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Climate Shock Transmission and Risk Inference for Kredit Evaluation *

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Abstract. Sudden and irregular climate-related risks are increasingly expected to pose significant threats to the economy and the stability of the financial system. Existing risk assessment methods in the financial sector remain insufficient to capture the complexity and abrupt nature of such climate shocks. This report provides an overview of current tools and approaches used in climate risk analysis, as well as a review of the relevant academic literature. Building on these foundations, we introduce a novel modeling framework, C-Strike, designed to capture climate risks from a bottom-up perspective while enabling top-down applications in the banking sector. The concept is illustrated through three case studies: an emission price shock, a 1-in-100 year flood in Northern Europe and a heat wave throughout Europe.

JEL Classification: D57, G21, G32, Q54, Q58

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1. Introduction

Climate change poses increasingly acute challenges to economic stability [Intergovernmental Panel on Climate Change (IPCC), 2021] and the resilience of financial institutions [Alogoskoufis et al., 2021]. As physical hazards such as floods, wildfires, and heatwaves become more frequent and severe, and as transition risks, such as policy changes or technological disruptions, gain momentum, traditional risk assessment frameworks used in the financial sector show clear signs of strain. Conventional models, which were developed to address cyclical macroeconomic risks or financial market volatility, struggle to account for the non-linear, uncertain, and highly asymmetric nature of climate-related risks.

At the same time, regulatory expectations around climate risk integration are accelerating. Supervisory authorities such as the European Central Bank (ECB) and the European Banking Authority (EBA) now require that banks actively consider environmental, social, and governance (ESG) risks in their risk management processes [ECB, 2020, EBA, 2024]. In particular, the ECB's plan to incorporate climate-related risks into the Supervisory Review and Evaluation Process (SREP) from 2025 onward highlights a shift towards capital-relevant treatment of these emerging threats. However, the methodological foundations required to quantify the impact of climate shocks, especially tail risks, are underdeveloped and contested.

The core difficulty lies in the nature of climate risks themselves. Unlike traditional financial risks, which can be modeled on established statistical distributions and historical data, climate risks have limited empirical precedence and deep structural uncertainty [Haas et al., 2023]. Their temporal dynamics stretch beyond the typical time horizons considered in risk modeling [Carney, 2015]; their manifestations are often abrupt and irreversible [Intergovernmental Panel on Climate Change (IPCC), 2021]; and their impacts cascade across sectors and geographies through complex, non-linear transmission channels [NGFS, 2019]. These features pose a fundamental challenge to existing stress testing and capital planning regimes.

In response, regulators and market participants have increasingly turned to climate scenario analysis as a tool to navigate uncertainty and inform risk-based decisions. Central to this approach are the long-

term climate scenarios developed by the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), which provide structured narratives of how climate and policy variables may evolve under different assumptions. Although these scenarios offer valuable information for macroprudential supervision and policy coordination, their utility for firm-level risk assessments is limited. NGFS scenarios tend to emphasize equilibrium paths over extended time horizons and are built using top-down modeling architectures [NGFS, 2024], making them ill-suited for identifying short-term, bottom-up credit risks in bank portfolios.

More recently, short-term NGFS scenarios have emerged to partially address these limitations. They feature a five-year horizon, introduce basic credit risk variables, and disaggregate some results at the sectoral level [NGFS, 2025]. Despite these improvements, they continue to reflect smooth narrative trajectories rather than abrupt shock events and retain a degree of model opacity that hinders granular interpretation. For banks seeking to quantify capital needs under climate stress conditions, this creates a persistent methodological gap.

To bridge this gap, we propose a new modeling framework: **C-STRIKE**—short for *Climate Shock Transmission and Risk Inference for Kredit Evaluation*. C-STRIKE is designed to simulate the transmission of climate shocks in a modular, out-of-equilibrium setting that prioritizes short-term effects, firm-level specificity, and methodological transparency. It moves beyond the narrative logic of long-term scenarios and adopts a shock-based modeling perspective that mirrors the structure of conventional financial stress tests, while accounting for the unique features of climate risk.

This paper introduces the conceptual foundations and technical implementation of C-STRIKE. Our framework captures the transmission of climate risk through three propagation layers: direct firm effects, supply chain linkages, and macroeconomic demand feedback, and allows users to simulate a broad range of physical and transition shocks. It draws on firm-level financial data, geospatial information, and input–output tables to model the real-economy pathways through which climate risks affect credit risk profiles.

In doing so, C-STRIKE aims to contribute to both supervisory and industry practice. For regulators, it offers a transparent and scalable tool for assessing banks' exposure to climate-related tail events. For

financial institutions, it provides a flexible platform for stress testing, risk heat mapping, and capital impact analysis.

The remainder of this report is organized as follows. Section 2 reviews the challenges of modeling climate-related tail risks and critically assesses the NGFS scenarios. Section 3 introduces the structure and mechanics of the C-STRIKE framework, followed by Section 4, which presents three demonstrator cases. Section 5 outlines technical model details, and Section 6 concludes with an outlook on future research directions.

2. Challenges of Modeling Climate-Related Tail Risks

Ever since Mark Carney's speech in September 2015, warning of climate change as the 'tragedy of the horizon', climate-related issues have been recognized as relevant risk factors for financial system stability. In 2020, the ECB correspondingly published 13 broad supervisory expectations on the management of climate-related and environmental risks to be implemented until the end of 2024 [ECB, 2020]. In response to these expectations, European banks have begun to integrate climate-related aspects into their risk management frameworks over the last few years. Although inroads have been made with regard to exploratory analyses and qualitative materiality assessments, many institutions still grapple with the difficulty of incorporating climate risk into the more quantitative parts of their risk management systems [Auzepy and Bannier, 2025].

2.1 Regulatory Expectations

Recognizing this development, the most recent EBA guidelines on the management of environmental, social, and governance risks emphasize the need to further quantitatively measure and monitor these risks in the future [EBA, 2025]. In particular, the guidelines set out the importance of more strongly considering the forward-looking impact of ESG risks through appropriate scenario analyzes. The fact that in recent years physical climate risks such as river flooding, extreme droughts, heat waves, or wildfires have manifested themselves with a frequency and to a degree not seen before, particularly in Europe, underscores the need for innovative and future-oriented risk measurement tools.

In the same vein, the ECB highlights the treatment of climate-related risks among persistent shortcomings in the banking sector that will need to be monitored with priority in the 2025-2027 supervision cycle [ECB, 2024]. In fact, starting in 2025, the ECB plans to explicitly incorporate climate change and nature-related risks in its Supervisory Review and Evaluation Process (SREP), allowing for a direct influence of climate risk on individual banks' capital needs through the so-called Pillar 2 requirements.

2.2 Characteristics of Climate Risks

The sustained gap between supervisory expectations on climate-related risks and the quantitative climate risk management practice of banks can be explained by the specific characteristics of these risks. Compared to conventional risk drivers in the financial system, they differ for several reasons. First, as the 'tragedy of the horizon' [Carney, 2015] implies, climate change is unfolding over several decades, which clashes with the typical one- to three-year time period considered in most bank risk management tools. Trying to reconcile these different time perspectives within the existing quantitative risk models obviously poses an enormous challenge. Second, due to the forward-looking nature of climate risks historical data on their manifestations are so far hardly available [Monasterolo, 2020]. Furthermore, the non-linearity of the occurrence of extreme climate-related events means that even the most recent observations need not provide a reliable guide for future climate risk developments [Ackerman, 2017].

As a consequence, banks cannot rely on empirical data when trying to estimate climate-related tail risks as they do for traditional risk drivers such as macroeconomic hazards (inflation, recession, etc.). Instead, they must model the loss function induced by climate risk using hypothetical scenarios. However, this modeling is complicated by deep uncertainties with regard to the link between climate change and ecosystems, for instance due to the crossing of planetary boundaries or the reaching of tipping points [Steffen et al., 2018]. The interdependency and endogeneity between climate risk on the one hand and climate policy, investment, and consumption decisions on the other further contribute to these difficulties [Battiston and Martinez-Jaramillo, 2018].

2.3 Long-Term NGFS Scenarios

The lack of reliable data and the complexities of modeling the relationship between climate-related variables and financial parameters therefore create enormous challenges for banks‘ risk management. In order to advance and overcome these methodological problems, in 2017 a large number of central bankers and regulators launched the Network of Central Banks and Supervisors for Greening the Financial System

(NGFS), which started developing climate scenarios as part of a coordinated working project. Initially, these scenarios were built to inform policy makers and regulators on how to reach climate goals more effectively and to compare the costs and benefits of different climate policies. However, supervisors eventually started to employ the NGFS scenarios also for system-wide climate stress tests (cf. ECB climate stress test 2022 [ECB, 2022]). As a consequence, many banks, in turn, deployed these centrally provided climate scenarios – or adaptations of them - in their own risk management frameworks [Auzepy and Bannier, 2025].

However, these high-level climate scenarios were never built to assess the resilience to climate risk of individual banks through stress tests [Baer et al., 2023]. Rather, and similarly to other climate scenarios provided by, e.g., the Intergovernmental Panel on Climate Change (IPCC) or the International Energy Agency (IEA), they were created to explore different sets of assumptions about how climate policy, emissions, and temperatures evolve. Via so-called damage functions, these political and scientific variables are then translated into quantitative trajectories of economic variables that subsequently allow to assess financial risk. The climate scenarios hence describe a path of development leading to a particular future outcome such as a hot-house world or a 'Paris-aligned' world.

In a typical stress test run by a bank, in contrast, a stress scenario is constructed around an exogenous shock to the system. This shock occurs with a given small probability so that the resilience of the financial institution to this extreme but plausible shock event can be tested. Its result is the derivation of tail risks from the stress event, whereas the NGFS climate scenarios yield the predefined - and hence 'smooth-path' - values of the outcome variables [Baer et al., 2023]. Although the latter is certainly informative for policy makers, it does not necessarily meet the needs of financial risk managers.

Despite these different approaches with respect to construction, the NGFS scenarios have the merit of delivering a standardized and, therefore, comparable view on banks' treatment of climate risk. This is clearly attractive from a supervisory perspective, but it may also be partially of interest to financial institutions themselves: At least in the early years of climate risk assessment, it should help them to overcome initial resistance and methodological uncertainties vis-a-vis considering climate risk as a relevant new risk driver. In order to better understand

that severe weaknesses lurk in the employment of the high-level NGFS scenarios as more refined stress tests, however, it is instructive to consider these scenarios in more detail.

The most recent version of the NGFS long-term climate scenarios explores seven different scenarios that fall into four categories: Orderly transition, Disorderly transition, Hot-house world, and Too little, too late [NGFS, 2024]. Each scenario is characterized by a distinct combination of physical and transition risk proxied by the development of CO2e emissions and carbon prices. The considered time period in these scenarios is typically until the end of the century, i.e. a long-term period until the year 2100. In order to assess the costs and benefits of climate policy, NGFS scenarios combine three different types of models: physical risk models, transition risk models (or Integrated Assessment Models (IAMs)), and macroeconomic models.[1] Physical risk models consider both acute and chronic effects from climate change that feed directly into the macroeconomic National Institute Global Economics Model (NIGEM) via asset damage and country productivity changes. The transition risk models feature three different IAMs that model the transmission channels of climate policy via energy systems, land and water use in combination with projected demographic and production trends. Similarly to physical risk models, these results feed into the macroeconomic model to derive the potential damage from climate transition risk.[2]

Indeed, the Integrated Assessment Models form the heart of the NGFS scenarios as they capture the potential climate change transition risks and provide the main scenario narratives. All IAMs are based on so-called Shared Socioeconomic Pathways (SSPs), which describe the demographic, socioeconomic, and technological drivers of climate change. Unfortunately, as Welch [2024] points out, the selection of individual drivers in SSPs is not based on empirical methods, but rather 'on the interests of the participating environmental social scientists'. An often found lack of transparency around the main assumptions used in SSPs also makes it extremely difficult for financial

[1] These overlap in part also with the modeling approaches of the IPCC and IEA scenarios.
[2] The most recent vintage of NGFS scenarios aligns the physical and transition risk assumptions in terms of temperature pathways. This is particularly important for the consideration of chronic physical risks, which are not interrelated with transition risk models but instead are estimated in an individual ex post model step [NGFS, 2024].

professionals to interpret the results of the model or test their validity [Baer et al., 2023]. In addition, the socioeconomic drivers in the IAMs are formulated as exogenous and hence independent to climate policy [Monasterolo et al., 2023]. This makes it particularly difficult to relate the SSPs consistently with the so-called Representative Concentration Pathways (RCPs), which are the second modelling ingredient to form the IAMs. In contrast to the rather ad hoc nature of SSPs, the RCPs derive temperature forecasts empirically from climate models that use assumed climate policies and SSP forecasts as input [Welch, 2024]. The individual IAMs employed in the NGFS scenarios differ mainly in their modeling of transmission channels within the chosen SSP/RCP combination, e.g. with regard to substitutability of energy sources.

Eventually both transition and physical risk models within each scenario feed into the macroeconomic NIGEM, mainly via energy- and emission-related variables but partly also with regard to economic output in specific industries according to physical damage functions. The NIGEM is a peer-reviewed global econometric model which represents a closed world where outflows from one country are matched with inflows to another country. Behavioral relations within this large model are econometrically estimated using historical data. Once the input from transition and physical risk models is fed into the NIGEM, it processes the effects on a large set of macroeconomic outcome variables such as GDP, unemployment rates, inflation rates, or real estate prices per country, according to national accounts. The outcome of the long-term NGFS scenarios is therefore highly aggregated and remains at the country level.

By construction, long-term NGFS climate scenarios are extremely difficult for banks and other financial institutions to reasonably adapt and employ in the form of stress tests. Their long-term time horizon, top-down modeling with often intransparent underlying assumptions, and a narrative that comes closer to a central scenario than a tail-risk scenario make them rather unsuitable for stress testing. The lack of a clear baseline scenario underscores this point because any examination of stress risk requires a straightforward formulation of a 'non-stressed' scenario. Although it would be clearly unrealistic to assume that the world could develop without any climate risk, it is less than clear how much and which climate risks to reasonably assume going forward. Finally, the high level of aggregation with respect to the outcome vari-

ables of long-term NGFS scenarios makes them difficult to incorporate into bank risk management frameworks that are typically based on a business sector structure.

2.4 Short-Term NGFS Scenarios

In order to better meet the needs of the financial sector, the NGFS also started to work on short-term climate scenarios, which were eventually introduced in 2025 [NGFS, 2025]. They do not only consider a shorter 5-year time frame, but also provide outcome data partly on a more disaggregated sectoral level (NACE2). Of the four short-term climate scenarios (Highway to Paris, Sudden wake-up call, Disaster and policy stagnation, Diverging realities), two consider only transition climate risk, one considers only physical climate risk and one accounts for both transition and physical climate risk at the same time. In addition to climate-related and macroeconomic outcome variables on an aggregate level, these short-term scenarios also offer credit risk-related variables such as probabilities of default or value-at-risk for representative sectoral firms. By employing three different models which focus on slightly different aspects of the climate-relevant macrofinancial environment (EIRIN, CLIMACRED, GEM-E3), and running them subsequently with one feedback loop via the macroeconomic model, the scenarios allow for a first consideration of macrofinancial dynamics. In contrast to longer-term NGFS scenarios, the modeling also takes into account the effects of monetary policy.

The short-term version of the NGFS scenarios also explicitly provides a baseline scenario. In this, the macroeconomic GEM-E3 model is based directly on the IMF's World Economic Outlook for 2023, which provides GDP projections for most countries around the world. This is complemented with emissions data derived from current climate and energy policies for major economies. However, it should be noted that this baseline scenario is built to be comparable with one of the long-term NGFS scenarios (Nationally determined contributions scenario).

The four different short-term climate scenarios are essentially combinations of individual transition risk paths from the long-term NGFS scenarios (mainly the Net zero by 2050 scenario), the baseline scenario described above, and distinct assumptions regarding physical climate risks. While the former two feed into the three models described above,

for instance via energy price or technology shocks in GEM-E3, carbon tax changes in EIRIN, or uncertainty shocks in CLIMACRED, physical climate risks are treated separately. They explicitly consider compounding 'dry' and 'wet' climate occurrences such as heatwave-drought-wildfire (HDW) events or storm-flood events (SF) in several regions at the same time, which appears reasonable given the increasing observation of such climate events in recent years. However, the modeling does not allow for endogeneity between physical risk and transition risk.

Although short-term NGFS scenarios hence alleviate some of the difficulties that financial institutions encounter when employing climate scenarios for stress testing purposes (shorter time horizon considered, higher granularity due to consideration of sectoral credit risk variables), other weaknesses remain. First, by construction, the scenarios still do not allow for calculation of tail risks as they follow predefined smooth pathways along the (now shorter) time frame. Although it is possible to argue that the outcome of the scenario is driven by transition or physical climate shock events, one cannot yet assess the true stress level attached to them. Second, both the short-term and long-term NGFS scenarios follow a top-down approach that allows for a disaggregation of outcome variables foremost on a geographical (country-wide) basis and for the short-term scenarios only on a sectoral (NACE 2 level) basis. Although this is an important step in the direction of more effective use of climate scenarios in the financial industry, for most banks this breakdown will typically still be too coarse to assess the true risk of climate stress contained in their portfolios. Finally, even short-term NGFS scenarios consider extremely complex macrofinancial models that make it difficult to attribute a specific outcome to individual steps along the climate risk transmission channel.

In the following, we present a modeling approach that tries to overcome some of these difficulties. By focusing on a bottom-up modeling approach, we can narrow down the transmission processes of the different climate shocks that we consider. This, in turn, allows us to keep the modeling of climate-induced credit risk effects relatively simple and to inject true climate 'stress' into the model.

3. C-STRIKE

The C-STRIKE framework "Climate Shock Transmission and Risk Inference for Kredit Evaluation" is designed to quantify short-term economic impacts of climate-related shocks across firms, sectors, and geographies. Built around a modular and out-of-equilibrium modeling architecture, C-STRIKE captures the direct, indirect, and macroeconomic demand effects of physical and transition risks. It leverages firm-level financial data, input–output matrices, and geospatial indicators to simulate how shocks propagate through real-economy channels and alter firms' financial profiles.

This section outlines the conceptual structure and operational logic of C-STRIKE, including its key modeling assumptions, propagation layers, and shock injection mechanics. To demonstrate the model's practical relevance and adaptability, we also present three stylized use cases—a carbon price shock, a regional flood event, and a heatwave-driven productivity loss—each implemented using real-world data. Together, these components showcase the analytical flexibility of the model and its suitability for applications in stress testing, portfolio diagnostics, and risk strategy development.

3.1 Concept

The C-STRIKE framework is developed to simulate the short-term transmission of climate-related shocks through the real economy in a modular, scalable, and transparent manner. It builds on firm-level financial and operational data to assess how climate shocks, whether physical or transition-related, propagate through company balance sheets, supply chains, and macroeconomic demand. The framework is specifically designed to support applications in credit risk analysis, regulatory stress testing, and strategic financial planning. This section outlines the key conceptual pillars of C-STRIKE, including its guiding narrative, multi-layer architecture, modeling logic, use cases, and current limitations.

3.1.1 Narrative

C-STRIKE—short for *Climate Shock Transmission and Risk Inference for Kredit Evaluation*—is a modular modeling framework designed to

simulate the short-term transmission of climate-related shocks through the real economy. It supports both physical and transition risk channels and is particularly suited to assessing capital demand under climate-related stress scenarios. The framework is characterized by five central features: (i) out-of-equilibrium dynamics, (ii) short-term accounting focus, (iii) multi-layered shock propagation, (iv) flexible shock specification, and (v) transparency and modular expandability.

Out-of-Equilibrium Shock Modeling Unlike traditional climate scenario analysis and stress-testing frameworks, many of which are rooted in long-term equilibrium-based macroeconomic models such as those developed under the NGFS, the C-STRIKE model adopts an out-of-equilibrium perspective. It assumes that climate-related events, such as policy shifts or extreme weather, generate sudden and asymmetric shocks that disrupt firms and propagate through the economy without returning to a new equilibrium within the model horizon. This approach better reflects the reality of abrupt and potentially destabilizing events, allowing for more accurate short-term assessments of capital needs under adverse conditions.

Short-Term Temporal Focus C-STRIKE is designed to assess the consequences of one-off shocks over a short time horizon, typically one year. The model operates on an annual accounting framework, using financial statement data to quantify the effects of shocks on firms' balance sheets and income statements within the same reporting period. This short-term focus enables a detailed understanding of immediate transmission mechanisms and financial consequences, making the model especially suitable for internal capital adequacy assessments (ICAAP) and supervisory stress-testing exercises. Long-run macroeconomic feedbacks, while important, fall outside the scope of the current design.

Multi-Layer Shock Propagation A core innovation of C-STRIKE is its ability to trace shocks through three distinct but interconnected layers:

1. **Direct Firm-Level Effects:** The model begins with a bottom-up shock injection at the Firm Level, such as a sudden increase in carbon pricing, a reduction in productivity due to a heat wave or a disruption from a flood event.

2. **Supply Chain Effects:** The initial shock is then propagated through inter-industry input–output relationships. Affected firms may pass on costs to downstream customers or absorb shocks received from upstream suppliers. This layer reflects how interconnected economic structures distribute climate-related pressures.
3. **Macroeconomic Demand Effects:** Finally, C-STRIKE models feedback effects from demand patterns, which further influence firm revenues. This step ensures that demand-side dynamics are also considered in the overall transmission path.

This layered design allows users to explore the entire transmission channel from shock origin to system-wide economic impacts.

Applicability to Diverse Shock Types C-STRIKE is not limited to a specific class of climate risks. Its design is intentionally versatile, enabling users to implement a wide range of shocks—including carbon taxation, weather extremes, or supply disruptions. The model includes a clear specification interface for shock design, enabling users to define stressors in terms of input variables, functional relationships, and propagation parameters. This versatility makes C-STRIKE adaptable to different institutional contexts and use cases, from prudential supervision to internal risk modeling.

Transparency and Modular Expandability The C-STRIKE framework is built for transparency. Each propagation step, whether affecting costs, revenues, or broader financial metrics, is explicitly modeled and traceable. This transparency is crucial for interpreting sector- and region-specific outcomes and for communicating results to internal and external stakeholders.

In addition, the model is structured to be modularly expandable. Users can integrate additional components such as probability-of-default (PD) and loss-given-default (LGD) models, macro-financial linkages, or financial market interaction modules. This modular architecture facilitates incremental development and customization, supporting ongoing methodological refinement and alignment with supervisory or regulatory requirements.

3.1.2 Building Blocks

As illustrated in Figure 1, C-STRIKE is designed as a multi-layer modeling framework that simulates the transmission of climate-related

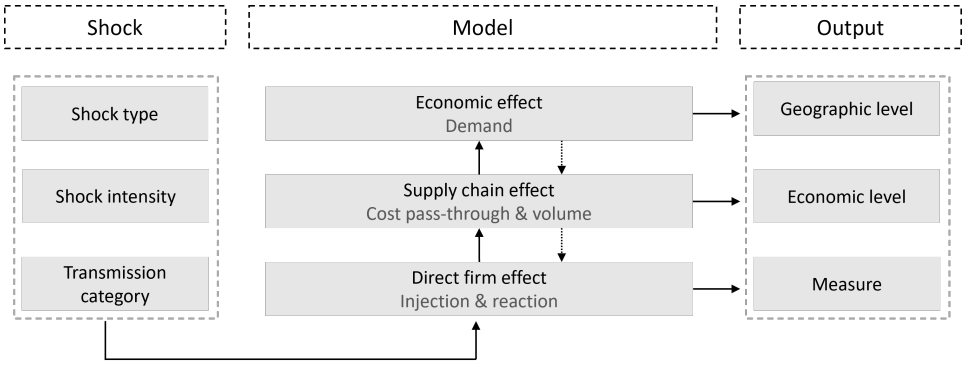

Fig. 1. C-STRIKE Overview

shocks through three economic levels: the firm, the supply chain, and aggregate demand. Each modeling step builds on the outputs of the preceding layer and enables a comprehensive assessment of the impact on financial performance across regions, sectors, and firm types.

1. Shock Specification To initiate a simulation in C-STRIKE, the user defines the characteristics of the climate-related shock along three dimensions:

- **Shock Type:** The nature of the shock must be specified, for example, a heat wave, flood, change in carbon prices, or technological disruption. Each shock type entails distinct transmission mechanisms and data requirements.
- **Shock Intensity:** The severity of the shock must be defined in probabilistic terms (e.g., 1-in-100-year), reflecting the institution's risk appetite and regulatory objectives, see Figure 2. Intensity assumptions influence both the magnitude and interpretation of the model outputs.
- **Transmission Category:** Four shock injection modes are supported: revenue shocks (sudden changes to revenue stream), fixed cost shocks (sudden increase in costs), variable cost shocks (sudden increase in costs with pass-through), and disruptions (shock to operations that affect revenue and cost similarly). Each transmission category follows distinct endogenous response rules and propagation paths, as detailed in the technical sections of this paper - for a short summary of revenue and cost effects, see Table 1.

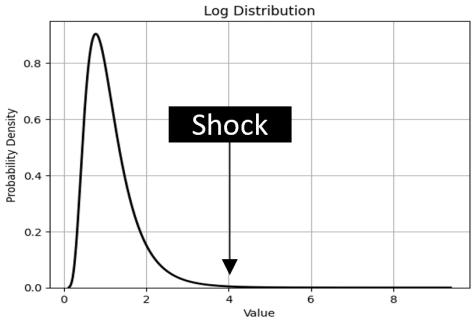

Fig. 2. Shock Level

Shock Category	Effect on Revenue	Effect on Cost
Revenue Shock	↓	→
Fixed Cost Shock	→	↑
Variable Cost Shock	↗	↑
Disruption Shock	↓	↓

Table 1 Overview of Shock Categories and Their Effects

2. Three-Layer Model Architecture Once the shock is specified, the model processes it through three layers of propagation:

1. **Direct Firm Effect:** The initial shock is injected at the firm level via an input variable such as revenue or cost. Depending on the shock type and transmission category, other P&L items and balance sheet components are adjusted endogenously to reflect first-order financial responses. The firm-level accounting system is then rebalanced to ensure internal consistency.
2. **Supply Chain Effect:** The shock propagates through sectoral production linkages using an input–output matrix. Two propagation mechanisms are supported:
   - *Cost Pass-Through Effect:* Applies when cost increases are partially or fully transmitted to downstream firms (e.g., due to higher carbon prices or energy costs).
   - *Volume Effect:* Applies when physical disruptions prevent the transfer of goods along the supply chain (e.g., due to factory shutdowns).

   Firm-level shocks are first aggregated to the sector level, passed through the input–output framework, and then disaggregated

back to firms based on sectoral shares. A second round of accounting updates ensures consistency at the individual firm level.

3. **Macroeconomic Demand Effect:** Final demand from households, governments, and non-profits is adjusted based on changes in sectoral output. The model assumes sticky demand and adjusts firm-level revenues accordingly. These revenue adjustments trigger further recalibration of costs and profitability at the firm level, completing the third shock layer.

All technical formulations and functional specifications for these three stages are described in detail in the accompanying technical sections.

3. Output Configuration C-STRIKE is designed to be flexible in terms of output resolution and focus. Users can configure outputs along three axes:

- **Geographic Granularity:** Results can be produced without spatial resolution, at the national level, or—if supported by data—at subnational (e.g., regional) levels. Geographic resolution depends primarily on the availability of geocoded firm and sectoral data.
- **Sectoral Detail:** Outputs can be aggregated at high-level industry classifications (e.g., NACE Level 1) or disaggregated into more granular sectors to capture idiosyncratic risk profiles. The more detailed the sectoral breakdown, the more accurately the model captures industry-specific vulnerabilities.
- **Output Measures:** The model provides delta-based outputs—i.e., changes in key financial variables such as revenue, costs, EBITDA, or profitability. Users may also attach additional modules to translate these impacts into forward-looking credit risk measures (e.g., changes in probability of default or loss given default).

3.1.3 Areas of Application

The modular structure and flexible specification of the C-STRIKE model allow it to be applied across a range of analytical settings within financial institutions and supervisory bodies. While the model is broadly adaptable, its development was particularly guided by three

core application areas: (i) climate risk heat mapping, (ii) economic capital impact analysis, and (iii) strategic macroeconomic scenario analysis.

1. Climate Risk Heat Mapping C-STRIKE supports the identification of climate-related risk concentrations within credit portfolios. By simulating the propagation of climate shocks and generating firm- or sector-level output deltas (e.g., changes in revenue or profitability), the model enables users to construct granular heat maps that highlight highly, moderately, or weakly affected regions and industry clusters.

The objective in this use case is not necessarily to derive precise numerical impacts, but rather to build a directional and relative understanding of exposure patterns. This form of analysis is especially useful for internal risk flagging, early warning systems, and qualitative disclosure frameworks. Users are encouraged to employ a broad set of impact metrics and effect classifications to differentiate between risk tiers and derive actionable insights from the model outputs.

2. Economic Capital Impact Analysis A second key use case involves the quantification of climate shock effects on a bank's credit risk capital buffers. Here, C-STRIKE functions as a foundational model for estimating scenario-driven changes in firm-level financials, which can then be fed into credit risk models to derive changes in default probabilities, loss given default (LGD), and tail credit losses.

This application requires high data granularity and strong alignment with internal credit risk frameworks. The focus lies on quantifying the financial institution's resilience under adverse climate scenarios—i.e., evaluating how well the institution remains capitalized given potential impairment and default flows triggered by the modeled shock. Outputs should be structured to align with ICAAP requirements or other supervisory expectations for credit stress testing.

3. Strategic Macroeconomic Scenario Analysis Beyond portfolio- and capital-oriented applications, C-STRIKE also serves as a tool for exploring macro-financial implications of climate scenarios. In this context, the model supports the development of strategic narratives around potential structural shifts in the economy—such as demand reallocation, sectoral transformation, or geographic concentration of risk.

For this use case, the emphasis lies less on precision and more on directional insight and scenario development. Institutions can use the model to inform strategy-setting, business model adaptation, and long-term risk planning. A broader set of variables and outputs (e.g., changes

in sectoral profitability, employment intensity, or regional stress profiles) may be relevant, with results categorized into qualitative tiers (e.g., low/medium/high impact) to support strategic decision-making.

3.1.4 Limitations

While C-STRIKE offers a novel framework for short-term, firm-level climate risk propagation, it remains under active development. Several limitations currently constrain the scope, modeling capabilities, and data infrastructure of the tool. These are summarized below along three dimensions: scope, modeling logic, and data architecture.

1. Scope The current version of C-STRIKE focuses exclusively on climate-related risk, particularly physical hazards (e.g., floods and heatwaves) and transition shocks (e.g., carbon pricing). However, the broader ESG landscape—particularly social and governance-related risk channels—is becoming increasingly relevant in regulatory and internal bank risk assessments. Future extensions of C-STRIKE should integrate additional ESG dimensions to reflect these evolving priorities.

Moreover, the geographic scope is currently limited to European firms and macroeconomic structures, primarily due to data availability and the use of the Eurostat FIGARO input–output tables and Orbis Amadeus firm-level data. Extending the framework to other regions would enhance its applicability for global institutions and enable cross-jurisdictional risk comparisons.

Importantly, the current model horizon is limited to a single-year shock. While well-suited to near-term risk assessments and ICAAP-aligned stress testing, a multi-period extension would be necessary for forward-looking capital planning and long-term strategic evaluations. Similarly, the framework does not yet integrate probability-of-default (PD) or loss-given-default (LGD) models, which would be essential for translating economic losses into credit risk metrics.

2. Modeling Assumptions and Structure C-STRIKE simulates climate shock impacts based on deterministic scenario pathways. While this supports transparency and tractability, it does not currently account for the uncertainty surrounding scenario selection or shock realization. A probabilistic simulation module—e.g., via Monte Carlo methods or scenario ensembles—could be added to capture ranges and distributions of potential outcomes.

Additionally, the current approach assumes static behavior by economic agents. For example, households and firms are not yet modeled as capable of substituting suppliers, adapting consumption patterns, or reallocating investment in response to shocks. Including substitution effects and basic agent behavior could enhance realism and dampen overestimation of rigid vulnerabilities.

Further, the supply chain propagation currently relies on standard input–output tables, which assume homogeneity within sectors. Extending the framework to incorporate firm-level supply chain networks or applying network-based modeling techniques could capture interdependencies and propagation channels more accurately, especially for large or systemically relevant firms.

3. Data Infrastructure Data availability and accessibility remain key constraints. While the model draws on robust sources (e.g., Orbis Amadeus, Eurostat), many institutions may lack access to the full underlying datasets. Increasing accessibility—either through public releases of derived indicators or through API-based integration—would improve usability and adoption.

Physical risk modeling is currently based on external data inputs. A future extension of C-STRIKE could integrate physical hazard layers (e.g., flood or heat projection models) directly into the framework, enabling more endogenous and dynamic modeling of physical climate risks.

Finally, the model would benefit from the inclusion of broader environmental and socioeconomic variables—e.g., land use, water stress, or demographic exposure—which could enrich the shock design and better represent heterogeneous vulnerability at the firm level.

3.2 Demonstrators

To illustrate the functionality and versatility of the C-STRIKE framework, we present three demonstrator scenarios that reflect distinct types of climate-related shocks and propagation channels: (i) a transition risk event in the form of an emission price shock, (ii) a physical risk scenario based on flooding in Northern Europe, and (iii) a productivity shock induced by a continent-wide heatwave. These demonstrators are selected to showcase how the model can accommodate different shock types, intensities, and transmission mechanisms. Each case highlights

a particular use of C-STRIKE, from estimating firm-level financial impacts to tracing systemic effects across sectors and geographies. The results are presented at various stages of the modeling process to emphasize the layered architecture of the framework and its applicability to real-world risk assessments.

3.2.1 Emission Price Shock

The first demonstrator illustrates the effects of a sudden and significant increase in carbon pricing - a prototypical transition risk scenario - modeled as an 'Emission price shock'. This scenario reflects the potential consequences of governments rapidly adjusting carbon prices to better reflect the social cost of emissions.

For this shock scenario, we use a novel machine learning based emission data set for a large set of unlisted firms in Europe. See 4.2.3 for more details.

Shock Type (including modeling assumptions) The scenario simulates a policy-driven revaluation of the price of carbon, motivated by the argument that current emission prices underrepresent the true social cost of greenhouse gas emissions. Following Tol [2023], we build on a comprehensive meta-analysis of published estimates of the Social Cost of Carbon (SCC), which demonstrates a fat-tailed distribution of values. Emission cost increases are imposed directly on firms based on their predicted Scope 1 emissions.

Shock Intensity The intensity of the shock is calibrated to represent a 99th-percentile tail event in the SCC distribution. This results in an abrupt increase in emission prices far exceeding typical market or policy forecasts, consistent with a sudden regulatory tightening or coordinated international action. The implied carbon price shock is applied uniformly across firms, scaled by their emission levels, thus preserving the fat-tailed distribution of exposure across the corporate population.

Transmission Category The emission price shock is modeled as a **variable cost injection**. Firms absorb the cost shock in the form of higher input costs. In line with the methodology outlined earlier in the paper, these cost increases are then propagated through the supply chain using cost pass-through coefficients r_j, which are based on sectoral producer price volatility. The propagation continues through the

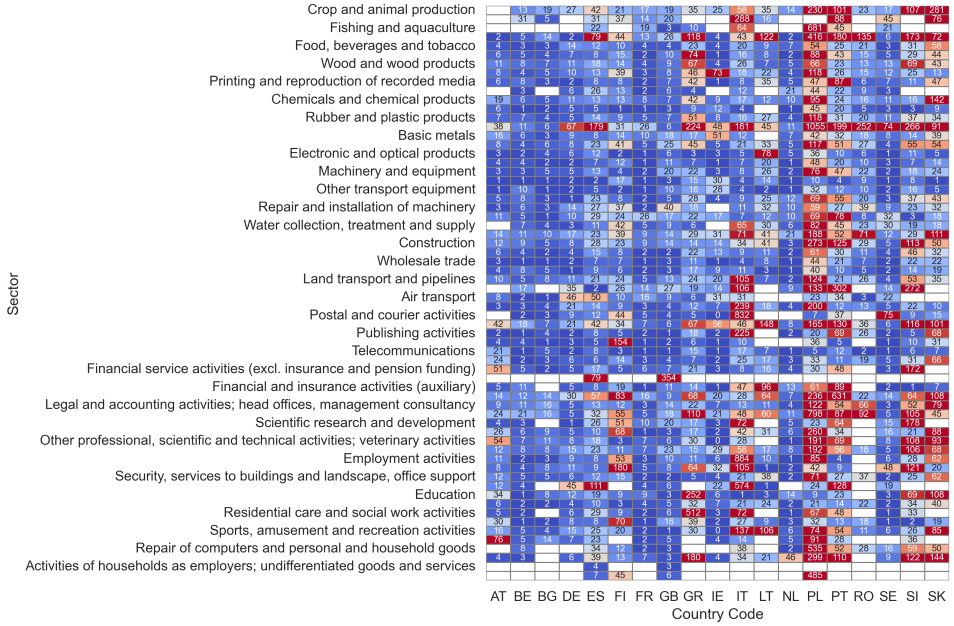

Fig. 3. Matrix of Emission Price Shock (Variable Cost after Macroeconomic Demand Effect)

macroeconomic demand layer, where sectoral output changes induce further demand-side effects.

Results and Interpretation Figure 3 presents the modeled increase in variable costs between countries and sectors after applying all three layers of the C-STRIKE framework. The figure displays the matrix of variable cost changes following the emission price shock, as computed at the macroeconomic demand layer.

The results reveal both sectoral and geographic variation. Most countries and sectors experience significant cost increases. The effect sizes vary strongly between countries. This heterogeneity may be partly attributed to the predictive model used to impute Scope 1 emissions for small and medium-sized enterprises. Nevertheless, the scenario demonstrates how a uniform policy shock can translate into differentiated cost pressures across sectors and countries.

Aggregate Results Across Layers Figure 4 summarizes the aggregate result of the emission price shock across all countries and sectors covered by the C-STRIKE framework. Rather than focusing on sector-

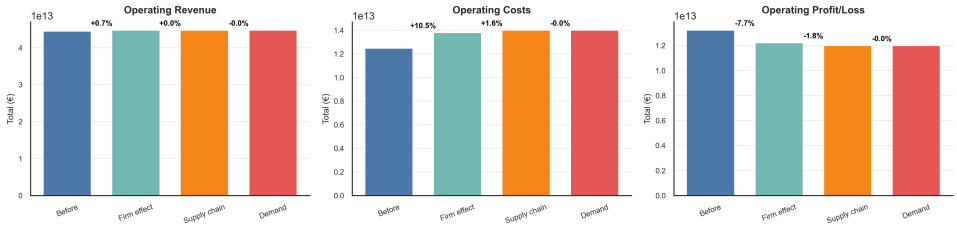

Fig. 4. Aggregate results of the Emission Price Shock across the Three Transmission Layers

or country-level heterogeneity, this figure aggregates the shock transmission at the level of the European economy as a whole.

Revenues show a modest jump already at the firm effect stage. This arises because, within the modeling framework, cost pass-through is partially implemented at this step, allowing firms to adjust prices upwards in response to higher emission costs. Consequently, the supply chain stage captures only the propagation of these higher costs to downstream firms, while the demand layer again adds little incremental effect.

The results also confirm that operating costs increase substantially as a direct consequence of the shock. The decomposition into the three transmission layers—the firm effect, the supply chain effect, and the demand effect—demonstrates that the largest impact occurs immediately at the firm level. The transition from baseline to firm effect is characterized by a sharp increase in operating costs, reflecting the direct imposition of higher emissions-related expenses. Additional increments occur in the supply chain layer, but of a more moderate magnitude. The macroeconomic demand layer induces only minor adjustments, consistent with the assumption of fixed final demand.

Operating profits also exhibit a pronounced decline at the firm level, where the bulk of the losses materialize. The supply chain layer introduces an additional, though considerably smaller, reduction, while the demand effect contributes only marginally. These results underscore that, under the current model calibration, the direct firm effect dominates the aggregate impact, while supply chain and demand channel play a secondary role. This distribution of effects is shaped by the assumed pass-through elasticities and by the maintained assumption of fixed final demand. In practice, higher pass-through rates or dynamic

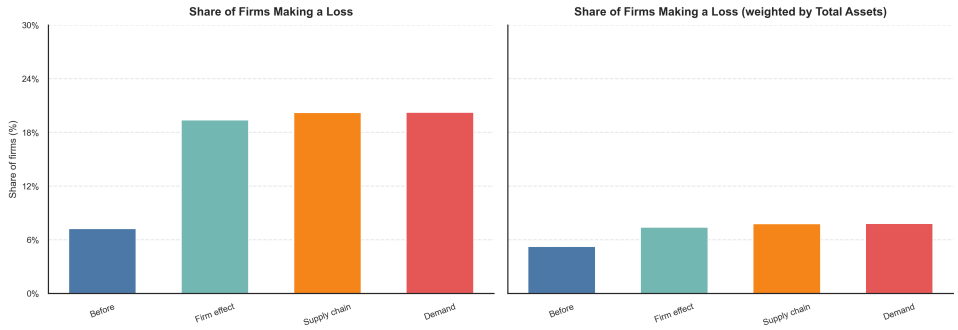

Fig. 5. Share of Firms Incurring Operating Losses under the Emission Price Shock

demand adjustments could redistribute the burden more heavily toward downstream firms or final consumers.

Firm-Level Loss Incidence A complementary perspective is provided in Figure 5, which reports the share of firms that incur operating losses under the emission price shock. The results highlight a substantial increase in the proportion of firms with negative operating profits, rising by a factor of approximately three when comparing the pre-shock baseline with the post-shock firm effect. This sharp increase reflects the vulnerability of small and medium-sized firms that operate with thinner margins and are therefore more exposed to sudden cost shocks.

However, when firms are weighted by total assets, the aggregate effect appears considerably more moderate. In this case, the share of companies operating at a loss increases only by around 50%. This discrepancy underscores the importance of distinguishing between unweighted firm counts, where smaller firms dominate, and asset-weighted measures, which better capture systemic implications for financial stability.

Taken together, the results illustrate how C-STRIKE enables a dual perspective: first, on accounting variables such as costs, revenues, and profits, and second, on financial resilience indicators such as the incidence of losses. The framework thus provides a structured basis for assessing how transition shocks may propagate through the real economy and translate into increased credit risk.

3.2.2 Flooding in Northern Europe

The second demonstrator investigates the financial consequences of a major river flood event in Northern Europe. This scenario is motivated by increasing regulatory and institutional demand for the inclusion of physical climate risk in credit risk models.

Shock Type (including modeling assumptions) The scenario simulates a large-scale flood event along Northern European river basins. Rather than modeling asset destruction directly, the focus is on operational disruption—i.e., the extent to which firm activity is curtailed due to proximity to flooded areas. Firms are geolocated using a multi-step procedure (see Section 4.2.4), and exposure is assessed by calculating the distance of each firm's headquarters to designated flood zones. Flood zone boundaries are based on the 100-year return period flood hazard data provided by the Copernicus Emergency Management Service.

To model the impact gradient, we apply an exponential decay function, where firms located within the flood zone experience full operational loss, while those at increasing distances experience progressively less disruption. Specifically, the firm activity loss is modeled as:

$$\text{Impact}(d) = \begin{cases} e^{-k \cdot d} & \text{if } d \leq 2 \text{ km} \\ 0 & \text{if } d > 2 \text{ km} \end{cases} \quad \text{with } k = \frac{\ln(100)}{2} \approx 2.30$$

where d is the distance to the flood zone in kilometers. This formulation ensures that firms at the flood edge ($d = 0$) experience total disruption, while effects become negligible beyond 2 kilometers.

Shock Intensity The intensity of the flood is specified as a 1-in-100-year event based on current climate conditions, reflecting the return period classification embedded in the Copernicus flood hazard model. This calibration reflects current physical risk exposure rather than forward-looking scenario projections, and is thus directly relevant to short-term risk capacity assessments under ICAAP and Pillar 2 expectations.

Transmission Category The flooding event is modeled as an **aggregate disruption**. That is, both revenue and variable costs are affected proportionally. Operational activity is curtailed due to physical inaccessibility or damage, leading to loss of revenue. At the same time,

variable costs decrease in proportion to the reduction in production (e.g., fewer materials purchased, lower energy usage). However, fixed costs remain largely unchanged and continue to burden affected firms, driving down profitability.

Results and Interpretation Figure 6 presents the change in operating revenues after applying the three propagation layers of the C-STRIKE model. The results are displayed at the macroeconomic demand stage, reflecting both direct firm-level disruption and second-round effects transmitted through the supply chain and final demand patterns.

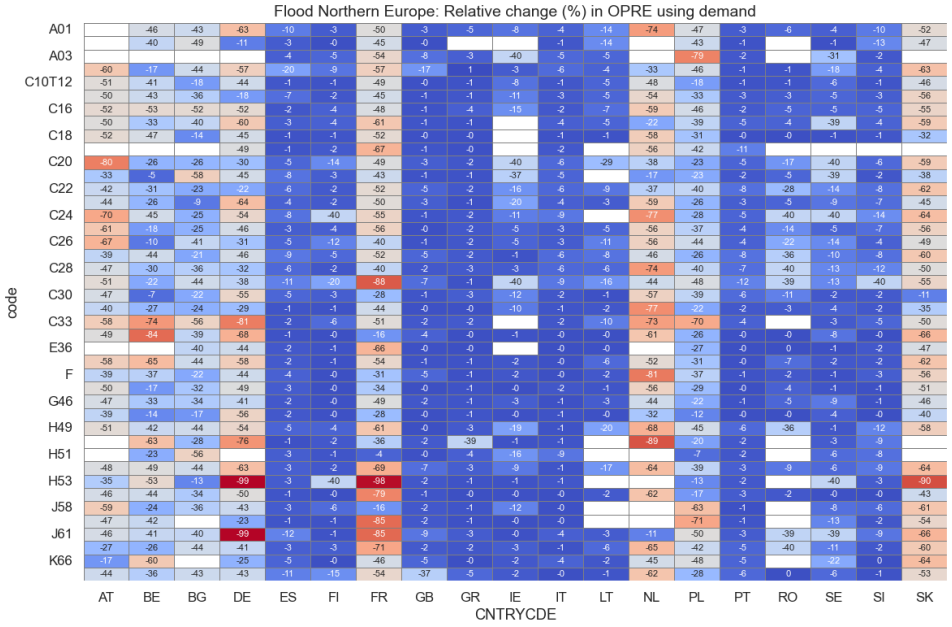

Fig. 6. Matrix of Flooding Shock in Northern Europe (Revenue after Macroeconomic Demand Effect)

Unsurprisingly, firms headquartered in Northern European countries—particularly those located near major river systems—experience the most significant revenue losses. However, the shock also affects firms in other regions through indirect supply chain and demand effects. Sectoral differences are also visible, consistent with the geographic distri-

bution of industries and their respective reliance on affected production hubs.

This demonstrator illustrates how spatially localized physical hazards can translate into wide-ranging financial impacts, validating the importance of firm-level geolocation data and dynamic hazard mapping in climate risk modeling.

3.2.3 Heatwave in Europe

The third demonstrator examines the effects of a severe heatwave across Europe, modeled as a uniform productivity shock affecting labor-dependent firms. This case reflects how physical climate risks can manifest through human capital channels—specifically through the impact of extreme heat on workforce efficiency and economic output.

Shock Type (including modeling assumptions) The shock is modeled as a continent-wide heatwave that reduces labor productivity. In this context, productivity is defined as revenue per employee. The reduction in productivity is translated into revenue losses at the firm level while keeping cost structures unchanged. The impact is firm-specific and determined by the firm's labor intensity—i.e., the number of employees relative to output. The effect function applies a stochastic distribution of losses informed by the empirical distribution of productivity across firms, modulated by a power-law transformation to dampen outliers.

Specifically, the productivity impact is drawn from a log-normal distribution with a median loss of 6%, subject to variation based on labor intensity. For a given firm i, the modeled productivity decline δ_i follows:

$$\delta_i = \left(\exp\left(\mu + \sigma_i \cdot z_i\right)\right)^{\alpha}, \quad z_i \sim \mathcal{N}(0,1)$$

where: - $\mu = \log(0.06)$ is the median productivity loss, - $\sigma_i = \sigma \cdot (1 + \theta \cdot (\mathrm{LI}_i - 1))$ scales with labor intensity $\mathrm{LI}_i = \frac{\mathrm{OPRE}_i}{\mathrm{EMPL}_i}$, - $\alpha \in (0,1)$ compresses the right tail.

This formulation ensures that firms with lower productivity per employee (i.e., higher labor intensity) are hit more severely.

Shock Intensity The intensity is anchored to empirical estimates from studies suggesting that large-scale heatwaves could result in GDP losses of up to 6% in Europe in a given year. Accordingly, we assume a median productivity decline of 6%, applied heterogeneously across firms through the distribution above. Given the regular occurrence of

heatwaves in recent years, the implied return period is shorter than for the flood scenario, suggesting a higher probability but generally lower severity.

Transmission Category The heatwave is modeled as a **revenue shock**. While productivity falls due to adverse weather conditions, cost structures—especially fixed costs and labor contracts—remain largely stable. Thus, the impact is captured by a decline in firm revenues without a proportional reduction in variable or fixed costs.

Results and Interpretation Figure 7 shows the modeled change in operating profitability after the heatwave, based solely on the direct firm effect. The results confirm a more homogeneous impact compared to the other demonstrators. Most firms in European regions experience moderate losses in profitability, but labor-intensive sectors suffer disproportionately. The relatively uniform geographic effect reflects the scenario design—an evenly distributed climatic event—but still reveals firm-level heterogeneity due to differences in labor intensity.

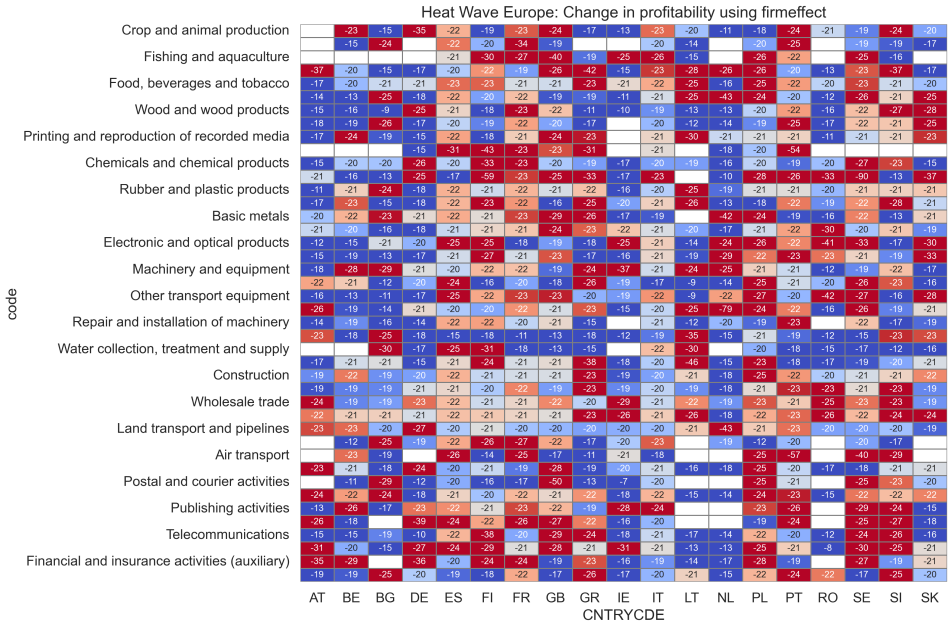

Fig. 7. Matrix of Heat Wave Shock (Operating Profitability of Direct Firm Effect)

This scenario highlights the importance of employee-level data and sectoral labor dependence in assessing vulnerability to climate-related productivity shocks.

4. Technical Documentation

4.1 Model

The C-STRIKE model simulates the transmission of climate-related shocks through a multi-layered framework that mirrors the structure of the real economy. It begins with firm-level exposure and expands through sectoral input–output linkages to capture indirect and macroeconomic effects. The model is modular and proceeds in three stages: (i) direct firm effect, (ii) supply chain propagation, and (iii) macroeconomic demand feedback. Each layer builds on the outcomes of the previous one and updates core accounting variables accordingly. The following sections detail each component of the model in sequence.

4.1.1 Shock Injection

C-STRIKE provides four distinct methods for injecting shocks into firm-level financials. The user must select one of these methods for each simulation step. Although multiple shocks may be applied sequentially, each injection should be defined individually to ensure model consistency.

The four injection options are:

1. Revenue Injection
2. Variable Cost Injection
3. Fixed Cost Injection
4. Disruption

1. Revenue Injection This injection assumes a change in revenue, typically a decrease, while costs remain unchanged. A typical scenario for this setting is a heatwave that leads to a productivity decline: output falls, but input costs (e.g., labor) remain constant.

2. Variable Cost Injection This method assumes simultaneous changes in both revenue and variable costs, but under conditions of asymmetric and sticky price behavior:

- *Asymmetry:* Revenue and cost changes are not proportional and follow different dynamics (see below).
- *Sticky prices:* Only the quantities (input and output volumes) change, while prices are relatively constant. C-STRIKE allows

for some cost pass-through based on industry-specific producer price variability (see below).

An example of this case is a sudden increase in emission prices. The firm first experiences a cost shock, but may be able to pass through part of the cost to downstream actors in the supply chain, either immediately or with a short time lag.

3. Fixed Cost Injection This approach models situations in which fixed costs increase while revenues remain constant. It is appropriate for scenarios involving physical asset destruction, such as damage caused by flooding. These shocks affect firm operations without initially altering output levels.

4. Aggregate Disruption In an aggregate disruption scenario, both revenue and cost decline proportionally. This is suitable for modeling the breakdown of operations, such as when a manufacturing plant ceases to function due to a natural disaster (for example, floods). This type of shock reflects temporary shutdowns that affect all aspects of firm operations in tandem.

4.1.2 Direct Firm Effect

The direct firm effect describes the immediate impact of a climate shock on a company's internal financials. This is the first point of contact in the shock transmission process and defines how the firm's stress-relevant variable $x_{i,t}$ evolves in response to an external shock s_t, where i indexes the firm and t denotes time.

Step 1: Shock Injection The shock s_t is introduced via a function that updates the stress variable $x_{i,t}$ based on its pre-shock value $x_{i,t-1}$ and the magnitude or direction of the shock:

$$x_{i,t} = f_{x,c}(x_{i,t-1}, s_t)$$

Here, $f_{x,c}(\cdot)$ is a shock type and category-specific transition function that determines how the shock propagates to the primary affected variable.

Step 2: Response of Other P&L Items Other profit and loss items, denoted $y_{i,t}$, may respond endogenously to the shock. Their values are determined by a second-order function of the updated shock variable $x_{i,t}$ and their own pre-shock values $y_{i,t-1}$:

$$y_{i,t} = f_{y,c}(x_{i,t}, y_{i,t-1})$$

The exact relationships depend on the selected shock category:

- **Revenue Injection:**
  In this case, the shock directly affects firm revenue, i.e., $x_{i,t} = R_{i,t}$, where $R_{i,t}$ denotes total revenue at time t. To determine the corresponding cost $C_{i,t}$, we assume a constant EBITDA margin. First, calculate the EBITDA margin in the previous period:

  $$\text{EBITDA}\%_{i,t-1} = \left(\frac{R_{i,t-1} - C_{i,t-1}}{R_{i,t-1}} \right) \times 100$$

  where $R_{i,t-1}$ and $C_{i,t-1}$ are pre-shock revenue and cost. Then, use this margin to estimate post-shock costs:

  $$C_{i,t} = R_{i,t} \cdot \frac{\text{EBITDA}\%_{i,t-1}}{100}$$

- **Variable Cost Injection:**
  Here, cost is the primary shock variable: $x_{i,t} = C_{i,t}$. Revenue adjusts in response to changes in cost via a pass-through mechanism:

  $$R_{i,t} = R_{i,t-1} + \Delta C_{i,t} \cdot r_j$$

  where $\Delta C_{i,t} = C_{i,t} - C_{i,t-1}$ is the cost change, and $r_j \in [0, 1]$ is the sector-specific cost pass-through rate for sector j, introduced in the supply chain section.
- **Disruption:**
  In disruption scenarios (e.g., due to physical damage or outages), cost is again the shock variable: $x_{i,t} = C_{i,t}$. Revenue is assumed to adjust proportionally based on the prior EBITDA margin:

  $$\text{EBITDA}\%_{i,t-1} = \left(\frac{R_{i,t-1} - C_{i,t-1}}{R_{i,t-1}} \right) \times 100$$

  $$\Rightarrow \quad R_{i,t} = \frac{C_{i,t}}{\text{EBITDA}\%_{i,t-1}/100}$$

Step 3: Solution of Remaining Variables All other firm-level accounting variables, denoted by $z_{i,t}$ (e.g., tax, interest, profits, or balance sheet items), are updated using definitional identities or structural accounting rules. These are generally written as:

$$z_{i,t} = f_z(x_{i,t}, y_{i,t})$$

where $f_z(\cdot)$ represents the set of mappings from core P&L items to all other required financial variables in the model.

4.1.3 Supply Chain Effect

The supply chain effect models how climate shocks propagate through the economy beyond the directly affected firm. It captures two mechanisms:

- the ability of firms to pass on part of the shock to downstream economic agents, and
- the exposure of firms to upstream shocks originating in other sectors or geographies.

We distinguish between two propagation channels:

1. Cost Pass-Through
2. Volume Effects

Option I: Cost Pass-Through The cost pass-through channel assumes that companies facing higher input costs may increase prices and thereby shift some of the burden to downstream clients. This propagation channel applies to Variable Cost Injections. This mechanism is modeled in two stages:

Step 1: Estimating Sector-Level Pass-Through Rates We use historical producer price volatility to empirically estimate pass-through capability by sector j. For each sector, we compute the average relative price change:

$$v_j = \frac{1}{T} \sum_{t=1}^{T} \frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}}$$

where $p_{j,t}$ denotes the producer price index for sector j at time t, and T is the total number of periods observed.

We rank sectors by their volatility v_j to derive the pass-through rate r_j, assigned by quantile as follows:

$$r_j = \begin{cases} 0 & \text{if } 0 \leq q_j \leq 0.2 \\ 0.25 & \text{if } 0.2 < q_j \leq 0.4 \\ 0.5 & \text{if } 0.4 < q_j \leq 0.6 \\ 0.75 & \text{if } 0.6 < q_j \leq 0.8 \\ 1 & \text{if } 0.8 < q_j \leq 1 \end{cases}$$

Here, q_j denotes the quantile rank of volatility v_j.

Step 2: Firm-Level Revenue Response At the firm level, if the firm experiences a change in cost $\Delta C_{i,t}$, the change in revenue $\Delta R_{i,t}$ due to cost pass-through is given by:

$$\Delta R_{i,t} = \Delta C_{i,t} \cdot r_j \quad \Rightarrow \quad R_{i,t} = R_{i,t-1} + \Delta R_{i,t}$$

Step 3: Network-Based Cost Propagation (Leontief) To account for second-order effects across sectors, we employ a cost-adjusted Leontief input–output framework. Rather than using physical units, we model the economy at the country–sector level using cost shares:

$$\mathbf{B} = \text{Cost Coefficient Matrix}$$

Each element b_{j_1,j_2} represents the share of inputs from sector j_1 in the total cost of sector j_2:

$$b_{j_1,j_2} = \begin{cases} \frac{\text{cost of inputs from sector } j_1}{\text{total cost of sector } j_2}, & \text{if } \frac{\text{cost of inputs from sector } j_1}{\text{total cost of sector } j_2} \geq 0.01 \\ 0, & \text{otherwise} \end{cases}$$

The total cost impulse across the economy is derived using the Leontief inverse:

$$\mathbf{C} = (\mathbf{I} - \mathbf{B})^{-1} \cdot \mathbf{f}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{f}$ is the direct cost impulse vector.

We distribute this sector-level propagation to firms using a proportional share rule. The firm-level cost increase attributable to supply chain propagation is:

$$\Delta C_{i,t} = C_{i,t,\text{direct}} \cdot \sum_j (C_{ij} \cdot \Delta R_{i,t})$$

where C_{ij} is the share of sector j in firm i's cost structure. The total cost after propagation becomes:

$$C_{i,t} = C_{i,t,\text{direct}} + \Delta C_{i,t}$$

Option II: Volume Effect In the volume-based propagation channel, we model shocks that result in physical reductions in production volumes (e.g., due to supply constraints or operational shutdowns). This method applies to Revenue Injections and Disruptions. Because physical volumes are indivisible and must be fully transferred, we assume a 100% pass-through rate:

$$\Delta C_{j,t} = \Delta P_{j,t}$$

Steps 1-3 from Option I apply.

In this setting, both cost and revenue move in tandem. To estimate revenue, we apply the inverse of the EBITDA margin from the direct firm effect

$$\text{EBITDA}\%_{i,t}^{\text{direct}} = \left(\frac{R_{i,t}^{\text{direct}} - C_{i,t}^{\text{direct}}}{R_{i,t}^{\text{direct}}} \right) \times 100$$

$$\Rightarrow \quad R_{i,t} = \frac{C_{i,t}^{\text{direct}}}{\text{EBITDA}\%_{i,t}^{\text{direct}}/100}$$

Final Step: Updating Remaining Variables As in the direct firm effect, all other accounting variables at the firm level are updated according to definitional relationships and financial identities:

$$z_{i,t} = f_z(x_{i,t}, y_{i,t})$$

4.1.4 Macroeconomic Demand Effect

The macroeconomic demand effect captures how climate shocks reduce final demand across sectors and geographies. This effect is distinct from

direct firm and supply chain impacts, as it reflects broader economic contraction in household and government consumption. It serves as the final propagation layer in the C-STRIKE framework.

Step 1: Sectoral Final Demand Weights We use input–output tables to determine each sector's exposure to final demand. For sector–region combination j, the total final demand share ϕ_j is calculated by summing cost coefficients across the relevant final consumption categories:

$$\phi_j = \sum_{k \in \{\text{Households, Government, NPISH}\}} b_{k,j}$$

where $b_{k,j}$ represents the share of inputs from sector j consumed in final demand category k.

Step 2: Sectoral Demand Change Estimation Next, we estimate the relative change in sector-level revenue resulting from prior supply chain effects. For each sector j, we compute:

$$\Delta^{\text{rel}} R_j = \frac{R_{j,t-1}^{\text{supplychain}} - R_{j,t}^{\text{supplychain}}}{R_{j,t-1}^{\text{supplychain}}}$$

This change reflects aggregate loss in sectoral revenue due to upstream and downstream disruptions.

Step 3: Firm-Level Revenue Adjustment under Demand Shock Each firm i receives a demand-adjusted revenue $R_{i,t}^{\text{demand}}$, derived from two weighted components:

- A corrected supply chain revenue scaled by the inverse demand shock: $\frac{R_{i,t}^{\text{supplychain}}}{1-\Delta^{\text{rel}} R_j}$
- A residual component that is not exposed to final demand

The resulting expression is:

$$R_{i,t}^{\text{demand}} = \left(\frac{R_{i,t}^{\text{supplychain}}}{1 - \Delta^{\text{rel}} R_j} \right) \cdot \phi_j + R_{i,t}^{\text{supplychain}} \cdot (1 - \phi_j)$$

Step 4: Updating Firm-Level Cost To update firm cost levels, we first calculate the effective profitability after the supply chain effect:

$$\text{EBITDA\%}_{i,t}^{\text{supplychain}} = \left(\frac{R_{i,t}^{\text{supplychain}} - C_{i,t}^{\text{supplychain}}}{R_{i,t}^{\text{supplychain}}} \right) \times 100$$

This profitability is used to infer the cost level under the demand scenario:

$$C_{i,t}^{\text{demand}} = R_{i,t}^{\text{demand}} \cdot (1 - (\text{EBITDA\%}_{i,t}^{\text{supplychain}}/100))$$

Step 5: Final Accounting Update As with prior shock layers, all other accounting variables are updated using definitional and structural relationships:

$$z_{i,t} = f_z(x_{i,t}, y_{i,t})$$

This includes operating profit, taxes, profit after tax, cash flow, balance sheet items, and financial ratios. These updates reflect firm-wide adjustments under diminished macroeconomic demand conditions.

4.2 Data

The C-STRIKE model is based on a rich and diverse data set that combines firm-level financial information with sectoral, spatial, and macroeconomic information. These data inputs are essential for parameterizing the model's three-layer structure: direct firm effects, supply chain propagation, and macroeconomic demand feedback. The core dataset is drawn from Amadeus and is supplemented with external geospatial, emissions, and employment estimates where primary data are missing. This section describes the structure and coverage of the underlying data and outlines the empirical strategies used to fill critical data gaps through predictive modeling and statistical integration.

4.2.1 Company Fundamentals

The implementation of the C-STRIKE model is based on a comprehensive firm-level dataset covering more than one million companies across Europe. The data originate from the Orbis Amadeus database, now operated by Moody's, and include detailed balance sheet, profit

and loss, and employment variables for firms of varying size, sector, and country of registration.

As illustrated in Figure 8, the sample includes not only large, publicly listed corporations but also a wide range of medium-sized and smaller enterprises.

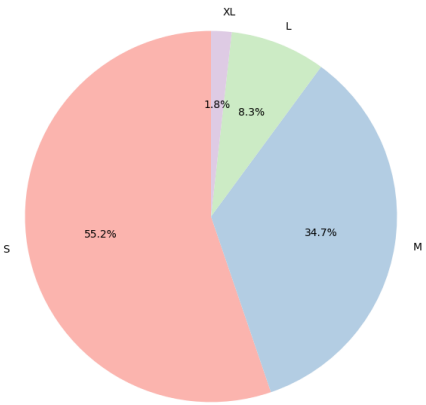

Fig. 8. Company Size Distribution

Figure 9 shows that observations are well distributed across all major NACE Level 1 sectors, with strong representation in industries relevant to financial risk analysis and sustainability assessments.

Figure 10 reveals significant country-level variation in data availability, with Italy, France, Spain, Portugal, and Sweden providing comparatively richer firm coverage due to more granular reporting regimes and national statistical infrastructure.

Table 2 provides summary statistics of key firm-level financial indicators. These include fixed and current assets, liabilities, revenues, costs, and employment metrics, all of which serve as inputs for the different stages of the C-STRIKE modeling framework.

4.2.2 Model Specification

The empirical specification of the C-STRIKE model requires two core inputs: (i) a multi-regional input–output matrix to trace inter-industry

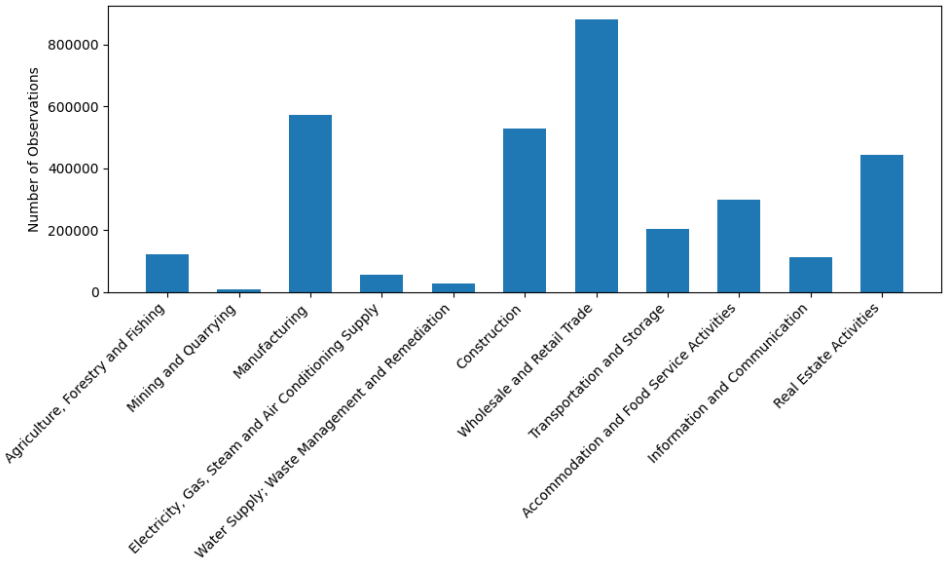

Fig. 9. Observations by NACE Level 1 Sector

dependencies, and (ii) time-series data on producer price variability to approximate sector-level cost pass-through rates.

Input–Output Matrix (FIGARO) To model the propagation of shocks through the supply chain as well as their impact on final demand, we rely on the FIGARO input–output framework provided by Eurostat. The FIGARO tables capture bilateral trade and input relationships between industry–country pairs within the European Union, as shown in Figure 11. These matrices are highly granular and record, for each sector j in country c, how goods and services flow to all other sectors and geographies.

We use two different components of the FIGARO system:

- Inter-industry flows for modeling cost propagation and indirect effects via the Leontief inverse.
- Final demand categories (households, government, NPISH) to compute sector-level exposure to consumption in the macroeconomic demand effect.

All values are converted into normalized cost coefficients to serve as inputs for shock propagation calculations. This ensures comparability across sectors and facilitates the use of matrix operations in the model.

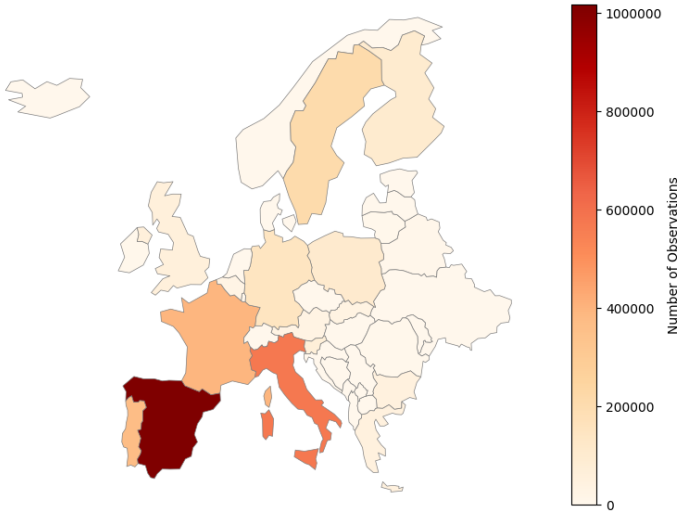

Fig. 10. Observations by Country

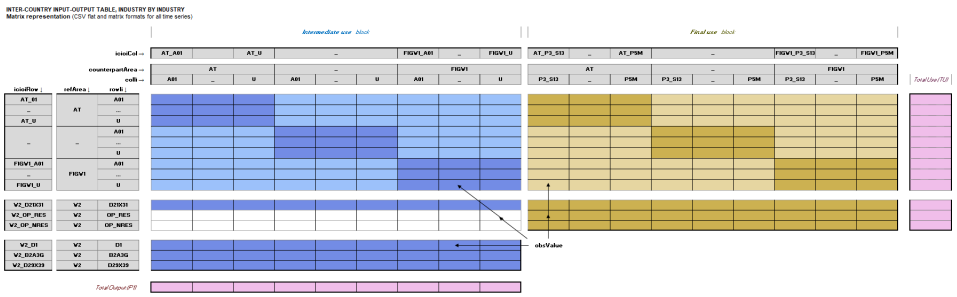

Fig. 11. Structure of FIGARO I/O Table (Source: Eurostat)

Producer Price Variability The second input used to calibrate the model is sector-level producer price variability. This indicator serves as the empirical basis for estimating cost pass-through rates r_j, which define the ability of firms in sector j to shift input cost increases to their customers.

We use the 2022 average of monthly producer price indices for European sectors as provided by Eurostat. These values are used to derive pass-through rates via a quantile-based mapping procedure, as previously described in the supply chain effect section.

	count	mean	std	min	25%	50%	75%	max
Intangible Fixed Assets (mn EUR)	4344838	2.26	288.94	-79.07	0.00	0.00	0.00	146041.38
Total Fixed Assets (mn EUR)	4362826	5.68	297.94	-161.97	0.01	0.10	0.54	123394.00
Other Fixed Assets (mn EUR)	4344752	3.73	275.95	-372.44	0.00	0.00	0.03	218655.00
Current Stock (mn EUR)	4402721	1.69	83.57	-91.88	0.00	0.02	0.20	52274.00
Debtors (mn EUR)	4029694	1.90	74.50	-88.53	0.00	0.04	0.26	39085.57
Other Current Assets (mn EUR)	4409368	5.58	998.42	-189.52	0.02	0.10	0.40	922649.89
Shareholder Funds (mn EUR)	3961987	1.45	81.07	-758.83	0.00	0.01	0.10	47347.48
Other Shareholder Funds (mn EUR)	3962039	5.96	337.13	-120433.93	0.01	0.11	0.58	177044.00
Long Term Debt (mn EUR)	4421257	5.10	947.32	0.00	0.02	0.10	0.42	1895000.00
Other Non-current Liabilities (mn EUR)	4421256	2.38	269.31	-2141.71	0.00	0.00	0.03	166531.00
Provisions (mn EUR)	3897225	1.44	192.34	-1.08	0.00	0.00	0.00	163931.00
Current Liabilities - Loans (mn EUR)	4313067	1.66	283.24	-5600.53	0.00	0.00	0.06	502953.00
Creditors (mn EUR)	4304338	1.64	77.84	-2.86	0.00	0.03	0.21	61486.64
Other Current Liabilities (mn EUR)	4333239	2.66	1395.13	-2392553.71	0.01	0.05	0.22	921135.21
Employees	3491964	49.01	1736.23	0.00	2.00	5.00	15.00	600278.00
Operating Expenses (mn EUR)	4421257	13.43	712.09	-1658.21	0.10	0.42	1.68	420634.00
Financial Expenses (mn EUR)	3979215	0.33	39.05	-2114.16	0.00	0.00	0.02	43503.37
Financial Income (mn EUR)	4275060	-0.06	40.92	-43503.37	-0.01	-0.00	0.00	14677.00
Material Costs (mn EUR)	2807093	7.11	415.18	-556.20	0.05	0.22	0.97	275799.00
Staff Costs (mn EUR)	2938987	2.59	123.37	-10.78	0.04	0.13	0.42	47002.00
Depreciation (mn EUR)	3176207	0.93	74.59	-1104.50	0.01	0.02	0.07	33206.00
Net Asset Turnover	4064202	2.53	11.59	0.00	0.11	0.93	2.59	1000.00
Collection Period	3828333	67.83	107.11	0.00	4.00	35.00	86.00	1000.00
Credit Period	4029530	61.71	109.30	0.00	7.00	28.00	67.00	1000.00
Profit per Employee (th EUR)	3156972	0.22	6.55	-32.38	0.00	0.00	0.03	2979.50
Revenue per Employee (th EUR)	3240114	2.44	43.14	0.00	0.08	0.17	0.70	30311.19
Cost per Employee (th EUR)	2516585	0.14	0.80	0.00	0.02	0.03	0.05	245.93
Shareholder Funds per Employee (th EUR)	2857230	1.28	16.05	0.00	0.02	0.06	0.28	3555.69
Working Capital per Employee (th EUR)	2841429	0.54	12.15	-36.46	0.00	0.02	0.08	3600.10
Total Assets per Employee (th EUR)	3329131	5.00	92.11	0.00	0.07	0.19	0.90	34343.06

Table 2 Descriptive Statistics

Figure 12 displays the input data. This is the evolution of producer price variability across sectors for 20 years using a three-month rolling mean of the relative price change for each sector.

4.2.3 Emission Data

A key challenge in simulating emission price shocks at the firm level is the limited availability of high-quality Scope 1 emissions data, particularly for small and medium-sized enterprises. While self-reported data exist for a subset of large listed firms, most companies in the dataset do not disclose their emissions. To address this, we apply a machine learning (ML)–based imputation approach that predicts firm-level Scope 1 emissions using available financial variables.

The method builds on the framework developed by Haas et al. [2025], which constructs predictive models using supervised learning on emission disclosures from listed firms in the LSEG Refinitiv database. In contrast to simpler relational or linear extrapolation techniques, this approach leverages a pipeline-optimization strategy in which multiple

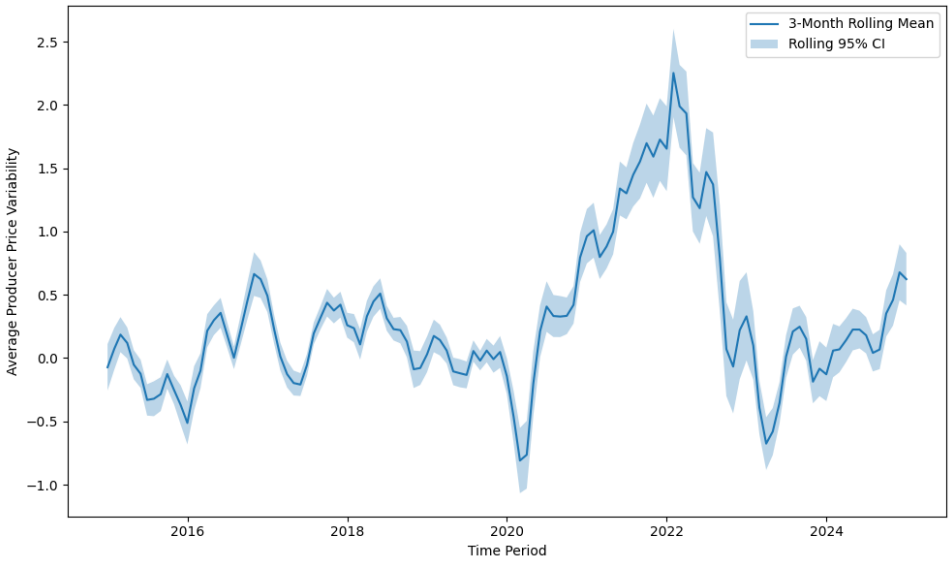

Fig. 12. Producer Price Variability - 3-Months Rolling Mean (Source: XXX)

preprocessing steps, feature sets, and regression algorithms are evaluated in parallel. As illustrated in Figure 13, a "horse race" is conducted between candidate pipelines based on cross-validation performance. The best-performing models—typically the gradient-boosting algorithms CatBoost and XGBoost—are then used to generate predictions for firms lacking observed emissions data.

Given the broader scope of the C-STRIKE dataset, which includes a large number of unlisted firms from the Amadeus database, we adapt and retrain the Haas et al. approach using our target population. The predictor variables are exclusively based on financial statement information, ensuring a wide coverage. As the data generating process may also change in this domaine shift, we apply additional correction procedures to ensure that the data are within valid bounds based on an ongoing work by one of the authors.

Figure 14 shows the resulting distribution of predicted Scope 1 emissions on a logarithmic scale. The distribution exhibits the expected long-tail shape: while a few firms exhibit very high direct emissions, the majority of firms show low to moderate emissions, consistent with their size and sectoral classification. These emission estimates serve as

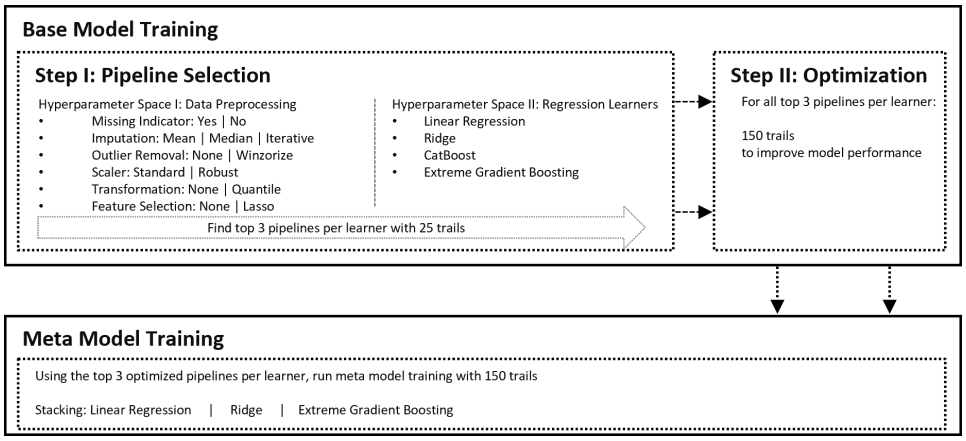

Fig. 13. ML Approach to Scope 1 Emission Estimation (Source: [Haas et al., 2025])

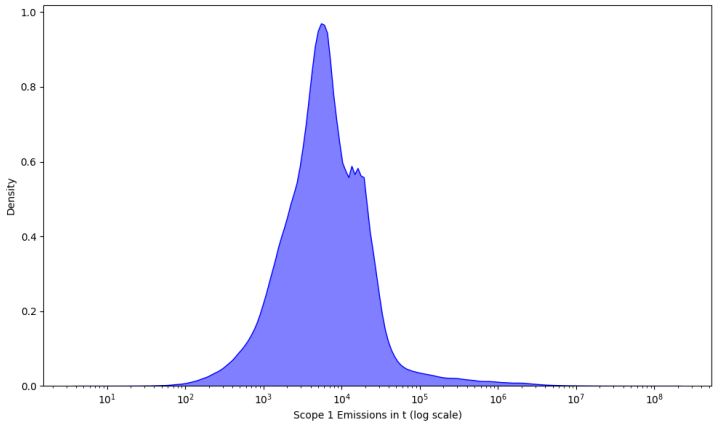

Fig. 14. Distribution of Scope 1 Emissions

the quantitative foundation for applying emission price shocks in the respective use case discussed later in the paper.

4.2.4 Location Data

To model flood shocks at the firm level, it is essential to determine the geographic location of each firm's headquarters. This allows us to simulate physical risk exposure based on spatial proximity to flood zones. The C-STRIKE framework uses geolocation data to compute

firm-specific distances to designated hazard areas and subsequently apply intensity-weighted shock functions.

We implement a multi-step geolocation strategy to maximize spatial coverage for firms in the Amadeus dataset:

1. **Integration of Orbis Location Data:** We enrich the Amadeus database with geospatial coordinates available from the Orbis database (also provided by Bureau van Dijk), which contains longitude and latitude information for a substantial number of firms. This step covers more than half of the firms in the sample but is insufficient for full spatial coverage.
2. **Incorporation of External Research Data:** To expand coverage, we incorporate the geolocation dataset developed by Bossut and Kempa [2025], who systematically matched Amadeus-Orbis firm records to spatial coordinates in the context of physical climate risk modeling. Their dataset significantly increases the share of firms with high-quality geolocation attributes.
3. **Custom Geocoding Based on Address Data:** For firms still lacking coordinates, we apply a custom geocoding procedure using city names, postal addresses, and country codes from the Amadeus records. We use OpenStreetMap's Nominatim service to retrieve precise coordinates based on full-text address queries.
4. **Fallback Geolocation via City Centroids:** For the remaining unmatched firms, we assign coordinates based on city centroids combined with country information. While less precise, this fallback method ensures that nearly all firms in the dataset are geolocated with a reasonable degree of accuracy.

This multi-source geolocation pipeline enables nearly full spatial coverage of firms, providing the geographic foundation for the flood shock scenario described in the relevant use case section.

4.2.5 Employee Data

Employee data are a critical input to modeling the heatwave shock, which operates via labor intensity—i.e., the ratio of employees to revenue. The extent to which a firm's operations are labor-intensive affects its vulnerability to heat-induced productivity losses and cost shocks.

The Amadeus dataset already contains employment information for approximately 70% of firms. However, to ensure model-wide applicability of labor-based shocks, we impute missing values using a machine learning–based approach. The prediction task is framed as a supervised regression problem, where the target variable is the log-transformed number of employees per firm:

$$y = \log(1 + \text{EMPL})$$

Feature Set and Preprocessing The feature set comprises over 30 financial statement variables—ranging from fixed assets to liabilities and revenue—as well as firm characteristics such as incorporation date and company category. Categorical variables (e.g., sector code, consolidation status) are encoded using supervised target encoding. All numeric features are standardized and extended via polynomial interactions:

$$\tilde{x}_i = \text{scale}\left(\text{poly}(\text{impute}(x_i))\right)$$

where polynomial terms are restricted to second-degree interactions.

Model Training and Stacking Two gradient boosting models, XGBoost and LightGBM, are trained and combined using a Ridge regression metalearner in a stacked ensemble:

$$\hat{y} = \text{Ridge}\left(\hat{y}^{\text{XGB}}, \hat{y}^{\text{LGB}}\right)$$

This stacked model is embedded in a pipeline that includes preprocessing and automatic feature selection (using tree-based importance scores). Model parameters are optimized via randomized search over hyperparameter grids, using negative mean squared error as the scoring metric and 3-fold cross-validation.

Application and Output The final trained model is applied to firms with missing employment data. Predictions are exponentiated and rounded to yield realistic employee estimates:

$$\widehat{\text{EMPL}} = \lfloor \exp(\hat{y}) - 1 \rfloor$$

This process significantly improves the coverage of labor data in the dataset at a high level of preditive power, enabling robust firm-level estimation of the heatwave shock channel across the entire C-STRIKE population.

5. Conclusion & Outlook

The growing urgency of climate-related financial risks calls for innovative tools that can capture the complexity, suddenness, and asymmetry of both physical and transition shocks. Traditional scenario-based models, while valuable for policy coordination and long-term orientation, often fail to meet the specific needs of financial institutions, particularly when it comes to short-term, firm-level credit risk assessments.

In this report, we introduced **C-STRIKE**—a modular, bottom-up modeling framework designed to simulate the transmission of climate shocks through the real economy in a transparent and scalable way. By tracking direct, supply chain, and macroeconomic demand effects of climate-related events, C-STRIKE provides a realistic and flexible platform to assess financial vulnerabilities, test credit exposures and inform strategic decision-making.

The model addresses several core limitations of existing approaches by embracing out-of-equilibrium dynamics, enabling short-term accounting consistency, and offering fine-grained disaggregation across firms, sectors, and geographies. Through a series of demonstrator scenarios, ranging from emission price shocks to floods and heatwaves, we showed how C-STRIKE can accommodate diverse climate stressors and provide actionable output for both supervisory and internal risk management purposes.

At the same time, the current implementation of C-STRIKE is only a first step in a broader methodological agenda. Several limitations offer fertile ground for further development:

- **Single-Year Horizon:** The model currently operates on a one-period time frame. Future versions will extend this to a multi-period structure to allow for the analysis of cumulative and dynamic effects, including recovery patterns and the compounding of risks over time.
- **Deterministic Shocks:** Shocks in the current framework are applied deterministically. Introducing a probabilistic layer, for example, via Monte Carlo simulation or scenario ensembles, would enable users to quantify uncertainty and generate distributions of potential outcomes.

- **Static Economic Agents:** Households and firms are currently assumed to behave statically. Incorporating behavioral responses such as supplier substitution, demand reallocation, or adaptive investments will improve the realism and resilience of the model dynamics.
- **Expanded Risk Dimensions:** While the focus is on climate-related financial risk, future extensions should include broader ESG factors (e.g., social and governance risks), which are increasingly relevant under evolving regulatory frameworks.
- **Global and Cross-Jurisdictional Scope:** The model currently emphasizes European firms due to data availability. Expanding the regional coverage to include non-European markets would increase relevance for global financial institutions.
- **Credit Risk Modules:** Future versions will integrate probabilistic credit risk measures such as probability of default (PD) and loss given default (LGD). This will allow for a more direct translation of economic shocks into risk-weighted asset impacts and capital requirements.

More broadly, we view C-STRIKE as part of a wider research and policy effort to build tools that are fit for purpose in an era of climate uncertainty. As supervisory expectations evolve and climate events become more pronounced, financial institutions will require robust, interpretable, and forward-looking approaches to quantify and manage these risks. We hope that C-STRIKE offers a valuable step in this direction and that future iterations, informed by practical applications and stakeholder feedback, will further enhance its utility and scope.

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