Appendix A. List of Central Banks in Speech Dataset

Our analysis covers 108 central banks each of which has at least one speech in our Central Bank Speech Dataset. We classify these central banks into advanced and emerging market economies as in the list below. This classification is based on IMF's classification for their World Economic Outlook (see https://www.imf.org/external/pubs/ft/weo/2021/01/weodata/groups.htm).

A.1 Advanced Economies:

European Central Bank, Bank of France, Bank of England, Deutsche Bundesbank, Netherlands Bank, Bank of Italy, Bank of Spain, Monetary Authority of Singapore, Central Bank of Ireland, Reserve Bank of New Zealand, Bank of Japan, Bank of Finland, Federal Reserve System, Central Bank of Norway, Bank of Greece, Bank of Canada, Hong Kong Monetary Authority, Swiss National Bank, Reserve Bank of Australia, Sveriges Riksbank, Danmarks Nationalbank, Banco de Portugal, Central Bank of Malta, Bank of Lithuania, Bank of Israel, Central Bank of Iceland, Bank of Korea, National Bank of the Republic of Austria, Czech National Bank, Central Bank of Luxembourg, National Bank of Belgium, Monetary Authority of Macao, Bank of Estonia Bank of Latvia, National Bank of Slovakia, Bank of Slovenia, Central Bank of Cyprus.

A.2 Emerging Market Economies:

Central Bank of Malaysia, Central Bank of the Philippines, Reserve Bank of India, Reserve Bank of Fiji, Bank of Mexico, The People's Bank of China, Bank Indonesia, Bank of Thailand, Bank of Mauritius, Central Bank of Trinidad and Tobago, National Bank of Poland, Central Bank of The Bahamas, Bank of Albania, Central Bank of Kenya, National Bank of Serbia, Central Bank of Barbados, Central Bank of Nigeria, Central Bank of Kuwait, South African Reserve Bank, Bank of Zambia, Bank of Uganda, State Bank of Pakistan, Central Bank of Chile, Central Bank of the Republic of Turkey, National Bank of the Republic of North Macedonia, Central Bank of Sri Lanka, National Bank of Romania, Bank of Papua New Guinea, Bank of Ghana, Central Bank of Bahrain, Bank of Botswana, Bulgarian National Bank, Central Bank of the Russian Federation, Bank of Namibia, Central Bank of Curaçao and Sint Maarten, Central Bank of Argentina, Saudi Central Bank, Reserve Bank of Malawi, Bank of Jamaica, Central Bank of Solomon Islands, National Bank of Ukraine, Eastern Caribbean Central Bank, Central Bank of the Republic of Kosovo, Central Bank of Bosnia and Herzegovina, Central Bank of Nepal, Central Bank of Seychelles, Bank of Sierra Leone, Central Bank of Brazil, Magyar Nemzeti Bank, Central Bank of the United Arab Emirates, Croatian National Bank, Bank of Algeria, Central Bank of Samoa, Bank Al-Maghrib (Central Bank of Morocco), Bank of Mozambique, Maldives Monetary Authority, Cayman Islands Monetary Authority, Central Bank of Colombia, Bank of Guyana, Reserve Bank of Vanuatu, Bank of Guatemala, Bank of Tanzania, Central Bank of Armenia, Central Bank of Aruba, Central Bank of Belize, Central Bank of Bolivia, Central Bank of Ecuador, Central Bank of Jordan, Central Bank of The Gambia, Central Bank of Uruguay, National Bank of Cambodia.

Appendix B. Text Analysis Tools

This methodological appendix describe text analysis techniques used in our paper.

B.1 Text pre-processing

In our text pre-processing step, we follow standard practices such as methodologies described in Bholat, et al. (2015), Benoit, et al. (2018), and Grimmer, et al. (2022).[1] The raw speech text contains many symbols for punctuation and common words such as "the" and "and" which do not add analytical value. As such, it is common to pre-process the raw text to reduce it down to its most valuable content. Text pre-precessing is regarded as an important step in text analysis to make text data handy and informative.

First, we strip out symbols and numbers. Second, we remove a subset of words that are very common. Very common words, so-called "stop words," include articles ("the," "a"), conjunctions ("and," "or"), forms of the verb "to be," and so on. We use the stop-word lists based on the SMART (System for the Mechanical Analysis and Retrieval of Text) Information Retrieval System developed at Cornell University in the 1960s.

Next, we recast words into their common linguistic root using a Part-of-Speech (PoS) tagger of the spaCy package for Python (Honnibal, et al., 2020). It can identify the grammatical class (part-of-speech) to which each word belongs—nouns, pronouns, verbs, etc.—and convert them into their base form by a lemmatization algorithm that uses some rules and a dictionary of irregular patterns. For example. the word "banks" will be converted to "bank," the word "saw" will be converted to "see," and the word "meeting" is converted to "meet" or "meeting" depending on its use in a sentence. Lemmatization reduces the number of unique types of words that carry the same information and makes a large corpus more manageable.[2] Moreover, the PoS tagger can identify noun phrases by dependency parsing. It is extremely useful in our analysis to treat noun phrases such as "climate change" as a combined word rather than two separate words "climate" and "change". The noun phrase "financial stability" has a specific meaning for central banks, and we prefer to use it rather than two common words "financial" and "stability."[3]

Finally, we remove a subset of words that are very rare. Our speech corpus includes $2,278,584$ sentences and $1,110,409$ unique word types after pre-processing as described above. We remove less frequent words from the corpus depending on the characteristics of the analysis, especially for those that require large computational resources and/or where low frequent words do not play an important role (but rather give noise) in results. Specifically, truncating words that appear less than 5 times for word embedding or 100 times for score calculation reduces the types of words to $127,926$ or $11,310$, respectively.

[1] We use the R package quanteda v.3.1.0 (Benoit, et al., 2018) to process text data and calculate statistics across speeches and sentences.

[2] Word stemming, another popular technique that discards the end of a word using a simple rule, is regarded as an approximation of lemmatization.

[3] Another popular way to deal with noun phrases is to take all combinations of n-grams, which is a phrase of length n in a sentence. However, using higher order n-grams significantly increases the number of word types in the vocabulary, so it requires an additional treatment for removing less informative phrases.

B.2 Methodology for identifying climate-related speeches

As described in Section 3.2, our methodology to identify climate-related speeches consists of two steps: the first step is to calculate a *climate speech score* based on a seed word (*"climate change"*) used to detect a set of potential climate related-speeches (pre-refinement); the second step is to refine the set of climate-related speeches using our own dictionary developed by a semi-automated way.

B.2.1 Climate Speech Score

The basic idea of our automated scoring method is based on Laver, et al. (2003) and Watanabe (2018). In a political economy context, Laver, et al. (2003) construct word scores using pre-selected *reference texts* that are from opposite political positions and use the scores to scale ideological positions of target texts. Watanabe (2018) uses simple *seed words* to generate a large training dataset for scoring without additional human interventions. Watanabe and Zhou (2020) advocate that Watanabe's method is useful for topic classification in the sense that researchers can effectively classify texts into multiple categories consistent with their specific interests. We modify these methodologies to fit our task of single topic identification. Concretely, our methodology of calculating a *climate speech score* and using it to identify (pre-refinement) climate-related speeches is the following:

1. Using a single seed word (*"climate change"*), we divide all speeches into 2 sets: *speeches that include the seed word* (S_{seed}) and *speeches that do not include the seed word* ($\bar{S}_{seed}$).

2. We construct *climate word score* for each word i by calculating relative word frequency between S_{seed} and $\bar{S}_{seed}$ as follows:

   $$\text{Climate Word Score}_i = \log(wf_{i,S_{seed}}) - \log(wf_{i,\bar{S}_{seed}}) \ ,$$

   where $wf_{i,S}$ is a normalised word frequency of word i in a set of speeches S calculated as the number of times word i appeared in a set of speeches S, divided by the total number of words in those speeches.

3. Using the *climate word scores*, we calculate *climate speech score* for each speech j by taking weighted average of word scores using (normalized) word frequencies as weights,

   $$\text{Climate Speech Score}_j = \sum_i (\text{Climate Word Score}_i \times wf_{i,j}) \ .$$

4. We identify a set of (pre-refinement) climate-related speeches ($S_{climate\text{-}related\,(pre)}$) that have a climate speech score greater than 0 (i.e., $\text{Climate Speech Score}_l > 0$ for $\forall l \in S_{climate\text{-}related\,(pre)}$).

B.2.2 Keyword Dictionary for Refinement

As described in Section 3.2, we find that the pre-refinement set of climate-related speeches successfully includes most speeches that we want to identified as climate-related, but it also includes lots of non-relevant speeches as well. We manually examine non-relevant speeches that have high climate speech scores and select keywords to exclude these speeches. Therefore, our refinement step can be thought of as defining the boundary of climate-related speech identification. We take the following iterative process for defining a keyword dictionary and obtaining the final set of climate-related speeches with the goal of automating as much of the process as possible.

1. We define high score speeches for keyword exploration ($S_0 \subset S_{climate\text{-}related\,(pre)}$) using an arbitrary threshold for the climate speech score, set to two standard deviations over the mean for all speeches (0.48 for climate speech score).

2. We explore a set of keywords ($D_{ref} = \{k_1, k_2, \ldots, k_N\}$) from the high score speeches (S_0) by the following iterative process.

   (a) In Iteration n, we select the single most climate-relevant keyword k_n from a exploration set of speeches S_{n-1} based on word frequency (the number of speeches in S_{n-1} that include the keyword) and our judgement (where we know that keywords that have a higher climate word score are more likely climate-relevant).

   (b) As an exploration set for the next iteration (S_n), we collect speeches that do not include the selected keyword k_n from the previous exploration set S_{n-1}.

   (c) Continue to itterate until we can no longer find any climate-relevant word in the exploration set.

3. Using the keyword dictionary (D_{ref}), we identify a set of (after-refinement) climate-related speeches the subset of (pre-refinement) climate-related speeches ($S_{climate\text{-}related} \subset S_{climate\text{-}related\,(pre)}$) which contain at least two separate sentences with any identified keywords.

B.3 Methodology for identifying other topics in climate-related speeches

In Section 4.2, we employ the *k-means algorithm* to identify topics in climate-related speeches. This method, which is one of the most standard tools for clustering, is used in conjunction with a word embedding technique following works by Mikolov, et al. (2013) (known as word2vec) and Pennington, et al. (2014) (known as GloVe). The combination of these techniques is suggested by Grimmer, Roberts, and Stewart (2022).[4]

The word embedding technique maps a large corpus into low-dimensional word vectors such that words which have similar meaning/usage are represented by similar vectors. More specifically, the GloVe algorithm is based on the model that takes the form,

$$(w_i - w_j)^T w_k = \log \frac{P(k|i)}{P(k|j)} \ ,$$

where: w_i denotes a word vector assigned for word i, and $P(k|i)$ indicates a word co-occurrence probability that word k appears in the context of word i. If word i and j are used for the similar contexts, $P(k|i)/P(k|j) \to 1$ and $(w_i - w_j) \to 0$. Based on the model, the GloVe algorithm finds the word vectors by conducting a weighted least square regression that assigns small weights to frequent co-occurrences.

[4]See also Kozlowski, Taddy, and Evans (2019) and Dieng, Ruiz and Blei (2020) for potential applications of word embedding other than using for clustering.

To measure the word co-occurrence probability (as a matrix form $\mathbf{C}$), we count occurrences of any words located 10 words before or 10 words after the target word, weighted by a decaying factor (1/"distance between the words"). We set the dimension of the word vectors to 300. In our corpus, the number of word types in vocabulary is $127,926$, so the $127,926 \times 127,926$ sized word co-occurrence matrix can be represented by $300 \times 127,926$ sized set of the estimated vectors where $\mathbf{C} = \mathbf{v}^T\mathbf{v}$.

When we have vector representations of the corpus, we can then apply the standard k-means algorithm to the vectors in order to classify them. In our implementation, we calculate sentence vectors by simply averaging the word vectors assigned in words in the corresponding sentence.[5] Using the sentence vectors as an input, the k-means algorithm minimizes the following objective function:

$$f(\mu, \mathbf{t}, \mathbf{v}) = \sum_{i=1}^{N} \sum_{t=1}^{T} d(v_i, \mu_t) \cdot I(c_i = t) \ ,$$

where: N is the number of sentences, T is the number of topics (clusters), $I(c_i = t)$ is a cluster indicator that equals to 1 if sentence i is assigned to topic t, and $d(v_i, \mu_t)$ is the distance between a vector of sentence i and a cluster center μ of topic t is given by squared Euclidean distance:

$$d(v_i, \mu_t) = \sum_{m=1}^{M} (v_{i,m} - \mu_{t,m})^2 \ ,$$

where: M is the dimension of the sentence vectors (set to 300 in our word embedding step) and $v_{i,m}$ is an element of sentence vector for sentence i. Using the results of the optimization, every sentence is assigned to a single topic whose cluster center is the closest to the sentence vector.

We set the number of clusters $K = 20$, and manually label the estimated clusters based on word clouds of sentences in the corresponding clusters as describe in Section 4.2. We discover 8 meaningful topics shown in Figure **??**, while other 12 clusters include specific names of countries and central banks, language frequently used in speeches (such as "today," "gentleman," and "attention") or general words (such as "figure," "percentage", and "year"), and are therefore not of our interests (i.e., they are so-called "garbage topics").

References

[1] Benoit, K., K. Watanabe, H. Wang, P. Nulty, A. Obeng, S. Müller and A. Matsuo (2018) "quanteda: An R package for the quantitative analysis of textual data." *Journal of Open Source Software*, 3(30), 774.

[2] Bholat, David, S. Hansen, P. Santos, and C. Schonhardt-Bailey (2015) "Text Mining for Central Banks: Handbook," *Centre for Central Banking Studies* (33). pp. 1-19.

[3] Dieng, A., F. Ruiz and D. Blei (2020) "Topic Modeling in Embedding Spaces." *Transactions of the Association for Computational Linguistics*, 2020; 8 439–453.

[5] We use sentence vectors for clusters rather than speech-level aggregation of word vectors. Every speech could include multiple topics in the speech, so the clustering results for speeches tend to be more ambiguous.

[4] Grimmer, Justin, Margaret Roberts and Brandon Stewart (2022) *Text as Data: A New Framework for Machine Learning and the Social Sciences*, Princeton University Press.

[5] Honnibal, Matthew, Ines Montani, Sofie Van Landeghem, and Adriane Boyd (2020) "spaCy: Industrial strength Natural Language Processing in Python."

[6] Kozlowski, A. C., M. Taddy, and J. A. Evans (2019) "The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings", *American Sociological Review*, 84(5), pp. 905–949.

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[10] Watanabe, K., (2018) "Newsmap: A Semi-Supervised Approach to Geographical News Classification," *Digital Journalism*, 6(3), 294-309.

[11] Watanabe, K., and Y. Zhou (2020) "Theory-Driven Analysis of Large Corpora: Semisupervised Topic Classification of the UN Speeches," *Social Science Computer Review*, February 2020.

Appendix C. Climate-specific Policy Tools

In our analysis in Section 4.1, we identify 65 keywords that indicate climate-specific policy tools from a total of $1,498$ climate- or green-related keywords (i.e., "Climate XXX" and "Green XXX") found in our corpus. We classify them into 6 categories: climate disclosure, climate risk management, green taxonomy, climate research, climate scenario analysis/stress testing, and green monetary policy/capital allocation. Table C.1 shows a complete list of those 65 keywords and their classifications into 6 categories.

Table C.1: Keywords for Climate-specific Policy Tools

Category	Climate-related Speeches	Keywords
All Speeches	734	
Climate Disclosure	128	climaterelatefinancialdisclosures, climatedisclosure, climaterelatedisclosure, climaterelatefinancialdisclosure, climaterelatedfinancialdisclosures, climateriskdisclosure, climatereporting, climaterelatereporting, climaterelatereportingobligation, climaterelatereportingrequirement, climaterelateriskdisclosure, climaterelatedisclosurerequirement
Climate Scenario Analysis / Stress Test	108	climatescenario, climatescenarioanalysis, climatestresstest, climatestresstesting, climaterelatescenario, climatescenarioexercise, climaterelatestresstest, climateriskscenario, climatebiennialexploratoryscenario, climateriskstresstest, climatechangescenario, climaterelatescenarioanalysis, climateriskmanagementscenarioanalysis, climateriskscenarioanalysis, climatedrivescenarioanalysis, climateriskstresstestanalysis, climatesensitivityanalysis, climatestresstestingsensitivityanalysis
Climate Risk Management	56	climateriskmanagement, climateriskanalysis, climateriskassessment, climaterelateriskmanagement, climateassessment, climatechangeriskassessment, climaterelateriskanalysis, climaterelateriskassessment
Green Taxonomy	36	greentaxonomy, greentaxonomygreenbondstandard, greenlabel, greenloantaxonomy, greencertification, greencredential, greencriterion, climaterelatecriterion, greenstandard
Green Monetary Policy / Capital Allocation	14	greenmonetarypolicy, greenqe, greenassetpurchaseprogramme, climategreeningmonetarypolicypolicy, greeningmonetarypolicy, climatechangefundprovisioningmeasure, greenmonetarypolicyassetportfolio, climatebasecentralbankpurchase, climateorientpurchase, greenassetpurchase, climatelinkcapitalinstrument
Climate Research	13	climateresearch, climatemodel, climatemodelling, climatechangeanalysis, climatevulnerabilityassessment, climatedataanalysis, climateriskassessmentmodel

Appendix D. List of Reviewed Speeches

Speeches Reviewed in Section 3.3 (Validity Checks)

[1] Noyer, Christian, (2008) "The history and future of corporate responsibility," Bank of France,, https://www.bis.org/review/r081106a.pdf.

[2] Hendar (2015) "Increasing cooperation between Indonesia's central bank and state police," Bank Indonesia, https://www.bis.org/review/r150309c.pdf.

[3] Lautenschlager, Sabine, (2017) "Cyber resilience - a banking supervisor's view," European Central Bank, https://www.bis.org/review/r170629a.pdf.

[4] Waas, Ronald, (2014) "Handling alleged payment system and currency exchange crime," Bank Indonesia, https://www.bis.org/review/r141023b.pdf.

[5] Diokno, Benjamin E., (2021) "Sustainability in investing," Central Bank of the Philippines, https://www.bis.org/review/r200807m.pdf.

[6] Elderson, Frank, (2018) "Let the future of finance be that of financing the future," Netherlands Bank, https://www.bis.org/review/r180503h.pdf.

[7] Lane, Philip R., (2016) "Dual perspectives on the insurance sector – consumer protection and financial stability," Central Bank of Ireland, https://www.bis.org/review/r160613c.pdf.

[8] Yue, Eddie, (2017) "New and important frontiers of financial development in 2017," Hong Kong Monetary Authority, https://www.bis.org/review/r180112d.pdf

[9] Suthiwartnarueput, Sethaput, (2021) "From resiliency to recovery and beyond—central bank policies for an uncertain world," Bank of Thailand, https://www.bis.org/review/r210909a.pdf

[10] Patra, Michael D., (2021) "BRICS—From acronym to global economic powerhouse," Reserve Bank of India, https://www.bis.org/review/r211128h.pdf

[11] Trichet, Jean-Claude, (2008) "Monetary policy in challenging times," European Central Bank, https://www.bis.org/review/r080606c.pdf.

[12] Yue, Eddie, (2021) "Hong Kong's positioning and prospect as an international financial centre," Hong Kong Monetary Authority, https://www.bis.org/review/r211209d.pdf.

[13] Macklem, Tiff, (2021) "The long and short of it - a balanced vision for the international monetary and financial system," Bank of Canada, https://www.bis.org/review/r211008c.pdf.

[14] Haldane, Andrew G., (2010) "The $100 billion question," Bank of England, https://www.bis.org/review/r100406d.pdf.

[15] Carney, Mark, (2018) "A transition in thinking and action" Bank of England, https://www.bis.org/review/r180420b.pdf

[16] Stournaras, Yannis, (2019) "Climate change - threats, challenges, solutions for Greece," Bank of Greece, https://www.bis.org/review/r190412g.pdf

Speeches Reviewed in Section 3.4 (Summary Statistics)

[1] Carse, David, (2000) "Environmental issues and their implications for financial institutions in Hong Kong," Hong Kong Monetary Authority, https://www.bis.org/review/r001129c.pdf.

[2] Goh, Chok Tong (2007) "Staying ahead of the Asian curve," Monetary Authority of Singapore, https://www.bis.org/review/r071105b.pdf.

[3] Boediono (2008) "Macroeconomic impact of climate change - opportunities and challenges," Bank Indonesia, https://www.bis.org/review/r080901c.pdf.

[4] Draghi, Mario, (2009) "The financial crisis - impact and responses," Bank of Italy, https://www.bis.org/review/r090507b.pdf.

[5] Tarantola, Anna Maria, (2010) "Women nurturing sustainable development," Bank of Italy, https://www.bis.org/review/r101208g.pdf.

[6] Provopoulos, George A., (2011) "The impact of climate change in Greece," Bank of Greece, https://www.bis.org/review/r110614a.pdf.

[7] Ibrahim, Muhammad, (2012) "Role and opportunities of the financial system in supporting green technology," Central Bank of Malaysia, https://www.bis.org/review/r121004g.pdf.

[8] Rambarran, Jwala, (2013) "Generating more inclusive economic growth through science and technology," Central Bank of Trinidad and Tobago, https://www.bis.org/review/r130806a.pdf.

[9] Padmanabhan, G., (2014) "Corporate sustainability a panacea for growth - values, convictions and actions," Reserve Bank of India, https://www.bis.org/review/r141021d.pdf.

[10] Carney, Mark, (2015) "Breaking the Tragedy of the Horizon: Climate Change and Financial Stability," Bank of England, https://www.bis.org/review/r151009a.pdf.

[11] Carney, Mark, (2016) "Remarks on the launch of the Recommendations of the Task Force on Climate-related Financial Disclosures," Bank of England, https://www.bis.org/review/r161216h.pdf.

[12] Stournaras, Yannis, (2017) "Climate change - challenges, risks and opportunities," Bank of Greece, https://www.bis.org/review/r170726e.pdf.

[13] Carney, Mark, (2018) "A transition in thinking and action," Bank of England, https://www.bis.org/review/r180420b.pdf.

[14] Delgado, Margarita, (2019) “Climate change. Challenges for the Financial System,” Bank of Spain, https://www.bis.org/review/r191211e.pdf

[15] Orr, Adrian, (2020) “Progressing climate action by driving transformational change,” Reserve Bank of New Zealand, https://www.bis.org/review/r201104f.pdf.

[16] Elderson, Frank, (2021) “All the way to zero – guiding banks towards a carbon-neutral Europe,” European Central Bank, https://www.bis.org/review/r210429h.pdf

[17] Mauderer, Sabine, (2022) “The economic power of sustainability and energy transition,” Deutsche Bundesbank, https://www.bis.org/review/r220718a.pdf

Speeches Reviewed in Section 4.1 (Climate Change, Financial Stability, and Macroprudential Policy)

[1] Lagarde, Christine, (2021) “Macroprudential policy in Europe – the future depends on what we do today,” European Central Bank, https://bis.org/review/r211208i.pdf.*“Effective climate policies would also benefit the financial sector. But macroprudential policymakers have a part to play, too, in identifying and mitigating the financial aspects of climate-related risks.”*

[2] Lane, Philip R., (2019) “Climate change and the Irish financial system,” Bank of Ireland, https://www.bis.org/review/r190206b.pdf.*“This calls for ongoing monitoring of climate risks, together with the development of climate-driven scenario analyses and stress tests. By extension, the results of such analyses may call for the appropriate macroprudential policies to mitigate these risks.”*

[3] Stiroh, Kevin, (2020) “Climate change and risk management in bank supervision,” Federal Reserve Bank of New York, https://www.bis.org/review/r200309b.pdf. *“...supervisors can focus on identifying and managing risks, both microprudential and macroprudential, that emerge along a transition path to a more sustainable economy”*

[4] Elderson, Frank, (2021) “Overcoming the tragedy of the horizon,” European Central Bank, https://www.bis.org/review/r211118d.pdf. *“Getting banks to develop action plans to comply with the expectations that the ECB set out in its guide on C&E risks was the first step in getting them to assess and develop their risk management capabilities.”*

[5] Menon, Ravi, (2021) “Being the change we want to see - a sustainable future,” Monetary Authority of Singapore, https://www.bis.org/review/r210609g.pdf. *“Developing a clear taxonomy for transition activities is especially relevant for Asia. Asia needs to sustain economic and social development while shifting to a lower carbon future. A taxonomy that includes both green and transition activities can support a progressive shift to greater sustainability.”*

[6] Elderson, Frank, (2018) “Let’s dance,” Netherlands Bank, https://www.bis.org/review/r180904c.pdf. *“We should remove all unnecessary obstacles to this transition. And assist the sector in creating com-*

mon definitions and standards. As well as provide the necessary guidance. The development of a sustainable taxonomy is a good example of this."

[7] Stournaras, Yannis, (2018) "Climate change - threats, challenges, solutions for Greece," Bank of Greece, https://www.bis.org/review/r190412g.pdf. *"Greece, along with other small countries in the climate-sensitive Mediterranean region, is expected to incur adverse effects from climate change. Acknowledging this fact, the Bank of Greece has been one of the first central banks worldwide to actively engage in the issue of climate change and invest significantly in climate research."*

[8] Breeden, Sarah, (2019) "Avoiding the storm - climate change and the financial system," Bank of England, https://www.bis.org/review/r190430k.pdf. *"Measuring these future risks from climate change to the economy and to the financial system is a complex task. A myriad of possible climate pathways – with different physical and transition effects – need to be translated into economic outcomes and financial risks looking ahead over many decades. To simplify that challenge, we need to focus not on what will happen but what might happen. To do that we can use scenario analysis – data driven narratives that help anchor our assessments of risk."*

[9] de Guindos, Luis, (2019) "Implications of the transition to a low-carbon economy for the euro area financial system," European Central Bank, https://www.bis.org/review/r191122e.pdf. *"The pilot test framework will be macroprudential in nature, and allow us to analyse the system-wide materiality of transition risks for banks' solvency, along with their lending capacity and the implications for the overall economy."*

[10] Carney, Mark, (2019) "TCFD: strengthening the foundations of sustainable finance," Bank of England, https://www.bis.org/review/r191008a.pdf. *"Supervisors of financial sector firms will also need to consider which metrics are most useful for different levels of assessment: - Microprudential, to assess how individual firms are managing climate-related risks - for example the impact of a physical or transition risk on a loan book. - Macroprudential, to consider how and whether individual exposures could scale up to systemic risk - Macroeconomic, to help understand how the financial system and economy interact in different climate transition scenarios."*

[11] Villeroy de Galhau, François, (2021) "The role of central banks in the greening of the economy," Bank of France, https://www.bis.org/review/r210211g.pdf.

[12] Mauderer, Sabine, (2019) "Central banks - a crisis manager for the climate?," Deutsche Bundesbank, https://www.bis.org/review/r191029b.pdf.

[13] Bailey, Andrew, (2021) "Tackling climate for real - the role of central banks," Bank of England, https://www.bis.org/review/r210602a.pdf.

[14] Matsen, Egil, (2019) "Climate change, climate risks and Norges Bank," Norges Bank, https://www.bis.org/review/r191108a.pdf.

[15] Weidmann, Jens, (2019) "Climate change and central banks," Deutsche Bundesbank, https://www.bis.org/review/r191029a.pdf.

[16] Diaz de Leon, Alejandro, (2021) "Remarks - How can central bankers and supervisors support climate risks and green finance and manage risks?," Bank of Mexico, https://www.bis.org/review/r210727a.pdf.

Speeches Reviewed in Section 4.2 (Other Topics in Climate-relate Speeches)

[1] Stournaras, Yannis, (2017) "Climate change - challenges, risks and opportunities," Bank of Greece, https://www.bis.org/review/r170726e.pdf.

[2] Stournaras, Yannis, (2019) "Climate change - threats, challenges, solutions for Greece," Bank of Greece, https://www.bis.org/review/r190412g.pdf.

[3] Elderson, Frank, (2021) "Forests and finance," European Central Bank, https://www.bis.org/review/r211123a.pdf.

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