Bank of England

# Climate policy and banks' portfolio allocation

**Staff Working Paper No. 1,149**
October 2025

**Giovanni Covi, Maren Froemel, Dennis Reinhardt and Nora Wegner**

Staff Working Papers describe research in progress by the author(s) and are published to elicit comments and to further debate. Any views expressed are solely those of the author(s) and so cannot be taken to represent those of the Bank of England or any of its committees, or to state Bank of England policy.

Bank of England

Staff Working Paper No. 1,149

# Climate policy and banks' portfolio allocation

Giovanni Covi,[1] Maren Froemel,[2] Dennis Reinhardt[3] and Nora Wegner[4]

## Abstract

How do banks respond to transition risk and which mechanisms drive this response? We shed new light on this question using data on granular international large exposures of UK banks. Climate policy is the main source of transition risk we use. We find that an increase in climate policy stringency on average leads to a decline in the share of lending that is exposed to transition risk. However, this finding is not uniform across banks: banks with a lower initial exposure to transition risk decrease their transition-risk exposure by more and increase their transition-aligned exposure, while banks with a high initial exposure to transition risk further increase their exposure to those sectors. We also find evidence supportive of outward international spillovers through banks' cross-border lending portfolios: banks increase transition risk-exposed lending to a given country if climate regulation gets tighter in other countries banks have such exposures to.

**Key words:** Transition risks, climate policy, large exposures, capital flows.

**JEL classification:** F42, G11, G21, G38.

---

(1) Bank of England. Email: Giovanni.Covi@bankofengland.co.uk
(2) Bank of England. Email: Maren.Froemel@bankofengland.co.uk
(3) Bank of England. Email: Dennis.Reinhardt@bankofengland.co.uk
(4) Bank of England. Email: Nora.Wegner@bankofengland.co.uk

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. We are grateful to Germanwatch e.V. for numerous helpful interactions with and sharing of their data and expertise. We also thank colleagues at the Bank of England, the International Banking Research Network (IBRN) climate initiative, participants at the Durham-Bristol Banking Policy Forum on 'Climate Change and Banking Regulation and Supervision', our discussant Sujiao Zhao and Steven Ongena for helpful comments in developing this project.

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

©2025 Bank of England
ISSN 1749-9135 (on-line)

# 1 Introduction

Climate change can have significant implications for the financial stability of the banking system (Bolton et al. 2020). Potential risks arise from the exposure of lenders to the realisation of physical risks, which lead to the destruction of assets due to adverse climate events, as well as transition risks, which are associated with the adjustment towards a low-carbon intensive economy.

This paper analyses whether and how banks adjust their exposure to transition risk in response to changes in policy. Transition risk can manifest itself in different ways. A growing literature aims at measuring different aspects and channels of both physical and transition risk including looking at how they interact with policy action.[1] This literature delivers implications for the design of effective climate policy both at the national as well as the international level by uncovering what (might) work well and what the sources of significant frictions are.

We use a unique supervisory bank-level dataset of large international loan exposures from a major international banking centre, the UK. These data can be disaggregated using granular sectoral information to identify exposures currently contributing to achieving the transition to net zero ("green") or those that are particularly prone to transition risk as activities need to be stopped or their carbon emissions reduced significantly to achieve the transition to net zero ("brown"). To classify exposures as green (contributing to the transition) and brown (subject to transition risk) we use the Transition Alignment Coefficient (TAC) and Transition Exposure Coefficient (TEC) both developed by Alessi & Battiston (2022). This allows us to estimate the effects of changes in realised transition risk on banks' portfolio allocation towards directly affected sectors. The structure of our international bank-level dataset further allows us to uncover international spillovers and the role of bank preferences.

Our measure of (realised) transition risk is climate policy stringency at the country level, proxied by Germanwatch's Climate Change Performance Index (CCPI). The CCPI tracks changes in the stringency of national climate policy frameworks - likely driven by but not limited to government policy - [2] - over time and thus allows us to estimate the effect of increases in climate policy stringency on banks' cross-country exposures.

We analyse how domestic and international lending and portfolio allocation of UK banks respond to climate policies taken abroad. In the first instance, we abstract from banks' global *reallocation* decisions and estimate the impact on country-specific exposure to transition risk relative to their overall climate policy-relevant exposure. We identify effects of climate policy over a two-year period, consistent with a focus on shorter-term transition risks and the difficulty of identifying longer term effects of changes in climate policy in bank lending data.

[1] See for example Ferentinos et al. (2023)

[2] The index doe not explicitly distinguish government policy from reguation, but importantly does not focus on regulation. See appendix for description

We find that that when a country increases its climate policy stringency, UK banks, on average, respond with a decrease in the share of lending to the country that is exposed to high transition risk. This finding is robust to various definitions of the share variable including the baseline measure of changes in the share of country-specific climate policy relevant (CPRS) exposures or exposures overall as well as broader measures such as total global exposures and bank capital. Banks do not however increase the share of their transition aligned lending to a country which increases its climate policy stringency. Our results seem consistent with a risk-based mechanism where banks manage their exposure to transition risk. We further use a disaggregated version of the CCPI into components that reflect policies incentivising green sectors versus those disincentivising brown sectors to understand if our main finding is driven by the broad climate policy measure, or, put differently, if the source of a change in climate policy stringency matters on average. The evidence suggests this is not the case: only the latter significantly reduce banks' exposures to transition risk. This asymmetry suggests that banks respond more strongly to direct regulatory risk than to incentives for green investment, at least in the short run.

The finding is not uniform across banks: banks with a lower initial exposure to transition risk in terms of their overall global portfolio decrease their transition-risk exposed lending by more if a country tightens its climate policy; or vice versa if a bank has a high initial share of lending exposed to transition risks it instead protects is brown lending portfolio. We also find that there is a group of banks – namely those with very low initial brown exposure shares - that increase their green transition-aligned lending to a country following an increase in climate policy stringency. This suggests heterogeneity in banks' approach to transition risk.

Furthermore, we analyse the international dimension of climate policy by constructing a measure of relative climate policy stringency across countries, and estimate cross-country spillovers based on bank-specific changes in climate policy stringency. We find that banks reduce their brown exposures in countries that tighten their climate policies relative to others in their portfolio. Conversely, banks increase their brown exposures in countries with relatively looser climate regulation, indicating that portfolio reallocation is influenced by international policy differentials. These findings provide evidence of spillover effects, where domestic climate policies may inadvertently shift carbon-intensive lending abroad, undermining global climate efforts.

Our paper contributes to the literature on the (international) transmission and effectiveness of climate policies via the banking sector. Studies find evidence for several channels through which climate policy has an impact on banks' portfolios and financial flows more generally. In response to increased climate policy stringency or regulatory risk, banks reduce lending to more carbon intensive firms (Laeven & Popov (2022)) or offer less favourable terms (Ivanov et al. (2023)) to firms that are more exposed. While other studies rely on firm- or loan-level information on emissions to capture the exposure to carbon taxation, we aggregate loan-level information to the sectoral and country level and use the aforementioned taxonomy to measure the exposure to climate policy more generally, given the broad nature of CCPI. Our dataset allows us to uncover dynamic substitution patterns—both across green vs brown sectors, across borders and across banks—that are difficult to detect without the combination of data coverage, granularity, and cross-country perspective employed here.

Notwithstanding impacts on reductions in carbon intensive portfolios, the literature finds potentially important spillover effects that are determined by misalignment in global climate efforts, i.e. differences in climate policy stringency across countries, although the direction and nature of impacts can differ, with potentially competing mechanisms that depend on the type of bank and sample of loans considered. Using syndicated loans, Benincasa & Ongena (2024), find that banks reduce lending to carbon intensive firms domestically and increase it abroad, but only in countries where climate policy is less stringent. Furthermore, the effect is stronger the larger the difference in regulation. Laeven & Popov (2022) find that brown exposures are rebalanced towards private firms highlighting a potential role for stricter climate policy to raise public awareness and increase reputational risk that may appear to be higher, as easier to disclose, for publicly listed firms.[3] However, Demirguc-Kunt et al. (2024) find that some foreign subsidiaries of global banks increase their overall lending to countries with more stringent regulation, while Ho et al. (2024) find evidence of positive spillovers for Hong Kong in response to more stringent regulation abroad, although banks rebalance towards borrowers with lower emissions intensity. Fourne & Li (2023) find an increase in overall lending using aggregate bank-based lending flow and find indicative evidence for a diversification effect for countries with a high degree of environmental stringency. However, the sample of loans and banks considered across these studies differ, as well as the level of aggregation. Our results confirm and extend findings on international spillovers by showing that banks actively reallocate exposures based on relative climate policy stringency. Furthermore, exploiting the heterogeneity between banks, we show that the effect is stronger when foreign policy stringency is weighted by banks' exposures to transition risk sectors.

The effect on banks' exposures may in fact depend on how strict initial regulation is, and on policy differentials across countries. Using the Paris Agreement as a 'shock', Mueller & Sfrappini (2022) find that banks decrease lending to more exposed firms only in Europe, whereas the opposite effect is observed in the US. Fourne & Li (2023)'s findings are consistent with the importance of relative stringency, as they find their diversification motive is driven by flows between more advanced countries, which tend to have higher policy stringency. While our initial analysis abstracts from climate policy differentials over time, we show that they are not driving our results.

Our paper also links to the literature exploring the role of heterogeneity at the bank level for the impact of climate policy on portfolio choice. An increase in climate policy stringency leads to an increase in regulatory risk for more exposed firms and lowers firms' prospective profits (increases their riskiness) Benincasa & Ongena (2024). Assuming banks take regulatory risk into account, stricter climate policy could have a different effect on banks, depending on their risk management. For instance, Mueller &

[3]Consistent with a role for an increase in reputational risk, Gianetti et al. (2024) find that firms who join public sustainability commitment initiatives underwrite more green bonds while extending more credit to more exposed firms on average

Sfrappini (2022) find that lending to more exposed firms was higher for banks with a lower capital base, proxying a risk-taking motive. At the same time, banks with a higher initial exposure to carbon intensive firms do not reduce their lending, which is consistent with our findings so far. This could highlight an additional role for specialisation in lending portfolios which may counteract the effect from increased regulatory risk.[4]

Finally, our results on the heterogeneous effects depending on the initial brownness of banks' portfolios relate to the literature on banks' climate preferences and greenwashing. One challenge to these studies is to identify what constitutes an adequate measure of a preference for green, and which measures, such as commitments to international public initiatives, act more like 'greenwashing', seeking to attract shareholders' support. The findings are also mixed in this case. Kacperczyk & Peydro (2024) find that banks who increase their SBTi[5]commitments, reduce lending to high (Scope I) emission firms, while Degryse et al. (2023) find a positive effect on volume and terms for less exposed firms, and Gianetti et al. (2024) find these firms underwrite more bonds. In contrast, Hale et al. (2024), using three different commitment proxies (PRI, TCFD and PRB[6]) and country-industry-level information on emissions, do not find a role for banks' commitments in reducing lending to more negatively exposed sectors. Moreover, they show that while early adopters of PRI had lower initial exposures to regulatory risk, they did not decrease their lending by more, although they do not directly explore the marginal impact of changes in climate policy.

Gianetti et al. (2024) and Gambacorta et al. (2023), both using granular credit data and textual analysis, find somewhat contrasting results for the relationship between firms' voluntary environmental disclosures and their lending patterns. While Gianetti et al. (2024) find that firms "that overemphasize environmental initiatives in their reports are no more likely to hold greener loan portfolios" and "thus appear to strategically report positive sustainability actions and withhold information about negative ones", Gambacorta et al. (2023) find that banks who actively express concern and discuss these exposures in their statements more, lend less to exposed firms. ESG ratings are another proxy of banks' climate change preferences. They are correlated with climate commitments and firms' disclosures (see discussion in Gianetti et al. (2024) and so subject to similar concerns. Demirguc-Kunt et al. (2024) find an increase in lending to countries that increase their climate stringency for global banks with high ESG ratings, and Ho et al. (2024) find evidence of less cross-border spillovers for these banks. Our Large Exposures dataset also comprises more visible loans than the average contained in banks' overall portfolio, which could imply that we may capture different reputational effects, more like those driving cross-border lending by global banks more broadly. Our findings suggest that banks respond more strongly to regulatory risk than to reputational incentives or green investment signals. This

[4]Although we do not control for adjustments elsewhere.

[5]Science-based Targets initiative, established in 2015 as a collaboration between several global non-profit organisations (NGOs) and United Nations Global Compact.

[6]PRI: United Nations' Principles for Responsible Investing, established in 2006. TCFD: Task Force on Climate-related Financial Disclosure, established by the Financial Stability Board in 2015. PRB: United Nations' Principles for Responsible Banking, created in 2019.

underscores the importance of policy design in shaping financial flows and managing transition risk.

We describe the construction of our dataset in more detail in Section 2 and discuss our empirical framework and results, including robustness in Section 3. Section 4 concludes.

## 2 Data

To assess banks' responses to climate-related shocks we rely on a UK-centric granular exposure-based dataset which capture UK banks' portfolio allocation through time, countries, and economic sectors. This dataset has been constructed by Covi & Raja (2022) leveraging upon confidential large exposure supervisory reporting (COREP 27-28 templates) which captures all UK banks' exposures above 10% of a bank's Tier 1 capital or above £260 million vis-à-vis any counterparty located worldwide. Using these data, we quantify the share of banks' exposures that are directed towards climate policy relevant sectors (CPRS) according to the classification developed by Battiston et al. (2017). The CPRS, in its most aggregate level, defines six economic sectors whose revenues could be affected positively or negatively in a disorderly low-carbon transition, based on their energy technology.[7]

This classification allows to aggregate exposures based on common sectorial characteristics such as: i) role in the energy value chain (technology), ii) role in the GHG emissions chain, iii) specific policy processes and iv) business model (input substitutability of fossil fuel). The CPRS classification provides an indication that certain sectors are more likely to be affected by transition risk but does not quantify the risk.

To distinguish exposures to activities that may be negatively affected by climate policy from those that are likely to benefit from climate policies, we use Transition-Exposure Coefficients (TEC) and Taxonomy-Alignment Coefficients (TAC), both developed by Alessi & Battiston (2022).

TAC provides a standardised measure of current greenness for those economic sectors covered by the EU Taxonomy[8] for the climate mitigation objective in terms of the share of activities in each sector that are currently aligned to the Taxonomy. Sectors covered by the Taxonomy are those that are seen to significantly contribute to the transition. TAC is set to zero for all other sectors, including those considered harmful and subject to high transition risk as well as those not or only mildly impacted by the transition. TEC provides a measure of transition risk reflecting the standardised transition potential of each sector (ie how difficult it is for a sector to transition) and hence the exposure to transition risk. Both TAC and TEC range from 0 to 1 and are used to proxy the level of greenness and transition risk of each NACE industrial sector and sub-sectors.[9]

Note that TEC and TAC do not provide details on sectors deemed mostly neutral with respect to the

[7]The CPRS sectors are: Fossil fuel, Utility, Energy-intensive, Buildings, Transportation and Agriculture
[8]Taxonomy: Link
[9]List of NACE codes from European Commission (2024), Retrieved: Link

transition to net zero. For these sectors, TAC and TEC are simply given a 0. We therefore look at both TAC and TEC separately. For example, two banks may have the same level of greenness (TAC) but a different exposure to transition risk (TEC) if one bank has a higher exposure to sectors considered neutral. Overall, our main dependent variables based on this dataset are the country-specific change in the share of TEC and TAC exposures in CPRS, respectively.

We then expand the dataset to include climate-related shock variables - main variables of interest - respectively, the degree of climate policy stringency across countries or CCPI index (German Watch, 2024) as well as the country-specific vulnerability index to physical climate risks proxied by the ND Vulnerability Index (Notre Dame University, 2024).[10]

In the following, we describe these datasets in turn. We start by describing in detail how we clean the dataset of large exposures to individual borrowers based in a range of countries, calculate climate-relevant exposures, and then aggregate this dataset to the bank-country-time or bank-country-sector-time dimension for our main analysis.

## 2.1 Granular exposure data

### 2.1.1 Building the dataset

The initial dataset on large exposures covers 598 UK banks - consolidated and unconsolidated group entities - reporting large exposures data over the period 2015q1 to 2024q1.The exposure measure we use is a proxy for gross debt exposure amounts (mostly loans) aggregated on a counterparty-obligor basis (at firm-level). In total the original dataset contains 305.000 bank-firm level exposures. We focus on the subset of exposures directed to the non-financial corporate sector (NFC) for our analysis.

We remove observations which are irrelevant for our analysis or cannot be mapped to the CPRS-TAC-TAC classification via NACE codes. As part of this we remove firms with NACE codes which are identified as “K” or ”O” (Financial and insurance activities and Public administration and defence, compulsory social security, respectively). We also remove those with either no or a single digit NACE code [11] as well as those NACE codes for which both TAC and TEC coefficients are equal to 0.[12]

In order to focus on banks which have sufficient large exposure data so that they can be assumed to vary those in the face of climate regulation, we further shrink the sample by setting the following selection criteria: a bank must have, on average, at least 2 exposures reported per quarter, and these

[10] Retrieved: Notre Dame University (2024), ND-GAIN Index. Retrieved:Link

[11] Nonetheless, we also show the implications of using 1-digit NACE codes including K and O for imputing climate-related exposures.

[12] Respectively, we remove firms belonging to this set of economic activities: J “Information and communication”, M “Legal and accounting activities”, P “Education”, Q “Human health and social work activities”, R “Arts, entertainment and recreation”, S “Other services activities”, T “Activities of households as employers”, and U “Activities of extraterritorial organizations and bodies” (European Commission, 2024).

exposures should be reported for at least 5 quarters.[13] Although the total number of banks reduces materially by applying this filter (≈ 80%), the number of exposures reported does not (16%), and even less in terms of £ amount. This is due to the fact that the large exposure reporting criteria based on the absolute threshold of £260 million is much more binding for large banks than for small banks. Overall, we lose very little information in terms of exposures due to these data cleaning procedures given the bulk of exposures is concentrated in few large banks.[14]

Next, we match the CPRS classification, as well as TEC and TAC coefficients via each firm's NACE code and add bank-specific controls such as capital ratios, total assets and liquidity metrics. Finally, we compute the share of transition risk and greenness of an exposure multiplying the TAC and TEC coefficients by the exposure amount.[15] means that activity will be likely to be abandoned (). The sum of TAC and TEC coefficients do not sum to 1 since they are not the complement of each other, but they approximate the degree to which a sector will be benefiting from or penalized by the climate transition. Similarly, we identify whether an exposure falls within the CPRS category of NACE codes and classify the full exposure amount as CPRS exposure.[16]

Our main explanatory variables of interest (i.e. climate variables such as changes in climate regulation) are at the country-quarter level rather than at the level of large exposures to individual firms. We aggregate the large exposures by bank-country-sector-quarter. In our baseline, we aggregate further the sectoral dimension to arrive at a bank-country-quarter dataset with 31 banks, 37 quarters and 43 countries with a total of 11.500 observations.[17] As a last step, since we may still have gaps on a bank country level over time, we fill the dataset with imputed missing exposure values when the exposure is missing in certain quarters to achieve a balanced panel. By adding this synthetic exposure to the data, we increase the number of observations to 22.667. Overall, this dataset, although it covers only large exposures to mainly large corporates, it is representative of total UK banks' loan exposures to the non-financial corporate sector, capturing roughly £330 billion of exposures as of 2024q1 (40% of the total). The dataset allows to disentangle and quantify the interplay between greenness and transition risk in banks' portfolios, and how banks may change portfolio composition given country-specific climate-related shocks.

[13] We test the robustness of our results to this assumption by increasing the criteria to 4 and 10, respectively.

[14] For instance, the three largest banks capture roughly 40% of total reported observations, whereas the top-10 banks cover 77% of total information.

[15] These coefficients range between 0 and 100%, and they reflect the low vs high carbon-intensive nature of that corporate in that NACE sector. For example, a sector with a TEC coefficient of 0 means that no transition will be required, whereas a coefficient of 100%

[16] CPRS sectors can be positively or negatively impacted by the low-carbon climate transition.

[17] As explained in detail later, aggregating across sectors allows us to calculate more reliable economy-wide shares of green (TAC) or brown (TEC) exposures in CPRS compared to sector-level green vs brown shares which can be based on a limited number of raw large exposures for some of the smaller sectors.

Table 1: UK banks' CPRS, TEC and TAC exposures over time (Yearly Average)

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | AVG |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **TOTAL** | 284 | 280 | 270 | 238 | 257 | 261 | 247 | 316 | 310 | 329 | 279 |
| CPRS | 196 | 200 | 190 | 165 | 184 | 189 | 179 | 223 | 216 | 228 | 197 |
| TEC | 112 | 113 | 111 | 100 | 107 | 118 | 111 | 127 | 122 | 127 | 115 |
| TAC | 18 | 16 | 16 | 15 | 15 | 12 | 15 | 21 | 23 | 26 | 18 |
| CPRS ratio (TOT) | 68.9% | 71.2% | 70.5% | 69.5% | 71.8% | 72.3% | 72.5% | 70.6% | 69.9% | 69.5% | 70.6% |
| TEC ratio (TOT) | 39.4% | 40.4% | 41.3% | 41.9% | 41.7% | 45.0% | 44.9% | 40.3% | 39.4% | 38.5% | 41.1% |
| TAC ratio (TOT) | 6.2% | 5.8% | 6.1% | 6.2% | 5.9% | 4.8% | 6.1% | 6.5% | 7.4% | 7.9% | 6.4% |
| TEC ratio (CPRS) | 57.2% | 56.7% | 58.5% | 60.3% | 58.0% | 62.2% | 61.9% | 57.0% | 56.4% | 55.4% | 58.2% |
| TAC ratio (CPRS) | 9.0% | 8.2% | 8.7% | 8.9% | 8.2% | 6.6% | 8.4% | 9.3% | 10.6% | 11.3% | 9.0% |

Note: ratios are calculated over total exposures amounts.

### 2.1.2 Climate transition exposures: risk versus greenness

Table 1 reports UK banks' aggregated exposures across countries and sectors (in £ billion) vis-à-vis the relevant set of non-financial corporates exposed to a low-carbon climate transition. In this respect, we find that on average over time roughly 70.6% of total exposures can be classified as climate policy relevant (CPRS), 41.1% are exposures subject to transition risk, whereas 6.4% may benefit from the climate transition.[18] Given TEC and TAC shares do not sum to 1 since some business activities may be unaffected by climate transition, it is also relevant to look at their ratios in terms of CPRS exposures so as to disentangle the interplay between greenness and transition risk in banks' climate-related exposure allocation. In this respect, we find that on average transition risk exposures account for 58.2% of banks' climate relevant exposures, whereas green exposures account for 9% of total CPRS allocation. Notably we find that the TEC share has progressively reduced since 2015, passing from 57.2% to 55.4% in 2024, whereas the degree of portfolio greenness has improved from 9% to 11.3%. This evidence potentially highlights how banks may have started to acknowledge climate transition risks as part of their portfolio allocation, and to adjust their portfolio composition over time to reflect this risk-return trade-off from climate externalities (positive and negative). However, at this point this stylized fact can represent only some preliminary evidence of UK banks' climate impact awareness and banks' re-pricing of climate risk via portfolio re-balancing portfolio. In this respect, the objective of this paper is precisely to shed light upon the role of climate policies and climate shocks in driving this variation across time and countries. In the next sections we are going to dig deeper into the cross-country differences and sectoral contribution.

[18]These estimates differ in terms of magnitude from since they divide the CPRS, TAC and TEC exposures by the overall exposure amount to the broader non-financial corporate sector. We don't use this broad denominator since we prefer to consider only those sectors that affect TEC and TAC shares (that is with positive coefficients). By using their approach, we would get an average CPRS, TEC and TAC share respectively of $30.8\%, 18\%$ and $2.8\%$. These numbers are aligned with EA-based investors' financial portfolios allocation $(22.8\%, 11.7\%$ and $2.8\%)$.

Table 2: UK banks' CPRS, TEC and TAC exposures by Top-10 Country as of Q1 2024

| COUNTRY | | TOTAL | CPRS | TEC | TAC | CPRS ratio | TEC ratio | TAC ratio |
|---|---|---|---|---|---|---|---|---|
| | | (£ Billion) | | | | (% of total exposures) | | |
| US | United States | 89.6 | 64.8 | 22.5 | 2.4 | 72% | 25% | 2.7% |
| UK | United Kingdom | 82.3 | 53.9 | 36.1 | 6.3 | 65% | 44% | 7.6% |
| KR | Rep. of Korea | 23.7 | 23.7 | 12.7 | 0.3 | 100% | 54% | 1.3% |
| IN | India | 12.1 | 12.1 | 8.6 | 3.5 | 100% | 71% | 29% |
| CN | China | 12.1 | 10.4 | 5.6 | 2.3 | 86% | 46% | 19% |
| AE | United Arab Emirates | 23.5 | 10.1 | 9.0 | 0.4 | 43% | 38% | 1.8% |
| ES | Spain | 10.8 | 9.8 | 3.0 | 6.8 | 91% | 28% | 63% |
| JP | japan | 14.2 | 9.8 | 7.7 | 0.2 | 69% | 54% | 1.7% |
| DE | Germany | 11.5 | 9.7 | 7.4 | 1.8 | 84% | 64% | 16% |
| FR | France | 9.6 | 7.8 | 7.5 | 0.0 | 81% | 78% | 0.0% |
| TOP-10 | | 289 | 212 | 120 | 24 | 73% | 42% | 8% |
| Total | | 329 | 228 | 127 | 26 | 69.5% | 38.5% | 7.9% |

Note: The table does not report countries where the share of TEC, TAC or CPRS exposures is equal to 0. However, the total amount includes exposures to all countries.

### 2.1.3 Geographical distribution of banks' climate-related exposures

Banks' portfolio allocation to climate-related exposures do vary over time as we have shown, and may also vary across countries depending on climate-related country specific shocks, among other factors. In this respect, Table 2 reports the distribution of banks' climate exposures vis-à-vis the top-10 country destinations where NFCs of our selected sample are located. We find that the top-10 country destinations as of 2024q1 account for roughly 88% of total portfolio allocation, and 93% of climate related exposures thereby highlighting a strong degree of portfolio concentration. For instance, exposures to US and UK jurisdictions represent more than half of total portfolio allocation. Nonetheless, we find strong cross-country heterogeneity in climate-related estimates. For instance, the green share is at the highest in Spain (63%), followed by India (29%), China (19%) and Germany (16%). Contrary, no green exposures are present vis-a-vis France, and very little in Korea (1.3%), United Arab Emirates (1.9%) and Japan (1.8%). From a transition risk perspective, we find that there is not complementary with the green exposure share. In fact, those countries with a high green share also exhibit relatively high shares to transition risk exposures, with Spain the only exception. Contrary, UK banks' large exposures to the US show a low green share (TAC) and at the same time a low transition risk share (TEC), further corroborating this finding. In the end, we want to highlight that there could be cases in which CPRS share is relatively low, but most of it consists of transition risk exposures as in the case of United Arab Emirates (AE). The research question we aim to investigate is whether banks have modified their exposure allocation through time and potentially due to climate policies implemented domestically or internationally.

In this respect, Figure B1 in the Appendix provides the time-series evolution of CPRS, TEC and TAC exposures for UK jurisdiction and the rest of the world (RoW) against their total large exposures vis-a-vis, respectively in panel (a), (b) and (c). We find that CPRS exposures to UK and ROW corporates seem to align over the entire period of the analysis, with only few differences in the first

Table 3: UK banks' CPRS, TEC and TAC exposures by NACE Economic Sector as of Q1 2024

| NACE | Sector | TOTAL | CPRS | TEC | TAC | CPRS ratio | TEC ratio | TAC ratio |
|---|---|---|---|---|---|---|---|---|
| | | (£ Billion) | | | | (% of total exposures) | | |
| C | Manufacturing | 162.2 | 131.1 | 68.0 | 0.7 | 81% | 42% | 0.4% |
| B | Mining and Quarrying | 29.7 | 29.7 | 28.1 | 0.0 | 100% | 95% | 0% |
| D | Electricity | 25.4 | 24.1 | 3.7 | 18.5 | 95% | 14.4% | 73% |
| L | Real Estate | 13.3 | 13.3 | 9.3 | 2.0 | 100% | 70% | 15% |
| F | Construction | 11.5 | 10.9 | 4.1 | 4.7 | 95% | 35.4% | 40.7% |
| H | Transport | 8.0 | 8.0 | 7.4 | 0.0 | 100% | 92.4% | 0.2% |
| G | Trade | 52.0 | 6.0 | 6.0 | 0.0 | 11.6% | 11.5% | 0% |
| A | Agriculture | 5.3 | 5.3 | 0.0 | 0.0 | 100% | 0% | 0% |
| … | … | … | … | … | … | … | … | … |
| | Total | 329 | 228 | 127 | 26 | 69.5% | 38.5% | 7.9% |

Note: The table does not report sectors where the share of TEC, TAC or CPRS exposures is equal to 0. However, the total amount and the share are calculated including exposures to all sectors.

part of the sample period. Contrary, the TEC exposure ratio is higher for the UK allocation than the RoW, widening from 2019 onwards, whereas the opposite is true for the UK TAC ratio, which shows a lower contribution to the total than the RoW, although recently it improved. This is consistent with the cross-country estimates reported in Table 1.

### 2.1.4 Sectoral distribution of banks' climate-related exposures

Banks' portfolio allocation to climate-related exposures also materially varies across sector of economic activity given their sub-industry-specific degree of transition risk (TEC) and return (TAC) and related exposure allocation. In absolute terms, considering the CPRS sectors reported in Table 3, the largest share of portfolio allocation goes to the manufacturing sector with 131.1 billion, or 57% of total CPRS exposures across all sectors which stand at 229 billion. Nonetheless, this sector is materially more exposed to transition risk than returns, TEC and TAC exposure ratio stands at 42% and 0.4%, respectively.

Next, we find that the sectors mining and quarrying (£29.7 billion) and electricity (24.1 billion), are in the second and third position, respectively accounting for 13% and 10.5% of total climate relevant exposures. If the former sector contributes mostly to increase the share of total transition risk exposures, reporting a TEC ratio of 95%, the latter instead is the greatest contributor to portfolio greenness with 18.5 billion or 71% of total TAC estimates. In the end, Real Estate, Construction and Transport sectors account in total for 14% of total CPRS contribution, respectively £13.3, £10.9 and £8 billion. Among these three sectors we find a heterogeneous climate-related impact, with Real Estate activities being mostly affected by transition risk (70%), as are Transport activities (92.4%), whereas Construction activities may benefit most from the transition (40.7%) rather facing transition risk (35.4%). In absolute terms, Construction and Real Estate activities are respectively, the second

(£4.7 billion) and third (£2 billion) most important contributors to total TAC estimates.

### 2.2 Macroeconomic and climate-related data

As previously discussed, we aim to study the drivers of cross-country and time series variation in TAC and TEC ratios as share of CPRS exposures and CPRS ratio as share of total climate-related exposures. The time series variation in banks' portfolio composition can be driven by multiple factors such as time, bank, sector and/or country-specific factors. Our contribution focuses on isolating the impact of climate-related country-specific shocks such as a change in climate transition policies, domestically and internationally, which we proxy by Germanwatch's CCPI index which captures a change in climate action (stringency) in a specific country of time (See Appendix: Data for more information). In this respect, the aim is to assess whether an increase in the index corresponding to a policy tightening may induce banks to reallocate their exposures to a less stringent country, or to move into a greener portfolio composition. The top panel in Figure 1 shows the CCPI in 2023 across the countries in coverage, whereas the bottom panel shows cumulated changes over the latest two years, showing that countries differ both in terms of level of stringency at a point in time, as well as in changes over a three year horizon, which we will exploit in our empirical analysis. The CCPI is our preferred measure of climate policy given both its acknowledgment by policymakers and academics, as well as better overlap with the coverage of our dataset.

In addition, we add as controls to our analysis change in country-specific proxies for physical risks, which could interact with how banks respond to changes in climate regulation or interact with country-specific changes in regulation over time. There are multiple indexes capturing different degrees of physical climate vulnerabilities. We use the Notre Dame's vulnerability index which measures a country's exposure, sensitivity and capacity to adapt to the negative effects of climate change.

We source data for real GDP growth and inflation at the country level from the IMF WEO database.

## 3 Empirical Analysis

In this section, we describe our empirical framework and discuss main results and robustness exercises. We start by examining a simple specification before setting up the main empirical framework, baseline results and extensions where we focus on bank heterogeneity, green vs brown policies as well as relative climate policies and international spillovers.

Figure 1: Climate Change Performance Index: Levels vs Recent Cumulated Changes

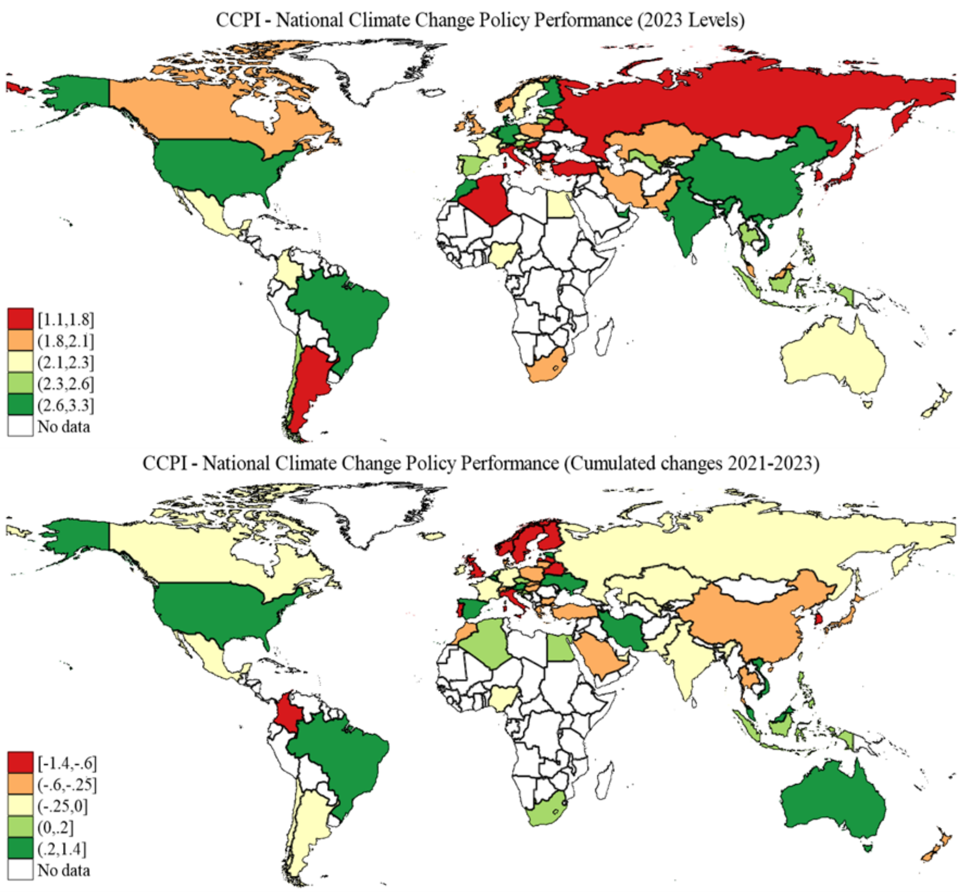


Table 4: Correlation between Exposures and CCPI

| | (1) TAC Transition Aligned Exp. Shares in CPRS | (2) TEC Transition Risk Exposed Exp. Shares in CPRS |
|---|---|---|
| CCPI_NAT | -0.0077 | -0.0484*** |
| | (0.0108) | (0.0184) |
| Constant | 0.1456*** | 0.5816*** |
| | (0.0274) | (0.0441) |
| Observations | 697 | 697 |
| R-squared | 0.0007 | 0.0075 |

Note: This table reports the estimation results for equation (1). The dependent variable is the share of green (TAC, col 1) or brown (TEC, col 2) exposures in total CPRS vis-à-vis country j. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are robust.

### 3.1 A first look at the data

As a sense-check and to motivate our analysis of banks' portfolio allocation, Table 4 and Figure 2 show the result from a pooled regression in equation (1) of the level of exposure shares on the level of climate stringency. Specifically:

$$y_{j,t} = \alpha + \beta_1 CCPI_{j,t} + \varepsilon_{j,t} \tag{1}$$

with $y_{j,t}$ being the share of green (TAC) or brown (TEC) exposures in total CPRS vis-à-vis country j and $CCPI_{j,t}$, the degree of climate policy stringency, or strictness of climate regulation in country j. We see that the share of TEC exposures is lower the stricter climate regulation. The TAC exposure is not significantly related. Figure 2 shows this visually and also highlights the variation of country-time exposures, which we will exploit in our analysis.

Table 5 shows the summary statistics from our main dataset at the bank-country-time level. There is significant variation in TAC and TEC exposures across bank- country-time observations, which goes beyond the averages documented in Table 1. This motivates further analysis exploiting the cross-sectional variation at the bank level to dig into the mechanisms of the results.

Figure 2: Correlation of Exposures with CCPI

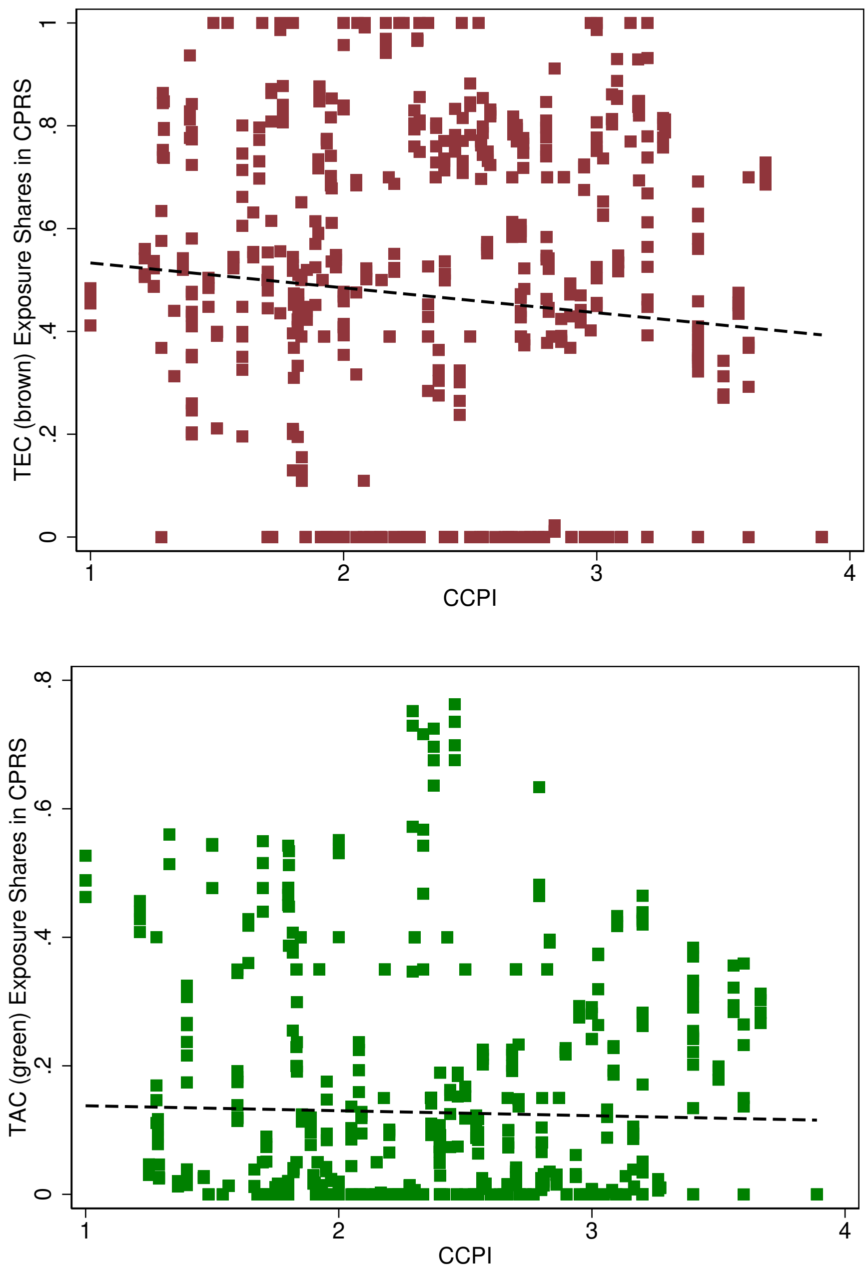


Table 5: Summary table of observations in panel variables

| Variables | Mean | Median | SD | Min | Max | Obs. |
|---|---|---|---|---|---|---|
| *Bank-country-quarter panel* | | | | | | |
| TAC exposure shares | 0.226 | 0.144 | 0.271 | 0 | 1 | 1,852 |
| TEC exposures shares | 0.721 | 0.716 | 0.263 | 0.072 | 1 | 2,472 |
| Change in TAC exposure shares | 0 | 0 | 0.036 | -0.113 | 0.124 | 1,662 |
| Change in TEC exposure shares | 0 | 0 | 0.052 | -0.164 | 0.165 | 2,215 |
| ΔCCPI_NAT | -0.007 | 0.05 | 0.384 | -1.343 | 1.35 | 7,727 |
| CCPI_NAT | 2.337 | 2.333 | 0.612 | 1 | 3.95 | 7,841 |
| Inflation | 0.646 | 0.5 | 0.872 | -1.637 | 3.772 | 8,403 |
| Real GDP Growth | 0.68 | 0.533 | 2.819 | -11.398 | 13.691 | 8,403 |
| Climate Vulnerability | 0.338 | 0.328 | 0.051 | 0.251 | 0.509 | 7,926 |
| Climate Readiness | 0.61 | 0.654 | 0.126 | 0.211 | 0.812 | 7,926 |
| *Overall bank portfolio incl. UK (bank-quarter)* | | | | | | |
| TAC exposure shares | 0.1 | 0.09 | 0.08 | 0 | 0.593 | 715 |
| TEC exposures shares | 0.583 | 0.625 | 0.194 | 0 | 1 | 715 |

### 3.2 Model specification

In our main empirical framework, we employ exposures aggregated to the bank-country level and adopt a more dynamic perspective by examining the relationship between changes in the stringency of climate policy regulation and changes in banks' portfolio exposures.

Equation (2) shows our baseline model specification.

$$\Delta y_{b,j,t} = \alpha + \beta_1 \Delta CCPI_{j,t} + \beta_2 \Delta CCPI_{j,t-4} + \gamma X_{j,t-1} + f_{b,t} + f_j + \varepsilon_{b,j,t} \tag{2}$$

with $\delta y_{b,j,t}$ the change in the share of TAC or TEC large exposures (relative to CPRS) from bank b to country j at quarter t.[19] $X_{j,t-1}$ are time-varying macro controls for the destination country that should capture factors driving the supply of and demand for loans to the destination country, including factors that affect capital flows but maybe be also related to changes in climate policy stringency. We include (lagged) GDP growth and inflation and the lagged ND indicators for country vulnerability and readiness, reflecting physical risks. $f_{b,t}$ and $f_j$ denote bank-date and country fixed effects, respectively. We run a set of regressions building up to this most restrictive specification. To

[19]We also run an annual specification with annual changes in exposures regressed on annual CCPI changes. Results are robust and available on request.

start with, we aggregate exposures across banks and run the specification in (3), a dynamic version of Table 4(with additional controls and fixed effects).

$$\Delta y_{j,t} = \alpha + \beta_1 \Delta CCPI_{j,t} + \beta_2 \Delta CCPI_{j,t-4} + \gamma X_{j,t-1} + f_t + f_j + \varepsilon_{j,t} \tag{3}$$

with $y_{j,t}$ now the changes in TAC/TEC exposures at the country level. This specification is closest to Fourne & Li (2023) who analyse the relationship between cross-border capital flows (distinguishing by assets) and climate policy stringency, although they cannot distinguish by type of exposure (or exploit variation at the bank level).

### 3.3 Baseline Results

In Table 6, we build towards our preferred baseline specification (columns 9 and 10), which includes the full set of fixed effects as well as controls. Columns (1) and (2) are the results from specification (3). As in the case of the unconditional correlation, an increase in climate policy stringency leads to a decline in TEC exposures. The cumulative decline is significant over a two-year horizon. We also estimate an increase in TAC exposures, but this is not statistically significant. The inclusion of country and time effects control for unobserved heterogeneity in the destination country such as average riskiness, and time-varying aggregate factors that could affect banks' exposure on average, such as overall climate policy stringency or other global factors.

Columns (3) - (10) use the disaggregated panel at the bank-destination country level (equation 2). Columns (3)-(4) use country, bank and time fixed effects, whereas (5)-(6) include country and bank-time fixed effects. While the point estimates on the one year change in the CCPI fall somewhat, the estimate of the cumulative effects on TEC exposures remains largely unchanged. The effect on TAC across horizons remains insignificant. Columns (7) – (8) and (9)-(10) include macro controls at the country-time level to control for factors that might affect banks' exposure to these countries, as well as the ND-index capturing physical vulnerability and readiness. In principle, we may already control for factors that affect overall loan supply (either through changes in loan demand or willingness to lend); however, changes in macro-financial conditions may affect sectors differently and could be systematically correlated with sectors exposed to climate change, for instance due to a larger cyclicality. Political economy factors could also induce correlations between macro-financial conditions and climate action efforts domestically, even though we may expect them to be more slowly moving in general. The baseline results remain relatively unchanged also in these specifications.

The results are quantitatively relevant. An increase in climate policy stringency of 1 unit (the index runs from 1 to 4 with a standard deviation of 0.6) decreases brown portfolios by around 4 percentage points over a two-year period.[20] This does not preclude longer-term effects further out which are

[20]The coefficients of -0.0074 and -0.0035 in column 8 measure the average effect on quarterly changes in brown

harder to measure within our regression framework and generally difficult to identify.[21] We explore the robustness of our results

### 3.3.1 Robustness

We perform several robustness checks in the measurement of our dependent variable, banks' large exposures, as well as the sensitivity of the results to macroeconomic or policy-related outlier events.

In Table A1, we focus on robustness in the construction of our dependent variables. Recall that our baseline measure is the change in the share of country-specific TAC or TEC large exposures in country-specific CPRS large exposures. In Table A1 across columns, we change the specification to broaden the denominator. In columns (1) to (4), we scale by country-specific large exposures rather than CPRS large exposures to make sure that definitions around what constitutes climate policy relevant sectors does not impact the results. The large exposures underlying this exercise focus on a subset of non-financial corporate sectors for which there is any presence of CPRS exposures. In columns (5) to (8), we change the sectors that underly large exposures to a broader set of sectors (i.e. all non-financial corporates sectors) but retain the focus on country-specific exposures. In columns (9) to (12), we scale country-specific green or brown exposures by all the exposures a bank has vis-à-vis all countries in the world, which in fact gives quantitatively larger changes a greater weight and is more akin to changes in the global porfolio of a given bank. Finally, in columns (13) to (16), we scale by CET1 capital to apply a scalar which is independent of the large exposure database. In all those cases, the key results on a tightening of climate regulation reducing brown lending shares remain robust.

exposures in the given year. Multiplied by 4 yields the annual effect.

[21] These are likely to be present for instance if banks do not actively divest all medium-term projects.

Table 6: Results for baseline specification

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Country-Time Panel | | Bank-Country-Time Panel | | | | | | | |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT | 0.0054 | -0.0140** | 0.0025 | -0.0070*** | 0.0018 | -0.0068*** | 0.0022 | -0.0074*** | 0.0015 | -0.0074** |
| | (0.0045) | (0.0060) | (0.0034) | (0.0021) | (0.0037) | (0.0023) | (0.0032) | (0.0025) | (0.0036) | (0.0028) |
| ΔCCPI_NAT_t-4 | 0.0014 | -0.0021 | -0.0012 | -0.0030* | -0.0032 | -0.0022 | -0.0011 | -0.0035** | -0.0033 | -0.0026 |
| | (0.0021) | (0.0036) | (0.0016) | (0.0016) | (0.0020) | (0.0027) | (0.0018) | (0.0015) | (0.0021) | (0.0025) |
| *Sum (effect over 2 years)* | ***0.00684*** | ***-0.0161**** | **0.00136** | **-0.00997***** | **-0.00142** | **-0.00904***** | **0.00113** | **-0.0109***** | **-0.00181** | **-0.00994***** |
| p-value | **0.238** | **0.0409** | **0.674** | **0.000291** | **0.654** | **0.00388** | **0.723** | **0.000228** | **0.570** | **0.000176** |
| Inflation_t-1 | | | | | | | -0.0005 | 0.0038* | -0.0006 | 0.0041 |
| | | | | | | | (0.0020) | (0.0022) | (0.0022) | (0.0024) |
| Real GDP Growth_t-1 | | | | | | | 0.0007 | -0.0013*** | 0.0009 | -0.0015** |
| | | | | | | | (0.0005) | (0.0004) | (0.0007) | (0.0006) |
| Climate Vulnerability_t-4 | | | | | | | -0.7474* | 0.4886 | -0.7875 | 0.6099** |
| | | | | | | | (0.4061) | (0.2849) | (0.4917) | (0.2744) |
| Climate Readiness_t-4 | | | | | | | -0.0381 | 0.0464 | -0.0507 | 0.0487 |
| | | | | | | | (0.0460) | (0.0361) | (0.0552) | (0.0505) |
| Observations | 431 | 463 | 1,389 | 1,882 | 1,312 | 1,775 | 1,389 | 1,878 | 1,312 | 1,768 |
| R-squared | 0.1038 | 0.0764 | 0.0653 | 0.0395 | 0.2223 | 0.1626 | 0.0720 | 0.0460 | 0.2294 | 0.1699 |
| FE | country, date | country, date | bank, country, date | bank, country, date | country bank*date | country bank*date | bank, country, date | bank, country, date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (3) (columns 1-2) and equation (2) (columns 3 to 10). The dependent variable is the change in the share of TAC or TEC (as indicated) large exposures relative to CPRS exposures from bank b to country j at quarter t. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

In Table A2, we add additional robustness checks regarding the extensive margin, accounting for potential outliers in changes of CCPI over time, as well as making sure that the Covid-19 episode does not unduly effect the results. Specifically, there are two ways we could code our baseline dependent variable when TEC or TAC exposures drop below the relevant reporting threshold. Our base case treats those instances as missing information as we cannot be sure if exposures drop to zero or drop just slightly below the threshold and we thus focus more on the intensive margin. In columns (1) and (2) of Table A2, we instead set those observations to 0 to check whether the inclusion of larger moves in exposure share along the extensive margin changes the results. This is not the case with point estimates remaining of similar size. In columns (3) and (4), we winsorise CCPI policy changes at the 2.5% level to check whether particularly large changes in climate policy stringency influence the results. In columns (5) and (6), we drop data for 2020 to make sure that changes around the Covid period unrelated to climate regulation don't impact the results. In both cases, the baseline results of declining brown shares following a tightening in climate stringency remain robust.

In Table A3, we return to the dependent variable. In our baseline, we employ gross exposures. However, banks can reduce their gross exposures by obtaining collateral or insurance or other mechanisms to reduce their actual exposure to a borrower. Our datasets include such 'net' exposures. Comparing the results in table A3 to the baseline results in table 6, we can see that the baseline results are similar in terms of significance and point estimates.

Lastly, in columns (5) - (12), we estimate our baseline specification separately for increases ("Tightening") and decreases ("Loosening") in the CCPI to test for asymmetries in the response of exposures. The results of the separate regressions suggest that while the cumulative impact coefficient is very similar, the impact from tightenings may take longer to take effect than those from loosenings (column (6)). We also note that in the specification with most granular fixed effects, the impact of loosening is estimated with larger precision. However, we cannot reject the hypothesis that the coefficients are the same in both cases.[22]

### 3.4 Bank heterogeneity

We now exploit cross-sectional heterogeneity in banks' exposure to transition risk by interacting lagged TEC shares $shY_{b,j,t-4}$, $Y \in (TAC, TEC)$, with the change in the climate policy index (4) to help understand potential mechanisms that drive these results. The shares are calculated as gross TEC exposures divided by gross CPRS exposures and lagged by one year and are averaged over the preceding 4 quarters.

[22]This result can also be obtained directly from running a regression with interaction terms.

$$\Delta y_{b,j,t} = \alpha + \beta_1 \Delta CCPI_{j,t} + \beta_2 \Delta CCPI_{j,t-4} + \delta_1 \mathbf{shY}_{b,t-4} \cdot \Delta CCPI_{j,t} \\ + \delta_2 \mathbf{shY}_{b,t-4} \cdot \Delta CCPI_{j,t-4} + \gamma X_{j,t-1} + f_{b,t} + f_j + \varepsilon_{b,j,t} \tag{4}$$

Table 7 shows the results. Columns (1) to (4) interact the CCPI with past brown (TEC) shares, while Columns (5) to (8) interact with past brown shares calculated on a net basis. Focusing first on changes in TAC exposures, Columns (1) and (5) show that banks with no TEC exposure increase their TAC exposure in response to an increase in climate policy stringency. This effect fades quickly for banks that have a more mixed portfolio. Turning to the effect on TEC exposures, banks with limited TEC exposure lower their TEC exposure further when climate policy stringency increases, but this effect is weakened, the higher the TEC share in their portfolios, and it even reverses for banks with a dominant TEC portfolio (columns 2,6). This counteracting effect is also robust to including country-date fixed effects in the regression (columns 4, 8).

The result could be due to a (sectoral) portfolio specialisation effect which is present for banks with larger initial TEC exposures In this sense, our findings are also consistent with Ho et al. (2024), who highlight the importance of borrower heterogeneity. Taken together, we find evidence that bank-level heterogeneity in exposures translates to differences in how banks respond to changes in climate policies.

### 3.5 Green vs brown exposures

So far we have abstracted from an important aspect of climate policies. Namely, to judge on the effect of climate policies on bank lending, it is important to know whether policies are subsidising green industries (such as subsidies for green energy) or taxing or otherwise disincentivising carbon-intensive industries (such as carbon taxes). The CCPI aggregates across categories, but changes might reflect distinct realisations of transition risk, eg. higher subsidies for renewable energy or higher carbon taxes.[23] In principle, both types of policies could affect transition risk-exposed and transition risk-aligned sectors. One hypothesis is that the direct impact could be asymmetric: All else equal, a higher cost of carbon-intensive production should reduce exposure more than greater incentives to reduce carbon intensity. We are able to shed light on this question based on a novel disaggregation of the CCPI data by Germanwatch: a CCPI index (”CCPI green”) specific to the strength of policies incentivising green industries and one index (”CCPI brown”) specific to the strength of policies disincentivising carbon-intensive industries. These data are available from 2017 to 2024 and for a subset of the countries included in the main CCPI dataset. This resulting sample accounts for roughly half of the number of observations compared to the baseline specification.

In Table 8, we introduce these indices step by step. The results in columns (1), (2) and (5) suggest

[23] Fourne & Li (2023) and Benincasa & Ongena (2024) also use the aggregate index, while others such as Kaldorf & Shi (2024) focus on carbon taxes.

Table 7: Bank heterogeneity

| Changes: | (1) TAC Transition Aligned Exp. Shares | (2) TEC Transition Risk Exposed Exp. Shares | (3) TAC Transition Aligned Exp. Shares | (4) TEC Transition Risk Exposed Exp. Shares | | (5) TAC Transition Aligned Exp. Shares | (6) TEC Transition Risk Exposed Exp. Shares | (7) TAC Transition Aligned Exp. Shares | (8) TEC Transition Risk Exposed Exp. Shares |
|---|---|---|---|---|---|---|---|---|---|
| ΔCCPI_NAT | 0.0252 | -0.0861*** | | | | 0.0246 | -0.0749*** | | |
| | (0.0198) | (0.0213) | | | | (0.0173) | (0.0173) | | |
| ΔCCPI_NAT_t-4 | 0.0246 | -0.0026 | | | | 0.0211 | -0.0065 | | |
| | (0.0155) | (0.0155) | | | | (0.0164) | (0.0152) | | |
| *Sum* | **0.0498*** | **-0.0887**** | | | | **0.0457**** | **-0.0814***** | | |
| p-value | **0.0722** | **0.0263** | | | | **0.0441** | **0.00516** | | |
| ΔCCPI_NAT * Brown Share | -0.0338 | 0.1269*** | -0.0233 | 0.1445** | * Brown Share | -0.0340 | 0.1107*** | -0.0004 | 0.1488*** |
| | (0.0323) | (0.0355) | (0.0518) | (0.0510) | (Net basis) | (0.0306) | (0.0302) | (0.0517) | (0.0421) |
| ΔCCPI_NAT_t-4 * Brown Share | -0.0482* | -0.0013 | -0.0475 | 0.0152 | * Brown Share | -0.0438 | 0.0053 | -0.0128 | 0.0405 |
| | (0.0273) | (0.0243) | (0.0338) | (0.0318) | (Net basis) | (0.0296) | (0.0240) | (0.0314) | (0.0240) |
| *Sum* | **-0.0820*** | **0.126**** | **-0.0707** | **0.160**** | | **-0.0778**** | **0.116**** | **-0.0132** | **0.189***** |
| *p-value* | **0.0604** | **0.0116** | **0.226** | **0.0383** | | **0.0353** | **0.0162** | **0.782** | **0.00294** |
| Controls | YES | YES | N/A | N/A | | YES | YES | N/A | N/A |
| Observations | 1,044 | 1,384 | 944 | 1,333 | | 1,044 | 1,384 | 944 | 1,333 |
| R-squared | 0.2337 | 0.1785 | 0.5540 | 0.4732 | | 0.2329 | 0.1765 | 0.5528 | 0.4729 |
| FE | country bank*date | country bank*date | country*date, bank*date | country*date, bank*date | | country bank*date | country bank*date | country*date, bank*date | country*date, bank*date |

Note: This table reports the estimation results for equation (2) adjusted to include interaction terms of climate policy with the share of TEC (brown) lending in CPRS exposures. The dependent variable is the change in the share of TAC or TEC (as indicated) large exposures relative to CPRS exposures from bank b to country j at quarter t. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

Table 8: Results for different types of climate policies

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_Green | -0.0067 | -0.0030 | | | -0.0085 | 0.0077 |
| | (0.0067) | (0.0066) | | | (0.0063) | (0.0091) |
| ΔCCPI_Green_t-4 | -0.0018 | -0.0080 | | | -0.0008 | -0.0043 |
| | (0.0064) | (0.0058) | | | (0.0075) | (0.0050) |
| *Sum (effect over 2 years)* | **-0.00850** | **-0.0110** | | | **-0.00926** | **0.00336** |
| p-value | **0.492** | **0.378** | | | **0.293** | **0.790** |
| ΔCCPI_Brown | | | 0.0010 | -0.0043 | 0.0038 | -0.0092 |
| | | | (0.0034) | (0.0031) | (0.0033) | (0.0060) |
| ΔCCPI_Brown_t-4 | | | 0.0012 | -0.0093*** | 0.0034 | -0.0117** |
| | | | (0.0053) | (0.0024) | (0.0049) | (0.0044) |
| *Sum (effect over 2 years)* | | | **0.00219** | **-0.0136**** | **0.00722** | **-0.0209*** |
| p-value | | | **0.796** | **0.0267** | **0.449** | **0.0627** |
| Inflation_t-1 | 0.0029* | -0.0004 | 0.0029 | -0.0008 | 0.0030* | -0.0011 |
| | (0.0016) | (0.0015) | (0.0016) | (0.0013) | (0.0016) | (0.0013) |
| Real GDP Growth_t-1 | 0.0007 | -0.0021*** | 0.0007 | -0.0021*** | 0.0007 | -0.0021*** |
| | (0.0007) | (0.0005) | (0.0007) | (0.0005) | (0.0007) | (0.0005) |
| Climate Vulnerability_t-4 | -0.7117* | 0.4630 | -0.9041* | 0.5283 | -0.7875** | 0.2779 |
| | (0.3891) | (0.8515) | (0.4376) | (0.7961) | (0.3154) | (0.8489) |
| Climate Readiness_t-4 | -0.1503* | 0.0615 | -0.1754* | 0.0718 | -0.1917*** | 0.0831 |
| | (0.0789) | (0.1967) | (0.0883) | (0.2079) | (0.0623) | (0.1791) |
| Observations | 616 | 770 | 615 | 766 | 615 | 766 |
| R-squared | 0.2582 | 0.2131 | 0.2576 | 0.2292 | 0.2597 | 0.2312 |
| FE | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (2) but with splitting CCPI into policies incentivising green vs disincentivising brown industries. The dependent variable is the change in the share of TAC or TEC (as indicated) large exposures relative to CPRS exposures from bank b to country j at quarter t. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

that changes in policies incentivising green industries did not have significant effects on the cross-border large exposures of UK-based banks. However, columns (4) to (6) suggest that policies taxing or otherwise disincentivising carbon-intensive industries have a significant and negative effect on UK banks' large cross-border transition risk exposed (TEC) exposures. The results are consistent with the hypothesis that a higher cost for carbon-intensive production should have a larger impact on these sectors after a realisation of transition risk (at least *directly*). However, we do not find a complementary result for 'green' policies for TAC or TEC sectors.

There are several, potentially offsetting, mechanisms which could explain this (absence of a significant) result[24]. Unfortunately, it is outside of the scope of our analysis to investigate whether policies subsidising green industries or technologies have more longer-run effects that appear via bank lending given the limited time series coverage of this disaggregate index. In sum, these results complement our evidence on the impact of climate policies on bank lending: they suggest that banks have reduced their TEC exposure in response to negative realisations of transition risk in the short term, while we do not find offsetting effects on TAC sectors or similar effects from greener policies.

### 3.6 Relative climate policies and international spillovers

We next turn to the international dimensions of domestic climate policies. In the previous sections, we showed evidence that banks' cross-border lending towards a given country responds negatively to more stringent *domestic* climate policies in that country, on average. Given banks' portfolios are international - all else equal - allocation decisions should depend on the *relative* stringency over time of climate policies abroad. This also suggests that cross-border lending by banks induces international spillovers, as for other domestic policies.[25] Recent studies suggesting such mechanisms include Benincasa & Ongena (2024) and Ho et al. (2024), and our results are consistent with their findings that domestic climate policies can indeed spill over abroad through the activities of global banks' portfolio decisions.

To understand the role of climate policy differentials across countries, we construct relative climate policy stringency at the bank-country level for each date. For each country $j$ in bank $b$'s portfolio at date $t$, we take the difference between the change in domestic CCPI ($j$) and foreign CCPI (non-$j$), weighted by foreign country exposure: $CCPI\_NAT\_Diff_{b,j,t} = \Delta CCPI_{b,j,t} - \sum_{k \neq j} sY_{b,k,t} \Delta CCPI_{b,k,t}$.[26] We then re-estimate equation (2) using the relative measure of changes in climate policy, $\Delta CCPI\_NAT\_Diff$ instead. Table 9 shows the results for a range of measures of foreign exposure to construct the weights (similar as to how we have constructed exposure). Columns (1) and (2) use total exposure, columns (3) and (4) use exposure to CPRS, while columns (5) and (6) and (7) and (8) use TEC and TAC exposure separately, respectively. The results confirm our findings from section 3.3 which abstracted from policy differentials: banks reduce their TEC exposure in countries that tighten their climate policies relative to others which they lend to. Notably, the estimated impact is almost unchanged from our baseline regressions and remains robust also across the choice of weights to construct the measure of foreign exposure.

Next, we investigate the role of outward spillovers by estimating how bank $b$'s exposure in country $j$

[24]Including the variation in green relative to brown policies over the horizon that we have data for, the impact on the attractiveness of lending for investment in green sectors vis-à-vis these sectors' financing needs, as well as the horizon with which effects from policies subsidising green sectors could materialise. At the same time, certain 'green' policies could increase investment incentives in TEC sectors, limiting banks' portfolio rebalancing towards TAC sectors and rationalising insignificant results.

[25]see eg. Bruno & Shin (2015), Correa et al. (2021) and Andreeva et al. (2023) for monetary policy

[26]Consistent with the previous regressions, the overall index excludes the UK.

at date $t$ changes in response to an increase in foreign, exposure-weighted, climate policy stringency. The measure of foreign climate policy stringency is constructed as above: $CCPI\_NAT\_ROW_{b,j,t} = \sum_{k \neq j} sY_{b,k,t} \Delta CCPI_{b,k,t}$. Table 10 shows the results for all choices of exposure weights for UK banks' foreign exposures in columns (1) to (6), again re-estimating equation (2). We include both bank-date as well as country-date fixed effects which allow us to absorb country-specific time-varying factors, including domestic regulation.

We find evidence of spillover effects: our estimates suggest that banks increase transition risk-exposed lending to country $j$ if climate stringency gets tighter in other countries banks have exposures to. Across specifications, the effect is significant after two years only when we look at banks' foreign CPRS and TEC-weighted exposures (columns (4) and (6), respectively), the latter estimated with (slightly) more precision. This result is consistent with banks actively managing their portfolios in response to transition risk over time, 'trading off' specific types of exposures across countries: while we see some adjustment in the short run when weighting by all exposures (column (2)), the effect is only persistent when we weight climate regulation by exposures that are affected by the change in climate policy. Interestingly, when weighting foreign climate policies by TAC exposures, we also find negative spillovers effect on TAC exposure, but this is offset over the medium term.

We also include results that focus on spillovers to the UK only in columns (7) - (12) of table 10.[27] The results are qualitatively similar to the cross-country case. However, we find a significant effect only when exposure-based changes in climate policy abroad are weighted by banks' brown (TEC) exposures, suggesting portfolio spillover effects based on the narrowest measure in our specification.

Taken together, we find evidence supporting the view that climate policy plays a role in banks' international portfolio decision of large exposures, with persistent negative effects on TEC exposures in countries that tighten their climate policies negative to others, but not necessarily a decline in overall exposure to these sectors, as they may be re-allocated to countries with less stringent policies, leading to (positive) international spillovers, climate policies.

[27]The UK is not included in our baseline panel on cross-border lending to exclude effects stemming from differences in the way that banks allocate lending to "home" versus cross-border counterparties. A study focused solely on the UK would need to overcome the identification challenge associated with no country variation in climate policy. However, we are here able to examine the spillover effects of exposure weighted foreign regulations to UK large exposure exploiting the bank heterogeneity in our dataset.

Table 9: Climate policies relative to the rest of the world

| | (1) | (2) | (3) | (4) | (5) | (6) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|
| CCPI Abroad weighted by: | All Exp | | CCPRS Exp | | TEC Exp | | TAC Exp | |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT_Diff | 0.0012 | -0.0060** | 0.0014 | -0.0060** | 0.0014 | -0.0059*** | 0.0024 | -0.0067** |
| | (0.0029) | (0.0022) | (0.0029) | (0.0021) | (0.0029) | (0.0019) | (0.0029) | (0.0026) |
| ΔCCPI_NAT_Diff_t-4 | -0.0028 | -0.0020 | -0.0030 | -0.0020 | -0.0030 | -0.0020 | -0.0032 | -0.0008 |
| | (0.0018) | (0.0019) | (0.0018) | (0.0019) | (0.0018) | (0.0019) | (0.0021) | (0.0023) |
| *Sum* | **-0.00156** | **-0.00800*** ** | **-0.00153** | **-0.00798*** ** | **-0.00169** | **-0.00794*** ** | **-0.000829** | **-0.00752*** ** |
| p-value | **0.499** | **2.42e-05** | **0.504** | **1.12e-05** | **0.460** | **6.96e-06** | **0.736** | **0.00197** |
| Inflation_t-1 | -0.0006 | 0.0040 | -0.0006 | 0.0040 | -0.0006 | 0.0040 | -0.0007 | 0.0041 |
| | (0.0022) | (0.0024) | (0.0022) | (0.0024) | (0.0022) | (0.0024) | (0.0022) | (0.0024) |
| Real GDP Growth_t-1 | 0.0009 | -0.0015** | 0.0009 | -0.0015** | 0.0009 | -0.0015** | 0.0009 | -0.0015** |
| | (0.0007) | (0.0006) | (0.0007) | (0.0006) | (0.0007) | (0.0006) | (0.0007) | (0.0006) |
| Climate Vulnerability_t-4 | -0.7838 | 0.6200** | -0.7855 | 0.6175** | -0.7872 | 0.6206** | -0.7784 | 0.6107** |
| | (0.4921) | (0.2697) | (0.4934) | (0.2704) | (0.4930) | (0.2705) | (0.5021) | (0.2833) |
| Climate Readiness_t-4 | -0.0505 | 0.0469 | -0.0501 | 0.0466 | -0.0503 | 0.0467 | -0.0474 | 0.0461 |
| | (0.0558) | (0.0503) | (0.0556) | (0.0502) | (0.0554) | (0.0503) | (0.0552) | (0.0518) |
| Observations | 1,312 | 1,768 | 1,312 | 1,768 | 1,312 | 1,768 | 1,312 | 1,768 |
| R-squared | 0.229 | 0.170 | 0.230 | 0.170 | 0.230 | 0.170 | 0.2301 | 0.1701 |
| FE | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (2) but with climate policy expressed as the change in domestic regulation minus the bank-specific exposure-weighted change in regulation in the rest of the world and with country-time fixed effects instead of country fixed effects. The dependent variable is the change in the share of TAC or TEC (as indicated) large exposures relative to CPRS exposures from bank b to country j at quarter t.The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

Table 10: Spillovers of climate policies

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Non-UK exposures (baseline panel) | | | | | | UK Exposures only | | | | | |
| CCPI Abroad weighted by: | All Exp | | CPRS Exp | | TAC Exp | TEC Exp | All Exp | | CPRS Exp | | TAC Exp | TEC Exp |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT_ROW | -0.0064 | 0.0537*** | -0.0195 | 0.0438*** | -0.0257** | 0.0407** | -0.0011 | 0.0315 | -0.0049 | 0.0271 | 0.0024 | 0.0375** |
| | (0.0283) | (0.0144) | (0.0330) | (0.0134) | (0.0108) | (0.0167) | (0.0082) | (0.0191) | (0.0076) | (0.0198) | (0.0063) | (0.0176) |
| ΔCCPI_NAT_ROW_t-4 | 0.0245 | -0.0092 | 0.0475* | 0.0030 | 0.0347*** | 0.0139 | -0.0077 | -0.0048 | -0.0119 | -0.0113 | -0.0092 | 0.0052 |
| | (0.0165) | (0.0197) | (0.0223) | (0.0153) | (0.0099) | (0.0140) | (0.0082) | (0.0189) | (0.0091) | (0.0192) | (0.0085) | (0.0182) |
| *Sum* | **0.0181** | **0.0445** | **0.0280** | **0.0468*** | **0.00909** | **0.0546**** | **-0.00879** | **0.0267** | **-0.0168** | **0.0158** | **-0.00685** | **0.0426*** |
| *p-value* | **0.512** | **0.162** | **0.206** | **0.0877** | **0.341** | **0.0453** | **0.436** | **0.319** | **0.144** | **0.571** | **0.465** | **0.0949** |
| Observations | 1,044 | 1,384 | 944 | 1,333 | 1,044 | 1,384 | 456 | 532 | 456 | 532 | 456 | 532 |
| R-squared | 0.2337 | 0.1785 | 0.5540 | 0.4732 | 0.2329 | 0.1765 | 0.1810 | 0.2082 | 0.1834 | 0.2073 | 0.1823 | 0.2103 |
| FE | country*date, bank*date | country*date, bank*date | country*date, bank*date | country*date, bank*date | country*date, bank*date | country*date, bank*date | bank, date | bank, date | bank, date | bank, date | bank, date | bank, date |

Note: This table reports the estimation results for equation (2) but with bank-specific exposure-weighted climate policy in the rest of the world (ROW) as the main independent variable. The dependent variable is the change in the share of TAC or TEC (as indicated) large exposures relative to CPRS exposures from bank b to country j at quarter t. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

# 4 Conclusion

This paper uses granular UK supervisory data on large international exposures based on Covi & Raja (2022) to analyse how banks adjust their portfolios in response to changes in transition risk abroad. We proxy transition risk by a country-level index tracking the climate action over time and a range of criteria (CCPI). We construct exposures as lending that is systematically related to transition risk (aligned, TAC ("green"), and exposed, TEC ("brown")), employing granular sectoral classifications. We distinguish between the responses of TAC and TEC exposures Our results point to a consistent and economically significant pattern: when a country tightens its climate policies, UK banks reduce their share of lending to transition-risk-exposed sectors in that country, with effects persisting at least over a two-year horizon. These portfolio shifts are not mirrored by commensurate increases in green lending, providing evidence that risk-mitigation motives dominate in the short run.

We further uncover heterogeneity in banks' responses, with low-exposure banks reducing their TEC exposures more aggressively, and in some cases increasing green exposures, while high-exposure banks may even protect existing portfolios—possibly reflecting portfolio specialisation or adjustment costs. Lastly, we provide evidence highlighting the international dimension: policy tightening in one jurisdiction can lead to an expansion of TEC lending elsewhere, consistent with spillover effects documented in recent cross-border finance literature. Importantly, policies that directly penalise carbon-intensive activities appear to have a stronger and more immediate impact on reducing TEC exposures than those that incentivise TAC sectors.

These findings contribute to the growing literature on the effect of transition risk through changes in climate policy on the banking sector. First, we provide evidence from supervisory data on banks' large international exposures from a major international banking centre. Second, we integrate a sector-specific taxonomy of transition alignment and risk exposure into an international analysis, offering a granular mapping between policy changes and lending patterns. Third, we uncover dynamic substitution patterns—both across sectors and across borders—that are difficult to detect without the combination of data coverage, granularity, and cross-country perspective employed here. Together, these contributions advance understanding of how climate policy stringency is transmitted through global banking networks and reinforce the importance of understanding cross-border linkages in the transmission and effect of transition risk. They also suggest several avenues for further research to uncover the mechanisms: First, to uncover the role of heterogeneities within TEC sectors for our results. Second, to probe further into the absence of significant impacts on transition-aligned lending. Third, to deepen our understanding of aggregate effect on banks' portfolio adjustment and the relative importance of cross-border spillovers.

Our results show that changes to climate policy are relevant to supervisors and potentially financial stability. The evidence so far suggests that as climate stringency increases, loans to firms more exposed to transition risk may become increasingly concentrated among fewer banks while other banks choose to reduce their lending to these sectors, thus potentially increasing the concentration of transition risk. International spillovers may mitigate or reinforce these dynamics over time, suggesting that integrating them into analytical frameworks for monitoring and scenario analysis can help strengthen resilience to transition-related external shocks in similar ways as for other external dynamics. At the same time, reduced lending by others may make it harder or more expensive for firms in TEC sectors to obtain lending required to successfully transition. This trade-off requires careful monitoring going forward.

## References


Alessi, L. & Battiston, S. (2022), 'Two sides of the same coin: Green taxonomy alignment versus transition risk in financial portfolios', *International review of Financial Analysis* .

Andreeva, D., Coman, A., Everett, M., Froemel, M., Ho, K., Meunier, B., Pedrono, J., Reinhardt, D., Lloyd, S., Wong, A., Wong, E. & Żochowski, D. (2023), 'Negative rates, monetary policy transmission and cross-border lending via international financial centers', *Bank of England Staff Working Paper* **1010**.

Battiston, S., Mandel, I., Monasterolo, I., Schuetze, F. & Visentin, G. (2017), 'A climate stress-test of the financial system', *Nature Climate Change* **7**, 283–288.

Benincasa, E. & Ongena, S. (2024), '"There is No Planet B", but for Banks "There are Countries B to Z": Domestic Climate Policy and Cross-Border Lending', *mimeo* .

Bolton, P., Despres, M., da Silve, L. A. P., Samana, F. & Svartzman, R. (2020), The green swan: central banking and financial stability in the age of climate change, Technical report, Bank for International Settlements.
**URL:** *https://www.bis.org/publ/othp31.pdf*

Bruno, V. & Shin, H. S. (2015), 'Capital flows and the risk-taking channel of monetary policy', *Journal of Monetary Economics* **71**, 119–132.

Correa, R., Paligorova, T., Sapriza, H. & Zlate, A. (2021), 'Cross-border bank flows and monetary policy', *The Review of Financial Studies* **35**(1), 438–481.
**URL:** *https://doi.org/10.1093/rfs/hhab019*

Covi, G. & Raja, C. (2022), 'Measuring capital at risk in the uk banking sector: A microstructural network approach', *Bank of England Working paper No.983* .

Degryse, H., Goncharenko, R., Theunisz, C. & Vadasz, T. (2023), 'When green meets green', *Journal of Corporate Finance* **78**.

Demirguc-Kunt, A., Pedraza, A. & Ruiz-Ortega, C. (2024), 'Global bank lending under climate policy', *IMF Economic Review* **72**, 858–901.

Ferentinos, K., Gibberd, A. & Guin, B. (2023), 'Climate policy and transition risk in the housing market', *Bank of England SWP Number 918* .

Fourne, M. & Li, X. (2023), 'Climate policy and international capital reallocation', *mimeo* .

Gambacorta, L., Polizzi, S., Reghezza, A. & Scanella, E. (2023), 'Do banks practice what they preach? brown lending and environmental disclosure in the euro area', *BIS Working Papers Number 1143* .

Gianetti, M., Jasova, M., Loumioti, M. & Mendicino, C. (2024), 'Glossy green" banks: The disconnect between environmental disclosures and lending activities', *ECB working papers* **No 2882**.

Hale, G., Meisenbacher, B. & Nechio, F. (2024), 'Industrial composition of syndicated loans and banks' climate commitments', *NBER Working Papers Number 32874* .

Ho, K., Lo, V. & Wong, A. (2024), 'International spillover of climate policy on bank lending: Evidence through the lens of foreign bank branches in hong kong', *mimeo* .

Ivanov, I., Kruttli, M. & WWatugala (2023), 'Banking on carbon: Corporate lending and cap and trade policy', *Review of Financial Studies* **37**, 1640–1684.

Kacperczyk, M. & Peydro, J.-L. (2024), 'Carbon emissions and the bank lending channel', *ECGI Finance Working Paper Number 991* .

Kaldorf, M. & Shi, M. (2024), 'Do firm credit constraints impair climate policy?', *Deutsche Bundesbank Discussion Paper* **29**.

Laeven, L. & Popov, A. (2022), 'Carbon taxes and the geography of fossil lending', *ECB Working Paper Number 2762* .

Mueller, I. & Sfrappini, E. (2022), 'Climate change-related regulatory risks and bank lending', *ECB Working Paper Number 2670* .

# Appendix A: Further Tables and Figures

Table A1: Robustness to definition of exposures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Changes in large exposures | | | | Changes in large exposures (broad) | | | | Changes in large exposures (bank-time) | | | | Changes in CET1 | | | |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT | 0.0027 | -0.0062** | 0.0018 | -0.0069*** | 0.0022 | -0.0061 | 0.0014 | -0.0075* | -0.0029 | -0.0685 | -0.0169 | -0.1323*** | -0.0030 | -0.0710 | -0.0070 | -0.0683 |
| | (0.0031) | (0.0026) | (0.0035) | (0.0022) | (0.0026) | (0.0036) | (0.0025) | (0.0042) | (0.0275) | (0.0728) | (0.0261) | (0.0304) | (0.0200) | (0.0434) | (0.0195) | (0.0660) |
| ΔCCPI_NAT_t-4 | -0.0008 | -0.0010 | -0.0026 | 0.0009 | 0.0016 | -0.0036 | 0.0003 | -0.0027 | 0.0194 | -0.1165 | 0.0269 | -0.0478 | 0.0217 | -0.1077* | 0.0168 | -0.1062 |
| | (0.0015) | (0.0019) | (0.0019) | (0.0025) | (0.0017) | (0.0023) | (0.0021) | (0.0029) | (0.0266) | (0.0825) | (0.0238) | (0.0666) | (0.0192) | (0.0590) | (0.0204) | (0.0665) |
| *Sum (effect over 2 years)* | **0.00192** | **-0.00728**** | **-0.000830** | **-0.00597**** | **0.00376** | **-0.00971**** | **0.00165** | **-0.0101**** | **0.0165** | **-0.185**** | **0.0100** | **-0.180**** | **0.0188** | **-0.179**** | **0.00984** | **-0.175*** |
| p-value | **0.517** | **0.0232** | **0.777** | **0.0244** | **0.342** | **0.0399** | **0.703** | **0.0435** | **0.457** | **0.0173** | **0.627** | **0.0219** | **0.418** | **0.0174** | **0.641** | **0.0822** |
| Inflation_t-1 | 0.0001 | 0.0052* | -0.0001 | 0.0054** | 0.0016 | 0.0064* | 0.0015 | 0.0041 | 0.0163 | 0.0010 | 0.0138 | -0.0299 | 0.0151* | -0.0239 | 0.0075 | -0.0129 |
| | (0.0021) | (0.0025) | (0.0022) | (0.0023) | (0.0011) | (0.0034) | (0.0011) | (0.0037) | (0.0119) | (0.0382) | (0.0130) | (0.0485) | (0.0079) | (0.0404) | (0.0087) | (0.0605) |
| Real GDP Growth_t-1 | 0.0008 | -0.0010 | 0.0010 | -0.0011 | 0.0003 | -0.0007 | 0.0005 | -0.0007 | -0.0015 | -0.0001 | -0.0041 | -0.0044 | -0.0011 | -0.0021 | -0.0046 | -0.0030 |
| | (0.0006) | (0.0006) | (0.0008) | (0.0008) | (0.0006) | (0.0005) | (0.0007) | (0.0005) | (0.0056) | (0.0144) | (0.0063) | (0.0056) | (0.0043) | (0.0068) | (0.0054) | (0.0047) |
| Climate Vulnerability_t-4 | -0.8098** | 0.3191 | -0.8472* | 0.5997* | -0.6284 | -0.3825 | -0.6454* | -0.0904 | -4.1883* | 5.4677 | -4.1991** | 3.6094 | -4.7685 | 7.7443 | -6.1604** | 7.9614 |
| | (0.3695) | (0.3715) | (0.4631) | (0.2933) | (0.3680) | (0.3849) | (0.3561) | (0.2835) | (2.1073) | (4.7154) | (1.8451) | (5.5977) | (3.4514) | (4.5388) | (2.7850) | (6.2237) |
| Climate Readiness_t-4 | -0.0405 | 0.0238 | -0.0479 | 0.0349 | -0.0068 | -0.0448 | -0.0148 | -0.0422 | -0.3529 | 0.5170 | -0.5572* | 0.6159 | -0.4093** | -0.0092 | -0.4316*** | 0.2118 |
| | (0.0495) | (0.0425) | (0.0598) | (0.0501) | (0.0286) | (0.0459) | (0.0400) | (0.0462) | (0.2340) | (0.7117) | (0.2924) | (0.6488) | (0.1444) | (0.3714) | (0.1358) | (0.3486) |
| Observations | 1,389 | 1,878 | 1,312 | 1,768 | 1,389 | 1,878 | 1,312 | 1,768 | 1,389 | 1,878 | 1,312 | 1,768 | 1,389 | 1,878 | 1,312 | 1,768 |
| R-squared | 0.0766 | 0.0408 | 0.2388 | 0.1814 | 0.0540 | 0.0497 | 0.2249 | 0.2029 | 0.0802 | 0.0496 | 0.2546 | 0.2791 | 0.0651 | 0.0741 | 0.2552 | 0.2867 |
| FE | country, date | country, date | country bank*date | country bank*date | country, date | country, date | country bank*date | country bank*date | country, date | country, date | country bank*date | country bank*date | country, date | country, date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (2) with adjustments to the exposures used to calculate the dependent variables measuring green or brown shares. In columns 1-4, changes in TEC (brown) or TAC (green) exposures are scaled by country-level large overall exposures rather than CPRS large exposures. In columns 5-8, TEC/TAC exposures are scaled again by large exposures but with those including a broader set of sectors (i.e. all non-financial corporates sectors). In columns 9-12, TEC/TAC exposures are scaled by the exposures a bank has vis-à-vis all countries in the world. In columns 13-16, TEC/TAC exposures are scaled by CET1 capital. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

Table A2: Robustness on specification choice

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Including "extensive" margin | | | | Winsorise CCPI changes | | | | Exclude 2020 | | | |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT | 0.0007 | -0.0070*** | -0.0001 | -0.0064** | 0.0022 | -0.0074*** | 0.0015 | -0.0074** | 0.0026 | -0.0086** | 0.0023 | -0.0085** |
| | (0.0015) | (0.0024) | (0.0016) | (0.0029) | (0.0032) | (0.0025) | (0.0036) | (0.0028) | (0.0032) | (0.0032) | (0.0036) | (0.0039) |
| ΔCCPI_NAT_t-4 | 0.0004 | -0.0025** | -0.0004 | -0.0034 | -0.0012 | -0.0035** | -0.0033 | -0.0026 | -0.0019 | -0.0036** | -0.0039* | -0.0026 |
| | (0.0007) | (0.0012) | (0.0010) | (0.0022) | (0.0018) | (0.0015) | (0.0021) | (0.0024) | (0.0017) | (0.0016) | (0.0022) | (0.0024) |
| *Sum (effect over 2 years)* | **0.00103** | **-0.00958*** ** | **-0.000463** | **-0.00986*** ** | **0.00102** | **-0.0109*** ** | **-0.00189** | **-0.0100*** ** | **0.000785** | **-0.0121*** ** | **-0.00156** | **-0.0112*** ** |
| p-value | **0.520** | **0.000753** | **0.810** | **0.00373** | **0.746** | **0.000206** | **0.554** | **0.000136** | **0.779** | **0.000717** | **0.626** | **0.00188** |
| Inflation_t-1 | -0.0006 | 0.0030 | -0.0008 | 0.0031 | -0.0005 | 0.0038* | -0.0006 | 0.0041 | -0.0010 | 0.0046 | -0.0013 | 0.0043 |
| | (0.0009) | (0.0018) | (0.0012) | (0.0020) | (0.0020) | (0.0022) | (0.0022) | (0.0024) | (0.0025) | (0.0027) | (0.0026) | (0.0032) |
| Real GDP Growth_t-1 | 0.0005*** | -0.0014*** | 0.0005*** | -0.0018*** | 0.0007 | -0.0013*** | 0.0009 | -0.0015** | 0.0003 | 0.0007 | 0.0006 | 0.0008 |
| | (0.0002) | (0.0005) | (0.0002) | (0.0004) | (0.0005) | (0.0004) | (0.0007) | (0.0006) | (0.0012) | (0.0005) | (0.0013) | (0.0005) |
| Climate Vulnerability_t-4 | -0.0793 | 0.2950 | -0.1024 | 0.4493** | -0.7479* | 0.4916 | -0.7876 | 0.6117** | -0.7866** | 0.3897* | -0.8797* | 0.4920** |
| | (0.1799) | (0.2136) | (0.1952) | (0.1933) | (0.4063) | (0.2852) | (0.4914) | (0.2744) | (0.3523) | (0.2094) | (0.4671) | (0.1908) |
| Climate Readiness_t-4 | -0.0170 | 0.0665* | -0.0223 | 0.0526 | -0.0381 | 0.0463 | -0.0509 | 0.0488 | -0.0342 | 0.0494 | -0.0529 | 0.0585 |
| | (0.0184) | (0.0350) | (0.0224) | (0.0402) | (0.0460) | (0.0360) | (0.0551) | (0.0503) | (0.0433) | (0.0438) | (0.0590) | (0.0559) |
| Observations | 2,561 | 2,561 | 2,454 | 2,454 | 1,389 | 1,878 | 1,312 | 1,768 | 1,206 | 1,641 | 1,134 | 1,537 |
| R-squared | 0.0400 | 0.0411 | 0.1409 | 0.1618 | 0.0720 | 0.0460 | 0.2294 | 0.1700 | 0.0750 | | 0.2299 | 0.1612 |
| FE | bank, country, date | bank, country, date | country bank*date | country bank*date | bank, country, date | bank, country, date | country bank*date | country bank*date | bank, country, date | bank, country, date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (2) with adjustments described in the robustness section and in the column headings. The data are quarterly from 2015Q1 to 2023Q4. Standard errors are clustered a the country-level.

Table A3: Robustness: further specifications

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Net Exposures | | | | Tightening | | | | Loosening | | | |
| Changes: | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares | TAC Transition Aligned Exp. Shares | TEC Transition Risk Exposed Exp. Shares |
| ΔCCPI_NAT | 0.0028 | -0.0079** | 0.0023 | -0.0081* | 0.0052 | -0.0077 | 0.0041 | -0.0077 | 0.0023 | -0.0143*** | 0.0008 | -0.0146*** |
| | (0.0042) | (0.0037) | (0.0049) | (0.0039) | (0.0070) | (0.0069) | (0.0072) | (0.0084) | (0.0048) | (0.0032) | (0.0057) | (0.0029) |
| ΔCCPI_NAT_t-4 | -0.0030 | -0.0014 | -0.0047 | -0.0009 | -0.0006 | -0.0083* | -0.0046 | -0.0068 | -0.0024 | -0.0024 | -0.0054 | -0.0008 |
| | (0.0028) | (0.0022) | (0.0031) | (0.0036) | (0.0028) | (0.0043) | (0.0033) | (0.0046) | (0.0039) | (0.0032) | (0.0047) | (0.0058) |
| *Sum* | **-0.000139** | **-0.00931*****| **-0.00241** | **-0.00907***** | **0.00456** | **-0.0159*** | **-0.000453** | **-0.0145** | **-7.87e-05** | **-0.0167***** | **-0.00456** | **-0.0154***** |
| p-value | **0.956** | **0.00651** | **0.450** | **0.00331** | **0.573** | **0.0604** | **0.956** | **0.107** | **0.987** | **2.13e-05** | **0.395** | **0.00329** |
| Inflation_t-1 | 0.0009 | 0.0018 | 0.0006 | 0.0022 | -0.0005 | 0.0037* | -0.0006 | 0.0040 | -0.0004 | 0.0037 | -0.0006 | 0.0040 |
| | (0.0012) | (0.0014) | (0.0016) | (0.0017) | (0.0020) | (0.0022) | (0.0021) | (0.0024) | (0.0020) | (0.0022) | (0.0022) | (0.0024) |
| Real GDP Growth_t-1 | 0.0007 | -0.0015*** | 0.0009 | -0.0019** | 0.0007 | -0.0013*** | 0.0009 | -0.0015** | 0.0007 | -0.0013*** | 0.0009 | -0.0015** |
| | (0.0005) | (0.0004) | (0.0006) | (0.0007) | (0.0005) | (0.0004) | (0.0007) | (0.0006) | (0.0005) | (0.0004) | (0.0007) | (0.0006) |
| Climate Vulnerability_t-4 | -0.6784** | 0.6486** | -0.7433* | 0.8485** | -0.7572* | 0.4984 | -0.7830 | 0.6236** | -0.7530* | 0.4538* | -0.8014 | 0.5694** |
| | (0.3176) | (0.2421) | (0.4188) | (0.3134) | (0.4352) | (0.3104) | (0.5092) | (0.2792) | (0.3847) | (0.2497) | (0.4869) | (0.2641) |
| Climate Readiness_t-4 | 0.0031 | -0.0021 | -0.0091 | -0.0002 | -0.0392 | 0.0503 | -0.0529 | 0.0545 | -0.0372 | 0.0438 | -0.0498 | 0.0444 |
| | (0.0391) | (0.0413) | (0.0503) | (0.0591) | (0.0460) | (0.0391) | (0.0550) | (0.0534) | (0.0463) | (0.0338) | (0.0562) | (0.0476) |
| Observations | 1,380 | 1,866 | 1,310 | 1,762 | 1,389 | 1,878 | 1,312 | 1,768 | 1,389 | 1,878 | 1,312 | 1,768 |
| R-squared | 0.0790 | 0.0444 | 0.2465 | 0.1786 | 0.0721 | 0.0447 | 0.2293 | 0.1687 | 0.0718 | 0.0467 | 0.2291 | 0.1708 |
| FE | bank, country, date | bank, country, date | country bank*date | country bank*date | bank, country, date | bank, country, date | country bank*date | country bank*date | bank, country, date | bank, country, date | country bank*date | country bank*date |

Note: This table reports the estimation results for equation (2). In columns (1-4), the dependent variable is the change in the share of *net* TAC or TEC (as indicated) large exposures relative to *net* CPRS exposures from bank b to country j at quarter t The data are quarterly from 2015Q1 to 2023Q4. In the remaining columns, the dependent variable are the baseline gross exposures. Standard errors are clustered a the country-level.

# Appendix B: Data

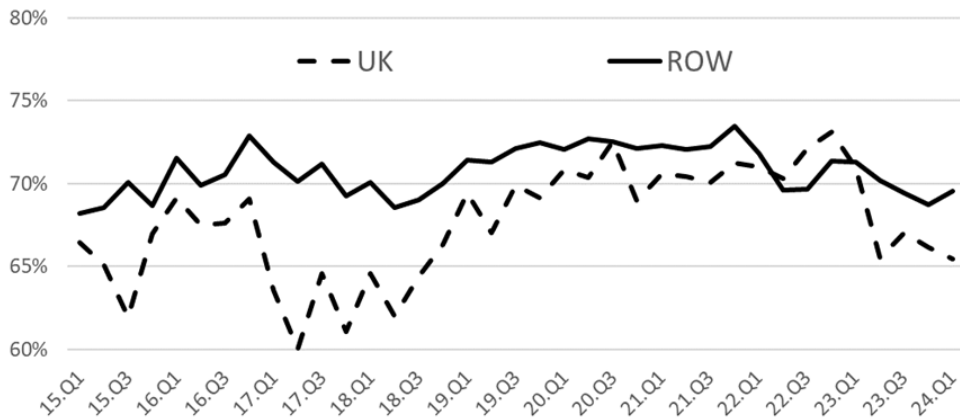
## Exposure data

Table B1: Data set construction summary

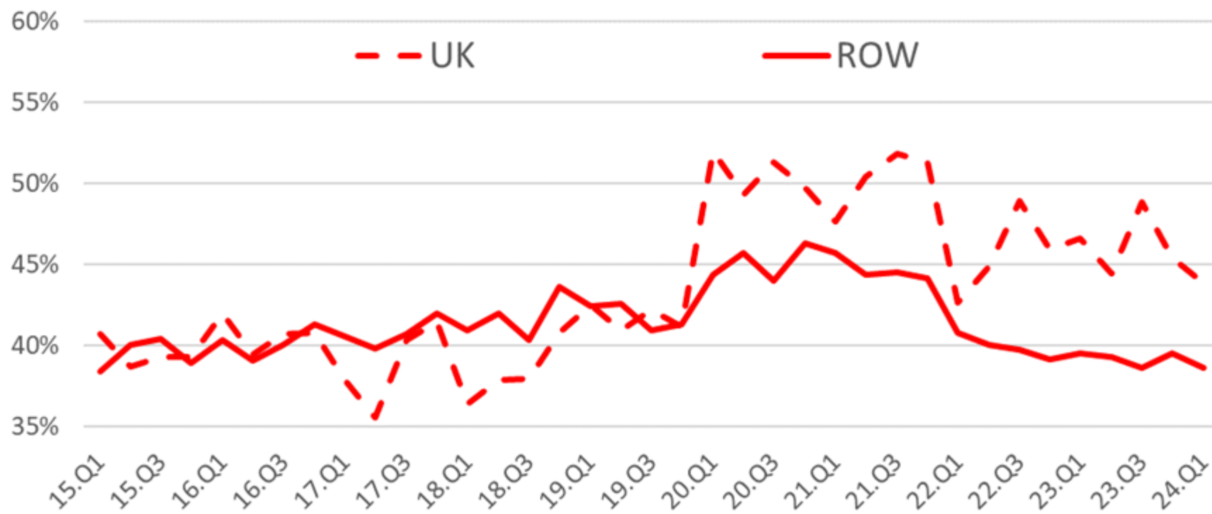
| Action | Observations | Banks | Firms | Countries |
|---|---|---|---|---|
| Full data set | 305000 | 598 | 7078 | >120 |
| Non-financial corporates | 86613 | | | |
| Remove NACE K, O or no NACE | 74309 | | | |
| Remove 1-digit NACE only | 33011 | 277 | | |
| Remove TAC and TEC both equal 0 | 24986 | 199 | | |
| Selection Criteria:<br>A bank reports at least 2 exposures per quarter<br>For at least 5 quarters | 24955<br>20930 | 176<br>33 | | |
| Aggregating by bank, country, sector quarter | 11500 | 31 | | 43 |
| Imputing missing observations | 22667 | 31 | | 43 |

Figure B1: UK Banks' Climate-Related Exposure Share in Total Exposures

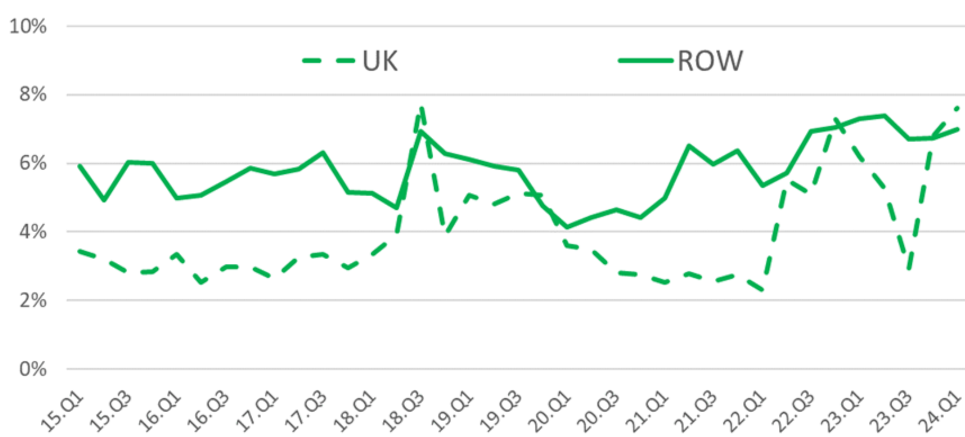
Panel (a) – Climate Policy Relevant Sector Exposures (CPRS)




Panel (b) – Transition Risk Exposures (TEC)




Panel (c) – Greenness (TAC)



## CCPI

The Climate Change Performance Index (CCPI), developed by Germanwatch, the NewClimate Institute, and the Climate Action Network, is an annual tool designed to evaluate and compare the climate action efforts of countries worldwide. First launched in 2005, the index aims to increase transparency in international climate policy by providing insights into how well countries are implementing climate protection measures. It assesses 59 countries, which together account for over 90% of global greenhouse gas emissions, on their progress toward meeting the goals of the Paris Agreement. The index is based on four key categories that assess a country's efforts in reducing (global) emissions: Greenhouse gas emissions (40%), evaluating a country's emissions trajectory in relation to alignment targets. Renewable energy (20%), assessing the share and growth of renewable energy sources in the national energy mix. Energy use (20%) reflecting efforts to improve energy efficiency. Lastly, climate policy (20%) evaluates the effectiveness of both domestic and international climate policies in supporting decarbonization efforts. The effectiveness of climate policies included in the Climate Change Performance Index (CCPI) is evaluated through both domestic ($CCPI_NAT$) and international ($CCPI_INT$) climate actions. It is assessed based on expert evaluations. Germanwatch consults around 400 climate and energy experts from NGOs, universities, and think tanks across the globe to rate national policies on their effectiveness in promoting emission reductions and supporting renewable energy.

These indicators together provide a comprehensive assessment of a country's contribution to global emission reductions. Each country is scored and ranked according to these indicators, with the top-performing countries receiving higher ranks. However, no country is ranked in the top three positions, as even leading nations have not yet achieved the level of action required to meet the Paris climate targets.