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ORIGINAL ARTICLE

The Impact of Transitory Climate Risk on Firm Valuation and Financial Institutions: A Stress Test Approach

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Abstract Addressing recent calls by European regulatory and supervisory authorities, we develop a new bottom-up climate risk assessment method to examine the resilience of the European banking industry regarding transitory climate risks. We illustrate our approach by estimating the impact of a 50–100 EUR carbon tax per tCO_2 equivalent on the valuation and default risk of STOXX Europe 600 firms. For about 5% of the sample firms, we find asset devaluation shocks larger than 30% and for about 16% of the firms probabilities of default (PDs) dropping below investment-grade level of 3%. At the sector level, our results yield asset devaluations shocks of 15–36% and new PDs of 5–34% for the six most affected sectors. Running a stress test on credit risk based on these results, we find a decrease in capital ratios between −1.2 and −1.6 percentage points for key regulatory capital ratios in the most adverse scenario while only addressing 36% of the bank's total risk-weighted assets. Our

Alexander Schult, Sebastian Müller, and Gunther Friedl developed the 6-step approach, the empirical strategy, and the stress test scenario together; Alberto Spagnoli and Alexander Schult conducted the modeling and empirical analyses. The manuscript was drafted and revised jointly by all authors. All authors read and approved the revised manuscript.

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analysis sheds light on the substantial transitory climate risk for asset portfolios of banks and contributes to the pressing question how to integrate climate risk into risk management and regulation of financial institutions.

Keywords Climate Transition Risk · Risk Management · Climate Stress Test · Financial Stability · ESG

MSC-Classification JEL classification · G21 · G28 · G32

1 Introduction

Climate change is an "existential threat [...]. There's no threat like it. [...] It's an economic imperative. I think it's a moral imperative to future generations." (Biden 2021b). With these words, US President Biden once again emphasized the urgent need for joint international climate action at the Virtual Leaders Summit on Climate in April 2021. Climate change and the dependency on fossil energy resources have gained new momentum in light of skyrocketing energy prices in 2022 and the widespread stop of gas imports from Russia. However, action still lags behind climate ambition, such as the Paris climate agreement targets of limiting global warming to 1.5 °C. Greenhouse Gas (GHG) emissions will have to be cut significantly within this decade to limit the occurrence of natural catastrophes and to stabilize the global temperature in the long run. Otherwise, the damage to the world and the global economy in the next decades will be drastic (World Meteorological Organization 2021).[1]

Consequently, sustainability has become a dominating topic in society, politics, the economy, and academia. Polls in Europe, North America, and Asia stating climate change as by far the largest threat of the decade show that climate change is deeply anchored in national societies (Fagan and Huang 2019; IMF 2021). The USA rejoined the Paris agreement and initiated the analysis of climate risk for the national economy (Shalal and Mason 2021; Biden 2021a) while China committed to stronger climate targets (World Resources Institute 2020). In Europe, the European Commission pursues the "European Green Deal", launched the "Sustainable Finance Action Plan" (European Commission 2018) and gradually extends the scope of the EU Emissions Trading Scheme (EU ETS) as the world's first and biggest carbon market to reduce EU's GHG emissions. Businesses face increasingly strict regulations on emissions reduction and acknowledge the relevance of sustainability. For example, the Value Balancing Alliance (VBA)[2] attempts to measure the impact of companies on society and capture it in the balance sheet (VBA 2021). In the academic stream,

[1] Estimates of the long-run impact vary, but for example, the Swiss RE Institute (2021) estimates the cost to be 18% of GDP in the next 30 years.

[2] The VBA consists of 20 large international companies such as BMW, SAP, or Deutsche Bank, the Big 4 Accounting firms, the Organisation for Economic Cooperation and Development (OECD), and some academic institutions.

there is a new research agenda on measuring non-financial risk in a broader context (Franke 2020).

Climate change and the fight against it may turn into financial risk. This financial risk due to climate change, or environmental risk, arises primarily because of two major types of risks. While *transitory risk* occurs in the transition to a low-carbon economy (this includes, for example, climate policy instruments such as a CO_2 price or tax, or a shift to more expensive, low-carbon technology), *physical risk* includes sudden extreme weather events (flooding or heavy storms, etc.,) or evolving effects (rise in temperature or sea level) (NGFS 2019, 2020a, b). The economic damage from these two risks, such as stranded assets (transitory risk) or business disruptions, capital scrapping, (uninsured) reconstruction, and replacement (physical risk), put the profitability and financial health of companies at risk. This, in turn, may also hurt the financial sector as a lender of capital for these companies and endanger the resiliency of financial institutions.[3]

This is why financial practitioners, key regulatory and supervisory authorities such as the European Banking Authority (EBA) and the European Central Bank (ECB), have started to integrate environmental risk into risk assessments because climate change together with the two very recent shocks, the COVID-19 pandemic and the energy crisis due to the war between Ukraine and Russia, poses a considerable risk for the resiliency of financial institutions (Kasinger et al. 2021). The EBA announced to include ESG (Environmental, Social, Governance) risks in the supervisory review process and to expect financial institutions to disclose climate risks and run climate stress tests (EBA 2019, 2021). The ECB required financial institutions to establish climate risk-management governance and to rapidly develop suitable climate-related stress test approaches by 2022 (ECB 2020; ESRB 2020). The results of the first stress test exercise, published in July 2022, indicate combined credit and market risk losses for 41 tested banks up to around €70 billion in a three-year time horizon for transition risk and two physical risk types. However, 90% of the climate risk assessment practices of financial institutions were not yet in line with the ECB's expectations as of February 2022 (Elderson 2022), and around 60% of banks lacked well-integrated climate risk stress-testing frameworks as of July 2022 (ECB 2022).

We address the issue of climate risk assessment methods and test the resiliency of the financial sector against transitory climate risk on the firm level. We focus on transitory climate risk because this type of risk appears more pressing in light of rising European and national environmental regulation in the near future. We develop a new generic 6-step climate risk assessment method that allows researchers, practitioners, and regulators to analyze the impact of transitory climate risk on the firm level. We apply this 6-step climate risk assessment method and run a climate stress test for credit risk of financial institutions in a classical stress test time horizon of 1–3 years by assuming national carbon tax levels of 50–100 EUR per CO_2 ton equivalent on top of the current European Trading Scheme (ETS) for the companies in the STOXX Europe 600 index. We collect all company-specific information in

[3] Even more, through reduced capital availability, the damage to the financial sector may feed back to the overall economy through reduced capital availability (contagion) and cause even more severe second-round effects that may put the resiliency of the financial sector even further at risk.

an extensive data set from Refinitiv Datastream. We end up with a final sample of 404 European firms after excluding 69 financial corporations due to their unique capital structure and excluding 127 firms due to their incomplete CO_2, financial or emission data. We construct four scenarios and capture the financial impact on the remaining 404 STOXX Europe companies through a Net Present Value (NPV) of future carbon tax payments. We put these NPVs in relation to the original asset value to yield firm-specific asset devaluation shocks and integrate them into the classical Merton model to calculate new probabilities of default (PDs).

We find for about 5% of the 404 companies asset devaluation shocks larger than 30% while about 16% of the firms face new PDs dropping below an investment grade level of 3% (Monnin 2018). On the sector level, we find asset devaluations of 15–36% in the most adverse scenario for the six most affected sectors (Travel & Leisure, Construction & Materials, Utilities, Basic Resources, Chemicals, Energy) that are also the most carbon-intensive ones. This leads to new PDs of 5–34% for those sectors after the transitory climate risk shock in the most adverse scenario that can be solely attributed to the carbon tax shock.[4] We run two robustness checks on the asset variance parameter. We bootstrap the volatility parameter and allow the asset variance to increase by 50% in reference to the most severe financial crisis experiences from the past. The substantial increase in the variance parameter would put many sectors, partly independent of their carbon-intensity, into financial distress through higher PDs across all four scenarios. The bootstrapped asset variance results remain robust and consistent with our main estimates.

We take these new "after transitory climate shock PDs" one step further and run a stress test for credit risk in line with Basel III and EBA requirements with publicly available exposure data on the sector level of a large European bank. By addressing 36% of the bank's risk-weighted assets (RWA) for corporate credit risk exposure, we find a drop in CET1 percentage points up to -1.2%, in Tier1 up to -1.4% and in total capital ratio up to -1.6%, respectively. The results vary substantially by scenario. We find the most drastic results in our most adverse scenario 4 with a carbon tax of 100 EUR per CO_2 ton equivalent, an abrupt introduction of the tax, a pass-through rate onto consumers of 50%, and no adaptation capabilities of companies to reduce their carbon footprint in the next three years. In light of the typical stress test time horizon of 1–3 years, we do not integrate macroeconomic development into our model.[5] We discuss further assumptions and input parameters feeding into

[4] The partially high PDs in our analysis compared with empirically observed PDs can be explained by the original Merton model with its strict default assumption once the value of assets falls below the value of debt and by the expectations of market participants that may have priced in, to some extent, higher carbon tax levels (Delis et al. 2018).

[5] An unfavourable macroeconomic development due to climate change is likely to worsen the results in the model. The multi-macroeconometric National Institute Global Econometric Model (NiGEM) model provided by the National Institute of Economic and Social Research of the University of Oxford puts together various macroeconomic models about commodities, labour markets, trade, or public households based on the NGFS climate scenarios and their forecasts of macroeconomic development. These are built on the Intergovernmental Panel on Climate Change (IPCC) predictions (Intergovernmental Panel on Climate Change 2000).

our analysis and the resulting magnitude of impact in Sect. 4.8 "Reconciliation and discussion".

Our study is one of the first to combine the impact of transitory climate risk on the valuations of a cross-European firm sample ("bottom-up") with a standard stress test of a large European bank. Our paper is targeted at researchers, practitioners, and regulatory agents and contributes to the existing literature in two ways.

First, we consolidate and summarize the enormous diversity in different climate stress test approaches for transitory climate risk from the literature and develop one generic, overarching 6-step approach as an umbrella. This 6-step approach may serve as starting point to assess the impact of (long-term) transitory climate risk on credit risk "bottom-up" or "top-down" in the short run of 1–3 years. Our 6-step approach addresses three substantial shortcomings of current climate risk assessments: Firstly, these are often "top-down" as they measure the climate risk-related credit risk on the country or sector level, for instance, Vermeulen et al. (2018, 2019); Reinders et al. (2020), and are thus arguably too aggregated for granular, idiosyncratic risk assessment on the issuer or firm level. Our 6-step approach is a major contribution because financial institutions measure their operational idiosyncratic credit risk on the issuer or firm level rather than the country or sector level. Secondly, most approaches (Vermeulen et al. 2018, 2019; Reinders et al. 2020) project climate risk far into the future up to 10–50 years, and do not allow practitioners to measure their climate risk exposure along the credit lending cycle in a short-run stress test time horizon of 1–3 years.[6] This holds in part also for the current stress test approaches by the ECB (ECB 2021, 2022). Thirdly, the majority of prior studies stop after computing the impact of climate risk for selected P&L or balance sheet items without computing the actual credit risk in the next step. This does not suit the core purpose of a stress test to measure the resiliency of financial institutions against climate risk for credit risk.

Second, we apply our 6-step approach and provide detailed estimations of the impact of transitory climate risk on the valuations of the largest European firms and the credit risk of one financial institution based on its 2019 Pillar III disclosure. Our results with asset devaluations of 15–36% and new PDs 5–34% generally confirm the substantial climate risk exposure of companies and financial institutions in the few existing studies. Our results also show that the exposure to transitory climate risk differs not only across sectors but also across firms within a given sector. We find that the most affected sectors, on average, are also the ones with the largest heterogeneity across firms within the sectors.

Our results are below the maximum impact of previous academic studies, mainly due to the assumptions regarding the level of the carbon tax (50–100 EUR in our case) and the stable macroeconomic environment. For example, Vermeulen et al. (2019) find a loss in asset values of EUR 48–159 billion or 5–11% of the portfolio value of financial institutions with banks being the least affected. Monnin (2018) computes a loss in asset value of 18.7–64.5% and an increase in PDs of 0.29–3.34%

[6] In particular, studies that are based on the Network for Greening the Financial System (NGFS) climate change scenarios (Base case, orderly and disorderly transition, hot house world) do not account for the measurement of credit risk in the short run.

for two issuer cases. Reinders et al. (2020) provide asset valuation shocks of 31–89% for the most affected sectors by Statistical Classification of Economic Activities in the European Community (NACE) and a loss for the Dutch banking sector of 0.3–3.2%. While they compute top-down estimates on the sector level over a 10-year horizon without firm-specific insights, we compute 404 final firm-level estimates and aggregate them by sector over a short-term stress time horizon of 1–3 years.

Our results are partly in line, partly higher than the first stress test results of regulatory and supervisory authorities such as the ECB or the Bank of France. However, since the central banks apply a "top-down" stress test approach, i.e., they measure the climate risk on the country or sector level by following the NGFS scenarios long into the future until 2050, the comparability of those results to our results remains limited.

The paper is structured as follows. The next chapter introduces ESG risks and climate risks in the financial context. Chapt. 3 consists of a literature overview on climate risk stress testing. Chapt. 4 presents the conceptual 6-step approach on how to run climate stress tests for transitory climate risk. In addition, it encompasses the empirical analysis of the financial impact of a carbon tax and illustrates the effect of such a policy on the Basel III credit risk metrics and capital ratios of a European bank. The chapter concludes with Sect. 4.8 "Reconciliation and discussion" in which we reflect on the various assumptions and data inputs driving our results. Lastly, Chapt. 5 summarizes our study.

2 Environmental risk in the financial sector

Awareness of sustainability, nowadays often referred to as ESG in research (Bassen and Kovács 2008; Jain et al. 2016; Rezaee 2016) and financial practice (CFA Institute 2015; Eccles and Stroehle 2018; MSCI ESG Research 2019), is undoubtedly on the rise in the financial sector. The amount of assets managed under the Principles for Responsible Investment (PRI 2019) has grown significantly in recent years. Rating agencies like Moody's and Fitch have developed their own ESG scores and new providers such as ISS or Sustainalytics emerged on the market. MSCI and other asset managers have launched dedicated ESG funds that select their assets based on ESG criteria (MSCI 2021; Tillier 2021).

Out of the 3 ESG criteria, the progress towards institutionalized regulation is the most pronounced in the environmental (E) aspect. The Task Force on Climate-Related Financial Disclosures (TCFD), a global expert network of 32 members selected by the Financial Stability Board of the BIS (Bank for International Settlements) founded in 2015, and the NGFS, an association of international central banks founded in 2017 (NGFS 2018), provide definitions of climate risk, discuss transmission channels of climate risk into financial risk or provide initial case studies on how to measure the impact of environmental risk on financial stability.[7] These initiatives

[7] In 2020, the NGFS has published three case studies on the impact of climate risk. One of them guides regulators on how to integrate climate risk assessment into regulation; The TCFD has published, for exam-

aim to increase transparency and efficiency in financial markets[8] and ultimately to mobilize private capital towards an emission-free economy.

The initiatives above by the TCFD and NGFS appear to guide the advancing regulation of ESG and environmental (E) risk in particular. In 2019, the EBA announced an update of its supervisory review and evaluation process (SREP) of the Basel III Pillar 2 requirements to include ESG risks. In early 2021, the EBA published a letter about the disclosure requirements of ESG risks in Pillar 3, requiring banks to disclose climate risks, mitigating actions, and their Green Asset ratio based on the EU taxonomy. The EBA's main objective is to achieve more transparency on climate-related risks (e.g., exposure of assets to carbon-intensive activities) and their evolution in the transition to a carbon-neutral economy.

The first step by the ECB towards a more structured management of environmental risks in European banking was a guide on environmental risk in 2020. The ECB demanded that financial institutions treat environmental risks as drivers of existing risk categories (Credit risk, market risk, etc.) in business strategy and risk management frameworks, measure and manage climate risk as the other risk metrics and develop climate risk-related stress testing by the end of 2022. Recent publications by regulatory and supervisory agents provided financial institutions in Europe (Banque de France 2021; EBA 2021; ECB 2021) with guidance about expectations and outcomes on the one hand and with concrete tools and methodologies on the other hand. In January 2022, the ECB released a methodology for the first climate-stress test and its results in July 2022.[9] All these steps illustrate the enormous relevance of climate stress testing for the entire financial sector.[10]

We specify the different approaches and methodologies towards climate stress tests to test the resiliency of financial institutions against climate risk in the next chapter.

3 Literature review

3.1 Top-down studies

"Top-down" or macro-approach studies analyze the impact of climate risk on sectors, countries, or regions without company-specific insights.

One of the first studies that shed light on the impact of climate risk on the financial sector was Weyzig et al. (2014). They estimated the exposure of European financial institutions to fossil fuel-intensive sectors to be roughly 1 trillion EUR, and the potential losses due to a quick breakthrough towards a low-carbon economy

ple, the 2019 report reflecting on the "Climate value at risk" including 12 case studies about climate risk estimations.

[8] "Increasing transparency makes markets more efficient and economies more stable and resilient" (Michael Bloomberg, Chair of TCFD, TCFD 2017)

[9] The results are discussed in Sect. 3 literature review.

[10] Parallel efforts run on the national level, for example, by German BaFin, the Bank of France, or the Bank of England as National Competent Authorities (NCA) on the (future) handling of environmental and sustainability risk.

based on a high-level shock equal to 3% of total assets for pension funds, 2% for insurance companies and 0.4% for large banks. The Cambridge Institute for Sustainability Leadership (2015) analyzed the impact of the transition towards a carbon-free economy from the macroeconomics perspective based on the Intergovernmental Panel on Climate Change (IPCC) scenarios. They computed lower economic growth for the transition phase but comparably higher growth in the long run compared to the “No mitigation” scenario. They also estimated a fictional portfolio with 40% equity weight would lose 15–20% of its value in 2015–2020. Dietz et al. (2016) estimated the “Climate value at risk” of global financial assets to be equal to 1.8% or 2.5 trillion USD based on a representative global financial asset portfolio. Similar to Cambridge Institute for Sustainability Leadership (2015) and other studies, they claimed that limiting global warming early on avoids long-run cost of climate change.[11]

The two most relevant studies for our approach come from authors at the Dutch central bank, De Nederlandsche Bank (DNB). Vermeulen et al. (2019) assess the impact of a disruptive transition to a low-carbon economy for more than 80 Dutch financial institutions (banks, pensions funds, and insurers) with a total value of EUR 2.3 trillion from 56 NACE industry sectors. Their approach follows four steps. First, they develop four transition stress scenarios (“narratives”) over the two dimensions of climate policy intervention and energy technology development. Second, they generate key macroeconomic key variables such as interest rate, GDP, trade, using a multi-country macro-econometric model from the National Institute Global Econometric Model (NiGEM) and translate the above “narratives” into concrete model inputs (e.g., CO_2 prices into commodity prices). Third, they calculate “transition vulnerability factors” to map some of the macroeconomic results on NACE industry level to yield the vulnerability of sectors towards transitory climate risk. Lastly, they run classical stress tests and compute financial losses in credit and market risk for stocks, loans, and bonds. They find that banks suffer only a 1–3% potential asset value loss compared to 9–11% for insurers and 5–10% for pension funds, largely driven by an increase in risk-free interest rates in their macroeconomic analysis. CET1 ratios of Dutch banks could decline by up to 4 percentage points compared to their level in 2018/2019 (16%).

Reinders et al. (2020) analyze the impact of introducing a EUR 100–200 carbon tax along four different transition stress scenarios (timing-related and passing-through to consumers) for the stability of the Dutch banking sector. Based on the four scenarios and the CO_2 emissions of the sector, they calculate an NPV of future carbon tax payments and use Merton’s contingent claims model to compute new valuations and PDs in a Distance-to-Default (DtD) approach. Then, they use detailed exposure data for the three largest Dutch banks to calculate losses and extrapolate the results to the Dutch banking sector. The most affected NACE-classified industries are utilities and manufacturers of commodities, with valuation shocks of up to 31–89%. Depending on scenarios, losses in market value are equal to 4–63%

[11] They find that limiting global warming to 2° reduces the expected losses by 0.6–1.2% and preserves about 800 bn. USD of assets of that global financial asset portfolio.

of CET1 capital and 3.2% of total assets in the Dutch banking sector, mainly caused by losses in corporate loans and debt.

Regulatory and supervisory agents across Europe, most notably the Bank of England, Bank of France, EBA, and ECB, have recently provided financial institutions with further guidance on climate stress testing (Bank of England 2021; Banque de France 2021; ECB 2021). Spyros Alogoskoufis et al. (2021) from the ECB ran a first climate stress test consisting of three main modules. First, the reliance on the NGFS scenarios regarding the future macroeconomic development until 2050. Second, a mapping of financial institutions' granular loan and security exposure with firms' climate and financial information. Third, the impact of transitory and physical risk on credit risk figures such as PDs or expected loss. The analysis focuses on the financial sector's actual credit and loan exposure, particularly to carbon-intensive sectors. The PDs of the most affected sectors may rise up to 11–37.5% relative to the orderly transition scenario by the NGFS.

The Bank of France ran a first climate stress test in 2020, covering 75% of the technical insurance provisions and 85% of the total assets of French banks based on the three NGFS scenarios until 2050. The approach starts with a static balance sheet until 2025, in line with traditional supervisory stress testing. Then they add the climate and macroeconomic developments from the NGFS scenarios until 2050 in a "dynamic balance sheet approach" into the stress test. For physical risk, the analysis yields an increase in loss ratios for claims related to natural disasters up to two to five times and a rise in premiums by 130–200% to compensate for these losses. For transition risk, the annual cost of credit risk[12] would rise by 22.4–32.4%, while the impact remains comparably limited with PDs on aggregate sector, reaching 3% only for coke and refined petroleum products (Banque de France 2021).

The first climate stress test that the ECB conducted as "learning exercise" for financial institutions consists of three core modules. First, a qualitative questionnaire to asses the climate risk frameworks. Second, the exposure of the bank's income streams to GHG-emitting sectors. Third, a "bottom-up stress test projection" for short-run and long-run climate transition risks, and physical risks (floods, drought, or heatwaves). The results published in July 2022 reveal that the share of interest income from the most GHG-emitting sectors amounts to about 60%, while credit and market risk losses due to transition risk and physical risk amount to about €70 billion in a short-term three-year time frame (ECB 2022).

Further studies from the private sector, such as Mercer LLC (2019), Howard and Patrascu (2017), Eceiza et al. (2020) also estimate the effect in different metrics (e.g., EBITDA at risk or portfolio losses of MSCI indices) and generally confirm the conclusion that climate risk indeed drives financial risk.[13]

[12] This credit risk proxy is calculated by dividing the total annualized provisioning flows for each time interval by the average exposure over the same time interval.

[13] Howard and Patrascu (2017) show detailed carbon exposures and integrate a carbon tax into the P&L of companies that is partly offset by price increases and pass-through rates for consumers. The remainder is modeled into the cash-flows and EBITDA of key benchmark indices, yielding EBITDA at risk of roughly 12% for the S&P 500 and MSCI up to 16.5% for MSCI Emerging Markets. A study by Eceiza et al. (2020) from McKinsey & Company analyzed, among others, the impact of flooding in Florida on a mortgage

3.2 Bottom-up studies

Only a few studies compute the impact of climate risk on the firm level, most likely due to higher complexity and data availability on the corporate level.

Battiston et al. (2017) apply a network-based stress test methodology and divide the potential climate risk into first and second-round effects. Based on classical Value at Risk (VaR) analysis of exposures of large European banks, they conclude: "An early and stable policy framework would allow for smooth asset value adjustments and lead to potential net winners and losers. In contrast, a late and abrupt policy framework could have adverse systemic consequences". Based on a "green" and "brown" scenario, they compute a VaR of less than 1% in a brown scenario for the largest 50 Euro-Area banks.

Monnin (2018) describes an approach used by Carbon Delta[14] to measure how a transition risk shock could change the set of assets eligible for purchase by the ECB's corporate sector purchase program (CSSP) by looking at 875 securities from 166 issuers, equivalent to 73% of ECB's CSPP portfolio. The global temperature rise goal is broken down on the country, sector, and finally, firm level. They then add national required CO_2 prices to the required CO_2 reductions and integrate this into a DtD approach. The results show an increase in PDs from two issuers of +0.29% (Utilities) and +3.34% (Materials), yielding a post-shock PD for the Materials company of 4.77%. This PD would be below the required investment-grade PD of 3% and make the asset no longer eligible for the CSSP program (Monnin 2018).

Grippa and Mann (2020) analyze the impact of climate risk on the Norwegian economy and financial sector in three transmission channels. They find about 4% of all corporate bank exposures dropping below an ICR of 1 or 2 based on different domestic CO_2 prices, loan losses up 0.9% for a global CO_2 price of 150 USD, and asset devaluation for households, banks, and pensions to 5–11% in the case of oil output reductions to limit CO_2 scope 3 emissions.

Faiella et al. (2021) use administrative and survey data to compute the impact of four one-off carbon taxes (€50, €100, €200, and €800 per CO_2 ton) through higher energy prices for Italian households and firms. Based on demand elasticities and projected changes in their energy mix, they derive the impact of higher energy prices on households' disposable income and on firms' EBITDA. Then, they calculate the share of vulnerable households and firms at risk of their debt. The results with a taxation of €50–200 per ton do not have a big effect on financially vulnerable households and firms. The results are also still below those in the sovereign debt crisis, also even in the most severe case of €800 per ton.

Table 1 summarizes the most relevant prior climate stress testing literature from above and illustrates the diversity in different approaches taken along the three following dimensions:

portfolio loss rate and compounded a loss rate of 0.5–7.25% subject to the specific scenario. These numbers become even more drastic when these losses are compared with those in the financial crisis of 2.95%.

[14] Carbon Delta, founded in 2016, is a financial technology firm based in Zürich which assesses the climate resilience of firms and their assets.

Table 1 Overview of most relevant climate stress test literature

Author & Year	Scope	Financial impact metrics	Sectors	Country
Banque de France (2021)	Top-down	Credit exposures, PDs, cost of risk	Various	France
Bank of England (2021)	Top-down	GDP, interest rates	Banking & Insurance	UK
ECB (2021)	Top-down	PDs, expected losses, credit and loan exposure	Various	EU
Reinders et al. (2020)	Top-down	NPV of future carbon tax payments, asset valuations, PDs, CET1 ratio	Banking	Netherlands
Vermeulen et al. (2019)	Top-down	Loss in asset value by credit and market risk, GDP, interest rates, CET1 ratio	Various	Netherlands
Dietz et al. (2016)	Top-down	Value-at-Risk, GDP growth, cash flow, loss in asset value	Various	Global
CISL (2015)	Top-down	Performance of asset classes	Industry sectors	Global (US, UK, DE, JP, BR, CN)
Weyzig et al. (2014)	Top-down	Carbon bubble risks, potential losses	Finance	EU
Faiella et al. (2021)	Bottom-up	Household income, EBITDA	Energy	Italy
Grippa and Mann (2020)	Bottom-up	Profit, ICR, loss in asset value	General economy & finance	Norway
Monnin (2018)	Bottom-up	Loss in asset value, PDs	Various	EU
Battiston et al. (2017)	Bottom-up	Value-at-Risk	Various	EU & US

Notes: Most relevant literature ordered by top-down/bottom-up classification and year. Bottom-up = firm level, top-down = national/sector level. Financial impact metrics reflect the specific metrics in each study for which the impact of (transitory) climate risk is computed.

- The actual unit level on which the analysis is conducted, i.e., top-down (national/sector level) or bottom-up (firm level)
- The financial impact metrics for which the stress test is conducted, e.g., balance sheet, P&L, or other figures
- The sectors and countries in scope

While the diversity in these three dimensions can be summarized comparably conveniently in a table, the potential fourth dimension, "conceptual and methodological approach", is not depicted because the description of this dimension would become too complex in a table. Some calculate demand curves for oil-and-gas consumption (Grippa and Mann 2020), others compute transition vulnerability factors on NACE sector level (Vermeulen et al. 2019), others project demand elasticities to derive new energy mix, Reinders et al. (2020) use the NPV of future tax payments before calculating assets losses and PDs.

Overall, the number of academic studies analyzing the impact of (transitory) climate risk on individual firm level is limited because the topic has only recently gained enormous relevance for the financial sector. This momentum comes, on the one hand, from the rising financial risk due to climate change[15] for the economy and the financial sector as capital lender, on the other hand from the push by regulators and supervisors (Bank of England 2021; Banque de France 2021; ECB 2021, 2022).

We appreciate all the prior studies that have initiated the debate about suitable approaches towards climate stress testing to accurately measure transitory climate risk and allow financial institutions to manage their exposure to it. In particular, we acknowledge the work of Reinders et al. (2020) because we rely on their idea to calculate a scenario-based NPV of carbon tax payments, deduct this NPV from the value of the assets to compute asset devaluation shocks, and derive final PDs with the Merton Model on sector level.

Nevertheless, the existing approaches, including Reinders et al. (2020) have three limitations that we address in our analysis. First, most of these approaches do not allow for a granular, idiosyncratic analysis on the firm level (bottom-up) of P&L or balance sheet items that identifies vulnerable firms within a sector.[16] Monitoring the aggregated exposure of financial institutions to climate risk on the sector level may be appropriate from a supervisory and regulatory perspective. However, risk management practitioners in both asset and credit risk management need to monitor their risk more granularly on the asset or issuer level. Second, the majority of top-down studies, for example, Reinders et al. (2020) and those by the central banks follow the NGFS scenarios (Base case, orderly and disorderly transition, and hot house world) with a very long prediction time frame of 10–30 years until 2050. This brings substantial uncertainty because many assumptions are made long into the future and may need to be revised due to reversed events in the short run, e.g., ad-hoc political carbon legislation. These long-term forecasts may lose their initial added value for financial practitioners who also need to monitor their financial risk in the short run. Third, prior work often calculates the impact of transitory climate risk on P&L or balance sheet items but not on credit risk (See the literature overview in Table 1). This is not consistent with the rationale of a practical stress test to measure the resiliency of financial institutions against transitory climate risk.

Our study addresses these three shortcomings and contributes to the climate stress test literature in two dimensions. First, we provide a conceptual, overarching approach to assess the impact of transitory climate risk on firm valuations and the resiliency of financial institutions in terms of credit risk in a generic 6-step approach. This 6-step approach summarizes the different approaches in one 6-step framework that regulators, researchers, and practitioners can use as a starting point to develop both top-down and bottom-up (on firm-level) climate stress tests. Our framework could easily be expanded to market risk of portfolios as well. Second, we provide

[15] The European Environment Agency, for example, estimates that economic losses due to extreme weather events amounted to EUR 446 billion in the European Economic Area between 1980 and 2019.

[16] For example, there might be a huge difference between producing or distributing companies within the energy sector that may have different climate-risk exposure due to different carbon emission levels. Another example is travel & leisure. Here, airlines have a different exposure than hotels.

idiosyncratic estimates for the impact of transitory climate risk on STOXX Europe 600 companies and for the credit risk of a European bank example to illustrate the applicability of the 6-step approach. We want to highlight that, in contrast to many other studies, we stick to traditional stress test time horizons of 1–3 years, allowing risk management on the firm level in the short run. This is particularly relevant because of rapidly changing national carbon legislation and is also in line with parts of the short-term climate stress testing approach used by the ECB.

4 Estimation of the impact of transitory climate risk

4.1 The generic 6-step approach

We propose to compute the impact of transitory climate risk on credit risk and financial stability with a 6-step approach. These six steps can be considered as an overarching umbrella around many different climate stress test approaches, be it top-down, bottom-up or any hybrid format. They can serve as an initial step for researchers and practitioners to develop their own climate transitory risk stress tests to measure the resiliency of financial institutions against climate risk.

The section is structured as follows: We begin with the conceptual description in Fig. 1 and then apply the concept in our empirical analysis. We present the four constructed scenarios (step 1 in the approach), the dataset and emission exposure of our companies in the sample (step 3), and the Merton model to quantify the impact of transitory climate risk on asset devaluations and PDs of firms (step 4 and 5) including two robustness tests. Ultimately, we derive the impact on the capital requirement ratios in line with the Basel III regulation (step 6).

Step 1 **Define transitory risk scenarios** The first step lies in the top-down definition of overarching scenarios as "future (climate) states of the world", for example the five Shared Socioeconomic Pathways (SSPs). They project the future state(s) of the world concerning climate, population, economics, or technological progress. Embedded in those scenarios should then be concrete assumptions about transitory climate risk, for example, a change in climate policy (e.g., CO_2 tax) or a shift to more expensive low-carbon technology triggered by specific technological breakthroughs or changing consumer preferences (e.g., towards sustainable business models). The scenarios have a clear top-down character as the projections will be made mostly on the world- or national-level.

Step 2 **Break-down of scenarios on the macroeconomic/sectoral level** The overarching scenarios as "future state of the world" need to be broken down into the concrete macroeconomic development of nations, regions, or sectors. On the national/regional level, macroeconomic figures such as exchange rates, trade, interest rates, GDP, consumption, investment, or R&D development must be projected. On the sector level, the sector's size, competitiveness, or technological progress needs to be assessed. The result is a projection of the economic development of countries or sec-

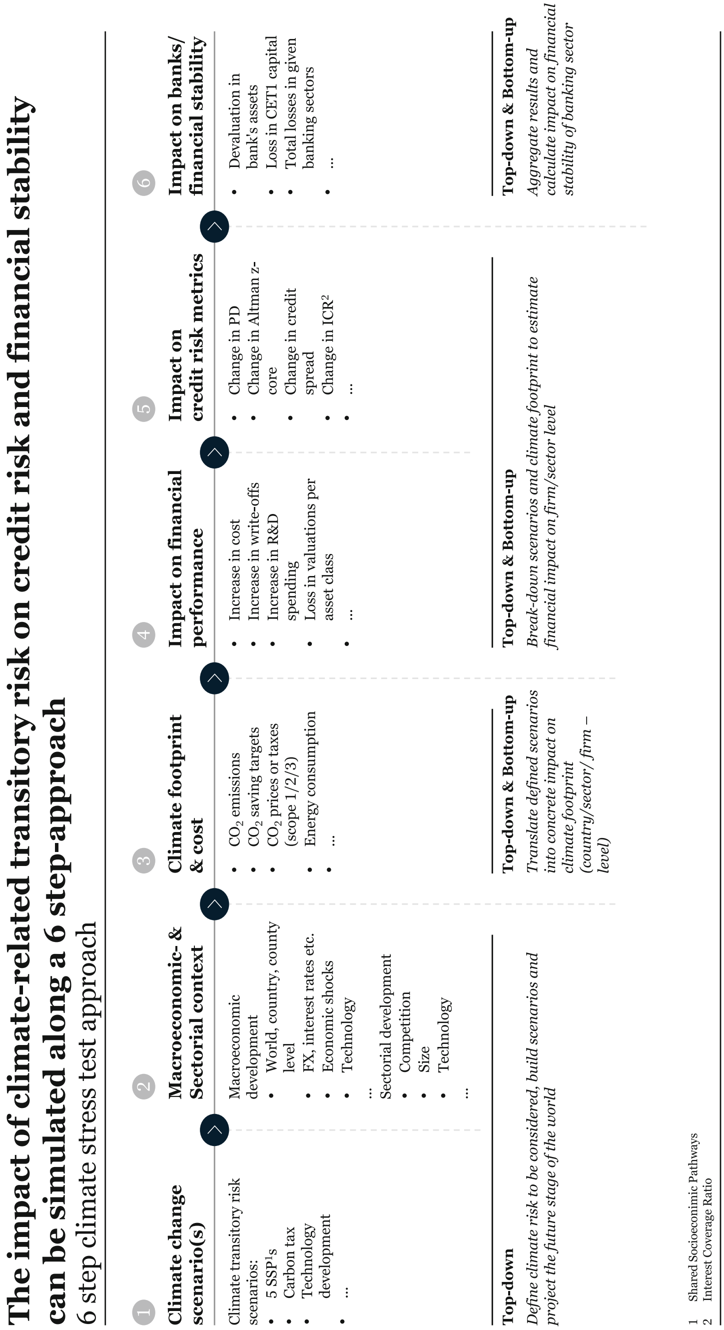

Fig. 1 Generic 6-step framework to measure the financial impact of transitory climate risk

tors, given the transitory risk scenarios from step 1. Again, this approach is primarily top-down unless a sector's competitiveness or technological progress would also be broken down on the firm level.

Step 3 **Develop climate the footprint & cost** In the next step, the climate footprint and its potentially associated costs must be compiled. These costs can often include the amount of CO_2 and the potential tax or price of CO_2 emission. Alternatively to the carbon exposure, Monnin (2018) describes a way to break down the globally aligned CO_2 saving targets on county and sector (Step 2) levels. If the impact of transitory climate risk is computed on the firm level, then carbon exposure needs to be available on the firm level. In this case, step 3 is already a hybrid of the top-down and bottom-up approach.

Step 4 **Calculate the impact on financial performance** Once the carbon footprint and its cost are estimated, the financial impact can be computed. For instance, the impact can be integrated into the valuations of assets through simple NPV cash-flow models, as cost or write-offs (for example, on stranded assets) into P&L, into profitability figures such as EBITDA (Bouchet and Le Guenedal 2020; Howard and Patrascu 2017) or into balance sheet items. Depending on the assumptions and macroeconomic projections, other inputs, such as the WACC or the risk-free interest rate, can also be integrated into the calculations. Step 4 can be applied both top-down or bottom-up.

Step 5 **Compute the impact on credit risk metrics** The impact on financial performance from step 4 can then be translated into standard supervisory risk figures. One example is the integration of asset devaluations into credit risk by computing PDs in a DtD-approach. Alternatively, and not in line with official supervisory stress testing as established by the EBA and ECB, other credit risk metrics such as the Altman z-core (through assets and earnings) or credit spread (through differences in bond yields) could also be used (Badayi et al. 2020; Liu and Ge 2012). Again, this step can be top-down and/or bottom-up.

Until this point, we have disregarded any portfolio of financial institutions. Instead, we have compiled the impact of transitory climate risk on the firm or sector level. In other words, we have not conducted a climate stress test as prescribed by the regulatory authorities. This follows in step 6.

Step 6 **Calculate the impact on banks/financial sector – credit risk** After having computed the impact of transitory climate risk on sectors or firms and their most relevant credit risk metrics, one can integrate the latter into the Capital Requirements Regulation (CRR) framework to compile the risk-weighted assets (RWA). The impact of climate risk on total assets, CET1 or Tier 1 capital ratios then reflects the increased financial risk that financial institutions are exposed to. This last calculation step can be executed based on sector or firm-level exposure for aggregated national financial sectors (Reinders et al. 2020; Vermeulen et al. 2019) or for individual institutions.

4.2 Scenarios

Similarly to Vermeulen et al. (2019); Grippa and Mann (2020); Faiella et al. (2021), we develop different scenarios to model the impact of a transitory climate risk policy around the following three dimensions due to the high degree of uncertainty about the future ecological, political, and economic development around the cost of carbon, or a potential response by firms:

- The tax rate per ton of CO_2
- The adaptation capabilities of companies to reduce their carbon footprint in light of the upcoming increase in carbon price due to the introduction of the carbon tax
- The pass-through rate of this tax rate for consumers

4.2.1 Tax-rate per ton of CO_2

We assume an effective carbon tax of either €50 or €100 per tCO_2. According to the World Bank (2017), the carbon price should be set within €50 and €100 per tCO_2 to reach the Paris Climate Agreement goals. Furthermore, Rogelj et al. (2013) argue that a global carbon price of €100 would yield a $\sim$ 95% probability of keeping global warming below 3°C, an $\sim$ 85% probability of keeping it below 2.5°C, and a $\sim$ 70% probability of keeping it below 2°C. However, when the social costs of carbon are considered[17], the price can easily increase to hundreds of € per tCO_2, depending on how present energy consumption is weighted against future benefits stemming from reduced emissions (Poelhekke 2019). In other words, our two tax scenarios are also rather conservative compared to, for instance, Reinders et al. (2020), with up to €200 per tCO_2 or Bach (2019) with up to €180 for Germany until 2030 to meet the climate targets as of 2019. In light of the heterogeneous CO_2 price/tax rates levels in Europe across countries[18], we assume the tax rates to be uniformly applied across all sectors on the national level. Depending on the current level and scope of national emission regulations, this is equivalent to either an introduction of- or a rise in the tax rate. Moreover, we assume that a rise in the cost of carbon for firms due to the market-price mechanism and gradually fewer available certificates of 2.2% per year since 2021 in the ETS is already priced in by the markets. Our actual asset valuation and PD shocks then only result from a sudden, exogenous shock of an increase in carbon tax to 50 and 100 EUR tCO_2 on the national level across all sectors in the EU.

[17] Social cost of carbon and of other GHG are defined as "The monetary value of net harm to society associated with adding a small amount of that GHG to the atmosphere in a given year" by the Group IWG on Social of Greenhouse Gases (2021) for example.

[18] For example, Germany has a price of 25 EUR per ton for fuel and heating, whereas in Scandinavia, prices for several sectors are substantially higher.

4.2.2 Adaptation capabilities of companies

An increase in CO_2 prices through the carbon tax policy may affect companies' ideal choice of energy mix. In the more favorable scenarios, we assume that these companies reduce their CO_2 emissions by 25% compared to the last reported values of their ESG disclosures. This number is derived from specific case examples in our sample across industries such as Health Care, Grocery Stores, Utilities, or Basic Resources. Another interpretation is the emergence of a sudden green technology shock that makes renewable energy sources relatively more efficient for companies (Vermeulen et al. 2019), allowing companies to substitute fossil fuel energy with renewable sources and reduce their carbon footprint more easily, even in the short run. On the contrary, in the adverse scenarios, we assume zero CO_2 emission reduction capabilities in the short term. This can be explained in two ways. First, companies could be surprised by the abrupt introduction of the carbon tax and have no time to reduce their carbon footprint within our stress test time horizon of 1–3 years, for example, because they lack the required skills, resources, or technology. Second, companies, now faced with additional costs for emissions due to the exogenous shock of a rise in carbon tax to 50 and 100 EUR tCO_2, ceteris paribus, may deem, at least in the short run, the marginal cost of emission reduction to be higher than the NPV of future carbon tax payments, for example in the case of high emission intensity or high emission reduction efforts in the recent past. In this case, companies may opt not to reduce their emissions voluntarily.

4.2.3 Pass-through rates for consumers

In line with Reinders et al. (2020), we integrate a pass-through rate component into our model because increasing costs for CO_2 emissions due to a new or higher emission tax rate can be passed by firms onto consumers through higher prices to offset the financial burden (Cludius et al. 2020). The specific pass-through rate usually depends on the competitiveness or price sensitivities of the entire economy or specific sector (Smale et al. 2006). Since the carbon tax can be interpreted as a consumption tax on the allowance to emit CO_2, we follow the VAT literature and use empirical VAT tax pass-through rates for the Eurozone from Benedek et al. (2020) of 50–80%. In order to create an adverse scenario, we assume the lowest pass-through rate of 50% in the most severe scenario.

Table 2 Definition of the four constructed scenarios

Scenario	Tax rate (€ per tCO_2)	CO_2 Emission reduction (%)	Pass-through rate (%)
1	€50	−25%	80%
2	€50	0%	80%
3	€100	−25%	50%
4	€100	0%	50%

Notes: CO_2 emission reduction compared to last reported emissions from Refinitiv Datastream as of June 2021.

We then combine the three dimensions and construct four scenarios based on the assumptions above to illustrate the magnitude of transitory climate risk impact. We start with relaxed assumptions in scenario one and gradually tighten up the assumptions along the three input dimensions: tax rate, adaptation capabilities, and pass-through. Finally, we generate one adverse scenario 4 in line with common stress test practice. Our constructed scenarios then reflect the bandwidth of the potential impact of transitory climate risk and account for the high degree of uncertainty regarding future ecological, economic, and political development.

With regards to the timing of the tax, we assume an abrupt implementation of the policy across all scenarios because an abrupt implementation better fits the purpose of a stress test with a typical time horizon of up to three years and provides better insight into the credit resiliency of both companies and financial institutions.[19] In contrast to other approaches, for example, Reinders et al. (2020) or parts of the ECB stress test methodology, we aim to provide insights into the direct short- and medium-run financial impact of transitory climate risk due to the large uncertainty of long-run forecasts over 10–30 years.

4.3 Data and emission exposure

The sample for our analysis consists of the companies included in the STOXX Europe 600 price index. We exclude 127 companies due to incomplete 1 GHG emission data or, in some cases, due to incomplete financial data, and 69 financial corporations (banks, insurance companies, and other financial corporations) due to their unique capital structure. Typically, financial corporations have much higher leverage compared to non-financial corporations. Therefore, applying a structural credit risk model to such corporations may lead to highly distorted results (Duan and Wang 2012). We do not observe a selection bias in the way that carbon-intensive sectors avoid publication of CO_2 scope 1 data. Instead, most incomplete data stems from rather low carbon-intensive sectors such as Tech, Health Care, or Financial Services. Only 3% stems from the six most carbon-intensive sectors. We end up with a sample of $n = 404$ European publicly listed companies. The market prices of the stocks for calculations in the model are taken from 1 January 2015 until 1 June 2021. Accounting data is taken from the companies' most recently available financial statements as of the time of writing, in most cases, the fiscal year 2020 statement.

Before diving into the impact of transitory climate risk on the valuations of firms and credit risk, we present the CO_2 emissions on the individual firm and aggregated sector level in order to get a first glimpse at the potential vulnerability of companies and sectors to new or rising cost for CO_2 emissions. In Fig. 2 and for all other plots, the dots represent values for each of the 404 companies. In contrast, the markers of

[19] A phase-in implementation would not fit our analysis for the following rationale. We chose the time horizon of 1–3 years to stick to common stress test procedures and to avoid forecasting highly uncertain effects of climate change and economic development long into the future. Then, the terminal value of the discounted cash flows is the major driver in determining the asset shocks, particularly over a short time horizon of 3 years. In this case, a phase-in implementation would not much change the results.

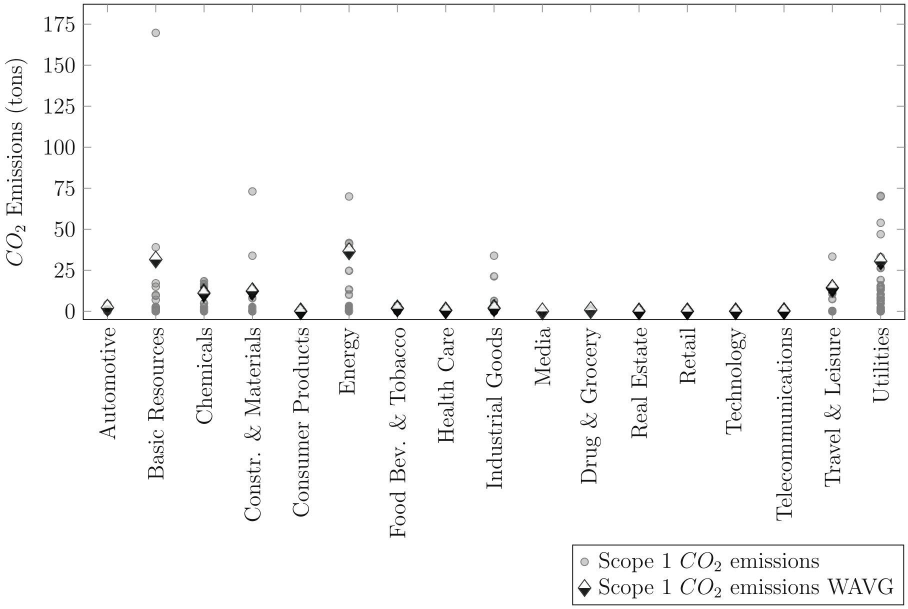

Fig. 2 Scope 1 CO_2 emissions by ICB (Industry Classification Benchmark) supersector. *Notes:* The dots represent values for each of the 404 single companies, the markers of white and black triangles the weighted average (WAVG) by total liabilities of the single companies within a sector. Emissions and later on asset shocks and PDs are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. Industry classification by ICB (Industry Classification Benchmark)

white and black triangles represent the weighted average (WAVG) by total liabilities of the single companies within on the sector level. We weight emissions, later on also asset shocks and PDs, by total liabilities per firm within a sector in order to approximate banks' credit exposure on the asset side of their balance sheet.

Fig. 2 reveals two core insights: First, there are carbon-intensive industries with Energy, Utilities, Basic Resources, Construction & Materials, Chemicals, and Travel & Leisure with high emissions on average over the entire sector, while sectors such as Consumer Products, Health Care or Media have comparably low emissions. Second, there is a big difference in standard deviations over the sectors: One group of sectors has companies with emissions on the lower and upper end, e.g., Basic Resources, Utilities or Energy. Another group of sectors has a very low standard deviation in the emissions per firm, e.g., Media, Drug & Grocery or Retail. In other words, the heterogeneity in emissions across firms within sectors is linked to some extent to the average carbon-intensity of the sector.

The carbon emission exposure can vary, however, by the definition of the actual scope of carbon emissions. Therefore, Table 3 presents again the scope 1 CO_2 emissions on the sector level from Fig. 2 plus the relationship between the direct

Table 3 Scope 1 and Scope 3 CO_2 emissions

	Scope 1 (Mln. ton)		Scope 3-to-1 Ratio		Scope 3 (Mln. ton)	
Industry	Value	Rank	Value	Rank	Value	Rank
Automotive	2.17	7th	81.61	4th	177.09	4th
Basic Resources	31.56	2nd	6.15	12th	194.09	3rd
Chemicals	11.08	6th	2.94	13th	32.58	6th
Constr. & Materials	12.34	5th	0.91	16th	11.23	9th
Consumer Products	0.07	13th	140.10	1st	9.81	10th
Energy	36.57	1st	9.78	9th	357.65	1st
Food, Bev. & Tobacco	1.80	9th	8.05	10th	14.49	8th
Health Care	0.63	11th	7.56	11th	4.76	13th
Industrial Goods	1.90	8th	119.72	3rd	227.47	2nd
Media	0.01	17th	19.24	8th	0.19	16th
Drug & Grocery Stores	0.76	10th	20.80	7th	15.81	7th
Real Estate	0.02	16th	22.58	6th	0.45	15th
Retail	0.05	15th	138.12	2nd	6.91	12th
Technology	0.07	14th	2.42	14th	0.17	17th
Telecommunications	0.20	12th	43.23	5th	8.65	11th
Travel & Leisure	14.26	4th	0.30	17th	4.28	14th
Utilities	30.52	3rd	2.22	15th	67.75	5th

Notes: Direct scope 1 and indirect 3 CO_2 emissions on the sector level from Fig. 2 plus the relationship between direct scope 1 CO_2 emissions and indirect scope 3 CO_2 emissions. Multiplying scope 1 emissions and the ratio scope 3-to-1 yields indirect scope 3 emissions. Industry classification by ICB sectors.

scope 1 CO_2 emissions and indirect scope 3 CO_2 emissions generated by customers to unveil the difference between scope 1 and scope 3 emissions across industries.[20]

Table 3 reveals three industry groups. The first group comprises the most carbon-intensive industries: Energy, Basic Resources, and Utilities. The average company in these industries produces CO_2 scope 1 emissions of 30.52–36.57 million tons per year. The companies in these industries have a comparably low scope 3-to-1 ratio, meaning that the bulk of the pollution is generated by their own production rather than by electricity generation (scope 2) or customers (scope 3). The second group comprises mildly brown industries such as Materials, Chemicals, Construction, and Travel & Leisure, with average scope 1 CO_2 emissions ranging from 11.08 to 14.26 yearly million tons. The third group includes "green" industries with very low scope 1 emissions but higher scope 3-to-1 ratio or high overall scope 3 CO_2 emissions. These sectors include Automotive, Consumer Products, Industrial Goods or Drug & Grocery stores, Retail or TelCo. Automotive and Industrial Goods are among the four sectors with the highest scope 3 emissions across all 17 sectors.

Fig. 2 and Table 3 reveal substantial differences among sectors in their reliance on carbon emissions to run their business. They also indicate that the vulnerability to new/rising CO_2 costs highly varies among sectors and firms since the carbon tax will be paid based on the reported emission level minus potential emission reduction capabilities. In addition, Table 3 reveals that the potential vulnerability of firms and

[20] Scope 2 includes also indirect GHG emissions from purchasing electricity or heating.

sectors heavily depends on the actual scope of emissions effectively falling under carbon taxation. Since our analysis is based on scope 1 emissions, the reported emissions do not fully reflect all social costs of carbon[21] to account for the impact of climate change that would arise upstream or downstream in the value chains, particularly not for sectors with high scope 3-to-1 ratio or high scope 3 emissions.

4.4 The model

We estimate PDs for publicly listed companies through Merton's structural option pricing model (Merton 1974). The underlying assumption of this model is that the value of a firm's assets follows a geometric Brownian motion.[22] It is a stochastic process that models a stock's price change in an infinitesimal time interval (Giordano and Siciliano 2015). Following Stojkoski et al. (2020)'s notation, yields:

$$dx(t) = x(t)[\mu dt + \sigma dW(t)] \tag{1}$$

with $x(t)$ as stock price, μ as stock drift, σ as stock volatility, and $W(t)$ a standard Brownian motion (Stojkoski et al. 2020).[23] This implies that the equity returns $\frac{x(t+\Delta t)-x(t)}{x(t)}$ are log-normally distributed with mean equal to $\mu\Delta t$ and standard deviation equal to $\sigma\Delta t$ (Giordano and Siciliano 2015). The Merton model assumes a simple capital structure, where the firm's debt consists of one large outstanding bond with face value L and maturity T. The bond maturity is computed as the weighted average of the firm's short-term liabilities (with a maturity of one year) and long-term liabilities (with a maturity of 13 years[24]).

In Merton's standard structural model, the equations for market values of equity and debt, following the notation of Reinders et al. (2020) are:

$$MV_D = Le^{-r_f(T-t)} - Le^{-r_f(T-t)}N(-d_2) - V_t N(d_1) \tag{2}$$

$$MV_E = V_t N(d_1) - Le^{-r_f(T-t)}N(d_2) \tag{3}$$

Where:

$$d_{1_t} = \frac{\ln\left(\frac{V_t}{L}\right) + \left(r_f + \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V\sqrt{T-t}} \tag{4}$$

[21] Again we refer to Group IWG on Social of Greenhouse Gases (2021) for the definition of social cost of carbon.

[22] We skip the firm indices i in this Sect. 4.4 to keep the notations simple.

[23] We keep the notation $x(t)$ from Stojkoski et al. (2020) here at this point for consistency reasons because later on in Merton's Model, V is defined as the value of the assets. Using V for two different notations (stock price and value of assets) may confuse the reader.

[24] According to the OECD report "Corporate Bond Market Trends, Emerging Risks, and Monetary Policy" the average maturity of investment grade corporate bonds in 2019 was 13 years.

$$d_{2_t} = \frac{\ln\left(\frac{V_t}{L}\right) + \left(r_f - \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V\sqrt{T-t}} \tag{5}$$

In the above equations, L is the face value of the firm's liabilities, r_f is the risk-free interest rate[25], T is the current maturity of the firm's liabilities, t is the time at which we will compute PDs (in our case, t is equal to 1), $N(x)$ is the distribution function of the standard normal distribution evaluated at x, μ is the firm's drift rate, V_t is the value of assets, and σ_V is their volatility. We can then define probabilities of default PD and distance to default DD by replacing r with the stock-specific drift rate μ:

$$\mathrm{DD} = N(d_1) = N\left(\frac{\ln\left(\frac{V_t}{L}\right) + (\mu + \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}}\right) \tag{6}$$

$$\mathrm{PD} = N(-d_2) = N\left(-\frac{\ln\left(\frac{V_t}{L}\right) + (\mu - \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}}\right) \tag{7}$$

Therefore, in equation (7), the firm is assumed to default when the value of the firm's assets falls below the book value of its total liabilities. This is important to note since this default point assumption is more strict and severe than, for example, the approach taken by external rating agencies. The firm-specific drift μ can be calculated using the capital asset pricing model (Krishna and Vaughan 2016):

$$\mu = r_f + \beta_m(E_m - r_f) \tag{8}$$

r_f is again the risk-free rate equal to the value of the yield of a German 15-year bond, β_m the measure of the stock's daily fluctuation in relation to the market movement. β_m is computed in an OLS regression of daily logarithmic stock returns and daily logarithmic market returns. In our case, the market is the STOXX Europe 600 price index. E_m is the annualized mean of the daily logarithmic returns of the market.[26] The time frame for this analysis again equals 1 January, 2015 until 1 June, 2021. We replace the commonly used risk-free rate r_f (or r in the classical Merton model notation) in equations 6 and 7 (See for example in McNeil et al. 2015, Chapt. 8, Credit Risk Management, p. 332–334) with the firm-specific drift μ computed by the above CAPM approach to void the underlying risk neutrality assumption of the Black-Scholes-Merton framework. While the risk-neutral probabilities of the

[25] We deviate in this case from the classical Merton Model notation by using r_f instead of r to remain consistent over all equations in our model in which we use the risk-free interest rate. We take the value of 15-year German bonds because 10-year German bonds had negative yields at the time of writing. Negative yields would not correspond to an accurate risk-free interest rate because investors pay indeed for a risk-free, secure asset.

[26] To annualize daily logarithmic market returns, we multiply their average across the time horizon by 250, assuming that there are 250 trading days in one year.

Black-Scholes equations are suitable for pricing financial derivatives, the physical "real-world" probabilities (of exercising the option in the Black-Scholes notation) including risk premiums may be more adequate from a risk management perspective (Jorion 2003).[27]

Since the initial total market value of assets V_t and the total asset volatility σ_V are not readily observable, they are determined by solving the following system of equations (Bouchet and Le Guenedal 2020):

$$MV_E = V_t N(d_1) - Le^{-r(T-t)} N(d_2) \tag{9}$$

$$\sigma_E = \sigma_V N(d_1) \frac{V_t}{MV_E} \tag{10}$$

The system of equations above can be solved numerically for V_t and σ_V by assuming a value of 1 for $N(d_1)$ and the following initial conditions:

$$V_t = MV_E + L \tag{11}$$

$$\sigma_V = \sigma_E \frac{MV_E}{V_t} \tag{12}$$

In turn, it follows that distance to default is high only when $N(d_1)$ approaches 1 (Goswin 2021). Now we can solve the system of equations numerically until the following expression is minimized:

$$\min \left[\left(\frac{Model\,MV_E}{Observed\,MV_E} - 1 \right)^2 + \left(\frac{Model\sigma_E}{Observed\sigma_E} - 1 \right)^2 \right] \tag{13}$$

That is, we continue to iterate the system of equations (9) & (10) with the assumptions from (11) & (12) for V_t and σ_V until the values of MV_E and σ_E obtained from the modelled replication ($Model\,MV_E$, $Model\sigma_E$) are as close as possible to their actual values as observed ($Observed\,MV_E$, $Observed\sigma_E$) in our data collection from Refinitiv.[28]

Asset valuation shocks are then determined by discounting the negative cash flows from carbon tax fees in our scenarios to their present value. The amount of each year's cash outflow is determined by multiplying the company's yearly CO_2 emissions in tons $\gamma_{t,i}$ minus the potential emission reduction factor θ, multiplied by the tax fee τ for each year t. The tax fee and emission reduction factor are unit and time-invariant per scenario construction. The discount rate equals each company's specific weighted average cost of capital (WACC). Furthermore, companies are expected to respond to such policies by passing a portion of these negative cash

[27] See also Giordano and Siciliano (2015) on the difference between risk-neutral probabilities and real-world probabilities in pricing and forecasting assets from a conceptual perspective and Liu et al. (2007); Bliss and Panigirtzoglou (2004) from an empirical perspective.

[28] In other words, we plug in the results from a system of equations (11) & (12) into the system of equations (9) & (10) and minimize (13) to ensure that initial, modelled solutions ($Model$) for (9) & (10) reach the true, observed values ($Observed$) from our gathered Refinitiv data input.

flows to the demand side by increasing their prices. The competitive response is called pass-through rate ϕ. Therefore, the net present value of future carbon taxes for a given company can be expressed as follows:

$$NPV_{tax} = \sum_{t=1}^{T} \frac{-(1-\theta)\gamma_t(1-\phi)\tau}{(1+WACC)^t} \tag{14}$$

We extract the $WACC$ for all firms in our sample from Refinitiv Workstream to ensure one uniform approach for compiling the weighted cost of capital across all firms in our sample.[29] The calculation in Refinitiv Workstream for each firm is given by:

$$WACC = C_E * W_E + C_D * W_D \tag{15}$$

With C_E equal to cost of equity, W_E the weight of equity, C_D the cost of debt including the tax shield, and W_D the weight of debt.[30] Lastly, we compute the asset shocks by dividing the net present value of the carbon tax by the company's total asset value:

$$\omega = \frac{NPV_{tax}}{V} \tag{16}$$

The asset shock ω represents the company's asset value loss resulting from discounting the emission policy tax to the present value in relation to the original asset value V. The value of the assets for a given company after the shock is then:

$$V^* = (1-\omega)V \tag{17}$$

Therefore, the equations for the market value of a firm's equity and debt become:

$$MV_D^* = Le^{-r(T-t)} - Le^{-r(T-t)}N(-d_2^*) - (1-\omega)V_t N(d_1^*) \tag{18}$$

$$MV_E^* = (1-\omega)V_t N(d_1^*) - Le^{-r(T-t)}N(d_2^*) \tag{19}$$

[29] This implies that the inputs feeding into the WACC calculations by Refinitiv, for example, the r_f, and the resulting COE parameter might be slightly different from the input we use and the result we get for the firm-specific drift rate, for example, due to slightly different time-horizons or a different benchmark index for the market risk premium.

[30] Short-term cost of debt is based on the 1-year yield of the firm's appropriate debt curve, and the long-term-term cost of debt is based on the 10-year yield of the firm's appropriate debt curve. Cost of equity C_E is based on an inflation-adjusted risk-free rate based on the 10-year GDP growth forecast, $beta$ is estimated as stock movement compared to the respective country-specific main index, and the market risk premium equal to full-year earnings yield multiplied by the implied dividend payout ratio plus the 10-year GDP forecast growth.

Where:

$$d_1^* = \frac{\ln\left(\frac{(1-\omega)V_t}{L}\right) + (\mu + \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}} \tag{20}$$

$$d_2^* = \frac{\ln\left(\frac{(1-\omega)V_t}{L}\right) + (\mu - \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}} \tag{21}$$

And the equations for distance to default and PDs under shock become[31]:

$$\mathrm{DD}^* = N(d_1^*) = N\left(\frac{ln(\frac{(1-\omega)V_t}{L}) + (\mu + \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}}\right) \tag{22}$$

$$\mathrm{PD}^* = N(-d_2^*) = N\left(-\frac{\ln\left(\frac{(1-\omega)V_t}{L}\right) + (\mu - \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}}\right) \tag{23}$$

4.5 Results

4.5.1 Asset valuation shocks

We begin with the impact of the carbon tax policy on the value of firms' assets before addressing the impact of these asset devaluations on PDs. Asset shocks are calculated with equation (16), the ratio between the NPV of the carbon tax payments and the company's total asset value before the carbon tax payments. The two following plots in Fig. 3 show the asset shocks ω for the least and most severe scenarios 1 and 4, respectively, scenarios 2 and 3 can be found in the Appendix. Again, the dots represent individual companies' asset shocks, the markers with white and black triangles represent sector-level averages weighted by total liabilities per firm within a sector, as shown in the following equation:

$$\omega_J = \sum_{i=1}^{I} \frac{L_i}{\sum_{i=1}^{I} L_i}\omega_i \quad \forall J \in \mathrm{ICB}_S \tag{24}$$

ω_j is the total liabilities' weighted average asset shock of ICB supersector J, L_i is company i's total liabilities, and ω_i is the company i's specific asset shock. We again weight the sector averages by liabilities per firm to approximate the asset side of financial institutions, that is the credit exposure toward companies.

In order to facilitate the interpretation of the two plots, we also provide the actual numbers of the sector-wide asset shocks in Table 4, in this case also for scenarios 2 and 3:

[31] We note again that we skipped the firm indices i in this Sect. 4.4 to keep the notations simple.

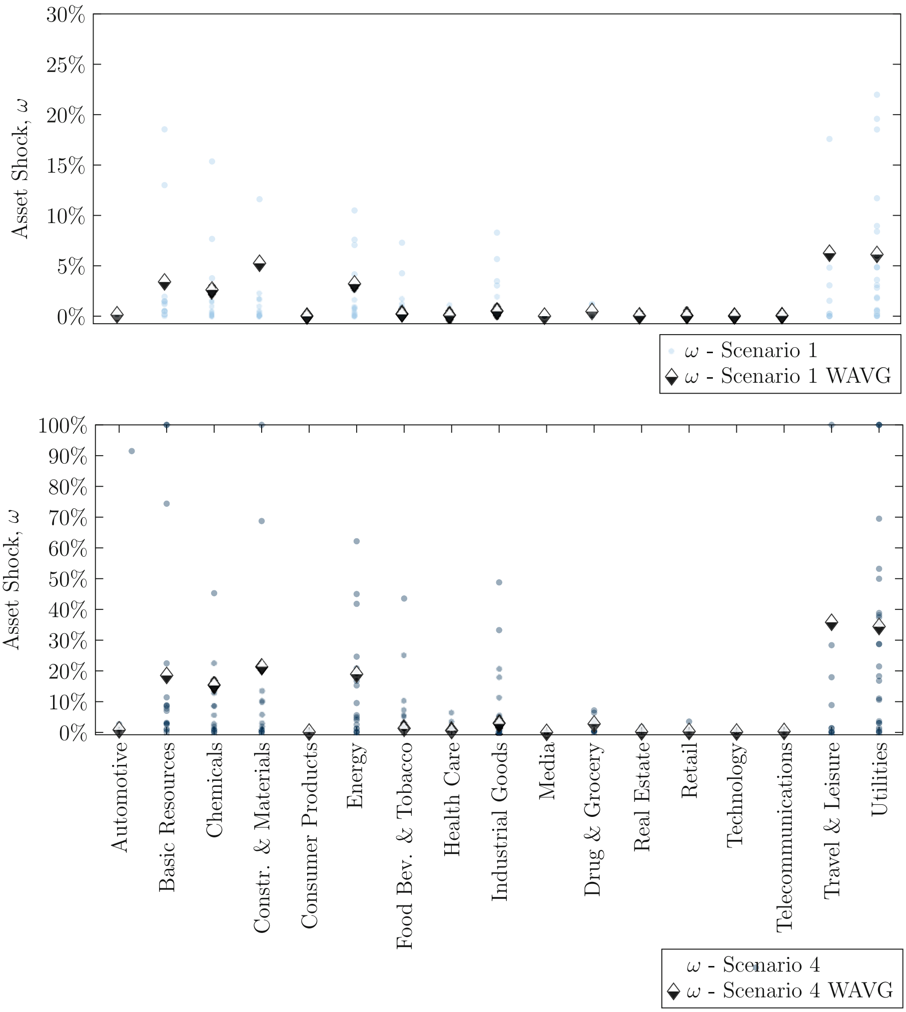

Fig. 3 Asset Shocks, ω – Scenarios 1 and 4. *Notes:* Asset devaluation shocks for scenarios 1 and 4. The dots represent values for each of the 404 single companies, the markers of white and black triangles the weighted average (WAVG) by total liabilities of the single companies within a sector. Asset shocks are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. Industry classification by ICB. Maximum asset shock in scenario 1 set at 30% for readability reasons. To illustrate the bandwidth of asset shocks in scenario 4, asset shocks in scenario 4 are shown up to 100%

The asset devaluation shocks are the consequence of the NPV of future carbon tax payments relative to the pre-shock value of the assets. Therefore, the drivers of the asset devaluation shocks are the initial CO_2 emissions, the tax rate, the emission reduction capabilities of companies, the pass-through rate from equation (14), and the cost of capital, given the initial asset valuation. Since the initial CO_2 emissions and the cost of capital are external data extracted from Refinitiv and time-invariant

Table 4 Asset Shocks by ICB supersector, scenarios 1, 2, 3 and 4

	Scenario 1 ω	Scenario 2 ω	Scenario 3 ω	Scenario 4 ω
Automotive	0.14%	0.17%	0.71%	0.84%
Basic Resources	3.40%	3.95%	16.38%	18.53%
Chemicals	2.61%	3.08%	13.03%	15.39%
Constr. & Materials	5.25%	6.21%	19.45%	21.31%
Consumer Products	0.02%	0.02%	0.10%	0.12%
Energy	3.20%	3.79%	16.02%	18.94%
Food, Bev. & Tobacco	0.23%	0.27%	1.13%	1.33%
Health Care.	0.10%	0.12%	0.52%	0.61%
Industrial Goods	0.51%	0.60%	2.56%	3.01%
Media	0.00%	0.01%	0.02%	0.02%
Drug & Grocery Stores	0.46%	0.55%	2.32%	2.76%
Real Estate	0.03%	0.04%	0.17%	0.20%
Retail	0.05%	0.06%	0.27%	0.31%
Technology	0.02%	0.03%	0.11%	0.13%
Telecommunications	0.05%	0.06%	0.27%	0.32%
Travel & Leisure	6.25%	7.40%	31.26%	35.82%
Utilities	6.13%	7.28%	30.24%	34.43%

Notes: Asset devaluation shocks per scenario from Fig. 3 written in numerical notation. Asset shocks are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. All numbers rounded to 2 digits. Industry classification by ICB.

per firm, the impact hinges solely on the assumptions for the three remaining drivers in each scenario: tax rate, emission reduction capabilities, and pass-through rate.

The impact in magnitude rises from scenario 1 to 4 due to the nature of the designed scenarios, with scenario 1 creating the lowest and scenario 4 creating the most severe shock, yet not linearly. While the impact from scenario 1 to 2 rises only by a fifth in percentage points (e.g., from 0.14% to 0.17% for Automotive), it jumps fivefold from scenario 1 to 3 (0.71% for Automotive) and sixfold from scenario 1 to 4 (0.84% for Automotive). This non-linear spike in magnitude over scenarios 2 and 3, in particular, is due to the variation in the input parameter and is consistent across all sectors and single firms as long as the asset devaluation shocks are below 100%.

The asset devaluation shocks reveal three types of industries by the magnitude of impact. The first group of industries suffering the highest asset devaluations are Travel & Leisure and Utilities, with asset shocks ranging from 6.13% in scenario 1 to 35.82% in scenario 4. For the former, the main drivers of industry-wide asset devaluation are the airline groups Lufthansa AG and International Consolidated Airlines Group SA, with asset devaluations ranging from 17.59–100% and 3.06–17.95%, respectively[32] and the passenger sea transportation company Carnival PLC with asset devaluations ranging from 1.53–8.89%. These three companies ac-

[32] Other airlines do not disclose exact values for scope 1 CO_2 emissions and therefore could not be included in the sample. In other words, we somewhat underestimate the impact of the carbon policy on the Travel & Leisure sector as a whole.

count for 67.28% of the sector's total liabilities in the sample. The second group with substantial asset devaluations from 2.61% in scenario 1 to 21.31% in scenario 4 are Construction & Materials, Basic Resources, Chemicals, and Energy. In Energy, firms directly generating or producing energy drive the results, while more service- and distribution-oriented companies experience lower asset devaluations. In Basic Resources, the results are mainly driven by firms that extract and cast metals, while firms manufacturing paper or household products show a lower impact. Lastly, the remaining industries in the sample suffer small and arguably manageable asset devaluations. These are Consumer Products, Food & Beverage, Health Care, Industrial Goods, Media, Drug and Grocery Stores, Real Estate, Retail, Technology, and Telecommunications. Asset shocks for this group of industries range from 0.00% in scenario 1 to 3.01% in scenario 4.

Those industries that suffer the highest sector averages of asset devaluation shocks are also the ones with the biggest heterogeneity within each sector. The least affected industries with sector-average asset devaluation shocks below or around 1% (e.g., Automotive, Consumer Products, or Retail) exhibit a homogeneous picture even in scenario 4 with almost no dots beyond 5–10%. In contrast, the six most affected industries with asset devaluation shocks larger than 15% in scenario 4 exhibit some companies with numbers in the single-digit percentages, some in the range of 10–50% and even a few cases beyond 50%. Measured in standard deviation, the six most affected sectors are around 0.2–0.3, whereas all the other sectors are below 0.05. Looking at the minimum and maximum asset devaluation shock reveals the same picture. While in four out of the six most affected industries, the difference between minimum and maximum shock is equal to 100% in scenario 4, it is below 10% for 8 of the low-affected sectors and two times around 40–50% (Industrial Goods and Food, Beverage, and Tobacco). Therefore, and in contrast to all prior top-down sector-level studies, our analysis reveals considerable differences in the impact of transitory climate risk not only among sectors but also among firms within a given sector. This is again one of our major contributions. Nevertheless, the heterogeneity among sectors and firms within a sector largely depends on the chosen industry classification. The more granular the industry classification, the less heterogeneity within a sector we can expect because firms with similar carbon risk profiles would be classified as the same industry. Then, only the heterogeneity among sectors remains, revealing the most vulnerable industries exposed to transitory climate risk.

The asset shock ω can be interpreted in two ways depending on the specific scenario. In scenarios 1 and 3, with emission reduction of 25%, the policy successfully incentivizes companies to change their energy mix towards cleaner energy. At the same time, the asset devaluation is due to companies writing off obsolete brown assets (Vermeulen et al. 2019). In scenarios 2 and 4, without emission reduction capabilities, the policy is insufficient to incentivize firms to switch to greener energy sources. This means that firms will continue to operate in a "business as usual" environment and, consequently, bear the total amount of company asset devaluation as yearly cash outflows of tax payments while keeping brown assets in their balance sheets (Vermeulen et al. 2019).

4.5.2 Probabilities of default

Based on the above asset devaluation shocks, we now present the results of our calculations of PDs. Each firm's PD is calculated using equations 7 and 23 for pre-shock and post-shock PD, respectively. Figs. 4 and 5 show each company's PD in the two outer scenarios 1 and 4 compared to their pre-shock value. Scenarios 2 and 3 can be found again in the Appendix.

The markers representing the ICB supersector specific PDs are calculated in the same way as for asset shocks:

$$\mathrm{PD}_J = \sum_{i=1}^{I} \frac{L_i}{\sum_{i=1}^{I} L_i} \mathrm{PD}_i \quad \forall J \in \mathrm{ICB}_S \tag{25}$$

In the above equation, PD_j is the total liabilities' weighted average PD of ICB supersector J, L_i is company i's total liabilities, and PD_i is the company i's specific asset shock for a given scenario.

In order to isolate the effect of carbon taxation on credit risk, we also illustrate the difference between post-shock and pre-shock values of PDs. This number unveils the effect of carbon taxation alone on the future creditworthiness of a company.

The following example for Automotive will facilitate the interpretation of the table: New PDs between 0.46 and 0.49 together with PD spreads in square brackets of 0.01 to 0.04 percentage points across scenarios 1 to 4 for the Automotive sector yield a pre-shock PD of 0.45.

Compared to the asset valuation shocks, PDs are driven not only by the NPV of future carbon tax payments and its corresponding ingredients from equation (14) but also largely by the leverage in a non-linear manner. Figs. 4 and 5 together with Table 5 clearly show the big increase in PDs from scenario 2 to 3 due to an increase in carbon tax from €50 to €100 and the lower pass-through rate of 50% instead of 80%. The big increase, particularly for the six most affected sectors from scenarios 2 to 3 is also illustrated in Fig. 9. For the most affected sectors, there are firms already in the scenario 3 with a PD equal to 100% due to their higher leverage compared to other firms with similar levels of initial CO_2 emissions. We note again that the Merton model, in its pure form, implies rigorous default assumptions. In practice, we are confident not to observe such high default rates for various reasons. We return to the reconciliation and implication of our results in Sect. 4.8.

The PD results again reveal two groups of industries. On the one hand, there are heavily affected "brown" sectors such as Basic Resources, Construction, and Materials, Energy, Travel & Leisure, and Utilities with sector-average PDs. Interestingly, the sector-average PDs for Chemicals (5.05) and Energy (6.81) are substantially lower than the PDs of the other heavily affected sectors, also compared to their corresponding asset shocks. This indicates that these two industries, on average, operate with comparably lower leverage than the other industries. On the other hand, there are "green" sectors, such as Telecommunications, Technology, or Real Estate, experiencing comparably negligible effects in most cases.

Energy companies experience an increase in aggregated PD ranging from 0.22% to 5.90% to final PDs after the shock of 1.13–6.81%. In our sample, a few com-

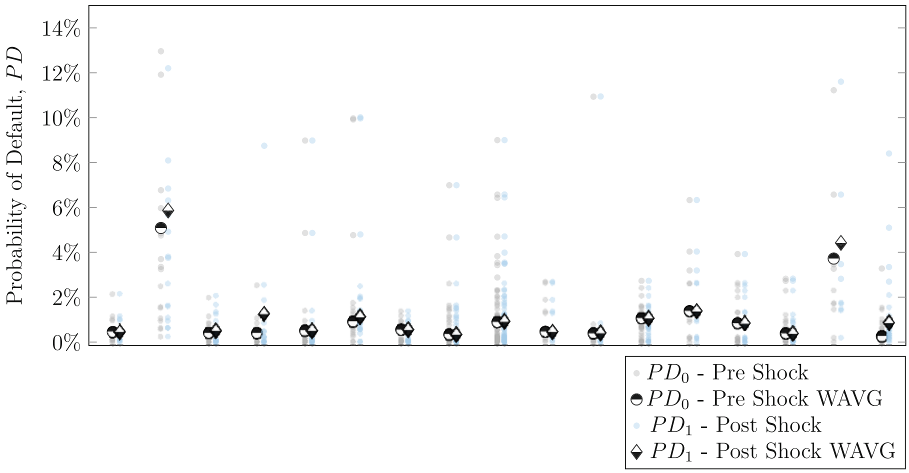

Fig. 4 PDs compared to pre-shock state by ICB supersector, scenario 1

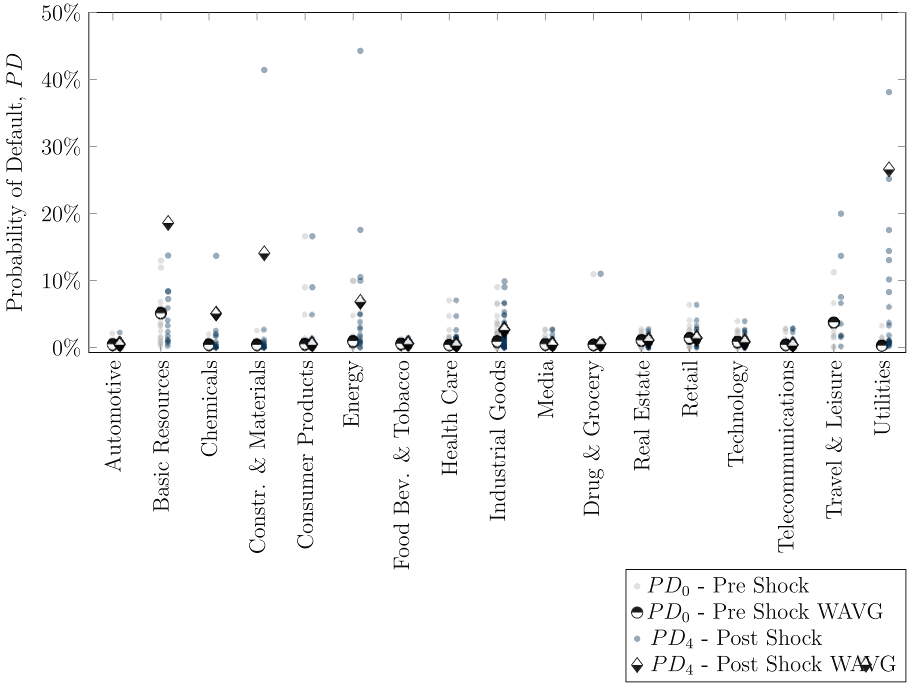

Fig. 5 PDs compared to pre-shock state by ICB supersector, scenario 4. *Notes:* PDs for scenarios 1 and 4. The dots reflect again the firm-specific values while the white and black markers represent sector-average values weighted (WAVG) by total liabilities per company within a sector. The left-side dots and markers in each ICB supersector column represent PDs before the exogenous policy shock, the right-side dots and markers represent post-shock PDs. PDs are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. Industry classification by ICB. To enhance the readability and visibility of the graph, the scale of visible PDs is limited to 15% and 50%, respectively. However, there are indeed companies in both plots facing higher PDs than those two thresholds, respectively

Table 5 New PDs and PD spreads vs. pre-shock state for scenarios 1 to 4

	Scenario 1 PD	Scenario 2 PD	Scenario 3 PD	Scenario 4 PD
Automotive	0.46[+0.01]	0.46[+0.01]	0.49[+0.03]	0.49[+0.04]
Basic Resources	5.86[+0.78]	6.02[+0.94]	15.87[+10.79]	18.57[+13.49]
Chemicals	0.51[+0.10]	0.53[+0.13]	3.76[+3.36]	5.05[+4.65]
Constr. & Materials	1.27[+0.87]	1.78[+1.38]	12.09[+11.69]	14.05[+13.65]
Consumer Products	0.51[+0.00]	0.51[+0.00]	0.51[+0.00]	0.51[+0.00]
Energy	1.13[+0.22]	1.18[+0.28]	4.64[+3.74]	6.81[+5.90]
Food, Bev. & Tobacco	0.56[+0.01]	0.56[+0.01]	0.59[+0.04]	0.59[+0.04]
Health Care	0.34[+0.00]	0.34[+0.00]	0.36[+0.02]	0.36[+0.02]
Industrial Goods	0.92[+0.04]	0.93[+0.05]	1.96[+1.07]	2.66[+1.77]
Media	0.47[+0.00]	0.47[+0.00]	0.47[+0.00]	0.47[+0.00]
Drug & Grocery Stores	0.41[+0.04]	0.42[+0.05]	0.52[+0.22]	0.55[+0.27]
Real Estate	1.06[+0.02]	1.06[+0.02]	1.07[+0.03]	1.08[+0.06]
Retail	1.39[+0.01]	1.39[+0.01]	1.41[+0.03]	1.41[+0.03]
Technology	0.85[+0.00]	0.85[+0.00]	0.85[+0.01]	0.85[+0.01]
Telecommunications	0.39[+0.00]	0.39[+0.00]	0.39[+0.01]	0.39[+0.01]
Travel & Leisure	4.42[+0.70]	4.85[+1.13]	33.39[+29.67]	34.21[+30.49]
Utilities	0.86[+0.61]	1.20[+0.95]	21.72[+21.47]	26.58[+26.33]

Notes: Asset devaluation shocks per scenario from Fig. 3 written in numerical notation. Asset shocks are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. All numbers rounded to 2 digits. Industry classification by ICB.

panies are involved in services ancillary to energy production, such as distribution, wholesale, and equipment manufacture. The shocks affect these firms slightly less than companies directly manufacturing refined petroleum products. The results are generally comparably homogeneous across the sample.

Travel & Leisure companies show an aggregated PD spread ranging from 0.70% in scenario 1 to 30.49% in scenario 4 to final PDs after the shock of 4.42–34.21%. Again, the two airline companies are the primary drivers of this increase. In contrast, other companies in the sector, e.g., gambling and betting activities, tour operators, hotels, and other accommodation services companies, are barely affected due to their low CO_2 emissions. These sub-sectors account for only 52.38% of the sector's total liabilities in our sample.

Utilities is one of the most affected industries, showing the second largest PD spreads from 0.61% in scenario 1 to 26.33% in scenario 4 to final PDs after the shock of 0.86–26.58%. Although the results are highly homogeneous among the firms in the sector, utility companies involved in the collection, treatment, and supply of water, which constitute a tiny portion of the whole sector, show a relatively low impact on PDs. The main driver in the sector-wide PD increase are companies producing and distributing electricity.

Basic Resources companies show a PD spread ranging from 0.78% to 13.49% to final new PDs of 5.86–18.57%, driven by companies involved in mining and casting metals. Companies manufacturing paper, household, and sanitary products are less affected.

Lastly, the results for Construction & Materials companies are homogeneous except for a cement manufacturing company, which shows a scenario 4 PD of 100%, and a building materials company, which shows a scenario 4 PD of 30.82%. Together, these two companies account for 19.48% of the sector's total liabilities in our sample. Overall, the industry exhibits PD spreads ranging from 0.87% in scenario 1 to 13.65%, leading to new PDs after the shock of 1.27–14.05%.

In sum, we can draw three main conclusions from the results. First, there are heavily affected sectors experiencing severe asset shocks and dangerous increases in PDs due to transitory climate risk, while other sectors with low scope 1 emissions remain almost unaffected. The six most affected sectors are also the ones with the highest scope 1 carbon emissions, see Table 2. Second, the heterogeneity among companies within the most affected sectors is higher than within the barely affected sectors. Third, the results show the severe risk for financial institutions in asset management and credit lending due to the asset shocks and increased PDs. This risk can pose a considerable threat for the financial sector's resiliency and stability.

In the next section, we run two robustness checks on the precision of the estimated asset volatility σ_V in our analysis, which is a crucial determinant of our derived PDs, see equation (23).

4.6 Robustness

In this section, we examine how changes in the key parameters of the Merton model may affect our conclusions. The entire data input is based on the most recent available data from financial statements as of June 2021. While most of the data input is extracted as given in the Refinitiv databases, only a very few parameters in the calculations must be estimated. This holds mainly for the variance of the asset value σ_{V_t} estimated in equation (12). We assume the variance of the asset value to be constant in our stress test analysis.

We acknowledge, however, that once a very severe scenario similar to our scenarios 3 and 4 materializes, the variance of the asset value may no longer remain constant but may increase temporarily, as observed in past financial crisis times. If our severe scenarios 3 or 4 became a reality with a substantial impact on the operating business and financial liquidity, specifically of carbon-intensive companies, one could expect a substantial impact on the value of firms and their volatility.

Moreover, we do not know the exact, true parameters of the asset value V_t and its variance over time σ_{V_t} because we can only observe the values as they occurred between January 2015 and June 2021 without fully knowing the true underlying distribution. The fact that we go back 6.5 years in stock market data with up to 1600 daily stock market returns in the sample to compute the equity volatility σ_{E_t} as input for the calculation of the asset volatility σ_{V_t} in equation (12) gives us confidence in the precision of our derived PDs. Yet, we acknowledge that our extracted data sample may not be entirely representative of the true distribution of the equity volatility σ_{E_t} and through (12) as input for asset volatility σ_{V_t}.

Therefore, we run two robustness tests to validate our estimation of the non-observable asset volatility σ_{V_t}. First, we take increases in equity volatility from severe financial crisis times as a reference and integrate them into estimating asset volatility in equation (12) to account for higher asset volatility in a potential stress test scenario. Second, we bootstrap the observed daily stock market returns from which we derive the equity volatility σ_{E_t} and finally, the asset volatility σ_{V_t} through equation (12). We walk through the approach and results in the following.

4.6.1 Increase in volatility

Our analysis of the impact of transitory climate risk in the form of a carbon tax between €50–100 per tCO_2 constitutes a severe stress test for the resiliency of financial institutions, despite the assumption of a pass-through rate and adaptation capabilities of companies. Such a stressful time period may lead to a financial crisis in which the volatility of asset prices rose considerably in the past. Examples include the crash in October 1987, the Dotcom crisis in 2000/2001, the financial crisis in 2008/2009, or the COVID-19 pandemic in the spring 2020. Once we include not only the times of heavy slumps in asset prices but also the more consistent post-crisis recovery phases with still slightly higher volatility, we still note an increase in equity volatility of about 50–60% over the time frame of 1963–2020.[33] Although we do not expect such drastic scenarios as the four referenced financial crises to materialize due to transitory climate risk in the form of carbon taxes of €50–100 per tCO_2, we acknowledge that the assumption of constant asset volatility σ_{V_t} may be oversimplifying and underestimating the risk of economic shocks.

Therefore and to simulate a financial crisis induced through an abrupt transitory climate risk policy in the form of a carbon tax of €50–100, we allow the equity volatility σ_{E_t} to increase by 50% (in relative terms, not in percentage points) as a robustness test for our analysis. A higher equity volatility σ_{E_t} feeds into our model by estimating the asset volatility in equation (12).

We rerun the entire analysis by sticking to all key assumptions and parameters besides the increase in volatility, ceteris paribus. The exact results can be found in Table 7 in the Appendix. The numbers reveal a severe increase in all levels of PDs because the initial level of PD before the effect of our carbon tax, "PD 0", increases considerably across all sectors due to the higher equity volatility. Even carbon-efficient sectors such as Media, Real Estate or Technology face PD levels before the transitory climate risk shock between 3.06 (Utilities) and 20.24 (Basic Resources). In contrast, the rise in PD spreads from scenarios 1 to 4, reflecting the actual increase in PDs due to our designed transitory climate risk shock, remains robust. While the PD spreads remain comparably low in scenarios 1 and 2, they jump in scenarios 3 and 4 to 27.10 (Utilities) and 44.38 (Travel & Leisure) in scenario 3 and 31.83 (Basic Resources) to 45.28 (Travel & Leisure) in scenario 4, respectively.

In addition, even carbon-efficient sectors now face a substantial increase in PDs across all four scenarios due to the substantially higher initial pre-shock "PD 0", pushing up all the other PDs 1–4 as well. At the same time, the PD spreads remain comparably consistent with the main analysis results in Table 5. In other words, if our designed transitory climate risk scenarios induced a financial crisis scenario with increasing volatility up to +50%, the volatility would put the entire economy at

[33] 50–60% is based on the assessment of a US equity sample from CRSP/Compustat.

severe risk, and the difference between carbon-efficient and carbon-intensive sectors vanishes compared to our core analysis.

We want to highlight, however, that such high PDs already in the pre-shock state of 3–9% would be the result of a severe economic crisis. This is a rather unlikely scenario for us. Instead, we would expect policymakers and central banks to initiate strong and substantial countermeasures to calm the markets and stabilize the economy in the short run. We further argue why we believe not to observe such high numbers in reality in Sect. 4.8.

4.6.2 Bootstrapping

Even in our substantially large sample of 6.5 years with up to 1,600 daily equity returns, the equity returns distribution may not represent the true distribution of the equity returns and thus the underlying equity volatility σ_E. Therefore, we bootstrap the daily equity returns. We run this bootstrap approach with the Stata option "bootstrap" for estimation commands. We use first the standard approach with randomly and independently distributed drawings with replacement based on the initial idea of Efron (1979). Then, we follow the non-overlapping block-bootstrap approach with block length equal to one month of trading days (Carlstein 1986; Politis and Romano 1994) to take into account the serial correlation of stock market returns (Fama 1970; Campbell and Mankiw 1987; Ball and Kothari 1989; Campbell et al. 1997). For each firm, we draw 500 daily stock returns from our entire data sample per replication and replicate this process 1,000 times. We limit our number of draws per replication to 500 to generate a sufficiently large sub-sample of our overall sample that is nevertheless sufficiently smaller than our overall sample. We take these bootstrapped, re-sampled daily equity returns for each firm to compute 1,000 different equity volatilities σ_E and integrate them into the computation of 1,000 different asset volatility σ_V values for each company. We then compute 1,000 different company PDs and different sector average PDs weighted by total liabilities per company within a sector for our four defined scenarios. This approach allows us to reduce the uncertainty about the true equity volatility parameter σ_E that substantially drives our asset volatility σ_V and, through the Merton model, subsequently also the firm-specific PDs. This approach also allows us to generate confidence intervals for the weighted sector average PDs to further enhance the precision of our derived PDs. The mean and 95% confidence interval of the estimated sector-weighted average PDs in Table 8 for the outer two scenarios 1 and 4 illustrate the bandwidth of PD estimations across the scale.

The bootstrapped results confirm the validity and precision of our derived PDs from the main section in Table 5. While the intervals on 95% are considerably small even for the heavily affected sectors with PDs greater than 10% in scenario 4, for which we could have expected bigger intervals, their range is also very close to the initial main estimates. The maximum deviation between our initial PD estimate and the closest confidence interval bound range in Table 9 is about one percentage point (18.57 vs. 19.59% as the upper interval bound for Basic Resources in the block-bootstrap), and otherwise often between 0.2 and 0.7 percentage points. Moreover, the difference between the approach with randomly distributed and block-wise, non-overlapping draws with 0.2 to 0.4 percentage points for PDs and confidence interval bounds is comparably small.

Therefore, the bootstrapped results underline the previous conclusion: Transitory climate risk induced through a carbon tax of €50–100 per tCO_2 is a substantial driver of financial risk for the most carbon-intensive sectors, while carbon-efficient sectors remain almost unaffected.

4.7 Impact of transitory climate risk on Basel III capital ratios

We assess the effect of transitory climate risk on a large European bank's Basel III capital ratios in a standard stress test. The PDs for the scenarios presented in the previous section are used to recalculate the risk-weighted assets (RWA) of corporate loan exposures amounting to 36% of the bank's total RWA.[34] We find an overview of corporate loans by industry in the banks' Pillar III disclosure of the bank. The corresponding post-shock RWAs stem from the Basel III framework risk weight functions[35], with the newly calculated PDs and the corresponding average LGDs disclosed by the bank as input.[36] We compute the pre-shock RWAs and measure the differences between post-shock and pre-shock RWAs for each scenario. The differentials are then added to the reported total RWAs to recalculate capital ratios.

Again, we assume a stable macroeconomic environment throughout the scenarios to isolate the financial impact of transitory climate risk. We recognize, however, that if such drastic scenarios materialize, the effects on capital ratios would likely be much more severe. We conduct our calculations now on the industry level since

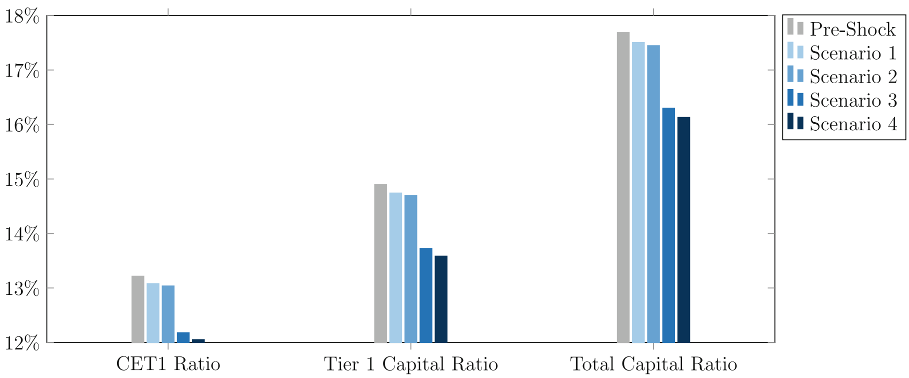

Fig. 6 Basel III capital ratios by scenario. *Notes:* Post-shock Basel III capital ratios by scenario after our stress test exercise for the one European bank example. Input for the stress test results are the firm-specific PDs from previous tables per individual scenario

[34] The percentage takes into account other credit risk exposures (such as loans to institutions, governments, associations, etc.), market risk RWA and operational risk RWA.

[35] The bank calculates corporate loans' RWA using the Standardised Approach, the Foundation IRB approach, and the Advanced IRB approach. For procedural coherence, we calculate each portion of the RWA using the same methodology chosen by the bank.

[36] For corporate loan exposures, the bank provides average measured LGDs (Loss given default) by the range of PDs. We choose the LGD for each industry according to which range the post-shock PD falls.

Table 6 Basel III capital ratios by scenario

	CET1 Ratio	Tier1 Capital Ratio	Total Capital Ratio
Pre-Shock	13.22%	14.90%	17.69%
Scenario 1	13.08% [−0.14]	14.74% [−0.15]	17.50% [−0.18]
Scenario 2	13.04% [−0.18]	14.69% [−0.20]	17.45% [−0.24]
Scenario 3	12.18% [−1.04]	13.73% [−1.17]	16.30% [−1.39]
Scenario 4	12.05% [−1.16]	13.59% [−1.31]	16.13% [−1.56]

Notes: Capital ratios after the climate policy shock under the constructed scenarios 1 to 4 and change versus pre-shock state in percentage points in brackets.

we lack loan exposure data on the issuer/firm level. To do so, we assume that the sectors in the pillar III disclosure are now entirely and exclusively composed of the final 404 companies in our final sample. In other words, we assume that the final 404 companies in our sample aggregated on the NACE level represent the exact corporate credit exposure of this bank. We show the results of our analysis for three main capital ratios that banks are required to comply with under the Basel III regulation:

The numerical values to Fig. 6 are depicted in Table 6.

Our analysis leads to a decrease in CET1 ratio ranging from 0.14% to 1.16% percentage points, a decrease in Tier 1 capital ratio ranging from 0.15% to 1.31% percentage points, and a decrease in Total Capital ratio ranging from 0.18% to 1.56% percentage points. Again, we want to highlight that we are addressing only about one-third (36%) of the bank's total RWA. Therefore, the results represent only a part of the risk this bank would face in the assumed scenarios. Nevertheless, the drop in capital ratios would be substantial for the European bank.

4.8 Reconciliation and discussion

In this section, we discuss the magnitude and scale of the results of our analysis by reflecting on our constructed scenarios, the characteristics of the Merton Model, and further input parameters used in our model.

First, our scenario assumptions across the input factors tax rate, pass-through rate, and emission reduction capabilities: Our tax rate assumption of 50–100 EUR per tCO_2 is on the lower end of the bandwidth of carbon tax rates or prices in literature (World Bank 2017; Poelhekke 2019; Bach 2019; Reinders et al. 2020; Rogelj et al. 2013). From that perspective, our analysis somewhat underestimates the effects of new/rising prices for carbon. On the contrary, these new/higher costs for carbon are, presumably, partially priced in already by market participants in their analysis of particularly carbon-intensive sectors over a stress test horizon of the next three years (Delis et al. 2018). However, the exact extent is hard to derive from the overall market for two reasons: First, national legislation on carbon taxes/prices varies considerably (see, for example, Scandinavian countries vs. Germany) over a cross-country European data sample such as the STOXX Europe 600. Second, expectations of the future development of the cost of carbon and the scope of sectors and emissions as captured by the EU ETS might also vary across market participants.

Regarding the pass-through rates, there is a wide bandwidth of assumptions in the empirical literature for the pass-through rate of rising costs on the input side. This rate depends on the competitiveness and price sensitivities over sectors and countries, ranging from 0.8–0.2 for the analyzed sample (Benedek et al. 2020). This range is also in line with many other studies in this field, for example Carbonnier (2007); Kosonen (2015); Cludius et al. (2020). Therefore, with our assumption of 0.8 and 0.5 in the most adverse scenario, we are in the mid-range of the scale and do not stretch the scale of this input parameter to the most adverse case. A pass-through rate lower than 50% to the detriment of firms would yield even more severe results in our analysis.

The timing of the tax is assumed to be abrupt in all four scenarios as opposed to phase-in because this better fulfills the purpose of standard stress tests with a time horizon of up to three years. From this perspective, our analysis is more on the adverse side. However, since the terminal value in NPV calculations accounts for the large majority in NPV calculations, a phase-in approach would reduce the magnitude of results only to a limited extent.

Lastly, we integrate emission reduction capabilities by firms to respond to the rising cost of carbon of 0–25% over a time frame of three years, a number we derived from selected analyzed case examples over various industries over the previous 3–5 years. This number might be hard to achieve for some carbon-intensive firms over one year. However, since we also have many low-carbon firms in the sample, an emission reduction by 25% over the next three years seems plausible from our analyzed case examples in light of the rising cost of carbon, making carbon-free energy sources relatively more attractive, in particular for carbon-intensive sectors.

Regarding the Merton model, our analysis somewhat overestimates the impact because the original Merton model implies a strict default assumption whenever the book value of assets falls below the book value of debt. This issue could be resolved with commercial proprietary models such as the one from Moody's, which is unavailable to us. This model uses an adjusted Merton model by running an empirical function of PDs on the theoretically calculated ones from the original Merton model, yielding substantially lower PDs (Nazeran and Dwyer 2015).

For simplicity and to sustain the focus of the analysis on the climate stress test procedure, we assume the cost of capital to be constant.[37] Yet, we acknowledge the reasoning of other scholars suggesting that this may constitute a simplifying assumption. Pastor et al. (2019), for example, analyze the financial and real effects of sustainable, ESG-related investing in an equilibrium model. They show that once financial agents derive relative utility from holding green assets instead of brown assets and once agents care about the "social" impact and the produced externalities of firms, agents are willing to pay more for greener firms, reducing the cost of capital for green firms and increasing them for brown firms. Also, in an equilibrium model, Heinkel et al. (2001) show that exclusionary ethical investment with fewer investors holding assets of polluting firms may lead to a drop in share price and

[37] Relaxing the assumption of constant cost of capital and manually computing the accurate forward-looking cost of capital for 404 individual firms would add another driver of uncertainty and complexity to our analysis.

higher cost of capital of these polluting firms. This increase in the cost of capital may incentivize polluting firms to switch to green technology once the higher cost of capital outweighs the cost of switching. These equilibrium concepts are consistent with empirical findings, for example, Chava (2014) or El Ghoul et al. (2011), who find a lower cost of capital for greener firms and higher cost for brown firms mainly due to different ex-ante return expectations. One practical angle for the adjustment of the cost of capital could, for example, be the brown "carbon beta" factor to account for the systematic risk of brown assets as provided by CARIMA ("Carbon Risk Management"). This former project has become a company (Wilkens et al. 2019). In sum, we may underestimate the effect for brown firms and sectors with constant cost of capital.

In the application of the results to the pillar III disclosure of a European Bank, the scope of the analysis is limited to the credit risk of large corporations, excluding about two-thirds of total RWAs of credit exposure to other debtors as large corporations, e.g., public states or small and medium enterprises (SME). Excluding SMEs leads to a lower overall addressable share of RWA in the pillar III disclosure and a lower impact on the capital ratios per se. However, since (non-listed) SMEs might suffer more from the higher/new cost of carbon than large corporations because of fewer available financing sources (for example, large corporations may use a secondary offering of stocks while SMEs cannot do so), the impact of only looking into large corporations might be even further underestimated.

In addition, our constructed scenarios may trigger second-round effects, via an unfavourable macroeconomic environment, on other bank credit exposures through various direct and indirect transmission channels (NGFS 2020b). For example, the higher cost of carbon in the short run can lead to an overall lower financial performance by carbon-intensive sectors, resulting in lower macroeconomic growth over the entire economy, lower creditworthiness of state and corporate bonds, and higher credit risk for bank exposures. Although a pass-through rate and carbon emission capabilities by firms could be considered as a second-order reaction to the rising cost of carbon, both factors reduce the negative impact on firms in our model. At the same time, the second-round effects in the macroeconomic cycle would produce even more severe results.

Given the above discussion, our asset devaluations with a maximum of 35.8% for the most affected sector appear more plausible and realistic compared to 89% asset devaluation (Reinders et al. 2020) to us. The drop in capital ratios of up to -1.6% percentage points, that is -11.8% (-1.6 divided by 13.22) of the 13.22% pre-shock CET1, with addressable RWA of 36% also appears more plausible than a jeopardizing 30–63% reduction of CET1 capital from Reinders et al. (2020) for carbon taxes of 100–200 EUR. When comparing our results with Monnin (2018), we see somewhat similar asset devaluation shocks in our analysis but substantially lower PDs for the two presented companies. Compared to the analysis by the central banks and the EBA, our results are partly more severe. This can be explained by the entirely different approach the central banks use. While their results depict the results for 2025–2050, our results illustrate the impact in the next three years. This perspective helps practitioners measure and manage their climate risk exposure in the short run.

Finally, we acknowledge that our analysis of STOXX Europe 600 companies and their credit risk relies on publicly available data from financial statements and ESG reports unavailable for most SMEs. Even for 127 out of the largest 600 European companies listed in the STOXX Europe 600, we lack complete GHG scope 1 emissions in the ESG reports. Although the new EU legislation aims to include up to 49,000 companies in the non-financial reporting directive[38], it will take some time until smaller companies also can and will publish reliable non-financial data in a standardized framework. For now, our analysis aims to facilitate research in this field and support practitioners and regulators in developing suitable climate risk assessment tools.

Our results confirm the proposition presented in the introduction: Climate risk poses a considerable threat to the real economy and the financial sector as investors and lenders. In particular, the results illustrate the substantial risk for carbon-intensive sectors and firms to climate risk. In contrast, low-carbon sectors and firms are hardly affected by the rising cost of carbon under the constructed scenarios. Nevertheless, our results, particularly for the more severe scenarios, should be interpreted carefully and set in the context of the above explanations. These are stress test results and not expectations about asset devaluation shocks and dangerously high rises in PDs over entire sectors.

5 Conclusion

If not readily dealt with, climate change will severely increase extreme precipitation, drought, and lethal heat waves. This may disrupt global supply chains, damage infrastructure, and endanger the population in the areas that are at risk. Estimations of the cost of climate change illustrate the risk for both firms and financial institutions. Therefore, regulators have requested financial institutions to develop suitable stress test methods by 2022 (ECB 2021; Banque de France 2021; Bank of England 2021). We develop a generic 6-step concept summarizing both bottom-up and top-down stress test approaches. We then apply this concept and estimate the impact of transitory climate risk on firm's solvency and their creditor's resiliency. We introduce a carbon tax of 50–100€ per CO_2 equivalent and calculate the impact on asset valuations of the STOXX Europe 600 companies in our four constructed scenarios. We find asset devaluations greater than 15% for 43 or about 10% out of the 404 final firms in our sample and asset shocks greater than 30% for 25 firms in the adverse scenario. Aggregated on the sector level by weighted liabilities per firm within a sector, we find asset devaluations between 15.4% and 35.8% for the six most affected ICB supersectors. In contrast, the other 11 sectors are only barely affected.

We then take these asset devaluation results and estimate the impact on PDs. On the firm level, we find for 66 out of 404 firms (about 16%) in the final sample new PD levels larger than the investment-grade threshold of 3% in the most adverse

[38] See the Proposal for a Directive of the European Parliament and of the Council on the scope of the amended Corporate Sustainability Reporting Directive (CSRD).

scenario. For the six most affected sectors, we find new sector-average PDs between 5.1% and 34.2%. We take these PDs and calculate the effect on capital ratios of a large European bank, resulting in a decrease in the capital ratios from −1.2 to −1.6% if the final 404 firms in our sample from the STOXX Europe 600 companies were representative of the exact corporate credit exposure of this bank.

We acknowledge that our asset devaluation shocks and particularly PDs are higher than the empirically observed default rates because we deploy the classical Merton model in which companies default when their asset's value falls below their value liabilities' value. Although our PDs are somewhat higher than actual observed default rates, our asset devaluation shock results are lower than those of Reinders et al. (2020); Vermeulen et al. (2019). Our results are partly in line, partly larger than those of regulators and supervisors. They confirm the magnitude of the risk companies and financial institutions face in light of climate change and the fight against it.

In light of further increasing CO_2 prices in the future, companies and financial institutions need to be able to estimate the effect of the rising cost of CO_2 emissions on their P&L and balance sheets and identify tailor-made strategies to reduce their CO_2 footprint (World Bank 2017). Since the financial sector is under additional pressure from regulators to develop its climate-related stress tests, we urge researchers to contribute further methods and models for climate stress testing that ideally combine a firm-level approach with top-down macroeconomic forecasts in the short run.

6 Appendix

6.1 Bootstrapping

In this subsection of the Appendix, we provide more details on our bootstrapping approach to better understand the impact of the estimated equity volatility parameter on our derived PDs in the main section. In the following, we add the firm indices i with $i = 1, ..., n$ to highlight the firm-specific values.

The equity volatility parameter σ_{E_i} drives our asset volatility σ_{V_i} through equation (12).[39] The asset volatility σ_{V_i} drives, in turn, through the Merton model and, subsequently, the firm-specific PDs. Since the distribution of the equity returns, even in our sample with a substantially long time horizon over 6.5 years with up to 1,600 daily stock market returns, may not represent the true distribution of equity returns and thus the underlying true equity volatility parameter σ_{E_i}, we bootstrap the daily equity returns in our sample to gain additional insight into the underlying distribution of the equity returns and the equity volatility parameter σ_{E_i}. Bootstrapping the daily equity returns for a number of draws per replication allows us to generate a "new", different equity volatility σ_{E_i} per replication, a new asset volatility σ_{V_i}

[39] Again, we estimate the market value of assets V_i as the sum of the market value of the equity MV_{E_i} and the face value of the firm's total liabilities L_i based on the inputs extracted from Refinitiv. We leave out the subscript t at this stage in the notation of the market value of the assets for simplicity and consistency in this subsection.

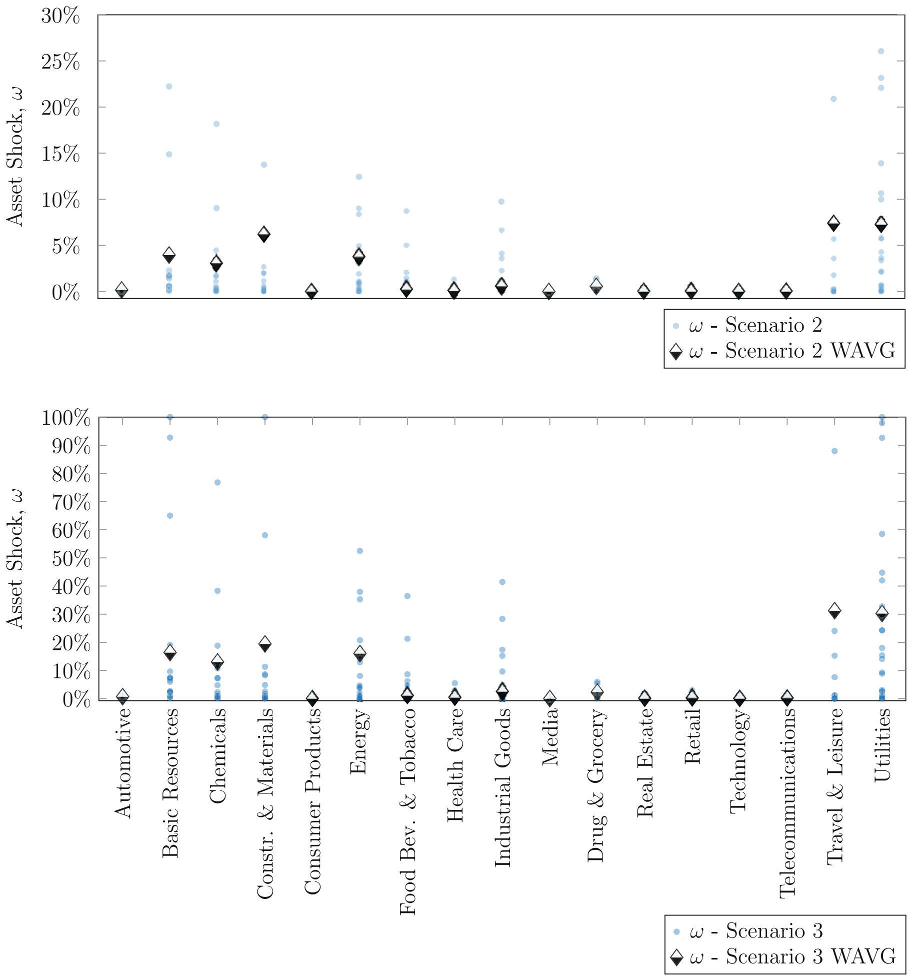

Fig. 7 Asset Shocks, ω – Scenarios 2 and 3. *Notes:* Asset devaluation shocks for scenarios 2 and 3. The dots represent values for each of the 404 single companies, the markers of white and black triangles the weighted average (WAVG) by total liabilities of the single companies within a sector. Asset shocks are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. Industry classification by ICB. Maximum asset shock in scenario 2 set at 30% for readability reasons. To illustrate the bandwidth of asset shocks in scenario 3, asset shocks in scenario 3 are shown up to 100%

and through the Merton Model, finally a new PD for each firm and each sector on aggregate level. Over all these bootstrap replications of the daily equity returns and the calculations in the Merton Model outlined in Sect. 4.4, we can then generate confidence intervals of the derived PD_i providing us with additional insight into the precision and validity of our initially derived results in the main section.

As with most computations, we run the Bootstrapping command in Stata using the "bootstrap" command. This command runs a common bootstrap procedure, randomly and independently with replacement, from our sample going back to the idea

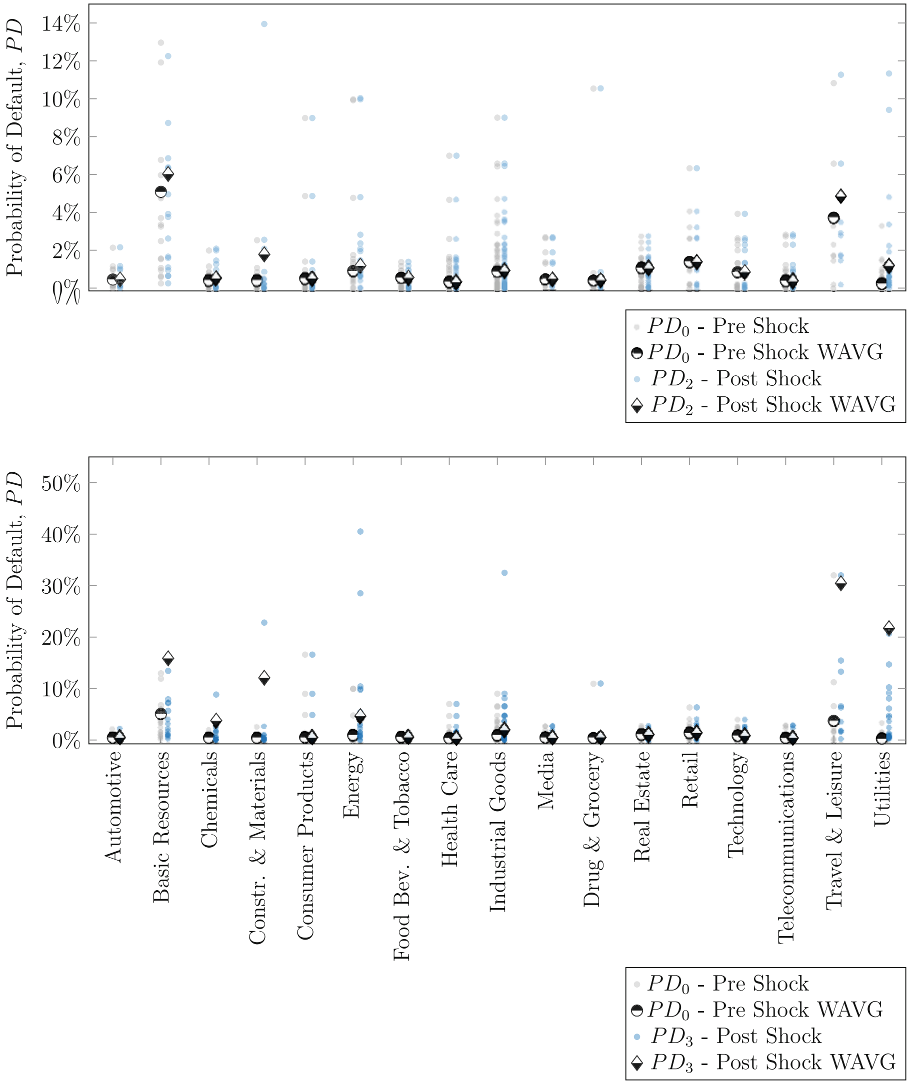

Fig. 8 PDs compared to pre-shock state by ICB supersector, Scenarios 2 and 3. *Notes:* PDs for scenarios 2 and 3. The dots reflect again the firm-specific values while the white and black markers represent sector-average values weighted by total liabilities per company within a sector. The left-side dots and markers in each ICB supersector column represent PDs before the exogenous policy shock, the right-side dots and markers represent post-shock PDs. PDs are weighted by total liabilities per company within a sector to approximate the credit exposure of banks on the asset side of their balance sheet. Industry classification by ICB. To enhance the readability and visibility of the graph, the scale of visible PDs is limited to 15% and 50%, respectively

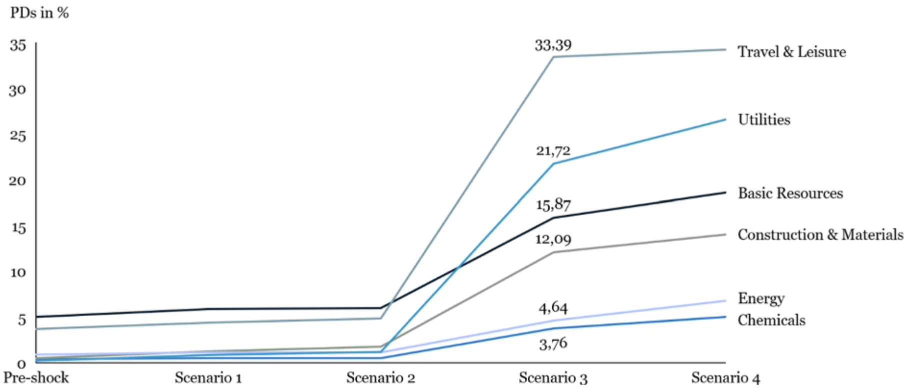

Fig. 9 New PDs in % over scenarios 1–4; 6 most affected sectors. *Notes:* New PDs over scenarios 1–4 for the 6 most affected sectors from column 3 in Table 5 to illustrate the big increase in PDs from scenario 2 to 3

Table 7 PDs and PD spreads vs. pre-shock state for scenarios 1 to 4 – Increase in volatility

	PD 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Automotive	4.49	4.52[+0.03]	4.53[+0.04]	4.65[+0.17]	4.69[+0.2]
Basic Resources	20.24	21.40[+1.16]	21.61[+1.37]	29.84[+9.6]	31.83[+11.6]
Chemicals	5.20	5.67[+0.47]	5.77[+0.57]	9.85[+4.65]	11.37[+6.17]
Constr. & Materi-als	4.58	6.56[+1.98]	7.21[+2.62]	17.55[+12.97]	19.28[+14.69]
Consumer Prod-ucts	4.60	4.60[+0.00]	4.60[+0.00]	4.61[+0.01]	4.61[+0.01]
Energy	7.15	8.03[+0.89]	8.22[+1.07]	14.29[+7.15]	16.63[+9.49]
Food, Bev. & Tobacco	5.14	5.17[+0.03]	5.18[+0.04]	5.32[+0.18]	5.35[+0.22]
Health Care	4.06	4.08[+0.02]	4.09[+0.03]	4.17[+0.11]	4.19[+0.13]
Industrial Goods	6.32	6.46[+0.14]	6.49[+0.16]	7.77[+1.45]	8.30[+1.98]
Media	4.41	4.41[+0.00]	4.41[+0.00]	4.42[+0.00]	4.42[+0.00]
Drug & Grocery	4.12	4.24[+0.12]	4.26[+0.14]	4.77[+0.66]	4.92[+0.80]
Real Estate	7.96	7.97[+0.01]	7.97[+0.01]	8.00[+0.04]	8.01[+0.05]
Retail	8.98	8.99[+0.02]	9.00[+0.02]	9.06[+0.08]	9.07[+0.09]
Technology	7.70	7.70[+0.00]	7.71[+0.01]	7.72[+0.02]	7.73[+0.03]
Telecommunications	3.45	3.46[+0.01]	3.46[+0.01]	3.5[+0.05]	3.51[+0.06]
Travel & Leisure	13.85	16.32[+2.48]	17.29[+3.45]	44.38[+30.54]	45.28[+31.43]
Utilities	3.06	5.01[+1.95]	5.62[+2.56]	27.1[+24.04]	32.41[+29.35]

Notes: New post-shock PDs and PD spreads compared to pre-shock “PD 0” state in square brackets in percentage point difference. PD spreads in brackets calculated as difference between the new PD (the number in front of the bracket) and its corresponding pre-shock state (not stated in the table for simplicity). Results after increasing equity volatility for all companies in the sample by +50% or multiplying it by 1,5. All sector-wide averages again weighted by liabilities per company within a sector. All numbers rounded to 2 digits

Table 8 PDs and confidence intervals for scenarios 1 and 4 – Bootstrapped estimations with 1,000 replications

	Scenario 1		Scenario 4	
	PD Mean	95% Conf. Interval	PD Mean	95% Conf. Interval
Automotive	0.501	[0.491–0.512]	0.535	[0.524–0.546]
Basic Resources	6.596	[6.550–6.642]	19.348	[19.298–19.397]
Chemicals	0.513	[0.507–0.519]	4.957	[4.945–4.969]
Constr. & Materials	1.273	[1.260–1.286]	14.062	[14.045–14.080]
Consumer Products	0.250	[0.247–0.254]	0.252	[0.249–0.256]
Energy	1.553	[1.533–1.574]	7.322	[7.281–7.364]
Food, Bev., & Tobacco	0.703	[0.690–0.716]	0.746	[0.732–0.760]
Health Care	0.392	[0.387–0.396]	0.413	[0.409–0.418]
Industrial Goods	1.051	[1.041–1.061]	2.787	[2.777–2.797]
Media	0.656	[0.647–0.666]	0.657	[0.648–0.667]
Drug & Grocery Stores	0.573	[0.565–0.581]	0.733	[0.723–0.742]
Real Estate	1.242	[1.231–1.254]	1.256	[1.244–1.267]
Retail	1.881	[1.856–1.906]	1.914	[1.889–1.939]
Technology	0.926	[0.914–0.938]	0.931	[0.919–0.943]
Telecommunications	0.508	[0.501–0.514]	0.518	[0.511–0.524]
Travel & Leisure	5.022	[4.949–5.095]	34.882	[34.800–34.963]
Utilities	0.872	[0.865–0.880]	26.604	[26.577–26.631]

Notes: Mean and 95% confidence intervals of weighted sector average post-shock PDs in %. All sector-wide averages again weighted by liabilities per company within a sector. All numbers rounded to 3 digits. Results based on bootstrapped equity volatility with 1,000 replications and 500 randomly distributed draws of daily equity returns with replacement per replication per company.

of Efron (1979). We limit the number of draws per replication to 500 in order to generate a sufficiently large sub-sample of our maximum sample of about 1,600 daily equity returns that is nevertheless sufficiently smaller than our overall sample. The identification of a suitable number of replications has evolved into an entire literature strand in the field of bootstrapping, for example Efron and Tibshirani (1986); Berkowitz and Kilian (2000); Davidson and MacKinnon (2000); Andrews (2002); Dudek et al. (2016), and depends on among others, the purpose, the data generation process, the sample size or the bootstrapping method. In theory, the number of replications should be infinitely large. This may be problematical for computation reasons and not always necessary if the estimated results for the bootstrapped parameter, in our case the equity volatility σ_{E_i} and subsequently the confidence intervals of PD_i, converge quickly. Scholars suggest that 1,000 replications are a good start and might even be sufficient if the results converge quickly with increasing replications (Efron and Tibshirani 1986, 1994; Hansen 2010). Since this is the case for the results of the mean PDs and corresponding confidence intervals, we follow this recommendation.[40] We run the bootstrap command in Stata to draw 500 equity returns with replacement over 1,000 replications, insert the 1,000 resulting equity

[40] In fact, we start with 250 replications and gradually increase up to 500 and 1,000 replications. We observe that the results with 250 and 1,000 replications are already quite similar and converge substantially.

Table 9 PDs and confidence intervals for scenarios 1 and 4 - Bootstrapped estimations per monthly blocks with 1,000 replications

	Scenario 1		Scenario 4	
	PD Mean	95% Conf. Interval	PD Mean	95% Conf. Interval
Automotive	0.512	[0.501–0.522]	0.546	[0.535–0.557]
Basic Resources	6.803	[6.750–6.856]	19.542	[19.486–19.599]
Chemicals	0.643	[0.636–0.651]	5.116	[5.102–5.131]
Constr. & Materials	1.356	[1.339–1.373]	14.139	[14.12–14.158]
Consumer Products	0.653	[0.645–0.660]	0.655	[0.647–0.663]
Energy	1.686	[1.660–1.712]	7.508	[7.457–7.559]
Food. Bev.. & Tobacco	0.757	[0.741–0.773]	0.802	[0.786–0.819]
Health Care	0.415	[0.411–0.419]	0.437	[0.433–0.442]
Industrial Goods	1.133	[1.119–1.146]	2.873	[2.860–2.887]
Media	0.681	[0.672–0.690]	0.682	[0.673–0.691]
Drug & Grocery Stores	0.607	[0.602–0.613]	0.779	[0.772–0.786]
Real Estate	1.434	[1.419–1.450]	1.448	[1.433–1.464]
Retail	1.967	[1.940–1.993]	2.001	[1.974–2.028]
Technology	0.967	[0.955–0.978]	0.973	[0.961–0.984]
Telecommunications	0.533	[0.528–0.539]	0.544	[0.539–0.549]
Travel & Leisure	5.212	[5.129–5.295]	35.095	[35.003–35.187]
Utilities	0.975	[0.968–0.982]	26.726	[26.700–26.752]

Notes: Mean and 95% confidence intervals of weighted sector average post-shock PDs in %. All sector-wide averages again weighted by liabilities per company within a sector. All numbers rounded to 3 digits. Results based on bootstrapped equity volatility with 1,000 replications and cluster-wise draws of stock returns per month-year combination per replication per company.

volatilities σ_{E_i} into the asset volatilities σ_{V_i} computation and ultimately plug these, in turn, into the PD equations to generate 1,000 different PDs per firm. We take these 1,000 PDs per firm and generate mean PD_i and confidence intervals aggregated on sector level. The results for scenarios 1 and 4 are depicted in in Table 8.

Until this point, we assumed for simplicity that the daily equity returns are iid (independently and identically distributed) and run the bootstrapping with replacement independently from the previous draw. Yet, prior literature has detected a serial correlation between stock returns over a short-and long-term time horizon, for example, Fama (1970); Campbell and Mankiw (1987); Ball and Kothari (1989); Campbell et al. (1997). Scholars developed various bootstrapping techniques to address this issue in a bootstrapping approach (Politis and Romano 1994; Dudek et al. 2016). One of them is the block bootstrap approach initially developed by Hall (1985), Carlstein (1986), and Kunsch (1989). Instead of drawing independently and randomly each observation from the sample and assuming iid of stock returns, this approach involves drawing monthly clusters of daily stock market returns. It thus sustains the serial correlation pattern within the re-sampled clusters (Flynn and Peters 2004; Ng et al. 2013).[41] Again, we run the bootstrap command in Stata, this time clustered by

[41] The issue about finding the appropriate block length has formed a separate literature strand, for example Hall (1985); Politis and Romano (1994); Politis and White (2004). For simplicity and because of the

months of daily equity returns, over 1,000 replications. We insert the 1,000 resulting equity volatilities σ_{E_i} into the asset volatilities σ_{V_i} computation and ultimately plug these, in turn, into the PD equations to generate per firm 1,000 different PDs. We take these 1,000 PDs per firm and generate mean PD_i and confidence intervals aggregated on sector level. Scenario 1 and 4 results are again depicted in Table 9.

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