_{0,h}(L) z_{t-1}\right] \\ &\quad + I_{t-1}\left[\alpha_{1,h} + \beta_{1,h} x_t + \Psi_{1,h}(L) z_{t-1}\right] + \epsilon_{t+h} \end{aligned} \quad (2)$$

where I_t is a dummy variable that discriminates the state when the shock occurs. In our framework, I_t takes value 1 when a disaster is occurring at time t and 0 otherwise. Therefore, the (non-linear) responses of y are allowed to be different in the two states, that is, when a disaster is occurring ($I_t = 1$) and in "normal" times ($I_t = 0$), and we will not find evidence of non-linear effects when $\beta_{0,h} = \beta_{1,h}$ in (2), for $h = 0,1,2, \ldots$. Despite being a widely used tool in macroeconomic analysis, mostly appreciated for its simplicity, flexibility, and robustness to model misspecifications (see, e.g., Ramey 2016), LP method presents some drawbacks and limitations. In particular, Herbst and Johannsen (2021) show that the use of LPs with persistent time series and small sample sizes can lead to biased point estimates of the impulse responses. Moreover, within the state-dependent framework in (2), Gonçalves et al. (2023) point out that, if the state is endogenous, the LP estimator is unable to recover the population response. Note, however, that these limitations do not apply to our analysis. First, the daily time series we use is long and not persistent (see Table 2 and discussion in Section 2.6). Second, since the shocks of interest, that is, severe climate-related disasters, can be considered as exogenous, the CDS impulse response functions do not depend on the state regarding the occurrence of shocks.

2.2 | Financial Data

To investigate whether and how the exposure to transition risk affects firms' credit risk, we use the 5-year CDS index constructed by Refinitiv Datastream for North America (NA), and Europe (EU) Energy companies as dependent variables.[7] As CDS contracts reflect the market price for the underlying asset's credit risk, they incorporate a risk premium that allows us to study to what extent this risk premium is affected by the exposure to climate transition risk.

Our analysis commences in 2010, to exclude the effects of the 2008 financial crisis, and concludes at the beginning of 2020, to exclude the pandemic shock, for a total of $T = 2631$ observations. Figure 1 depicts the evolution of the DataStream Energy 5-year CDS indices for the North American and the European companies during the considered period. The main descriptive statistics are shown in the upper portion of Table 1. Interestingly, one of the biggest increases in the CDS index is recorded just after the conclusion of the UN Climate Change Conference (COP21) held in Paris, on December 12, 2015, which led to the stronger-than-expected Paris Agreement.

2.3 | Transition Risk Indices

To capture transition risks, we employ two media-based indices: (i) the Transition Risk Index (TRI) developed by Bua et al. (2024), with a European focus; and (ii) the Media Climate Change Concerns (MCCC) index by Ardia et al. (2023), with a focus on the United States.[8] The dynamics of these indices are depicted in Figure 2, while the descriptive statistics are reported in Table 1.

Bua et al. (2024) develop indicators for both physical and transition risks. Their underlying corpus of text is extracted from Reuters News articles (in English) focusing on the European region. After having constructed two vocabularies for each of the two dimensions (physical and transition) based on authoritative text, the authors compare the vocabularies and media news using cosine similarity.[9] We here focus only on the one focusing on transition risks (TRI). To identify the unexpected change in climate change concerns and capture the shock component for the TRI transition risk index, we consider the standardized prediction errors from an autoregressive model with 11 lags and a linear deterministic trend estimated using an enlarged sample size from the beginning of 2005 to the end of 2022.[10]

Ardia et al. (2023) build instead on a corpus derived from widely circulated US newspapers and two major newswires (Associated Press Newswires and Reuters News). Authors compute their

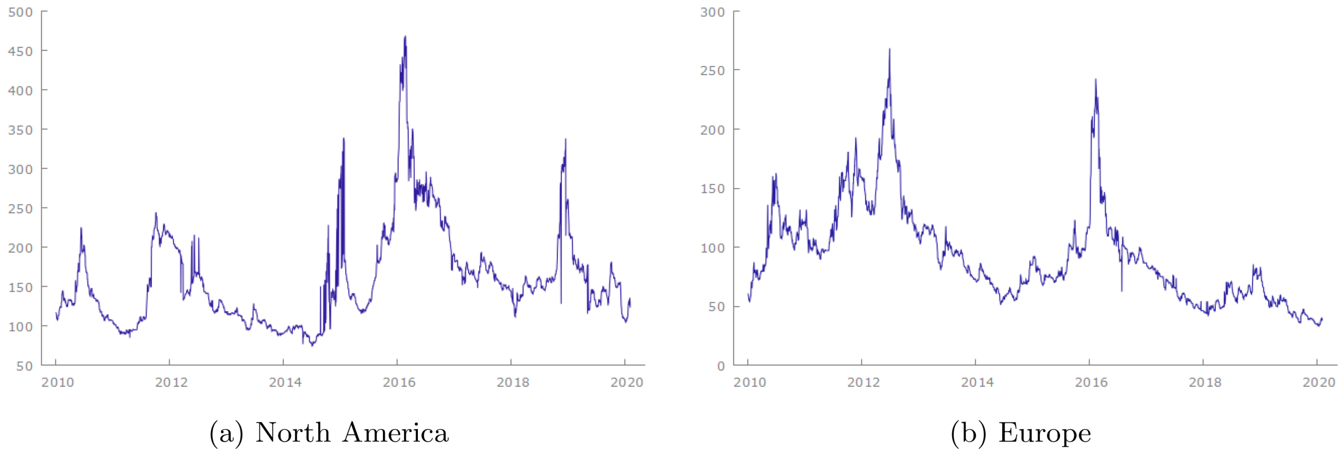
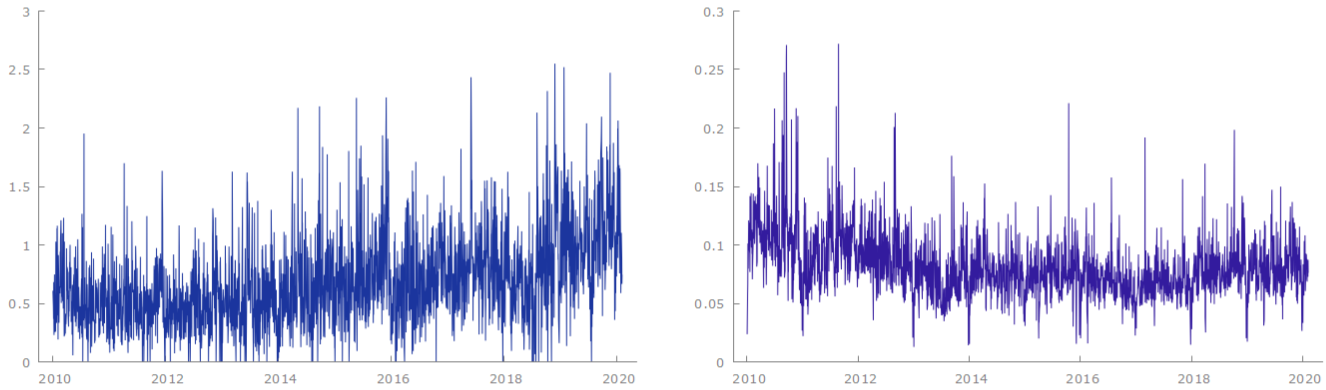


FIGURE 1 | Energy 5-year CDS indices for North America and Europe from January 4, 2010 to February 5, 2020. *Source:* Datastream.

TABLE 1 | Descriptive statistics for the variables considered in the analysis. Daily data from January 4, 2010 to February 5, 2020.

Variable	Mean	Median	SD	Min	Max
Dependent variables					
EU energy 5Y CDS	89.26	78.05	39.16	32.96	268.47
NA energy 5Y CDS	168.96	148.18	77.83	74.59	666.66
Climate concern indices					
TRI	0.081	0.078	0.026	0.013	0.272
MCCC	0.738	0.673	0.418	0.000	2.724
BusinessImpact	0.654	0.587	0.393	0.000	3.299
GovPrograms	0.665	0.528	0.516	0.000	6.207
Climate disaster dummies					
EU disasters	0.026	0.000	0.159	0.000	1.000
NA disasters	0.057	0.000	0.233	0.000	1.000
Control variables EU					
STOXX 600	0.020	0.049	1.06	−12.19	8.07
Brent	0.008	0.000	2.74	−64.37	41.20
EU Spread3M1D	0.244	0.157	0.273	−0.105	1.17
iTraxx	81.75	71.23	33.70	41.26	208.00
Control variables NA					
S&P-500	0.044	0.042	1.068	−12.77	8.97
WTI	0.027	0.000	2.64	−28.22	30.02
US Spread 3M1D	0.039	0.025	0.138	−4.88	0.61
CDX	75.39	69.82	21.08	43.86	149.87
US Gov 5Y CDS	17.73	15.39	9.06	5.47	47.99

daily MCCC index as the square root of the average of the standardized source-specific climate change concerns, where ‘concern’ captures the percentage of words related to risk and the scaled difference between negative and positive words. Using a Correlated Topic Model, the authors are also able to disaggregate their corpus into 30 distinct topics, which they aggregate into larger “themes” (Business impact, Environmental impact, Societal debate, Research). In our analysis, we complement the analysis of the aggregate MCCC index with the theme (Business impact) and topic (Government programs) that more closely represent transition risks, especially when driven by policies.[11] To identify the unexpected change in climate change concerns and capture the shock component for the MCCC transition risk, Ardia et al. (2023) use an augmented autoregressive (ARX) model, controlling for the potential effects of financial markets, energy-related, and macroeconomic variables. We instead consider the standardized prediction errors from the autoregression



(a) MCCC (North America) (b) TRI (Europe)

FIGURE 2 | Dynamics of the MCCC index (Ardia et al. 2023) and the TRI index (Bua et al. 2024). Daily data from January 4, 2010 to February 5, 2020.

with nine lags and a quadratic deterministic trend.[12] An analogous approach has been adopted to identify the shocks for the Business impact theme and the Government programs topic.

Interestingly, Figure 6 shows that the MCCC index remains relatively flat until approximately 2015, after which it follows an upward trend. In contrast, the TRI index primarily declines until 2014, then stabilizes, exhibiting only a modest overall increase—less pronounced than the uptrend in MCCC. According to Bua et al. (2024), the largest shock to the TRI coincides with news published on 24/08/2011, which highlighted alarmingly high EU GHG emissions requiring urgent reductions. This shock appears to have triggered a sustained downward trend in the TRI index, lasting until the end of 2015, around the time of the Paris Agreement. Following this milestone, growing concerns over climate change seem to have shifted the trend upward. A possible explanation involves the internalization of transition-related concerns by the media. As decarbonization evolves from a novel, disruptive idea to an established public perspective, the marginal impact of transition news may decline over time. Increasingly salient events may be required to make a significant impact on the news cycle. This could explain why, in Europe—where emission reduction became a policy focus earlier than in the United States—the trend differs. A substantial portion of transition risk news may have already been internalized by both the media and the public in previous years.

2.4 | Climate Disaster Dummies

We construct a binary indicator to identify temporal periods impacted by notable climate-related disasters in Europe and North America. These encompass droughts, extreme temperatures, floods, glacial lake outbursts, landslides, storms, and wildfires. Our analysis relies upon the International Emergency Events Database (EM-DAT), a comprehensive repository regularly updated by the Centre for Research on the Epidemiology of Disasters (CRED).[13] We aim to investigate the extent to which the incidence of major climate disasters, leading to a consistent number of casualties and damages, can influence the perception of transition risk.

To create our indicator, we aggregate the presence of each disaster and its corresponding impact at the daily level, enabling an evaluation of their magnitude. Two key measures are used to capture the intensity of each disaster: the number of total deaths and the estimated damages (denominated in thousands of US dollars). To identify the most severe disasters, we consider the interaction between the two measures, requiring both to exceed the 75th percentile for Europe and the 90th percentile for North America. The choice of adopting different thresholds to identify the most severe climate-related disasters in NA and EU lies in the different multiplicity and duration of these episodes in the two regions. As shown by the means reported in Table 1, the sample frequencies for the identified disasters in EU and NA are 2.6% and 5.7%, respectively. Therefore, despite the threshold used for EU is smaller than the one adopted for NA, the number of days in our sample in which we observe a major climate-related disaster in EU is less than half the number of days spotted in NA. Indeed, we find that the episodes recorded in NA are more long-lasting than EU, and thus overall we observe a higher number of days impacted by climate-related disasters in North America. We compute the percentile values using the historical data encompassing the period from 2000 to 2022. We select a longer time frame compared to the one used in our analysis to capture possible trends in recent years, where the number of disaster episodes and/or their severity may have increased. We derive a dichotomous dummy variable that captures the days affected by the most intense climate-related disasters within the examined time frame (from 2010 to 2020).[14] When a disaster occurs during a non-trading day, we postpone it to the first trading day available in our sample. This is because we expect that the reaction (if any) of the financial market to a transition risk shock happened during a non-trading day would materialize as soon as the market reopens. In finance, this is a stylized fact known as the "weekend effect." According to the conditions listed above, the disaster events that we consider in our analysis are those with more than 14 deaths and 681,454,750 USD of damages for EU and more than 45 deaths and 7,735,658,000 USD of damages for NA. Additionally, we perform the analysis with broader thresholds, specifically using the 60th percentile for Europe and the 80th percentile for the United States, to include more disaster events. The results with these thresholds are provided in "Analysis With Broader Disaster Thresholds" of Appendix A.

2.5 | Control Variables

In the LP analysis, we include a set of control variables in vector z_t in (1) and (2). The list and descriptive statistics of these variables are reported in the bottom portion of Table 1.

Specifically, for the North American CDS index, we control for: (i) the stock market dynamics proxied by the daily percentage (log-)return on the S&P 500 index; (ii) the overall corporate credit market risk proxied by the (5-year) CDX Index composed of 125 of the most liquid North American companies with investment grade credit ratings; (iii) the spread between the Federal Reserve 3-month and the overnight interest rates (Spread3M1D) as a proxy for both credit risk and market liquidity in the US; (iv) the sovereign credit risk proxied by the US 5-year CDS index; and (v) the (log-)change in the West Texas Intermediate (WTI) crude oil price.

The controls employed for the European CDS index are: (i) the stock market dynamics proxied by the daily percentage (log-)return on the Eurostoxx 600 index; (ii) the overall corporate credit market risk proxied by the (5-year) iTraxx index of the 125 most liquid European companies with investment-grade credit ratings; (iii) the spread between the Euribor 3-month and the Eonia (overnight) interest rates (EUSpread3M1D) as a proxy for both credit risk and market liquidity in Europe; and (iv) the (log-)change in the Brent crude oil price.

In the cross-border analyses presented in Section 3.3, we incorporate controls for the corresponding CDS market, as detailed in Table 1, while examining transition risk index shocks and climate-related disasters in the other region. Specifically, while the dependent variable y_t and controls z_t in (1) and (2) pertain to one region, the shock x_t and the disaster dummy variable I_t correspond to the other region.

2.6 | Unit Root Tests

As mentioned in Section 2.1, the use of LPs with persistent time series can result in biased point estimates of the impulse responses (Herbst and Johannsen 2021), and the LP framework generally assumes covariance stationarity (see, e.g., Plagborg-Møller and Wolf 2021).

To address this, we first investigate the presence of unit roots in the variables used in our analysis. Specifically, we employ several unit root tests, including the Augmented Dickey-Fuller (ADF) test, which accounts for lagged differences to address serial correlation; the Phillips-Perron (PP) test, which handles serial correlation and heteroskedasticity in the error terms; the Zivot-Andrews (ZA) test, which allows for a single endogenous structural break in the time series; and the Elliott-Rothenberg-Stock (ERS) test, which is similar to the PP test but is more powerful for detecting unit roots. In all these tests, the null hypothesis is non-stationarity.

The results, summarized in Table 2, show that most time series satisfy the covariance stationarity assumption, as the null hypothesis of non-stationarity is generally rejected at least at the 10% significance level. However, there are exceptions. The European Energy 5-year CDS index is found to be non-stationary in two out of four tests (ZA and ERS). Notably, extending the sample to the end of 2022 provides strong evidence of stationarity. Evidence of non-stationarity also arises for the iTraXX index, used as a control for Europe, but only in the ERS test (not in the other three tests). The spread between the 3-month and overnight interest rates in Europe (EUSpread3M1D) is identified as non-stationary in all tests except ZA. Importantly, excluding the EUSpread3M1D variable from the analysis produces results consistent with those reported in Section 3. This robustness supports the validity of our findings despite these isolated cases of non-stationarity.

3 | Results

This section presents and discusses the results of our empirical analysis. We start by employing linear local projections (Section 3.1) and later move to a non-linear analysis with the inclusion of climate disasters (Section 3.2). Finally, we consider the spillover effects between North America and Europe by investigating the cross-border effects in Section 3.3. Additional analyses and robustness checks are discussed in Appendix A. Moreover, all numerical results are reported in the tables in "Beta Coefficient Tables" Appendix A.

3.1 | Linear Local Projections

Figure 3 depicts the impulse responses, for $h = 0, 1, \ldots, 20$, of the 5-year CDS for the Energy companies in North America and Europe using the linear LPs in (1), with four lags for the controls. The four panels report the results for the two aggregate indicators (MCCC for US and TRI for Europe) and for the two sub-indices of MCCC more closely related to transition risks (Business impact theme and Government programs topic).

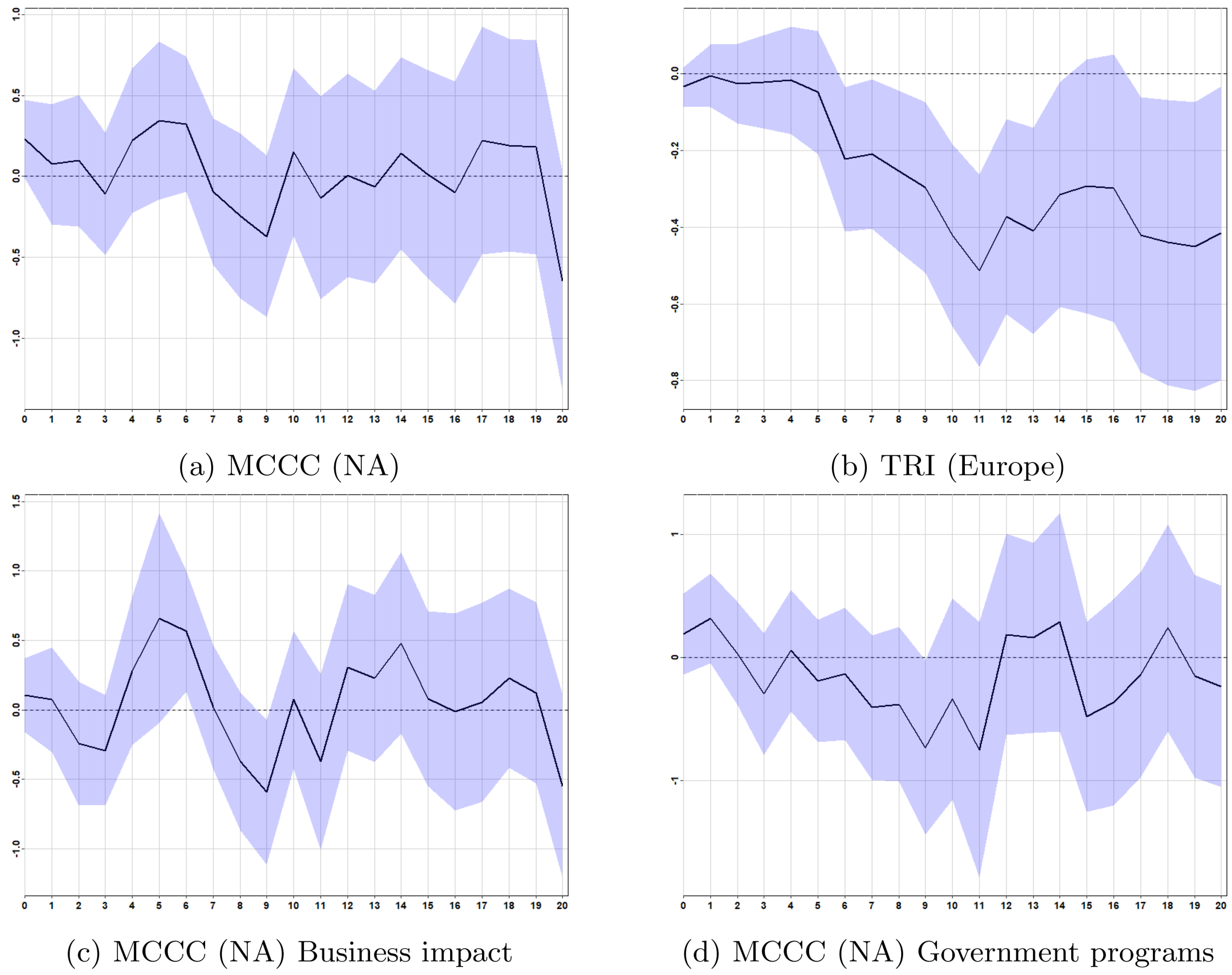
First, let us focus on the impact of MCCC shocks in North America (Figure 3a,c,d). We find very mild evidence of significant responses to a (one standard deviation) transition risk shock for the North America 5-year CDS index. Specifically, we only find that a shock of the Business impact theme leads to a positive response of the NA Energy 5-year CDS after six trading days. No significant results can be found for both the aggregate MCCC index and the selected topic Government programs.

Conversely, the response of the European 5-year CDS index to a one standard deviation shock of the transition risk index (TRI) is more evident, albeit of the opposite sign compared to expectations (Figure 3b). In particular, we find that the impact is not significant in the short-run, not even instantaneously, and becomes negative (and significant at 68% level) after six trading days after the transition risk shock occurred. Moreover, such negative impact has not fully reabsorbed even after $h = 20$ trading days. Therefore, a shock on the TRI index provides a puzzling evidence of a reduction of the (medium-run) credit risk for the European energy companies. The latter result is rather counter intuitive, as we would expect a shock of the transition risk to negatively affect the credit risk of "dirty" companies.

TABLE 2 | Unit root test results for the variables considered in the analysis. Daily data from January 4, 2010 to February 5, 2020.

Variable	ADF	PP	ZA	ERS
EU Energy 5Y CDS	−3.251**	−3.451***	−4.134	7.483
NA Energy 5Y CDS	−6.137***	−6.358***	−7.709***	0.827***
TRI	−35.083***	−49.335***	−28.883***	0.084***
MCCC	−37.151***	−53.097***	−31.049***	0.068***
BusinessImpact	−37.490***	−54.293***	−31.595***	0.095***
GovPrograms	−36.668***	−51.446***	−31.098***	0.099***
STOXX 600	−36.792***	−49.729***	−30.136***	0.034***
Brent	−35.779***	−50.314***	−29.802***	0.094***
EU Spread3M1D	−2.002	−2.008	−7.336***	22.294
iTraXX	−3.706**	−3.359*	−5.386**	13.172
S&P-500	−36.523***	−54.295***	−31.352***	0.055***
WTI	−37.251***	−54.766***	−30.441***	0.113***
US Spread3M1D	−21.039***	−35.081***	−19.438***	0.283***
CDX	−4.339***	−3.901**	−5.225**	5.242**
US Gov 5Y CDS	−6.640***	−8.636***	−7.335***	1.683***

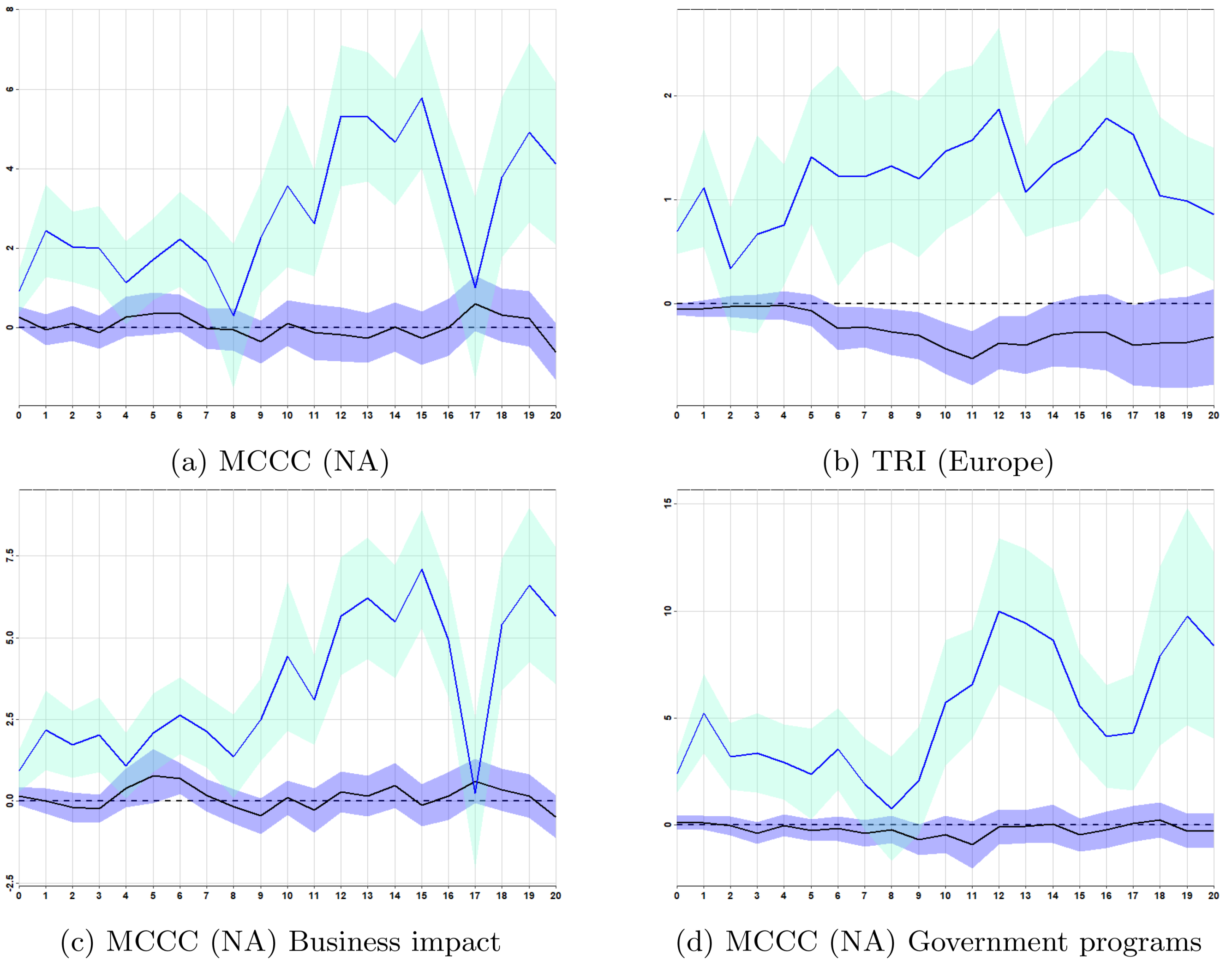
Note: ***, **, * denote significance levels at 1%, 5%, and 10%, respectively. Results for the climate concern indices are related to their standardized shocks (see Section 2.3 for details).



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

FIGURE 3 | LPs for the baseline (linear) model in (1) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. HAC confidence intervals are reported at the 68% significance level.



(a) MCCC (NA)

(b) TRI (Europe)

(c) MCCC (NA) Business impact

(d) MCCC (NA) Government programs

FIGURE 4 | LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.

These results, that is, the mild significance of the responses in NA and the reversed effect in EU, call into question the ability of the linear specification in (1) to properly capture the responses of the CDS to shocks on the transition risk.

3.2 | Non-Linear Local Projections

We now consider the non-linear LPs using the state-dependent regression in (2). Here the interaction variable I_t is defined as the occurrence of a major climate-related disaster (using the dummy variables defined in Section 2.4) to investigate whether the energy companies' credit risk responds differently to a transition risk shock when also physical risk (proxied by the occurrence of a disaster) kicks in.

Figure 4 shows the non-linear LPs for the North American 5-year CDS index to a (one standard deviation) shock of the aggregate MCCC index (Figure 4a), the Business impact theme (Figure 4c), and the Government programs topic (Figure 4d), and the LPs for the European 5-year CDS index to a shock of the TRI index (Figure 4b). The results in Figure 4 show evidence of non-linear effects for the energy companies' credit risk when, in addition to transition risk, also a severe climate-related disaster occurs (brighter lines), with respect to periods when no major disaster is ongoing (darker lines). This evidence is further supported by Figure 5, which plots the difference between $\beta_{1,h}$ and $\beta_{0,h}$ for $h = 0, 1, \ldots, 20$.

First, let us focus on the impact of MCCC shocks in North America. We note that, in the absence of a major climate-related disaster (depicted in darker lines and confidence bands in Figure 4), that is, when only transition risk is accounted for by the market, the reaction is very close to zero and, in general, not significant for all the indices considered. This highlights that, overall, the credit risk of North American energy companies is not actually affected by shocks of transition risk per se. However, the impact increases (and significantly so) when also a major climate-related disaster occurs. In particular, as can be seen by the brighter lines and confidence bands in Figure 4a,c,d, the combination of transition risk and climate-related disaster causes an instantaneous ($h = 0$) and short-run ($h = 1$,2,3) positive response. Moreover, we

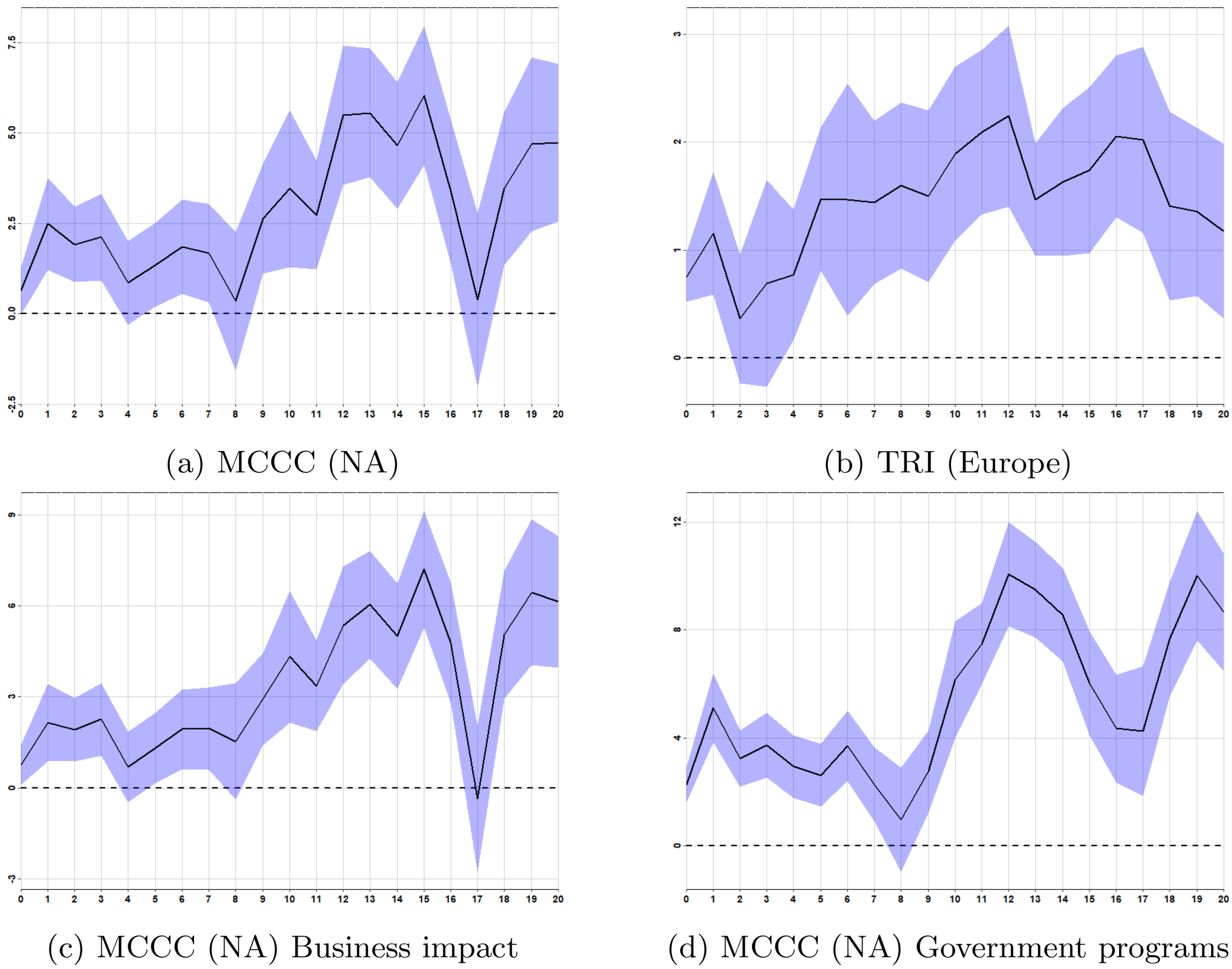
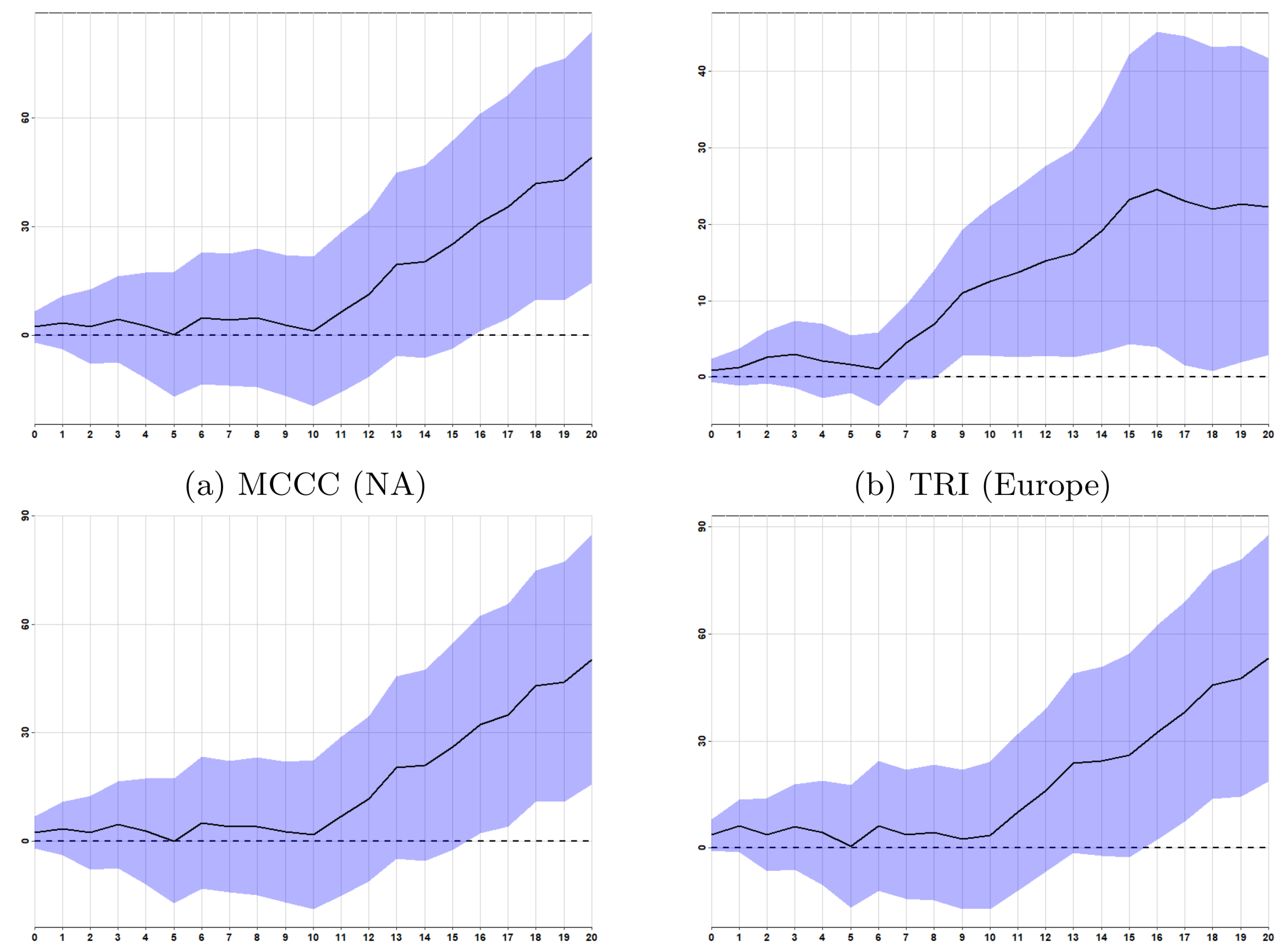


FIGURE 5 | Difference $(\beta_{1,h} - \beta_{0,h})$ for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. HAC confidence intervals are reported at 68% significance level.

find evidence of a positive and significant response of the North American 5-year CDS index also after nine trading days after the transition risk shock, when this takes place in combination with the occurrence of a severe climate-related disaster. Such effect is not absorbed even after $h = 20$ trading days (and becomes again significant for $h = 18, 19$ for Business impact theme and Government programs topic). From these results, we note that the strongest effect is found for the Government programs topic of the MCCC index, where the distance between the LPs with and without major disasters is more pronounced. This is highlighted by the large, significant difference between $\beta_{1,h}$ and $\beta_{0,h}$, for $h = 0, \ldots, 20$, as shown in Figure 5. Interestingly, these effects remain significant up to $h = 50$ trading days, as evidenced in Figure A2 in "Longer Time Periods" of Appendix A.

The presence of non-linear responses is also evident for the European CDS index. In particular, Figure 4b shows that the credit risk response for the EU energy companies increases significantly in the presence of a severe climate-related disaster, highlighting that the credit markets react to (the materialization of) physical risks. Indeed, we find evidence of a positive and significant instantaneous response ($h = 0$), after $h = 1$ trading day and for h between 4 and 20—see the brighter lines and confidence bands in Figure 4b. Conversely, the impact of a transition risk shock when no major disasters occur (darker lines and confidence bands in Figure 4b) basically retraces the dynamics obtained using the linear model depicted in Figure 3b.

One may argue that the presence of a severe climate-related disaster per se is the main cause for the reaction of the CDS markets. To account for this, in Figure 6 we show the difference between the intercepts in model (2), $\alpha_{1,h} - \alpha_{0,h}$, and the corresponding 68% confidence intervals. These plots allow us to capture the impact on the (unconditional) CDS index mean when a disaster occurs, independently of the transition risk. Therefore, if this difference is positive and significant, then the 5-year CDS index increases on average as a consequence of the materialization of a major climate-related disaster per se. For North America, we observe that the estimated difference between the two intercepts is generally always positive, albeit not significant in the short-run (up to $h = 16$ trading days), and becomes significant afterward for all the MCCC-based indices considered (see Figure 6a,c,d). This



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

FIGURE 6 | Difference $(\alpha_{1,h} - \alpha_{0,h})$ for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. HAC confidence intervals are reported at 68% significance level.

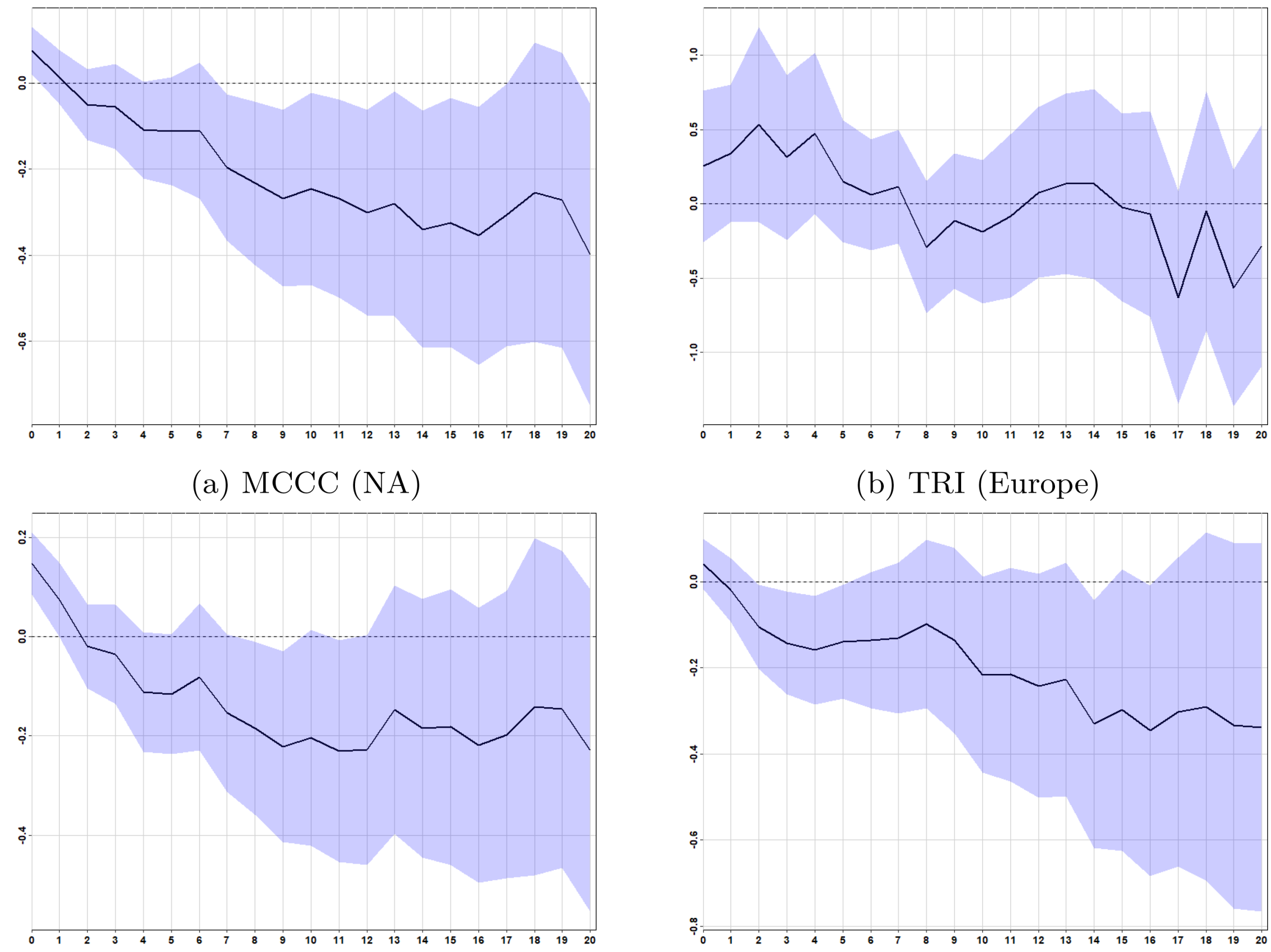
evidence highlights that the North American CDS index (unconditional) mean is indeed affected by major climate-related disasters, independently of transition risks, in the mid-run and that this effect is still present after $h = 20$ trading days. Similarly, for Europe, we find evidence of mid- and long-run unconditional effects: Figure 6b shows that the difference $\alpha_{1,h} - \alpha_{0,h}$ becomes significant after $h = 8$.

3.3 | Cross-Border Effects Between CDS Markets

As an additional step of our analysis, we consider whether cross-border effects between the NA and EU CDS markets are present.[15] In particular, we investigate whether a shock of the European (North American) transition risk index has an impact on the North American (European) energy companies' CDS, with—and without—the presence of a severe climate-related disaster in Europe (North America). Hence, we consider both the linear and non-linear LPs in (1) and (2), where the dependent variable (y_t) is the CDS index of one region (either NA or EU) while the transition risk shock (x_t) and, in the case of the state-dependent regression in (2), the climate-related disaster $(I_t = 1)$ occur in the other region.

Figures 7 and 8 show the results for the linear and non-linear LPs, respectively. The linear impulse responses, for $h = 0, 1, \ldots, 20$, of the 5-year CDS for the Energy companies in Europe following a one standard deviation shock in the North American MCCC index, as well as in the two sub-indices for the Business impact theme and the Government programs topic, are reported in Figure 7a,c,d, respectively. From these results, we find (mild) evidence of a positive and significant instantaneous ($h = 0$) (linear) cross-border effect for the EU energy companies' credit risk after a shock of the aggregate MCCC index and Business impact (but not Government programs). However, these cross-border effects become negative (and often significant) in the following trading days. Conversely, the impact of a shock of the European TRI index on the North American Energy companies CDS is generally not significant (see Figure 7b).

As for the cases discussed in Section 3.2, however, employing a state-dependent LP approach allows us to capture interesting non-linearities. In particular, the impulse responses depicted in Figure 8 shows that adding major climate-related disasters to the picture leads to a significant positive impact of the transition risk shock, even when such shock and disaster happen in



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

FIGURE 7 | Cross-effect LPs for the baseline (linear) model in (1) using MCCC index, Business Impact theme, and Government Programs topic shocks for Europe and TRI shock for North America. HAC confidence intervals are reported at the 68% significance level.

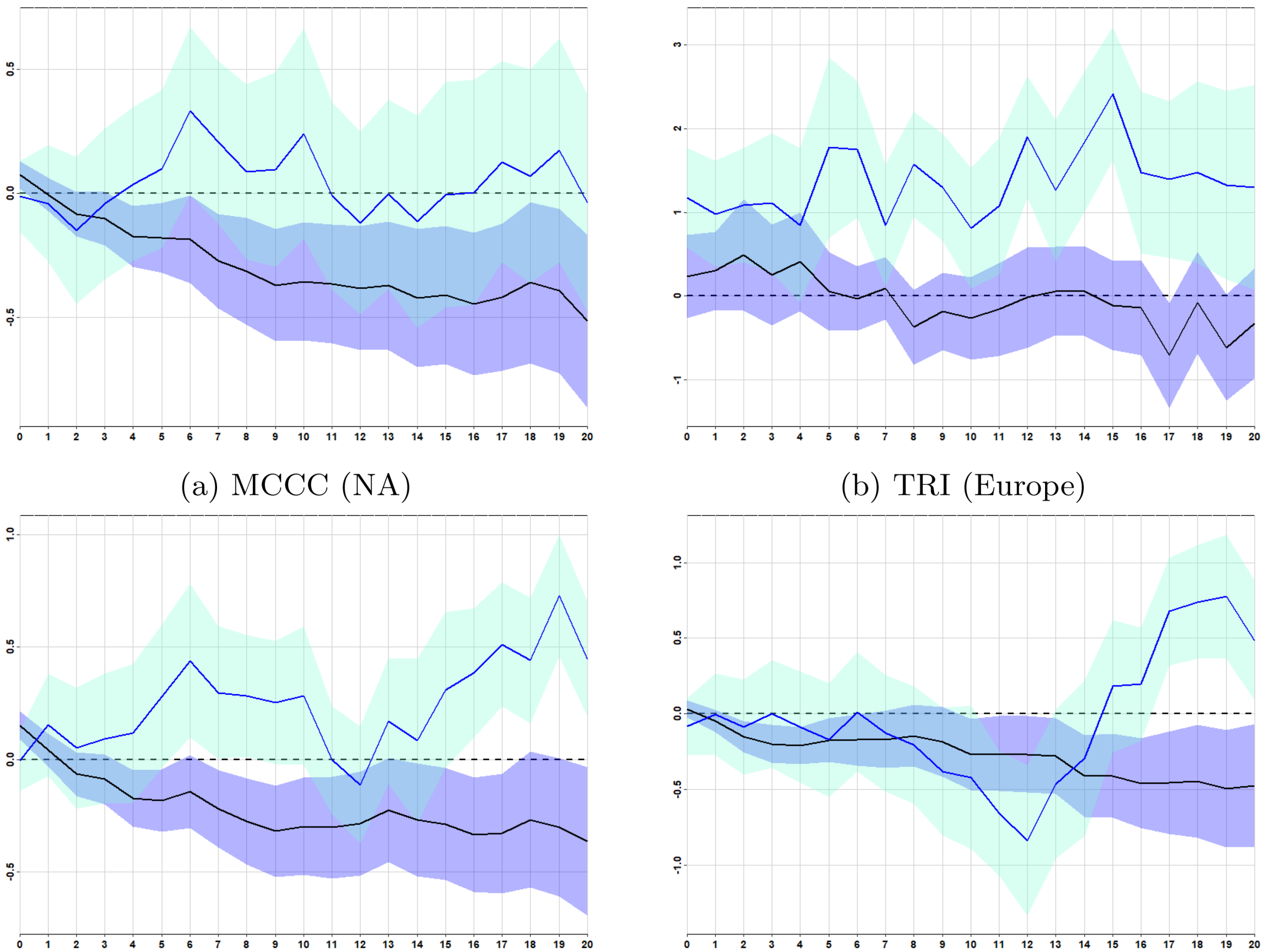
the other region. This evidence is much stronger in North America (Figure 8b) with respect to Europe (Figure 8a,c,d), where the cross-border effect of a TRI shock on the NA 5-year Energy companies' CDS index is found significantly positive for almost all $h = 0, 1, \dots, 20$. These results can be explained by multiple reinforcing factors. First and foremost, they are in line with the explicitly sought-after European global leadership in climate policies and green technological advancements. European pioneering policy stances have often signaled subsequent steps in the same direction by other jurisdictions (Oberthür and Dupont 2021). Second, Europe appears to be a key global hub for what concerns both supply chains in energy markets and financial market interlinkages. Our results are indeed consistent with those from Pagnottoni et al. (2022), who find that climate-related disasters in Europe have a particularly significant impact also on distant countries.

4 | Conclusions

A reasonable expectation exists that fossil- and carbon-intensive firms might be negatively affected by a low-carbon transition. It is still unclear, however, to what extent transition-related risks are internalized by financial investors. In this paper, we provide a novel investigation of the impact of media-based measures of transition risks on the credit risk of energy companies in both Europe and North America, as measured by their CDS indices.

Using both linear and non-linear local projections, we find that a shock in media-based transition risks affects CDS indices only when combined with tangible physical climate-related impacts. In other words, the prospect of transition-related losses as captured by the public debate is not salient per se for financial investors. It becomes salient only in the wake of climate-related disasters, which increase the likelihood of a policymaker implementing climate action. Our results are broadly consistent with the evidence found in equity markets, where an unexpected increase in climate change concern entails a market reaction that penalizes "dirty" companies (Pástor et al. 2021; Ardia et al. 2023).

Our analysis would benefit from a number of additional refinements. For instance, our regions of focus (Europe and North America) are large, with climate-related disasters affecting a specific territory not necessarily having an impact on the entire



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

FIGURE 8 | Cross-effect LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for Europe and TRI shock for North America. The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.

region. Although the empirical evidence we provide is significant, a more spatially disaggregated data would likely offer additional insights. Another possible limiting factor is related to the use of two distinct transition risk perception measures computed using different methods, begging the question of whether our results would be robust to the application of the same index to the two regions.

Despite these limitations, our findings offer valuable insights for policymakers and financial market participants. First, as is often the case in sustainable finance, our results underscore the critical need for enhanced disclosure of transition risks to enable markets to price them more effectively. Second, they emphasize the importance of preparedness for climate-related disasters, calling for robust policy efforts to advance both climate mitigation and adaptation strategies. Finally, they point financial analysts toward the necessity of integrating climate scenarios into credit risk models and developing sophisticated hedging strategies to manage transition risks effectively.

A promising avenue for future research lies in developing a theoretical framework to deepen the understanding of the mechanisms through which transition risk impacts energy firms' credit risk. Such a framework could complement the empirical findings presented in this paper by providing a structured analysis of the channels and factors at play, such as regulatory changes, market adaptations, and firm-level responses to transition dynamics. A further area for future research could involve the investigation of CDS bid-ask spreads. This data, when available, may provide additional insights into market liquidity and investor sentiment, potentially enhancing the understanding of risk beyond the scope of the current analysis.

Acknowledgments

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] While other sources of emissions exist (e.g., land use), the wide majority of greenhouse gas emissions stems from fossil-fuelled energy (GCP 2022).

[2] See Campiglio et al. (2023) for a recent overview of the literature.

[3] CDS are financial contracts where three main parties are involved: (i) a borrower (in our case, the energy company) who issues a debt security and sells it to a lender willing to buy it; (ii) the lender, who purchases the bond and is, in principle, exposed to credit risk (i.e., the default of the borrower); and (iii) a third party investor, who sells a CDS contract to the lender, assuming the risk of default of the borrower, at a price. If a debt is covered by a CDS, the lender is covered by the risk of default of the borrower. CDS markets are often active and liquid, and tend to be very responsive to new information, possibly because dominated by professional investors, who are more likely to possess the analytical capacity to identify and internalize relevant information (Blanco et al. 2005; Longstaff et al. 2005).

[4] Non-linear—or compound—impacts of different sources of risk (in our case, transition, and physical) have been investigated in the sustainable finance literature. For instance, Gourdel et al. (2022) investigate the joint impact of transition and physical risks on European companies' investment decisions in the low-carbon transition, while Dunz et al. (2023) analyze the compounding of the pandemic and climate risks on banks' lending and government's policy. In this paper, we focus on transition risk and its combination with the realization of a severe climate-related disaster (materialization of physical risk), which may amplify the impact on the energy companies' credit risk of the transition risk alone.

[5] Faccini et al. (2023) have daily frequency data but their series ends at the end of 2018. Engle and Campos-Martins (2020), Kapfhammer et al. (2020) and Meinerding et al. (2022) all have data with monthly frequency. Bessec and Fouquau (2021) and Bessec and Fouquau (2022) have instead weekly data.

[6] Namely they show that LPs with p lags as controls and VAR(p) estimators agree approximately at impulse response horizons $h \leq p$.

[7] We consider the 5-year maturity indices as these CDS are the most liquid and traded on the market and, hence, the ones more rapidly and robustly responding to shocks.

[8] The MCCC index is freely available at https://sentometrics-research.com, while the TRI index is available at https://www.policyuncertainty.com/Climate_Risk_Indexes.html. We thank the authors of Bua et al. (2024) for sharing their data for an earlier version of this paper.

[9] Cosine similarity is a measure of similarity between two vectors defined as the cosine of the angle formed between the two vectors in the vector space. It is calculated by dividing the dot product of the two vectors by the product of their lengths.

[10] We have chosen to use an enlarged sample to construct the shock component, aiming to model the dynamics of the TRI index more accurately and estimate its shocks as effectively as possible by specifying the best possible autoregressive model to ensure non-autocorrelated residuals.

[11] The 10 top keywords for the Government programs topic are: project, money, fund, program, year, development, government, budget, funding, plan.

[12] Although their model is more general than ours, the AR(9) model with non-linear trend allows us to achieve non-autocorrelated residuals.

[13] EM-DAT documents and classifies natural disasters worldwide, offering detailed insights into their characteristics. The dataset is maintained by CRED/UCLouvain and is available at https://public.emdat.be.

[14] In both North America and Europe, a limited number of climate disasters, among those identified as the most severe, are characterized by an absence of specific initiation dates, with reference solely to the respective months. In the NA context, five such events occurred, all of which were droughts, as it is particularly challenging to establish the precise commencement and conclusion of these events. We thus conduct an investigation using the *New York Times* to determine whether there were articles pertaining to these particular occurrences. In two cases, where a clear starting date is unavailable, we assume the first day of the month as the starting point. Similarly, 17 major climate disasters with unspecified initiation dates took place in Europe. These are mainly extreme temperature variations, plus isolated instances of droughts, wildfires, and floods. Analogous to the approach taken in the NA context, we conduct a comprehensive online investigation encompassing diverse platforms and journals. In the absence of a distinct start date, precisely in 10 cases, it is assumed that disasters originated on the first day of the respective month.

[15] The international contagion of transition risk has garnered increasing attention. Espagne et al. (2023) study the cross-border risks faced by countries along the transition, proposing a taxonomy of these risks and analyzing the channels through which cross-border risks are transmitted. Carattini et al. (2022) also focus on this topic, finding the contagion of transition risk to be mainly due to financial frictions and cross-border banking flows.

References

Antoniuk, Y., and T. Leirvik. 2024. "Climate Change Events and Stock Market Returns." *Journal of Sustainable Finance & Investment* 14: 42–67. https://doi.org/10.1080/20430795.2021.1929804.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht. 2023. "Climate Change Concerns and the Performance of Green vs. Brown Stocks." *Management Science* 69, no. 12: mnsc.2022.4636. https://doi.org/10.1287/mnsc.2022.4636.

Barnichon, R., and C. Brownlees. 2019. "Impulse Response Estimation by Smooth Local Projections." *Review of Economics and Statistics* 101: 522–530. https://doi.org/10.1162/rest_a_00778.

Barth, F., B. Hübel, and H. Scholz. 2022. "ESG and Corporate Credit Spreads." *Journal of Risk Finance* 23: 169–190. https://doi.org/10.1108/JRF-03-2021-0045.

Bats, J. V., G. Bua, and D. Kapp. 2024. "Physical and Transition Risk Premiums in Euro Area Corporate Bond Markets." *ECB Working Paper Series* 2899: 1–31. https://doi.org/10.2139/ssrn.4712740.

Bauer, M. D., D. Huber, G. D. Rudebusch, and O. Wilms. 2022. "Where Is the Carbon Premium? Global Performance of Green and Brown Stocks." *Journal of Climate Finance* 1: 100006. https://doi.org/10.1016/j.jclimf.2023.100006.

Bessec, M., and J. Fouquau. 2021. "A Green Wave in Media, a Change of Tack in Stock Markets." https://doi.org/10.2139/ssrn.3924837.

Bessec, M., and J. Fouquau. 2022. "Green Attention in Financial Markets: A Global Warning." *Annals of Economics and Statistics* 148: 29–64. https://doi.org/10.2307/48706309.

Blanco, R., S. Brennan, and I. W. Marsh. 2005. "An Empirical Analysis of the Dynamic Relation Between Investment-Grade Bonds and Credit

Default Swaps." *Journal of Finance* 60: 2255–2281. https://doi.org/10.1111/j.1540-6261.2005.00798.x.

Blasberg, A., R. Kiesel, and L. Taschini. 2022. "Carbon Default Swap - Disentangling the Exposure to Carbon Risk Through CDS." In *Centre for Climate Change Economics and Policy Working Paper 416/Grantham Research Institute on Climate Change and the Environment Working Paper 391*, 1–67. London School of Economics and Political Science.

Bolton, P., and M. Kacperczyk. 2021. "Do Investors Care About Carbon Risk?" *Journal of Financial Economics* 142: 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008.

Bolton, P., and M. Kacperczyk. 2023. "Global Pricing of Carbon-Transition Risk." *Journal of Finance* 78: 3677–3754. https://doi.org/10.1111/jofi.13272.

Bourdeau-Brien, M., and L. Kryzanowski. 2017. "The Impact of Natural Disasters on the Stock Returns and Volatilities of Local Firms." *Quarterly Review of Economics and Finance* 63: 259–270. https://doi.org/10.1016/j.qref.2016.05.003.

Bua, G., D. Kapp, F. Ramella, and L. Rognone. 2024. "Transition Versus Physical Climate Risk Pricing in European Financial Markets: A Text-Based Approach." *European Journal of Finance* 30, no. 17: 1–35. https://doi.org/10.1080/1351847X.2024.2355103.

Campiglio, E., L. Daumas, P. Monnin, and A. von Jagow. 2023. "Climate-Related Risks in Financial Assets." *Journal of Economic Surveys* 37, no. 3: 950–992. https://doi.org/10.1111/joes.12525.

Carattini, S., G. Kim, G. Melkadze, and A. Pommeret. 2022. *Carbon Taxes and Tariffs, Financial Frictions, and International Spillovers*. American Economic Association/Allied Social Science Association Meetings.

Carbone, S., M. Giuzio, S. Kapadia, J. S. Krämer, K. Nyholm, and K. Vozian. 2021. "The Low-Carbon Transition, Climate Commitments and Firm Credit Risk." *ECB Working Paper Series* 2631: 1–68.

Christ, J., T. Hertel, and J. Kocian. 2022. "Corporate Sustainability Performance and the Cost of Debt – An Analysis of the Impact of Country- and Industry-Specific Climate Risk Exposures." *SSRN Electronic Journal* 2022: 1–63. https://doi.org/10.2139/ssrn.4135247.

Cortez, M. C., N. Andrade, and F. Silva. 2022. "The Environmental and Financial Performance of Green Energy Investments: European Evidence." *Ecological Economics* 197: 107427. https://doi.org/10.1016/j.ecolecon.2022.107427.

Dunz, N., A. Hrast Essenfelder, A. Mazzocchetti, I. Monasterolo, and M. Raberto. 2023. "Compounding COVID-19 and Climate Risks: The Interplay of Banks' Lending and Government's Policy in the Shock Recovery." *Journal of Banking & Finance* 152: 106306. https://doi.org/10.1016/j.jbankfin.2021.106306.

El Ouadghiri, I., K. Guesmi, J. Peillex, and A. Ziegler. 2021. "Public Attention to Environmental Issues and Stock Market Returns." *Ecological Economics* 180: 106836. https://doi.org/10.1016/j.ecolecon.2020.106836.

Engle, R. F., and S. Campos-Martins. 2020. "Measuring and Hedging Geopolitical Risk." *SSRN Electronic Journal* 2020: 1–27. https://doi.org/10.2139/ssrn.3685213.

Espagne, E., W. Oman, J. F. Mercure, et al. 2023. "Cross-Border Risks of a Global Economy in Mid-Transition." IMF Working Papers 2023, 1. https://doi.org/10.5089/9798400254550.001.

Faccini, R., R. Matin, and G. Skiadopoulos. 2023. "Dissecting Climate Risks: Are They Reflected in Stock Prices?" *Journal of Banking & Finance* 155: 106948. https://doi.org/10.1016/j.jbankfin.2023.106948.

GCP. 2022. "Global Carbon Budget 2022." Technical Report Global Carbon Project.

Gonçalves, S., A. M. Herrera, L. Kilian, and E. Pesavento. 2023. "State-Dependent Local Projections." Federal Reserve Bank of Dallas, Working Papers 2023. https://doi.org/10.24149/wp2302.

Gourdel, R., I. Monasterolo, N. Dunz, A. Mazzocchetti, and L. Parisi. 2022. *The Double Materiality of Climate Physical and Transition Risks in the Euro Area. ECB Working Paper 2665*. European Central Bank.

Herbst, E. P., and B. K. Johannsen. 2021. "Bias in Local Projections." *Finance and Economics Discussion Series* 2020: 1–62. https://doi.org/10.17016/FEDS.2020.010r1.

Hsu, P. H., K. Li, and C. Y. Tsou. 2023. "The Pollution Premium." *Journal of Finance* 78: 1343–1392. https://doi.org/10.1111/jofi.13217.

Huynh, T. D., and Y. Xia. 2021. "Panic Selling When Disaster Strikes: Evidence in the Bond and Stock Markets." *Management Science* 2021: 4018. https://doi.org/10.1287/mnsc.2021.4018.

Ilhan, E., Z. Sautner, and G. Vilkov. 2021. "Carbon Tail Risk." *Review of Financial Studies* 34: 1540–1571. https://doi.org/10.1093/rfs/hhaa071.

IPCC. 2023. "Summary for Policymakers." In *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by H. Lee and J. Romero, 34. IPCC.

Jordà, Ò. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95: 161–182. https://doi.org/10.1257/0002828053828518.

Jordà, Ò., and A. Taylor. 2024. *Local Projections. Technical Report w32822*. National Bureau of Economic Research. https://doi.org/10.3386/w32822.

Kapfhammer, F., V. H. Larsen, and L. A. Thorsrud. 2020. Climate Risk and Commodity Currencies. https://doi.org/10.2139/ssrn.3754679.

Kölbel, J. F., M. Leippold, J. Rillaerts, and Q. Wang. 2022. "Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks Affects the CDS Term Structure*." *Journal of Financial Econometrics* 22, no. 1: nbac027. https://doi.org/10.1093/jjfinec/nbac027.

Longstaff, F. A., S. Mithal, and E. Neis. 2005. "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From the Credit Default Swap Market." *Journal of Finance* 60: 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x.

Meinerding, C., Y. S. Schüler, and P. Zhang. 2022. Shocks to Transition Risk. https://doi.org/10.2139/ssrn.3654155.

Monasterolo, I., and L. De Angelis. 2020. "Blind to Carbon Risk? An Analysis of Stock Market Reaction to the Paris Agreement." *Ecological Economics* 170: 106571. https://doi.org/10.1016/j.ecolecon.2019.106571.

Oberthür, S., and C. Dupont. 2021. "The European Union's International Climate Leadership: Towards a Grand Climate Strategy?" *Journal of European Public Policy* 28: 1095–1114. https://doi.org/10.1080/13501763.2021.1918218.

Pagnottoni, P., A. Spelta, A. Flori, and F. Pammolli. 2022. "Climate Change and Financial Stability: Natural Disaster Impacts on Global Stock Markets." *Physica A: Statistical Mechanics and its Applications* 599: 127514. https://doi.org/10.1016/j.physa.2022.127514.

Pástor, Ľ., R. F. Stambaugh, and L. A. Taylor. 2021. "Sustainable Investing in Equilibrium." *Journal of Financial Economics* 142: 550–571. https://doi.org/10.1016/j.jfineco.2020.12.011.

Peillex, J., I. El Ouadghiri, M. Gomes, and J. Jaballah. 2021. "Extreme Heat and Stock Market Activity." *Ecological Economics* 179: 106810. https://doi.org/10.1016/j.ecolecon.2020.106810.

Plagborg-Møller, M., and C. K. Wolf. 2021. "Local Projections and VARs Estimate the Same Impulse Responses." *Econometrica* 89: 955–980. https://doi.org/10.3982/ECTA17813.

Ramelli, S., A. F. Wagner, R. J. Zeckhauser, and A. Ziegler. 2021. "Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections." *Review of Corporate Finance Studies* 10: 748–787. https://doi.org/10.1093/rcfs/cfab010.

Ramey, V. 2016. "Macroeconomic Shocks and Their Propagation." In *Handbook of Macroeconomics*, vol. 2, 71–162. Elsevier. https://doi.org/10.1016/bs.hesmac.2016.03.003.

Ramey, V. A., and S. Zubairy. 2018. "Government Spending Multipliers in Good Times and in Bad: Evidence From US Historical Data." *Journal of Political Economy* 126: 850–901. https://doi.org/10.1086/696277.

Stock, J. H., and M. W. Watson. 2018. "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments." *Economic Journal* 128: 917–948. https://doi.org/10.1111/ecoj.12593.

Worthington, A., and A. Valadkhani. 2004. "Measuring the Impact of Natural Disasters on Capital Markets: An Empirical Application Using Intervention Analysis." *Applied Economics* 36: 2177–2186. https://doi.org/10.1080/0003684042000282489.

Appendix A

Robustness Checks

Analysis With Broader Disaster Thresholds

We repeated the analysis by considering a broader set of disaster events, specifically adjusting the thresholds to the 60th percentile for Europe and the 80th percentile for North America. The disaster events included in this analysis are those with more than 7 deaths and damages exceeding 361,299 USD for Europe, and more than 22 deaths and damages exceeding 2,826,915 USD for North America. In this case, the percentages of disasters are 4.6% (15.5%) for EU (NA). As expected, the results depicted in Figure A1 show a lighter impact on the credit risk of energy firms for NA. Conversely, the impact for EU (Figure A1b) is similar to the one observed in Figure 4b.

Longer Time Periods

As shown in Figures 4 and 5, evidence of positive non-linear effects persists beyond $h = 20$ trading days following the shock. To investigate longer-term dynamics, we extend the analysis to $h = 50$ trading days ahead. The results, presented in Figures A2 and A3, for the non-linear LPs and the difference $\left(\beta_{1,h} - \beta_{0,h}\right)$, respectively, reveal moderate mid- to long-term impacts. These effects are particularly evident for shocks related to the Government Programs topic of the MCCC index in North America (see Figures A2d and A3d). Interestingly, and consistent with the (overall) linear response for the EU, we observe a slightly significant negative mid-run impact around $h = 30$ trading days for European energy companies. However, this impact dissipates within a few trading days, turns positive, and eventually becomes non-significant by $h = 50$ (see Figures A2b and A3b).

Smooth Local Projections

To enhance understanding of both linear and non-linear effects, this section presents all the non-linear LPs in Figures 4 and 8, smoothed using the B-spline smoothing methodology proposed by Barnichon and Brownlees (2019).

The results obtained by minimizing the penalized residual sum of squares through generalized ridge estimation are shown in Figures A4 and A5, for the linear and non-linear LPs, respectively.

Cumulative Local Projections

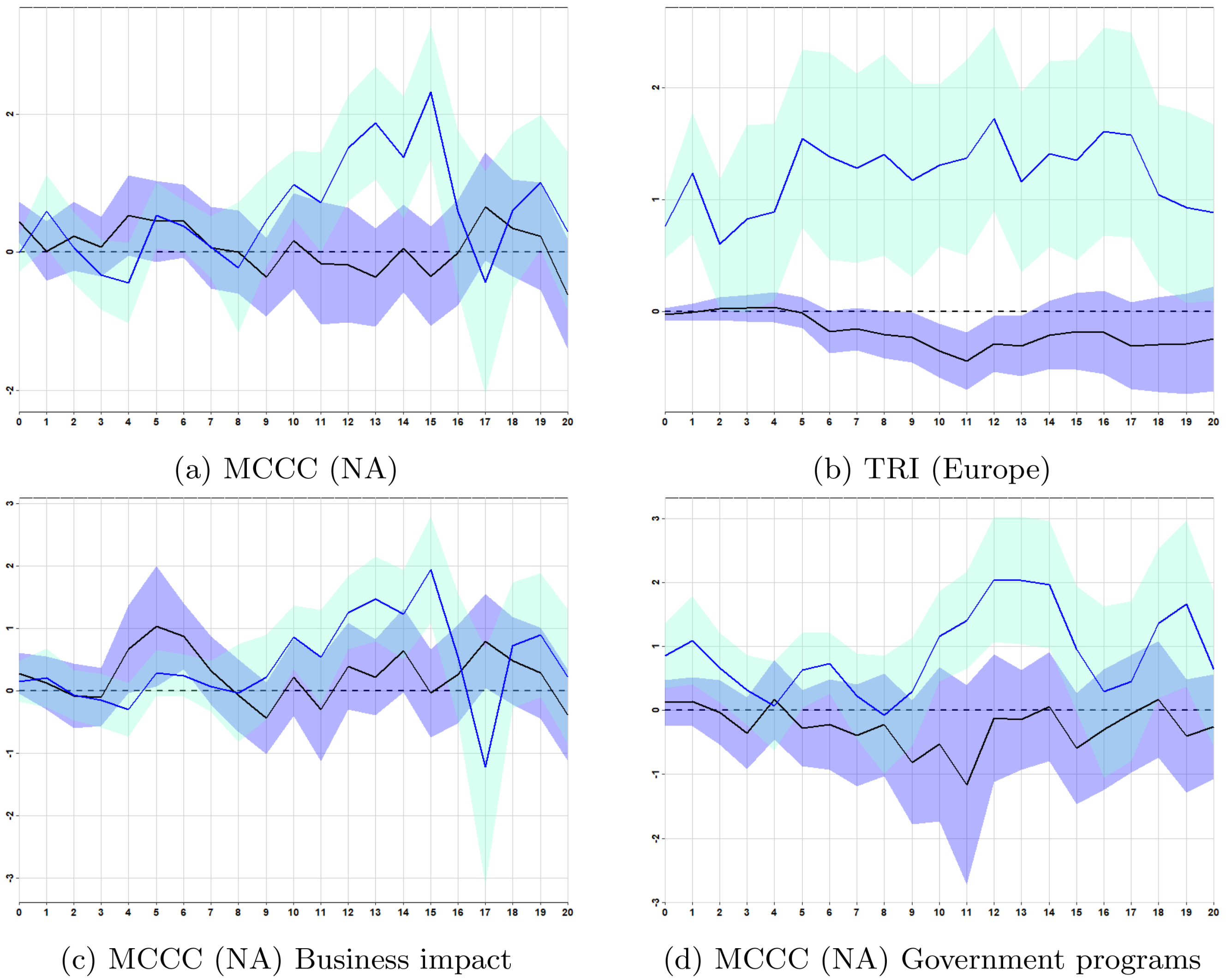
As the non-linear effects of the LPs depicted in Figures 4 and 5 persist beyond $h = 20$ trading days, and in some cases even beyond $h = 50$ trading days (see Figures A2 and A3), we extend our analysis to investigate the presence of long-run effects.

Specifically, we examine cumulative LPs, as outlined in Jordà and Taylor (2024). The results, presented in Figure A6 for $h = 50$, provide strong evidence of significant long-run effects when the transition risk combines with physical risk manifestations (i.e., severe climate-related disasters) in both North America and Europe.

Beta Coefficient Tables

This section reports the numerical results for the linear and non-linear LPs depicted in the figures.

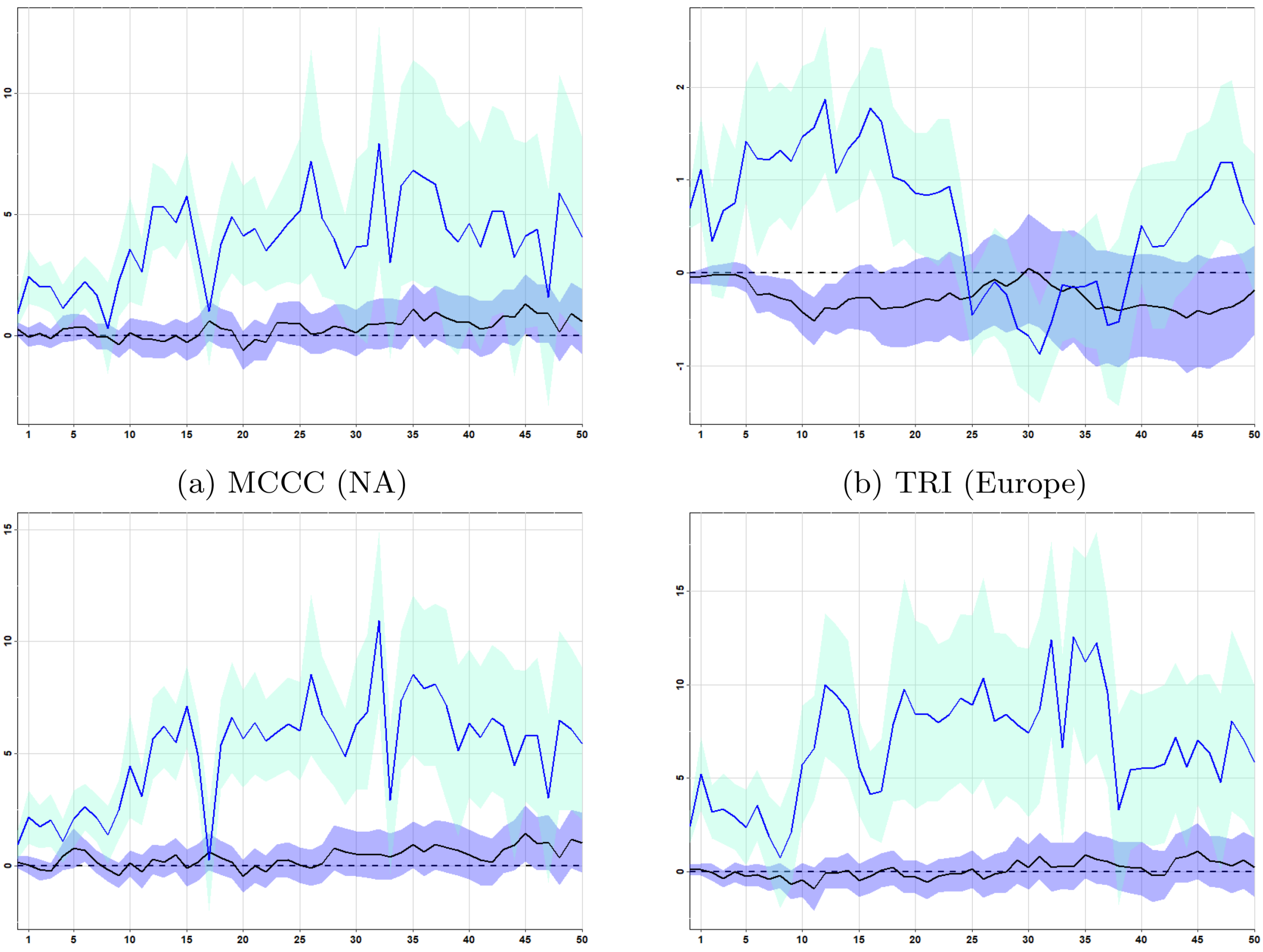
Table A1 presents the beta coefficients of the baseline linear model shown in Figure 3, $\beta_{0,h}$ and $\beta_{1,h}$ from the non-linear LPs depicted in Figure 4, along with their differences depicted in Figure 5. Table A2 provides the results from the cross-effect LPs illustrated in Figures 7 and 8.



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

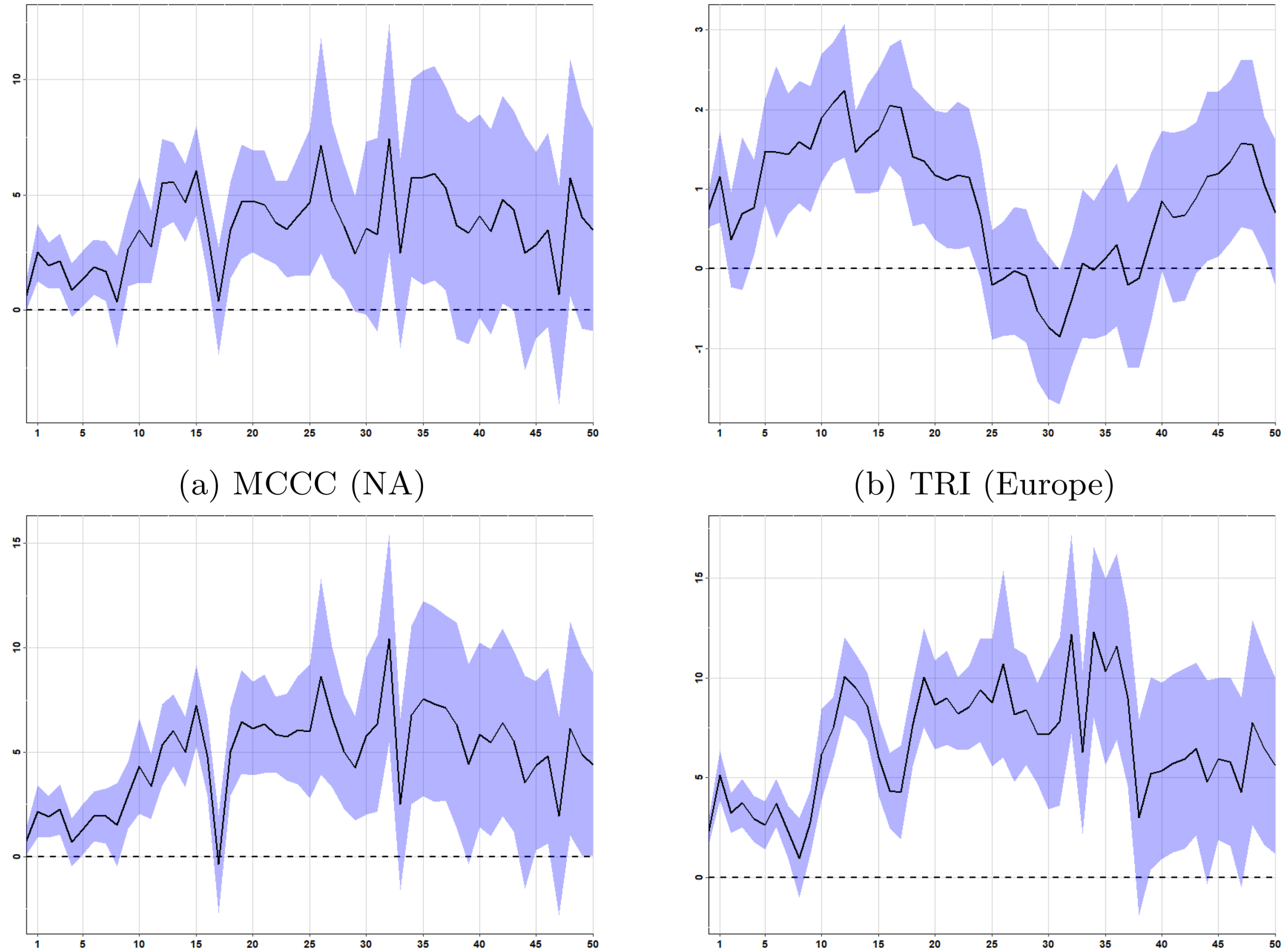
FIGURE A1 | LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe (using the 80th and 60th percentiles, respectively). The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.



(a) MCCC (NA) (b) TRI (Europe)

(c) MCCC (NA) Business impact (d) MCCC (NA) Government programs

FIGURE A2 | LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe for $h = 0, \ldots, 50$. The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.



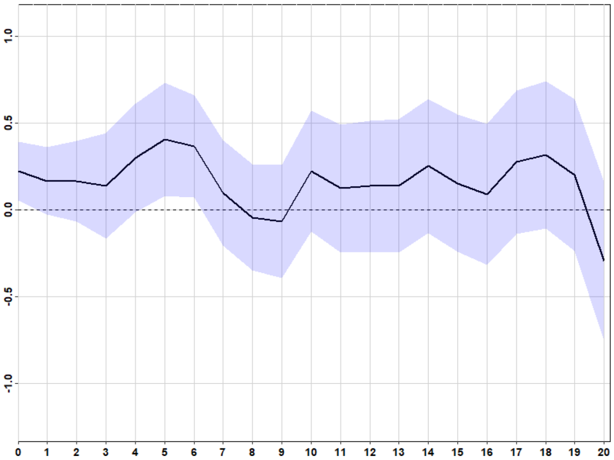
(a) MCCC (NA)

(b) TRI (Europe)

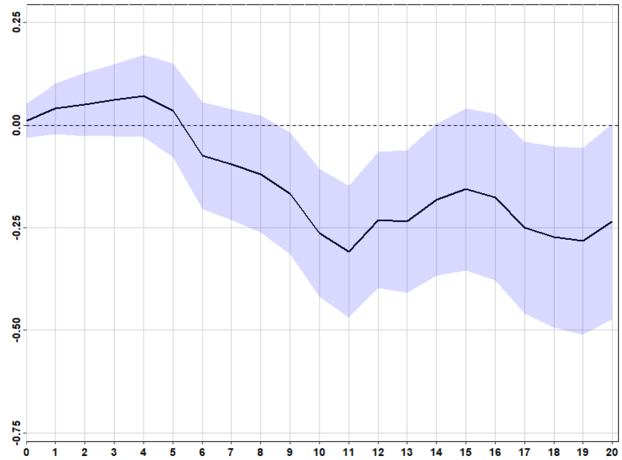
(c) MCCC (NA) Business impact

(d) MCCC (NA) Government programs

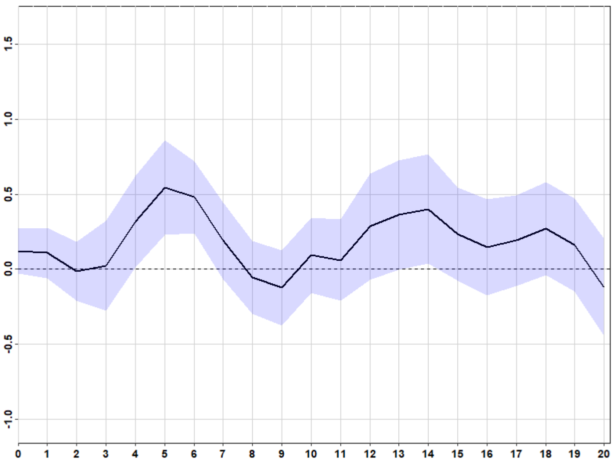
FIGURE A3 | Difference $(\beta_{1,h} - \beta_{0,h})$ for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe for $h = 0, \dots, 50$. HAC confidence intervals are reported at 68% significance level.



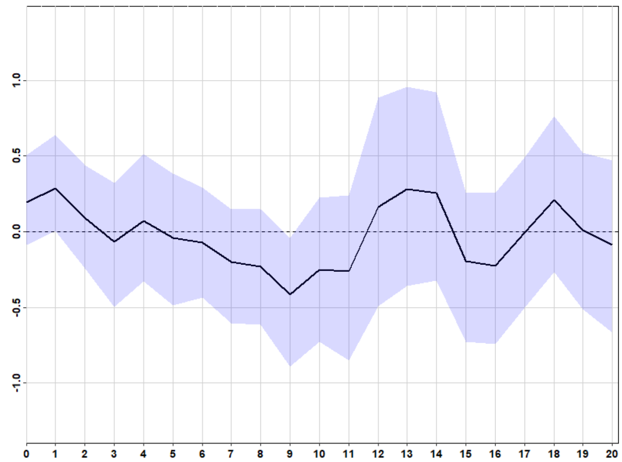
(a) MCCC (NA)



(b) TRI (Europe)



(c) MCCC (NA) Business impact



(d) MCCC (NA) Government programs

FIGURE A4 | Smoothed LPs for the linear model in (1) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. HAC confidence intervals are reported at 68% significance level.

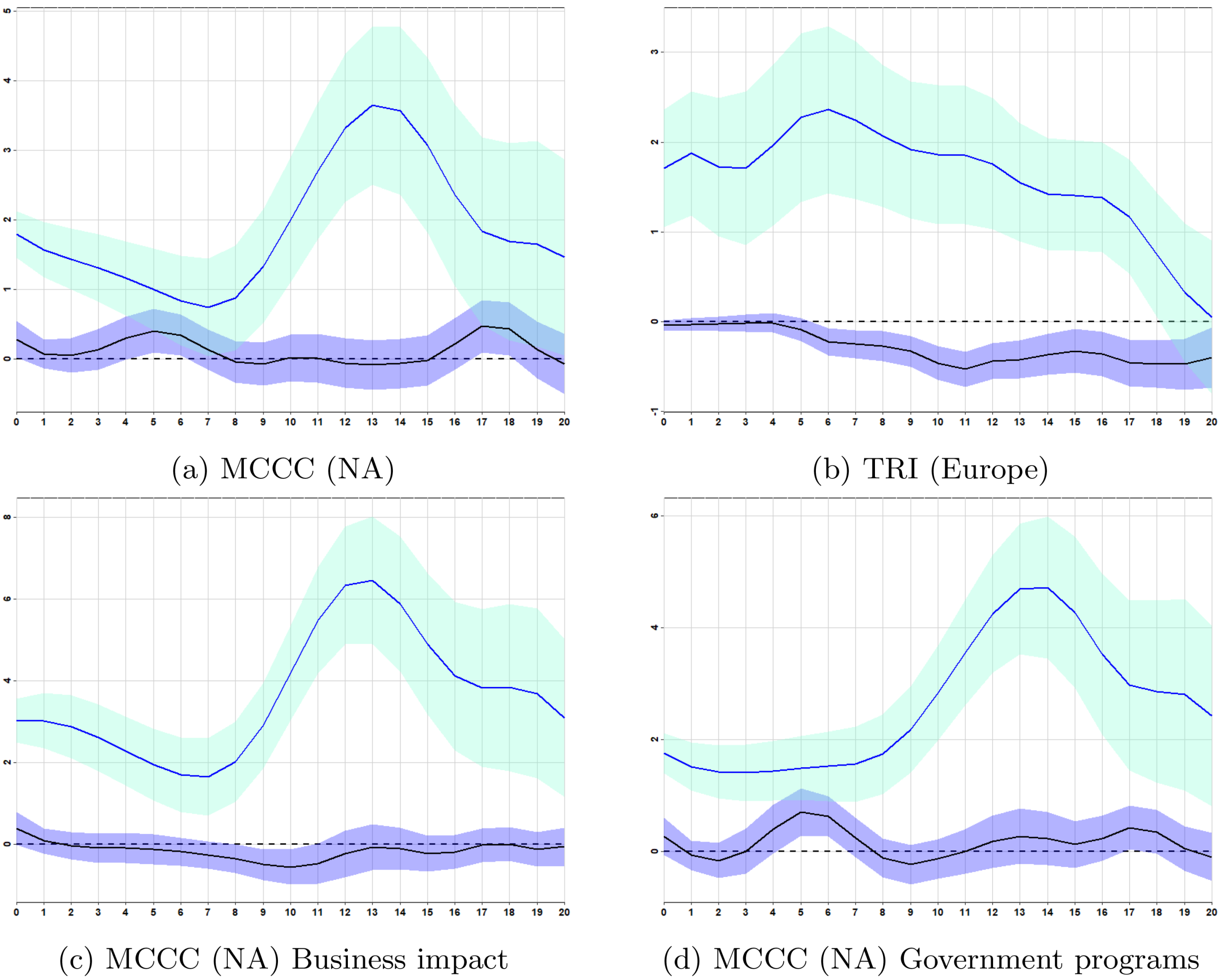
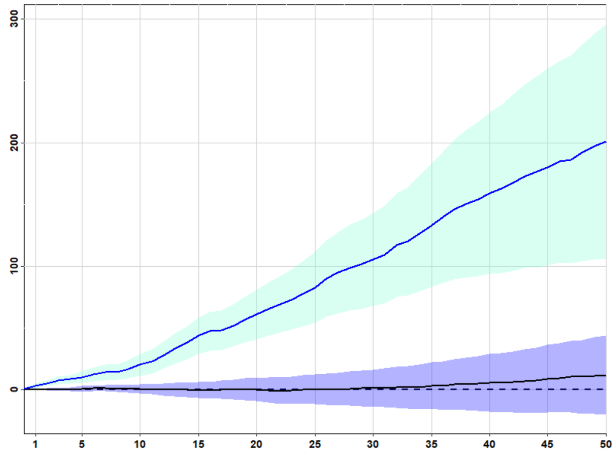
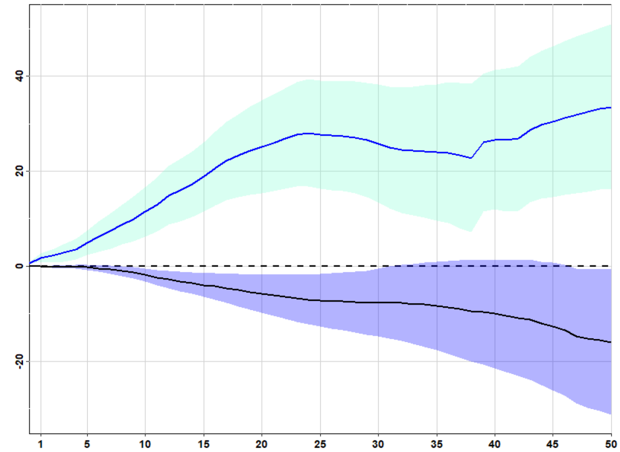


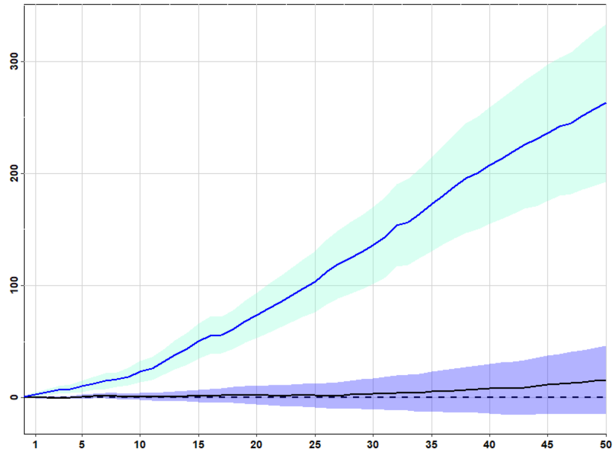
FIGURE A5 | Smoothed LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.



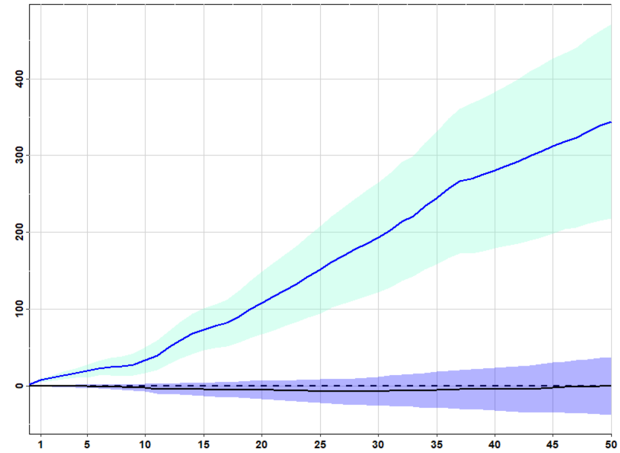
(a) MCCC (NA)



(b) TRI (Europe)



(c) MCCC (NA) Business impact



(d) MCCC (NA) Government programs

FIGURE A6 | Cumulative LPs for the non-linear model in (2) using MCCC index, Business Impact theme, and Government Programs topic shocks for North America and TRI shock for Europe. The brighter line includes the disaster dummy ($I_t = 1$), while the darker one does not ($I_t = 0$). HAC confidence intervals are reported at 68% significance level.

TABLE A1 | LPs for the baseline (linear) model in (1) and non-linear model in (2), using MCCC index, Business Impact theme (BI), and Government Programs topic (GP) shocks for North America and TRI shock for Europe. These results are plotted in Figures 3–5. Asterisks denote significance at 68% level.

	Linear				Non-linear											
h	$\hat{\beta}_h^{TRI}$	$\hat{\beta}_h^{MCCC}$	$\hat{\beta}_h^{GP}$	$\hat{\beta}_h^{BI}$	$\hat{\beta}_{0,h}^{TRI}$	$\hat{\beta}_{1,h}^{TRI}$	$\Delta\hat{\beta}_h^{TRI}$	$\hat{\beta}_{0,h}^{MCCC}$	$\hat{\beta}_{1,h}^{MCCC}$	$\Delta\hat{\beta}_h^{MCCC}$	$\hat{\beta}_{0,h}^{GP}$	$\hat{\beta}_{1,h}^{GP}$	$\Delta\hat{\beta}_h^{GP}$	$\hat{\beta}_{0,h}^{BI}$	$\hat{\beta}_{1,h}^{BI}$	$\Delta\hat{\beta}_h^{BI}$
0	0.008	0.312*	0.244*	0.215	−0.052*	0.699*	0.751*	0.267*	0.916*	0.649*	0.121	2.401*	2.28*	0.164	0.931*	0.766*
1	0.048	0.157	0.369*	0.183	−0.042	1.115*	1.157*	−0.058	2.439*	2.497*	0.119	5.225*	5.106*	0.013	2.167*	2.154*
2	0.054	0.250	0.132	−0.038	−0.024	0.340	0.364	0.104	2.025*	1.921*	−0.028	3.211*	3.240*	−0.183	1.732*	1.915*
3	0.067	0.041	−0.212	−0.089	−0.027	0.667*	0.694*	−0.117	2.004*	2.121*	−0.369*	3.368*	3.737*	−0.230	2.029*	2.259*
4	0.073	0.373	0.158	0.485	−0.014	0.757*	0.771*	0.269	1.130*	0.861	−0.003	2.940*	2.943*	0.404	1.091*	0.687
5	0.051	0.499*	−0.103	0.869*	−0.063	1.412*	1.475*	0.348	1.709*	1.361*	−0.236	2.385*	2.621*	0.771	2.090*	1.319*
6	−0.123	0.480*	−0.023	0.771*	−0.236*	1.230*	1.466*	0.359	2.223*	1.863*	−0.162	3.554*	3.717*	0.689*	2.618*	1.929*
7	−0.119	0.102	−0.268	0.273	−0.221*	1.220*	1.441*	−0.023	1.663*	1.686*	−0.373	1.913	2.286*	0.171	2.127*	1.956*
8	−0.165	−0.035	−0.237	−0.094	−0.270*	1.324*	1.595*	−0.059	0.295	0.355	−0.208	0.762	0.970	−0.160	1.370*	1.530
9	−0.207	−0.184	−0.597	−0.337	−0.301*	1.201*	1.502*	−0.361	2.269*	2.630*	−0.679	2.084	2.763*	−0.445	2.491*	2.936*
10	−0.332*	0.342	−0.216	0.320	−0.426*	1.467*	1.893*	0.107	3.570*	3.463*	−0.429	5.727*	6.155*	0.109	4.432*	4.323*
11	−0.415*	0.057	−0.614	−0.128	−0.520*	1.571*	2.091*	−0.118	2.620*	2.737*	−0.916	6.583*	7.499*	−0.274	3.092*	3.366*
12	−0.265*	0.203	0.321	0.546	−0.372*	1.867*	2.239*	−0.170	5.322*	5.492*	−0.084	9.983*	10.067*	0.286	5.651*	5.364*
13	−0.311*	0.121	0.291	0.458	−0.393*	1.077*	1.469*	−0.259	5.301*	5.560*	−0.066	9.436*	9.502*	0.163	6.206*	6.043*
14	−0.207	0.342	0.442	0.724	−0.291*	1.339*	1.630*	0.012	4.670*	4.658*	0.063	8.632*	8.569*	0.488	5.491*	5.003*
15	−0.189	0.185	−0.348	0.308	−0.267	1.475*	1.742*	−0.265	5.780*	6.045*	−0.456	5.569*	6.025*	−0.114	7.107*	7.220*
16	−0.200	0.067	−0.239	0.212	−0.273	1.778*	2.051*	0.006	3.391*	3.385*	−0.214	4.141*	4.354*	0.154	4.937*	4.782*
17	−0.320	0.389	−0.014	0.277	−0.392*	1.628*	2.020*	0.608	0.999	0.391	0.070	4.320*	4.251*	0.619	0.249	−0.369
18	−0.330	0.354	0.355	0.436	−0.374*	1.037*	1.411*	0.314	3.777*	3.463*	0.231	7.894*	7.662*	0.355	5.403*	5.048*
19	−0.343	0.337	−0.036	0.322	−0.367*	0.987*	1.354*	0.225	4.918*	4.693*	−0.265	9.752*	10.017*	0.155	6.610*	6.455*
20	−0.301	−0.480	−0.119	−0.334	−0.315	0.860*	1.175*	−0.614	4.119*	4.733*	−0.256	8.398*	8.655*	−0.479	5.662*	6.141*

TABLE A2 | Cross-effect LPs for the baseline (linear) model in (1) and non-linear model in (2), using MCCC index, Business Impact theme (BI), and Government Programs topic (GP) shocks for North America and TRI shock for Europe. These results are plotted in Figure 8. Asterisks denote significance at the 68% level.

	Linear				Non-linear							
h	$\hat{\beta}_h^{TRI}$	$\hat{\beta}_h^{MCCC}$	$\hat{\beta}_h^{GP}$	$\hat{\beta}_h^{BI}$	$\hat{\beta}_{0,h}^{TRI}$	$\hat{\beta}_{1,h}^{TRI}$	$\hat{\beta}_{0,h}^{MCCC}$	$\hat{\beta}_{1,h}^{MCCC}$	$\hat{\beta}_{0,h}^{GP}$	$\hat{\beta}_{1,h}^{GP}$	$\hat{\beta}_{0,h}^{BI}$	$\hat{\beta}_{1,h}^{BI}$
0	0.253	0.075*	0.040	0.148*	0.230	1.171*	0.075*	−0.011	0.031	−0.082	0.152*	−0.005
1	0.338	0.014	−0.019	0.074	0.300	0.980*	−0.004	−0.040	−0.049	−0.003	0.043	0.154
2	0.532	−0.050	−0.104*	−0.018	0.489	1.083*	−0.084	−0.148	−0.152*	−0.087	−0.065	0.050
3	0.312	−0.054	−0.142*	−0.035	0.251	1.111*	−0.102	−0.042	−0.200*	−0.001	−0.087	0.092
4	0.474	−0.108	−0.159*	−0.111	0.406	0.846	−0.173*	0.037	−0.210*	−0.087	−0.173*	0.117
5	0.151	−0.111	−0.139*	−0.116	0.056	1.772*	−0.178*	0.097	−0.175*	−0.172	−0.182*	0.281
6	0.061	−0.109	−0.136	−0.080	−0.028	1.747*	−0.184*	0.333	−0.172*	0.011	−0.141	0.439*
7	0.115	−0.195*	−0.131	−0.153	0.09	0.842*	−0.273*	0.206	−0.17	−0.129	−0.220*	0.296*
8	−0.291	−0.232*	−0.098	−0.184*	−0.372	1.572*	−0.314*	0.088	−0.145	−0.205	−0.275*	0.282*
9	−0.115	−0.267*	−0.137	−0.221*	−0.184	1.295*	−0.370*	0.095	−0.187	−0.384	−0.319*	0.252
10	−0.186	−0.245*	−0.216	−0.203	−0.266	0.811*	−0.355*	0.239	−0.270*	−0.420	−0.297*	0.282
11	−0.081	−0.268*	−0.215	−0.231*	−0.16	1.073*	−0.365*	−0.009	−0.262*	−0.657*	−0.303*	−0.002
12	0.077	−0.300*	−0.241	−0.228	−0.017	1.901*	−0.382*	−0.119	−0.267*	−0.838*	−0.285*	−0.113
13	0.135	−0.279*	−0.227	−0.147	0.060	1.258*	−0.372*	−0.003	−0.281*	−0.466	−0.225	0.170
14	0.133	−0.34*	−0.330*	−0.184	0.06	1.838*	−0.422*	−0.113	−0.411*	−0.294	−0.269*	0.083
15	−0.023	−0.324*	−0.298	−0.182	−0.112	2.416*	−0.410*	−0.005	−0.411*	0.182	−0.288*	0.310
16	−0.069	−0.354*	−0.346*	−0.219	−0.137	1.477*	−0.446*	0.004	−0.459*	0.194	−0.335*	0.385*
17	−0.631	−0.306*	−0.301	−0.197	−0.707*	1.391*	−0.419*	0.127	−0.454*	0.676*	−0.329*	0.512*
18	−0.050	−0.253	−0.289	−0.141	−0.079	1.478*	−0.359*	0.070	−0.445*	0.738*	−0.268	0.441*
19	−0.564	−0.272	−0.334	−0.146	−0.613	1.325*	−0.393*	0.173	−0.496*	0.775*	−0.301	0.730*
20	−0.281	−0.399*	−0.338	−0.228	−0.322	1.299*	−0.515*	−0.039	−0.475*	0.483*	−0.364*	0.446*