Financial Economics of the Transition to a Low-Carbon Economy

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Preface

The transition to a low-carbon economy demands the replacement of carbon-intensive capital at unprecedented scale. Whether that replacement proceeds credibly depends on how well commitments can be assessed, progress measured, and financial instruments priced accordingly. This thesis examines these questions through three papers.

The first paper develops a scoring rule for climate transition plans in sectors where emissions are difficult to abate, weighting disclosed components according to their statistical association with observed changes in emissions intensity. The second paper examines which sustainability performance metrics financial professionals find most useful, drawing on an industry survey to identify persistent frictions in assurance, comparability, and institutional capacity. The third paper develops a theoretical valuation framework for sustainability-linked bonds, instruments whose financial terms are contingent on the issuer's environmental performance. Grounded in a stochastic-volatility process, the framework treats sustainability performance as a priced state variable, capturing its evolving uncertainty alongside interest-rate and credit risk. Numerical illustrations drawn from landmark corporate and sovereign issuances suggest how contract design and data quality shape the sensitivity of spreads to transition credibility.

Taken together, the three papers offer a framework for the economics of the transition: one that connects planning to measurement, and measurement to valuation.

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Introduction

> *Any economic system requires a set of rules, an ideology to justify them, and a conscience in the individual which makes him strive to carry them out.*
>
> Joan Robinson (1962, p. 18)

The transition to a low-carbon economy demands the replacement of carbon-intensive capital at considerable scale. Whether that replacement proceeds credibly depends on how well commitments can be assessed, progress measured, and financial instruments priced accordingly. Climate change remains a large, persistent externality that standard markets under-price. Global temperatures have briefly exceeded 1.5 °C above pre-industrial levels on a rolling annual basis (Tollefson, 2025), and estimates indicate that nearly USD 7.5 trillion in annual capital allocation is required each year through 2030 to stay on track with the 1.5 °C scenario (CPI, 2024a). The costs of inaction compound the challenge; extreme weather events resulted in USD 264 billion in losses in 2022 alone, exacerbating socioeconomic vulnerabilities worldwide (Romanello et al., 2023).

Climate transition finance (hereafter used interchangeably with "transition finance") channels capital toward the replacement of carbon-intensive industrial structures rather than the mere funding of already clean sectors (Caldecott, 2022b). Green finance concentrates on projects that already deliver clear environmental benefits; transition finance, by contrast, targets high-emitting activities that do not yet meet those standards but are on a credible pathway to doing so (Hyun and H. Lee, 2025). The distinction is one of direction rather than state: transition finance prioritises forward-looking alignment with decarbonisation trajectories over present-day compliance with environmental thresholds (Schumacher, 2023).

The proliferation of net zero commitments, which are pledges to balance the amount of greenhouse gases (GHG) emitted with the amount removed from the atmosphere, the tightening of regulatory mandates for climate-related disclosures, and the rapid expansion of sustainability financing instruments all point to the growing scale of transition finance (GFANZ, 2022b; Tracker, 2023; TFMR, 2024; TPT, 2022). Despite these advancements, the gap between corporate climate pledges and their real-world impacts remains wide: only about 1% of organisations disclosing through CDP fulfil all key indicators for a credible climate plan, raising concerns about misleading claims and inconsistent approaches (CDP, 2023a).

In this thesis, I examine the economics of this transition through three dimensions: planning, measurement, and valuation.

- *Plans* are credible, capital-backed commitments that sequence technologies and expenditures against sectoral pathways.
- *Metrics* are decision-useful indicators that map actions to outcomes and support cost-effective control, comparability and assurance.
- *Valuation* estimates the intrinsic worth of climate-linked financial instruments by modelling how sustainability performance affects their cash flows and risk. Where market prices diverge from that estimate, the gap signals potential mispricing.

While informed by environmental economics and sustainability transitions, the thesis is grounded in financial economics, applied to questions raised by the low-carbon transition. The three papers engage with credible commitment, incentive alignment, and the role of information and valuation in driving real-economy decarbonisation.

Drawing on Schumpeter's (1939, p. 1033) account of how investment in new technologies drives structural change, *plans* are treated as commitment devices that direct capital towards alternative technological trajectories under uncertainty. They are understood not merely as statements of strategic intent (Babcock et al., 2022), but as deliberate instruments for reallocating financial capital to enable shifts in technology and market organisation. In this context, I examine sustainability outcomes using metrics that assess alignment with ecological thresholds, such as planetary boundaries, and that serve as proxies for real-world decarbonisation. Echoing Daly's (1991, pp. 220–222) insight that markets cannot determine when ecological limits are breached, I stress the role of independently set scale constraints within which capital allocation and efficiency gains must be assessed.

Valuation, the third dimension, extends beyond static discount-rate models. I consider how risk premiums and discount rates can better reflect the long-term uncertainties of climate change, as well as the structural risks associated with the transition away from fossil fuels, a point noted by Stern (2007, p. 173). Together, these three perspectives inform the framework of the thesis: plans as commitment devices, metrics as proxies for progress within ecological limits, and valuation as a means of incorporating long-term climate risk into financial instruments.

To address the challenge of aligning finance with sustainability, this thesis is structured around three interrelated studies, each examining a key dimension: planning, measurement, or valuation. The final drafts of each paper were reviewed by my supervisor and co-authors.

- Paper A. *Climate transition plans' assessment in hard-to-abate sectors:* A sector-grounded scoring framework for airlines that weights plan disclosures by their empirical association with short-run emissions outcomes.

- Paper B. *Climate transition finance metrics effectiveness: An industry perspective*: A global survey of financial practitioners examining how they perceive the effectiveness of transition finance metrics, with econometric analysis of the gap between perceived usefulness and actual data availability.
- Paper C. *Sustainability-linked bonds: modelling for sustainability performance*: A stochastic bond-valuation model that embeds evolving sustainability metrics and plan credibility into cash flows for sustainability-linked bonds.

Collectively, these studies show how planning works as a commitment device, how measurement enables cost-effective control and comparability, and how valuation converts credibility into risk signals and spreads.

Each paper contributes empirical results and methodological tools relevant for financial practitioners, policymakers, and scholars. My aim is twofold: to clarify what effective planning, measurement, and valuation look like in practice, and to provide tools that improve how climate performance is assessed and reflected in the value of financial instruments.

Background

Transition finance is a deliberate 're-embedding' of finance and investment into society's larger goals, a concept that resonates with Polanyi's critique of the self-regulating market (Polanyi, 2024, Chapter 10). It resists the notion of the self-regulating market by recalibrating how we value land, labour, and capital. This approach corresponds to the concept of 'sustainability transitions,' in which the interaction of social, economic, political, and technological forces drives the large-scale adoption of new technologies (Geels et al., 2016; Geels and Schot, 2007).

Despite the rise in net-zero commitments and new reporting standards for transparent transition plans (Tracker, 2024; TPT, 2023a), major concerns remain about whether these pledges will result in real, lasting decarbonisation, especially in sectors that rely heavily on carbon-intensive operations. The task of designing sound transition finance frameworks is compounded by global regulatory discrepancies, uncertain technological pathways, and challenges in incorporating climate risks into valuation models (NGFS, 2023b; UNFCCC, 2024b). It is against this background that I examine the three interrelated dimensions of the economics of the transition: planning, measurement, and valuation. Planning establishes credible commitments, measurement tracks progress against those commitments, and valuation estimates whether financial instruments reflect the underlying sustainability performance.

Plans. Corporate transition plans set out the path from baseline operations to progressively more sustainable ones (L. Shi and Fitzgerald, 2023). Well-specified plans clarify

near-, medium-, and long-term emissions targets, define the technologies to be deployed, and articulate governance structures for ongoing accountability (ISSB, 2022). Such clarity not only reduces the risk of greenwashing but also helps coordinate procurement, R&D, and finance toward shared climate objectives (GFANZ, 2022b).

Yet, developing plans is complicated by the lack of universally agreed-upon methodologies for assessing the credibility of disclosed information. While non-binding standard setters like the Transition Pathway Initiative (TPI) and Science Based Targets initiative (SBTi) set out broad guidelines, sectoral nuances may demand specialised metrics that capture unique operational constraints and technological frontiers. This situation is especially evident in hard-to-abate sectors, where incremental improvements, such as using sustainable aviation fuels (SAFs) or implementing partial electrification strategies, can be overshadowed by uncertainties in demand growth, regulation, and technology breakthroughs.

Policymakers increasingly view thorough transition plans as necessary for financial stability, encouraging central banks and regulators to evaluate how well financial institutions and corporates are preparing for a low-carbon economy (NGFS, 2023b). This regulatory push has increased the demand for systematic, data-driven tools that can distinguish genuinely ambitious transition commitments from inconsistent pledges. In this context, Paper A evaluates data-driven approaches to assessing the credibility of transition plans, treating key disclosure elements as more reliable signals of alignment with actual carbon performance and complementing expert judgement with an auditable, data-driven baseline.

Metrics. Decision-useful metrics translate plans into measurable progress and cost-effective control. I argue that their value lies in comparability, assurance, and proximity to outcomes, rather than in the breadth of reporting dashboards. This comparability enables investors, regulators, and the public to track progress toward decarbonisation goals and guide capital flows. However, the wide range of sustainability indicators, such as carbon intensity and ESG ratings, raises concerns about consistency, comparability, and the potential for greenwashing (Kathan et al., 2025; Zhou et al., 2024).

One of the most contentious challenges involves pinpointing material and ambitious climate performance targets (Bolay et al., 2024). While many corporates might stress emission reductions alone, broader ecological and social indicators are also important. Finding the right balance among these various metrics is complicated by data unavailability and fragmented green taxonomies (Chan et al., 2024), creating persistent uncertainties that hamper large-scale adoption and effective benchmarking as shown in Paper B.

In response, policymakers and international standard-setting bodies have begun to prioritise the development of unified disclosure frameworks, such as the International

Sustainability Standards Board (ISSB). Yet, the complexity of capturing real-world performance remains acute, above all for industries that face structural impediments to immediate decarbonisation. Paper B examines how frontline financial practitioners perceive and interpret transition finance metrics, identifying the barriers and conditions that shape metric effectiveness.

Valuation. Pricing reflects what the market currently pays for an asset; valuation estimates what the asset should be worth, given a structured analysis of its risks and cash flows. The two constantly inform each other: market prices are the starting point for most valuations, and valuations, once widely adopted, shape prices over time. How markets price climate risk, in particular, shapes the cost of capital for both sustainable and carbon-intensive projects (Owolabi et al., 2024). Evidence indicates that markets do incorporate climate risks into valuations, raising the cost of capital for high-emitting firms (e.g., Trinks et al., 2020). In practice, however, measuring climate risk involves considerable uncertainties, relating both to the physical impacts of climate change and to the direction of future regulations. As a result, pricing signals are often inconsistent or incomplete (Eren et al., 2022).

Sustainability-linked bonds (SLBs) and loans (SLLs) attempt to address this by tying coupon step-ups or loan margin adjustments to the achievement of predefined performance targets. While such structures can align financial incentives with climate objectives, initial pricing can be subject to investor hype or lack of robust modelling, sometimes resulting in mispricing (Mielnik and Erlandsson, 2022). Over time, if targets are not met or if the instruments' credibility is questioned, the resulting adjustments may be too small to reflect the shortfall in climate action (Berrada et al., 2022). Paper C addresses the gap between observed prices and intrinsic worth by introducing valuation models that incorporate stochastic volatility, nonlinear transitions, and issuers' transition credibility. The results concern valuation conditional on instrument design. Where step-ups are small, prices are unlikely to transmit the full externality. The paper therefore derives design thresholds for step-up sizes and KPI materiality that deliver target spread sensitivities under plausible transition scenarios.

Taken together, the three dimensions reinforce one another: credible planning reduces uncertainty, which strengthens measurement, which in turn improves the precision of valuation.

Objectives

This thesis studies how planning, measurement, and valuation interact to deliver real-economy decarbonisation under uncertainty. The overarching objective is to examine

whether credible commitments, decision-useful metrics, and risk-sensitive valuation can be made to reinforce one another in practice, and where current frameworks fall short.

The first objective concerns the credibility of corporate transition plans as commitment devices. If plans are to direct capital toward alternative technological trajectories, as the Schumpeterian framing requires, their disclosed components must carry verifiable information about future emissions performance. Existing frameworks rely heavily on expert judgement, which limits replicability and cross-sectoral comparability. This thesis develops a correlation-based scoring system, applied to the airlines industry, that weights disclosure components according to their empirical association with short-run emissions outcomes. The aim is to provide an auditable, outcome-driven alternative that addresses a persistent gap in how plan credibility is evaluated. With such a baseline in place, regulators and investors can benchmark airlines' commitments against observed emissions performance rather than relying on self-reported narratives alone.

The second objective turns from real-economy commitments to the information infrastructure on which capital allocation decisions rest. Markets can only discipline transition performance if the metrics available to intermediaries are decision-useful, comparable, and grounded in reliable data. Paper A showed that plan credibility can be scored against emissions outcomes; here, the focus shifts to the metrics that financial institutions use to track and report their progress. A survey of over two hundred professionals reveals that practitioners whose organisations have partially or fully implemented transition plans are, paradoxically, the most sceptical of existing metrics, whose underlying data they find incomplete and whose scope they consider too narrow for the complexity of large-scale decarbonisation. Identifying these gaps enables standard-setters to concentrate on fewer, assured, outcome-proximate indicators that practitioners can verify and that feed directly into asset valuation.

The third objective asks whether financial instruments can be designed to transmit transition risk into cash flows, so that the cost of capital responds to the credibility of climate commitments rather than to static classifications. Sustainability-linked bonds offer a natural testing ground: their coupon adjustments are contractually tied to performance targets, yet existing pricing rarely reflects the non-linear uncertainties inherent in meeting those targets. A Heston-based stochastic volatility model embeds evolving sustainability performance, transition plan credibility, and sectoral peer rankings into the pricing of coupon step-ups. By moving beyond generic yield differentials, the framework allows climate-related risks and issuer commitments to be more accurately reflected in bond prices. The resulting design thresholds for step-up sizes and KPI materiality offer issuers and regulators a quantitative basis for calibrating incentive structures in future sustainability-linked instruments.

The thesis adopts an article-based structure, with each study addressing one dimension through a tailored methodology. Together, the three articles trace how planning shapes measurement, how measurement informs valuation, and how valuation in turn reflects back on the credibility of plans and the rigour of metrics.

Methods and data

The three studies employ complementary empirical strategies (structured disclosure analysis, survey research, and stochastic financial modelling), each matched to the character of its research question.

Assessing transition plan credibility requires moving beyond expert judgement toward a replicable baseline. A review of climate pathways and seventeen reporting standards informs a structured questionnaire, refined through expert workshops, that scores eighty-four airlines across five disclosure dimensions: foundations, implementation, engagement, governance, and metrics and targets. Weights for each element are derived from their correlation with short-run emissions intensity, adjusted for operational confounders through stratification and partial correlations, and tested via cross-validation and bootstrapping.

Gauging metric effectiveness calls for direct evidence from practitioners. A global survey of over two hundred professionals, spanning banks, asset managers, insurers, and asset owners, supplies the empirical base. An ordered probit model isolates how institutional characteristics shape perceptions of usefulness, corrected for non-response through a Heckman procedure and for frame imbalances through post-stratification weights. Coverage error from the LinkedIn-based sampling frame is acknowledged as a limitation.

Valuing sustainability-linked bonds poses a distinct challenge: sustainability performance evolves stochastically and coupon adjustments are path-dependent. A Heston stochastic volatility framework, implemented via Monte Carlo simulation, accommodates these features, with transition plan scores and sectoral peer rankings conditioning the probability of target achievement. The empirical application draws on primary bond-issuance documents, SLB frameworks, and transition plan assessments from corporate and sovereign issuers. The model's demand for high-quality, contemporaneous data on operational and external risk factors constitutes its principal limitation.

Outline of the thesis structure

This thesis examines transition finance through a literature review and three empirical research articles. The literature review first establishes the theoretical foundations of

climate transition finance, discussing the shift from traditional green finance to a finer focus on supporting decarbonisation in hard-to-abate sectors. It then examines the challenges of planning for climate transitions, including the development of credible climate pathways, the governance of sectoral lock-ins, and the persistent credibility gap in corporate disclosures. The review further investigates performance measurement, tracing the complexities of evolving metrics, data limitations, and the barriers to effective performance assessment in transition finance. Finally, it turns to the market mechanisms of climate risk valuation and the need for time-varying valuation models that account for sector-specific risks and regulatory uncertainties.

The thesis is structured to build a cumulative argument across its components. Section 2 presents the literature review, outlining the academic debate that frames each paper. Sections 3, 4 and 5 contain the three research articles that form the core of the analysis. The conclusion synthesises the results, stressing the importance of credible transition plans, the effectiveness of outcome-proximate metrics, and the incorporation of entities' probability of meeting climate targets into asset valuation. It also acknowledges key limitations, including data constraints, definitional ambiguities and methodological challenges in valuation models. Finally, it outlines directions for future research, focusing on improved credibility assessments, the prioritisation of decision-useful metrics, and more flexible approaches to risk valuation.

1

Review of the Literature

Laissez-faire was planned; planning was not.
Karl Polanyi (Polanyi, 2024, p. 147)

The exponential growth of capital marketed as "sustainable" over the last fifteen years has coincided, paradoxically, with persistent increases in global emissions. This paradox has intensified scholarly and policy interest in transition finance. Unlike approaches that focus on the edges of an already green economy, transition finance typically targets the carbon-intensive core of global production systems. Transition finance prioritises "direction" over "state" by embedding forward-looking regulatory and credit-allocation mechanisms to steer carbon-intensive firms onto credible decarbonisation pathways, rather than merely funding existing low-carbon assets. Public policy tools that steer credit (e.g., monetary or prudential measures) are complementary context and are discussed as enabling conditions, not as part of the definitional core of transition finance. For example, Campiglio (2016) analyses how banking and monetary policy tools can redirect commercial bank credit even when the starting point is emphatically non-green. Such an orientation places heavy analytical weight on forward-looking credibility, meaning a clear set of "talk" indicators (e.g., interim GHG targets and governance structures) and "walk" indicators (e.g., assured absolute emissions reductions and renewable-energy strategies), so that investors can be confident capital raised today will drive technology adoption, behavioural change, and policy alignment tomorrow (Colesanti Senni et al., 2025).

Because it must contend with legacy assets, political lock-in and social distributional effects, transition finance sits at the overlap of multiple research fields. Work in socio-technical transitions stresses path dependence and the need for coordinated phase-out of incumbent technologies (Geels and Schot, 2007). Corporate finance studies examine how contract design can connect the cost of capital to climate or environmental performance (He et al., 2013; Y. Wang et al., 2024). At the same time, environmental economics research stresses public good features such as credible information, stable policy signals and project preparation capacity, which markets alone often fail to provide adequately (Bolton and Kacperczyk, 2021; Fischer and Newell, 2008; Kotchen, 2005). Yet empirical results remain fragmented and sometimes contradictory. For instance, evidence on a

greenium (the yield discount that green bonds enjoy relative to comparable conventional bonds) is mixed across samples and methods; several reviews find a modest issuance greenium in some segments, with size and persistence varying by market, tenor and period (Caramichael and Rapp, 2024). Bridging these silos requires a framework capable of tracking how strategic intent becomes measurable progress and, in the end, investable risk.

I organise the literature around three mutually reinforcing dimensions: transition plans, sustainability performance metrics and valuation. The dimension covering plans investigates how sectoral strategies and institutional logics translate into corporate transition plans that must be both ambitious and feasible. The second dimension focuses on the metrics and data infrastructures that render progress visible, probing why some indicators mobilise capital while others generate noise. The valuation dimension examines how to estimate the intrinsic worth of transition instruments by modelling the uncertain evolution of sustainability performance, and how market pricing reflects, or fails to reflect, credible climate paths in asset values. Together, these sections provide the conceptual scaffolding for the thesis's three papers, each of which interrogates one node in the triad while demonstrating the interdependence of all three.

1.1 Foundations of climate transition finance

1.1.1 Shift from green finance to transition finance

The shift from green finance to transition finance reflects a systemic recognition that decarbonisation requires replacing carbon-intensive industrial structures rather than merely funding "already green" sectors. Green finance, traditionally focused on renewable energy and energy efficiency projects (Ante, 2024), has been criticised for neglecting high-emission industries central to global GDP and employment (Tandon, 2021). The difference between green and transition finance lies in their purposes and scopes: while green finance concentrates on clear environmental benefits, transition finance seeks economy-wide transformation (Hyun and H. Lee, 2025). For example, a bond that funds a new solar farm is green finance: it creates a new clean asset. A loan that helps a steelmaker retire coal-fired blast furnaces and switch to hydrogen-based production is transition finance: it incentivises the replacement of an existing carbon-intensive asset rather than the creation of an additional clean one.

Within transition finance, two main perspectives arise. The broader conceptualisation defines it as the provision of financial products and services that enable entities to direct their activities toward environmental and social sustainability (Caldecott, 2022b).

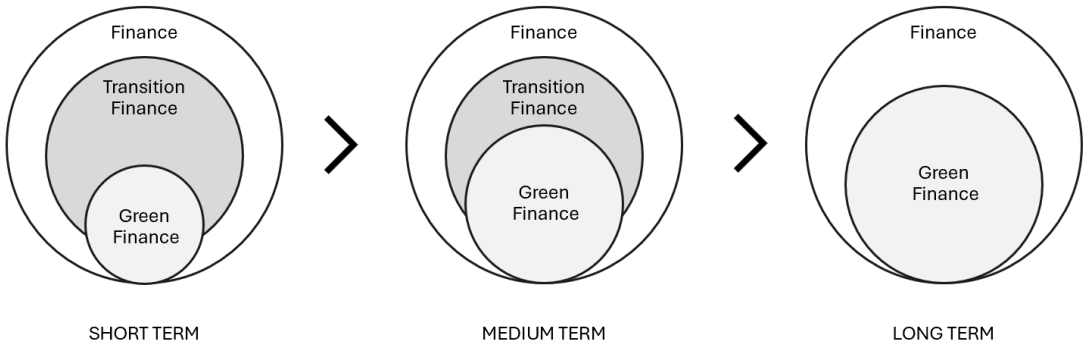
Conversely, a narrower view sees transition finance through a Schumpeterian lens of creative destruction. Innovation disrupts established systems to drive economic change. This approach focuses on hard-to-abate sectors such as steel and aviation, which face challenges like technological lock-in, high capital needs and strong path dependencies. In both perspectives, the challenge stems from carbon lock-in, the path-dependent nature of carbon-intensive assets that, while costly to build, become relatively inexpensive to operate and, over time, reinforce political, market, and social factors that make low-carbon transitions difficult (Fisch-Romito et al., 2021). This dynamic is evident in stranded asset networks within energy systems, where interdependencies among fossil-fuel infrastructure generate systemic inertia (Erickson et al., 2015).

While these perspectives differ in focus and scale, they should be seen as complementary rather than contradictory. The narrow approach sharpens analytical attention on the sectors facing the most acute decarbonisation challenges, allowing the development of sector-specific instruments and governance mechanisms. This thesis primarily adopts the broad approach, examining plans, performance metrics, and valuation across the transition finance field. Paper A, however, applies the narrow perspective, focusing specifically on hard-to-abate sectors to develop a sector-grounded scoring framework for airline transition plans.

Despite the consensus around the capital replacement problem, debates in the sustainability transitions field persist about whether transition finance enables genuine decarbonisation or perpetuates carbon-intensive systems. While some scholars argue that transition labelling can encourage incremental progress (e.g., Wang, 2025; Zhao et al., 2024), others warn of misalignment, where firms conflate climate-risk management with genuine emissions reductions, relying on superficial disclosures under voluntary reporting frameworks, hedging carbon-price exposure through derivatives, or relocating production to jurisdictions with lower environmental standards, thereby securing finance without any substantive plan to align operations with net-zero pathways (Caldecott, 2022a).

This tension turns on whether transition finance functions as a temporary mechanism for structural change or institutionalises carbon lock-in under new labels. According to the European Commission (2023), transition finance should be time-bound: in the short term, it supports high-impact activities that may not yet meet environmental thresholds but are on a credible pathway to doing so; over the long term, as transition trajectories mature, these activities are expected to meet green performance standards and be reclassified accordingly. Rather than replacing green finance, transition finance allows its future expansion by converting the eligibility of assets through forward-aligned capital allocation. Transition finance, properly governed and credibly structured, is thus not an alternative to green finance but its necessary precursor.

Figure 1.1 Relationship between green and transition finance over time



Source: European Commission (2023).

1.1.2 Transition finance in practice

Climate transition finance principles are starting to inform the design of bonds, loans, private-equity vehicles, managed phase-out funds, guarantees, and insurance products. To evaluate these instruments systematically, I adopt a six-factor appraisal framework that questions whether an instrument: (1) follows a credible pathway aligned with climate science, (2) delivers marginal impact, (3) requires capital expenditure specificity, (4) achieves climate materiality in absolute terms, (5) embeds conditional incentives linked to performance outcomes, and (6) ensures verifiable measurement and transparent reporting.

Table 1.1 summarises each factor in one-line definitions. The framework is heuristic and not yet validated against empirical work, but it synthesizes emerging themes in corporate-finance, environmental economics and accounting research. The framework focuses on climate credibility and financial integrity rather than distributional equity or stakeholder governance concerns, reflecting the scope of the three papers. Applying this common lens allows me to probe how transition plans shape instrument design, whether performance metrics capture genuinely material outcomes, and how valuation models internalise the probability of under- or over-performance; weaknesses in any single dimension can undermine the instrument's transition credentials.

Table 1.1 Analytical taxonomy of six evaluative dimensions for transition-finance

Factor	Concise definition
Pathway alignment	Alignment of emissions trajectories with recognised sectoral pathways and time-bound carbon budgets, ensuring dynamic efficiency and consistency with economy-wide decarbonisation targets.

Factor	Concise definition
Marginal impact	The net emissions reduction attributable to a financial intervention, relative to a counterfactual (business-as-usual) scenario.
Capex specificity	Allocation of capital to identified technologies or assets with highest emissions reduction per unit of expenditure
Climate materiality	Delivers emission cuts that are material in absolute terms relative to both the issuer's baseline and the sector's carbon budget.
Incentive compatibility	Financial or contractual mechanisms (e.g., coupon step-ups, margin ratchets) designed to align agent behaviour with climate objectives.
Verifiability and governance	Institutional mechanisms that ensure ex post observability, third-party assurance, enforceability of covenants, and standardised disclosures.

Source: Author's conceptual framework.

Of the six factors, pathway alignment anchors the framework. Climate pathways are sector-specific trajectories that define the rate and timing of emissions reductions needed to meet temperature targets. Matching financial instruments to these pathways matters because real-options models demonstrate that firms postpone irreversible low-carbon investment when regulatory signals are uncertain (Noailly et al., 2022; Sendstad and Chronopoulos, 2020). Embedding a Paris-aligned trajectory in deal documentation can reduce perceived uncertainty and, when enforceable, lower the option value of delay (Mielnik and Erlandsson, 2022). Guidance from IIGCC (2024) translates the option-value logic into fund governance: funds are advised to stipulate that a rising share of committed capital is "managed in alignment with net zero", oblige full Scope 1–3 disclosure and rolling five- to ten-year Paris-aligned reduction targets for portfolio companies, and empower funds' advisory committees to withhold new commitments or escalate if those milestones are missed.

Yet a pathway is only convincing if the capital deployed is genuinely additional: it must drive emissions reductions that would not have occurred under a business-as-usual counterfactual (Michaelowa et al., 2019). This means investment must change real-economy outcomes rather than merely reallocating capital among owners (Kölbel et al., 2020). A clear example of marginal impact outside the debt domain is found in the growing role of green venture capital (GVC). As Dhayal et al. (2023) show, GVC firms have increasingly supported early-stage cleantech ventures. These include carbon capture start-ups and green hydrogen prototypes. Such ventures often face challenges in attracting commercial funding because of long development timelines, uncertain regulations and limited exit opportunities. These equity investments de-risk innovation at the technology frontier and build credibility for future blended-finance or public-private capital mobilisation. By targeting under-served but high-impact innovation segments, GVC performs a catalytic role in transition finance, expanding the universe of investable decarbonisation pathways.

Once additional capital has been mobilised, it must be allocated to specific capital expenditures that enable decarbonisation. While economic theory on irreversibility cautions that undifferentiated capital injections risk entrenching carbon lock-in (Arthur, 1989), recent empirical evidence corroborates this concern. A global assessment of coal phase-out finance found that schemes lacking binding closure covenants diverted funds into life-extension retrofits, thereby prolonging plant operation beyond planned retirement dates (Jakob et al., 2020). Even concessional capital that demonstrably reduces renewable weighted-average costs of capital by up to five percentage points in emerging markets can be misallocated if rigorous asset-screening criteria are absent (Calcaterra et al., 2024). Embedding such asset-level conditionality and competitive allocation principles within transition-finance frameworks is therefore necessary to increase emissions abatement and to shield investors from stranded-asset risk.

Climate materiality refers to the point at which a firm's GHG emissions become material for both the climate system and financial decision-makers. It has become a key criterion for assessing credible transition finance strategies. Empirical evidence indicates that many firms continue to rely on intensity-based targets, which measure emissions relative to economic output, allowing total emissions to rise despite apparent efficiency gains. For instance, a study found that once renewable energy certificates are excluded, companies' scope 2 emissions trajectories lose alignment with the 1.5 °C target, despite favourable intensity metrics (Bjørn et al., 2022). A review of corporate emission targets with 2020 deadlines revealed that nearly 40% were either missed or withdrawn without penalty, revealing a marked accountability gap (Jiang et al., 2025). This discrepancy shows the necessity for absolute emission reduction targets, which set clear limits on total emissions and are directly comparable to global carbon budgets. Financial markets are beginning to price in climate materiality, with higher emissions intensities linked to increased stock-price volatility and widening bond spreads for high-emitting issuers (M. Shi, 2024). To ensure credible effectiveness, transition finance instruments must be anchored in science-based, absolute emission reduction pathways, covering scope 1–3 emissions, and subject to rigorous verification.

If missing climate targets carries only a modest cost, moral hazard emerges. Agency theory posits that if penalties are too weak, agents lack sufficient deterrents and may simply shirk their responsibilities (Eisenhardt, 1989). Embedding conditional incentives into financial instruments can strengthen these deterrents and better align issuer behaviour with long-term transition goals. For example, most sustainability-linked bonds still impose only token penalties: across 427 issues the median coupon step-up is only 25 basis points (Feldhütter et al., 2024), while SLBs simultaneously pay marginally higher baseline coupons than comparable conventional bonds (Oude Lansink & Kapelko, 2025). This

combination of modest step-up penalties and higher baseline rates suggests the penalty structure provides insufficient deterrent effect relative to the cost of shareholder-friendly alternatives such as short-term share buy-backs. Alternatively, sustainability-linked derivatives (SLDs) embed contractual triggers that adjust cash-flows automatically. ISDA's *Sustainability-Linked Derivatives: KPI Guidelines* (2021) together with the *SLD Clause Library* (2024) set out standard clauses that raise the running spread or require a cash payment if a climate KPI is missed. Whether SLD penalties are large enough to alter behaviour remains an open empirical question.

None of these incentives works without solid governance and disclosure. This dimension refers to enforceable investor rights such as covenants, board seats or veto powers, and access to timely, assurance-grade disclosures on climate-related KPIs. Anchored in agency theory, such arrangements curb post-contractual shirking in settings of asymmetric information and long investment horizons (Eisenhardt, 1989) and, by guarding against selective disclosure and the 'greenwash' risks that selective reporting creates, help ensure that reported transition progress is both thorough and credible (Lyon and Montgomery, 2015). From an economic standpoint, strong governance rights reduce transaction costs and moral hazard, enabling more efficient capital allocation. Empirical studies validate this logic. R. Lee and Zakota (2024) find that environmental covenants appear in 54% of contracts of their sample and are added mainly for borrowers with higher environmental risk, showing that lenders deploy these tailored governance rights to keep monitoring costs down and stop risky behaviour, which in turn steers capital towards firms that handle their environmental exposures more responsibly.

Viewed as a framework for scholarly synthesis rather than market prescription, these six dimensions work as an organising compass for a literature that is growing faster than its conceptualisation. The framework links each study to one of the six factors introduced in Table 1.1 (pathway alignment, marginal impact, capex specificity, climate materiality, incentive compatibility, and verifiability and governance), each of which can be read as a testable mechanism. This approach organises diverse findings under clear categories, helps trace areas of agreement, exposes gaps and reveals contradictions. Developed iteratively alongside the empirical work, the compass helped sharpen the analysis in this thesis by revealing how emerging transition-finance instruments can be examined from multiple disciplinary perspectives and how such analysis measures up against the claims being made.

1.1.3 Transition finance barriers and levers

The transition finance literature points to six persistent frictions that constrain capital allocation and identifies corresponding levers that may help to relax them. These six capture distinct stages of the investment chain, from project economics through information provision to institutional readiness, and together they account for the principal reasons capital fails to flow at the required scale: (1) risk–return misalignment, (2) regulatory and policy uncertainty, (3) limited project pipeline, (4) information asymmetries, (5) institutional capacity constraints, and (6) reputational and social risks.

The first and most persistent barrier, return–risk misalignment, stems from the capital structure of many transition assets. Long payback periods (Ameli et al., 2021), regulatory exposure (OECD, 2023), and foreign exchange risks (CPI, 2024b) create return distributions that sit outside institutional mandates. Classic models of credit rationing under asymmetric information (Stiglitz and Weiss, 1981) resonate with this problem: when lenders cannot distinguish between low- and high-risk borrowers, raising interest rates exacerbates adverse selection and moral hazard. As a result, rather than pricing in the risk, lenders ration credit; leading to the denial of financing even for projects with a positive expected value. One lever to overcome these hurdles lies in blended finance structures, whereby concessional public or philanthropic capital assumes first-loss exposure (Flammer et al., 2025; NGFS, 2023a). This reallocates risk in a manner that shifts the risk–return profile of transition assets closer to the efficient frontier for private investors. The impact is magnified when the blended tranche is paired with a well-designed contract for difference (CfD). In particular, a financial CfD linked to a reference index can hedge price risk without conditioning on project output; it does not hedge volume risk. Production-linked CfDs stabilise revenue per MWh but may affect dispatch incentives. The trade-off should be explicit (Schlecht et al., 2024). By stabilising cash flows without muting price signals, such contracts sharpen investment incentives and further narrow the return–risk gap.

However, instruments cannot mitigate risk effectively if the underlying policy environment remains unstable. Regulatory uncertainty over emissions pricing, phase-out mandates or taxonomy criteria has been shown to slow corporate decision-making. It increases investment hurdle rates and ultimately discourages capital from flowing into low-carbon projects (Haas et al., 2023). The real-options literature on irreversible investment (Dixit and Robert S. Pindyck, 1994) formalises this "wait-and-see" effect: under uncertainty, firms rationally delay committing to irreversible projects. As Baldursson and Fehr (2004) demonstrate, under tradable-quota regimes, price volatility exposes firms to risk, prompting risk-averse behaviour and investment deferral. In contrast, emissions taxes offer price certainty, removing this source of risk and thus the incentive to delay.

Providing a stable policy trajectory through long-term carbon price corridors, legislated decarbonisation schedules and consistent reporting obligations reduces the value of waiting to invest. This encourages a stronger and more timely response from the private sector. These interventions resemble public goods, as their benefits extend across all market participants by lowering systemic uncertainty and enabling long-term contracting.

Even in jurisdictions with more stable policy signals, the flow of capital is often bottlenecked by a lack of bankable projects. Real-asset pipeline gaps persist due to insufficient early-stage equity (Meckling et al., 2022), underdeveloped project sponsors (Steffen et al., 2018), and socio-technical barriers to feasibility and permitting (Nacke et al., 2024). This barrier is well-theorised as a market failure involving public information goods. Feasibility studies, engineering plans and impact assessments are necessary for making projects bankable. They often function as public information goods, as they are non-rivalrous and non-excludable. Once produced, their benefits can extend well beyond the original funder (El-Zein and Hedemann, 2016). Japan's Green Transformation (GX) strategy illustrates both the potential and the limitations of government-led pipeline expansion. In response to institutional bottlenecks, the GX Basic Policy (Japan, 2023) directs public investment towards demonstration projects, technology development and feasibility preparation. These activities are often underfunded because they are non-rivalrous and non-excludable in nature. By establishing a dedicated fund and providing tax incentives for low-carbon innovation, the policy attempts to de-risk early-stage project development and attract private finance. However, as Ohta and Barrett (2023) argue, these efforts are constrained by the prevailing techno-institutional complex: funding priorities continue to favour incumbent interests, such as nuclear and hydrogen, over mature renewables, and institutional leadership remains centralised within METI. Thus, while Japan's GX illustrates a pathway to partially overcoming the project preparation gap, its selective approach and limited support for decentralised renewable deployment suggest that its capacity to broadly expand the bankable project pipeline remains contingent on deeper structural reforms.

Alongside physical pipeline constraints, transition finance is frequently hampered by data and reporting deficits. Markets depend on transparent, standardised, and verifiable data to assess issuer credibility and instrument quality. However, divergent emissions accounting methodologies (Jia et al., 2023) and incomplete asset-level disclosures introduce considerable informational frictions. Recent work demonstrates that mandatory carbon disclosure reduces firms' cost of capital, consistent with signalling theory (Xu et al., 2024). Likewise, empirical evidence suggests that ESG ratings divergence obscures comparability and contributes to inefficient pricing (Berg et al., 2022). These frictions can be alleviated through a combination of regulatory and technological solutions. Mandatory

third-party assurance, now embedded in the EU's Corporate Sustainability Reporting Directive (2022), can address inconsistency, while digital MRV (measurement, reporting, verification) platforms enable real-time, tamper-resistant emissions tracking. By turning transparency into a verifiable asset, these interventions transform public-good data deficits into private investable signals.

The institutional architecture of finance itself also imposes binding constraints. Many asset managers and banks face internal resourcing limitations, inflexible mandates, and liquidity rules that discourage exposure to long-duration, transition-linked instruments. These constraints (resourcing, mandate rigidity, and liquidity rules) are not purely technical; they reflect the historic separation between financial performance metrics and sustainability outcomes. Liquidity regulation, for instance, still defines high-quality liquid assets almost entirely by credit-rating and market-liquidity tests (BIS, 2022); because most transition bonds fall outside those parameters, banks must hold them outside the high-quality liquidity assets buffer and fund them with costlier, more stable liabilities, even when their underlying credit risk is modest. Adjusting prudential rules to reflect the systemic value of decarbonisation, alongside targeted capacity-building, is needed. The Network for Greening the Financial System exemplifies this approach, advancing climate-risk integration through standardised scenarios, technical guidance, and supervisory training.

Finally, reputational and social risks form a persistent disincentive to engagement with transition assets or entities, especially in sectors perceived as "brown." Investors seek compensation for the reputational stigma and the risk of stranded assets associated with the sale or relabelling of high-emitting assets that lack credible transition plans. This leads to a measurable carbon-risk premium for carbon-intensive firms (Bolton and Kacperczyk, 2021). This aversion to high-emission investments is further supported by theory: the model developed by Heinkel et al. (2001) suggests that exclusionary preferences by a subset of ethical investors can raise the cost of capital for polluting firms, creating a financial penalty that discourages continued investment in high-emission activities. In contrast, firms that provide credible environmental information may gain a reputational premium. However, recent evidence suggests that this benefit is weakened when disclosures are seen as greenwashing, which can lead to a decline in corporate value (Zhou et al., 2024). Together, these dynamics show the growing financial materiality of corporate environmental behaviour in shaping investor sentiment and capital allocation.

These interventions, which include concessional capital, policy stabilisation, project preparation, data assurance, institutional strengthening and social safeguards, are not sufficient on their own to provide complete solutions. However, each targets a distinct friction that has historically constrained climate-aligned investment. When embedded within a supportive structural environment, their combined application can incrementally

reshape risk–return profiles, improve asset visibility, and expand the investable universe. Rather than relying on coordination per se, effective transition finance depends on addressing these foundational gaps through persistent and differentiated intervention.

1.2 Plans under uncertainty: credible commitment in hard-to-abate sectors

1.2.1 Sectoral pathways and transition uncertainty

Plans reduce the option value of delay by tying management to time-sequenced investments consistent with sectoral pathways. Under policy and technology uncertainty, they function as coordination devices that transform public signals into private capital allocation. While early action can help avoid long lasting environmental harm, emissions reductions often involve sunk costs that create an incentive to delay. In such cases, waiting for better information before committing to costly measures can be a rational strategy (R. S Pindyck, 2021). The dilemma is amplified in industries with long-lived assets (e.g., aircraft, blast furnaces or oceangoing vessels), which risk entrenching carbon-intensive infrastructure for decades. These sectors are especially susceptible to carbon lock-in: a condition in which technological systems and institutions co-evolve in a path-dependent manner, reinforcing incumbent fossil-based technologies and hindering transitions to low-carbon alternatives (Unruh, 2000).

Under such conditions, credible sectoral pathways can function as coordination devices by shaping shared expectations about when technologies will become viable and what forms of policy support are likely to materialise. Grubb et al. (2021) highlight that sector-specific policies and deployment trajectories help align innovation efforts and investment decisions under uncertainty. In parallel, Krabbe et al. (2015) demonstrate how sectoral pathways can be operationalised through methods such as the Sectoral Decarbonisation Approach (SDA), offering a transparent mechanism for setting science-based corporate targets consistent with economy-wide mitigation scenarios.

Sector-level roadmaps translate global carbon budgets into time-sequenced actions. For instance, in aviation, meaningful near-term progress is expected by 2030 through the scaling up of sustainable aviation fuel (SAF) blending and operational improvements. From the 2040s, these measures are projected to transition towards hydrogen propulsion technologies, including liquid hydrogen combustion and fuel cells, with synthetic kerosene providing a bridging option (Tiwari et al., 2024). In steelmaking, early gains from efficiency improvements and scrap-based recycling are expected to transition, by mid-century, to hydrogen-based direct reduction and iron ore electrolysis, supported by carbon capture

and renewable energy (Rumsa et al., 2025). In cement production, early gains from fuel switching and clinker substitution are projected to transition, by mid-century, to large-scale deployment of carbon capture and storage (CCS), with deeper cuts relying on integrated approaches combining CCS and biomass fuels (Cavalett et al., 2024). In shipping, near-term gains from efficiency and drop-in biofuels are expected to give way, from the 2040s, to scalable adoption of ammonia, renewable alcohols and synthetic fuels, with carbon removals enabling near-zero life-cycle emissions by 2050 (Müller-Casseres et al., 2024). Sequencing matters because fuels, infrastructure and technology must co-evolve; premature investment in a single lever risks stranded assets, whereas synchronised deployment can yield network benefits and declining unit costs.

Building on this, the empirical evidence presented in this thesis shows how climate pathways can be systematically integrated into a quantitative framework for assessing transition plans. For instance, in Paper A we develop an association-weighted appraisal that maps pathway levers into disclosure items and weights them by adjusted correlations with short-run intensity changes. The objective is not prediction but an internally consistent, non-expert baseline that is auditable and portable across sectors.

Climate pathways can act as quasi-public goods, structuring expectations and aligning diverse actors by reducing information asymmetries, guiding R&D and investment priorities, and offering reference points for regulatory frameworks such as mandates or carbon pricing (Rosenbloom, 2017; Rosenbloom, 2018). In their absence, planning becomes fragmented and idiosyncratic, raising financing costs, delaying coordination, and impeding collective progress. Although transition strategies often stress broad levers such as fuels, technologies, and operational shifts, modelling frameworks frequently over-homogenise these processes. In reality, energy system transformations are shaped by diverse regional resource endowments, institutional capacities, and policy contexts. As such, pathway alignment must reflect the variation in innovation systems and accommodate differentiated starting points (Grubb et al., 2021).

Incorporating sectoral pathways into transition plans strengthens their credibility and creates the practical conditions necessary for transition finance to operate effectively. By anchoring decarbonisation strategies in recognised, sector-specific trajectories, companies provide financiers with the clarity and comparability needed to assess alignment with global climate goals, differentiate between credible and non-credible transitions, and channel capital accordingly. Sectoral pathways enable consistent interpretation of targets, timelines and technological assumptions, making it possible to structure instruments such as sustainability-linked bonds or transition-labelled finance around measurable progress. In Paper A, we found that many carriers remain some distance from this ideal: only 24% of the sampled airlines disclosed transition targets that had undergone independent

verification, and a mere 26% reported certified sustainable aviation-fuel pathways. These disclosure gaps point to the need for pathway-specific metrics if transition finance is to distinguish credible from merely cosmetic plans. As noted in the IFRS Foundation's guidance on IFRS S2 (2025), disclosures grounded in sectoral context fulfil expectations for material climate-related information and strengthen their decision-usefulness.

1.2.2 Institutional logics and the political economy of planning

Climate-transition planning unfolds in a dense multi-level governance setting where state mandates, voluntary initiatives and soft-law standards interact. Jurisdictions such as the UK have moved to mandate credible 1.5 °C-aligned plans; under the EU's CSRD, transition-plan disclosures are required where material for financial years starting in 2024; Australia and Singapore are phasing in disclosure regimes based on ISSB S2. Brazil and China have signalled steps toward alignment (TPT, 2024). Parallel soft frameworks such as the International Sustainability Standards Board rules for climate-related metrics and the Science Based Targets initiative for target-setting validation rely on reputational incentives and peer pressure rather than legal enforcement. Research on sustainability transitions shows that such hybrid governance architectures can both accelerate and fragment collective action, as firms manage overlapping institutional logics of market competition, regulatory compliance and normative legitimacy (Fuenfschilling and Truffer, 2016).

Within firms, a climate-related transition plan represents the strategic outcome of setting transition goals and planning actions towards a lower-carbon or climate-resilient economy, serving as a signal that shapes internal capital allocation, research priorities and governance structures (IFRS Foundation, 2025). While such plans are intended to steer investment away from high-carbon assets, evidence suggests that public commitments often fail to translate into measurable emissions reductions, revealing a disconnect between strategy and implementation (Coen et al., 2022). Aviation evidence reinforces this pattern. Paper A proposes an association-weighted disclosure score as a baseline alternative to expert-weighted schemes. By design it does not claim causal effects or forecasting power. Component-level associations indicate that implementation-type disclosures carry the strongest empirical signal for short-run intensity changes, whereas governance-only items contribute mainly to credibility signalling. We therefore present the composite score as an auditable, disclosure-based proxy and report component weights to inform future, more structural work when longer panels are available.

In this context, disclosure requirements play a broader role than merely promoting transparency: they help to redefine strategic priorities, influencing which technologies

attract funding and how executive incentives are linked to climate objectives. Translating plans into action increasingly depends on internal mechanisms that reinforce accountability. Firms that embed climate targets into remuneration schemes and apply internal carbon pricing demonstrate stronger alignment between pledges and operational decisions (Berger-Schmitz et al., 2023). Yet credible transition planning requires more than ambition. Sound plans include clear near-term capital expenditures, set measurable interim targets and establish oversight mechanisms to ensure follow-through. These elements have been shown to improve the reliability of corporate net-zero claims (Chan et al., 2024).

Corporate power and contestation lie at the core of transition planning. Decarbonisation pathways shape which technologies attract subsidies, which assets face the risk of premature write-down, and which labour groups are exposed to redundancy. Planning documents often become contested spaces. Incumbent industries use them to protect sunk costs, while civil society groups advocate for stronger emissions reductions. Evidence from oil majors shows a growing disjuncture between climate rhetoric and material commitments: firms have markedly increased their use of net-zero and transition language while continuing to prioritise fossil-fuel investment (M. Li et al., 2022). This discursive shift is paralleled by a political strategy; companies most exposed to climate-policy risk also tend to increase lobbying expenditure, suggesting that advocacy remains central to preserving high-carbon business models (Lantushenko and Schellhorn, 2023).

Including just transition principles in planning adds difficulty but is necessary for securing social licence and lasting political support. Neglecting who bears the costs of decarbonisation invites resistance, as shown by the EU's Just Transition Mechanism, designed to mitigate regional inequality and social pushback (Abram et al., 2022). Political economy models demonstrate that fossil-fuel workers facing uncompensated losses are more likely to oppose climate policy, while credible packages of retraining, direct transfers and local investment expand the scope for negotiated exits (Aklin, 2025). In China, up to 36.9% of the coal power sector's 1.88 million jobs could be at risk by 2045 without early intervention, with coal-dependent cities especially exposed (Yuan et al., 2023). Similar risks apply to oil phase-outs, where poorly sequenced or equity-blind strategies can reinforce structural injustice despite falling extraction volumes (F. Sanchez and Linde, 2023). Embedding strong worker and community provisions from the outset strengthens legitimacy and reduces the likelihood of policy reversal as transition pressures intensify.

For financial markets, transition plans that navigate these institutional dynamics provide two advantages. First, they reduce reputational risk by demonstrating that climate commitments rest on verifiable milestones, rather than on promises that yield delayed or uncertain returns (J. Li et al., 2025). At the same time, the absence of rigorous accountabil-

ity mechanisms enables many companies to quietly revise, delay, or abandon their targets without facing market, media, or reputational consequences. One-third of corporate targets effectively "disappear" from public view, with no penalties for underperformance (Jiang et al., 2025). These dynamics reinforce what Köhler et al. (2019) term "paper plans": climate strategies that comply with disclosure norms while leaving core business models and socio-technical systems largely unchanged.

A core credibility challenge in corporate climate reporting lies in the inconsistency of emissions data. While Scope 1 emissions are relatively consistent across commercial datasets, reliability declines for Scope 2 and drops sharply for Scope 3 (Busch et al., 2022). Estimation models often diverge: ISS Scope 3 figures align with Bloomberg or Refinitiv in none of the cases tested within a 1 percent range, with correlations around 55 percent and mean errors exceeding 100 percent (Nguyen et al., 2023). Even reported Scope 3 data from Bloomberg and Refinitiv match only 68% of the time. This matters because Scope 3 typically accounts for over 75% of corporate emissions (Hadziosmanovic et al., 2022). Yet companies often disclose only a few, low-materiality categories (Nguyen et al., 2023). Despite such uncertainty, ESG ratings rarely reflect it. Agency scores correlate weakly (average 0.54), with differences driven largely by divergent methodologies (Berg et al., 2022). Ratings also respond more to governance disclosures than to real emissions cuts (Tayan et al., 2022), reinforcing the need for transparent, standardised and verifiable carbon metrics. Applying a partial-correlation approach in Paper A, we show that the apparent association between transition plan disclosures and emissions intensity weakens once operational variables such as fleet age and passenger load are taken into account, unless disclosure data are consistently normalised across firms.

To sum up, literature converges on four core design principles for credible corporate climate transition plans. First, near-term targets are needed: interim emissions budgets aligned with sectoral decarbonisation pathways, typically spanning no more than five years, are more credible than back-loaded pledges, as they mitigate reliance on future carbon removals and reduce delivery risk (e.g., TPT, 2023b). Second, alignment of capital expenditure with climate targets is a key marker of commitment and transparency, especially when tracked against Paris-aligned pathways (IIGCC, 2023). Third, interim checkpoints such as milestone reviews, sustainability-linked debt covenants and executive remuneration tied to climate performance help convert medium-term uncertainty into staged accountability (EU Platform on Sustainable Finance, 2025). Fourth, governance transparency, through board-level climate committees, independent assurance of climate data and stakeholder engagement, reduces ambiguity and strengthens the credibility of corporate climate commitments (Morrison et al., 2025). Such mechanisms are increasingly expected by investors and regulators to ensure that sustainability strategies are enforceable

rather than merely aspirational (Abdullah et al., 2024).

Empirical evidence from the airline industry in Paper A therefore affirm, and extend, the four design principles outlined above. A quantitative framework that pairs sectoral pathways with empirically weighted disclosure indicators can identify the plan components most closely associated with near-term emissions performance while remaining adaptable as new evidence emerges. By demonstrating the feasibility of this approach in a sector characterised by long-lived assets and fragmented regulation, we provide a transferable template for assessing transition-plan credibility in other hard-to-abate industries, thereby moving the literature beyond conceptual prescriptions towards operational, sector-tailored evaluation.

1.3 Metrics: decision-usefulness, assurance and data infrastructure

1.3.1 Reframing metrics: from carbon foot-printing to capital discipline

Metrics moved from legitimacy to capital discipline as investors began to require indicators that support cost-effective control, capital budgeting and compliance with policy instruments. In the 1990s, corporate GHG reporting was mainly a tool for reputational legitimacy rather than strategic transformation. Carbon disclosure functioned as a transparency exercise, a passive reflection of externalities, anchored in legitimacy theory, which frames such reporting as a means to maintain societal approval (Bazhair et al., 2022). Over the past decade, the role of sustainability metrics has shifted. They are now used by investors to assess environmental risks and opportunities, directing capital towards more sustainable assets (OECD, 2025). Backward-looking emissions data no longer suffice. Investors increasingly look for forward-looking indicators that account for firms' transition strategies, risks, and future viability (Robeco, 2024). As noted in recent climate finance research, frameworks based solely on historical data risk underestimating climate-related risks, and forward-looking assessments are needed for aligning investments with net-zero goals (Gasparini et al., 2024). Sustainability metrics have thus moved from the periphery of voluntary reporting to the core of financial analysis and capital allocation.

A clearer taxonomy of climate transition metrics is needed, as they can fall into three functional families: risk-linked, alignment-linked, and impact-linked. In the framework adopted here, risk-linked metrics quantify how climate hazards translate into financial risk, often via portfolio volatility. For instance, Dietz et al. (2016) estimate that under a business-as-usual trajectory, climate change could reduce global financial asset values by up to 16.9% in the worst case. Bolton and Kacperczyk (2021) find that firms with

higher carbon emissions tend to earn higher equity returns, suggesting investors require compensation for transition risk. A more targeted measure is carbon beta (Huij et al., 2024), which captures stock return sensitivity to a pollutive-minus-clean portfolio, revealing that high-carbon-beta stocks underperform when climate news intensity rises. Carbon tail risk (Ilhan et al., 2021), derived from equity options, indicates that carbon-intensive firms are more exposed to downside risk, especially during spikes in public climate attention. Second, alignment-linked metrics, by contrast, track the distance between a company or portfolio's emissions trajectory and science-based temperature pathways. These include implied temperature scores, which translate a firm's projected emissions into a warming estimate, and capital alignment ratios, which compare the proportion of capital aligned with 1.5 °C pathways to that which is misaligned (Team, 2021). Third, impact-linked metrics aim to measure real-economy outcomes. Early work on adaptation uses an input–output–outcome–impact chain to track results, helping map financial flows to societal benefits and reducing risks of "selective impact" (Leiter et al., 2019; Mullan and Ranger, 2022). For example, Xie et al. (2023) show that decarbonising the US power system can create new jobs but may leave low-skilled workers vulnerable, while Reay (2024) notes that unless workforce inequalities are addressed, the net-zero transition could entrench social disparities. Capturing such labour and equity dimensions through just-transition indicators ensures that financial decisions generate both environmental and social value.

As metrics diversify, a fragmented standard-setting field seeks coherence. The International Sustainability Standards Board's IFRS S2 standard (issued June 2023) requires entities to disclose climate-related risks and opportunities that could affect cash flows, access to finance or the cost of capital, including governance, strategy, risk management and metrics and targets (IFRS, 2023). In the European Union, the Sustainable Finance Disclosure Regulation obliges financial-market participants with more than 500 employees either to disclose principal adverse impacts on sustainability factors or to explain why they do not (EBA, ESMA and EIOPA, 2024); the Corporate Sustainability Reporting Directive embeds a double-materiality perspective by requiring companies to report both on how sustainability issues affect financial performance and on how their activities impact society and the environment (Adams et al., 2021). Although the convergence is partial (e.g., IFRS S2 focuses on enterprise value while EU rules emphasise societal impact), the trend is unmistakable: disclosure once deemed voluntary is becoming a fiduciary expectation, and metrics are shifting from "nice-to-have" to indispensable tools for managing transition risk, alignment and impact.

Underlying these frameworks is a rapidly evolving data infrastructure. Asset-level repositories (e.g., Climate TRACE, 2025) enable bottom-up footprint estimation and challenge the dominance of proprietary vendor models. Satellite imagery, remote sensing

and digital measurement-reporting-verification platforms now provide near-real-time emissions data. For instance, near-real-time datasets can compile hourly or daily power-generation data for 37 countries and can be updated with a latency of between one day and one month (Zhu et al., 2023). The use of big data from remote-sensing technologies and smart devices is changing emission compilation methods, allowing near-real-time estimates that address long-standing reporting delays (Guevara et al., 2023). Yet, asymmetries persist: smaller investors and civil society actors often lack access to high-resolution data, and the methodologies behind many commercial ESG scores remain opaque, a problem compounded by the low inter-rater agreement documented in Section 2.3 (Berg et al., 2022). Without transparent data pipelines, the allocative potential of sophisticated metrics risks being captured by information gatekeepers.

Taken together, these developments mark a decisive shift: sustainability metrics are no longer static disclosures but evolving instruments of capital discipline. They inform risk premia, steer research-and-development budgets, and shape executive incentives.

1.3.2 Why metrics miss the mark: cognitive, structural and sectoral constraints

The expansion of sustainability indicators has not translated into commensurate gains in decision-usefulness. Metric proliferation is a primary culprit. As firms respond simultaneously to the International Sustainability Standards Board baseline, the EU's emerging double-materiality requirements and a crowded field of voluntary scorecards, they produce disclosure sets that satisfy multiple audiences but dilute signal-to-noise ratios. Chatterji et al. (2016) show that commercial CSR ratings from different providers barely converge; even after aligning measurement scopes and weightings, correlations remain low, which implies measurement error and potential misallocation of capital. Earlier work found that environmental ratings summarise past pollution but do not reliably predict future violations (Chatterji et al., 2009). Subsequent studies suggest that inconsistent ratings impose costs on firms: Christensen et al. (2021) report that greater ESG disclosure increases rating disagreement and that higher disagreement is associated with higher return volatility and a lower probability of issuing external finance. Gibson Brandon et al. (2021) similarly find that stock returns are positively related to ESG rating disagreement; investors demand a risk premium when disagreement is high.

Even when reporting frameworks converge, behavioural and organisational biases hinder effective use. Simon (1955)'s behavioural model of rational choice emphasised that decision-makers face bounded rationality and must simplify complex environments using heuristics. In a metric-dense context, such simplification can lead to "indicator myopia", where managers focus on the most visible or compensable key performance indicators.

This reflects a broader dynamic observed in economics: when statistical patterns are turned into control targets, they often lose their reliability (Goodhart, 1984). These behavioural dynamics help explain why sustainability managers may chase disclosure scores rather than tackling complex decarbonisation challenges. Compounding this problem is the inconsistency of carbon data across providers, especially for Scope 2 and 3 emissions, as discussed in Section 2.3 (Busch et al., 2022).

Generic metrics are especially ill-suited to hard-to-abate industries. The Bank for International Settlements notes that emissions-intensity ratios are intuitive but have important shortcomings. For instance, intensity measures do not indicate whether a firm is lowering its absolute emissions because higher revenues or pricing changes can reduce intensity without any change in operational emissions (Jegarasasingam, 2025). Consequently, intensity benchmarks may reward firms that cut production or raise prices while penalising those investing in capital-intensive decarbonisation projects. Chenet et al. (2021) argue that reliance on market-based risk disclosures and scenario analysis is limited because climate-related financial risks are characterised by radical uncertainty and cannot be fully priced.

Another tension lies in the credibility–comparability trade-off. Harmonised, easy-to-audit metrics support benchmarking but risk obscuring heterogeneity in firm strategies and supply-chain exposures. Jegarasasingam (2025) warns that intensity metrics can be distorted by currency or price effects and should not be interpreted as evidence of actual decarbonisation.

Data asymmetries and proprietary barriers further limit the effectiveness of advanced metrics. Open geospatial data can yield asset-level environmental insights but remains unevenly accessible. Intergovernmental organisations and NGOs often restrict such data for commercial use or lack the resources to generate high-frequency datasets, leaving private providers to bridge these gaps (WWF, World Bank and Global Canopy, 2022). This uneven access can entrench information advantages for large investors who can afford premium feeds, leaving smaller institutions reliant on delayed or modelled estimates and potentially exacerbating regulatory arbitrage.

Collectively, these cognitive, structural and sectoral constraints explain why many target-focused frameworks fail to drive capital reallocation at the speed implied by climate science. Recognising these shortfalls is important for developing practitioner-led innovations (e.g., smart KPIs, logic-model tracking and valuation integration) that seek to restore the link between measurement and material progress.

1.3.3 Closing the performance gap: practitioner insights and emerging fixes

In Paper B, we present survey evidence from finance professionals that reveals the persistent limitations of transition-finance metrics. In particular, we find that indicators tied to absolute emissions reduction and low-carbon innovation are considered most decision-useful, yet these same metrics suffer from the greatest data deficits. Similar patterns emerge in broader literature, with Amel-Zadeh & Serafeim (2018) showing that institutional investors cite poor reliability and comparability as major impediments to using ESG data effectively. Conversely, headline figures such as portfolio carbon intensity are judged only moderately helpful for capital allocation. Recent reviews of machine-learning methods in climate finance note that forward-looking metrics require large volumes of high-quality data, yet data availability, reliability and granularity remain considerable obstacles (UNEP FI, 2024). The paradox, that the most valued metrics are also the most data-poor, suggests the gap is structural rather than merely technical.

In Paper B, when we mapped against the structural barriers (return–risk misalignment, policy uncertainty, project-pipeline gaps, data asymmetry, institutional-capacity limits and reputational risk) most widely used transition-finance metrics address only a subset of constraints. This finding aligns with evidence suggesting that traditional financed-emissions and temperature-alignment metrics are heterogeneous and often backward-looking; they reveal carbon exposure but say little about pipeline gaps or just-transition risks (Bingler et al., 2022). This fragmentation further helps explain why disclosures frequently fall short of translating into disciplined capital flows.

A wave of smarter key performance indicators is beginning to address these shortcomings. A systematic review of machine-learning applications in climate finance shows that AI-enhanced metrics can integrate satellite data, sectoral pathways and policy scenarios to produce adaptive baselines and early-warning thresholds (Alonso-Robisco et al., 2023). A more recent study similarly argues that high-resolution satellite data provide objective, real-time information on land use and deforestation, improving the timeliness and credibility of climate-risk analytics (Alonso-Robisco et al., 2025). These developments point toward adaptive carbon budgets that automatically adjust as technology costs or regulatory timelines shift.

Complementing smart KPIs is logic-model integration. A monitoring framework developed by the FAO for national development banks outlines how mitigation, adaptation and resilience indicators can be structured using input–output–outcome chains to track climate-finance effectiveness (Bockel and Vian, 2016). This approach helps financial institutions clarify how disbursements (inputs) support specific project outputs and ultimately deliver measurable climate outcomes, closing the gap between financial intent and real-economy decarbonisation.

Looking ahead, research agendas converge around four emerging priorities. First is the integration of climate metrics into valuation frameworks as we did in Paper C, where financial terms are directly tied to decarbonisation performance. Studies emphasise that externally assured and governance-aligned metrics strengthen market credibility and improve capital allocation incentives (Haq and Doumbia, 2022). Second is the inclusion of social KPIs capable of tracking labour and equity impacts, which remain under-reported in standard disclosures (IFC, 2023). Third is the development of indicators capable of informing sovereign-bond pricing (Flugge et al., 2021). Fourth is the promotion of open-data protocols. Ensuring open, interoperable access to high-resolution emissions and physical-risk data is key to overcoming market-power imbalances and supporting equal opportunity in climate risk assessment (UNDRR and CGFI, 2022).

These emerging research priorities closely mirror the results from Paper B, which demonstrates that practitioners working within institutions that have partially or fully implemented transition or adaptation plans tend to express greater scepticism toward widely used transition-finance metrics. This inverse relationship suggests that standardised metrics may fail to capture the organisational complexity required to steer real-economy decarbonisation. By aligning smarter, context-rich metrics with credible transition plans (Section 2.2) and with incentive-consistent valuation and pricing instruments (Section 2.4), transition finance can move beyond compliance, evolving into a discipline that materially advances net-zero outcomes.

1.4 Valuation and pricing: from climate risk to transition instruments

1.4.1 Why climate risk should be priced: carbon premia and stranded-asset risk

Valuation and pricing are related but distinct. Valuation is a theoretical exercise: estimating an instrument's intrinsic worth by modelling expected cash flows, default probabilities, and discount rates. Pricing is market-driven: what buyers and sellers actually transact at, shaped by supply and demand, liquidity, and relative value. In liquid, efficient markets the two converge; for illiquid or complex credits, such as sustainability-linked bonds, they can diverge materially, and that divergence is where analytical insight matters most. Climate transition finance relies on capital markets to channel investment towards the low-carbon transition, and both valuation frameworks and market pricing mechanisms determine whether that allocation is efficient. Asset-pricing research increasingly recognises climate change as a priced risk factor. Engle et al. (2020) construct climate-news indices from newspapers and build dynamic mimicking portfolios that hedge innovations in that news,

showing how standard tools can manage climate risk. Bansal et al. (2016) augment long-run risks models with temperature dynamics and show that temperature risks command positive premia. Policy-tipping models demonstrate that abrupt regulatory shifts can strand reserves and capital (van der Ploeg & Rezai, 2020). Together, these frameworks underpin valuation of transition instruments such as SLBs, the focus of Paper C, whose pay-offs are explicitly tied to climate performance.

Empirical evidence across asset classes shows that climate risks are priced, shaping the cost of capital for the transition. In equities, carbon-intensive firms earn higher returns, consistent with a carbon premium (Bolton and Kacperczyk, 2021). Reinforcing this, temperature risk carries positive premia and depresses equity valuations in a long-run risks framework (Bansal et al., 2016). In credit, banks charge higher spreads to firms with larger fossil-fuel reserves, especially post-2015 and for longer maturities (Delis et al., 2024). Fixed income shows a modest greenium at issuance for green bonds, typically a few basis points (Caramichael and Rapp, 2024), though this premium may reflect investor demand for labelled instruments rather than a direct pricing of transition risk. These patterns demonstrate that investors already respond to climate risk in ways directly relevant for valuing SLBs in climate transition finance, setting the stage for the modelling approach in Paper C.

The repricing of climate risk unfolds through several channels that also shape capital flows in climate transition finance. First, policy announcements can trigger immediate market adjustments: for example, changes in the perceived likelihood of the U.S. Inflation Reduction Act passing prior to its enactment caused valuations of high- and low-emission firms to move sharply in opposite directions, reflecting sector-specific transition exposures (Bauer et al., 2023). Legal action is another catalyst: climate-related lawsuits lead to statistically significant declines in defendant share prices, with average abnormal returns of -0.41% for filings or negative decisions, and effects exceeding -1.5% for major emitters (Sato et al., 2024). Shifts in investor sentiment, amplified by media and online discourse, can accelerate or reverse revaluations (Santi, 2023). Commodity markets react in parallel: greater perceived probability of stringent climate policy depresses fossil-fuel futures prices, consistent with the "green paradox" mechanism (Norman and Schlenker, 2024). For SLBs, including those examined in Paper C, such shocks alter the perceived probability of meeting sustainability performance targets (SPTs), directly influencing the contingent cash-flow component of their valuation.

Regulatory and supervisory measures are embedding climate risk into present valuations, reinforcing its influence in transition finance. The Network for Greening the Financial System has developed scenarios for climate-related financial risks under different transition pathways, now widely applied by financial institutions (Holden et al., 2024). In

2022, the European Central Bank conducted its first climate-risk stress test, covering 104 significant institutions, and found that over 60% of their non-financial corporate interest income derives from the 22 most greenhouse-gas-intensive sectors (ECB, 2022). The exercise revealed large data gaps, limited integration of climate risk into credit risk models, and a need for sounder long-term strategies, but it also acted as a catalyst for improving governance, customer engagement, and scenario analysis. By requiring institutions to evaluate climate exposures at defined future dates and disclose the results, these initiatives effectively shorten the horizon over which transition and physical risks enter pricing, mirroring the time-bound nature of SLBs. This regulatory context makes forward-looking performance assessments central, a principle at the core of the valuation framework developed in Paper C.

Taken together, advances in theory, empirical evidence, observed market transmission channels and evolving supervisory frameworks make clear that climate risk is no longer peripheral to asset valuation; it is a core determinant of capital flows in the low-carbon transition. SLBs crystallise these dynamics: their value depends not only on conventional credit risk but also on the probability of meeting climate-related performance targets, effectively embedding transition risk into contractual cash flows. By clarifying how climate premia emerge, propagate and intensify under market and regulatory forces, this section sets the stage for the analytical framework in Paper C, which applies stochastic climate-risk modelling to assess SLB valuation and its role in mobilising climate transition finance. The evidence above operates across both dimensions introduced at the start of this section: theoretical frameworks identify climate premia (valuation), while market data confirm that investors transact on these premia (pricing). For SLBs, the divergence between the two is especially pronounced, motivating the modelling approach in Paper C.

1.4.2 Where current valuation models fall short

Although the evidence reviewed above demonstrates that climate risk is increasingly recognised as a priced factor, translating these insights into rigorous valuation practice remains challenging. Most valuation practice still relies on toolkits designed for near-stationary environments, such as discounted-cash-flow playbooks, Value-at-Risk spreadsheets, and single-run stress tests. These approaches can misstate forward risk in a transition shaped by path-dependent policy tightening and non-linear technology diffusion (Battiston et al., 2017). Standard net-present-value exercises typically assume a single, deterministic carbon-price path, even though policy tends to arrive in lumpy, uncertain steps and interacts with both risk premia and discount rates. Asset-pricing research shows that policy events and climate news can shift expected returns and correlations, with the effects strongest under

high uncertainty (Giglio et al., 2021; L. Pástor and Veronesi, 2012; Ľ. Pástor and Veronesi, 2013). Yet many scenario-based studies, including, in their empirical applications, Battiston et al. (2017) and Dietz et al. (2016), continue to impose smoothly rising carbon prices, overlooking the stochastic and compounding effects of sequential shocks, a dynamic that can leave long-lived assets facing convex downside risk.

Even when carbon premia are acknowledged, applying a uniform "brown discount" obscures important sector-specific constraints and heterogeneous exposures. Option-implied measures show that downside carbon tail risk varies widely across firms and industries, with some sectors facing significantly higher probabilities of extreme losses than others (Ilhan et al., 2021). Cross-sectional return evidence further indicates that firms with higher absolute emissions tend to earn higher expected returns, consistent with a priced carbon risk factor rather than a flat penalty (Bolton and Kacperczyk, 2021). At the portfolio level, hedging strategies based on climate news reveal that sector responses are uneven: shocks can raise expected returns in some industries while lowering them in others (Engle et al., 2020). Treating all carbon-intensive assets as if they carry identical risk premia ignores this heterogeneity, which in turn weakens the precision of capital-allocation signals (L. Pástor et al., 2022).

Data and model limitations further weaken current valuation practices. ESG indicators are often noisy and inconsistent across data providers, complicating measurement, back-testing, and model validation (Berg et al., 2022). Widely used integrated assessment models typically hard-code key parameters such as discount rates, damage functions, and policy paths, creating an illusion of precision while masking deep uncertainty. In reality, these models are highly sensitive to contested assumptions and are ill-equipped to capture the fat-tailed risk profile of climate damages, where the likelihood of catastrophic outcomes is materially higher than Gaussian models imply (R. S Pindyck, 2021; Weitzman, 2009). These models also omit endogenous technology responses, despite theoretical evidence that policy-driven directed technical change can materially shift cost curves, innovation patterns, and expected returns (Acemoglu et al., 2012).

Behavioural and market-microstructure effects add another layer of complexity to climate-risk valuation. Large inflows into sustainable funds can mechanically compress the yields of green assets, lowering their *ex ante* expected returns. Paradoxically, green assets may still realise high returns in the short run, but these gains are typically concentrated in periods of unexpectedly heightened environmental concerns or shifts in investor preferences, reflecting unanticipated demand shocks rather than a persistent risk premium (L. Pástor et al., 2022). In fixed-income markets, the observed "greenium", the yield discount on green bonds relative to comparable conventional bonds, reflects a combination of investor preference effects and liquidity differences (Zerbib, 2019).

Event-study evidence further suggests that part of the greenium may be explained by issuer-level commitments and signalling effects (Flammer, 2021). Without disentangling these components, the green label can obscure the underlying exposure to transition risk, reducing the informational value of prices for capital allocation.

Finally, what might be called the "dashboard problem", the tendency for scenario dashboards to convey false precision, looms large: exogenous, static scenarios can encourage false confidence in point estimates even though model uncertainty and tail risks dominate at long horizons (R. S Pindyck, 2021; Weitzman, 2009). Without adaptive models that update as social, technological and political feedbacks unfold, the current toolkit remains misaligned with a system characterised by deep uncertainty and endogenous transition dynamics. Recognising these gaps sets the stage for the approach in Paper C, which develops an adaptive, credibility-sensitive valuation framework explicitly designed for the stochastic, sector-heterogeneous and belief-driven nature of transition finance.

1.4.3 Towards dynamic, credibility-sensitive valuation frameworks

To address these shortcomings, recent climate-finance modelling has shifted from static, single-path valuations toward frameworks that embed stochastic climate-risk factors directly in the stochastic discount factor (SDF). One approach incorporates news-based climate shocks that move the SDF through priced, risk-manageable factors, as demonstrated by Engle et al. (2020). Another channel emphasises preference- and model-uncertainty effects, which make discount rates state- and belief-dependent; Barnett et al. (2020) show that accounting for ambiguity aversion in climate models can magnify the social cost of carbon by a factor of two or more. A third strand uses intensity-based hazard models, allowing default and jump risks to vary across regimes, following the credit-risk modelling of Duffie and Lando (2001). Empirically, carbon premia vary widely across firms and sectors (Bolton and Kacperczyk, 2021), and survey evidence confirms that climate risk is priced across multiple asset classes (Giglio et al., 2021).

SLBs provide a natural proving ground for dynamic, option-consistent credit valuation frameworks. Their coupon step-ups, activated when issuers fail to meet pre-defined SPTs, create contingent cash flows whose value depends on the probability of failure, its correlation with underlying cash-flow risk, and investor risk aversion; the same structural logic behind reduced-form credit models (Duffie and Singleton, 1999). Large-sample evidence from Feldhütter et al. (2024) shows that SLB pricing is highly sensitive to penalty size: most step-ups are 25 bps (occasionally 50 bps), the ESG label itself commands only a modest 1–2 bps premium ("sustainium"), and market-implied target-miss probabilities average 14–39 % depending on KPI assumptions. Prices are generally consistent with

fundamentals, but the prevalence of low penalties, especially in hard-to-abate sectors, limits the incentive effect. In these contexts, larger, outcome-salient penalties could exert greater influence on spreads and strengthen the link between climate-transition credibility and financing costs.

Building on reduced-form credit models (Duffie and Lando, 2001), credibility and the quality of sustainability performance targets (SPTs) can be formalised as state variables that influence default intensities and recovery rates under incomplete information. In such a setting, investors update beliefs as issuers meet or miss interim checkpoints, leading to spread tightening when credibility improves and widening when doubts emerge. This mechanism aligns with survey evidence showing institutional investors price both disclosure quality and carbon risk (Krueger et al., 2020). Option-implied measures of downside carbon risk confirm higher tail-risk premia for carbon-intensive firms, especially when climate attention spikes (Ilhan et al., 2021). Together, these findings underline the case for incorporating credibility-sensitive dynamics into SLB valuation, as developed in Paper C.

These principles extend beyond SLBs to other contingent-payoff instruments. For example, catastrophe bonds transfer extreme event risk to capital markets, with payouts linked to pre-defined triggers such as windspeed thresholds. Like SLBs, these instruments require valuation models that can accommodate state-contingent payoffs, but unlike SLBs they do not embed issuer credibility as a risk dimension (Froot, 2001). In sovereign debt markets, climate risk is also priced: vulnerability to climate change is associated with higher borrowing costs, whereas greater resilience reduces spreads, with these effects being especially pronounced in developing economies (Beirne et al., 2021; Cevik and Jalles, 2022). Yet SLBs occupy a distinct position at the intersection of fixed-income pricing, climate-risk factor modelling and credibility assessment, making them uniquely suited to operationalise this agenda. Paper C implements a stochastic-volatility credit-risk model with embedded climate-risk factors and belief updating to quantify how market and regulatory shocks feed into SLB spreads, offering an empirically grounded tool for valuing climate transition finance.

2

Climate Transition Plans' Assessment in Hard-to-Abate Sectors: Evidence from Airlines

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As industries navigate the transition to net-zero emissions, aviation faces unique challenges balancing growth with decarbonisation. Air travel demand is set to triple by mid-century, yet credible plans and robust assessment tools remain scarce. This study introduces a correlation-based scoring framework evaluating transition plans using data from 84 airlines, representing 75% of industry emissions. Key plan components (foundations, implementation, engagement, governance, and metrics) were coded into binary indicators and weighted by their adjusted association with short-term carbon performance, using stratification and partial-correlation adjustments for fleet age and passenger load. Results indicate that implementation-type disclosures carry the strongest associational signal for lower near-term intensity; governance items contribute primarily as credibility signals in disclosure. The framework is a scalable, disclosure-based baseline that can complement expert-assessment schemes and provide auditable inputs for regulators and investors, without asserting causal effects. (JEL Q54, L93, Q58, D22)

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2.1 Introduction

As the global community intensifies efforts to reach net-zero emissions, industries that rely heavily on fossil fuels face a triple challenge. They must meet growing demand, manage technological uncertainty and respond to mounting pressure to decarbonise. The aviation industry exemplifies these tensions. With air travel demand projected to triple by mid-century (ATAG, 2021), current low-carbon propulsion technologies remain technologically immature, and airlines must simultaneously address their significant non-CO_2 climate impacts (Brazzola et al., 2022; Dray et al., 2022; D. S. Lee et al., 2021). In response, aviation companies are increasingly developing and disclosing climate transition plans (CTPs) to align with the Paris Agreement's objectives (NGFS, 2023b). However, the credibility and efficacy of these plans remain uncertain, particularly in a sector characterised by fragmented regulation, long asset lifecycles, and uncertain technological pathways.

Recent assessments indicate that while nearly 22% of organisations reported having a climate transition plan in 2022, only about 0.01% fully complied with all reporting indicators (CDP, 2023a). This discrepancy underscores a critical gap: existing frameworks often rely on expert judgement or sector-agnostic benchmarks that fall short of capturing whether sector-specific high-level commitments translate into tangible emissions reductions. In aviation, as in other hard-to-abate sectors such as heavy-duty trucking, shipping and steel, there is a pressing need for transparent and data-driven tools to evaluate the actual impact of disclosed strategies.

This paper introduces a novel, correlation-based scoring framework that quantitatively evaluates the credibility of airlines' CTPs by linking specific plan components to short-term carbon performance. Since transition planning is still an emerging and largely voluntary practice, long-term assessments remain unfeasible due to limited historical data. Our approach uses empirically derived weights to evaluate key elements such as foundational emissions targets, implementation measures like the use of sustainable aviation fuels and new aircraft technologies, stakeholder engagement and governance practices. This provides a replicable and objective alternative to other forms of assessment.

At the core of our methodology is a structured questionnaire that evaluates 12 critical sub-elements of a transition plan derived from the revision of science-based climate pathways for the aviation sector. For each sub-element, we derive weights based on their statistical association with short-term carbon performance, measured as the proportional change in emissions intensity (CO_2 per revenue passenger-kilometre). Recognising that operational factors such as fleet age and passenger load influence emissions performance, we refine our estimates using both stratification and partial correlation techniques to

estimate the unique association of each transition plan component. Data from 84 airlines, representing approximately 75% of global aviation emissions (CAPA and Envest, 2024), underpin the analysis. Rigorous cross-validation and bootstrapping confirm that the weight estimates are stable and robust across different subsamples, ensuring the reliability and replicability of the scoring system.

The results highlight that implementation measures, particularly investments in advanced, fuel-efficient aircraft technology, have the strongest association with emissions performance. Clear foundational targets and robust governance mechanisms, including independent third-party verification, are also strongly associated with lower short-term emissions intensity. Despite these strengths, disclosure gaps persist, particularly in areas such as sustainable aviation fuel (SAF) certification and external validation of climate targets.

When compared to existing assessment frameworks such as ACT and TPI, our approach offers several advantages. Rather than relying solely on expert judgement, we derive weights empirically from emissions data, minimising subjectivity and enhancing transparency. By explicitly accounting for operational confounders, the framework aims to reduce the risk that score differences reflect structural disparities among airlines rather than genuine differences in strategic ambition. This quantitative approach not only provides a replicable methodology for evaluating CTPs in the airlines industry but also offers a transferable model for other hard-to-abate sectors facing similar decarbonisation challenges.

Despite its strengths, the study has some limitations. The binary classification of transition plan elements, while necessary for comparability, may oversimplify nuanced strategies. Self-reported data also introduce the potential for incomplete or exaggerated claims. Additionally, the emphasis on short-term emissions performance might not fully capture long-term decarbonisation pathways, particularly given the evolving technological and regulatory landscape. Addressing these challenges will require the integration of more granular qualitative data, longitudinal analysis, and refinements to improve the framework's applicability across different sectors.

The remainder of the paper reviews climate pathways and reporting standards relevant to aviation, outlines the methodology used to develop the assessment framework, presents empirical findings, and compares the results with existing evaluation methods. It concludes by discussing key insights, limitations, and policy implications, as well as future directions for improving the assessment of climate transition plans in hard-to-abate industries.

2.2 Climate Pathways and Reporting Standards

2.2.1 Sectoral climate pathways and key transition levers

A climate pathway refers to a strategic trajectory outlining measures and milestones required to achieve specific emissions reduction goals over time (UNFCCC, 2024a). Our analysis of four global climate pathways for the aviation sector, summarised in Figure 1, incorporates four key climate pathways: the International Energy Agency's (IEA) Net Zero by 2050 Roadmap (IEA, 2021; IEA, 2022), the Mission Possible Partnership's (MPP, 2022) prudent scenario, the One Earth Climate Model (OECM) 2.0 (S. (Teske, 2019; S. Teske et al., 2022; UTS, 2022), and the International Civil Aviation Organization's (ICAO, 2022b) Long-Term Aspirational Goal (LTAG).

Each pathway takes a unique approach to achieving carbon neutrality but aligns on key aspects. All climate pathways underscore three transition levers for aviation decarbonisation: fuels, technology, and operations, each built on distinct strategies and assumptions. The ICAO scenario covers the narrowest scope, focusing exclusively on international aviation and leveraging offsets, while the IEA outlines a more gradual approach encompassing both domestic and international aviation. All scenarios prioritise advanced technologies, operational efficiencies, and SAFs (including bioenergy and synthetic fuels). Operational improvements deliver near-term emissions reductions, while the long-term success of bio- and synthetic fuels, as illustrated in the OECM and IEA models, hinges on significant renewable energy inputs and infrastructure expansion. Despite varying decarbonisation rates, all pathways concur that tackling residual emissions in hard-to-abate sectors and reducing reliance on oil will require a blend of innovative aircraft technologies, optimised operations, and scalable low-carbon fuel production to achieve net-zero emissions by 2050.

A more comprehensive analysis of climate pathways, as outlined in Table 1, provides a structured approach for understanding the aviation sector's requirements in pursuing decarbonisation targets. In an era where timely and effective climate action is critical, focusing on these key aspects ensures that transition plans are both aligned with global objectives and tailored to the sector’s unique challenges, such as high energy demands and complex supply chains. This focused analysis not only enhances the relevance and urgency of the aviation industry's efforts but also offers a transferable model for other hard-to-abate sectors. By identifying and distilling the essential levers for climate transition, standard setters and regulators can develop robust and actionable plans that drive sustainable progress, setting a precedent for industries facing similar decarbonisation obstacles.

GHG scopes, types and temperature alignment. The differing GHG scopes and

timelines across these pathways highlight the need for airlines to address both direct and indirect emissions to meet climate goals. Notably, the IEA, MPP, and OECM pathways include aviation's Scope 1, 2, and 3 emissions, whereas ICAO focuses exclusively on Scopes 1 and 2, leaving a critical gap in addressing upstream emissions from suppliers and manufacturers. This limited focus risks underestimating the significant contribution of indirect emissions to the sector's overall climate impact.

Furthermore, while the IEA, MPP, and OECM pathways aim for net-zero by 2050, ICAO extends its timeline to 2070, diminishing the urgency for immediate measures such as fleet modernisation and infrastructure improvements. Another key challenge is the insufficient attention to non-CO_2 emissions, including contrails and nitrogen oxides, which are substantial contributors to aviation's warming potential (CAT, 2022; Grewe et al., 2021; IPCC, 1999). An important consideration for airlines' transition planning is that emerging regulations may increasingly expand to address non-CO_2 impacts and full supply-chain (e.g., European Commission, 2024). These evolving regulatory pressures are also likely to influence global route networks and hub strategies, as carriers assess environmental compliance costs and operational constraints across regions with differing policy stringency.

All pathways ultimately aim for the net-zero goal, but their projected residual emissions by 2050 and alignment with the 1.5°C target vary significantly, presenting airlines with operational and strategic challenges. For instance, the OECM pathway anticipates zero residual emissions by mid-century, while the IEA, MPP, and ICAO estimate remaining emissions of 0.14–0.23 Gt CO_2. However, ICAO's alignment with the 1.5°C target has been questioned, with Climate Action Tracker indicating a warming trajectory closer to 3–4°C under current policies (CAT, 2022).

For airlines, bridging the gap between net-zero ambitions and actual emissions trajectories may require proactive fleet upgrades, stringent fuel efficiency measures, and early investment in SAF infrastructure. The challenge is further intensified by non-CO_2 emissions, where strategies like contrail avoidance and improved air traffic management could help mitigate radiative forcing. Consequently, research suggests that credible transition plans must incorporate a shift to alternative energy carriers, such as zero-carbon fuels, hydrogen, or electricity, that have lower indirect climatic impacts (Brazzola et al., 2022).

Fuel mix and policy assumptions. SAFs are a central transition lever of all four pathways, yet there is little consensus on the pace and scale of their deployment. While all frameworks recognise SAFs, such as biofuels, synthetic fuels, and hydrogen, as crucial for reducing dependence on fossil fuels, the level of detail provided varies significantly. The MPP and IEA pathways include clear policy assumptions, such as subsidies, blending mandates, and infrastructure investments, sending stronger signals for airlines and airports

to prepare for SAF adoption. Additionally, the MPP, OECM, and ICAO pathways highlight the importance of government-industry collaboration but lack specific policy mechanisms to enable large-scale SAF production and deployment.

The reliance on SAFs also poses challenges for airports, which need to invest in suitable infrastructure for fuel storage and handling. From an airline economics perspective, SAF costs remain significantly higher than conventional jet fuel (Watson et al., 2024), meaning early adopters may face a competitive disadvantage unless supported by strong policy incentives. Additionally, SAF availability is uneven across regions, driven by disparities in biomass resources and industrial capacity (B. Wang et al., 2024). This regional variation could alter the global competitive landscape. Carriers based in regions with abundant feedstocks and supportive policies may be able to access more affordable supplies of sustainable aviation fuel, while others may find it difficult to meet blending mandates or reach decarbonisation targets.

Technology and demand assumptions. New aircraft low carbon technological innovation is critical for achieving net-zero emissions, yet the pathways' assumptions about future technologies must contend with continued demand growth in aviation. Hydrogen-powered aircraft and carbon capture are widely considered pivotal for decarbonising the sector, but only the IEA provides detailed timelines and cost estimates for deploying these technologies. At the same time, historical trends of 3% annual demand growth in aviation, coupled with 1–2% annual efficiency gains, create a significant gap that cannot be closed by technological improvements alone (Bergero et al., 2023; Gössling and Humpe, 2020). Airlines in high-growth markets, particularly in Asia-Pacific, may find it especially difficult to reconcile ambitious expansion plans with stringent climate targets unless they adopt innovative fleet strategies and next-generation airframes. Similarly, carbon capture solutions remain nascent and energy-intensive, raising questions about scalability and cost-effectiveness, especially where grid decarbonisation is not proceeding at a commensurate pace (Smith et al., 2023). In the interim, stakeholders such as maintenance, repair, and overhaul (MRO) providers may face growing pressure to retrofit existing fleets, requiring extensive certification processes across multiple jurisdictions (Rahn et al., 2024).

Carbon price and carbon budget. The absence of carbon pricing in most pathways creates uncertainties in financial planning for airlines, further complicating their climate transition. Among the four pathways, only the IEA explicitly incorporates carbon pricing as a lever to drive decarbonisation, whereas the MPP, OECM, and ICAO rely on broader policy measures without explicit cost signals. The carbon budgets allocated to the aviation sector also differ significantly, with the IEA and MPP each assigning 18 Gt CO_2 for 2020–2050, compared with OECM's 20 Gt and ICAO's range of 16–44 Gt. This divergence creates substantial uncertainty regarding the sector's allowable emissions,

particularly in relation to alignment with the Paris Agreement's goal. For airlines, unpredictable carbon pricing or budget allocations pose real economic and strategic risks, as retrofitting existing fleets or procuring newer, more efficient aircraft depends on a clear understanding of future costs. Fuel suppliers might also be slow to invest in sustainable fuel plants if the business model is underpinned by uncertain carbon credits. In jurisdictions where carbon taxes or emissions trading schemes are emerging, airlines that have not planned for higher operating costs could face abrupt financial strain, potentially affecting route viability and competitive positioning.

Investment requirements, asset-level considerations and just transition. Investment requirements and social considerations pose critical challenges to the aviation sector's transition, with potential repercussions for both airlines and related industries such as airports and fuel suppliers. The Energy Transitions Commission estimates that the sector will need investments of up to USD 70 billion annually until 2050 to achieve net-zero goals (ETC, 2023). While the IEA provides partial estimates of these costs, the MPP, OECM, and ICAO lack detailed financial projections, creating uncertainties for airlines and financiers. Asset turnover represents another major obstacle, as airlines face the possibility of stranded assets if high-emitting aircraft are retired prematurely without adequate (Marobhe and Kansheba, 2024). A just transition, although central to maintaining workforce stability and community support, is only partially recognised in ICAO's framework and largely absent from the others. Insufficient attention to labour retraining and local community impacts may jeopardise social licence to operate, emphasising the importance of integrating equity considerations into fleet renewal and operational transformations. (European Transport Workers' Federation (ETF), 2022; Khosla et al., 2023). The reliance on carbon offsets also varies, with OECM envisioning minimal use while the IEA, MPP, and ICAO acknowledge them as an interim solution. In practical terms, airlines and airports in industrialised nations may find it easier to access green finance and de-risk large-scale infrastructure investments, but carriers in emerging economies could struggle to finance early retirements and new low-emission fleets without concessional lending or targeted policy interventions. Over the longer term, the interplay between policy clarity, capital availability, and socially inclusive transition planning will determine whether the aviation sector can achieve deep decarbonisation while preserving economic viability and public support.

2.2.2 Gaps and overlaps in reporting standards

Based on our review of key climate pathways, we identified three primary decarbonisation levers for aviation: fuels, technology, and operations. Fuels focuses mainly on scaling

SAFs to cut lifecycle emissions through clear targets, supplier engagement, and certification compliance. New aircraft technology involves investing in fuel-efficient airframes, engines, and emerging hydrogen or electric propulsion, supported by research and development. Operations and infrastructure include optimised flight routes, advanced air traffic management, and energy-efficient airports, deliver immediate emissions reductions. Carbon capture and offsets were excluded from a short-term perspective as they are costly, uncertain, and policy-dependent (Smith et al., 2023), whereas fuels, technology, and operations offer more scalable and effective decarbonisation. We review 17 guidelines from trade associations, standard setters, target-setting verifiers, and jurisdictional expectations in the European Union, the United States and the United Kingdom. Table 2 provides an overview of these frameworks, categorising them by their coverage of climate goals, sectoral pathways, and the three transition levers, highlighting areas of alignment and gaps in guidance.

Climate goals and pathways. Most reporting frameworks recognise the importance of establishing science-based, sector-specific emissions targets, which underscores the necessity for a consistent set of metrics that capture the entire emissions footprint. However, discrepancies remain. For instance, SBTi advocates Well-to-Wake (WTW) fuel assessments, while ACT and TPI may rely on Tank-to-Wake (TTW) measures when comprehensive data is lacking. IFRS and ISO propose alternative methodologies, contributing to fragmented reporting. The upshot, reflected in Table 2, is that while all frameworks stress clear climate goals, they vary in how they define sectoral pathways, especially regarding non-CO_2 impacts and Scope 3 emissions (TPI, 2021a). Enhanced coordination across these standards would ensure that airlines have a harmonised basis for setting and monitoring climate targets, ultimately strengthening the credibility of transition plans.

Fuels. SAFs, spanning biofuels and synthetic alternatives, are widely viewed as the most pragmatic near-term lever to reduce emissions by up to 80% oils (IEA, 2021).[1] These "drop-in" synthetic fuels, which are compatible with existing aircraft, provide an interim solution by significantly reducing soot and non-CO_2 emissions (Airbus, 2023; European Commission, 2020) and are often favoured over newer aircraft technologies in the short term (WEF, 2020). To meet net-zero targets, the IEA estimates that SAF's usage must increase from under 0.1% in 2021 to 10% by 2030 and between 45% and

[1]Five techniques currently exist for producing jet fuel that blends with conventional fuel up to 50% without needing aircraft modifications (ATAG, 2021). These are Hydro-processed Esters and Fatty Acids (HEFA) using plant or animal oils, Fischer-Tropsch (FT) process converting biomass into fuel, Alcohol-to-Jet (ATJ) method turning ethanol into jet fuel, Direct Sugars to Hydrocarbons (DSHC) converting sugars directly into fuel, and Power-to-Liquid (PtL) synthesizing fuel from carbon dioxide and hydrogen. The US Department of Energy (2020) notes that research could reduce costs of these methods in the short term. Each method's feasibility varies based on feedstock availability, technological progress, costs, and regulatory factors.

90% by 2050 (IEA, 2021). Such growth will require expanded production capacity and supportive policies, including taxes and blending mandates. Moreover, Table 2 shows that frameworks handle SAF integration inconsistently: while all acknowledge SAFs' importance, many stop short of prescribing specific targets or governance requirements for their adoption. Such variance complicates benchmarking and cost management, as airlines struggle to align capital investments and stakeholder engagement around SAF procurement. Some guidance documents (ICAO, 2022a; WEF, 2020; WEF, RMI and PwC, 2022) encourage certification to validate sustainability claims, but no single standard addresses the entire lifecycle, including supply chain emissions, scaling challenges, and economic incentives (ASTM, 2022; ATAG, 2021; EPRS, 2020; EPRS, 2022; FAA, 2021; ISCC, 2022; NLR and SEO, 2021; RSB, 2023; UK DfT, 2022). This gap underscores the need for unified metrics and transparent reporting to guide SAF rollouts in line with net-zero trajectories

Technology. In the longer term, breakthroughs in propulsion systems (hydrogen, battery-electric) and more efficient airframes are pivotal for deep decarbonisation (IATA, 2023a). By 2030, hydrogen propulsion, battery-powered solutions for commuter aircraft, and SAFs are expected to become increasingly viable. Although Table 2 reveals broad support for these technologies across disclosure frameworks (e.g., IFRS, GFANZ), detailed implementation roadmaps remain sparse. Airlines often must define their own targets and demonstrate progress, creating wide variability in how transition risks and opportunities are reported. Some standards, such as ACT, include indicators for assessing fleet renewal schedules and the emissions "lock-in" of conventional aircraft, but do not offer comprehensive performance indicators to track R&D investments or technology maturation. Jurisdictional policies, like the UK Jet Zero Strategy or the EU's Destination 2050, encourage collaboration on emerging technology but similarly lack uniform adoption metrics. The resulting patchwork can impede cross-industry comparisons and hinder collective progress toward net-zero goals.

Operations. Operational measures, including optimising flight routes, reducing aircraft weight, and improving airport infrastructure, offer immediate and scalable ways to cut fuel burn and emissions. These strategies can be augmented by demand management (e.g., innovative ticket pricing or encouraging rail over short-haul flights) and are often the most cost-effective initial steps for airlines. However, as illustrated by Table 2, existing standards (IATA, ATAG, SBTi, ACT) diverge on specific operational KPIs. While all acknowledge the crucial role of efficiency improvements, few provide concrete, airline-specific metrics that can be audited over time (NLR and SEO, 2021; UK DfT, 2022). Without standardised reporting on flight path optimisation or passenger load factors, for example, it remains difficult to benchmark progress or enforce accountability. This

fragmentation highlights the need for a more unified approach. Linking operational metrics to broader climate goals and sectoral pathways is essential if airlines are to turn best practices into robust and verifiable transition plans.

2.3 Climate transition plans' assessment

Based on our review of climate pathways and key transition levers, we developed a questionnaire to create a scoring framework that assesses the credibility of airlines' climate transition plans. Unlike existing methodologies, our approach derives component weights based on their adjusted association with short-term carbon performance, informing regulatory oversight and investor due diligence; it is not a forecasting or causal-evaluation tool. Given the uncertainties in climate pathways, particularly in hard-to-abate sectors, a data-driven methodology offers a more robust alternative to expert judgment alone. Drawing on established reporting guidelines (GFANZ, 2022a; TPT, 2023b), our framework evaluates five key components (Foundations, Implementation, Engagement, Governance, and Metrics & Targets) providing a scalable and consistent tool to assess airlines' progress toward low-carbon operations.

Given that corporate transition plans are still in their early stages and mostly depend on self-reported data without strong and standardised benchmarks, assessments often rely on a check-box approach. At this level, the focus is on whether companies disclose required information rather than on its quality, completeness, or accuracy. A preliminary credibility assessment can determine whether self-reported data meet basic disclosure requirements, appear logically consistent, and align with sector expectations. However, a true integrity assessment, which evaluates ethical commitment, transparency, and completeness, requires deeper analysis. Without independent audits and established benchmarks, it remains difficult to verify the actual substance of a company's transition plan. As the field matures and more standardised, independently verified data become available, both credibility and integrity assessments will improve. For now, conclusions should be seen as provisional, recognising the need for further verification and deeper technical evaluation.

Appendix A lists the 12 questions organised along four sectoral topics (climate goals, fuels, technology, and operations), each linked to relevant subsets of the five components above (a simplified version appears in Table 3). For example, in the Foundations section, we examine the establishment and transparency of both short- and long-term emissions targets, while the Governance criteria verify independent target confirmations and SAF certifications aligned with recognized standards. Our Implementation review focuses on the uptake of SAFs and low-carbon aircraft technologies, and the Engagement evaluation

assesses collaborations with suppliers, manufacturers, and policymakers. The Metrics and Targets section then considers how airlines set and track specific, quantifiable non-GHG measures.

The tailored criteria acknowledge that different components require distinct evaluative approaches. While establishing clear emissions targets is critical for climate goals, detailed implementation strategies are more pertinent for fuel usage and technology adoption. Similarly, although rigorous governance is essential for credible climate goals and SAF certifications, it is less applicable to operational strategies lacking established benchmarks.

The validation process was guided by an advisory board of experts from a wide range of organisations. These included NGOs such as CDP, ADEME, the UK Transition Plan Taskforce, RMI, WEF and TPT; airlines; trade associations such as IATA and the International Transport Forum at the OECD; academic institutions including ETH Zurich, the Smith School of Enterprise and the Environment, and University College London; as well as government bodies such as the UK Government. This multidisciplinary panel, all actively engaged in the aviation decarbonisation debate, collaborated under the Chatham House Rule to foster an open and candid dialogue. The confidentiality assured by this rule was essential in enabling experts to provide honest and critical insights into the preliminary questionnaire, ensuring that all contributions were free from attribution concerns and allowed for a truly constructive review.

The methodological approach unfolded over two structured roundtable workshops. The first workshop, held on 2 March 2023, was dedicated to validating climate pathway conclusions and identifying the key dimensions necessary for robust climate transition plans. During this session, participants engaged in detailed discussions regarding the clarity, relevance, and comprehensiveness of the initial questionnaire items, offering both qualitative feedback and quantitative ratings where applicable. This collaborative session helped pinpoint areas in need of refinement, notably leading to discussions around the alignment dimension of the transition plans and set the stage for subsequent revisions.

The second workshop, convened on 13 June 2023, built upon the insights garnered from the initial session by focusing on refining the assessment criteria and integrating early feedback from the questionnaire design. Experts revisited the revised draft, ensuring that the modifications accurately captured the complexities and nuances of airlines' climate transition plans while aligning with current debates on aviation decarbonisation. This iterative process, underpinned by rigorous discussions and consensus-building, ultimately resulted in a robust, validated instrument.

Data. We collected data on climate strategies that began implementation in 2021 and were reported in 2022 by reviewing official, publicly available sustainability reports and the airlines' official websites. Our study focused on IATA member airlines that

pledged to achieve net-zero carbon emissions by 2050, a commitment announced in 2021. Of the 305 IATA members, which account for over 80% of global operations, only 84 (approximately 30%) had publicly available climate strategies. Nevertheless, these 84 airlines were responsible for nearly 75% of the global airline industry's total carbon emissions in 2022 (CAPA and Envest, 2024).

We employed a questionnaire featuring two distinct response options not to oversimplify but to distil the most critical transition levers into clear, actionable insights. Each question, supported by detailed guidance (see Appendix A or Table 3), addresses a fundamental action, such as whether an airline has set short- or medium-term climate goals in addition to its long-term net-zero commitment. It also captures key measures, including the disclosure of sustainable aviation fuel certification. This dichotomous format offers a practical, standardised framework for benchmarking and progress monitoring (e.g., CDP, 2023) while drawing on established survey methodology (Krosnick, 1999) to reinforce its validity and reliability. Although there is a recognised risk of oversimplification (Marsden and Wright, 2010), our approach intentionally isolates the essence of pivotal transition actions in a manner that is both rigorous and accessible for industry application, ultimately providing a quantifiable basis for assessing progress and developing comprehensive transition strategies.

Assessment results. Figure 2 charts our evaluation of the airline industry's climate transition plans based on self-disclosed data from 2022. The analysis is indicative, not exhaustive, as it reflects only what companies choose to reveal. The heatmap quantifies the proportion of airlines meeting our criteria, offering a snapshot of disclosure patterns, highlighting both strengths and gaps. Our focus is on completeness, not the quality of disclosures, which may underrepresent efforts due to confidentiality or omissions.

Our findings reveal that 73% of airlines meet the criteria for fuels implementation disclosure, and 81% satisfy the requirements for new technology adoption, which indicates an active pursuit of operational strategies aimed at reducing emissions. Furthermore, 74% of airlines have disclosed initiatives to improve operational efficiency. These figures underscore the industry's commitment to integrating sustainable practices and technologies.

Moderate compliance levels, indicated by lighter shades, suggest that while there is substantial engagement with SAF suppliers (64%) and a 48% positive response regarding airlines' engagement strategies to uptake new aircraft technologies, there remains considerable room for growth. Disclosure of metrics and targets for SAF uptake (43%) and new aircraft technologies (48%) demonstrates progress in setting measurable goals, yet the industry must further establish and communicate clear, quantifiable benchmarks.

The lowest compliance levels are evident in governance areas. For instance, only 24% of airlines have their climate transition targets independently reviewed. Few disclose

essential details such as GHG scopes or reference established science-based climate pathways like the ones reviewed in Section 2.2. Similarly, just 26% provide information on the certifications for the SAF they purchase or intend to use. This disclosure often lacks important details about the specific types of sustainable aviation fuel and the recognised certification bodies, such as the Roundtable on Sustainable Biomaterials or the International Sustainability and Carbon Certification. It also frequently omits the methodology used in these certifications. The lack of such positive disclosures in both independent third-party verification and SAF certification suggests a significant gap in rigorous oversight and external validation.

Regarding engagement strategies to uptake new aircraft technologies, the 48% positive response indicates that nearly half of the airlines disclose their involvement with aircraft manufacturers and participation in R&D initiatives. These disclosures include partnerships aimed at developing electric or hydrogen-powered aircraft and other innovative solutions, as well as the exchange of market data with suppliers to foster technological advancements. While this reflects some progress in operational strategies, it contrasts with the notably weaker performance in governance areas.

Overall, the airline industry has made promising progress in implementation and operational strategies. However, weaknesses in governance, particularly in the independent verification of climate targets and the disclosure of sustainable aviation fuel types and certifications, highlight the need for greater transparency and stronger oversight. This focus on disclosure completeness is especially valuable, as it establishes a baseline for understanding the nascent stage of voluntary climate-related reporting and provides a foundation for future improvements.

2.4 Climate transition plans' score

Our scoring system employs a novel methodological approach to address the lack of data-driven tools for evaluating the credibility of Corporate Transition Plans (CTPs). The framework utilises three distinct methodologies: (1) a baseline correlation approach, (2) a stratified correlation approach to account for confounding factors, and (3) a partial correlation approach adjusting for key influencing variables. These techniques quantify the unique association of each CTP component with short-term carbon performance, offering a data-driven alternative to conventional expert-judgement weighting methods (e.g., TPI or ACT). By leveraging observable performance data, our approach reduces subjectivity and enhances replicability, providing a more objective basis for evaluating transition plans.

The framework is informed by studies reporting that environmental information

disclosure is associated with lower emissions, and evidence that mandatory GHG disclosure is linked to subsequent reductions. For instance, X. Yang et al. (2022) found that improved disclosure quality leads to decreased emissions, while L. Yang et al. (2021) showed that mandatory GHG emissions disclosure drives significant reductions. While more advanced multivariate methods could offer deeper insights, the nascent state of transition plan disclosures and limited historical data currently preclude such approaches. Nevertheless, our framework provides a practical tool under data constraints and establishes a foundation for future, more sophisticated methodologies. This aligns with emerging trends in sustainability research calling for empirical, outcome-driven metrics (Gautam et al., 2025; Sherif et al., 2022) and builds on evidence that data-based measures enhance transparency and accountability in corporate climate strategies (Ding et al., 2023).

2.4.1 Data and definitions

Our dataset includes measures of carbon dioxide (CO_2) emissions, fleet characteristics, and passenger load, alongside twelve binary indicators of transition plan components derived from our prior assessment (see Section II). Carbon performance is measured by emissions intensity ($Y = CO_2/RPK$), where RPK (revenue passenger-kilometres) standardises emissions per unit of passenger travel. Data was sourced from CAPA-Centre for Aviation (CAPA and Envest, 2024), which offers comprehensive industry emissions data and the control variables used in this study. Control variables include fleet age (a proxy for technological modernity) and passenger load factor (a measure of capacity utilisation), both of which influence emissions intensity (Brueckner and Abreu, 2017; Dray et al., 2022). In the stratified correlation approach, control variables categorise airlines into bins (low, medium, high) based on tercile thresholds, with adjusted emissions intensity calculated by subtracting bin-specific means. In the partial correlation approach, they are explicitly controlled for as confounders, isolating the association between transition plan components and emissions intensity

To assess short-term carbon performance, we calculate the proportional change in emissions intensity as: $Y = (I_{2023} - I_{2019})/ I_{2019}$, where I_{2019} represents the emissions intensity in 2019 (a period preceding the COVID-19 pandemic) and I_{2023} denotes the intensity in 2023, after the pandemic's disruptive effects (Sun et al., 2022). Using a stable pre-disruption baseline minimizes the risk of incorporating anomalous data that could distort the assessment of true underlying trends in emissions performance.

Each airline's transition plan is characterised by a set of binary sub-elements derived from our questionnaire $\{X_1, X_2, \ldots, X_{12}\}$, where $X_i = 1$ indicates the presence of sub-element i (e.g., implementation strategy of SAF) and $X_i = 0$ its absence. The goal

is to determine the relative importance of these sub-elements in influencing carbon performance.

2.4.2 Correlation-based scoring framework

Baseline Correlation Approach. We first quantify the association between each transition plan sub-element and emissions intensity change Y using the point-biserial correlation coefficient (Demirtas and Hedeker, 2016), defined as:

$$r(X_i,\ Y) = \frac{\mu_1 - \mu_0}{\sigma_Y}\sqrt{\frac{n_1 n_0}{n^2}} \tag{1}$$

where:

- μ_1 and μ_0 are the mean values of Y for airlines with $X_i = 1$ and $X_i = 0$, respectively,
- σ_Y is the standard deviation of Y,
- n_1 and n_0 denote the number of airlines with $X_i = 1$ and $X_i = 0$, and
- $n = n_1 + n_0$ is the total number of airlines.

Under our sign-retaining weighting scheme, each sub-element's weight is defined so that sub-elements negatively correlated with emissions intensity change (i.e., those associated with lower emissions) contribute positively to the airline's final score, while sub-elements with positive correlations contribute negatively. Let $r(X_i, Y)$ denote the point-biserial correlation between sub-element X_i and the proportional change in emissions intensity Y. We then define the weight for sub-element X_i as

$$\omega_i = -\frac{r(X_i, Y)}{\sum_{j=1}^{12} \left|r(X_i, Y)\right| + \varepsilon}. \tag{2}$$

In this formulation, the numerator $-r(X_i, Y)$ flips the sign of the correlation so that a negative $r(X_i, Y)$ (which is beneficial) results in a positive weight. The denominator normalizes the weights by the total absolute correlation across all sub-elements, ensuring that the relative importance is maintained. Thus, if $r(X_i, Y) < 0$, then $\omega_i > 0$, indicating that the presence of X_i is linked to a reduction in emissions intensity. Conversely, if $r(X_i, Y) > 0$, then $\omega_i < 0$, indicating that the presence of X_i is linked to higher emissions intensity.

Using these weights, we define the baseline transition plan score for airline k as

$$Score(k) = \sum_{i=1}^{12} \omega_i X_i(k), \tag{3}$$

Where $X_i(k)$ equals 1 if airline k includes sub-element i in its transition plan and 0 otherwise. With this scoring framework, an airline incorporating more "beneficial" sub-elements, those yielding positive weights, will achieve a higher overall score. Conversely, if an airline's plan is dominated by sub-elements yielding negative weights, its overall score will be lower. This baseline score provides a clear measure of the association signal of disclosed plan components with short-term emissions intensity.

While this approach may raise potential circularity concerns, it is worth noting that the primary objective is neither to predict nor to infer causal effects on short-term performance, but to construct an internally consistent score reflecting the quality of airlines' transition plans. Due to data constraints, the implementation focuses on very short-term correlations. This short-term focus may not fully capture long-term decarbonisation trajectories, which depend on sustained investments and innovation, and could be influenced by external factors such as regulatory changes, fuel price fluctuations, or macroeconomic conditions. We acknowledge that any lack of correlation with short-term performance could result from missing components, limitations in measurement, or contextual factors. To address circularity, cross-validation and bootstrapping demonstrate the stability of weights across subsamples, ensuring robustness (see Appendix C).

Adjust for confounding factors. To account for potential confounding factors like fleet age and passenger load, correlations can be computed using adjusted emissions performance metrics or partial correlations.

A stratified approach accounts for confounding effects from fleet age and passenger load, airlines are first categorised into bins based on these variables. Specifically, fleet age (Z_1) and passenger load (Z_2). are each divided into three quantile-based groups (low, medium, and high) using tercile thresholds. This stratification method ensures that each bin (g) represents a unique combination of fleet age and passenger load levels, which are critical determinants of emissions intensity (Dana and Greenfield, 2019). Quantile-based stratification of operational variables aligns with aviation emission frameworks that segment flight phases to isolate confounding effects (B. Wang et al., 2024). For each subgroup, the mean emissions intensity is calculated as:

$$\overline{Y}_g = \frac{1}{n_g} \sum_{k \in g} Y_k, \tag{4}$$

where n_g is the number of airlines in bin g. The adjusted performance for airline k is then defined as:

$$Y_{adj}(k) = Y_k - \overline{Y}_g, \tag{5}$$

where g is the bin containing airline k. We use these to calculate weights as the

sign-retaining framework (Equations 2 and 3).

Alternatively, by conditioning on numeric covariates through compute partial correlations (Erb, 2020), which measure the association between sub-element X_i and the proportional change in emissions intensity Y, while conditioning on fleet age (Z_1) and passenger load (Z_2). Expressing the partial correlation in terms of the inverse of the correlation matrix, let R be the correlation matrix for the variables (X_i, Y, Z_1, Z_2) and denote its inverse by $\Omega = R^{-1}$. Then, the partial correlation is given by

$$r\,(X_i,\ Y|Z_1,\ Z_2) = -\frac{\Omega_{X_i,Y}}{\sqrt{\Omega_{X_i,X_i}\,\Omega_{Y,Y}}}. \tag{6}$$

These partial correlations replace $r(X_i, Y)$ in the calculation of weights and scores.

Because raw scores can be negative (if an airline's plan includes many sub-elements that are positively correlated with emissions), we shift the scores to ensure they are non-negative. First, we compute the minimum score across all airlines and subtract this minimum from every airline's score so that the smallest score becomes zero. Finally, we normalise the shifted scores to the range [0, 1] for better interpretability.

2.5 Results

The score we propose is a disclosure-based proxy that weights plan components by adjusted associations with lower short-term emissions intensity. It is not a causal or forecasting metric and should be interpreted as a baseline alternative to expert-weighted schemes. The results of our correlation analyses highlight key insights into the relationship between CTPs elements and short-term carbon performance in the airlines industry. The derived weights serve as a central diagnostic tool that reflects the relative importance of each disclosure element in constructing a credible, long-term decarbonisation strategy, rather than acting as direct predictors of immediate emissions reductions. Each weighting method (baseline, stratified, and partial) offers a distinct perspective on the importance of sub-elements and their potential association with carbon performance in the short-term (see Figure 3). Therefore, weights are interpreted as associations, and validation tests assess weight stability, not forecasting accuracy.

Overall, implementation strategies in new aircraft technology consistently receive high weights, highlighting a strong associational signal between these disclosures and lower short-term emissions intensity. While these investments may not lead to immediate carbon reductions, the weight pattern is consistent with a strategic commitment that follows historical trends of improving efficiency. Similarly, robust climate targets and governance components, including the disclosure of science-based short-, medium-, and long-term

emissions goals and the presence of independent third-party verification, attract significant weights; these elements are fundamental in establishing transparent accountability and strategic direction, which are critical for long-term progress despite their indirect short-term effects on emissions metrics. Moreover, elements related to stakeholder engagement and the setting of metrics and targets receive moderate yet consistent weights, reflecting their role in ensuring ongoing transparency, collaborative monitoring, and continuous improvement.

Overall, this weight analysis provides a nuanced perspective on the relative importance of disclosure elements. External pressures, such as strict European carbon pricing or changing incentives in the United States, may lead to varying disclosure priorities across regions, although these factors are not directly modelled in the scoring. While each individual disclosure element may not translate into immediate emission reductions, their combined weight signals an airline's readiness to pursue sustainable practices and provides a framework for identifying strategic gaps in its transition plan. In essence, these weights do not quantify a direct causal impact on short-term emissions, but rather highlight which aspects of the climate transition plan most effectively convey an airline's long-term commitment to decarbonisation, thereby guiding stakeholders on where to focus improvements and monitor future progress in an industry marked by both rapid technological evolution and complex regulatory landscapes.

Our cross-validation and bootstrapping analyses demonstrate that the weight estimates used to construct the composite transition plan score are robust and stable. By repeatedly deriving weights through random data splits and extensive resampling, we show that key strategic dimensions consistently receive similar weights, as evidenced by narrow confidence intervals and minimal variability across iterations (see Appendix C for detailed tables and boxplots). These cross-validation and bootstrapping results suggest weight stability across resamples; these checks assess internal stability, not out-of-sample predictive performance.

The stratified approach is useful when relationships are non-linear and collinear, as it reduces sensitivity to operational heterogeneity by comparing like with like. It mitigates, but does not eliminate, confounding from unobserved factors; partial-correlation and stratification are therefore complementary diagnostics. While partial correlation accounts for confounders, it assumes linear relationships. These conditions may not hold in real-world aviation data, where confounder interactions are often nonlinear (e.g., diminishing returns to fleet age efficiency gains). The stratification method, by contrast, imposes no parametric assumptions and handles collinearity by design, as quantile-based binning isolates confounder strata without requiring matrix inversion. Critically, cross-validation (Appendix C) confirms that stratification stabilizes weights across resamples,

whereas partial correlation exhibits sensitivity to outliers and covariance shifts (e.g., skewed passenger load distributions).

Comparing our weights with the ACT and TPI methodologies highlights both common ground and noteworthy contrasts. ACT strongly emphasises tangible emissions-reduction measures such as fleet renewal, mirroring the consistently high weight assigned to new aircraft technology implementation in our results. ACT's principle-based modules also allow adaptive re-weighting for factors like subcontracted operations, paralleling our stratification and partial methods that adjust for operational variables. Although governance exhibits moderate values in our system, it plays a similar enabling role in ACT, where it integrates into overarching strategic modules (e.g., scenario planning, risk management). Unlike our correlation-based approach, which focuses on near-term carbon outcomes, ACT combines recent performance with forward-looking qualitative assessments of how well companies align with climate goals. This can amplify the perceived importance of strategy and governance even when their short-term effects appear more indirect.

By contrast, TPI's *Management Quality Staircase* approach introduces a more process-oriented framework, using binary indicators to map a company's maturity across five management levels. TPI does not link practices directly to near-term emissions outcomes. Instead, it focuses on the gradual adoption of governance, disclosure and strategic behaviours such as setting targets, verifying emissions and carrying out scenario planning. This staged progression aligns with our finding that Governance and foundational Climate Goals gain additional weight once operational confounders are adjusted for in the partial approach. However, TPI's design does not explicitly measure short-term performance changes, whereas our correlation-based system links sub-elements (like Implementation and Foundations) to carbon performance through observed associations. Despite these methodological differences, all three perspectives agree on key levers for reducing emissions. These include technology adoption, strong targets and solid governance. However, they differ in how they balance near-term data, principle-driven flexibility and the maturity of corporate processes.

Figure 4 shows the distributions of our three scoring methods: baseline, stratified and partial. These offer insights into how airlines' transition plans relate to short-term carbon outcomes. The baseline method yields the highest mean (0.6048) and median (0.6942), suggesting that, without explicitly adjusting for operational factors, airlines with strong foundational or implementation measures stand out more clearly. Interestingly, despite this, the baseline method has the smallest standard deviation (0.3342), indicating that its range is shaped more by direct correlations than by a wider spread of scores.

The stratification method lowers the mean (0.5747) and median (0.6054) while slightly increasing the overall spread (standard deviation of 0.3386). By accounting for operational

factors such as fleet age and passenger load, this approach redistributes scores for some airlines, resulting in a more dispersed distribution. Partial scores (mean = 0.5694, median = 0.5997) closely follow the stratified distribution but with a slightly lower mean and a modestly reduced standard deviation (0.3367). This suggests that treating confounders as continuous variables refines the scoring, slightly reducing overall variability.

Despite these differences, all three methods share the same minimum (0) and maximum (1) and produce broadly similar rankings of airlines' transition plan strengths. While the stratification and partial methods shift the central tendencies downward and slightly alter the spread, their density curves remain closely aligned with the baseline approach. This consistency suggests that the core relationship between transition plan sub-elements and short-term carbon performance remains robust across all three methods.

Airlines such as JetBlue Airways, Aer Lingus, Iberia, and Azul distinguish themselves with comprehensive climate transition planning disclosures that integrate robust operational, foundational, and governance measures. JetBlue's commitment to net zero by 2040, supported by a pledge to use increasing volumes of sustainable aviation fuel by 2030, reflects a balanced approach. Similarly, Aer Lingus and Iberia have set clear targets (e.g., 10% SAF usage by 2030) . These firms disclose measurable activities and targets consistent with our indicators. They also actively invest in emerging technologies, with initiatives in hydrogen research and electric aviation helping to support their broader decarbonisation strategies. However, it is important to note that while these top performers showcase robust disclosure practices, our analysis focuses solely on disclosure points and does not claim that they are fully aligned with the Paris Agreement or any specific climate pathway. Even as some high performers (for example, Delta and Air France-KLM) display occasional gaps in governance or foundational disclosures, the overall narrative among top performers reflects a commitment to transparent, data-driven pathways that satisfy increasingly stringent investor and stakeholder expectations, as well as evolving regulatory and market demands.

In contrast, airlines such as Kenya Airways, VietJet Air, and Juneyao Airlines score at or near zero, showing limited disclosure across our indicators. We do not assess Paris alignment or future performance; lower disclosure may be perceived as higher transition-plan risk by investors and stakeholders. These carriers often fail to articulate foundational goals, lack well-defined governance mechanisms, and do not provide meaningful stakeholder engagement frameworks. Their disclosures are largely narrative and lack quantifiable targets or concrete strategies to incorporate emerging technologies such as SAF, hydrogen, or electric aviation, thereby falling short of the rigorous standards demanded by global investors and regulators . The lack of external validation or detailed operational measures raises serious credibility concerns. It suggests that these airlines

may struggle to align with net-zero 2050 goals. This misalignment could limit their access to capital and weaken their competitive position in a market that is increasingly shaped by climate commitments.

When comparing our scores with other approaches (TPI and ACT), we found that pairwise rank correlations (assessed using Spearman's and Kendall's) indicate moderate convergence between the scoring systems, although a divergence becomes apparent when categorising airlines into quartiles, with TPI deviating most notably from our method (see Appendix B). This divergence arises from fundamental differences in objectives and methodological design: our stratified approach isolates the correlation between transition plan disclosures with short-term emissions intensity changes, adjusting for operational confounders like fleet age and passenger load, while TPI evaluates governance maturity through binary indicators and benchmarks companies against Paris-aligned pathways, prioritizing procedural adherence over short-term outcomes. ACT, by contrast, balances qualitative assessments (e.g., R&D investments, policy engagement) with quantitative metrics, aligning recent performance with forward-looking climate scenarios. Our comparative analysis also employed non-parametric techniques, including rank transformation to harmonise disparate scales, and utilised Cohen's and Fleiss' kappa alongside the Friedman test to robustly evaluate both continuous and categorical agreement. It is important to note that our sample sizes differ considerably (84 observations for CTP compared with 39 for TPI and 24 for ACT), which may affect the statistical power and generalisability of the comparisons. Detailed methodology and scores are provided in Appendix B. Key takeaways from this analysis are that although the overall rankings are moderately aligned, the systems are not interchangeable due to significant differences in performance categorisation, underscoring the impact of methodological discrepancies on climate performance measurement. While our method focuses on outcome-linked disclosures, TPI emphasises process maturity, and ACT integrates strategic alignment, each framework serves distinct purposes, enabling stakeholders to address both immediate emissions impacts and long-term decarbonisation pathways.

2.6 Discussion

This study presents a novel score based on an association-weighted, disclosure-based baseline. It facilitates auditable benchmarking and sensitivity analysis of plan components across firms. It does not establish causality or forecast emissions paths. Results are conditional on self-reported data, short-run outcomes and adjustment for observed operational variables. We report component weights to guide future structural, or panel designs as longer histories become available. Beyond its immediate use in aviation, a

sector that reflects the challenges of hard-to-abate industries, the approach is intended as a blueprint for other sectors facing similar decarbonisation hurdles. These include heavy-duty trucking, shipping, steel and petrochemicals. By assigning empirically derived weights to key elements like technology adoption, foundational targets, and governance practices, the framework offers a replicable, transparent tool to assess and benchmark progress across diverse, carbon-intensive sectors.

Although the weights do not establish causality, they are informative for three reasons. First, they test whether an airline's disclosed plan is internally consistent with its observed short-term carbon performance: an airline that reports comprehensive implementation measures and exhibits lower emissions intensity is, at minimum, not contradicting its stated strategy. Second, deriving weights from observable data provides an empirical complement to ACT's expert-panel weights and TPI's management-quality staircase, and the moderate rank-correlation convergence with both frameworks (Appendix B) suggests the empirical weights capture systematic features of plan quality rather than noise. Third, the cross-validation and bootstrapping results in Appendix C show that the weights are stable across different data splits, pointing to a systematic pattern rather than a sample-specific artefact.

What do these results tell us? Across all three estimation methods, implementation measures in new aircraft technology and foundational climate targets attract the largest positive weights, while governance and stakeholder engagement elements contribute moderately but consistently. The implication is straightforward: airlines whose plans pair concrete operational commitments with quantified targets tend to show lower short-term emissions intensity; plans confined to narrative statements do not. For investors and lenders, the weights identify which plan components are most closely associated with lower emissions intensity, providing a replicable screening input for credit committees and due-diligence processes; disclosure gaps in high-weight elements such as technology implementation or science-based targets can flag transition-plan risk without requiring proprietary models. For regulators and standard-setters, the exercise shows that a score built entirely from public disclosures can sit alongside expert-based assessments such as ACT and TPI. As jurisdictions move toward mandatory transition plan disclosure, for instance under the UK Transition Plan Taskforce guidelines or the EU Corporate Sustainability Reporting Directive, a reproducible, association-weighted benchmark could inform supervisory review and help prioritise where verification requirements would be most productive. For airlines themselves, the weight hierarchy signals that implementation-type disclosures, particularly concrete technology investment commitments, carry a stronger associational signal than narrative governance statements, which may help firms direct disclosure effort where it is most consequential.

Three pathways may generate the observed association between implementation and lower short-term intensity. First, a direct operational effect: airlines that invest in newer, fuel-efficient aircraft reduce CO_2 per revenue passenger-kilometre through improved fleet-level efficiency. This is the most straightforward channel, but it carries a caveat: the short-term signal may partly capture efficiency gains from fleet renewal rather than structural decarbonisation, since an airline can lower its intensity metric by retiring older narrowbodies while its absolute emissions continue to grow with capacity expansion. Second, selection and signalling: airlines with a stronger underlying commitment to decarbonisation are more likely both to invest in low-emission technologies and to disclose those investments, so that the co-movement reflects organisational capability rather than a direct disclosure-to-emissions channel. Third, common regulatory pressure: airlines operating under stringent carbon pricing or emissions trading face simultaneous incentives to upgrade fleets and to report transition strategies, generating a correlation driven by external policy rather than by disclosure itself. These pathways are not mutually exclusive, and the framework cannot distinguish between them. Complementing the emissions-intensity metric with indicators that capture different dimensions of transition effort, such as green capital expenditure, contracted SAF volumes, or asset-level fleet commitments, could help separate efficiency-driven improvements from deeper structural shifts.

Traditional assessments of corporate climate strategies have typically relied on expert judgments, which often lack objectivity and transparency. Our data-driven approach builds on recent trends in sustainability research that call for quantifiable and outcome-oriented methods. It complements established expert judgment frameworks. It also offers a way to track how the associational strength of disclosed components varies across samples and over time. This innovation can inform regulatory oversight and investor due diligence by providing auditable inputs.

While the proposed framework provides a transparent and replicable method for evaluating transition plans, a number of limitations warrant discussion. The reliance on self-reported data may introduce bias, and the binary coding of plan elements, though necessary for standardisation, can oversimplify complex strategies. Additionally, although the framework controls for fleet age and passenger load, other factors discussed in Section 2.2, such as regulatory environment, SAF costs, regional feedstock availability, and carbon pricing exposure, are not explicitly modelled and may confound the observed associations. A related limitation concerns the temporal structure of the data: the performance metric spans 2019–2023, yet the transition plan disclosures reflect strategies implemented from 2021 and reported in 2022, meaning that the earlier portion of the performance window precedes the observed plans. While the associational framing does not require temporal precedence, this overlap should be borne in mind when interpreting

the weights. Moreover, maintaining comparability over time is a fundamental challenge for both expert judgement and data-driven scoring methodologies, as evolving industry standards and external conditions necessitate periodic recalibration. While expert judgement approaches rely on fixed benchmarks and historical normalisation to ensure continuity, data-driven methods dynamically adjust weights based on adjusted association with short-term carbon performance, making them more sensitive to sample variations. Addressing these challenges requires a combination of rolling calibration with stable anchor datasets, statistical normalisation techniques, and a hybrid model that balances fixed components with adaptive updates to preserve both methodological integrity and responsiveness to industry shifts.

Future research should aim to refine the calibration process by incorporating longitudinal data that captures evolving industry practices and external conditions. Expanding the framework's application to other hard-to-abate sectors will test its versatility and uncover sector-specific adjustments. Additionally, integrating more granular qualitative data could complement the binary scoring system, thereby providing deeper insights into the effectiveness of various transition strategies. Addressing temporal comparability with hybrid approaches will be crucial for ensuring that the framework remains a reliable tool for ongoing monitoring and evaluation.

2.7 Conclusion

The central finding of this paper is that credibility in airline transition plans is an outcome-linked property. Implementation measures, above all investment in new aircraft technology, and independently reviewed foundational targets carry the strongest associational signal with lower short-term emissions intensity. Governance and stakeholder engagement contribute, but their informational value is modest unless anchored to verifiable operational commitments.

As discussed above, the association between implementation and lower short-term intensity admits multiple causal interpretations, including direct fleet-efficiency effects, selection and signalling, and common regulatory pressure. The score therefore measures consistency between disclosed plans and near-term intensity performance, not alignment with an absolute emissions pathway. Distinguishing between these pathways will require panel data and quasi-experimental designs as longer time series become available.

The paper makes three contributions. It introduces a correlation-weighted, disclosure-based scoring method that provides a replicable, auditable alternative to expert-panel assessments of transition plan quality. It demonstrates that the empirical weights converge moderately with ACT and TPI rankings while being derived entirely from public data and

a published formula, making the approach reproducible without proprietary inputs. And it shows, through cross-validation and bootstrapping, that the weight structure is stable across subsamples, lending confidence that the associations reflect systematic features of plan quality rather than artefacts of a single data split.

Several limitations qualify these results. The framework relies on self-reported disclosures, which may reflect strategic presentation rather than operational reality. Binary coding of plan elements aids standardisation but inevitably simplifies complex strategies. Although fleet age and passenger load are controlled for, other confounders, including regulatory environment, SAF costs and carbon pricing exposure, are not explicitly modelled. The temporal overlap between the performance window (2019–2023) and the disclosure period (2021–2022) means that part of the outcome precedes the observed plans; while the associational framing does not require temporal precedence, this should temper interpretation. Future research should extend the analysis to other hard-to-abate sectors, incorporate longitudinal data to track how weights evolve as industry standards change, and employ difference-in-differences or instrumental-variable designs to move closer to causal identification.

3

Climate Transition Finance Metrics Effectiveness: An Industry Perspective

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Climate transition finance metrics (TFMs) have become crucial for directing capital toward low-carbon pathways, yet their credibility, availability of high-quality data, and perceived usefulness for achieving near-term climate targets remain uncertain. We systematically examine TFMs reported by the largest global financial institutions (banks, insurers, asset owners, and asset managers) and survey 219 practitioners to assess TFM usefulness versus data availability. Our analysis uncovers a persistent gap: widely adopted TFMs such as climate risk exposure and green financing metrics are regarded as moderately to highly useful, yet the underlying data is often incomplete or fragmented. Regression analysis reveals two dominant patterns. Organisations with partially or fully implemented climate transition or adaptation plans are systematically more critical of existing TFMs, suggesting that narrowly focused metrics fail to capture the operational complexity of mature climate strategies. Conversely, perceived exposure to climate-related market risk is the strongest positive predictor of TFM usefulness, indicating that near-term financial pressures drive demand for these tools. These findings imply that regulators should pair metric mandates with data-quality provisions, standard-setters should broaden metric scope to encompass intermediate outputs and social safeguards, and institutions should invest in the data infrastructure underpinning credible transition reporting. (JEL Q56, Q54, G32, O32)

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3.1 Introduction

Climate transition finance, distinct from broader climate finance or green finance, specifically focuses on mobilising capital to facilitate the shift from high-carbon to low-carbon economies. This strategic approach enables financial institutions to reduce greenhouse gas (GHG) emissions and drive systemic changes toward sustainable, low-carbon pathways. Central to these efforts are climate transition finance metrics (TFMs), quantitative tools that benchmark and assess the alignment of financial flows with climate objectives. Beyond emission reductions, this financing seeks to drive innovation, strengthen climate resilience, and expedite the phasing out of high-emitting assets (Caldecott, 2022b; CBI, 2022; GFANZ, 2023b; Harnett et al., 2023; TFMR, 2024). The urgency of these initiatives is underscored by 2024 being confirmed as the warmest year on record, with the first calendar-year global mean at or above ~1.5 °C above the 1850–1900 baseline (Tollefson, 2025), much earlier than the expectation laid out in IPCC's Sixth Assessment Report written just several years earlier (2021-2023) and marking a critical point in the escalating climate crisis. Additionally, socio-political tensions surrounding net zero commitments have rapidly intensified, notably in the United States, where major financial institutions are retreating from key alliances amidst increasing political scrutiny. Against this backdrop, our analysis examines how financial practitioners evaluated climate transition finance metrics during the early phase of a structural shift in the politics and practice of sustainable finance.

The survey was conducted between 25 September and 1 October 2024, during a period when ESG politicisation, already underway, was intensifying ahead of the U.S. presidential election. This coincided with rising scrutiny of net-zero commitments, especially in the United States. Regulatory divergence was also growing: the EU's CSRD had come into force, the UK implemented an anti-greenwashing rule and consulted on mandatory transition plans (FCA, 2024), while the U.S. SEC's climate rule was paused amid legal challenges. Meanwhile, jurisdictions such as Singapore, Japan, and Canada began aligning with ISSB S1/S2 standards (IFRS, 2025), reinforcing a global floor despite diverging political narratives.

Despite being in the early stages of adoption, TFMs are increasingly recognised as vital tools for translating climate commitments into actionable strategies. However, concerns persist regarding the credibility and efficacy of TFMs in achieving near-term climate goals. Critics argue that although these metrics theoretically align with decarbonisation objectives, they often lack the necessary data granularity and standardisation to effectively influence financial decision-making or redirect capital flows (FRC, 2023; OECD, 2024). Furthermore, as TFMs expand to encompass aspects like financial stability and just

transitions, the interpretive frameworks of financial practitioners become more critical. These practitioners, serving as essential intermediaries between abstract metrics and actual capital flows, significantly shape the future direction of climate transition finance.

TFMs transcend technical tools; they are social constructs influenced by institutional norms and professional practices. Their perceived usefulness hinges on how practitioners interpret and implement them, balancing competing incentives and temporal pressures. Metrics that prioritise short-term gains may align with immediate objectives but risk overlooking the systemic transitions required for long-term climate goals. Consequently, metrics actively shape priorities and practices, embedding specific values and assumptions (Tichenor, 2020). Therefore, understanding practitioners' perceptions is crucial for assessing whether TFMs have the potential to steer financial flows effectively toward meaningful climate outcomes.

This study investigates a central research question: how do financial professionals perceive the effectiveness of TFMs in achieving near-term climate targets, and how does the availability of high-quality data constrain their implementation? The question matters because a metric that practitioners regard as decision-useful but for which adequate data cannot be obtained offers limited practical value; conversely, a metric with strong data support but low perceived usefulness is unlikely to influence capital allocation. We therefore evaluate TFMs along two dimensions. The first is perceived effectiveness, understood as decision usefulness: the degree to which practitioners consider a given metric useful for advancing four climate goals (reducing greenhouse gas emissions, supporting low-carbon innovation, strengthening climate resilience, and facilitating the phase-out of high-emitting assets). The second is the availability of high-quality data: whether, in practitioners' experience, data of sufficient quality to implement a given metric can in practice be obtained. The gap between these two dimensions is itself informative: it reveals where metrics are conceptually valued but operationally constrained. To address this enquiry, this study employs a survey-based approach, a widely adopted method in industry and government to capture professional judgments, priorities, and decision-making tendencies. Similar survey-based methodologies have proven effective in finance research, including studies on the valuation of climate risk disclosures (Ilhan et al., 2023), the integration of environmental, social, and governance factors into investment decisions (Eccles et al., 2017), and the pricing of climate risks by investors and governments (Stroebel and Wurgler, 2021).

Although some organisations monitor TFMs or assess their credibility, comprehensive cross-sector analyses of practitioner perceptions remain at best incomplete, are scarce even among climate aware markets and firms, and largely unavailable elsewhere. This study addresses that gap through a global survey of 219 financial practitioners at the world's largest institutions, combined with econometric modelling. Three principal findings emerge.

First, practitioners rate widely adopted TFMs as moderately to highly useful for near-term climate goals, yet report that the high-quality data needed to implement them is only moderately available, exposing a usefulness–data gap that undermines operational credibility. Second, organisations that have partially or fully implemented climate transition or adaptation plans are systematically more critical of existing metrics, suggesting that current TFMs are poorly calibrated to the operational complexity of mature climate strategies. Third, perceived exposure to climate-related market risk is the strongest positive predictor of TFM usefulness, indicating that near-term financial pressures drive demand for these tools. These findings carry direct policy implications: regulators designing mandatory disclosure requirements should pair metric mandates with explicit data-quality provisions; standard-setters should broaden metric scope to include intermediate outputs and social safeguards; and financial institutions should invest in the data infrastructure that underpins credible transition reporting.

3.2 Results

We used a three-step approach to evaluate the TFMs that financial institutions employ to meet near-term climate targets. First, we collected TFMs from official climate strategy documents and categorised them, creating a foundation for our global survey. Second, we surveyed industry professionals to elicit their self-reported assessments of each TFM along two dimensions: perceived effectiveness (the degree to which the respondent considers the metric decision-useful for advancing a given climate goal) and the availability of high-quality data for its implementation. These are subjective professional judgements, not objective measures of metric performance; their value lies in revealing how the practitioners who design and apply TFMs appraise them. This phase also incorporated expert elicitation to investigate the future potential of climate change-related innovations (Morgan, 2014; Verdolini et al., 2018). Third, we applied econometric modelling (Heckman ordered probit) to analyse the factors influencing these perceptions. By integrating these steps, our study offers both a systematic mapping of current TFMs and an empirical account of how financial practitioners appraise and apply these metrics (see Methods section for further details).

3.2.1 Identifying and categorising transition finance metrics

Drawing on climate strategies from the 100 largest global financial institutions (specifically, the 25 largest in each of four sectors: banks, insurers, asset managers, and asset owners, representing nearly USD 100 trillion in assets or assets under management, as applicable),

we identified nearly 1,500 transition finance metrics (TFMs), categorised into ten types (see Figure 3.1 and the Appendix for definitions). Eight types were derived from revised climate strategies, with two additional categories (financial losses from climate damages and financing/investing in climate adaptation) added through survey validation to address adaptation and resilience as key components of transition finance.

As depicted in the first and fourth rows of Panel A of Figure 3.1, banks led in reporting green financing commitments and implementing financing restrictions on fossil fuels. These are associated with their critical roles in large-scale project financing and underwriting. Additionally, research indicates that restrictions on coal or unconventional oil and gas may not result in financial harm to investors and even reduce carbon exposure of investment portfolios (Hunt and Weber, 2019; Plantinga and Scholtens, 2021). However, focusing on exclusionary metrics alone can mask the risk that carbon-intensive assets might simply be transferred to entities operating under less stringent or less transparent climate policies, ultimately undermining overall climate objectives (Duchin et al., 2024; Gözlügöl and Ringe, 2023; Malek, 2022; Marupanthorn et al., 2024). The interpretation of these indicators requires scrutiny of time horizons, greenwashing risks, and divergent regional regulatory drivers, including membership churn in voluntary alliances and standards that shape the design and disclosure of TFMs.

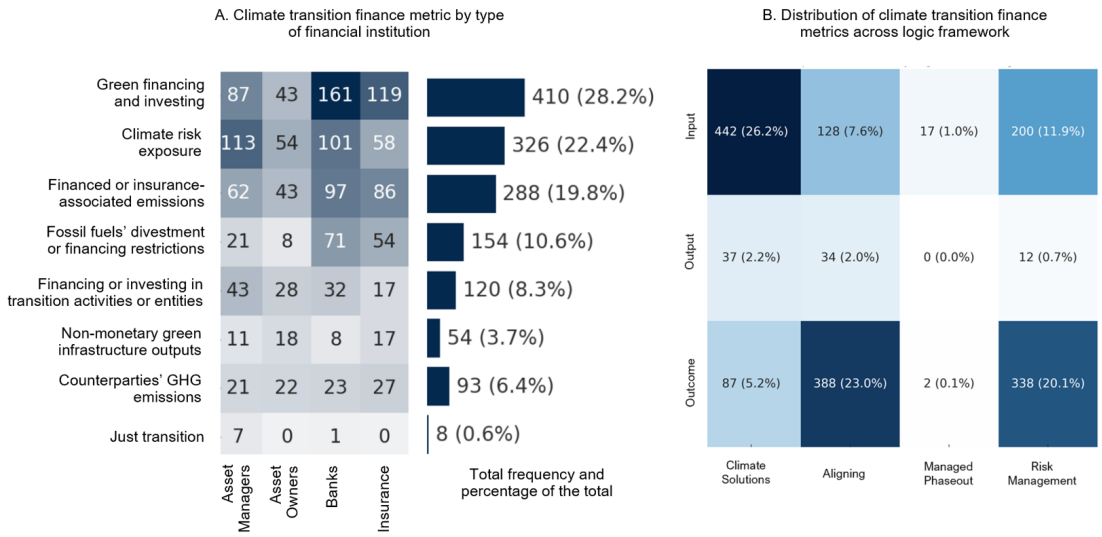

Figure 3.1 Typology of metrics reported by 100 global largest financial corporations

Note: The figure summarises climate-related metrics reported by 100 financial institutions, using a methodology described in the Methods section. Metrics were categorised as inputs (e.g., Green Financing or Investing; Financing or Investing in Transition Activities or Entities; Financing or Investing in Climate Adaptation; Fossil Fuels' Divestment or Financing Restrictions), outputs (e.g., Non-monetary Green Infrastructure Outputs; Just Transition), or outcomes (e.g., Climate Risk Exposure; Counterparties' GHG Emissions; Financed- or Insurance-associated Emissions; Financial Losses derived from Climate-related Damages). While most categories were observed in the sample, Financial Losses derived from Climate-related Damages and Financing or Investing in Climate Adaptation emerged in other parts of the

analysis. Institutions were filtered and reclassified to ensure relevance to climate financing and investment. Metrics associated with climate services were excluded due to their indirect relationship with financing flows. In total, 1,463 metrics were reviewed: 365 from asset managers (N=25), 216 from asset owners (N=24), 504 from banks (N=21), and 378 from insurance companies (N=24), representing over $110 trillion in assets under management. Countries where these institutions are headquartered include United States (N=26), United Kingdom (N=10), France (N=7), Japan (N=7), China (N=6), Germany (N=5), Canada (N=5), Netherlands (N=3), United Arab Emirates (N=3), Singapore (N=2), Switzerland (N=2), South Korea (N=2), and Others (N=20). Document collection cut-off was 31 October 2024.

A second major category of TFMs centres on climate risk exposure (e.g., the second row of Panel A of Fig. 3.1), with asset managers and banks leading in reporting metrics such as Weighted Average Carbon Intensity (total carbon emissions from investments, adjusted for the size of each investment) or climate Value at Risk (potential losses an entity or portfolio could face due to climate-related risks), driven by Task Force on Climate-Related Financial Disclosures (TCFD) guidelines and the demand for responsible investment products (PRI, 2022; TCFD, 2021). While these metrics enhance credibility, inconsistencies typically arise from methodological differences, highlighting the need for standardised definitions and peer review (IIGCC, 2024). The Glasgow Financial Alliance for Net Zero's (GFANZ) transition finance principles (climate solutions, aligning, and managed phase-out) offer a framework for TFMs' disclosures (GFANZ, 2023b), but our findings suggest elevating risk management as an additional transition finance element as it could act as a gatekeeper to evaluate and continuously monitor the integrity of funded projects, reducing reputational and operational risks for financiers (CBI, 2023). Further, incorporating risk management would address transition uncertainties, such as technological viability or policy shifts (CBI and UN Global Compact (CFO Coalition for the SDGs), 2023), ensuring that financial institutions do not simply shift carbon-intensive assets elsewhere but actually contribute to systemic decarbonisation.

Among the least frequently reported metrics in our review were just transition, counterparties' GHG emissions, and non-monetary green infrastructure outputs. These categories, shown in the last three rows of Panel A in Fig. 3.1, are vital for holistic climate action but remain less prevalent in industry reporting. From a general perspective, these dimensions often require more complex, cross-sector data or demand socio-economic measures (e.g., workforce impacts, community engagement) that extend beyond the traditional purview of financial accounting. For instance, just transition metrics involve evaluating how workers and communities are affected by shifts away from high-emitting industries (Dutta et al., 2023; Galanis et al., 2025), a domain not typically reflected in conventional financial indicators. Industry-specific factors also contribute to the low visibility of these metrics: banks and asset managers may focus on shorter-term risk and return metrics that fit neatly into established disclosure frameworks, whereas tracking counterparties' emissions or social impacts are resource-intensive and likely subject to inconsistent or incomplete data.

Employing a logic model framework grounded in established evaluation approaches (Mayne, 2015) provides a structured method to elucidate how TFMs contribute to varying functions in achieving climate objectives (see Figure 3.2). Inputs (e.g., green bond issuances, fossil-fuel exclusion policies) outline institutions' upfront commitments. Outputs (e.g., volume of financed renewable capacity, establishment of internal scenario-based risk tools) reflect interim progress. Outcomes (e.g., reduced portfolio carbon intensity, actual decline in exposure to high-risk assets) capture the end results.

By placing TFMs within this continuum, we offer another perspective on both strengths and shortcomings in current reporting. On one hand, institutions are increasingly recognising climate imperatives, as reflected in robust input- and risk-focused metrics. However, the lack of mid-level output measures reflecting decarbonisation/resilience gains and inconsistent attention to managed phase-out highlight the need for detailed, forward-looking data. This data could be organised into decarbonisation and phase-out strategies that account for external factors like regulatory environments, compensation for affected parties, and market-driven crowding out (Brutschin et al., 2022; Do and Burke, 2023). Ultimately, the logic framework underscores the importance of linking finance and investment decisions to climate outcomes, rather than treating them as separate endeavours.

3.2.2 Surveying financial practitioners on the usefulness of TFMs

Using the ten metric categories derived from the stocktake described in Section 3.2.1 as the basis for our survey instrument, we asked practitioners to provide their own assessment of each metric's decision usefulness for financing and investment decisions. The outcome variable throughout this section is therefore a self-reported perception of how useful a given metric is for advancing a stated climate goal, not an objective measure of the metric's actual impact. Assessments were elicited separately for each of four climate goals, reported in a fixed order consistent with all figures: (A) reducing economy-wide GHG emissions, (B) fostering low-carbon technology innovation, (C) strengthening climate resilience, and (D) managing the phase-out of high-emitting assets. We contacted 2,177 individuals at the 280 largest financial institutions who hold climate or sustainability roles. Of these, 700 opened the invitation and 219 completed the questionnaire, a completion rate of 31.3% of opens (10.1% of delivered invitations). Sector representation among respondents was balanced: asset managers 27%, banks 28%, insurers 24%, and asset owners 21%.

The sample skewed toward developed markets, with the United States and the United Kingdom most represented, which is expected given that we targeted the world's largest financial institutions and conducted the survey exclusively in English, a limitation acknowledged in our study. To mitigate potential selection bias, we issued targeted email

reminders based on individual characteristics such as gender (47% female, 52% male, 1% other), career experience (median 4–6 years in climate or sustainability), and organisational context. Regarding institutional climate strategies, 82 participants (37%) reported that their organisation's transition plan was "in progress," 60 (27%) indicated partial implementation, and 35 (16%) reported full implementation. The remaining 20% stated that their organisation did not yet have a transition plan. Similar patterns were observed for climate adaptation strategies, as detailed in the Methods section and the Appendix.

We summarised our survey findings by calculating mean responses from a balanced five-point Likert scale across four climate objectives, measuring perceived usefulness of each TFM (from "not useful" to "extremely useful") and the availability of high-quality data for TFM implementation (from "not available" to "always available"). These two dimensions are juxtaposed in Figure 3.2, where the upper-right quadrant is highlighted as a high-alignment zone, indicating metrics that combine relatively higher perceived usefulness with stronger data availability. Where a Heckman selection model detects significant selection bias (LR test for $\rho \neq 0$, $p < 0.05$), we report its direction and magnitude. Because the procedure rests on joint normality assumptions and an exclusion restriction that is difficult to verify conclusively, the correction is best read as a diagnostic: it reliably establishes the presence and direction of the bias rather than a precise point estimate of the unbiased mean. Details of the modelling are provided in the Methods section. Finally, following our transition finance logic framework, we label each TFM in Figure 3.2 as inputs, outputs, or outcomes, showing their roles in achieving climate goals.

A central finding is that practitioners rate many commonly tracked TFMs as moderately to highly useful for advancing the four stated climate goals, yet report that the high-quality data needed to implement those same metrics is only moderately available (see Fig. 3.2). Climate risk exposure metrics (#1 in Fig. 3.2) and green financing commitments (#8), for instance, consistently receive upper-tier usefulness ratings across goals ranging from emissions reduction to low-carbon innovation, yet the raw ratings for their associated data availability remain closer to mid-range values. Other metrics fare worse still on the data dimension. This gap between perceived usefulness and reported data accessibility suggests that although practitioners recognise the value of these metrics for guiding capital allocation, they often rely on fragmented or proprietary datasets, limiting comparability and consistency. Since late-2023, many large US financials have also reduced public ESG-related statements, a pattern widely described as 'greenhushing' (Naidu and Jessop, 2024), which plausibly depresses the visibility and comparability of TFM-relevant datasets during our window. This could be influenced by uncertainty grounded in misalignment between the scope of climate models versus the specific requirements of financial risk analysis, compounded by the spatial distribution of firms' physical assets and supply

chains, as well as the varying levels of organisational preparedness among entities (Fiedler et al., 2021; Hain et al., 2022). Consequently, the widely reported metrics may not always translate into a robust analytical foundation for portfolio realignments or credible progress assessments.

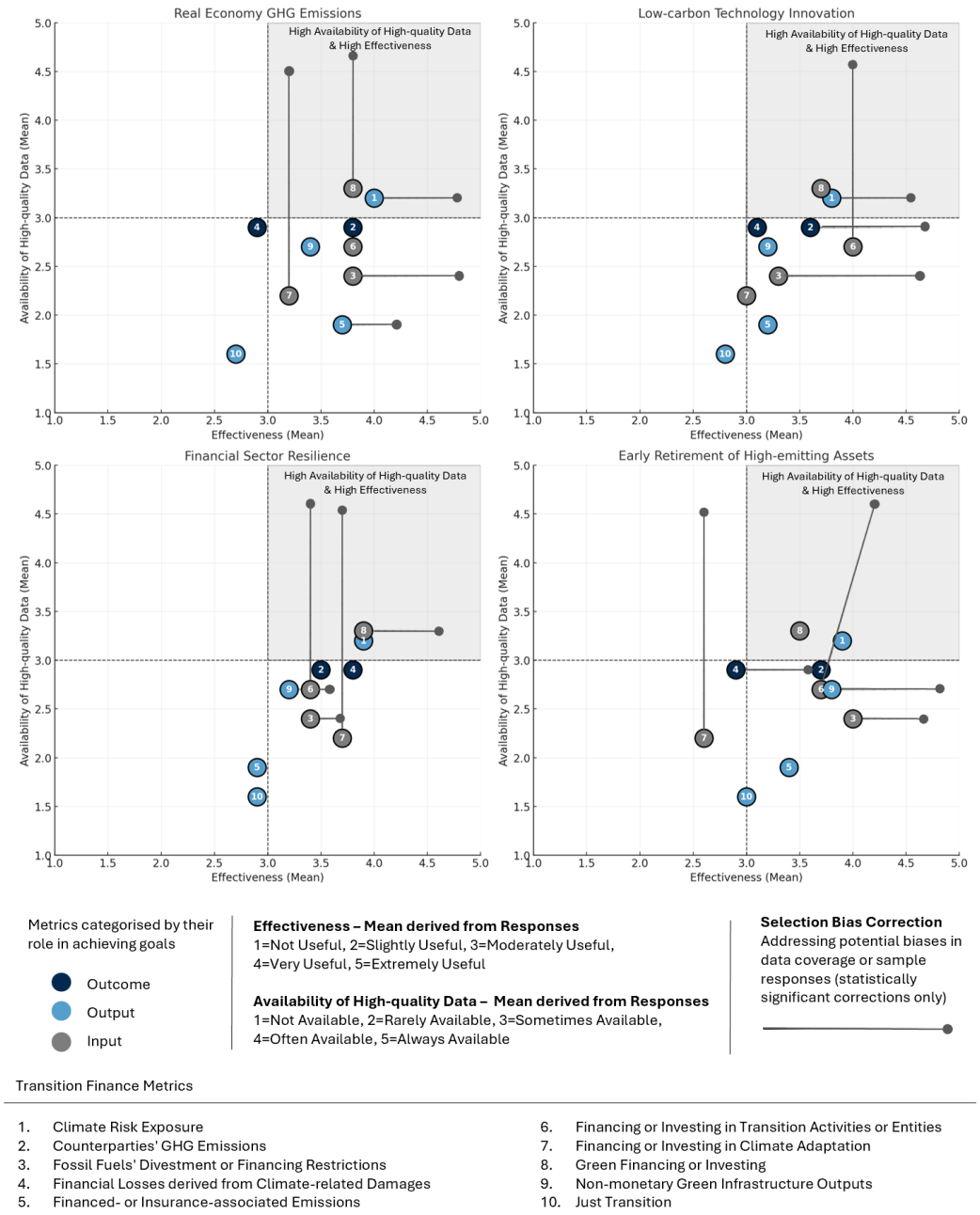

Figure 3.2 Perceived usefulness and availability of high-quality data for transition finance metrics, by climate goal

Note: Each panel corresponds to one of four climate goals (A–D). Axes report mean practitioner ratings on a five-point Likert scale: usefulness (horizontal, 1 = "not useful" to 5 = "extremely useful") and data availability (vertical, 1 = "not available" to 5 = "always available"). Filled coloured circles show unadjusted sample means. Where a Heckman selection model detected significant selection bias ($\rho \neq 0$, $p < 0.05$), a line extends to a grey circle marking the bias-adjusted estimate; line length reflects the estimated magnitude of the bias (see text for underlying assumptions). If no line is shown, no significant bias was detected. Colours denote metric type: Outcome (dark blue), Output (light blue), Input (grey). Numeric labels identify individual metrics (see Figure 3.1). The grey-shaded quadrant (means ≥ 3 on both axes) marks a high-alignment zone used as an interpretive aid.

Despite pockets of excellence in terms of potential effectiveness, significant gaps persist in the availability of high-quality data and in metric scope. Metrics on financed- or insurance-associated emissions exhibit low data availability, reflecting difficulties in incorporating sector-specific carbon footprints and reconciling indirect emissions sources (Y. A. Huang et al., 2009). Divestment or transition-financing policies often lack quantification of real-economy impacts, raising concerns about greenwashing and incomplete disclosures (Wang, 2025). Just transition metrics, covering social protections and equity safeguards, are rarely reported and rated less useful, partly due to their complexity and differing regional priorities, equitable labour transitions in developed economies versus mitigating socioeconomic disruptions in emerging markets (Galanis et al., 2025; Vrontisi et al., 2024). Climate adaptation financing is also seen as misaligned with priorities like decarbonisation and innovation, mirroring the slower global diffusion of adaptation technologies, especially in low-income countries (Touboul et al., 2023).

Divergent perceptions of TFMs across industry sectors are shaped by each sector's core business models and time horizons. Banks value TFMs as catalysts for fostering the adoption of low-carbon technology innovation through standardised frameworks like the EU Taxonomy, which align with lending practices and enable access to sustainability-focused market segments(Edwards et al., 2023; European Commission, 2023). However, they acknowledge a paradox: while promoting sustainability, TFMs may undermine financial stability by diverting investment from lower-risk assets and introducing volatility from investments relying on uncertain technological advancements. Insurers, bound by stringent capital and solvency rules (Ivantsova et al., 2021), prioritise climate risk exposure metrics aligned with their risk assessments and models (CISL and Deloitte, 2024), whereas fund managers respond to short performance cycles and investor demands by focusing on transition-related investment strategies (Guagliano, 2020), likely due to advancements in portfolio alignment methodologies (GFANZ, 2022d; IIGCC, 2024; SBTi, 2024). In contrast, asset owners, including pension funds and sovereign wealth funds, emphasise long-term real economy transformations and increasingly prioritise managing climate risk, including divestments from fossil fuels.

Because not all contacted practitioners chose to respond, the raw sample means may not reflect the views of the broader population. To gauge the direction and approximate scale of this non-response bias, we estimate a Heckman ordered-probit that jointly models the decision to complete the survey and the practitioner's rating of each TFM. The correction adjusts the expected perceived-usefulness and perceived-data-availability scores for systematic differences between respondents and non-respondents; it does not convert subjective ratings into objective performance measures. Relative to the raw means, the bias-adjusted estimates are materially higher for several categories. The largest movements

occur for fossil-fuel divestment, transition finance, and climate adaptation: for example, the adjusted data-availability means rise by about +1.9 points for transition finance and +2.3 for adaptation; adjusted perceived-usefulness scores for fossil-fuel divestment increase by +0.7 to +1.3 across several goals, and transition finance increases by about +0.5 for the phase-out goal (see Fig. 3.2 and Table 10 in the Appendix). These shifts indicate that once self-selection and covariates are accounted for, practitioners at institutions active in these areas rate the corresponding metrics as more useful, and their data as more accessible, than the raw averages suggest.

Focusing on the perceived-usefulness axis in Figure 3.2, corrections are consistently upward, meaning that non-respondents would, on average, have rated a given metric as more decision-useful than the observed sample did. The largest corrections appear for fossil-fuel divestment and financing restrictions (metric #3), which shifts by approximately +1.0 to +1.1 across the emissions-reduction and innovation goals. Climate risk exposure (metric #1) is corrected upward by +0.5 to +0.8 depending on the goal, and green financing (metric #8) by +0.4 to +0.6. Transition financing (metric #6) shows more modest corrections (+0.3). In the climate resilience panel, the pattern shifts: green financing (#8) receives the largest correction (+0.6), consistent with the sector's emphasis on investable pathways. Across all four goals, no downward corrections are observed, suggesting that non-response is concentrated among respondents less engaged with transition metrics and that the raw means, if anything, understate perceived usefulness. As noted above, these corrected magnitudes should be read as indicative of the direction and approximate scale of the bias rather than as precise population estimates.

Finally, situating TFMs within an input–output–outcome logic model framework reveals important structural imbalances. Inputs (e.g., capital committed to green bonds) are often well-documented, whereas some end outcomes (e.g., overall portfolio carbon intensity) are increasingly measured and reported. However, the review of "mid-level" outputs that connect resource allocations to measurable decarbonisation or resilience gains, such as explicit reductions in high-emitting assets, appears more sporadic. Incorporating more robust output indicators could help close the loop between climate risk management and tangible emission reductions, preventing instances where risk-awareness does not translate into portfolio adjustment. This gap also underscores the need to elevate risk management as a key dimension of transition finance, aligning with TCFD guidelines that call for integrated assessment of climate-related opportunities and risks.

3.2.3 Analysing practitioner perceptions using econometric modelling

Building on the raw and bias-adjusted summaries presented previously, we estimated ordered probit models to examine how respondents' profiles and organisational contexts are associated with how they rate the decision usefulness of TFMs. By integrating practitioner assessments of TFMs with indicators such as climate strategies and perceived exposure to climate-related risks, we aimed to clarify the contexts in which certain metrics are rated as more (or less) useful. In cases where selection bias was detected, we used a Heckman correction within the ordered probit framework, aligning the model with the adjusted mean results observed earlier (see Methods for details). This approach integrated two key findings from the raw data: (1) TFMs like green financing and fossil-fuel divestment often rank highly in perceived usefulness but face uneven data availability, and (2) institutions with robust data or partially or fully implemented climate strategies often appraise these metrics differently from the rest of the sample.

Two findings dominate Figure 3.3. First, respondents whose organisations have partially or fully implemented climate transition or adaptation plans systematically rate TFMs as *less* useful. Adaptation-plan status is the single strongest negative predictor across the forty regressions, reaching significance in the large majority of metric–goal combinations (Tables 2–9), with coefficients often between -0.6 and -1.0. Transition-plan status follows a similar pattern: every significant coefficient is negative, and the effect is especially pronounced for green financing and green infrastructure metrics (Tables 6–7, with coefficients as large as -1.5). Strikingly, respondents at organisations with adaptation plans rate adaptation financing metrics among the *least* useful (Table 6), and those with transition plans are most critical of green financing and green infrastructure metrics (Tables 6–7). Three factors may explain this pattern. Organisations with mature climate strategies are likely to recognise the multiple, interrelated challenges (technology overhauls, supply-chain restructuring, stakeholder engagement) that single-purpose metrics fail to capture. Short-term pessimism may also play a role: if tangible benefits from ambitious plans are not yet evident, respondents may discount metrics whose signals appear premature. Finally, higher internal benchmarks could prompt more critical views of commonly used metrics, which may appear overly simplistic relative to the scope of a fully developed transition or adaptation programme.

Second, perceived exposure to climate-related market risk is the strongest and most consistent positive predictor: every significant coefficient is positive, spanning virtually all ten metrics and four climate goals (Tables 2–9). The effect is especially broad for climate adaptation financing and green financing metrics (Tables 6–7), where market-risk coefficients are significant across all four goals. This suggests that practitioners anticipating asset revaluation, stranded fossil-fuel assets, or carbon-market volatility actively seek out

metrics that can guide portfolio decisions toward less carbon-intensive sectors. The finding aligns with research showing that investors demand higher returns to compensate for exposure to carbon-related risks (Bolton and Kacperczyk, 2021) and that transparent climate reporting can reduce uncertainty and bolster investor confidence (Eccles et al., 2014; Bender et al., 2019).

Beyond these two dominant patterns, professional experience (>7 years in climate and sustainability) is positively associated with the perceived usefulness of climate-risk exposure and counterparties' GHG emissions metrics (Tables 2–3) but does not significantly differentiate perceptions for other metric categories, suggesting that experience sharpens appreciation of established, well-understood indicators rather than newer ones. Physical, policy, and technological risks generally produce inconsequential coefficients, implying that respondents do not view them as material for immediate decision-making; these risks are often perceived as too uncertain, too long-horizon, or insufficiently captured by existing TFM frameworks compared with market concerns.

Taken together, the patterns in Figure 3.3 reveal a clear tension: organisations that have advanced furthest in implementing climate strategies are the most critical of existing metrics, while those most exposed to market-driven climate risks are the strongest advocates for them. This divergence suggests that the current TFM toolkit is perceived as better suited to signalling market-relevant risk than to supporting the operational complexity of mature transition and adaptation programmes.

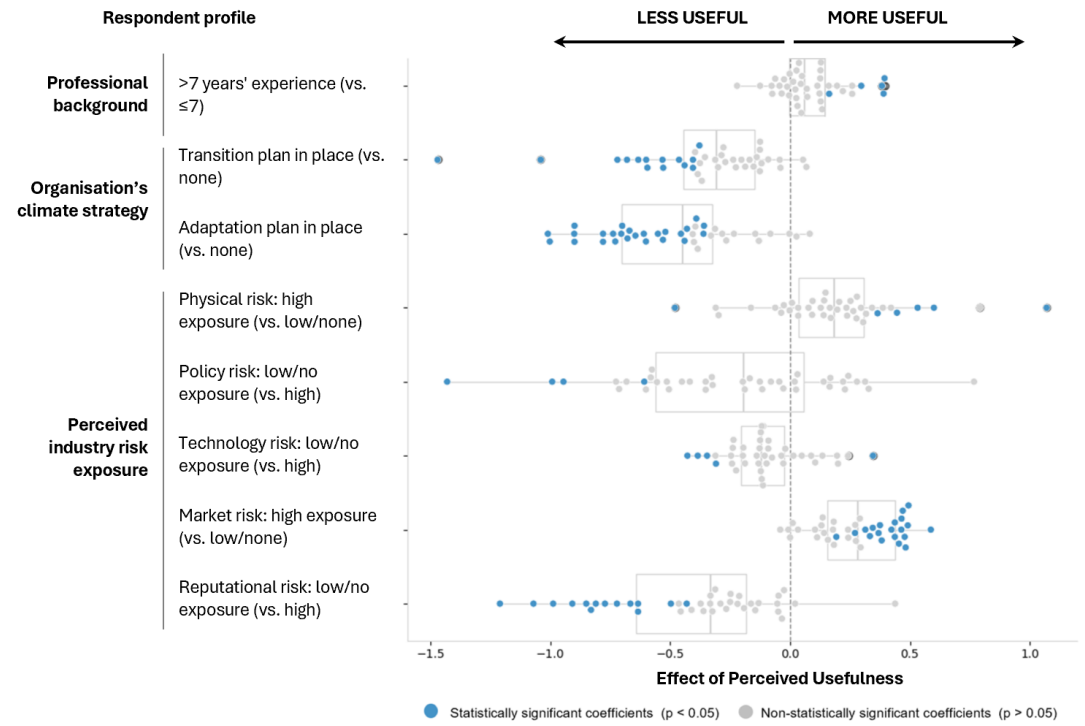

Figure 3.3 How practitioner experience, organisational climate plans, and perceived climate-risk exposure shape the perceived usefulness of transition finance metrics

Note: The figure summarises forty independent ordered-probit regressions (ten metric categories × four climate goals; see Tables 2–9 in the Appendix for full output). Rows are grouped into three blocks: professional background (experience in climate and sustainability), organisation's climate strategy (implementation status of transition and adaptation plans), and perceived industry risk exposure (physical, policy, technology, market, and reputational). Each sub-label specifies the binary coding direction and reference category (e.g., ">7 years' experience (vs. ≤7)"). Each dot is the estimated coefficient from one of the forty models. Blue dots are statistically significant ($p < 0.05$); grey dots are not. Dots to the right of zero indicate that practitioners with the stated profile rate the metric as *more* useful for the corresponding climate goal; dots to the left indicate they rate it as *less* useful. Boxes span the interquartile range across the forty models, with the line marking the median. Where selection bias was detected, a Heckman correction was applied (see Methods and Appendix).

3.3 Discussion

Global green finance flows have expanded to approximately USD 1.3 trillion annually, yet this remains a fraction of the estimated USD 8.4 trillion required each year until 2030 to meet net-zero targets (CPI, 2023). Our survey of 219 practitioners at the world's largest financial institutions sought to determine whether TFMs can bridge the gap between these commitments and concrete, near-term decarbonisation outcomes. The results point to three interrelated tensions.

First, practitioners rate widely adopted TFMs as moderately to highly useful for advancing near-term climate goals, yet report that the underlying data is only moderately available, underscoring the importance of improvements in data reliability (Zhang, 2023). Indicators related to just transitions and insured emissions are notably under-reported, despite their vital role in promoting equitable decarbonisation (Fankhauser et al., 2022). These gaps reinforce the view that transition finance remains fragmented (TFMR, 2024) and extend critiques cautioning against a narrow focus on net-zero targets without addressing the broader scope of economy-wide decarbonisation (Fankhauser et al., 2022). Second, practitioners at organisations with partially or fully implemented transition and adaptation plans are systematically more critical of existing TFMs. As our regression results suggest, this scepticism likely reflects heightened awareness of the operational complexity that single-purpose metrics fail to capture, higher internal benchmarks, and the absence of tangible short-term benefits from ambitious plans. The rising influence of the anti-ESG movement (Edmans, 2023) may compound this critical stance by raising broader questions about the legitimacy of current transition finance initiatives.

Developments since our survey closed align with its findings. The Net-Zero Insurance Alliance collapsed under antitrust pressure and re-emerged with weaker terms (Scott, 2025). Further exits from net-zero alliances followed in banking and asset management, while support for environmental proposals dropped in the 2025 US proxy season (Jessop, 2024; White, 2025). These shifts reflect waning climate ambition and reinforce our finding that practitioners at institutions already implementing transition plans favour broader, risk-integrated TFMs over single-purpose indicators.

Third, among the climate-risk factors examined, perceived exposure to market risk stands out as the strongest and most consistent positive predictor of TFM usefulness: practitioners who report high exposure to asset revaluation, stranded assets, or carbon-market volatility rate metrics as more decision-useful across virtually all metric–goal combinations. This reflects a pragmatic orientation toward near-term financial consequences that feel concrete and actionable. Physical, policy, and technology-related risks, by contrast, produce largely insignificant coefficients, indicating that practitioners view these as either too distant

or too uncertain to factor into current assessments of TFM utility. This pattern reveals a tension between near-term market accountability and the long-horizon nature of most climate risks, and suggests that future policy efforts should focus on making slower-moving risks more legible within existing financial models and reporting frameworks.

These tensions carry direct implications for financial regulators, standard-setters, and the institutions they supervise.

The usefulness–data gap is sharpest for the metrics that matter most. Climate risk exposure metrics (#1) and green financing commitments (#8) sit in the upper tier of perceived usefulness across all four goals, yet their data availability scores cluster around the midpoint of the scale. For a regulator designing mandatory disclosure requirements, prescribing these metrics without investing in the underlying data infrastructure will produce disclosures that are formally compliant but practically unreliable. Frameworks such as the EU CSRD, the UK TPT disclosure standard, and the ISSB S1/S2 baseline should therefore pair metric mandates with explicit provisions for data quality assurance, third-party verification, and cross-jurisdictional interoperability, particularly for financed emissions and insurance-associated exposures, where our survey records the lowest data availability scores.

The input–output–outcome imbalance revealed by our logic-model analysis points to a second regulatory gap. Current reporting concentrates on commitments (inputs, such as green bond volumes) and portfolio-level indicators (outcomes, such as weighted average carbon intensity), but mid-level outputs that connect capital allocation to decarbonisation progress remain sporadic. Supervisors should require institutions to report intermediate milestones: managed asset retirement schedules, contracted technology adoption rates, and phase-out timelines with quantified scope. Without these, a regulator cannot distinguish between an institution that is actively winding down carbon-intensive exposures and one that has merely reclassified or transferred them to less regulated entities.

Third, just transition and climate adaptation metrics are the least reported and least favourably rated categories in our survey, yet they capture dimensions (labour displacement, community resilience, adaptive capacity) that determine whether a transition is socially sustainable. Regulators incorporating transition plan disclosure requirements, such as those under the UK TPT or the EU Green Deal Industrial Plan, should mandate reporting on social safeguards alongside environmental indicators, rather than treating them as voluntary or supplementary fields.

Finally, the Heckman corrections indicate that raw survey averages systematically understate both perceived usefulness and data availability for several metric categories, most notably fossil-fuel divestment and transition financing. This suggests that the institutions most actively engaged in transition finance hold more favourable views of these metrics

than the broader sample implies. For policymakers, this is a cautiously encouraging signal: among early adopters, the tools are considered decision-useful. The challenge lies in extending comparable data access and institutional capacity to the wider population of regulated entities.

This work is shaped by specific limitations. First, the sample primarily comprised large, English-speaking financial institutions headquartered in developed markets, meaning that emerging market and developing economy perspectives remain under-represented. Second, reliance on practitioner self-reporting can introduce biases linked to institutional culture and career incentives. Third, the cross-sectional design may not capture evolving perceptions, especially as new policies, technological breakthroughs, and regulatory developments reshape transition finance. Fourth, the survey asked respondents about the availability of high-quality data without further specifying what "high-quality" means; respondents therefore interpreted the qualifier according to their own professional standards, which may vary across institutions and jurisdictions. The construct nonetheless captures a practically relevant signal: whether the data that practitioners consider adequate for implementing a given metric is accessible to them. Finally, observed greenhushing in North American filings (Naidu and Jessop, 2024) and communications during our fieldwork window may bias perceptions of "data availability" downward relative to actual internal data stocks, especially for TFMs that are politically salient.

Future research should broaden its scope to a wider range of geographies, thus capturing a more diverse set of business models, regulatory contexts, and adaptation challenges. Longitudinal studies tracking how evolving TFMs, especially those emphasising 'just transitions' and adaptation, affect capital allocation decisions and emissions over time would offer valuable insights. Furthermore, qualitative interviews or case studies could deepen our understanding of the organisational processes through which practitioners operationalise TFMs. Finally, collaborations between policymakers, industry groups, and civil society organisations could facilitate the standardisation of data and definitions, ensuring that TFMs not only measure climate progress but actively catalyse it.

In sum, practitioners regard TFMs as useful tools for advancing near-term climate goals, but their assessments reveal a persistent gap between perceived decision usefulness and the availability of high-quality data needed for implementation. Closing this gap is not merely a technical exercise. It requires coordinated action: regulators mandating comparable disclosures, standard-setters broadening metric scope to encompass intermediate outputs and social safeguards, and financial institutions investing in the data infrastructure that underpins credible transition reporting. Without these steps, transition finance metrics risk remaining aspirational rather than operational.

3.4 Methods

This section outlines the methodologies employed in developing, validating, and analysing the TFMs framework, detailing a rigorous combination of data-driven processes, survey design, statistical modelling, and expert validation.

3.4.1 Climate transition finance metrics framework

To construct the TFM typology, we began with the 25 largest global financial institutions in each of four sectors (banks, insurers, asset managers, and asset owners) identified from sources such as the Sovereign Wealth Fund Institute, the Thinking Ahead Institute, and S&P Global (S&P Global Market Intelligence., 2024; SWFI, 2024b, 2024a; TAI, 2023). Institutional sustainability and climate strategy documents, as well as ESG reports, were compiled into a corpus.

A RAG methodology(Hameed, 2023) was implemented as follows. Initial data extraction converted the PDF files into machine-readable text using the python PyPDF2 library. Recognising that large textual inputs can challenge embedding models, we employed a systematic segmentation procedure implemented through LangChain's CharacterTextSplitter. By dividing the corpus into chunks of approximately 800 characters with an overlap of 200 characters, we ensured that contextual coherence was maintained while respecting token limitations. This careful chunking process balanced data granularity with computational tractability.

Once the text was segmented, each chunk was embedded into a high-dimensional semantic vector space using OpenAI's pretrained embeddings. These embeddings transformed unstructured text into numerical representations that capture semantic relationships between words, phrases, and concepts. Next, the FAISS vector database enabled efficient similarity searches across the embeddings. By querying the vector store with prompt-engineered requests and sample metrics drawn from a separate Excel file, the system retrieved text segments likely containing references to TFMs. Employing the LangChain libraries and OpenAI LLMs for the query-answering chain allowed us to contextualise and refine the results, ensuring that identified metrics were grounded in the retrieved documents rather than confabulated by the language model.

To mitigate the risk of hallucination, where the model might produce plausible-sounding but erroneous metrics, a random sample of approximately 20% of the extracted TFMs was subjected to manual verification by the research team. This human-in-the-loop step ensured that selected metrics were authentically present in the source documents and aligned with official climate transition strategies. Additional validation was secured through consultations with secretariats of the GFANZ and the Transition Finance Market

Review. Their expert insights confirmed that the final set of ten TFMs reflected commonly recognised, quantitative measures directly relevant to key climate objectives. This combination of automated retrieval, human oversight, and expert validation yielded a robust typology of TFMs suitable for subsequent survey-based assessment.

3.4.2 Survey design and validation

Participants completed an anonymous survey providing demographic and institutional information before rating ten climate transition finance metrics across two distinct dimensions. Section 2 of the survey instrument asked respondents to rate the perceived usefulness of each metric on a five-point Likert scale (from "not useful" to "extremely useful"). Section 3 then asked, separately for each metric, about the availability of high-quality data, rated from "not available" to "always available" (see the Appendix for the full instrument). Note that the survey did not ask about data availability and data quality as separate constructs; it asked a single question about a combined concept: whether data of high quality is available for implementing each metric. The qualifier "high-quality" was not further specified; respondents therefore interpreted it according to their own professional standards, which may vary across institutions and jurisdictions. Despite this limitation, the construct captures a practically relevant signal: whether the data that practitioners consider adequate for implementing a given metric is, in their experience, accessible. Both scales balanced simplicity with sufficient detail, promoting reliable responses. The survey focused on four key climate goals (enabling the reduction of GHG emissions, supporting innovation in low-carbon technologies, strengthening climate resilience, and facilitating the phase-out of high-emitting assets) within a 2030-time horizon.

3.4.3 Population and sampling

The survey was directed at professionals within the world's largest financial institutions (specifically, banks, asset managers, insurance companies, and asset owners) who hold climate- or sustainability-related roles.

Initially, we identified the 280 largest financial institutions, split evenly across four industry sectors (70 per each sector: banks, insurers, asset managers, and asset owners). We then used LinkedIn to target 10 random employees from each institution, for a planned total of 2,800 potential participants. The search criterion combined the institution's name with "climate" or "sustainability" to ensure respondents had relevant expertise.

Of the 2,800 invitations sent, 2,177 were successfully delivered (some invitations bounced due to outdated emails or invalid addresses). This sampling method can be characterised as a non-probability, purposive approach (because we intentionally focused

on professionals known to have climate- or sustainability-related job functions) combined with random selection within each institution's relevant employee pool. Although this approach does not yield a fully random sample of the broader financial sector, it ensures a balanced representation of institutions and professional roles actively engaged in climate-related finance.

Out of the 2,177 delivered invitations, 700 recipients opened the survey link, and 219 completed the questionnaire, representing a completion rate of 31.3% among those who opened the invitation. While this figure underscores the selectiveness of our sample, it reflects a reasonable engagement level for a targeted, industry-facing survey.

3.4.4 Survey instrument and design

Prior to the main rollout, the questionnaire was piloted with secretariats from GFANZ and academic experts from the Oxford Sustainable Finance Group and the Sustainable and Green Finance Institute (SGFIN) at the National University of Singapore (NUS). Feedback primarily concerned the survey's overall structure, leading to the inclusion of adaptation-related metrics and clearer reference to climate-related risks. Additionally, minor wording adjustments were made to ensure question clarity. This iterative process improved face validity and reduced potential ambiguity in how participants interpret key terms.

3.4.5 Data collection procedures

The survey was dispatched via email on 25 September 2024 and remained open until 1 October 2024. A random subsample of approximately one-third of those who had not yet responded received a final-day reminder to encourage participation. Notably, the survey period overlapped with Climate Week NYC (21–28 September 2024), an event that might have heightened awareness of climate finance issues. The survey also concluded before the subsequent U.S. election, recognised by some institutions as a potential turning point in climate policy.

The online questionnaire was administered using QuestionPro. Settings were configured to prevent submission of incomplete responses and to offer "Don't know" options where appropriate, minimising guesswork while still capturing uncertainty. Respondents' identities remained confidential, as no personal identifiers were collected.

One notable limitation is the limited coverage of emerging markets. Because our goal was to target the largest global financial institutions, the final sample naturally skewed toward established players in developed markets. Additionally, we only offered the survey in English, which may have posed language barriers for non-English speakers.

Nevertheless, this approach aligns with our focus on major industry participants, who are more likely to operate internationally and maintain English-language capabilities.

3.4.6 Data analysis

From the outset we systematically tested for selection bias across all TFMs to determine whether our final sample of respondents was representative of the broader population. Where the correlation parameter ρ from the selection equation was significantly different from zero, we concluded that standard estimation would be biased. Consequently, in Figure 3.2, we present Heckman-adjusted means only for those metrics exhibiting non-random response patterns, while retaining raw means for others. Likewise, for Figure 3.3, we employed an ordered probit specification augmented with a selection equation solely when significant selection bias was detected; otherwise, a standard ordered probit model was sufficient. The methodological details of these procedures are elaborated below.

We examined participants' perceptions of metric usefulness, measured by a five-point Likert scale ranging from 1 ("not useful") to 5 ("extremely useful"). All explanatory variables, including demographics, industry affiliations, and levels of experience, were collected within the same survey. Our principal concern was whether non-random participation might bias estimates of how these explanatory variables affect the perceived usefulness scores. The theoretical framework rested on a Heckman-type ordered probit approach, which combines an ordered probit model for the outcome with a probit model for sample selection(Chiburis and Lokshin, 2007).

The outcome equation is specified as an ordered probit model. Let Y_j be the ordinal response for individual j, taking values in {1,2,3,4,5}. Assume there is an unobserved continuous latent variable Y_j^* given by

$$Y_j^* = x_j\beta + \varepsilon_j,$$

where x_j includes binary indicators for high versus low experience, the implementation status of climate transition plans, the implementation status of climate adaptation plans, and perceived exposures to physical, policy, technological, market, and reputational risks; it also incorporates industry affiliation dummies (for banks, asset managers, insurers, and asset owners) as well as survey-specific controls such as the receipt of a reminder and respondent gender. Here, β is a vector of coefficients, and ε_j is a normally distributed error term with mean zero and unit variance. The observed response Y_j is determined via threshold cutpoints:

$$Y_j = h \quad if \quad \kappa_{h-1} < Y_j^* \leq \kappa_h, \quad h = 1, \ldots, 5,$$

where $\kappa_0 = -\infty$, $\kappa_5 = +\infty$, and κ_1, κ_2, κ_3, κ_4 are estimated thresholds.

To assess whether non-random participation could bias our estimates, we modelled two processes jointly: the outcome equation for the 1–5 usefulness ratings and a selection equation for survey completion. The selection equation captures self-selection into response by modelling the probability that a contacted individual completes the survey; this allows the outcome estimates to be adjusted for differences between responders and non-responders. Let S_j be an indicator where $S_j = 1$ signifies that individual j completed the survey, and $S_j = 0$ indicates otherwise. The probability of selection is modelled using a standard probit equation:

$$S_j = 1\{z_j\gamma + u_j > 0\},$$

where z_j is a vector of covariates hypothesised to influence survey participation. In our analysis, z_j explicitly includes a binary indicator for whether a reminder email was sent to the respondent and a binary indicator for self-reported gender (coded as 1 for male and 0 for non-male). The error term u_j is assumed to be normally distributed with mean zero and unit variance. If the error term ε_j in the outcome equation is correlated with u_j (e.g., if $\rho \neq 0$), then standard ordered probit estimates on the observed sample would be inconsistent, necessitating joint estimation via the Heckman correction procedure.

The Heckman-type ordered probit model estimates these two equations simultaneously under the assumption that (ε_j, u_j) jointly follow a bivariate normal distribution with correlation ρ. If $\rho \neq 0$, there is evidence of selection on unobservables, and a joint maximum-likelihood procedure is required to obtain consistent parameter estimates for both β and γ. We employed Stata's heckoprobit, which implements this maximisation by integrating over the bivariate normal distribution of the error terms(StataCorp LLC, 2023a).

After estimating the model, a likelihood-ratio or Wald test typically evaluates the null hypothesis $\rho = 0$. Rejecting $\rho = 0$ indicates that unobserved factors influencing whether an individual responds are correlated with unobserved factors influencing how those individual rates the metrics. In this situation, the Heckman-type approach is necessary to avoid biased estimates. Failing to reject $\rho = 0$ implies no detectable selection on unobservables, in which case one may simplify the analysis using a standard ordered probit model on the observed data only.

To sum up, the modelling process consists of estimating the two-equation system jointly. If significant correlation between the error processes is found, the resulting Heckman-type estimates are retained. If not, the selection equation is dropped, and the simpler ordered probit specification becomes the final model. This staged approach ensures that estimates of the effect of key survey-collected controls, such as experience

levels, industry affiliation, and demographic features, are not confounded by unobserved selection mechanisms that might otherwise bias the interpretation of how respondents perceive metric usefulness.

In estimating the Heckman-type ordered probit, we compute standard errors using both robust estimators and bootstrap resampling. The robust approach mitigates potential model misspecification by relaxing assumptions about the exact form of heteroskedasticity, while bootstrap methods provide a flexible way to approximate the sampling distribution of parameter estimates, particularly valuable when the theoretical large-sample properties of estimators may be sensitive to complex survey structures or smaller effective sample sizes. These practices add robustness to our inference regarding whether selection bias exists and how strongly each predictor affects the ordinal outcome. Detailed results for these estimations, including full coefficient tables and diagnostic checks, are reported in the Appendix.

Upon detecting significant selection bias, specifically when the LR or Wald tests reject the null hypothesis that $\rho = 0$, we utilise the estimated parameters from the Heckman-type ordered probit model to adjust the mean values of the Likert-scale outcomes. In these cases, for each respondent, we computed the linear predictor $\widehat{y}_j^*$ and applied the estimated threshold parameters $\hat{\kappa}_1,\ \hat{\kappa}_2,\ \hat{\kappa}_3,\ \hat{\kappa}_4$ to calculate the predicted probabilities $P(Y_j = h)$ for each Likert category $h = 1, \ldots, 5$. The adjusted expected outcome was then derived as a weighted sum of these probabilities:

$$\widehat{Y}_j = \sum_{h=1}^{5} h \cdot P(Y_j = h).$$

This adjustment ensures that the mean values reflect the underlying population parameters, accounting for the selection bias identified. By incorporating both the ordinal structure of the responses and the selection mechanism, the adjusted means provide an unbiased measure of participants' predicted perceptions of metric usefulness. The detailed results are provided in the Appendix.

3.4.7 Ethical and legal compliance

This study adhered to the University of Oxford's Research Ethics Committee (CUREC) guidelines (Reference SOGE1A2021-238). All participants were required to click a mandatory consent checkbox before accessing the full questionnaire, and no personal data (e.g., names or email addresses) were stored. All survey data are securely retained on the University of Oxford OneDrive for Business, with access restricted to authorised research team members.

4

Sustainability-Linked Bonds: Modelling for Sustainability Performance

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We develop a theoretical valuation framework for sustainability-linked bonds (SLBs) that accounts for the stochastic volatility of sustainability performance metrics using a Heston process, and is the first to integrate transition plan assessments into probability calibration. The model simulates KPI pathways to estimate the probability of meeting SLB targets and translates these into present-value adjustments, quantifying the financial value of issuer credibility. We illustrate the framework through the first corporate SLB (Enel, 2019) and the first sovereign SLB (Republic of Chile, 2022), demonstrating its sensitivity to transition plan quality and its capacity to flag potential pricing misalignments. As the SLB market matures and longer KPI time series become available, the framework can support both buy-side and sell-side decision-making by providing an independent, probability-based benchmark for sustainability-linked risk. (JEL G12, Q54, G32, C61, G11)

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4.1 Introduction

Sustainability-linked bonds (SLBs) are debt instruments whose coupon steps up or down according to the issuer's progress against predefined sustainability performance targets (SPTs). Where green bonds ring-fence proceeds for environmental projects and conventional bonds carry no sustainability conditionality at all, SLBs place no constraint on the use of funds yet make the cost of borrowing contingent on measurable outcomes such as emissions reduction. The issuer's transition credibility thus becomes a priced feature of the instrument. Yet valuing that feature remains difficult, and without credible valuation the incentive structure that distinguishes SLBs from other labelled debt is weakened. This paper develops a theoretical framework, grounded in stochastic volatility modelling, for estimating the intrinsic value of SLBs and diagnosing when market prices may diverge from the sustainability commitments they are meant to reflect.

Existing models typically assume constant volatility and smooth evolution of the underlying key performance indicators (KPIs), using Geometric Brownian Motion (Ibe, 2013, chap. 9) and overlooking the policy-driven shocks and nonlinear dynamics that characterise sustainability metrics in practice (e.g., Chekriy et al., 2023; Mielnik and Erlandsson, 2022). Shrinkage estimators improve statistical stability but may misrepresent individual KPI behaviour (Feldhütter et al., 2024). These limitations risk mispricing SLBs, misaligning investor incentives, and undermining capital allocation at a moment when the market's credibility is already under scrutiny (L.P, 2024).

This paper develops a theoretical valuation framework that replaces constant-volatility assumptions with a stochastic volatility process calibrated to issuers' sustainability trajectories and transition plans. While existing models focus largely on pricing, which captures current trading conditions, we concentrate on intrinsic valuation, modelling the uncertain and often nonlinear evolution of KPIs to estimate the fundamental worth of SLBs. By distinguishing between the option-like features of SLBs (associated with the uncertainty of meeting targets) and the non-pecuniary "greenium" investors are willing to pay for sustainability exposure, the framework enables a more robust assessment of sustainability risk and opportunity. We illustrate it through two numerical cases: the first corporate SLB (Enel, 2019) and the first sovereign SLB (Republic of Chile, 2022). These applications demonstrate the model's mechanics and sensitivity under current data constraints; as the market matures and longer KPI time series become available, the framework can support investment decision-making and more credible capital allocation into the sustainability transition.

We operationalise this framework by modelling SLB yield spreads using a hybrid structure that combines stochastic processes and scenario-based calibration. To capture the

non-constant volatility of sustainability performance, we embed a Heston process (Heston, 1993), with parameters conditioned on issuers' transition plan scores and peer rankings. Target achievement probabilities are estimated through a GARCH-based mean-reverting process, incorporating Monte Carlo simulations to reflect nonlinear KPI trajectories. Drawing on U. Erlandsson et al. (2022), we calibrate the model to decompose observed spreads into components attributable to risk and investor sustainability preference. The framework is applied to two landmark SLBs: Enel, which issued the first corporate SLB in 2019, and the Republic of Chile, which issued the first sovereign SLB in 2022. These cases are natural benchmarks because they offer the longest available time series of sustainability KPIs and represent the two principal issuer classes in the market (see Appendix A).

Backtesting and convergence analysis suggest that the model captures the underlying stochastic dynamics with reasonable accuracy. By incorporating transition plans, it captures shifts in sustainability performance beyond historical trends; for instance, raising Enel's probability of meeting its 80% renewable energy capacity (REC) target from 43% to 53% and reducing the step-up value from 111.89 to 91.81 basis points. It similarly reflects Chile's rapid renewable capacity expansion and greenhouse gas (GHG) reductions in line with national policy. The model addresses the shortcomings of constant volatility and GBM assumptions by applying a Heston-GARCH framework with bootstrapped parameters to improve robustness. It is the first to integrate transition plan assessments into probability calibration, offering a forward-looking tool to evaluate issuer credibility, flag potential pricing misalignments, and better assess sustainability-linked risks.

The remainder of this chapter is structured as follows. The next section outlines the valuation framework. The empirical case studies on climate mitigation follow. A discussion of contributions and limitations precedes the conclusion. Appendices include analyses on non-constant volatility, parameter estimates, and model validation.

4.2 Framework

Our valuation model uses the Heston process (Heston, 1993) to capture the stochastic volatility and non-linear dynamics of sustainability performance metrics, improving upon constant-volatility models based on GBM (e.g., Chekriy et al., 2023; Mielnik and Erlandsson, 2022). By integrating issuers' climate-related transition plans, the model calibrates initial volatility and drift to better estimate the probability of meeting SLB targets, which is then factored into present value calculations. It accounts for volatility clustering and discontinuities (Fiorentini et al., 2002; Grasselli, 2017), recognising that issuers may follow complex transition paths. Using two stochastic differential equations, it simulates

both variance and metric levels, combining trends and shocks. Monte Carlo simulations produce a range of KPI outcomes, enabling probabilistic risk assessment aligned with Stoep et al. (2014), and offering a more robust SLB valuation under uncertainty (see Appendix A).

4.2.1 Valuation components

To estimate the present value of a SLB, we decompose it into two components building on the approach of Mielnik and Erlandsson (2022). First, the non-contingent component, akin to a plain vanilla bond, represents the baseline value using standard discounted cash flow methods. Second, the contingent component reflects potential adjustments to the bond's terms based on the issuer's sustainability performance. As a result, the overall valuation equation is:

$$SLB_0 = SLB_0^1 + SLB_0^2 \tag{1}$$

Our framework decomposes SLB valuation into a standard bond pricing model combined with an option-theoretic component to capture uncertainty in sustainability performance, building on classic work in option pricing and credit risk (Black and Scholes, 1973; Merton, 1974; Tuckman and Serrat, 2022). The contingent component, SLB_0^2, functions like an option payoff and is added to the non-contingent bond value. While treated additively for clarity, we acknowledge potential interactions between fixed-income valuation and broader sustainability risks.[1] The greenium, reflecting investor demand for SLBs, is separate from the option-like component, as it captures perceived rather than realised sustainability performance. Together, these elements show that SLBs incorporate sustainability risks through both contingent and non-contingent mechanisms. Although simplified in our model, this distinction helps clarify how differing risk perceptions and outcome-based incentives shape SLB pricing. [2]

Non-contingent Component, SLB_0^1. The non-contingent component, SLB_0^1, reflects the bond's traditional financial characteristics, such as fixed coupon payments and face

[1]The integration of broad sustainability risks extends beyond those captured by the contingent component of our model. We acknowledge that this area requires further research, particularly given the growing impact of environmental factors, regulatory changes, and climate change effects on credit ratings and yield spreads(Battiston and Monasterolo, 2020; Javadi and Masum, 2021; Seltzer et al., 2024). Additionally, the role of credit rating agencies in evaluating and communicating climate risk has been recognised as pivotal (Ciummo et al., 2022; Mathiesen, 2018), with market perceptions adjusting creditworthiness based on companies' carbon footprints and associated default risks (Capasso et al., 2020), highlighting the evolving landscape of financial valuation in the context of sustainability.

[2]This broader perspective has been explored in extensive research studies (e.g., Abdul Razak et al., 2020; Bolton and Kacperczyk, 2020; Höck et al., 2020; Seltzer et al., 2024; O. Weber et al., 2010; O. Weber et al., 2015).

value, which are discounted to their present value. Formally, the present value of the bond's non-contingent component cash flows, SLB_0^1, is expressed as:

$$SLB_0^1 = \sum_{t=1}^{n} \frac{C}{(1+r)^t} + \frac{F}{(1+r)^n} \tag{2}$$

where:

- n: Total number of coupon payment periods remaining until the bond matures. It is calculated by multiplying the number of years remaining until maturity by the payment frequency (the number of coupon payments per year).
- C: The fixed coupon payment.
- r: Periodic discount rate or yield per period. It is used to discount each of the bond's cash flows (coupon payments and face value) to their present value.[3]
- F: The face value of the bond, which is repaid at maturity.

Contingent component, SLB_0^2. Unlike conventional bonds, SLBs embed SPTs that can alter cash flows after the target date τ_j. The contingent component, SLB_0^2, therefore prices the option-like coupon adjustment that depends on the issuer's performance, drawing on contingent-claims methods developed for options and corporate liabilities (Black and Scholes, 1973; Merton, 1974). It deliberately excludes standard cash flows such as principal and coupons paid before τ_j. The focus is solely on the expected changes to coupons after the target date. [4]

In terms of the SLB incentive structure, for each sustainability metric x_i there is a corresponding target K_i, which represents the performance goal that the issuer aims to achieve by the target observation date τ_j. For each metric x_i, a metric-specific adjustment factor $\gamma_i(t)$ adjusts the coupon payment based on the issuer's performance in relation to K_i at time t_i. This factor can account for three incentive structures: coupon step-up, coupon step-down, and two-way adjustments. This requires a conditional structure that can distinguish between the issuer's performance outcomes:

$$\gamma_i(t) = \begin{cases} \gamma_{i,+} & if\ x_i < K_i\ at\ t_i \\ \gamma_{i,-} & if\ x_i \geq K_i\ at\ t_i \end{cases} \tag{3}$$

[3]This framework can differ from other approaches that consider market prices of zero-coupon bonds (Mielnik and Erlandsson, 2022), which may implicitly include the risk-free rate, credit spreads, and other market factors affecting the pricing of risk-free and risky bonds. In contrast, we assume constant coupon payments for simplicity, given that we account for the variability in coupon rates due to SPTs in SLB_0^2.

[4]This mechanism is similar to that of Treasury Inflation-Protected Securities (TIPS), which adjust coupon rates in response to inflation to safeguard investors' purchasing power (Shen and Corning, 2001). Unlike TIPS, however, SLB_0^2 emphasizes sustainability performance, underscoring the increasing integration of sustainability considerations into financial valuation.

This notation captures the conditions under which the coupon payment will be adjusted upwards ($\gamma_{i,+}$ for a step-up scenario) if the issuer's performance falls short of the sustainability target, or downwards ($\gamma_{i,-}$ for a step-down or two-way scenario) if the target is met or exceeded. The formulation adopts a higher-is-better convention: for metrics where lower values indicate better performance (e.g., GHG emissions), the comparison operator is reversed accordingly, as detailed in the note to Table 4.4. For expositional clarity, the valuation framework is presented on a per-metric basis; in the implementation, the model is applied independently to each metric j. Based on these possible incentive structures, we can define:

$$E[\Delta] = p \cdot \gamma_{i,-} + (1-p) \cdot \gamma_{i,+} \tag{4}$$

where p is the probability of achieving the sustainability targets, $\gamma_{i,-}$ is the coupon payment adjustment if the target is met (typically a reduction or no change), and $\gamma_{i,+}$ is the coupon payment adjustment if the target is not met (typically an increase). Note that $\gamma_{i,+}$ and $\gamma_{i,-}$ are expressed in monetary units (i.e., the periodic cash-flow increment or decrement), so that the expected adjustment $E[\Delta]$ can be discounted directly. We can formulate SLB_0^2 as:

$$SLB_0^2 = \sum_{t=\tau_j+1}^{n} \frac{E[\Delta]}{(1+r)^t} \tag{5}$$

where $E[\Delta]$ is the expected adjustment based on the probability of meeting or failing to meet the sustainability target. It accounts for the potential step-up or step-down in the coupon rate after the target observation date τ_j. This concept resonates with Romano and Touzi (1997)'s exploration of pricing in uncertain markets, emphasising how economic fluctuations influence asset values.

While direct studies on SLB-specific adjustments remain limited, the underlying principles align with established financial risk management practices. For instance, the probability adjustment in SLB valuation parallels bilateral counterparty risk adjustments explored by Lipton and Savescu (2014), where the value of an exposure changes based on the evolving probability of default. Similarly, our model adjusts the SLB's step-up valuation according to the changing likelihood of meeting SPTs, using probabilistic modelling to incorporate future uncertainty into present valuations. Although not explicitly modelled here, understanding correlations between multiple KPIs is also crucial, as they affect the joint probability of target achievement and the likelihood of step-up activation. Positive correlations increase the chances of simultaneous success or failure, making coupon outcomes more predictable, while negative correlations may act as a hedge, offsetting risks across KPIs and influencing overall bond performance.

4.2.2 Sustainability performance metrics: simulated pathways

In this section, we introduce the SDEs and Monte Carlo simulations that underpin the calculation of the probability used in SLB_0^2. These probabilistic methods model the dynamic behaviour of sustainability metrics over time, capturing the inherent uncertainties and volatility associated with the issuer's performance. By simulating numerous potential pathways for these metrics, we derive the likelihood that the issuer meets the specified sustainability targets, which directly informs the adjustment factor $E[\Delta]$ in the contingent component of the bond's valuation.

The first SDE models the variance (volatility) of sustainability performance metrics:

$$dv_j(t) = \kappa_j \left(\theta_j - v_j(t)\right) dt + \xi_j \sqrt{v_j(t)}\, dW_{v_j}(t) \tag{6}$$

where:

- $v_j(t)$: The instantaneous variance of the j-th sustainability metric at time t.
- κ_j: Mean reversion speed, quantifying how fast the variance $v_j(t)$ reverts to its long-term average level θ_j.
- θ_j: Mean reversion level, representing the long-term average to which the variance $v_j(t)$ is expected to revert.
- ξ_j: Volatility of the variance (also called the "volatility of volatility"), which measures the randomness in the changes of $v_j(t)$ itself.
- $v_j(0)$: The initial level of the variance the j-th sustainability metric at time zero, not explicitly stated in the equation but required for simulations.
- $dW_{v_j}(t)$: Wiener process associated with the variance of the j-th sustainability metric, representing the stochastic component that introduces randomness. [5]

Equation 6 demonstrates the mean-reverting nature of volatility, where it gravitates toward a long-term mean. It features a mean-reversion term, $\kappa_j \left(\theta_j - v_j(t)\right) dt$ and a stochastic term $\xi_j \sqrt{v_j(t)}\; dW_{v_j}(t)$ which collectively facilitate both the attraction to the mean and the adjustment for random volatility spikes. Estimating the parameters

[5]Monte Carlo simulations are selected for implementing $dW_V(t)$ in the Heston model due to their flexibility, scalability, and effectiveness in modelling complex stochastic processes. While alternatives like the Euler-Maruyama and Milstein methods offer numerical solutions (Higham, 2001), Broadie and Kaya (2006) suggest that these methods fall short in accurately capturing the complexities of mean-reverting stochastic volatility and the correlation between metric values and volatility. Glasserman (2003) further elaborates on the superiority of Monte Carlo simulations in financial engineering, highlighting their adaptability and efficiency in simulating complex stochastic behaviours and their effectiveness in managing the intricate aspects of financial models in high-dimensional settings. This blend of adaptability, efficiency, and the ability to accurately simulate non-linear dynamics and nuanced behaviours of financial metrics solidifies the preference for Monte Carlo simulations over other methods, despite the latter's potential advantages in various modelling scenarios.

(mean reversion speed, mean level of variance, and volatility of variance) typically requires advanced modelling due to their non-observability in historical data. [6]

The rate of change in the sustainability metric's value, S_j, is similarly modelled using a second SDE coupled with Equation 6:

$$dS_j(t) = \mu_j S_j(t)dt + \sqrt{v_j(t)}S_j(t)\, dW_{S_j}(t) \tag{7}$$

where:

- $S_j(t)$: Value of the j-th sustainability metric at time t.
- μ_j: Drift component for the j-th sustainability metric, representing the expected rate of change or growth in the absence of volatility.
- $v_j(t)$: The instantaneous variance of the j-th sustainability metric's rate of change at time t, derived from the variance process (Equation 6).
- $dW_{S_j}(t)$: Wiener process for the j-th sustainability metric, introducing randomness into the metric's evolution.[7]

In the standard Heston framework, a correlation parameter ρ_j governs the covariance between the two Wiener processes, $\mathrm{d}W_{v_j} \cdot \mathrm{d}W_{S_j} = \rho_j\, \mathrm{d}t$. Our implementation accommodates this correlation; however, for parsimony, the SDEs are presented above in their marginal form.

The model employs distinct simulations for each sustainability metric, leveraging $S_j(t)$ with a specifically calibrated drift μ_j to anticipate growth adjustments. For metric j, independent simulations project its trajectory, assessing if the sustainability target K_j is met by the target observation date τ_j with success defined as $S_j(\tau_j) \geq K_j$. Probabilities of meeting targets are individually calculated, deriving from the proportion of paths exceeding

[6]The literature on estimating mean reversion rates, long-term volatility, and the volatility of volatility within financial contexts is comprehensive. Elliot et al. (1999) and F. H. Sanchez and Palacio (2013) have made significant contributions to the estimation of mean reversion rates. Elliot et al. utilized a Hidden Markov Model, whereas Sanchez and Palacio advocated for a one-factor mean reversion process. In the area of long-term volatility, Flint et al. (2015) provide a detailed review of models for long-term volatility. Their analysis covers everything from simple historical volatility estimations to advanced econometric models, both deterministic and stochastic, and they introduce novel nonparametric methods like break-even volatility and canonical option valuation. Regarding the estimation of volatility of volatility, Alghalith et al. (2020) and Dokuchaev (2014) suggest the use of nonparametric estimators. Alghalith et al. focus on addressing time-variant volatility factors. Cvitani et al. (2006) and Danielsson (1994) focus on numerical estimation techniques, employing a Markov Chain process and simulated maximum likelihood methods, respectively.

[7]While the Wiener process $dW_{S_j}(t)$ captures the inherent uncertainty in the evolution of the j-th sustainability metric, it is important to note that this formulation assumes the randomness is independent of other market factors unless explicitly modelled otherwise. However, the sustainability performance may be correlated with broader market conditions, potentially requiring a more complex stochastic process to capture these interactions. For instance, introducing a correlation term between $dW_{S_j}(t)$ and the Wiener process governing general market volatility could provide a more nuanced understanding of how market conditions impact the likelihood of meeting sustainability targets.

K_j by τ_j, providing a precise statistical foundation for evaluating the achievement likelihood of each distinct sustainability goal. While the foundational SDEs of the Heston model serve as the basis for our approach, our method incorporates significant adaptations to reflect sustainability commitments through time-dependent parameters.

To sum up, Figure 4.1 provides a conceptual diagram illustrating the volatility of potential outcomes for SPTs in the context of SLBs. The x-axis represents time, specifically highlighting the target observation date τ_j when the issuer's performance is assessed against the target K_j. The multiple simulated paths for the sustainability metric S_j demonstrate the theoretical variability in possible future outcomes. The shaded areas indicate the range of these outcomes: the darker shaded region shows the probability p of the issuer meeting or exceeding the target $P(S_j(\tau_j) \geq K_j)$, while the lighter shaded region represents the probability 1-p of not meeting the target $P(S_j(\tau_j) < K_j)$. This conceptual visualisation aids in understanding the theoretical volatility and likelihood of achieving the specified SPTs, thereby influencing the financial valuation and risk assessment of SLBs.

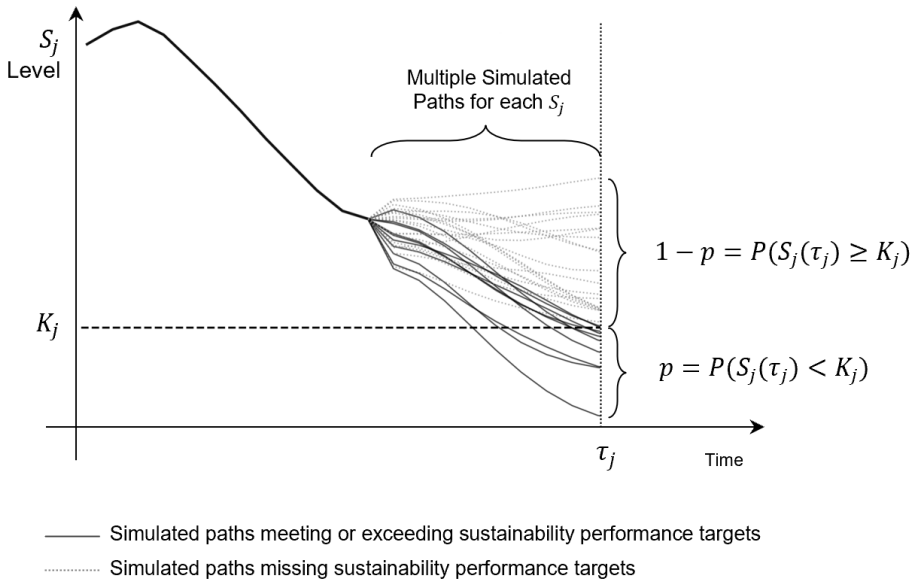


Figure 4.1 Conceptual diagram of Monte Carlo simulated pathways and volatility for sustainability performance metrics

Sources: Authors' concept.

4.2.3 Integrating issuer's climate transition plans

Incorporating transition plan scores and peer rankings into financial models aligns with emerging academic research underscoring the significant impact of sustainability perfor-

mance on companies' risk profiles and their ability to meet SPTs. This approach is rooted in the growing recognition within the academic community that sustainability factors are increasingly material to financial valuation and risk assessment (Clark et al., 2015; Dietz et al., 2016; Khan et al., 2016). To formalise this integration, we introduce two transition plan effects, score and rank, into the model framework.

Let ϕ represent the transition plan score of the issuer, with higher scores indicating a robust commitment to managing sustainability challenges effectively. Clear transition plans provide more certainty regarding the demand for climate solutions, allowing investors to make more informed decisions (UNEP-FI and PRI, 2023). This potential reduction in uncertainty could lead to an improvement in the credit profiles of companies with high TP scores. Given this backdrop, in our model, we set an inverse relationship between ϕ and the initial level of the variance, v_0: the higher the quality of transition plan, the lower the initial volatility in our model. This reflects a decreased uncertainty and risk associated with their forward-looking and well-managed sustainability plan.

The adjusted level of the variance, v', can be expressed as follows:

$$v' = v_0 \left(1 - \frac{\phi - \phi_{\min}}{\phi_{\max} - \phi_{\min}}\right) \tag{8}$$

where:

- v_0 is the initial level of the variance.
- $\phi_{\min}$ and $\phi_{\max}$ represent the minimum and maximum possible values of the transition plan score, respectively.

This approach ensures a score effect between 0 and 1. As ϕ increases, indicating stronger sustainability management, the score effect decreases due to an increase in the fraction $\frac{\phi - \phi_{\min}}{\phi_{\max} - \phi_{\min}}$, leading to reduced v'. Such an approach provides transparency and intuitive understanding of the impact of transition planning on sustainability outcomes.

Scores and rankings within the same system should typically correlate, influencing both volatility and drift similarly. A higher rank (lower numerical value, with 1 being the highest) should keep the drift close to its baseline level, while a higher score should decrease volatility. This is because higher ranks reflect superior management and lower associated risks, and higher TP scores indicate more effective sustainability management.

The baseline drift μ_0 can be either positive or negative, depending on the nature of the sustainability performance metric. For example, for GHG emissions, we should expect a negative drift, whereas for renewable energy capacity, we should expect a positive drift. To reflect this, the adjusted drift μ' can be expressed as follows:

$$\mu' = \mu_0 \left(1 - \frac{R}{P+1}\right) \tag{9}$$

Here, μ_0 denotes the baseline drift, which can be positive or negative depending on the type of metric (e.g., downward for GHG emissions, upward for renewable energy capacity). The rank effect (driven by rank, R) quantifies the issuer's relative performance among its peers, P, with a higher rank indicating superior performance. The rationale for this approach is twofold: First, the model incentivises issuers to achieve higher ranks to keep the drift close to its baseline level. Second, a higher rank results in a smaller adjustment to the drift, reflecting better performance and stability; while a lower rank leads to a greater adjustment, penalising poorer performance.

To sum up, the integration of transition plan scores and peer rankings into financial models for SLBs is justified by the statistical rationale that higher transition plan scores (ϕ) reduce initial volatility (v_0), while higher peer rankings (R) result in lower adjustments to the baseline drift (μ_0). This is based on assuming a correlation between effective transition plans and competitive performance, where higher scores and ranks indicate better sustainability management and lower associated risks.

The variance adjustment v' and the drift adjustment μ' both reflect a linear relationship intended to capture an effect ranging from 0 to 1. However, both the direction and magnitude of these effects need to be calibrated using empirical evidence. This represents a critical area for further research, particularly as transition planning becomes more common practice across industries. The variance adjustment acknowledges this linear inverse relationship as a basic starting point, while the drift adjustment captures the expected trend in sustainability performance. The baseline drift can be either positive or negative depending on the metric's nature. Higher-ranked entities, indicating superior sustainability performance, will exhibit less significant adjustments, meaning their drift remains closer to the baseline.

It is important to recognise that a better transition plan can reduce the present value of the option component (SLB_0^2) because the likelihood of achieving the SPTs increases, resulting in fewer upward adjustments to the coupon rate. However, this outcome remains beneficial for the issuer as they can still benefit from a premium associated with issuing SLBs, with investors valuing the enhanced credibility and lower risk of achieving sustainability outcomes. Moreover, the credibility of robust transition plans provides broader benefits beyond the SLBs, including improved reputation, lower overall borrowing costs, better stakeholder relations, and potentially enhanced market valuation.

4.3 Empirics

In this section, we present two numerical illustrations of the proposed framework, applying it to the two founding instruments of the SLB market to demonstrate its mechanics,

sensitivity, and diagnostic value.

4.3.1 Methods

Case studies and data. For the selected case studies, we gather quarterly and annual time series data on the sustainability performance metrics included in SLB transactions under analysis (see details in each case study). The two cases represent the founding instruments of the SLB market. Enel, a multinational electric utility, issued the first corporate SLB in September 2019, with renewable energy capacity (REC) as its KPI. The Republic of Chile issued the first sovereign SLB in March 2022, linking coupon adjustments to GHG emissions and Non-Conventional Renewable Energy (NCRE) capacity. Because stochastic volatility estimation requires sufficiently long KPI time series, these pioneering issuers, with quarterly data extending back to 2014 (Enel) and 2015 (Chile NCRE), offer the most robust empirical basis currently available. As the SLB market matures and more issuers accumulate multi-year KPI histories, the framework can be applied more broadly.

Parameters estimation. To compute drift and initial volatility from historical KPIs, we first convert the data into logarithmic returns,[8] which are suitable for metrics exhibiting exponential growth or multiplicative behaviour. Following Hull (2022, chap. 23) and Bollerslev (1986), we apply a GARCH model to estimate the parameters of the stochastic volatility SDE (see Equation 6). [9] As detailed in Appendix B, we ensure stationarity through data transformation, then estimate the intercept, sensitivity to past squared residuals, and variance persistence. The mean reversion level is the intercept divided by one minus the sum of sensitivity and persistence, while mean reversion speed is one minus that sum. Volatility of variance is the average of squared conditional variances, and correlation with volatility is calculated via the normalised covariance between past returns and future

[8]Specifically, if P_t, represents the KPI at time t, the logarithmic return r_t, between times t and $t-1$ is given by $r_t = \log(P_t) - \log(P_{t-1})$. The sequence of these logarithmic returns is denoted as $\{r_t\}$. The drift, μ, of the KPIs is then calculated as the mean of these logarithmic returns, expressed as $\mu = \frac{1}{n}\sum_{t=1}^{n} r_t$, where n is the total number of returns. The initial volatility, σ, is quantified as the standard deviation of these returns, defined by $\sigma = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(r_t - \mu)^2}$. This measure of volatility reflects the average deviation of the logarithmic returns from their mean, capturing the variability or spread in the returns.

[9]While the GARCH (1,1) model we used does exhibit some limitations, such as small sample size and potential insignificance of individual parameter estimates, these issues do not critically undermine our objective of estimating mean reversion characteristics. For example, small sample sizes (e.g., fewer than 250 data points) can introduce bias and high variability in individual parameter estimates (D. Huang et al., 2008). However, the parameters used in our adapted-Heston model (mean reversion level and speed) are functions of these individual estimates and, therefore, tend to be more stable because they aggregate these effects. To further improve the reliability of these estimates, we employ bootstrapping, which mitigates bias and variability by smoothing out the impact of outliers and sample-specific anomalies across multiple resampled datasets. This approach ensures that our mean reversion characteristic estimates are more consistent and robust, even when dealing with small sample sizes and potential instability in parameter estimates.

variance. [10]

Model validation. To validate our model's predictive accuracy and robustness, we apply a twofold approach: backtesting and Monte Carlo convergence analysis (Appendix D). Backtesting assesses out-of-sample performance by calibrating parameters on part of the time series and testing against withheld data, helping to evaluate ex-post accuracy and mitigate overfitting (Escanciano and Olmo, 2011). Convergence analysis examines statistical reliability across simulations with varying path counts, confirming stability and robustness against sampling variability fluctuations (Galitzine and Boyd, 2015). Stabilisation of the mean with more paths also indicates sufficient time series length. While these methods offer a rigorous validation framework, they do not account for structural shifts or external shocks that may affect future model performance.

Valuation. The valuation model for SLBs employs a deterministic framework, adjusting future coupon payments based on a probability-weighted mechanism to account for the uncertainty of achieving sustainability targets. It calculates annual cash flows by projecting coupon payments before and after the target observation date, incorporating both a standard rate and a step-up rate contingent upon target attainment. Present value calculations are performed using a constant annual discount rate, summing discounted cash flows to determine the bond's total PV. The model assumes a static discount rate throughout the bond's term and a binary outcome for the step-up mechanism. For a detailed explanation of how the probability outcomes are factored into the SLB's present value calculation, refer to Equations 3, 4 and 5.

4.3.2 Corporate SLB: renewable energy capacity

Overview. Enel, a leading Italian energy firm and a key participant in the SLB market, recently faced a notable development. It missed a Sustainability Performance Target (SPT), which triggered a 25-basis point increase in the coupon rate of the affected bonds. This marks the first such occurrence in the SLB market (Sustainable Fitch, 2024). This was triggered by delays in coal plant phase-out and exacerbated by geopolitical crises, such as Russia's invasion of Ukraine. These challenges could have led to an additional USD 89 million in additional interest (Ritchie and Vossos, 2024). Despite this setback and amid a declining trend in SLB issuances since 2021, Enel's failure serves as a pivotal test of the ambitious nature of SLB targets and the substantial financial implications involved, potentially marking a turning point for the market.

[10] In our case studies, we observed mixed stability: while some bootstrap estimates consistently reflected stable mean reversion levels and speeds, others showed variability. As higher-frequency sustainability data becomes more available in the future, bootstrapping is likely to become an even more effective tool for deriving reliable mean reversion characteristics from such time series. Specific details and supporting analyses can be found in Appendix A, Table A4.

Table 4.1 Enel's input data for stochastic model.

ISIN Code	Input	Data
XS2244418609	Issuer	EFI NV
	Face value	GBP 500
	Coupon Rate	1% (annual)
	Issuance year	20 October 2020
	Maturity year	20 October 2027
	KPI	Renewable energy capacity (%)
	Target observation date	60% (2023)
XS2589260723	Issuer	EFI NV
	Face value	EUR 700
	Issue price	98.877
	Coupon Rate	4% (annual)
	Yield	3.373%
	Coupon step-up	25 basis points (bps)
	Issuance year	20 February 2023
	Maturity year	20 February 2043
	KPI*	Renewable energy capacity (%)
	Target observation date	80% (2030)

Sources: Refinitiv (2024) and Enel (2024).

Note: (*) The KPIs incorporated into this financial structure include the Scope 1 GHG emissions Intensity relating to Power Generation (gCO2eq/kWh), and the Proportion of Capex aligned with the EU Taxonomy (%). Given the extensive data series available for Enel's RECs, we have selected REC as the primary metric for modelling, rather than the other KPIs originally integrated into this transaction. This selection is driven by the robustness of the REC data set, which facilitates more accurate simulation and analysis.

We apply our model to two specific bond transactions issued by Enel (see Table 4.1), analysing the impact of simulated REC outcomes on the bonds' initial valuations. Although Enel included GHG emissions metrics in their SLB terms, the short duration of the reported data limits its utility in our model. For the first transaction (ISIN XS2244418609), we illustrate the evolution of simulated REC outcomes with each new quarterly report as the 2023 target observation date approaches. In the second transaction, we estimate the bond's initial valuation by considering the likelihood of achieving its sustainability target, factoring in the effect of Enel's climate transition plan.

Key performance indicators. We focus on Renewable Energy Capacity (REC) as a KPI within Enel's SFL framework, using quarterly data from financial reports since 2014 to enhance model accuracy (Enel, 2024). Compared to annual GHG emissions, REC offers a more granular view of sustainability performance. While quarterly GHG data is not yet standard, it is increasingly feasible for financial institutions to request estimates, with some energy firms like Shell (2023) and TotalEnergies (2024) beginning to report quarterly. Figure 4.2 shows Enel's REC trajectory: the black line reflects data up to Q3 2020, aligned with SLB XS2244418609 and its 60% REC target by 2023, while the grey line extends to Q1 2023, corresponding to SLB XS2589260723 and its 80% target. Both trends show steady growth, underscoring Enel's expanding renewable energy

commitment.

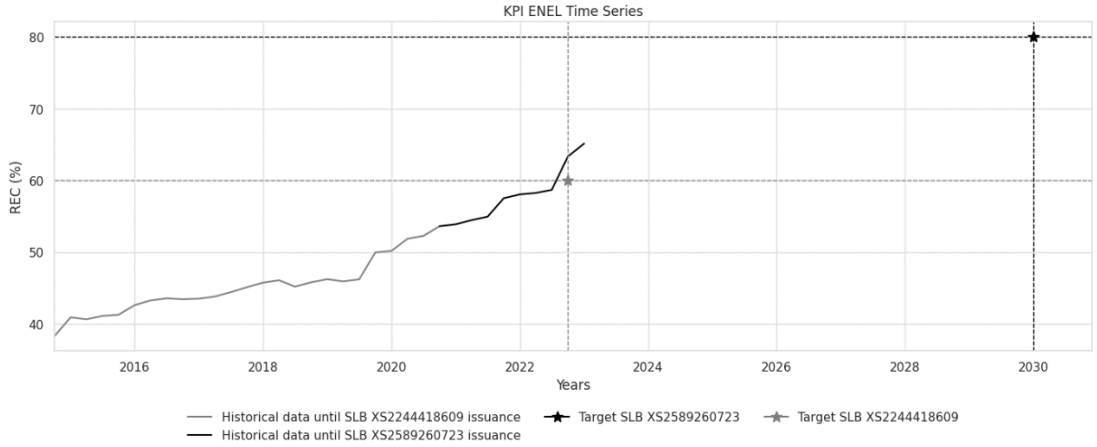


Figure 4.2 Enel's renewable energy capacity since 2014 and targets towards 2030.
Source: Enel (2024).

Probability Outcomes. The first SLB (ISIN XS2244418609) illustrates how our model initially projected low but gradually increasing probabilities of Enel meeting its 60% REC target by 2023, demonstrating the model's adaptability to new data and changing conditions (Appendix E). For the second SLB issued in 2023 (ISIN XS2589260723), we take into account Enel's strong performance in the ACT evaluation. It ranked third out of 68 electric utilities with a score of 69.3 (ACT and WBA, 2023). This performance is used to adjust the initial drift and volatility. The transition plan model predicts a 53% probability of achieving the 80% REC target by 2030, compared to 43% under the baseline. McNemar's test confirms a statistically significant improvement, and Cohen's d shows a small to medium effect size, highlighting the measurable impact of Enel's transition strategy. Table 4.2 also introduces the "threshold of indifference," marking the REC level where target achievement is equally likely. The baseline and transition models produce thresholds of 74% and 81%, respectively. Enel's 80% target falls close to this balanced point. This indicates a well-calibrated yet ambitious sustainability commitment.

Table 4.2 Ambition of Enel REC targets: probabilistic outcomes

	ENEL REC
$\widehat{P}(S_n \geq k)$ [a]	0.43
Baseline Model	
$\widehat{P}(S_n \geq k)$ [a]	0.53
Transition Plan Model	
McNemar's Test [b]	213.87***
Cohen's d (95% CI) [c]	0.205
	(0.177, 0.233)
SLB (ISIN XS2589260723) Target	80%
Model-derived Target at the 50% Probability Level	74%
Baseline Model [d]	

	ENEL REC
Model-derived Target at the 50% Probability Level *Transition Plan Model* [d]	81%

Note: ([a]) The probability of simulation outcomes S_n meeting a specified condition relative to threshold k are indicated as $\widehat{P}(S_n \geq k)$ to denote the probability of meeting or exceeding the targets. ([b]) Test the symmetry of changes across two conditions. It evaluates the significance of the shift from non-achievement to achievement (or vice versa) between paired simulations. A p-value below 0.001 strongly rejects the null hypothesis of no effect, underscoring the transition plan's efficacy. ([c]) Measures the standardised difference in means between the two scenarios with the 95% confidence interval included. Effect sizes are categorised as small (0.2), indicating a subtle influence; medium (0.5), suggesting a noticeable and practical impact; and large (0.8), representing a substantial effect that can significantly justify strategic decisions or policy changes. ([d]) Refers to the threshold of indifference, at which the baseline and transition plan simulation models predict a 50% chance of achieving the specified target. This threshold indicates a balanced likelihood of success or failure, reflecting the point at which the likelihood of meeting the sustainability performance target is equal to the likelihood of not meeting it.

Robustness and validation of the model. The robustness of our model is supported by backtesting and Monte Carlo convergence analysis (see details in Appendix D). The former analysis reveals that our baseline model slightly underestimates REC post-2022, while the transition plan model tends to overestimate in earlier quarters. Moreover, the Monte Carlo convergence analysis demonstrated that increasing the simulation paths from 100 to 10,000 stabilised the mean output values and reduced the standard deviation, indicating strong convergence. These results suggest that the model captures the underlying stochastic processes with reasonable accuracy, maintaining predictive quality across varied scenarios and scale expansions, and supporting its robustness for projecting Enel's REC trajectories.

Sensitivity analysis. Figure 4.3 presents a sensitivity analysis for the second SLB, illustrating how adjustments to Enel's transition plan score and industry rank affect the probability of meeting its sustainability targets. By varying drift and volatility parameters across different scenarios, the model shows that rank has a stronger impact than score, emphasising Enel's competitive position as a more influential factor. The shading in the plot uses darker tones to indicate higher probabilities. This visual cue reinforces the effect. These results suggest the model prioritises industry standing over score when benchmarking performance, highlighting competitive rank as a key driver in the probability of achieving sustainability goals.

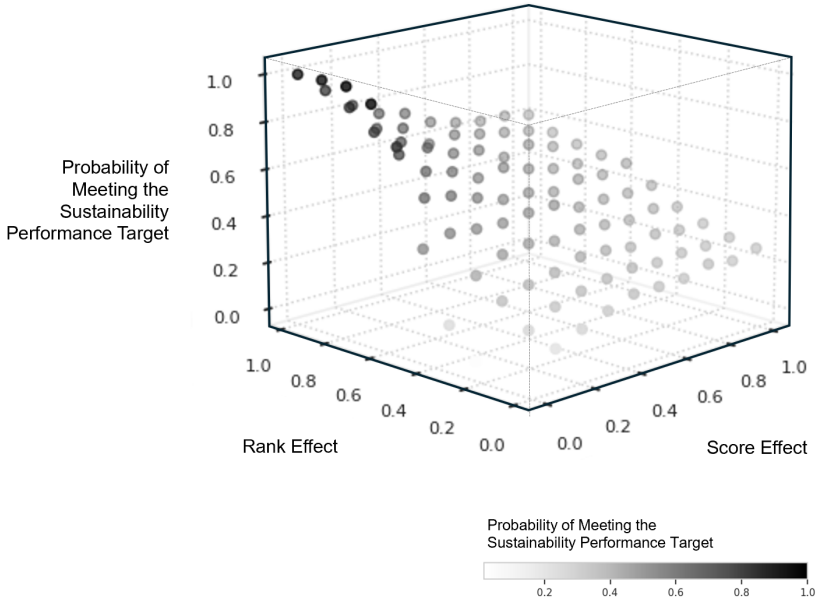


Figure 4.3 Impact of transition plan score and rank on sustainability target achievement probabilities

Valuation. We conducted a sensitivity analysis to assess how varying probabilities of meeting SPTs affect the present value of Enel's second SLB, in relation to different step-up/down rates (Figure 4.4; darker shades indicate higher values). The SLB prices climate mitigation similarly to an option, with the step-up reflecting the risk of missing targets. The vanilla bond is valued at EUR 775.03, while the SLB, which includes the step-up, is valued at EUR 782.87. Incorporating the transition plan raises the likelihood of success, slightly reducing the SLB's value to EUR 781.46 by lowering the expected return from the step-up. For a 25 bps step-up, the standard SLB's imputed step-up value is 111.89 bps of notional, dropping to 91.81 bps when accounting for the transition plan, highlighting its role in risk reduction. These results suggest that future SLBs could tailor step-up rates to the credibility of transition plans, balancing financial incentives with issuer ambition and offering a less punitive, more investable structure.

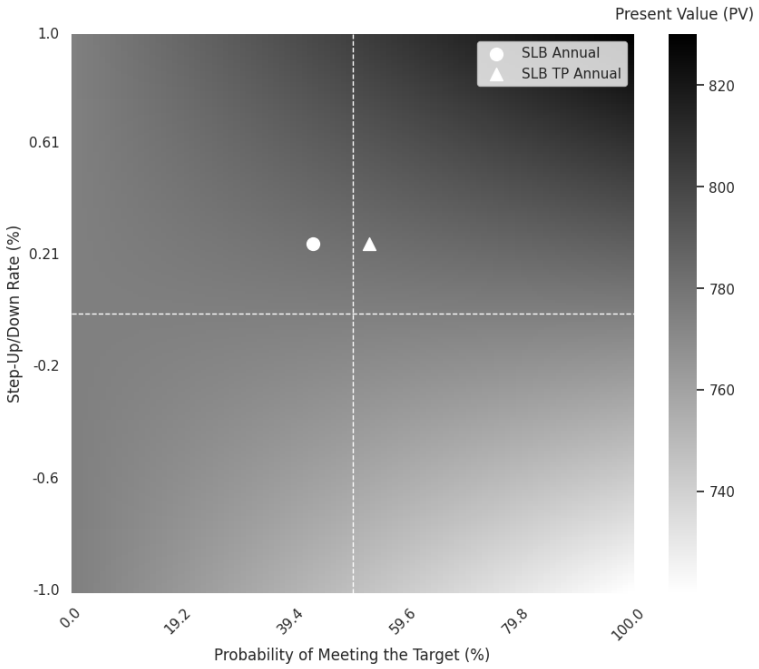


Figure 4.4 Evaluating the present value of Enel's SLB under different scenario probabilities and incentive structures

4.3.3 Sovereign SLB: GHG emissions and non-conventional renewable energy

Overview. In July 2022, the Chilean government issued its first sovereign SLB, integrating two KPIs related to their Nationally Determined Contributions (NDCs) to the Paris Agreement, updated in 2020, and non-conventional renewable energy (NCRE) as part of its strategy. Since then, it has issued USD 8.6 billion of debt across seven sovereign SLBs (L.P, 2024).

Table 4.3 Republic of Chile SLB' input data for stochastic model

ISIN Code	Input	Data
US168863DY16	Issuer	Republic of Chile
	Face value (M)	USD 2,000
	Issue price	99.92
	Coupon	4.340% (semi-annual)
	Yield	5.164%
	Issuance year	07 March 2022
	Maturity year	07 March 2042
	KPIs	MtCO2 and NCRE Generation, as the percentage generated in the National Electric System, measured in megawatt hours (MWh)
	Target(s) observation date(s)	95 MtCO2 by 2030 and achieve a maximum of 1,100 MtCO2 between 2020 and 2030. 60% NCRE by 2032

Sources: Government of Chile, Ministry of Finance (2022) and Refinitiv (2024).

Key performance indicators. Chile's SLB framework focuses on two climate mitigation KPIs. The first KPI targets reducing GHG emissions to no more than 95 million tonnes

of CO2 equivalent by 2030, with a total emissions budget of no more than 1,100 million tonnes from 2020 to 2030, in alignment with Chile's Paris Agreement commitments and its long-term goal of achieving GHG neutrality by 2050. The second KPI aims to increase the proportion NCRE in Chile's electricity mix to 60% by 2032.

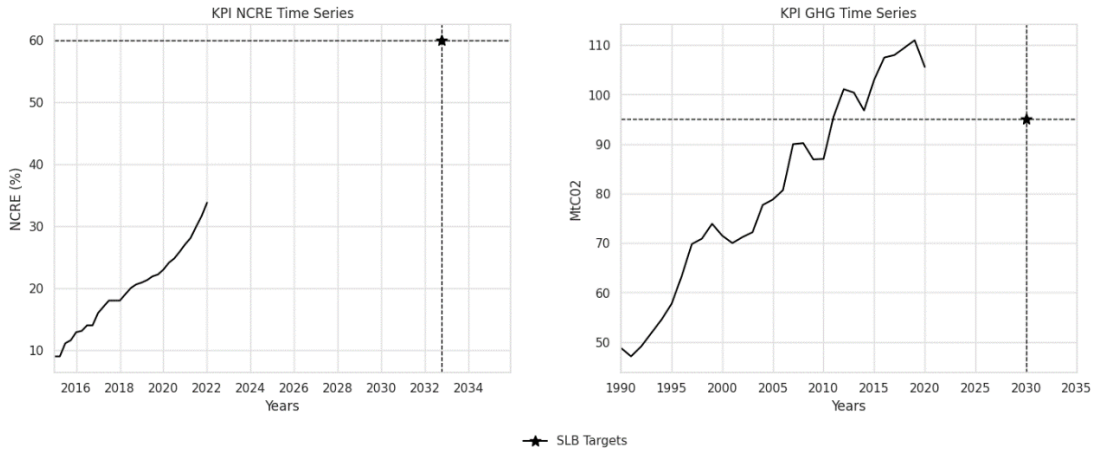


Figure 4.5 Chile's NCRE Capacity (2015-2022) and GHG emissions (1990-2020) towards 2032 targets

Source: Ministry of Environment (2022) and National Electricity Coordinator of Chile (2024).

Our empirical analysis draws on official data sources, including historical GHG emissions from 1990 to 2020 (Ministry of Environment (Chile), 2022) and quarterly reports on non-conventional renewable energy (NCRE) from 2015 to 2022 provided by Chile's National Electricity Coordinator (CEN, 2024). The use of quarterly NCRE data is well-suited to stochastic modelling, capturing seasonal patterns and market dynamics that enhance simulation accuracy. While understanding correlations between KPIs could enrich the analysis, the limited five-year overlap between datasets prevents a robust joint probability assessment, constraining the scope for more advanced multivariate modelling.

Probability outcomes. For Chile's SLB, we incorporate the transition plan score and rank effects (see Section II.C) based on Chile's performance in the Climate Action Tracker's net-zero targets assessment. Chile ranks second out of 40 countries, with a score of 7.[11]

Table 4.4 Republic of Chile SLB' probability of meeting the targets

[11]Climate Action Tracker assesses countries' net zero targets across nine dimensions, encompassing emissions coverage, international aviation and shipping targets, reductions or removals beyond their borders, legal status, separate reduction and removal targets, review processes, comprehensive planning for carbon dioxide removal, and clarity on the fairness of the targets. Each dimension is rated as fully fulfilled, partially fulfilled, or not fulfilled, with a score of 1, 0.5, or 0 respectively. This assessment includes 40 countries (CAT, 2024).

	NCRE	GHG Level	Cumulative GHG
$\widehat{P}(S_n \sim k)$ [a] *Baseline Model*	0.58	0.63	0.57
$\widehat{P}(S_n \sim k)$ [a] *Transition Plan Model*	0.70	0.69	0.62
McNemar's Test [b]	315.29***	176.14***	71.89***
Cohen's d (95% CI) [c]	0.248 (0.220, 0.277)	0.184 (0.156, 0.219)	0.102 (0.074, 0.130)
SLB (US168863DY16) Target	60	95	1100
Model-derived Target at the 50% Probability Level / *Baseline Model* [d]	68	91	1018
Model-derived Target at the 50% Probability Level / *Transition Plan Model* [d]	76	73	925

Note: ([a]) The probability of simulation outcomes S_n meeting a specified condition relative to threshold k are denoted as $\widehat{P}(S_n \sim k)$, where ∼ symbolises the context-dependent comparison operator, encompassing both exceeding and not exceeding scenarios. For instance, in scenarios where ∼ represents NCRE targets, we use $\widehat{P}(S_n \geq k)$ to denote the probability of meeting or exceeding these targets, whereas for GHG related KPIs, $\widehat{P}(S_n \leq k)$ is used to represent the probability of meeting or not exceeding specific emission limits. ([b]) Test the symmetry of changes across two conditions. It evaluates the significance of the shift from non-achievement to achievement (or vice versa) between paired simulations. A p-value below 0.001 strongly rejects the null hypothesis of no effect, underscoring the transition plan's efficacy. ([c]) Measures the standardised difference in means between the two scenarios with the 95% confidence interval included. Effect sizes are categorized as small (0.2), indicating a subtle influence; medium (0.5), suggesting a noticeable and practical impact; and large (0.8), representing a substantial effect that can significantly justify strategic decisions or policy changes. ([d]) Refers to the threshold of indifference, at which the baseline and transition plan simulation models predict a 50% chance of achieving the specified target. This threshold indicates a balanced likelihood of success or failure, reflecting the point at which the likelihood of meeting the sustainability performance target is equal to the likelihood of not meeting it.

Table 4.4 compares the baseline and transition plan models across three KPIs: NCRE, GHG levels, and cumulative GHG emissions. The transition plan model includes the issuer's transition plan score and results in higher probabilities of meeting targets. For NCRE, the probability increases to 70%, compared to 58% in the baseline model. It also shows improved outcomes for GHG-related metrics. Statistical testing using McNemar's test confirms significant differences in target achievement, while Cohen's d indicates small to medium effect sizes. The table also reports model-derived thresholds at the 50% probability level (threshold of indifference). For NCRE, the SLB target of 60 is more conservative, falling below both model thresholds (68 baseline, 76 transition plan), suggesting a cautious stance. In contrast, the SLB targets for GHG level (95) and cumulative GHG (1100) fall within the model-derived thresholds. These thresholds range from 91 to 73 for GHG level and from 1018 to 925 for cumulative GHG. This indicates that the targets are well aligned with a balanced probability of success and failure. This implies the NCRE target is set conservatively, while the GHG-related targets are more neutrally calibrated.

Robustness and validation of the model. Model robustness is supported by backtesting and Monte Carlo convergence analysis (Appendix D). For Chile's NCRE, the transition

plan model, reflecting the country's climate leadership, better captures observed trends, including the early achievement of its 2025 goal by reaching 20% NCRE in 2020, up from 8% in 2015. While both models show right-skewed residuals, the transition model's more negative mean and lower standard deviation suggest greater accuracy in capturing rapid NCRE expansion. In the case of GHG emissions, the baseline model aligns with historical data but tends to overestimate emissions, whereas the transition model slightly underestimates them yet better reflects actual declines (see Figure 4.6). These results underscore the importance of integrating policy updates to maintain predictive accuracy. Monte Carlo convergence confirms improved model stability for NCRE with more simulations, while greater variability in the GHG model highlights the challenge of modelling under evolving policy conditions.

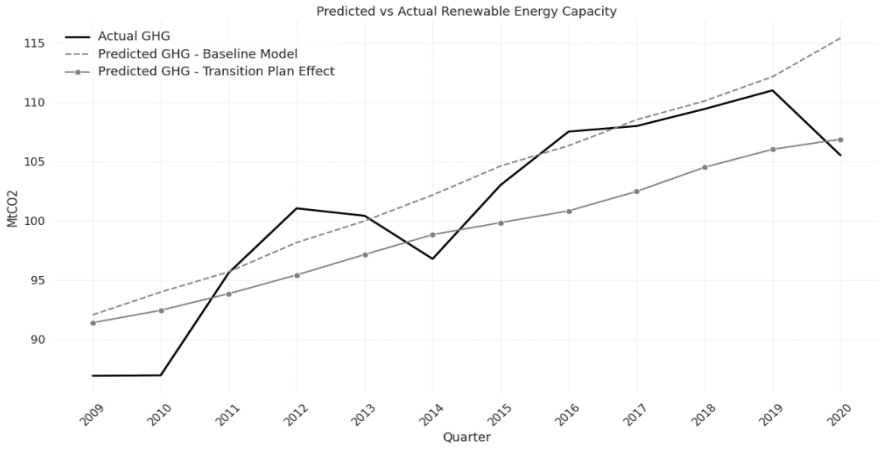


Figure 4.6 Longitudinal analysis of predicted vs. actual Chile's GHG: assessing stochastic model efficacy

Sensitivity analysis. Similar to Enel's model, the impact of the transition plan on the likelihood of achieving Chile's NCRE targets follows a consistent pattern in the sensitivity analysis for both score and rank effects. Figure 4.7 illustrates these effects through drift and initial volatility, revealing a nuanced trend indicating that the rank effect exerts greater influence on the probability of meeting sustainability targets than the score effect. This emphasises the importance of benchmarks when using any sustainability-related score.

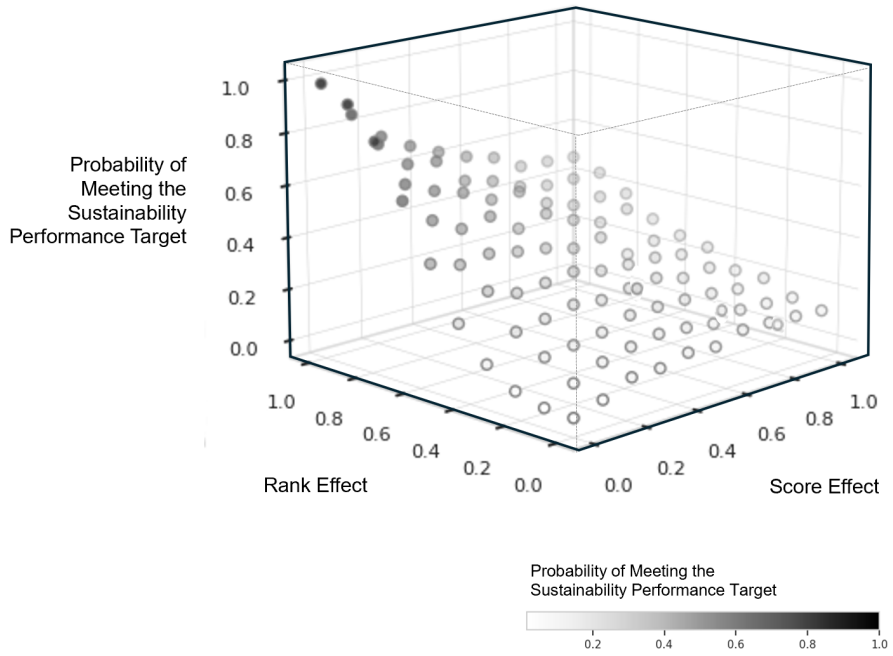


Figure 4.7 Impact of transition plan score and rank on sustainability target achievement probabilities for NCRE

Valuation. This case study evaluates two KPIs central to Chile's climate strategy, each linked to a 12.5 basis point coupon step-up if targets are missed. The vanilla bond, valued at USD 1,796, serves as a benchmark without sustainability features. The SLB, valued at USD 1,807, incorporates the step-ups, offering higher returns if Chile underperforms on environmental goals. When a transition plan assessment is included, the likelihood of success increases. As a result, the SLB's value drops slightly to USD 1,805, reflecting the lower probability of the step-up being triggered. Step-up valuations provide further insight: for a standard SLB, imputed values are 23.94 bps for GHG and 20.69 bps for NCRE, indicating market concerns over Chile's ability to meet these targets without additional measures. With the transition plan, GHG rises marginally to 24.04 bps, while NCRE drops to 17.17 bps, suggesting improved risk mitigation for NCRE. These results highlight the differing challenges across KPIs and suggest that tailoring step-up rates to specific risks can make future sovereign SLBs more attractive to investors while reinforcing national sustainability efforts.

4.4 Discussion

Spread analysis. The model developed in this analysis offers a benchmark for practitioners conducting spread analysis and a foundation for future academic research on SLB valuation. Discrepancies between market-implied premiums and model-derived

valuations for Enel and Chile demonstrate the model's potential to reveal undervalued risks. For Enel (ISIN XS2589260723), the market-implied premium of 8.2 bps at issuance falls below the model's imputed value, likely reflecting the firm's strong reputation, sustainable finance track record, and similarity between its SLB and a comparable green bond. Similarly, Chile's market-implied premium of 4.2 bps also underestimates risk, potentially due to early success in climate policy implementation and strong transition signals. The gap between model-derived and market-implied values does not necessarily mean the model is "right" and the market "wrong." Market spreads compress reputation effects, liquidity premia, and investor demand into a single number, whereas our model isolates the probability-weighted cost of target non-achievement based on the issuer's KPI trajectory and transition plan. When the model imputes a higher step-up value than the market implies, it signals that the market may be pricing in confidence in the issuer's sustainability credentials, confidence that is difficult to verify from historical KPI data alone. The model therefore serves as a complementary diagnostic: it flags cases where market pricing may underweight the stochastic risk of target failure, prompting investors and regulators to scrutinise whether the implied confidence is warranted. This approach also opens avenues for further research into how issuer credibility, policy context, and sustainability commitments influence SLB pricing under different market conditions.

External dependencies. Incorporating external dependencies can significantly improve model calibration accuracy. Recent SLB research highlights the importance of accounting for exogenous factors, similar to issuer-focused frameworks that distinguish internal performance from external influences (D. Wang et al., 2022). For example, when modelling renewable energy capacity, the regional energy mix and policy environments are critical inputs. These factors influence parameters such as the mean reversion level, speed, volatility, and correlations. These parameters are often estimated using GARCH (1,1) models. Policy shifts favouring renewables, for instance, may raise the mean reversion level, indicating a new equilibrium for energy portfolios. Similarly, climate risks such as extreme weather events and shifting regulatory landscapes influence variance volatility, reflecting heightened uncertainty. Integrating these external conditions into parameter estimation allows the model to more accurately reflect the complex interplay between sustainability initiatives and the broader environmental, regulatory, and market context.

Stakeholder implications. As the framework matures alongside the SLB market, it can offer stakeholders deeper insights into SLB performance. For issuers, it can inform target setting and bond structuring by revealing how transition plan quality translates into probability-weighted pricing. Investors can use the probability estimates and sensitivity analysis to assess whether market spreads adequately compensate for KPI failure risk, highlighting the role of transition plans in evaluating forward-looking performance. Reg-

ulators may find the framework useful for benchmarking issuer commitments against model-implied probabilities, and policymakers can draw on the link between SLB valuation and target achievement likelihood when designing disclosure requirements or incentive structures.

Data sources and quality. To improve model reliability, we emphasise the importance of robust validation methods that prioritise stability and precision. Using more granular data, preferably monthly or quarterly instead of annual, improves the detection and modelling of volatility patterns. This is especially useful in sectors such as water, waste, and energy, where such data is usually available. Monthly data strikes a practical balance between capturing intra-year variability and manageable processing demands. For KPIs with persistent volatility, models like GARCH are appropriate, while simpler models may suffice when such persistence is low. We also recommend identifying a subset of quantitative KPIs that require higher-frequency data to better account for uncertainty. To ensure data quality, especially in large-scale transactions involving sovereigns or multinational firms, third-party verification should be conducted at issuance and during ongoing monitoring.

4.5 Conclusion

This paper presents a theoretical valuation framework for sustainability-linked bonds that replaces the constant-volatility assumptions of existing models with a Heston stochastic volatility process, and is, to our knowledge, the first to integrate transition plan assessments into probability calibration. The numerical illustrations on Enel and Chile demonstrate the framework's mechanics and sensitivity, but should be read as proof-of-concept applications rather than definitive valuations: the SLB market is young, and the KPI time series required for robust parameter estimation remain short. As issuers accumulate longer performance histories and higher-frequency sustainability data becomes standard, the framework can be calibrated with greater precision.

Three conclusions follow from the analysis. First, the model quantifies the financial value of transition plan credibility. Incorporating Enel's transition plan raises the probability of meeting its 80% REC target from 43% to 53% and reduces the imputed step-up value from 111.89 to 91.81 basis points, a tangible measure of how forward-looking sustainability commitments translate into bond economics. Second, the model serves as a diagnostic tool for both sides of the market. For *issuers*, it supports target calibration: by revealing the "threshold of indifference" (the KPI level at which target achievement is equally likely), it helps structure step-up rates that are ambitious yet credible, reducing the risk of punitive coupon adjustments that discourage future SLB issuance. For *investors*, it provides an

independent estimate of the probability-weighted cost of target failure, enabling them to identify SLBs whose market spreads may underweight sustainability risk. Third, by making the financial consequences of sustainability performance explicit and quantifiable, the framework strengthens the incentive mechanism at the heart of the SLB instrument, and thereby supports decarbonisation goals. When issuers can see precisely how their transition plans affect bond economics, and investors can verify those claims against a stochastic benchmark, the market is better equipped to distinguish genuine transition commitments from superficial ones.

Conclusion

No hablemos de hechos ... son meros puntos de partida para la invención y el razonamiento. En las escuelas nos enseñan la duda y el arte del olvido.

Jorge Luis Borges (1975, Chapter 8)

The transition to a low carbon economy is not merely a technical or financial challenge but a test of institutional coherence, credibility and resolve. As this thesis has shown, the tools exist to link ambition with impact, yet their effectiveness depends on how they are designed, governed and applied. In drawing the threads together, this conclusion reflects not only on what has been uncovered but on what it suggests about the evolving role of finance in shaping the future it seeks to support.

4.6 Discussion: plans, metrics and pricing as a co-evolving economic system

In this thesis, I asked what it takes for finance to move from climate ambition to climate impact in the real economy. Plans act as commitment devices, metrics provide information for cost-effective control, and pricing supplies incentives through policy and capital markets. When any one fails, disclosure theatre dominates; when all three connect, transition finance can drive real decarbonisation.

Conceptually, I reframe plans as levers for directional investment under uncertainty in a Schumpeterian sense, not just a list of milestones (Schumpeter, 1939). Performance metrics are permit monitoring against ecological scale and absolute limits, not intensity alone (Daly, 1991). Pricing translates transition credibility into risk premia under long horizons and non-linear shocks, consistent with the argument that discounting and risk should reflect climate uncertainty (Stern, 2007). This synthesis connects evolving practice around net zero planning and disclosure (e.g., GFANZ, 2022a; ISSB, 2023) with asset-pricing evidence that climate risk is priced in returns and spreads (Engle et al., 2020; Bolton and Kacperczyk, 2021), while acknowledging data divergence that can blunt incentives (Berg et al., 2022).

Empirically, the contribution is cumulative. Paper A shows that credibility in transition plans is an outcome-linked property. A correlation-weighted, sector-grounded scoring approach in aviation links disclosed plan components to short-term changes in emissions

intensity after adjusting for confounders. Implementation levers and independently reviewed interim targets carry information; generic governance language does not unless anchored to verifiable action. Paper B brings the practitioner lens to performance. A survey of finance professionals and econometric analysis reveal strong support for a lean set of assured, outcome-proximate indicators and scepticism toward sprawling dashboards, especially among institutions that have partially or fully implemented transition plans. Paper C puts performance inside the price. A theoretical valuation framework, grounded in the Heston stochastic-volatility process, treats sustainability performance as a state variable that drives step-up probabilities in sustainability-linked bonds and conditions spreads on plan credibility and data quality. Numerical illustrations based on the first corporate SLB (Enel, 2019) and the first sovereign SLB (Chile, 2022) suggest that well-designed penalties can make consequences enforceable rather than merely declaratory, though the model serves as a complementary diagnostic rather than a definitive market predictor.

Together, the studies demonstrate how to bind strategic intent, measurable progress and investable risk. For firms, near-term targets, capex alignment and assured KPIs are gating items for credibility and cost of capital. For investors and structurers, fewer, better, auditable metrics and earlier, larger, symmetric ratchets improve price discovery. For policymakers, sectoral pathways and assurance shorten the feedback loop between action and price. The next subsections trace this logic through Papers A to C.

4.6.1 Main findings from the three papers

Paper A. In the first paper, we examine the planning dimension of transition finance through the lens of the airline industry, a sector emblematic of long-lived assets, fragmented regulation, and carbon lock-in. We develop a correlation-weighted framework that tests whether specific disclosure elements in corporate transition plans co-vary with short-term changes in emissions intensity, using stratification and partial-correlation adjustments for fleet age and passenger load. The central finding is that credibility resides not in the rhetorical disclosure of a plan but in demonstrable implementation levers and independently reviewed interim targets. Governance, while important, conveys limited informational value unless anchored to verifiable action. These results challenge prevailing process-maturity assessments and support a shift toward sector-specific indicators that are proximate to real operational change.

The results reinforce a simple theoretical claim: in hard-to-abate sectors, credibility is an outcome-linked property, not a process label. Plans that merely name pathways and targets remain necessary but insufficient; only those that commit capital to the technologies,

fuels, and operational changes implied by those pathways move expected emissions. Controlling for fleet and utilisation altered the apparent signal substantially, revealing that the most decision-useful information lies in concrete engineering and procurement choices, rather than in standardised governance language. A caveat is in order: because the outcome metric is emissions intensity, the short-term signal may partly reflect fleet renewal efficiency rather than deeper structural decarbonisation; the score measures plan-performance consistency, not alignment with an absolute emissions pathway. Even so, the score rests entirely on public disclosures and a published formula, giving investors and lenders a replicable basis for screening plans and identifying where gaps in high-weight elements may call for further scrutiny. For regulators moving toward mandatory transition plan disclosure, the association-weighted approach offers a reproducible complement to expert-based assessments, one that can be updated as longer time series become available.

Methodologically, I found that simplicity can be a virtue in immature data environments. Binary indicators tied to observable actions travelled well across firms and jurisdictions, and their weighting could be recalibrated as new evidence appeared. Confounders are not a statistical nuisance but an inherent feature of this setting: without adjusting for them, one risks overstating the role of disclosure and understating the role of engineering. Looking ahead, I see two natural extensions: including non-CO_2 effects as EU monitoring began in January 2025 (European Commission, 2025), and stress-testing credibility against increasingly divergent jurisdiction-specific policy signals.

The practical implications are immediate in jurisdictions like the EU. Under the EU's ReFuelEU regulation, a minimum 2% share of SAF will be mandated at EU airports from 2025, rising to 6% by 2030 (European Parliament and Council of the European Union, 2023). Plans that fail to translate this into contracted volumes, certified feedstocks, and supply-chain arrangements will face both cost penalties and reputational risk. Yet global SAF supply is projected to remain well under 1% of total jet fuel in 2025, showing the need for transparent procurement commitments (IATA, 2024). Meanwhile, the EU's new non-CO_2 monitoring regime will open additional performance dimensions (e.g., contrail avoidance, NO emissions) that may re-rank perceived leaders and laggards (European Commission, 2025). In the UK, adoption of ISSB S1 and S2 standards will push transition plans into the realm of mandatory, assurance-grade disclosures (UK DBT, 2025), while internationally, CORSIA's first compliance phase will heighten scrutiny of residual emissions and offsetting claims.

When I began this research, I expected governance structure to carry greater explanatory power. However, the analysis led me to a different reading: governance is a multiplier, not a driver. It converts engineering and procurement into bankable claims but cannot substitute for them. This paper ends by exposing a tension that is addressed

directly in Paper B. The indicators most strongly linked to credible plans include absolute abatement, verified targets, and technology uptake. However, these are also the indicators that practitioners report as the most difficult to measure with confidence. Closing that gap between what matters and what can be measured is the next frontier.

Paper B. In the second paper, we asked a simple question: which transition-finance metrics help practitioners move capital toward near-term decarbonisation, and which merely signal intent. We mapped the metrics most used by 100 of the largest global financial institutions, then surveyed professionals across banks, asset managers, insurers and asset owners. Two patterns stood out. First, many widely cited indicators score as moderately to highly useful, yet the underlying data are only middling in quality. Second, respondents working inside organisations that have partially or fully implemented transition or adaptation plans tend to be more sceptical of the status quo toolkit. In short, implementation breeds scrutiny. Our econometric specification corrected for non-random response and confirmed that the main drivers of perceived usefulness are stable across robustness checks.

The surrounding policy context shifted while our fieldwork was under way. We launched the survey in late September 2024, and a portion of responses arrived before the political and legal turbulence that reshaped 2025's sustainable-finance debate. Since then, several financial institutions have stepped back from collaborative climate initiatives such as Climate Action 100+, and asset-manager participation has fragmented, a development widely reported at the time (Jessop, 2024). The US Securities and Exchange Commission adopted climate-disclosure rules in March 2024 but placed them on voluntary stay and later ceased defending them in court (Crenshaw, 2025), adding further uncertainty for data pipelines in the world's deepest capital market. By contrast, international standard-setters have pressed ahead. IOSCO's 2025 work programme prioritises implementation of the ISSB's S1 and S2 standards, and IOSCO updated its protocol with the IFRS Foundation to support jurisdictional adoption (IOSCO, 2025b). Several jurisdictions have moved toward or into ISSB-aligned reporting in 2025, reinforcing a baseline for comparability (IFRS, 2025). Supervisory scenario work in 2025 has elevated adaptation from a peripheral concern to a core stability issue. The NGFS's Phase V scenarios project higher macroeconomic damages from physical risks (NGFS, 2024), while European supervisors warn that clustered extremes could cut euro-area GDP within years (Furness, 2025). Rising climate-related insurance losses this year echo the message: resilience metrics now warrant equal footing with decarbonisation indicators.

Set against this backdrop, my reading of our evidence is more pointed than the paper's headline findings. Where data quality is uneven and politics is polarising, "fewer, better" metrics become a virtue rather than a constraint. Three shifts feel urgent.

First, promote output-level indicators that sit between inputs and end-outcomes. Portfolio-level financed-emissions and green-commitment tallies are necessary, but they need companion metrics that evidence real operational change over a two to three-year horizon: quantified phase-out schedules, contracted low-carbon capacity and technology uptake benchmarks. Our logic-model lens already pointed in this direction; the post-2024 turbulence makes it imperative.

Second, treat assurance and independence as gating items, not embellishments. The ISSB baseline and IOSCO's emphasis on implementation have raised the bar. In practice that means independent verification of interim targets and methodologies, transparent reconciliations of financed-emissions methods and clear audit trails for any taxonomy use. The OECD's 2025 review of ratings divergence underlines why this matters: without methodological clarity, comparability decays and incentives misfire (OECD, 2025). In Paper A, we showed that academic literature on ESG-rating divergence (e.g., Berg et al., 2022; Gibson Brandon et al., 2021) consistently points to scope, measurement, and weighting differences as persistent sources of noise; precisely the kinds of weaknesses that strong assurance and independence are meant to address.

Third, bring adaptation and just-transition metrics out of the "nice to have" corner. Our respondents rated these as harder to measure and less available, yet the NGFS and loss data now make their financial materiality unmistakable. Codifying a small set of sector-relevant adaptation indicators and social guardrails would address a clear gap and reduce reputational hazard.

A final note. I began this work imagining that the answer lay in more metrics. The past year has shown me that the real need is for better ones, built on credible foundations. The priority is not quantity but quality. That means open definitions and sector baselines; reproducible methods with independent assurance; clean data lineage from asset to portfolio; version control; and interoperability across jurisdictions. Most importantly, governance must tie indicators to real decisions, incentives and penalties. Smart KPIs hold promise, drawing on satellite and asset-level data to produce timely, outcome-proximate signals. But they work only under three conditions: auditability, human judgement and consequences. Without an audit trail, trust fades; without judgement, context disappears; without consequences, nothing changes. The lesson is simple: a lean, assured set of output-level metrics is likely to outperform sprawling dashboards, and can feed into pricing models without loss of meaning. The alternative is to automate today's confusion, and market it as progress.

For the thesis, this sets up Paper C. If markets are to price transition risk credibly, the indicators they ingest must be outcome-proximate, assured and portable across jurisdictions. That is the bridge from measurement to valuation that the bond-pricing model in

Paper C is designed to cross.

Paper C. In the third paper, we developed a theoretical valuation framework that treats sustainability performance as a state variable investors can price, not a marketing add-on. Grounding the model in the Heston stochastic-volatility process with path-dependent coupons, I linked target-miss probabilities to evolving KPIs and the credibility of transition plans, so that spreads respond to changing beliefs rather than fixed classifications. Numerical illustrations drawn from the first corporate SLB (Enel, 2019) and the first sovereign SLB (Chile, 2022) suggest that modest, back-loaded penalties rarely shift yields, and that belief-updating around interim checkpoints can reprice risk as new data arrive. The wider contention is that sustainability risk belongs inside the stochastic discount factor, not relegated to the appendices.

The 2025 market backdrop only strengthens that point. IOSCO warns of persistent greenwashing risks and calls for stricter KPI design and verification (IOSCO, 2025a), while ICMA has expanded its SLB Principles and KPI Registry towards greater sector-specificity (ICMA, 2024). Fitch has described recent high-profile target misses as a "watershed moment" that could restore credibility by proving targets can be ambitious and financially material (Sustainable Fitch, 2024). Yet step-ups often remain modest since many SLBs reprice only weeks after a miss is public, when updated coupon data reaches traders' screens, creating near risk-free arbitrage (Richardson and Loh, 2025). In other words, attentive traders can lock in gains simply by buying the bonds before the delayed price adjustment. The combination of weak incentives and slow price transmission leaves market discipline patchy, even when the format works in concept.

For the framework in Paper C, policy signals are not background noise, but core inputs to how the model prices SLBs. The Heston-based structure embeds sustainability performance as a state variable, with step-up probabilities updated as new data arrive. Those probabilities depend on two things: the credibility of the issuer's targets and the reliability of the data streams feeding the model. ISSB-aligned, assured disclosures (e.g., those envisaged in the EU's CSRD and the UK's SRS S1 and S2) reduce information risk and allow the hazard rates in the model to reflect actual transition progress. Weak or contested regimes, as in the US with the SEC climate rule stayed and state-level anti-ESG pushback, do the opposite: they raise uncertainty, slow belief updating, and blunt the link between performance and spreads. In Asia, rapid adoption of ISSB-aligned standards by Hong Kong, Singapore, Japan, China, India, and South Korea, alongside ASEAN's updated taxonomy, promises the kind of consistent, auditable inputs that the model requires to make step-ups bite. In short, the ability to turn performance credibility into priced risk hinges on the regulatory environment. Where policy delivers timely, comparable, and assured disclosures, the model's outputs can translate into enforceable

cash-flow consequences; where it does not, contract design must supply the missing discipline through larger, earlier, and better-defined penalties.

The framework provides not a final verdict on SLBs, but a complementary diagnostic for making them more effective. By combining sound contract design with reliable, verified performance data, these instruments can turn sustainability commitments into enforceable financial consequences and better price sustainability-related risks and opportunities. Data constraints (especially the limited secondary-market history of SLBs and the reliance on issuer-reported KPIs) mean that the model's outputs should be read as indicative rather than definitive; they illuminate pricing dynamics under stated assumptions, not observed equilibrium prices.

First, make pay-offs material and symmetric. Penalties should be large enough to matter at issuance, with two-way ratchets that also reward outperformance. The numerical illustrations suggest that larger, earlier step-ups can materially increase spread sensitivity to credibility signals.

Second, hard-wire verification and data flows. Independent KPI assurance and SPT reviews must be mandatory. Triggers should be tied to time-stamped, auditable sources, with penalties channelled to defined abatement or just-transition uses to avoid "pay-to-pollute" optics. IOSCO's 2025 agenda backs this market infrastructure.

Third, allow continuous belief-updating. Investors should be able to adjust implied miss probabilities as interim data arrive. This requires timely, ISSB-aligned disclosures and data vendors that push updates into trading systems without lag. The model's advantage comes precisely from this continuous repricing.

Fourth, link KPIs to real-economy levers. Sovereign SLBs have drawn demand by tying KPIs to policy tools; Slovenia's 2025 issuance, linked to national decarbonisation metrics, offered a clearer incentive narrative than many corporate frameworks (Slovenia, 2025). Corporate KPIs should be equally proximate, with technology uptake and absolute emissions against sectoral pathways at the centre. Finally, price legal and policy risk explicitly. Fragmented regulation in the US, and periodic rollbacks elsewhere, are not background noise, they shift hazard rates and fair spreads. Modelling these regime shifts alongside volatility is no longer optional.

Looking ahead, the framework could evolve to allow regime-switching discount rates that respond to climate news, to model sovereign-to-corporate spillovers when policy credibility shifts both curves, and to test indexed step-ups whose size moves with carbon prices or statutory penalties. The goal is straightforward: if sustainability performance is investable, it is priceable. And if it is priceable, it must be enforceable in cash flows, not just in disclosures.

4.6.2 Implications for transition finance research and practice

Looking across the three papers, I argue that transition finance only delivers real-economy impact when climate transition plans, sustainability performance metrics and pricing are treated as one joined-up system. Paper A recasts plan credibility as an outcome-linked property rather than a disclosure label, showing that capital-backed implementation choices and independently reviewed interim targets are what move expected emissions. Paper B explains why metrics must be few, assured and proximate to operational change so that practitioners can act on them. Paper C then embeds those signals in a theoretical valuation framework by treating sustainability performance as a priced state variable, so that, under the model's assumptions, cash flows reflect climate delivery rather than marketing. In combination, the thesis closes a persistent gap between theory and practice, specifying the informational sequence through which credible plans become decision-useful metrics and, in the end, enforceable prices.

The evidence points to an execution agenda inside firms and across the system. Internally, credibility requires near-term targets, capex alignment, auditable data lineage and governance that ties remuneration and financing terms to delivery. Externally, the utility of climate metrics depends on assurance, sectoral context and timely disclosure that can feed supervisory tools and trading systems without lag. As central banks, supervisors and standard-setters roll out ISSB-aligned reporting, climate stress tests and transition-plan expectations, the bottlenecks will be data quality, interoperability and contract design. Pricing instruments need earlier, larger and symmetric ratchets linked to time-stamped evidence to avoid pay-to-comply optics and to accelerate belief-updating. Prudential authorities will increasingly need micro-credible inputs if macro scenarios are to inform risk management and financial stability. The thread running through all of this is institutional capacity building: the skills, systems and audit trails that let organisations move from disclosure to discipline.

Finally, credibility has a moral as well as a financial dimension. Transition finance must help deliver absolute emissions reduction while respecting ecological limits and social fairness. That means prioritising indicators that capture real change in hard-to-abate sectors, alongside just-transition safeguards for workers and communities, and transparent rules that prevent shifting emissions or risks offshore. Penalties and incentives should be channelled to purposeful uses, not treated as the cost of doing business. Adaptation and resilience are financially material and ethically necessary, especially for vulnerable regions that face the sharpest physical risks yet the highest costs of capital. My conclusion is simple: when plans, metrics and prices are designed for truthfulness, comparability and consequence, they do more than improve portfolios. They help steer the financial system with a transition that is effective, legitimate and worthy of public trust.

4.7 Research Boundaries and Future Directions

No single thesis can capture the full complexity of transition finance, and the present work inevitably reflects boundary choices. These decisions, about sectors, data sources and methods, create blind spots. In recognising these limits, I seek to outline a research agenda that directly stems from them. Each limitation below is matched with a corresponding avenue for future work.

Data provenance and disclosure bias. The papers rely heavily on self-reported corporate data: annual reports and sustainability disclosures. Such information is subject to managerial framing, selective omission and strategic complication, classic forms of information asymmetry that have long been recognised in economics (Unruh, 2000). Even outcome-weighted scoring and third-party triangulation cannot eliminate the risk that firms under-report supply-chain emissions or overstate governance arrangements. Future research could reduce this bias by combining disclosure data with independent observational sources. Satellite remote sensing and near-real-time emission inventories are increasingly able to track power generation and industrial activity with fine spatial resolution (e.g., Climate TRACE, 2025). Researchers might integrate these data with blockchain-based procurement records to validate claims about sustainable fuel use or renewable-energy uptake. The governance of such data streams is itself a fertile area for investigation. Scholars could test whether sources like shared platforms for pooling remote-sensing, sensor and ledger data mitigate information asymmetry and whether federated or centralised stewardship best balances verifiability and commercial confidentiality.

Sectoral scope and external validity. By focusing on aviation, global finance and SLBs, the thesis inevitably under-represents sectors with very different transition pathways. For instance, agriculture, real estate and digital infrastructure each pose unique mitigation challenges. Agriculture entails soil-carbon sequestration, feed additives and biodiversity outcomes, while real estate involves landlord-tenant incentive splits and regional building codes; digital infrastructure is marked by energy-intensive data centres and cooling systems. Comparative studies could adapt the outcome-weighted scoring of Paper A to these contexts, identifying which disclosure items correlate most strongly with near-term emissions performance. Such work might reveal whether governance remains a dominant predictor of credibility or whether supply-chain traceability, demand-side management or regional policy salience become more important. A second line of enquiry is to expand the dual-materiality agenda by developing sector-specific metrics for adaptation and biodiversity co-benefits, especially in agriculture.

Survey design and common-method variance. Paper B relies on self-reported percep-

tions of metric usefulness. This invites common-method bias, whereby correlations arise from shared measurement rather than real association (Cohen et al., 2023). Although anonymity assurances and random item ordering were used, latent social desirability effects may persist. Future surveys could validate respondents' climate-strategy maturity against external ratings or audited disclosures, reducing endogeneity. Experimental vignette designs offer another avenue: by manipulating attributes of climate metrics (e.g., assurance level, time horizon, linkage to cash flows), researchers could test whether scepticism arises from data gaps, cognitive overload or fears of greenwashing. These experiments would build on established remedies for common-method bias and extend them into transition-finance research.

Econometric identification and causal inference. The correlation-based scoring in Paper A and the theoretical pricing framework in Paper C remain vulnerable to endogeneity. Unobserved variables such as corporate culture, political influence or macro hedging strategies may influence both credible planning and improved emissions outcomes, leading to biased estimates. Future research could address this by using quasi-experimental designs. Natural experiments, such as sudden regulatory shocks (e.g., a legally binding sustainable aviation-fuel mandate) or commodity price spikes, could provide exogenous variation to identify causal effects. Difference-in-differences frameworks would allow researchers to estimate the impact of transition-plan quality on emissions trajectories more robustly when more data becomes available. In cross-sectional settings, dynamic panel models with firm fixed effects and lagged instruments could control for autocorrelation and heteroskedasticity, refining effect-size estimates and improving out-of-sample predictive power. These econometric advances would align transition-finance research with best practice in causal inference.

Parameter non-stationarity and deep uncertainty. While we did not hard-code published climate pathways into the models, I inevitably estimated parameters over finite windows and assumed some local stability. The reality is far more volatile: climate-policy jumps, technological breakthroughs and shifts in public sentiment can produce structural breaks and fat-tailed risks that static or mean-reverting models understate. Future work should treat deep uncertainty as a design constraint, building models that can switch regimes, jump when conditions change, and update dynamically as new, assured data arrive. Robust-decision frameworks, Bayesian hierarchical updating, and open, auditable scenarios would all help to make transition-finance analytics resilient to the very shocks that will define the low-carbon transition.

Price discovery and market microstructure. The theoretical valuation framework in Paper C illustrates how credibility could feed into spreads under stated assumptions, but real-world pricing is messy. Because the model relies on numerical illustrations

rather than observed transaction data, its outputs are best understood as a complementary diagnostic, identifying where contract design may leave spreads insensitive to performance, rather than as predictions of market prices. Liquidity, investor preferences, and index rules all influence how and when information is incorporated into prices. The slow, sometimes incomplete, repricing documented in secondary markets suggests a need for more detailed work on the speed and completeness of market reactions, ideally through high-frequency event studies around KPI checkpoints, or microstructure analyses that distinguish between information effects and flow-driven noise. This could clarify whether contract redesign alone is enough, or whether complementary measures are needed to improve price discovery.

Acknowledging the limitations of this thesis is necessary for delineating where its results hold and where further work is needed. Transition finance remains a young field. By outlining the directions above, ranging from open data architectures and cross-sectoral deep dives to behavioural studies, and adaptive valuation frameworks, I hope to encourage a research agenda that builds on, and goes beyond, the work laid here.

Appendices

4.8 Appendix: Paper A

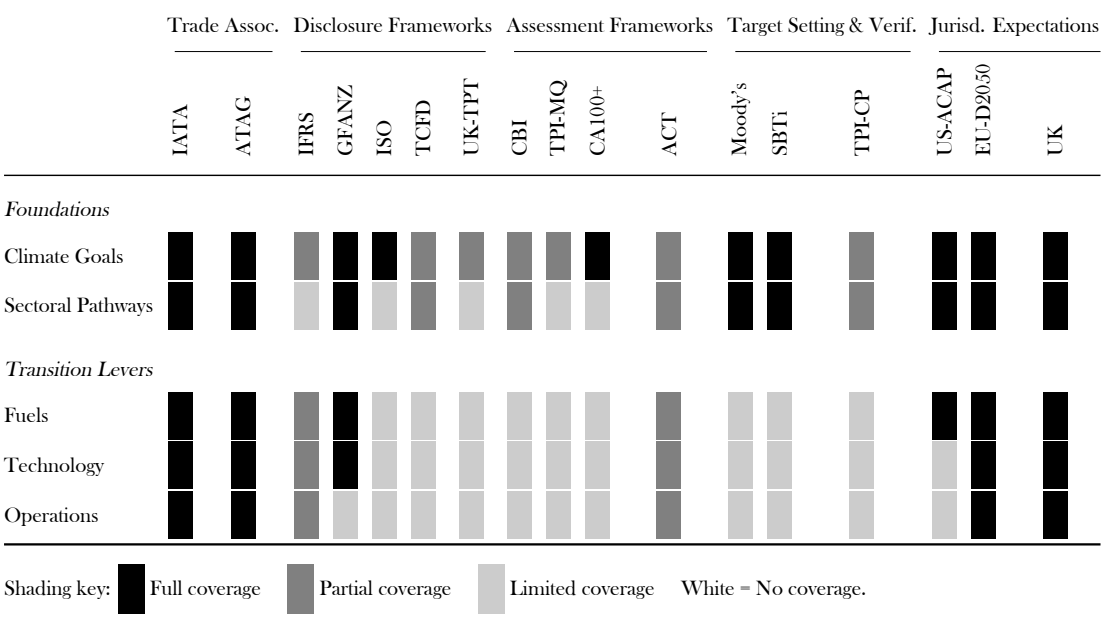
Tables

Table 1. Comparative analysis of climate pathways for the aviation sector: a summary of selected criteria and findings*

	IEA	MPP	OECM	ICAO
GHG Scopes	1, 2, 3	1, 2, 3	1, 2, 3	1, 2
Timeframe	2010-2050	2019 - 2050	2019-2050	2020-2070
GHG types	CO2	CO2	CO2	CO2
Carbon price	Yes	No	No	No
Carbon budget	18 Gt	18 Gt	20 Gt	16 – 44 Gt
Fuel mix supply	Yes	Yes	Yes	Yes
Policy assumptions	Yes	Yes	Yes	Yes
2050 GHG emissions	0.21 Gt	0.14 Gt	0 Gt	0.23 Gt
Temperature alignment	1.5º	1.5º	1.5º	1.5º **
Technology assumptions	Yes	Yes	Partially	Partially
Demand assumptions	Yes	Yes	Partially	Yes
Investment requirements	Partially	Partially	No	Partially
Asset-level considerations	Partially	Partially	Partially	Partially
Just transition	No	No	No	Partially
Reliance on offsets	Yes	Yes	No	Yes

Sources: Authors' analysis using data from ICAO, 2022; IEA, 2021, 2022; MPP, 2022; Teske et al., 2022.
Notes: (*) The selected criteria were derived from the GFANZ (2022c) assessment framework of climate pathways. (**) ICAO states that it aims to be aligned with a 1.5º scenario, while the CAT (2022) indicates that ICAO's target is consistent with at least 3°C of warming, if not 4°C.

Table 2. Airline sustainability reporting frameworks: overlaps, gaps, and net-zero alignment



Source: Authors' analysis using data from ATAG, 2021; FAA, 2021; GFANZ, 2023; IATA, 2022a, 2022b, 2023, 2023; IFRS, 2018; ISO, 2022; Moody's, 2021, 2022; NLR & SEO, 2021, 2021; SBTi, 2021; TCFD, 2021; TPI, 2021a, 2021b; UK DfT, 2022; UK TPT, 2022.

Note: This table maps the extent to which various sustainability reporting frameworks provide guidance on airlines' net-zero transition. Black cells indicate full coverage with explicit net-zero guidance, dark grey cells represent partial coverage with low-carbon guidance, and light grey cells highlight limited coverage where no direct guidance exists.

Table 3. Summary of assessment criteria

Topic	Key Questions (Simplified Version)	Short Guidance
Climate Goals *(Foundations & Governance)*	- Are there near/mid-term GHG targets in addition to net-zero? - Are they verified (e.g., by SBTi) or aligned with a recognized standard?	Look for publicly disclosed Scope 1–3 targets, methodology, and interim milestones. Check third-party reviews and alignment with science-based scenarios.
Fuels *(Implementation, Engagement, Metrics/Targets, Governance)*	- Is there a strategy to adopt sustainable aviation fuel (SAF)? - Are suppliers engaged? - Are there SAF metrics and targets? - Are SAF certifications disclosed?	Assess clarity on SAF goals, supplier partnerships, progress metrics, and recognized certifications (e.g., RSB, ISCC). Look for specific timelines and reporting on SAF uptake.
Technology *(Implementation, Engagement, Metrics/Targets)*	- Is the airline investing in low-emission aircraft technologies? - Are there partnerships with manufacturers? - Are there set metrics and targets for new tech adoption?	Look for R&D initiatives, plans for fuel-efficient aircraft, and public commitments or collaborations (e.g., electric/hydrogen aircraft). Check for measurable goals and timelines.
Operations *(Implementation, Engagement, Metrics/Targets)*	- Does the airline have strategies to improve operations/infrastructure for carbon reduction? - Is it working with third parties? - Are there measurable goals?	Examine disclosed efforts (e.g., route optimization, energy-efficient airports, advanced traffic management), partnerships, and time-bound metrics for improved carbon performance.

Note: This table is derived from Appendix A and provides a quick-reference summary of the full "Climate Transition Plans' Assessment Questionnaire."

Figures

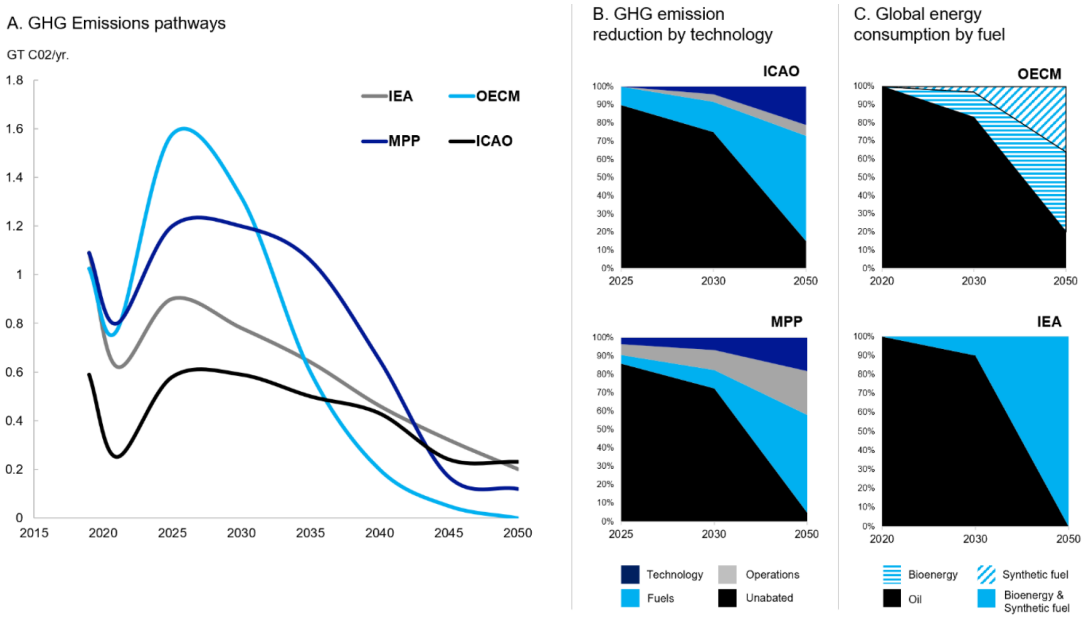


Figure 1. Selected climate pathways and key assumptions for the aviation sector

Source: Authors' analysis using data from ICAO, 2022; IEA, 2021, 2022; MPP, 2022; Teske et al., 2022.

Note: (A) The chosen pathways represent the aspiration to achieve net zero carbon emissions, addressing unmitigated emissions through carbon removal and capture technologies. We consider the Prudent Scenario for the MPP pathway and the IS2 scenario for the ICAO, which both rely on moderate assumptions regarding hydrogen and Power-to-Liquid fuels. (B) The technology pathways provide a broad overview of how advancements in aircraft technology (Technology), operational enhancements (Operations), and the use of sustainable aviation fuels (Fuel) are expected to contribute to greenhouse gas (GHG) emission reductions by 2050. (C) Regarding the global energy consumption in the aviation sector, the OECM and the IEA offer a breakdown of the proportion of bioenergy, synthetic fuel, and oil expected to be utilized by 2050.

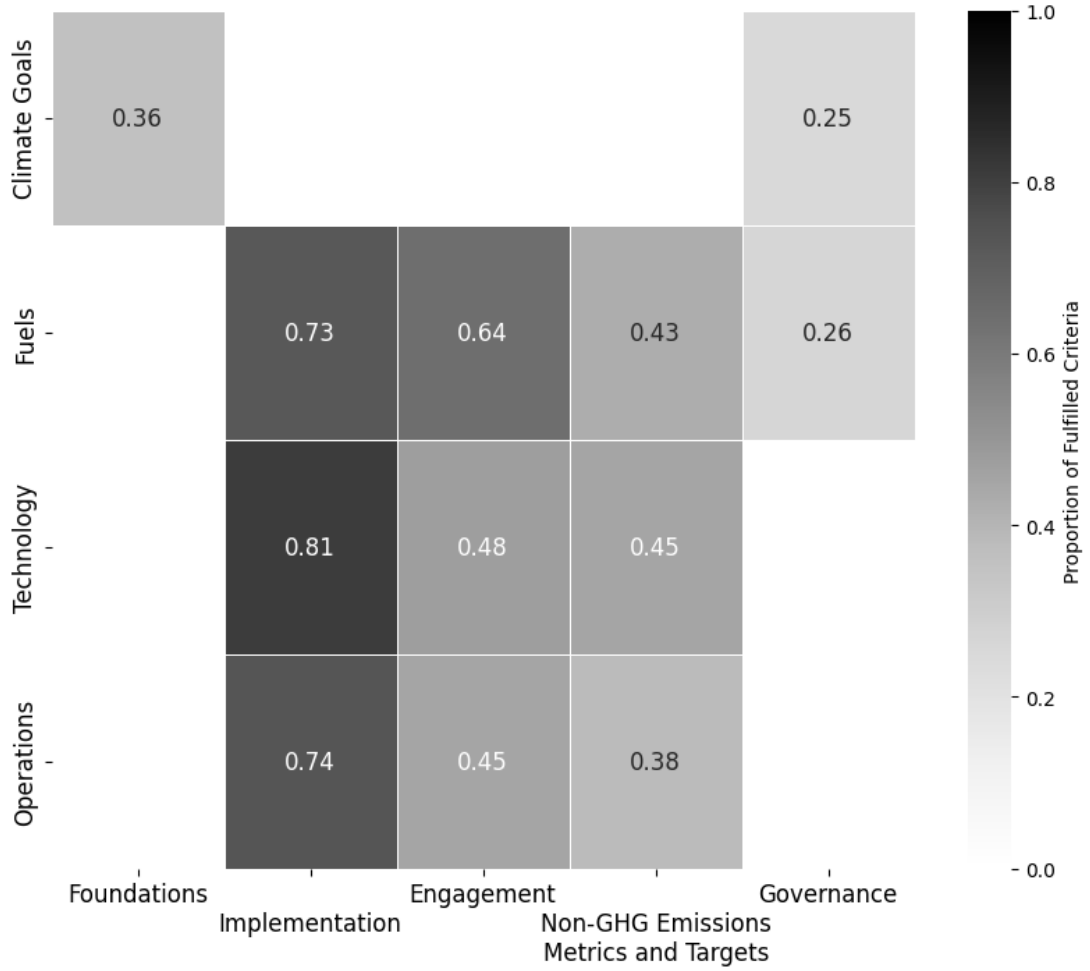


Figure 2. Proportion of positive responses from surveyed airlines against the transition plan assessment

Source: Authors' analysis.

Note: The colour gradient represents the percentage of airlines meeting specific criteria: darker shades indicate higher compliance or disclosure, while lighter shades indicate lower compliance. The criteria on the x-axis (Foundations, Implementation, Engagement, Metrics and Targets, and Governance) correspond to categories assessed in the questionnaire detailed in Appendix A. These results are based on publicly available information and reflect reported rather than actual performance.

Figure 3. Derived weights of climate transition plan sub-elements across correlation methods

Source: authors' analysis.

Note: this figure visualises the weights assigned to sub-elements of climate transition plans across three correlation-based methods: baseline (eqs. 1–3), stratified (eqs. 4–5), and partial (eq. 6). weights represent the relative importance of each sub-element (as a percentage) in influencing short-term carbon performance change. darker shades indicate higher weights, highlighting the sub-elements that exert the strongest influence on emissions performance. sub-elements are categorised under climate goals, fuels, technology, and operations to reflect their functional areas.

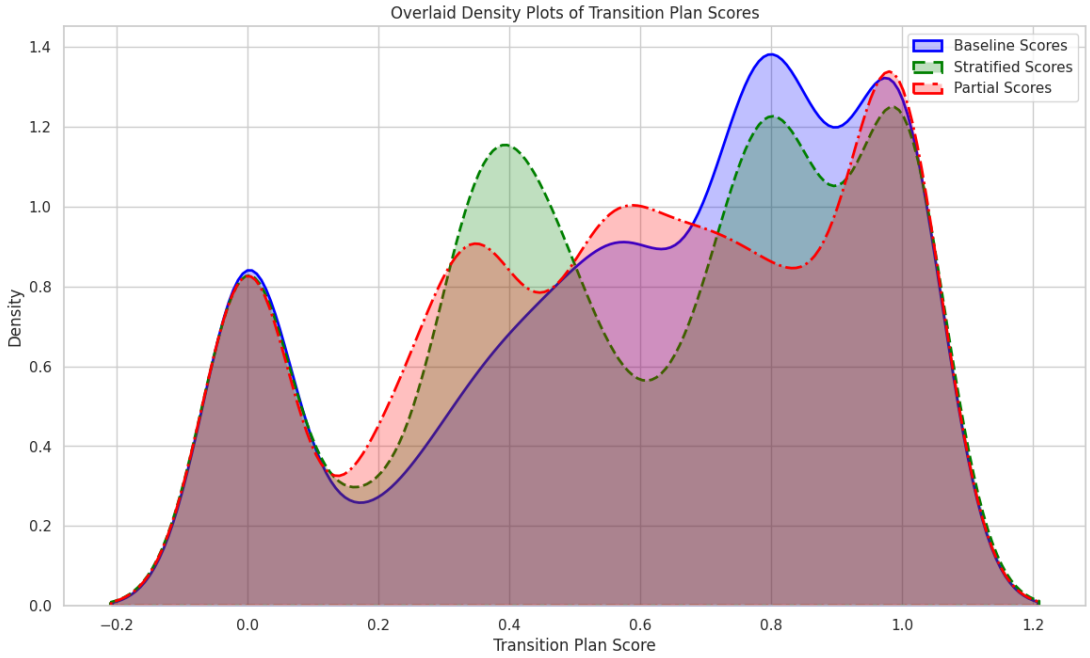


Figure 4. Comparison of density distributions for baseline, stratified, and partial transition plan scores

Source: Authors' analysis.

Note: This figure illustrates the kernel density estimates of transition plan scores under three distinct scoring methodologies: baseline, stratified, and partial. Each method reflects a different approach to controlling for operational confounders (e.g., fleet age, passenger load). The baseline method directly correlates sub-elements with emissions intensity, the stratification method accounts for group-level operational differences, and the partial method controls for confounding variables as continuous factors. The density plots are overlaid to highlight the similarities and differences in score distributions across methods.

Technical notes

A. CTP assessment questionnaire. Our transition plan assessment questionnaire is a tool designed to assess airlines' adherence to climate transition commitments across five dimensions. The questionnaire, structured for binary responses, is supported by over a dozen disclosure frameworks, with the GFANZ framework notably shaping its criteria. Each question is coupled with guidance and references that anchor it in industry standards. This format aims to ensure an unambiguous evaluation of whether companies' actions align with ambitious, science-based climate targets and strategies. As shown in Table A1, it is organised into five sections, each representing a dimension of climate transition.

Table A1. Climate transition plans' assessment questionnaire

Question	Guidance	Reference

Climate goals / Foundations *Code: a_foundations* 1. Has the airline established short- or medium-term climate goals in addition to its long-term commitment to net-zero emissions supported by science-based climate pathway?	Check if the airline publicly discloses its short-, medium-, and long-term greenhouse gas (GHG) emissions targets, including Scope 1, 2, and potentially Scope 3 emissions. Evaluate the transparency of their reporting by considering the context, methodology, and any exclusions from the targets. Utilize industry frameworks such as IATA RP 1678 for emissions allocation and ensure reporting in consistent units like kgCO2e/tonne.km or kgCO2e/passenger.km. Look for the inclusion of interim targets within a 3- to 5-year range and assess whether emissions sources are differentiated based on fleet usage. Climate pathways considered were the ones developed by ATAG, ICAO, OECM, and IEA.	CA 100+, ACT, TPT, GFANZ, TPI, CBI, US, CDP, ISO, ATAG, SBTI
Climate goals / Governance *Code: a_governance* 2. Have the airline's climate goals undergone verification by an independent third-party reviewer or are they aligned with an established standard?	Verify if the airline's climate transition targets have undergone an independent third-party review and check if the findings and scope of the assessment have been disclosed. Explore the Science Based Targets initiative (SBTi) registry to identify any targets that have been verified and aligned with a science-based scenario, specifically targeting a 1.5-degree Celsius pathway. Ensure the third-party verification details are accessible and confirm the credibility of the verifying organization. Look for information on the methodology used for verification and any standards or frameworks referenced.	CBI, GFANZ, ACT, CDP, TPT, ISO, SBTI
Fuels / Implementation *Code: a_implementation* 3. Does the airline have a strategy to increase sustainable aviation fuel usage in the short term?	Assess whether the airline publicly discloses its Sustainable Aviation Fuel (SAF) initiatives, goals, and progress. Look for transparent reporting on the adoption and scaling-up of SAF, including metrics such as total neat and blended SAF delivered, lifecycle emissions factors per SAF type, and CO2 emissions reductions achieved. Consider ICAO standards and IATA recommendations for reporting. Verify if the airline differentiates between domestic and international flights and includes specific short-term targets and timelines for SAF adoption. Review any partnerships or collaborations mentioned that support the scaling-up of SAF usage.	SBTI, IATA, ACT, US, ATAG
Fuels / Engagement *Code: a_engagement* 4. Is the airline engaged with sustainable aviation fuel suppliers to increase short-term usage?	Evaluate if the airline publicly discloses its engagement strategy with SAF suppliers. Look for criteria used to select and engage with suppliers and assess how the airline manages environmental and social risks in the SAF supply chain. Identify any initiatives involving policymakers and regulators to promote feedstock sustainability, expand SAF supply, and stimulate demand. Examples of engagement include signing offtake agreements, co-funding research and development, offering SAF support options, investing in production facilities, and integrating biofuels into fuel tendering. Ensure these initiatives are clearly detailed and supported by specific examples or case studies.	GFANZ, ACT, US, ATAG, IATA, IEA
Fuels / Metrics and Targets *Code: b_metricstargets* 5. Does the airline have metrics and targets for sustainable aviation fuel uptake?	Check if the airline has publicly disclosed specific metrics and targets for sustainable aviation fuel (SAF) uptake. Look for quantitative goals such as the percentage of total fuel consumption that will come from SAF, the volume of SAF to be used annually, and timelines for achieving these targets. Evaluate if the airline provides clear benchmarks for progress tracking, such as annual reports on SAF usage and CO2 emissions reductions achieved through SAF adoption. Ensure these metrics and targets align with industry standards and best practices, such as those recommended by IATA. Additionally, verify if the airline's SAF targets are part of a broader, long-term sustainability strategy.	IATA, GFANZ, US, ATAG
Fuels / Governance *Code: b_governance* 6. Has the airline disclosed the certifications for sustainable aviation fuels used or intended for use?	Verify if the airline discloses the certifications of the sustainable aviation fuels (SAF) it purchases or intends to use. Check for information about the specific certification bodies or standards, such as the Roundtable on Sustainable Biomaterials (RSB) or International Sustainability and Carbon Certification (ISCC). Ensure that the certifications align with recognized sustainability standards and demonstrate the SAF's contribution to emissions reductions. Look for details on the certification process and any third-party verifications to confirm the credibility and sustainability of the SAF used by the airline.	

Technology / Implementation *Code: c_implementation* 7. Does the airline have a strategy for investing in or adopting new aircraft technologies to improve carbon performance?	Evaluate if the airline discloses a strategy for investing in or adopting new aircraft technologies aimed at improving carbon performance. Look for details on investments in fuel-efficient and low-emission technologies, including specific aircraft models and technological advancements being pursued. Assess the progress in implementation, the impact on emissions reductions or fuel savings, and the plan for replacing carbon-intensive assets. Check the percentage of the fleet targeted for upgrades or replacement. Consider the maturity levels of the technologies being pursued and distinguish between advancements in airframe and propulsion systems. Additionally, look for any partnerships or collaborations with manufacturers or technology firms.	SBTI, IATA, GFANZ, TPI, EU, ISO, ATAG, CBI
Technology / Engagement *Code: c_engagement* 8. Is the airline engaged with manufacturers or technology firms to adopt new aircraft technologies?	Assess if the airline discloses its engagement strategy with aircraft manufacturers and its involvement in R&D initiatives focused on advancing low-emission technologies. Look for information on partnerships or collaborations to develop electric or hydrogen-powered aircraft or other innovative solutions. Evaluate how the airline exchanges market data and insights with suppliers to foster the advancement of low-emission technologies across the industry. Check for any specific projects or joint ventures aimed at accelerating the development and adoption of these technologies.	IATA, GFANZ, ACT, US, ISO, ATAG
Technology / Metrics and Targets *Code: c_metricstargets* 9. Has the airline established metrics and targets for adopting new aircraft technology to improve carbon performance?	Evaluate if the airline provides specific examples of investments in fuel-efficient and low-emission aircraft technologies, such as fleet renewal programs. Look for metrics and targets related to the adoption of these technologies, such as the percentage of R&D investment dedicated to low-emission technologies, the number of new aircraft technologies implemented, and the projected impact on carbon performance. Check if the airline sets clear timelines and measurable goals for integrating these technologies into their fleet.	GFANZ, ACT, US, EU, ISO, ATAG, SBTI
Operations / Implementation *Code: d_implementation* 10. Does the airline have a strategy to improve operations and infrastructure for better carbon performance?	Assess if the airline publicly discloses its strategy for enhancing operations and infrastructure to improve carbon performance. Look for initiatives such as optimizing flight routes, improving ground operations, implementing energy-efficient airport facilities, and adopting advanced air traffic management systems. Evaluate the transparency of their reporting on these initiatives, including any specific goals, timelines, and projected impact on emissions reductions. Check if the airline sets measurable targets for operational efficiencies and infrastructure improvements and monitors progress toward these targets.	SBTI, GFANZ, ACT, US, EU, ATAG
Operations / Engagement *Code: d_engagement* 11. Is the airline engaged with third parties to enhance operations and infrastructure for better carbon performance?	Determine if the airline publicly discloses its engagement with third parties to enhance operations and infrastructure for better carbon performance. Look for partnerships or collaborations with airports, air traffic management organizations, or other industry stakeholders. Assess whether the company participates in joint initiatives or projects aimed at improving operational efficiencies, such as implementing advanced air traffic management systems or developing energy-efficient airport facilities. Evaluate the transparency and details of these engagements, including specific goals, milestones, and the expected impact on carbon performance.	SBTI, GFANZ, ACT, US, EU, ATAG
Operations / Metrics and Targets *Code: d_metricstargets* 12. Has the airline set metrics and targets for improving operations and infrastructure to achieve better carbon performance?	Check if the airline has publicly disclosed specific metrics and targets for improving operations and infrastructure to enhance carbon performance. Look for detailed plans or strategies that outline measurable goals, such as reducing fuel consumption, improving energy efficiency at airport facilities, or decreasing ground operation emissions. Assess whether these targets are time-bound and aligned with broader climate objectives. Verify if the airline provides regular updates on progress towards these targets and if they use recognized frameworks or standards for reporting their performance.	SBTI, GFANZ, ACT, EU, ISO, ATAG

Sources: Authors' analysis using information from ATAG, 2021; FAA, 2021; GFANZ, 2023; IATA, 2022a, 2022b, 2023, 2023; IFRS, 2018; ISO, 2022; Moody's, 2021, 2022; NLR & SEO, 2021, 2021; SBTi, 2021; TCFD, 2021; TPI, 2021a, 2021b; UK DfT, 2022; UK TPT, 2022.

B. Convergence and divergence in airline CTP scores' rankings. This report summarises an analysis of three independent transition planning scoring systems: CTP (84 observations), ACT (24 observations), and TPI (39 observations). These systems rank

airlines in 2022. Our scoring system is CTP, the first of the three. The primary objective was to assess the degree of convergence or divergence among these scoring systems, focusing on both individual rankings and group categorisations.

To address the scaling differences, the raw scores were transformed into ranks, which allowed the use of statistical measures that are less sensitive to the original measurement scales. The associations between the rankings were first examined using Spearman's rank correlation coefficient and Kendall's tau, both of which provide insight into the monotonic and ordinal agreement, respectively (StataCorp LLC, 2023c). To obtain an overall measure of agreement among the three scoring systems, Kendall's coefficient of concordance was computed. Furthermore, to explore how the rankings translate into performance categories, the airlines were divided into quartiles. The agreement in these categorical groupings was then assessed through Cohen's kappa for pairwise comparisons and Fleiss' kappa for overall agreement (StataCorp LLC, 2023b). The Friedman test was also applied to determine whether the differences among the ranking methodologies were statistically significant (Demšar, 2006).

The pairwise associations between the rankings are summarised in Table B1. Spearman's rank correlations reveal moderate positive correlations between each pair of scoring systems. These results are supported by Kendall's tau values, which also indicate a moderate level of agreement.

Table B1. Pairwise rank correlations

Comparison	Spearman's	p-value	Kendall's	p-value
CTP vs ACT	0.609	0.0016	0.415	0.0053
CTP vs TPI	0.581	0.0001	0.446	0.0001
ACT vs TPI	0.539	0.0080	0.402	0.0100

When the airlines were categorised into quartiles, the agreement diminished. Table B2 displays the pairwise Cohen's kappa values and the overall Fleiss' kappa. The lower kappa values indicate that although the overall rankings demonstrate moderate convergence, the allocation of airlines into performance quartiles differs considerably among the scoring systems, with TPI diverging most markedly from CTP and ACT.

Table B2. Categorical agreement (quartile categorisation)

Comparison	Cohen's Kappa	Interpretation
CTP vs ACT	0.305	Fair agreement
CTP vs TPI	0.113	Slight agreement

ACT vs TPI	0.361	Fair agreement
Overall (Fleiss')	0.256	Fair agreement

The Friedman test further confirmed that the differences among the scoring methodologies are statistically significant, with a test statistic of 12.95 and a p-value of 0.0015. This significant result reinforces the view that the three scoring systems are not interchangeable, as they capture distinct aspects of transition planning performance.

In summary, the analysis demonstrates a moderate convergence among the transition plans' scoring systems when ranking airlines; however, the agreement weakens when the airlines are categorised into performance quartiles. The statistically significant differences revealed by the Friedman test emphasise that the scoring systems are not assessing transition planning in the same way, with TPI showing the greatest divergence relative to CTP and ACT. These findings highlight the importance of considering methodological differences when comparing transition plans' scores across different systems.

Table B3. Comparison of airline scores across methodologies

Airline	CTP	ACT	TPI	Airline	CTP	ACT	TPI
JetBlue Airways	1	–	13	Scoot	0.597406	–	–
Azul	1	–	11	Malaysia Airlines	0.596694	–	–
Iberia	1	–	–	Icelandair	0.573356	–	–
easyJet	1	–	15	LATAM Airlines	0.539268	10.7	9
Delta	1	13	15	Wizz Air	0.539268	–	12
Aer Lingus	1	–	–	AirAsia	0.538198	–	8
KLM Royal Dutch Airlines	1	–	–	Qatar Airways	0.533142	–	–
British Airways	1	–	–	Spirit Airlines	0.531608	–	3
IAG	1	25	17	Cebu Pacific	0.518736	–	–
Air France-KLM	1	17.1	14	TUI	0.488077	–	–
Air New Zealand	1	–	13	Agean Airlines	0.482305	–	–
Air France	1	–	–	Finnair	0.461664	–	–
American Airlines	0.985593	25.7	16	GOL	0.404346	–	–
ANA Holdings	0.985593	21.4	16	Emirates	0.404346	12.6	–
United Airlines	0.985593	25.1	14	Air China	0.37405	1.9	6
China Airlines Group	0.985593	11.6	13	Shandong Airlines	0.37405	–	–
Japan Airlines	0.957891	24.9	16	Asiana Airlines	0.369736		–
Qantas Group	0.943485	2.1	13	El Al	0.360774	–	–
Alaska Airlines	0.942773	8.1	10	Copa Airlines	0.345656		9
Southwest Airlines	0.879933	11.7	12	Avianca	0.345656	–	–
Jet2.com	0.879933	–	–	Air Canada	0.319381	–	15
SAS	0.865955	–	14	Aeromexico	0.312116	–	–
Pegasus	0.838964	–	–	IndiGo	0.312116	14.6	6
Lufthansa	0.824558	–	–	Thai Airways	0.311046	–	–
Lufthansa Group	0.824558	13.1	16	Royal Jordanian	0.311046		–
Viva Aerobus	0.800701	–	–	Etihad	0.253975	–	–
Volaris	0.800701	–	9	Frontier Airlines	0.218817	–	–

Vueling	0.7894	–	–	TAP Portugal	0.218817	–	–
Ryanair	0.772848	17.9	7	China Eastern	0.185529	1.6	6
Austrian Airlines	0.751565			China Southern	0.185529	4.9	6
Virgin Atlantic	0.718341	–	–	Kenya Airways	0	–	–
EVA Air	0.717119	–	11	VietJet Air	0	3.7	15
Cathay Pacific Group	0.716333	22.4	16	Juneyao Airlines	0		2
Norwegian Air Shuttle	0.691735	–	–	Sun Country Airlines	0	–	–
Eurowings	0.687197	–	–	Bangkok Airways	0	–	–
Brussels Airlines	0.685519	–	–	Spring Airlines	0	–	0
SWISS	0.681774	–	–	Hawaiian Airlines	0	–	9
Korean Air	0.681175	3.7	15	Hainan Airlines	0	–	–
Allegiant Air	0.623084	–	5	Jin Air	0	–	–
Singapore Airlines Group	0.601943	12.1	9	Croatia Airlines	0		–
Singapore Airlines	0.601943	–	–	Garuda Indonesia	0	–	–
Turkish Airlines	0.601943	9.4	16	Jeju Air	0	–	–

Note: Airlines are sorted based on the CTP methodology in descending order.

C. Cross-validation and bootstrapping methods for weight stability assessment. The primary objective of this analysis is to assess the stability and robustness of the weight estimates used to construct the composite transition plan score. In doing so, we mitigate concerns about circularity by ensuring that the weights are not simply overfitted to one sample but remain consistent and generalisable. Specifically, we evaluate three weighting approaches (baseline, stratified, and partial correlations) using two complementary methods: cross-validation and bootstrapping.

The dataset was repeatedly split into training and test subsets using different split ratios (e.g., 60%-40%). For each random split, weights were derived from the training set using the three correlation-based methods:

- Baseline weights: Derived from point biserial correlations between each binary sub-element and the raw carbon performance metric.
- Stratified weights: Derived after adjusting carbon performance by subtracting subgroup means based on fleet age and passenger load.
- Partial weights: Derived using partial correlations that control for fleet age and passenger load.

The training set weights from multiple splits were then aggregated and summarised in the following boxplots (refer to transition plan sub-elements' codes in Table A1).

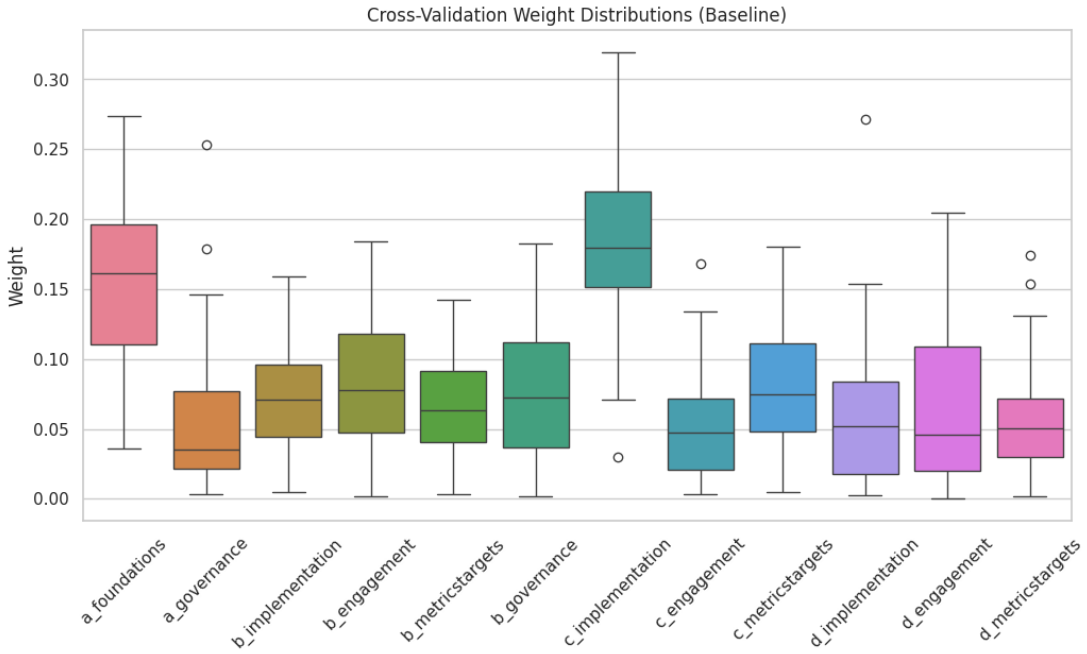


Figure C1. Cross-validation weight distributions (baseline)

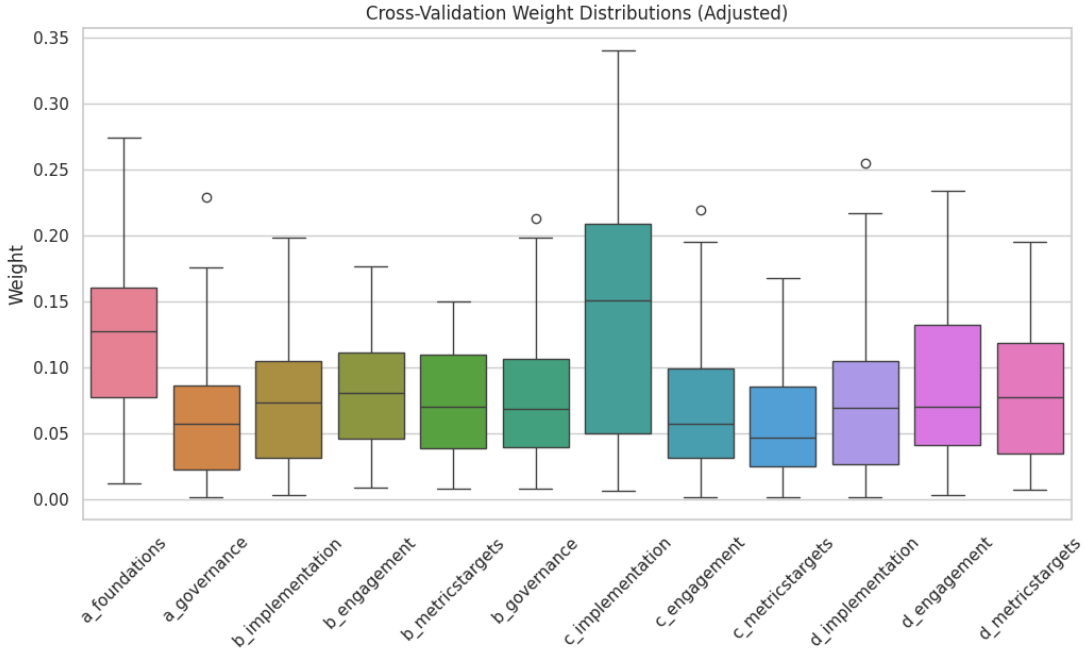


Figure C2. Cross-validation weight distributions (stratified)

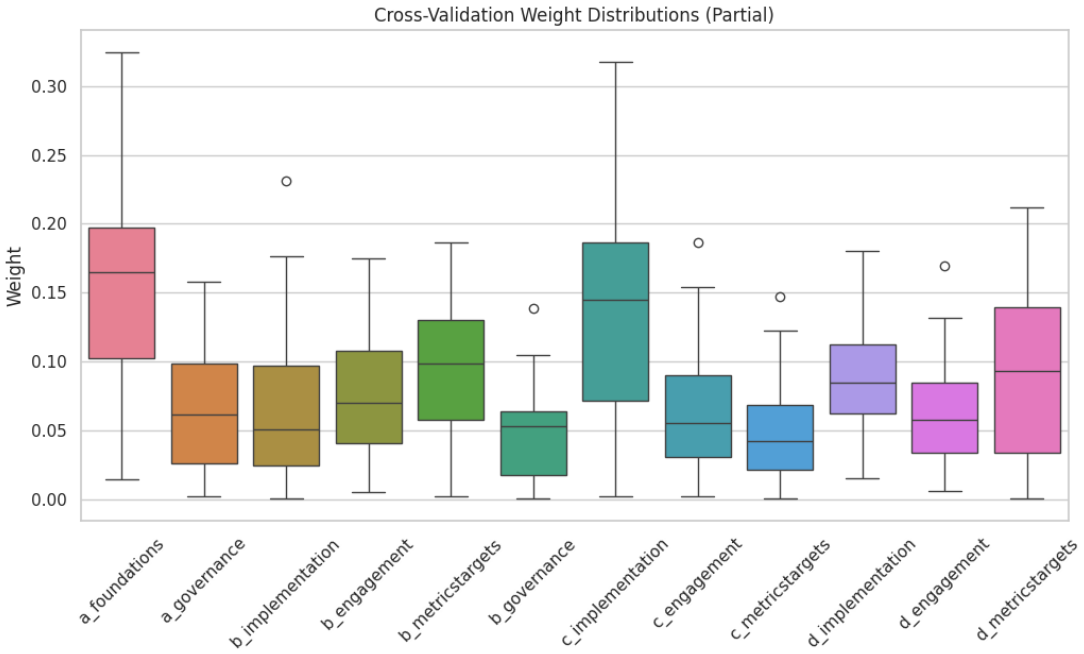


Figure C3. Cross-validation weight distributions (partial)

The full dataset was resampled with replacement over 1,000 iterations to generate a distribution of weight estimates for each sub-element. For each iteration, weights were computed using the same three methods. The stability of the weights was then assessed by summarizing these distributions with the following boxplots.

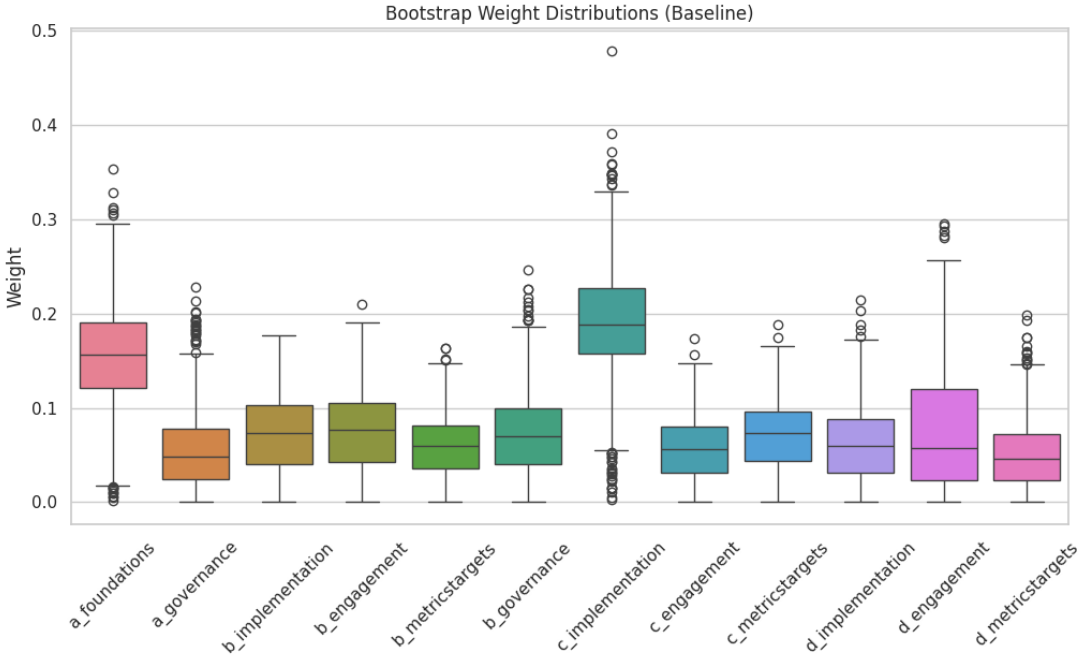


Figure C4. Bootstrap weight distributions (baseline)

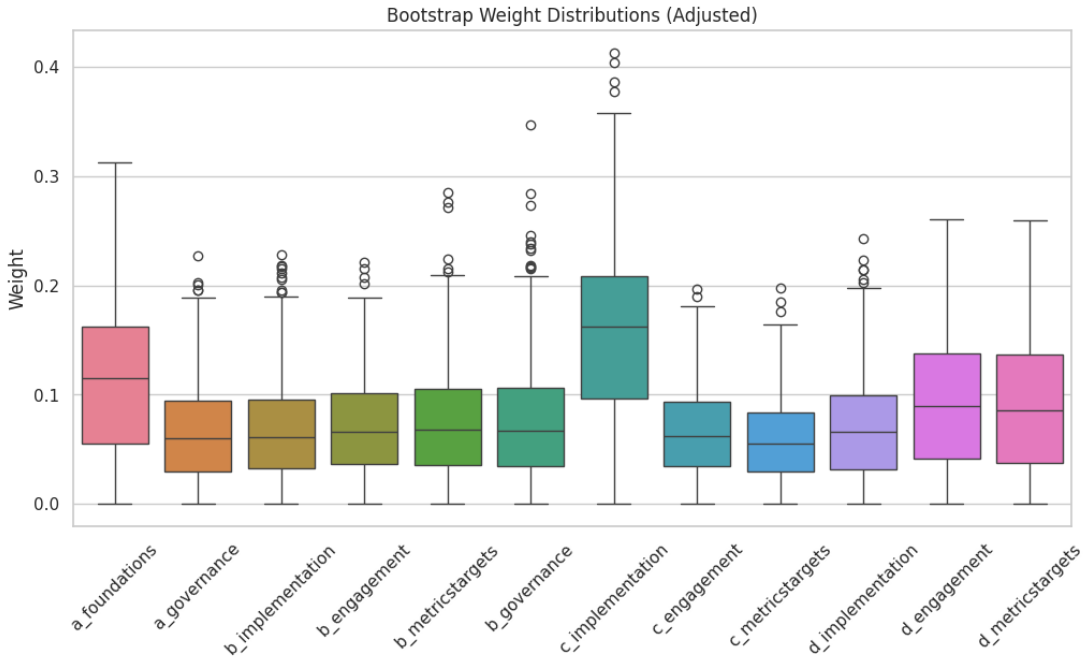


Figure C5. Bootstrap weight distributions (stratified)

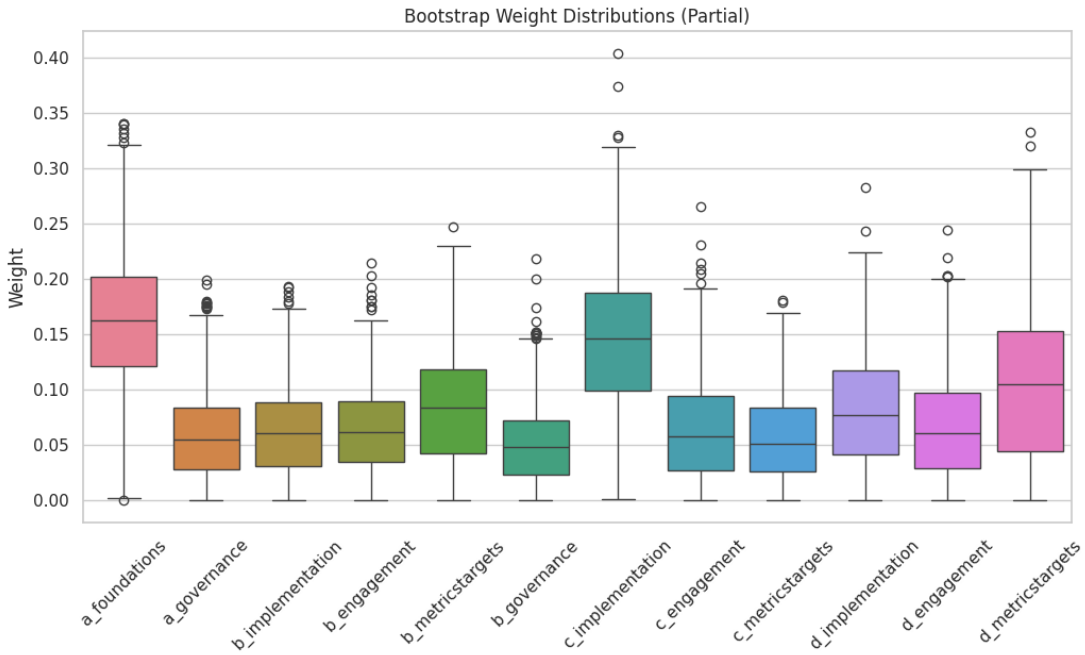


Figure C6. Bootstrap weight distributions (partial)

The analyses reveal that key strategic dimensions, particularly a_foundations and c_implementation, consistently receive higher weights across both methods. In the cross-validation procedure, weight estimates were stable across different subsamples, with only minor variability as indicated by similar distributions. Bootstrapping results further demonstrate narrow confidence intervals for the primary sub-elements (a_foundations and c_implementation), confirming that the weight estimates are robust to sampling variability.

Together, these findings provide strong evidence that the weights are stable and not driven by sample-specific idiosyncrasies.

4.9 Appendix: Paper B

A. Survey questionnaire

Survey title: Which Financial Sector Metrics Best Support the Shift to a Low-Carbon Economy?

Context: This survey is part of a research initiative by the Oxford Sustainable Finance Group at the University of Oxford. It aims to collect expert opinions on metrics employed by financial institutions to promote a transition to a low-carbon economy. The survey is anonymous and takes less than 10 minutes to complete. No personal data is collected. Ethical approval has been granted by University of Oxford CUREC (SOGE1A2021-238).

Section 1: Consent and participant information

- *Consent*: Yes, I consent; No, I do not consent.
- *Gender Identity*: Female, Male, Non-binary, Prefer not to say, Other: (blank space)
- *Primary Work Location*: (List of countries provided)
- *MSCI Market Classification Focus*: Developed Markets, Emerging Markets, Frontier Markets, Standalone Markets, Other.
- *Experience in Climate and Sustainability Field:* Less than 1 year, 1–3 years, 4–6 years, 7–10 years, More than 10 years.
- *Institutional Policies*:
  - *Climate Transition Plan*: Fully implemented, Partially implemented, In progress, Planned but not implemented, Not planned, N/A.
  - *Climate Adaptation Integration*: Fully integrated, Partially integrated, In progress, Planned but not integrated, Not planned, N/A.
- *Exposure to Climate Risks by 2030*
  - *Risk Categories:* Climate physical risks (e.g., extreme weather events), Policy and legal risks (e.g., regulatory changes), Technological risks (e.g., failure of new climate technologies), Market risks (e.g., rising costs of raw materials), Reputational risks (e.g., changing consumer preferences).
  - *Response Options:* No Exposure, Low Exposure, Moderate Exposure, Significant Exposure, High Exposure, Don't know.

Section 2: Perceived usefulness of metrics (repeated for each metric category)

The following question was administered separately for each of the ten metric categories listed below, substituting the category name into the prompt. Each module presented the same four climate goals and the same response scale, producing a 4 (goals) × 6 (response options) matrix per metric category.

Question prompt (example for the first category): "In your industry, how useful are metrics related to climate risk exposure for advancing the following goals over the next five years?"

- *Metric categories (one module each):* Climate risk exposure; Counterparties' GHG emissions; Fossil fuel divestment/financing restrictions; Financial losses due to climate damages; Financed or insurance-associated emissions; Financing/investing in transition activities or entities; Financing/investing in climate adaptation; Green financing or investing; Non-monetary metrics (e.g., renewable energy capacity); Just transition metrics (social guardrails).
- *Goals (rows in each matrix):* Enabling the reduction of GHG emissions, Supporting innovation in low-carbon technologies, Strengthening climate resilience, Facilitating the phase-out of high-emitting assets.
- *Response options (columns):* Not Useful, Slightly Useful, Moderately Useful, Very Useful, Extremely Useful, Don't know.

Section 3: High-quality data availability

Question prompt: "In your organisation's experience, how available is high-quality data for implementing each of the following metric types?"

- *Metric types:* Physical climate risk exposure, Transition risk exposure, Counterparties' GHG emission reductions, Fossil fuels divestment/financing restrictions, Financial losses due to climate damages, Financed/insurance-associated emissions, Financing/investing in transition activities, Financing/investing in climate adaptation, Green financing/investing, Non-monetary green infrastructure outputs, Just transition metrics.
- *Response options:* Not Available, Rarely Available, Sometimes Available, Often Available, Always Available, Unfamiliar.

Section 4: Open-ended questions

- *Suggestions for Additional Metrics*: Specify new metrics and evaluate their potential effectiveness for GHG reduction, innovation, resilience, and phase-out goals.

B. Climate transition finance metrics definitions

- *Climate risk exposure:* Climate risk exposure metrics assess the potential financial and operational risks that climate change poses to an organisation or investment portfolio, including examples such as physical risk assessments, climate value-at-risk (Climate VaR), or supply chain vulnerability.
- *Counterparties' GHG emissions*: Counterparties GHG emission reductions metrics measure the decrease in GHG emissions by entities that a financial institution has a relationship with, such as companies or projects they finance; for example, tracking the annual reduction in CO2 emissions from a portfolio of financed companies.

This differs from financed emissions, which quantify the total greenhouse gas emissions attributed to the financial institutions lending and investment activities, as financed emissions can be reduced by restricting financing to high-emission activities without necessarily achieving actual emissions reductions in the atmosphere.

- *Fossil fuel divestment/financing restrictions:* Divestment from fossil fuels metrics track the extent to which financial institutions withdraw investments from companies involved in the extraction, production, and distribution of fossil fuels; for example, measuring the percentage decrease in a portfolio's holdings of coal, oil, and gas companies over a given period.
- *Financial losses due to climate damages:* Financial losses from climate-related damages metrics measure the economic impact of climate-related events, such as natural disasters, on a financial institution's assets and operations; for example, calculating the total monetary loss incurred from floods, hurricanes, or wildfires within a fiscal year.
- *Financed or insurance-associated emissions:* Financed or insurance-associated emissions metrics quantify the greenhouse gas emissions that are linked to the financial institution's lending, investment, or underwriting activities; for example, measuring the total GHG emissions of projects and companies financed or insured by the institution over a specific period.
- *Financing/investing in transition activities or entities:* Metrics related to financing or investing in transition activities or entities measure the financial support provided to sectors and companies with robust climate transition plans or verified net-zero targets, especially those in hard-to-abate sectors; for example, tracking the capital allocated to heavy industries or utilities implementing substantial emissions reduction strategies.
- *Financing/investing in climate adaptation:* Climate adaptation metrics in terms of investment or finance refer to quantifiable measures that financial institutions use to assess and report the resilience of their portfolios to climate risks, such as the proportion of investments in climate-resilient infrastructure or the amount of capital allocated to projects that reduce vulnerability to climate change impacts; for example, a bank might report that 15% of its loan portfolio is directed towards climate-resilient agriculture initiatives.
- *Green financing or investing:* Green financing or investing metrics measure the financial support directed towards environmentally sustainable projects and initiatives; for example, tracking the issuance and allocation of green bonds to fund renewable energy projects or energy efficiency improvements.
- *Non-monetary metrics (e.g., renewable energy capacity):* Non-monetary metrics related to green infrastructure outputs measure the tangible outcomes of investments in sustainable projects without focusing on financial aspects; for example, assessing the installed capacity of renewable energy sources like solar or wind power in megawatts.
- *Just transition metrics (social guardrails):* Metrics related to just transition (social guardrails) assess the social aspects of transitioning to a low-carbon economy, ensuring that the shift is equitable and inclusive; for example, tracking the implementation

of programmes for retraining and redeploying workers from phased-out coal plants to new roles in renewable energy industries.

B. Survey engagement

Table 1B. Survey engagement metrics by industry: from initial contact to completion

Industry	Surveys Completed	Emails Opened	Survey Link Clicked	Response Rate	Click-Through Rate	Completion Rate (from Clicked)
Banks	149	91	61	40.94%	61.1%	67.0%
Insurance Firms	157	84	54	34.39%	53.5%	64.3%
Asset Owners	123	77	47	38.21%	62.6%	61.0%
Asset Managers	146	101	58	39.73%	69.2%	57.4%
Total	575	353	220	38.26%	61.4%	62.3%

Note: The table presents key survey engagement metrics. Emails Opened refers to the number of emails verifiably opened by recipients, indicating initial engagement with the survey invitation. Survey Link Clicked is the number of individuals who clicked on the link to access the survey. Surveys Completed represents the number of respondents who fully completed the survey. Response Rate (%) is the percentage of individuals who completed the survey out of those who opened the email. Click-Through Rate (%) indicates the percentage of individuals who clicked the survey link after opening the email. Completion Rate (from Clicked) (%) shows the percentage of individuals who completed the survey after clicking the link to access it.

C. Survey statistics using the Heckman ordered probit model

Here we provide additional technical details on the variables, model specifications, and full estimation results for our Heckman-type ordered probit models. It complements the main-text discussion by documenting the coding of variables, reporting detailed coefficient tables (Tables 2–9), and demonstrating the consistency and reliability of our findings. Finally, Table 10 presents adjusted and raw means for key outcomes, illustrating how we addressed any detected selection bias.

Table 1 lists the explanatory variables employed in our models, alongside their coding and rationale. Below is a concise summary.

Table A1. Definitions and rationale for explanatory variables used in the models

Variable	Definition	Rationale of expected effect on responses
Experience	Binary indicator taking the value 1 if the respondent reported "high" (4–5 years) climate/sustainability experience; 0 otherwise.	Greater expertise is hypothesised to raise perceived effectiveness of climate finance metrics.
Transition	Binary indicator = 1 if the respondent's organisation has partially or fully implemented climate transition plans (Likert scale 4–5); 0 otherwise.	Organisations already pursuing a decarbonisation trajectory may find transition metrics more relevant.

Adaptation	Binary indicator = 1 if the respondent's organisation has partially or fully implemented climate adaptation plans (4–5); 0 otherwise.	Engagement in adaptation measures should enhance the perceived importance of resilience-focused metrics.
Physical	Binary indicator = 1 if perceived exposure to physical climate risk is "very high" (5); 0 otherwise.	Individuals acutely aware of climate damages tend to perceive metrics addressing these risks as more beneficial.
Policy	Binary indicator = 1 if policy (regulatory) risk is perceived as low (1–2); 0 otherwise.	In the face of minimal policy pressure, the effectiveness of compliance-oriented metrics could be questioned.
Technology	Binary indicator = 1 if technology risk is perceived as low (1–2); 0 otherwise.	Lower perceived technology risk may lessen the perceived value of innovation-oriented finance metrics.
Market	Binary indicator = 1 if market risk is perceived as high (4–5); 0 otherwise.	High market volatility often increases belief in the utility of metrics for hedging climate-related uncertainties.
Reputation	Binary indicator = 1 if reputational risk is perceived as low (1–2); 0 otherwise.	Where reputational risk is considered minimal, the perceived need for climate metrics may be lower.
Industry*	Binary indicators for industry type (e.g., insurance, manufacturing, own operations, banking).	Different sectors confront distinct pressures, influencing the perceived relevance of climate finance metrics.
Reminder	Binary indicator = 1 if the respondent received a survey reminder; 0 otherwise.	This variable enters the selection equation, testing if reminders alter the likelihood of completing the survey.
Gender	Binary indicator = 1 if self-identified as male; 0 otherwise.	Gender identity can mediate perceptions of risk or sustainability.

Note. Each variable was coded based on survey responses (mostly on Likert scales, dichotomised at cutpoints 1–2 vs. 4–5). These definitions align with the conceptual framework described in the main text (see Figure 3).

We estimated a two-equation system, comprising an ordered probit model for the perceived effectiveness score (outcome equation) and a probit model predicting whether a respondent provided complete survey responses (selection equation). Both equations were jointly fitted under a bivariate normal assumption for the error terms, using maximum likelihood estimation. We report coefficient estimates for core predictors (e.g., experience, policy, physical risks) in Tables 2–9, using both robust and bootstrap standard errors to gauge the stability of the results and mitigate concerns over heteroskedasticity or small sample bias.

Although threshold cut points are part of the ordinal specification and industry dummies are included to capture sector-specific heterogeneity, their estimates and standard errors are omitted from the reported tables. Beyond space considerations, threshold parameters generally serve to map the latent continuous response to discrete ordinal categories and offer limited interpretative insight, while industry effects remain largely stable across specifications. These omitted details do not alter the main inferences and are available upon request for interested readers. The correlation coefficient ρ between the outcome and selection equations is also reported; whenever $\rho \neq 0$, the data indicate a significant selection process that could bias standard ordered probit estimates if not properly accounted for.

Columns labelled A, B, C, and D respectively correspond to: (A) Enabling the

reduction of GHG emissions, (B) Supporting innovation in low-carbon technologies, (C) Strengthening climate resilience, and (D) Facilitating the phase-out of high-emitting assets.

Numbers in the reported model coefficients represent TFMs following questionnaire structure: (1) Climate risk exposure, (2) Counterparties' GHG emissions, (3) Fossil fuel divestment/financing restrictions, (4) Financial losses due to climate damages, (5) Financed or insurance-associated emissions, (6) Financing/investing in transition activities or entities, (7) Financing/investing in climate adaptation, (8) Green financing or investing, (9) Non-monetary metrics (e.g., renewable energy capacity), (10) Just transition metrics (social guardrails).

The Heckman-type ordered probit estimates exhibit broadly consistent patterns in coefficient signs, magnitudes, and levels of significance across robust and bootstrap standard errors. We report the correlation coefficient ρ in each table to assess the necessity of a two-equation specification, with Wald tests used to determine whether $\rho=0$. Where $\rho\neq0$, the data confirm that ignoring the selection mechanism would bias standard ordered probit estimates. Nonetheless, key variables (e.g., experience, sector affiliation, and perceived risks) generally remain significant under both the naive and the selection-corrected models, indicating that the primary drivers of perceived metric effectiveness are stable. The similarity between robust and bootstrap standard errors further underscores the reliability of the inferences, while the consistency between raw and selection-adjusted outcomes (Table 10) bolsters confidence that the models adequately capture any non-randomness in the survey-completion process.

Table 2. Heckman ordered probit model estimation with robust standard errors: Effects on survey response usefulness for climate metrics (questions 1–3).

Variables & Tests	1. In your industry, how useful are metrics related to climate risk exposure for advancing the following goals over the next five years?				2. In your industry, how useful are metrics related to your counterparties' GHG emissions for advancing the following goals over the next five years?				3. In your industry, how useful are metrics related to fossil fuels' divestment or financing restrictions in advancing the following goals over the next five years?			
	A	B	C	D	A	B	C	D	A	B	C	D
Outcome Eq.												
Experience	0.164*	0.297**	0.162	-0.061	0.387*	0.022	0.286	0.201	0.114	0.072	-0.044	-0.062
	(0.096)	(0.150)	(0.190)	(0.208)	(0.203)	(0.148)	(0.274)	(0.235)	(0.119)	(0.103)	(0.156)	(0.152)
Transition	-0.270**	-0.378*	-0.206	-0.121	-0.090	-0.125	-0.375*	-0.244	-0.595**	-0.396	-0.355	-0.237
	(0.119)	(0.194)	(0.271)	(0.208)	(0.219)	(0.150)	(0.199)	(0.231)	(0.285)	(0.305)	(0.222)	(0.181)
Adaptation	-0.283	-0.70***	-0.294	-0.258	-1.00***	-0.64***	-0.382*	-0.171	-0.401*	-0.266	-0.52***	-0.330
	(0.119)	(0.221)	(0.274)	(0.220)	(0.342)	(0.212)	(0.220)	(0.126)	(0.222)	(0.339)	(0.181)	(0.204)
Physical	0.197	-0.163	-0.347	-0.064	0.235	0.008	-0.209	0.030	0.279	0.092	0.077	0.365*
	(0.141)	(0.224)	(0.216)	(0.238)	(0.306)	(0.193)	(0.335)	(0.383)	(0.172)	(0.276)	(0.248)	(0.205)
Policy	-0.190	-0.576	0.071	-0.346	-0.128	0.221	0.115	0.114	-0.028	-0.045	-0.945**	-0.323
	(0.211)	(0.419)	(0.468)	(0.386)	(0.311)	(0.307)	(0.338)	(0.228)	(0.323)	(0.305)	(0.441)	(0.356)
Technology	-0.113	-0.139	-0.269	0.073	-0.309*	-0.34***	-0.313*	-0.179*	-0.236	-0.106	-0.122	-0.125
	(0.090)	(0.163)	(0.155)	(0.343)	(0.168)	(0.126)	(0.172)	(0.107)	(0.185)	(0.120)	(0.167)	(0.151)
Market	0.194	0.482***	0.190	0.222	0.329	0.423**	0.339	0.124	0.136	0.243	0.369**	0.011
	(0.124)	(0.146)	(0.181)	(0.382)	(0.208)	(0.178)	(0.247)	(0.447)	(0.161)	(0.267)	(0.152)	(0.132)
Reputation	-0.373*	-0.464	-0.338	-0.670	-0.981**	-0.666**	-0.520	-0.428	-0.219	-0.266	-0.333	-0.431*
	(0.205)	(0.292)	(0.284)	(0.865)	(0.439)	(0.300)	(0.356)	(0.362)	(0.212)	(0.210)	(0.280)	(0.254)
Selection Eq.												
Reminder	0.133**	0.107	0.109	0.080	0.093	0.083	0.142*	0.175*	0.111	0.171**	0.107	0.143*
	(0.061)	(0.079)	(0.075)	(0.130)	(0.081)	(0.073)	(0.086)	(0.079)	(0.072)	(0.069)	(0.083)	(0.079)
Gender	-0.028	-0.105	-0.069	-0.093	-0.082	-0.095	-0.061	-0.058	-0.078	-0.060	-0.076	-0.065
	(0.062)	(0.072)	(0.070)	(0.074)	(0.074)	(0.065)	(0.073)	(0.067)	(0.063)	(0.057)	(0.075)	(0.070)
Diagnostics												
Wald χ^2	11.74	73.60***	68.73***	8.97	13.34	35.85***	1.30	20.79*	25.43**	164.79***	45.62***	0.000***
Corr (ρ)	-0.96	-0.57	0.76	0.64	-0.14	-0.82	-0.76	-0.92	0.89	-0.94	-0.21	0.00
LR Test	7.39**	15.37***	2.21	0.14	0.00	4.13*	28.16*	1.93	3.92*	19.71***	4.01**	–
Total N	2163	2161	2163	2163	2163	2163	2163	2163	2163	2159	2163	2163
Selected	205	203	205	205	205	205	205	205	205	201	205	205
Non-selected	1958	1958	1958	1958	1958	1958	1958	1958	1958	1958	1958	1958

Note: Robust standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

Table 3. Ordered probit model estimation with bootstrapped standard errors: Effects on survey response usefulness for climate metrics (questions 1–3).

	1. In your industry, how useful are metrics related to climate risk exposure for advancing the following goals over the next five years?				2. In your industry, how useful are metrics related to your counterparties' GHG emissions for advancing the following goals over the next five years?				3. In your industry, how useful are metrics related to fossil fuels' divestment or financing restrictions in advancing the following goals over the next five years?			
Variables & Tests	A†	B	C	D	A	B†	C	D	A†	B†	C	D†
Outcome Eq.												
Experience	0.164**	–	0.220	-0.077	0.390*	0.022	0.394**	0.383**	0.114	0.072	–	-0.062
	(0.142)	–	(0.192)	(0.176)	(0.171)	(0.136)	(0.159)	(0.170)	(0.181)	(0.157)	–	(0.132)
Transition	-0.270	–	-0.286	-0.139	-0.091	-0.125	-0.532**	-0.463**	-0.595**	-0.396	–	-0.237
	(0.149)	–	(0.279)	(0.300)	(0.270)	(0.173)	(0.275)	(0.267)	(0.247)	(0.281)	–	(0.191)
Adaptation	-0.283	–	-0.406	-0.313	-1.01***	-0.645**	-0.551**	-0.430*	-0.401	-0.266	–	-0.330
	(0.168)	–	(0.232)	(0.254)	(0.260)	(0.224)	(0.211)	(0.235)	(0.252)	(0.274)	–	(0.201)
Physical	0.197	–	-0.480**	-0.062	0.235	0.008	-0.298	-0.037	0.279	0.092	–	0.365*
	(0.218)	–	(0.300)	(0.398)	(0.345)	(0.263)	(0.258)	(0.222)	(0.277)	(0.251)	–	(0.181)
Policy	-0.190	–	-0.080	-0.451	-0.126	0.221	0.168	0.313	-0.028	-0.045	–	-0.323
	(0.370)	–	(0.494)	(0.397)	(0.389)	(0.513)	(0.667)	(0.858)	(0.470)	(0.123)	–	(0.344)
Technology	-0.133	–	-0.385*	0.088	-0.311	-0.346**	-0.42***	-0.309*	-0.236	-0.106	–	-0.125
	(0.146)	–	(0.165)	(0.158)	(0.205)	(0.162)	(0.145)	(0.152)	(0.167)	(0.100)	–	(0.123)
Market	0.194*	–	0.271*	0.272	0.334**	0.423**	0.47***	0.294	0.136	0.243	–	0.011
	(0.126)	–	(0.164)	(0.176)	(0.178)	(0.172)	(0.247)	(0.214)	(0.120)	(0.171)	–	(0.152)
Reputation	-0.373	–	-0.492	-0.85***	-0.98***	-0.666*	-0.722*	-0.830**	-0.219	-0.266	–	-0.431*
	(0.219)	–	(0.260)	(0.323)	(0.356)	(0.294)	(0.341)	(0.309)	(0.167)	(0.205)	–	(0.177)
Selection Eq.												
Reminder	0.133***	–	–	–	–	0.083	–	–	0.111	0.171**	–	0.143*
	(0.059)	–	–	–	–	(0.091)	–	–	(0.112)	(0.076)	–	(0.059)
Gender	-0.028	–	–	–	–	-0.095	–	–	-0.078	-0.060	–	-0.065
	(0.540)	–	–	–	–	(0.076)	–	–	(0.093)	(0.080)	–	(0.079)
Diagnostics												
Corr (ρ)	-0.96	–	–	–	–	-0.82	–	–	-0.89	-0.94	–	-0.75
LR Test	5.60**	–	–	–	–	0.79	–	–	3.32*	6.24*	–	1.35
Wald X^2	62.83***	–	42.71***	52.45*	75.65***	18.33*	84.33***	72.94***	135.78***	–	–	43.04***

Note: Bootstrapped standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***). Models employ the Heckman† procedure if selection bias is detected; otherwise, a standard ordered probit is used.

Table 4. Heckman ordered probit model estimation with robust standard errors: Effects on survey response usefulness for climate metrics (questions 4–6).

	4. In your industry, how useful are metrics related to financial losses derived from climate-related damages in advancing the following goals over the next five years?				5. In your industry, how useful are metrics related to financed or insurance-associated emissions in advancing the following goals over the next five years?				6. In your industry, how useful are metrics related to financing or investing in transition activities or entities in advancing the following goals over the next five years?			
Variables & Tests	A	B	C	D	A	B	C	D	A	B	C	D
Outcome Eq.												
Experience	0.096	0.150	0.125	-0.025	0.070	–	-0.098	-0.024	–	0.099	-0.001	0.128
	(0.290)	(0.168)	(0.156)	(0.133)	(0.145)	–	(0.126)	(0.129)	–	(1.659)	(0.123)	(0.142)
Transition	-0.290	-0.141	-0.66***	-0.226	-0.376	–	-0.211	-0.194	–	-0.148	-0.120	0.054
	(0.182)	(0.212)	(0.239)	(0.214)	(0.233)	–	(0.196)	(0.150)	–	(0.887)	(0.194)	(0.200)
Adaptation	-0.096	-0.213	0.082	-0.003	-0.78***	–	-0.338	-0.228	–	-0.255	-0.342	-0.130
	(0.213)	(0.226)	(0.219)	(0.183)	(0.221)	–	(0.238)	(0.306)	–	(2.327)	(0.238)	(0.170)
Physical	0.345	0.367	0.148	0.140	0.264	–	0.356	0.081	–	0.200	-0.249	-0.002
	(0.520)	(0.265)	(0.275)	(0.220)	(0.289)	–	(0.266)	(0.200)	–	(0.318)	(0.254)	(0.200)
Policy	-0.354	-0.683	0.232	-0.726	-0.992**	–	-0.457	-0.490	–	-0.518	-0.426	-0.608**
	(0.428)	(0.564)	(0.469)	(0.487)	(0.443)	–	(0.412)	(0.505)	–	(3.342)	(0.370)	(0.292)
Technology	-0.151	0.186	0.336*	0.135	-0.111	–	-0.031	-0.034	–	-0.188	-0.108	0.049
	(0.173)	(0.189)	(0.200)	(0.204)	(0.158)	–	(0.145)	(0.169)	–	(1.677)	(0.155)	(0.161)
Market	0.070	0.165	-0.002	0.142	0.494***	–	0.097	0.061	–	0.271	0.086	0.158
	(0.186)	(0.170)	(0.172)	(0.162)	(0.166)	–	(0.175)	(0.200)	–	(3.064)	(0.158)	(0.156)
Reputation	-0.199	-0.048	-0.402	-0.212	-1.07***	–	-0.726	-0.575	–	-0.247	-0.041	-0.361
	(0.277)	(0.307)	(0.268)	(0.263)	(0.284)	–	(0.455)	(0.451)	–	(1.508)	(0.281)	(0.295)
Selection Eq.												
Reminder	0.123	0.111	0.100	0.126	0.142*	–	0.126	0.115	–	0.099	0.118	0.113
	(0.077)	(0.084)	(0.084)	(0.080)	(0.083)	–	(0.078)	(0.074)	–	(0.129)	(0.082)	(0.082)
Gender	-0.096	-0.091	-0.086	-0.118	-0.053	–	-0.083	-0.095	–	-0.091	-0.069	-0.078
	(0.071)	(0.081)	(0.076)	(0.072)	(0.074)	–	(0.071)	(0.066)	–	(0.070)	(0.074)	(0.074)
Diagnostics												
Wald X^2	75.32***	15.40	25.74**	43.77***	92.15***	–	20.19*	21.05*	–	3.18	10.18	14.72
Corr (ρ)	-0.69	-0.40	-0.25	-0.66	-0.44	–	-0.67	-0.85	–	-0.96	-0.85	-0.38
LR Test	0.57	0.40	0.09	10.56	10.48***	–	1.39	1.20	–	0.00	1.27	10.58**
Total N	2155	2155	2162	2156	2157	–	2157	2159	–	2163	2163	2163
Selected	197	196	204	198	199	–	199	201	–	205	205	205
Non-selected	1958	1958	1958	1958	1958	–	1958	1958	–	1958	1958	1958

Note: Robust standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

Table 5. Ordered probit model estimation with bootstrapped standard errors: Effects on survey response usefulness for climate metrics (questions 4–6).

	4. In your industry, how useful are metrics related to financial losses derived from climate-related damages in advancing the following goals over the next five years?				5. In your industry, how useful are metrics related to financed or insurance-associated emissions in advancing the following goals over the next five years?				6. In your industry, how useful are metrics related to financing or investing in transition activities or entities in advancing the following goals over the next five years?			
Variables & Tests	A	B	C	D	A	B	C	D	A	B	C	D
Outcome Eq.												
Experience	0.126	0.161	0.129	–	–	-0.002	-0.125	-0.065	0.259	0.134	-0.004	–
	(0.158)	(0.161)	(0.147)	–	–	(0.143)	(0.176)	(0.151)	(0.161)	(0.146)	(0.187)	–
Transition	-0.385	-0.152	-0.68***	–	–	-0.368	-0.278	-0.300	-0.405*	-0.203	-0.169	–
	(0.266)	(0.215)	(0.188)	–	–	(0.250)	(0.237)	(0.188)	(0.232)	(0.283)	(0.232)	–
Adaptation	-0.145	-0.234	0.082	–	–	-0.395	-0.440*	-0.376*	-0.899***	-0.361*	-0.455**	–
	(0.269)	(0.276)	(0.239)	–	–	(0.261)	(0.261)	(0.226)	(0.219)	(0.188)	(0.207)	–
Physical	0.421	0.387	0.148	–	–	0.600*	0.446*	0.127	0.034	0.252	-0.310	–
	(0.307)	(0.280)	(0.344)	–	–	(0.317)	(0.268)	(0.258)	(0.300)	(0.284)	(0.250)	–
Policy	-0.418	-0.713	0.243	–	–	-1.43***	-0.555	-0.693	-0.352	-0.682	-0.514	–
	(0.657)	(0.678)	(0.601)	–	–	(0.390)	(0.890)	(0.557)	(0.299)	(0.559)	(0.420)	–
Technology	-0.197	0.200	0.346*	–	–	0.196	-0.036	-0.048	-0.118	-0.246	-0.122	–
	(0.228)	(0.163)	(0.196)	–	–	(0.133)	(0.199)	(0.169)	(0.166)	(0.227)	(0.164)	–
Market	0.104	0.179	-0.000	–	–	0.291	0.131	0.105	0.437**	0.382*	0.113	–
	(0.204)	(0.176)	(0.190)	–	–	(0.190)	(0.204)	(0.159)	(0.185)	(0.205)	(0.176)	–
Reputation	-0.248	-0.048	-0.411	–	–	-1.21***	-0.908**	-0.83***	-0.634**	-0.312	-0.034	–
	(0.340)	(0.369)	(0.279)	–	–	(0.374)	(0.357)	(0.263)	(0.285)	(0.289)	(0.270)	–
Selection Eq.												
Reminder	–	–	–	–	–	–	–	–	–	–	–	–
Gender	–	–	–	–	–	–	–	–	–	–	–	–
Diagnostics												
Corr (ρ)	–	–	–	–	–	–	–	–	–	–	–	–
LR Test	–	–	–	–	–	–	–	–	–	–	–	–
Wald X^2	122.45***	37.03***	119.27***	–	–	86.23***	45.43***	54.66*	91.54***	39.46***	31.22**	–

Note: Bootstrapped standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***). Models employ the Heckman† procedure if selection bias is detected; otherwise, a standard ordered probit is used.

Table 6. Heckman ordered probit model estimation using robust standard errors (survey questions 7-9).

	7. In your industry, how useful are metrics related to financing or investing in climate adaptation in advancing the following goals over the next five years?				8. In your industry, how useful are metrics related to green financing or investing in advancing the following goals over the next five years?				9. In your industry, how useful are non-monetary metrics related to green infrastructure outputs in advancing the following goals over the next five years?			
Variables & Tests	A	B	C	D	A	B	C	D	A	B	C	D
Outcome Eq.												
Experience	0.034	-0.018	0.118	0.045	0.169	0.032	0.037	-0.154	–	0.025	-0.012	-0.074
	(0.136)	(0.112)	(0.155)	(0.155)	(0.164)	(0.162)	(0.143)	(0.111)	–	(0.162)	(0.159)	(0.142)
Transition	0.054	-0.024	-0.175	-0.038	-0.603**	-1.45***	-0.60***	-0.205	–	-1.038***	-0.119	-0.440***
	(0.174)	(0.159)	(0.262)	(0.203)	(0.254)	(0.263)	(0.195)	(0.162)	–	(0.265)	(0.203)	(0.162)
Adaptation	-0.73***	-0.489*	-0.685	0.060***	-0.320*	0.031	-0.67***	-0.382*	–	-0.082	-0.601***	-0.359*
	(0.178)	(0.279)	(0.433)	(0.217)	(0.189)	(0.188)	(0.197)	(0.207)	–	(0.204)	(0.221)	(0.186)
Physical	0.123	0.180	-0.032	0.166	0.235	0.339	0.205	0.091	–	0.142	0.094	0.305
	(0.200)	(0.198)	(0.298)	(0.285)	(0.212)	(0.275)	(0.240)	(0.203)	–	(0.254)	(0.281)	(0.251)
Policy	-0.278	-0.347	-0.096	-0.169	0.012	0.755*	0.025	0.130	–	-0.582	-0.601	0.165
	(0.314)	(0.539)	(0.336)	(0.321)	(0.427)	(0.415)	(0.433)	(0.389)	–	(0.516)	(0.426)	(0.559)
Technology	-0.186	-0.087	-0.172	-0.236	-0.018	-0.222	0.014	0.178	–	-0.195	-0.090	-0.131
	(0.128)	(0.157)	(0.183)	(0.158)	(0.144)	(0.157)	(0.153)	(0.149)	–	(0.151)	(0.155)	(0.139)
Market	0.364**	0.224**	0.255*	0.344**	0.416***	0.453***	0.464***	0.131	–	-0.041	0.314*	0.242
	(0.172)	(0.107)	(0.150)	(0.154)	(0.133)	(0.171)	(0.127)	(0.297)	–	(0.163)	(0.178)	(0.203)
Reputation	-0.034	-0.029	-0.226	-0.129	-0.119	-0.761**	-0.497*	-0.622	–	-0.054	-0.456	-0.324
	(0.275)	(0.355)	(0.289)	(0.281)	(0.336)	(0.323)	(0.287)	(0.624)	–	(0.228)	(0.311)	(0.379)
Selection Eq.												
Reminder	0.133*	0.126	0.101	0.110	0.143*	0.110	0.141*	0.108	–	–	0.101	0.113
	(0.079)	(0.077)	(0.081)	(0.082)	(0.081)	(0.085)	(0.079)	(0.077)	–	–	(0.082)	(0.077)
Gender	-0.059	-0.042	-0.088	-0.078	-0.084	-0.069	-0.063	-0.051	–	–	-0.100	-0.091
	(0.079)	(0.079)	(0.073)	(0.075)	(0.072)	(0.076)	(0.072)	(0.077)	–	–	(0.074)	(0.074)
Diagnostics												
Wald X^2	66.59***	16.08	17.11	46.2***	54.81***	79.97***	101.34***	26.48***	–	60.99***	40.34***	38.17***
Corr (ρ)	-0.72	-0.90	0.42	-0.17	-0.58	-0.17	-0.58	-0.74	–	-0.4	-0.32	-0.94
LR Test	3.05	2.58	0.25	2.5	35.64***	1.62	15.57***	3.80	–	0.00	5.4**	4.11*
Total N	2160	2162	2162	2161	2163	2163	2163	2163	–	2161	2162	2162
Selected	202	204	204	203	205	205	205	205	–	203	204	204
Non-selected	1958	1958	1958	1958	1958	1958	1958	1958	–	1958	1958	1958

Note: Robust standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

Table 7. Ordered probit model estimation with bootstrapped standard errors: Effects on survey response usefulness for climate metrics (questions 7–9).

	7. In your industry, how useful are metrics related to financing or investing in climate adaptation in advancing the following goals over the next five years?				8. In your industry, how useful are metrics related to green financing or investing in advancing the following goals over the next five years?				9. In your industry, how useful are non-monetary metrics related to green infrastructure outputs in advancing the following goals over the next five years?			
Variables & Tests	A	B	C	D	A	B	C	D	A	B	C	D†
Outcome Eq.												
Experience	0.047	-0.035	0.127	0.045	0.196	0.031	–	-0.221	0.027	0.026	–	-0.074
	(0.175)	(0.173)	(0.163)	(0.141)	(0.175)	(0.190)	–	(0.160)	(0.177)	(0.190)	–	(0.142)
Transition	0.068	-0.126	-0.187	-0.040	-0.72***	-1.47***	–	-0.300	-0.126	-1.04***	–	-0.44***
	(0.220)	(0.233)	(0.222)	(0.232)	(0.253)	(0.246)	–	(0.247)	(0.222)	(0.338)	–	(0.162)
Adaptation	-1.002***	-0.90***	-0.738***	-0.61**	-0.391**	0.027	–	-0.53***	-0.780***	-0.082	–	-0.359*
	(0.263)	(0.275)	(0.255)	(0.274)	(0.178)	(0.200)	–	(0.197)	(0.236)	(0.181)	–	(0.186)
Physical	0.170	0.317	-0.026	0.166	0.277	0.342	–	0.128	1.070***	0.142	–	0.305
	(0.306)	(0.226)	(0.334)	(0.337)	(0.292)	(0.320)	–	(0.174)	(0.326)	(0.257)	–	(0.251)
Policy	-0.326	-0.505	-0.116	-0.168	0.031	0.767	–	0.229	0.019	-0.581	–	0.165
	(0.780)	(0.383)	(0.350)	(0.450)	(0.470)	(0.711)	–	(0.506)	(0.633)	(0.992)	–	(0.559)
Technology	-0.242	-0.098	-0.188	-0.239	-0.020	-0.225	–	0.243	0.105	-0.195	–	-0.131
	(0.175)	(0.155)	(0.182)	(0.181)	(0.162)	(0.164)	–	(0.178)	(0.203)	(0.153)	–	(0.139)
Market	0.491***	0.375***	0.275	0.345**	0.47***	0.454***	–	0.183	-0.007	-0.041	–	0.242
	(0.179)	(0.143)	(0.207)	(0.164)	(0.142)	(0.161)	–	(0.187)	(0.179)	(0.179)	–	(0.203)
Reputation	-0.025	0.021	-0.250	-0.131	-0.145	-0.772**	–	-0.81***	-0.332	-0.053	–	-0.324
	(0.281)	(0.206)	(0.364)	(0.257)	(0.388)	(0.348)	–	(0.270)	(0.233)	(0.243)	–	(0.379)
Selection Eq.												
Reminder	–	–	–	–	–	–	–	–	–	–	–	0.113
	–	–	–	–	–	–	–	–	–	–	–	(0.077)
Gender	–	–	–	–	–	–	–	–	–	–	–	-0.091
	–	–	–	–	–	–	–	–	–	–	–	(0.074)
Diagnostics												
Corr (ρ)	–	–	–	–	–	–	–	–	–	–	–	-0.94
LR Test	–	–	–	–	–	–	–	–	–	–	–	4.90**
Wald X^2	39.00***	91.16***	48.25***	41.51***	64.08**	90.58***	–	62.19**	66.69***	51.48**	–	–

Note: Bootstrapped standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***). Models employ the Heckman† procedure if selection bias is detected; otherwise, a standard ordered probit is used.

Table 8. Heckman ordered probit model estimation using robust standard errors (survey questions 10-11).

	10. In your industry, how useful are metrics related to just transition (social guardrails) in advancing the following goals over the next five years?				11. Availability of high-quality data for climate transition finance metrics							
Variables & Tests	A	B	C	D	6	7	–	–	–	–	–	–
Outcome Eq.												
Experience	0.023	–	0.117	0.013	0.086	0.085	–	–	–	–	–	–
	(0.139)	–	(0.171)	(0.144)	(0.080)	(0.099)	–	–	–	–	–	–
Transition	-0.039	–	-0.297	-0.517	0.234	-0.045	–	–	–	–	–	–
	(0.642)	–	(0.253)	(0.347)	(0.219)	(0.163)	–	–	–	–	–	–
Adaptation	-0.424	–	-0.695**	-0.663	-0.158	-0.025	–	–	–	–	–	–
	(0.292)	–	(0.340)	(0.410)	(0.203)	(0.285)	–	–	–	–	–	–
Physical	0.508	–	0.232	0.285	0.038	0.103	–	–	–	–	–	–
	(0.573)	–	(0.246)	(0.406)	(0.207)	(0.224)	–	–	–	–	–	–
Policy	0.132	–	0.309	-0.179	-0.263	-0.414	–	–	–	–	–	–
	(0.451)	–	(0.441)	(0.533)	(0.352)	(0.317)	–	–	–	–	–	–
Technology	-0.070	–	-0.073	-0.026	-0.140*	-0.053	–	–	–	–	–	–
	(0.165)	–	(0.173)	(0.168)	(0.085)	(0.169)	–	–	–	–	–	–
Market	0.096	–	0.029	0.454*	0.126	0.147	–	–	–	–	–	–
	(0.412)	–	(0.201)	(0.272)	(0.121)	(0.104)	–	–	–	–	–	–
Reputation	-0.114	–	-0.186	-0.281	0.024	-0.122	–	–	–	–	–	–
	(0.424)	–	(0.346)	(0.319)	(0.169)	(0.147)	–	–	–	–	–	–
Selection Eq.												
Reminder	0.131*	–	0.099	0.095	0.110*	0.050	–	–	–	–	–	–
	(0.076)	–	(0.085)	(0.129)	(0.062)	(0.072)	–	–	–	–	–	–
Gender	-0.074	–	-0.096	-0.098	-0.120**	-0.079	–	–	–	–	–	–
	(0.069)	–	(0.075)	(0.089)	(0.059)	(0.060)	–	–	–	–	–	–
Diagnostics												
Wald X^2	29.93**	–	11.37	9.11	70.79***	68.92***	–	–	–	–	–	–
Corr (ρ)	-0.86	–	-0.31	0.25	-0.95	-0.95	–	–	–	–	–	–
LR Test	2.92	–	0.06	0.01	8.05**	7.84**	–	–	–	–	–	–
Total N	2158	–	2161	2161	2162	2163	–	–	–	–	–	–
Selected	200	–	203	203	204	205	–	–	–	–	–	–
Non-selected	1958	–	1958	1958	1958	1958	–	–	–	–	–	–

Note: Robust standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

Table 9. Ordered probit model estimation with bootstrapped standard errors: Effects on survey response usefulness for climate metrics (questions 10–11)

	10. In your industry, how useful are metrics related to just transition (social guardrails) in advancing the following goals over the next five years?				11. Availability of high-quality data for climate transition finance metrics							
Variables & Tests	A	B	C	D	6†	7†	–	–	–	–	–	–
Outcome Eq.												
Experience	0.050	0.141	0.123	0.013	0.086	0.085	–	–	–	–	–	–
	(0.143)	(0.181)	(0.165)	(0.175)	(0.064)	(0.099)	–	–	–	–	–	–
Transition	-0.043	-0.633**	-0.312	-0.529*	0.234	-0.045	–	–	–	–	–	–
	(0.221)	(0.252)	(0.271)	(0.275)	(0.219)	(0.163)	–	–	–	–	–	–
Adaptation	-0.704**	-0.385	-0.729***	-0.678**	-0.158	-0.025	–	–	–	–	–	–
	(0.281)	(0.244)	(0.231)	(0.325)	(0.203)	(0.285)	–	–	–	–	–	–
Physical	0.792**	0.532*	0.238	0.296	0.038	0.103	–	–	–	–	–	–
	(0.342)	(0.308)	(0.338)	(0.318)	(0.207)	(0.224)	–	–	–	–	–	–
Policy	0.279	0.140	0.328	-0.189	-0.263	-0.414	–	–	–	–	–	–
	(0.282)	(0.802)	(0.544)	(1.378)	(0.352)	(0.317)	–	–	–	–	–	–
Technology	-0.091	-0.127	-0.075	-0.028	-0.140*	-0.053	–	–	–	–	–	–
	(0.161)	(0.198)	(0.172)	(0.194)	(0.085)	(0.169)	–	–	–	–	–	–
Market	0.182	0.587***	0.033	0.465***	0.126	0.147	–	–	–	–	–	–
	(0.169)	(0.169)	(0.192)	(0.170)	(0.121)	(0.104)	–	–	–	–	–	–
Reputation	-0.163	0.438	-0.192	-0.290	0.024	-0.122	–	–	–	–	–	–
	(0.338)	(0.379)	(0.416)	(0.477)	(0.169)	(0.147)	–	–	–	–	–	–
Selection Eq.												
Reminder	–	–	–	–	0.110*	0.050	–	–	–	–	–	–
	–	–	–	–	(0.062)	(0.072)	–	–	–	–	–	–
Gender	–	–	–	–	-0.120**	-0.079	–	–	–	–	–	–
	–	–	–	–	(0.059)	(0.060)	–	–	–	–	–	–
Diagnostics												
Corr (ρ)	–	–	–	–	-0.95	-0.95	–	–	–	–	–	–
LR Test	–	–	–	–	8.05**	7.26**	–	–	–	–	–	–
Wald X^2	55.89***	52.79*	55.24***	42.69	70.79	23.77*	–	–	–	–	–	–

Note: Bootstrapped standard errors in parentheses. Statistical significance: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***). Models employ the Heckman† procedure if selection bias is detected; otherwise, a standard ordered probit is used.

Table 10. Adjusted and raw means for perceived effectiveness and quality of climate metrics across survey questions with selection bias indicators

Outcome	Raw Mean	Adj. Mean	MSE	RMSE	Correlation	Selection Bias
Effectiveness (usefulness)	–	–	–	–	–	–
1A	4.0	4.8	1.510	0.917	0.48	Yes
1B	3.8	4.5	1.061	0.822	0.50	Yes
1C	3.9	–	–	–	–	No
1D	3.9	–	–	–	–	No
2A	3.8	–	–	–	–	No
2B	3.6	4.7	2.144	1.148	0.51	Yes
2C	3.5	–	–	–	–	No
2D	3.7	–	–	–	–	No
3A	3.8	4.8	1.744	.977	0.58	Yes
3B	3.3	4.6	2.999	1.434	0.51	Yes
3C	3.4	3.7	0.851	0.726	0.41	Yes
3D	4.0	4.7	1.236	0.851	0.39	Yes
4A	2.9	–	–	–	–	No
4B	3.1	–	–	–	–	No
4C	3.8	–	–	–	–	No
4D	2.9	3.8	1.896	1.147	0.52	Yes
5A	3.7	4.2	1.097	0.845	0.59	Yes
5B	3.2	–	–	–	–	No
5C	2.9	–	–	–	–	No
5D	3.4	–	–	–	–	No
6A	3.8	–	–	–	–	No
6B	4.0	–	–	–	–	No
6C	3.4	–	–	–	–	No
6D	3.7	4.2	1.169	0.858	0.25	Yes
7A	3.2	–	–	–	–	No
7B	3	–	–	–	–	No
7C	3.7	–	–	–	–	No
7D	2.6	–	–	–	–	No
8A	3.8	–	–	–	–	No
8B	3.7	–	–	–	–	No
8C	3.9	4.6	1.252	0.836	0.51	Yes
8D	3.5	–	–	–	–	No
9A	3.4	–	–	–	–	No
9B	3.2	–	–	–	–	No
9C	3.2	3.6	0.970	0.774	0.37	Yes
9D	3.8	4.8	1.853	1.065	0.55	Yes
10A	2.7	–	–	–	–	No
10B	2.8	–	–	–	–	No
10C	2.9	–	–	–	–	No
10D	3.0	–	–	–	–	No
	–	–	–	–	–	–
Availability of high-quality data	–	–	–	–	–	–
1	3.2	–	–	–	–	No

2	2.9	–	–	–	–	No
3	2.4	–	–	–	–	No
4	2.9	–	–	–	–	No
5	1.9	–	–	–	–	No
6	2.7	4.6	4.9	2.07	0.53	Yes
7	2.2	4.5	6.064	2.343	0.62	Yes
8	3.3	–	–	–	–	No
9	2.7	–	–	–	–	No
10	1.6	–	–	–	–	No

Note: Adjusted means are calculated to account for potential selection bias using a Heckman ordered probit model. For cases where selection bias was detected, predicted probabilities were used to generate adjusted means for each outcome category, which were then aggregated into expected values. The raw and adjusted means were compared, and measures of error (MSE and RMSE) and correlation between raw and adjusted values were calculated. While the adjusted means provide refined estimates, their magnitude should be interpreted with caution due to model assumptions; the primary insight lies in the direction and consistency of the adjustments, as they reflect systematic effects of selection bias on perceptions.

4.10 Appendix: Paper C

A: Geometric Brownian motion and constant volatility tests

To assess whether time series adhere to geometric Brownian motion (GBM) and maintain constant volatility, we employed a systematic statistical assessment. Recall GBM is a stochastic process often utilised (e.g., to model stock prices) under the assumption that the logarithm of the price follows Brownian motion with constant drift and volatility, implying that the variance of the process's logarithmic returns remains steady over time (Ibe, 2013).

Our analysis investigates the Enel-REC, Chile-NCRE, and Chile-GHG time series, revealing nuanced volatility and stationarity characteristics that challenge the constant volatility assumption necessary for a simple GBM model. While Chile-GHG shows stable variance outcomes to some extent, Enel-REC and Chile-NCRE exhibit significant time-varying volatility and inconsistencies in variance homogeneity. These findings highlight the limitations of consistent GBM for these data sets, with alternative models like the Heston model (which accommodates stochastic volatility and mean reversion), potentially offering a better fit by dynamically managing varying volatility levels across these series.

Augmented Dickey-Fuller (ADF) Test. This test is a statistical tool used to determine if a time series is stationary, specifically by testing for the presence of a unit root, which indicates non-stationarity (Dickey and Fuller, 1979). GBM inherently non-stationary because it follows a stochastic trend rather than reverting to a long-term mean. The non-stationarity of a GBM process arises from the fact that its logarithm follows a Brownian motion with drift, a process where the mean changes over time (Ibe, 2013). Therefore, applying the ADF test to a time series suspected of following a GBM process should typically indicate non-stationarity in both the original and logarithmically transformed series, as both should reflect the stochastic trend and drift characteristic of GBM.

In this analysis (see Table A1), the original series for Enel-REC, Chile-NCRE, and Chile-GHG were found to be non-stationary, aligning with the GBM assumption. However, when applying first differencing to Enel-REC and logarithmic returns to Chile-NCRE and Chile-GHG, these transformed series became stationary, which contradicts the expected behaviour under GBM. The differentiation in transformation approaches stems from the distinct nature of the data: Enel-REC and Chile-NCRE, which refer to renewable energy capacity, are subject to different dynamics than Chile-GHG, which tracks GHG emissions. The renewable energy capacity data often exhibit growth patterns that are better stabilised with differencing, reflecting their cumulative nature and allowing for the analysis of changes rather than levels. In contrast, GHG emissions, often subject to more direct policy interventions and seasonal fluctuations, may be more appropriately stabilised

using logarithmic returns to handle the multiplicative effects inherent in emission data.

Additionally, analysing the ADF test results with and without a deterministic trend provides a comprehensive understanding, as the trend component can significantly affect the stationarity of the series. The inclusion of both trend and no-trend analyses ensures that potential underlying trends are accounted for, offering a more nuanced interpretation of the time series' behaviour. Given these considerations, the stationary nature of the transformed series suggests that the simple GBM model may not fully capture the dynamics of these series, warranting further tests, particularly for constant volatility, to assess the presence of a GBM process.

Table A1. Augmented Dickey-Fuller Test results for stationarity in sustainability metrics and their transformed counterparts (with and without deterministic trend)

	No Trend			Trend		
Series	Test Statistic	Critical Values (1%, 5%, 10%)	Conclusion	Test Statistic	Critical Values (1%, 5%, 10%)	Conclusion
Enel REC	1.527	−3.646, −2.954, −2.616	Non-stationary	1.510	−4.499, −3.658, −3.269	Non-stationary
Δ Enel REC	−5.732***	−3.654, −2.957, −2.618	Stationary	−4.523***	−3.700, −2.976, −2.628	Stationary
Chile GHG	−1.310	−3.689, −2.972, −2.625	Non-stationary	−4.527**	−4.324, −3.581, −3.225	Stationary
ln (Δ Chile GHG)	−4.005**	−3.689, −2.972, −2.625	Stationary	−4.005**	−3.689, −2.972, −2.625	Stationary
Chile NCRE	1.693	−3.689, −2.972, −2.625	Non-stationary	1.510	−4.499, −3.658, −3.269	Non-stationary
Δ Chile NCRE	−4.523***	−3.700, −2.976, −2.628	Stationary	−4.523***	−3.700, −2.976, −2.628	Stationary

Source: Enel Financial Quarterly Reports (2009-2022) and Government of Chile, Ministry of Finance (2022).

Note: The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) was applied to assess the stationarity of time series datasets related to REC, GHG emissions, and NCRE metrics. The table summarizes the Augmented Dickey-Fuller (ADF) test statistics, corresponding p-values (indicated by *, **, ***), and critical values for each series in its raw form and after applying transformations such as first differencing, ΔY, and logarithmic returns, ln(ΔY). Stationarity is achieved when the ADF test statistic is lower than the critical values at conventional significance levels, and the p-value is sufficiently small (commonly <0.05), which rejects the null hypothesis of a unit root in the series. Post-transformation, all series achieved stationarity, indicating they can be used for further analysis without the confounding effects of trends or seasonality. The inclusion of the deterministic trend component accounts for a potential linear trend in the series, providing a more comprehensive understanding of the stationarity properties of the data.

Fitting a simple Brownian motion model. By fitting this model to the transformed time series, we can directly test the GBM hypothesis for these sustainability performance

indicators. The transformations include using first differences for renewable energy capacity and natural logarithms for GHG emissions. We then assess the residuals to evaluate the model's validity. According to the properties of GBM, where the logarithm of the variable follows a Brownian motion with drift, this approach should yield residuals that are normally distributed and exhibit constant variance throughout (Ibe, 2013).

The regression analysis shown in Table A2 for Enel-REC, Chile-NCRE, and Chile-GHG reveals varying adherence to GBM assumptions:

- Enel REC shows a significant intercept with a very low explanatory power, as indicated by its R-squared value. Although the intercept is statistically significant, the residuals do not meet the GBM assumptions of normally distributed residuals, as indicated by the Shapiro-Wilk test p-value (0.1056), and they display constant variance as confirmed by White's test p-value (0.1124).
- Chile NCRE mirrors Enel REC's results, with no significant slope and a significant intercept. The residuals also do not follow a normal distribution, and the variance is constant, suggesting challenges in meeting the GBM assumptions due to the distribution of residuals.
- Chile GHG, despite a similarly low R-squared, presents closer alignment with GBM principles among the three, evidenced by residuals that are normally distributed (Shapiro-Wilk p-value of 0.6751) and exhibit constant variance (White's test p-value of 0.9063). This suggests a better fit to the GBM model, although the explanatory power of the model remains limited.

While Enel-REC and Chile-NCRE struggle with the GBM model's fit and assumptions, Chile-GHG suggests a closer fit to GBM, albeit with limited model explanatory power. This analysis highlights the importance of evaluating the statistical properties of residuals when testing financial models like GBM (we do so via a GARCH model). A plausible hypothesis could be that GHG emissions are influenced by more volatile and unpredictable factors (such as economic activity and international climate agreements) that introduce stochastic trends, making the GBM model a good fit. In contrast, renewable energy capacity might be more stable and influenced by steady investments and long-term policies, leading to a time series that does not align as well with the GBM assumptions.

Table A2 Regression analysis and residual tests for time series data following a Simple Brownian motion model.

Time Series	Constant (Intercept)	Slope (x1)	R-squared	Normality Test (p-value)	Homoscedasticity Test (p-value)
Δ Enel REC	0.5554 (0.023)	0.0245 (0.106)	0.097	0.1056	0.1124
Δ Chile NCRE	0.5554 (0.023)	0.0245 (0.106)	0.097	0.1056	0.1124

ln (Δ Chile GHG)	0.0427 (0.010)	-0.0012 (0.209)	0.056	0.6751	0.9063

Note: Values in parentheses next to coefficients and intercepts indicate the p-values for those estimates. Model Specification: Each time series was modelled as a function of time using an Ordinary Least Squares (OLS) regression to estimate the parameters of a Simple Brownian Motion. The model assumes the form □=□0+□1□+□, where □ represents the transformed values of the time series (either first differences or natural logarithms), x represents time, and □ is the error term (Ibe, 2013). Statistical Tests: The normality of residuals was tested using the Shapiro-Wilk test, assessing the assumption of normally distributed errors essential for the validity of the model. Homoscedasticity, or constant variance of residuals, was evaluated using White's test, which checks for patterns in the squared residuals that might indicate heteroscedasticity. Significance Levels: Reported p-values test the null hypothesis that coefficients are zero (for intercept and slope) and that residuals follow normal distribution and constant variance assumptions. A p-value less than 0.05 is typically considered statistically significant, suggesting rejection of the null hypothesis at the 95% confidence level.

Fitting a GARCH model. The GARCH(1,1) model is useful in examining the assumptions of GBM and constant volatility by quantifying the persistence and impact of volatility shocks over time. GARCH(1,1), by parameterizing □ (long-term average volatility), □ (response coefficient to lagged squared residuals), and □ (volatility persistence), allows for the detection of volatility clustering and mean-reversion patterns. A significant □ and a □ summing to less than one contradicts the constant volatility assumption by showing time-varying volatility, thus providing empirical evidence against the simplifications in GBM.

The GARCH(1,1) model with a Generalized Error Distribution is specified to capture the tails and skewness in the distribution of returns, which are not typically modelled by normal distributions. This specification allows for a more accurate modelling of the asymmetry and leptokurtosis observed in Enel REC data, enhancing the model's ability to capture extreme values while maintaining robust parameter estimates. For Chile NCRE and Chile GHG series, we employ a GARCH(1,1) model with a Standardized Skew Student's t-distribution to accommodate the skewness and excess kurtosis in the data. This distribution is particularly useful for time series that exhibit asymmetry in their volatility structure, potentially due to leverage effects or other market dynamics that cause shocks to impact positively and negatively differently.

The results from the GARCH models provide nuanced insights into the volatility dynamics of each series. The significant □ values across the models suggests that recent shocks have a considerable immediate effect on volatility, indicating deviation from the constant volatility assumption in GBM. The substantial □ values, particularly in Enel REC, highlight strong volatility persistence, suggesting that once volatility increases, it tends to stay high for a period, further challenging the GBM assumption of constant volatility. These findings underscore the presence of time-varying volatility in the series, contrasting with the GBM postulate of a stochastic process with constant volatility.

The robustness of the results is underpinned by several factors. First, the use of robust error distributions (Generalized Error Distribution and Standardized Skew Student's t) improves model fitting and the reliability of inference by better accommodating the empirical characteristics of distributions (see Table A3). The use of GED and Student's t-distributions was necessary to capture the true distributional properties of the SPTs, which exhibit disruptive deviations from business-as-usual trajectories. Additionally, the application of statistical tests like the Ljung-Box and Engle's ARCH tests ensures that the models adequately capture the autocorrelation and Autoregressive Conditional Heteroskedasticity (ARCH) effects in the residuals. Non-significant results from these tests confirm that the models are well-specified and that the residual sequences are devoid of predictable patterns and heteroscedasticity, lending credibility to the volatility dynamics inferred from the GARCH parameters. These elements collectively affirm that the models are statistically sound and provide a reliable framework for assessing the volatility properties of the time series data.

Table A3. GARCH(1,1) model results for time series volatility analysis.

	Δ Enel REC GARCH (1,1) Generalized Error Distribution	Δ Chile NCRE GARCH (1,1) Standardized Skew Student's t	ln (Δ Chile GHG) GARCH (1,1) Standardized Skew Student's t
μ (mu)	0.005 *** (0.001)	0.077 *** (0.000)	0.2558 *** (0.076)
(omega)	0.135 *** (0.000)	0.195 *** (0.000)	0.0945* (0.151)
(alpha)	0.009 (0.089)	0.2736 *** (0.000)	0.000 (0.003)
(beta)	0.883 *** (0.090)	0.713 *** (0.000)	0.4835 * (0.838)
eta	1.495 *** (0.448)	12.313 *** (0.000)	248.2254 *** (50.938)
lambda		0.999 *** (0.000)	0.1345 (0.145)
AIC	-197.813	-71.383	46.264
BIC	-190.330	-63.390	54.672
Ljung-Box Test on Standardized Residuals	4.003	6.297	2.961
Ljung-Box Test on Squared Standardized Residuals	0.958	1.700	1.665
Engle's ARCH Test	2.446	2.290	3.709
Jarque-Bera Test	28.241	1.439	0.904

Note: Model Specification: Each series was modelled using a Constant Mean GARCH(1,1) model to capture the dynamics of volatility and returns. In this model framework, μ (mu) represents the expected mean return, providing insight into the average performance over the period analysed. (omega) establishes the baseline level of volatility absent recent shocks, indicating the inherent market stability or instability. (alpha) quantifies the immediate impact of past shocks on current volatility, highlighting how reactive the market is to changes, while (beta) measures how

long these effects persist, suggesting the durability of volatility following market disturbances. The parameters eta (eta) and lambda (lambda) are crucial for adjusting the skewness and kurtosis in the distributions used, which are tailored to the specific characteristics of each series' return distribution. Statistical significance: For each parameter, statistical significance is assessed through p-values, with those less than 0.05 typically considered significant, meaning the results are statistically robust against the hypothesis of no effect. A significance level of less than 0.05 is commonly denoted by *, less than 0.01 by **, and less than 0.001 by ***, each indicating increasingly stronger evidence against the null hypothesis. The model's adequacy is evaluated using the Log-Likelihood value; higher values suggest a better fit of the model to the observed data. Model comparison is facilitated by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where lower values indicate a preferable model in terms of explanatory power and simplicity. Additional diagnostics: Ljung-Box tests on both standardized and squared standardized residuals to evaluate autocorrelation; non-significant results here confirm the model's ability to adequately represent the data's volatility structure. Engle's ARCH Test checks for residual clusters of high volatility, with non-significant results suggesting good model specification. The Jarque-Bera Test assesses normality of the residuals; results not indicating deviation from normality validate the underlying assumptions of the model setup and its appropriateness for the data analysed.

Parameter estimation using bootstrapping. In bootstrapping, we repeatedly resample the original data with replacement to create many pseudo-samples. We then estimate the model parameters for each pseudo-sample. According to the Central Limit Theorem, the mean of these bootstrap estimates will tend to be normally distributed and stable, even if each individual estimate varies significantly. This stability is observed in our derived mean reversion level and speed parameters, which show consistent means and manageable standard deviations despite the variability in individual bootstrap samples. Specifically, for the Enel REC KPI, the mean reversion level is remarkably low at 0.0001, with the bootstrap mean at 0.0011 and a standard deviation of 0.0210, indicating some variability but overall consistency. The mean reversion speed also shows a robust estimate with a bootstrap mean of 0.7763 and a standard deviation of 0.3111. For the Chile NCRE KPI, the mean reversion level and speed similarly exhibit stability, with bootstrap means of 0.0160 and 0.7349, respectively, and acceptable standard deviations. However, the Chile GHG KPI displays a slight deviation with a lower mean reversion level (bootstrap mean 0.0026) and a higher mean reversion speed (bootstrap mean 0.9632), yet both remain within reasonable ranges. These results suggest that while some KPIs exhibit greater variability, bootstrapping generally provides reliable estimates for mean reversion characteristics, reinforcing its utility as an effective tool for analysing sustainability data.

Table A4. Bootstrap estimates for mean reversion parameters of sustainability metrics.

	Δ Enel REC	Δ Chile NCRE	ln (Δ Chile GHG)
Mean reversion level (θ)	0.0001	0.0149	0.1830
Bootstrap Mean θ	0.0011	0.0160	0.0026
Bootstrap Std θ	0.0210	0.0361	0.0005
Mean Reversion Speed (κ)	0.1073	0.0131	0.5165

Bootstrap Mean κ	0.7763	0.7349	0.9632
Bootstrap Std κ	0.3111	0.2236	0.0880

Note: This table presents the mean reversion parameters level and speed for three sustainability performance metrics. The original mean reversion parameters were derived from a GARCH (1,1) model result from Table A4. Bootstrap estimates provide the mean and standard deviation (Std) of these parameters across 1000 resampled datasets. The mean reversion level indicates the long-term average to which the metric reverts, while the mean reversion speed indicates the speed at which the KPI returns to this average.

B: Conditional variance series model

Using series transformations that ensure stationarity (see Appendix A), our model is parametrised by (constant term), α_1 (responsiveness to the last period's squared residual), and β_1 (persistence of past variances) and fit this model to the adjusted returns. The conditional variance series h_t is modeled as:

(1B) $h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1}$

where ϵ_t^2 is the conditional variance at time t, capturing the expected level of variance given past information. From the fitted model (see Appendix A, Table A3), the parameters ω, α_1, β_1 are extracted directly to estimate:

- *Mean reversion level, θ:* Calculated as $\theta = \frac{\omega}{1- \alpha_1 - \beta_1}$. This parameter reflects the equilibrium level toward which the series variance is expected to revert over time, which may encompass broader operational or sustainability trends.
- *Mean Reversion Speed, κ:* $\kappa = 1 - \alpha_1 - \beta_1$ indicates the rate at which variances adjust to the mean reversion level. In the context of quarterly or annual data, this speed might be slower than in financial applications, aligning with the infrequent update and less responsive nature of such data.
- *Volatility of Variance, ξ:* It is estimated as $\xi = \frac{1}{T}\sum_{t=1}^{T} h_t^2$, where h_t^2 represents the conditional standard deviation of returns at each time step and T is the total number of observations.
- *Correlation between the Sustainability Metric Change and its Volatility, ρ*: The correlation coefficient, denoted as $\rho_{r_{t-1,}\, h_t}$, is defined as $\rho_{r_{t-1,}\, h_t} = \frac{Cov(r_{t-1,}\, h_t)}{\sigma_{r_{t-1}}\, \sigma_{h_t}}$. This coefficient measures the relationship between past returns, $r_{t-1,}$, and future volatilities, h_t. Such a statistic is particularly insightful in non-financial contexts, suggesting how historical performance might influence perceived risks or volatilities in operational outcomes.

C. Parameter estimation and values

The estimation of the parameters within the adapted Heston model for sustainability metrics primarily used historical data analysis and statistical modelling techniques. The process began by calculating log returns from historical KPIs to establish a baseline for the drift using the mean of these log returns. Initial volatility was derived from the standard deviation of these log returns.

For the mean reversion characteristics, a GARCH model was fitted to the returns data (see Appendix A, Table A3). This model provided estimates for the long-term mean level of variance and the speed at which variance reverts to this mean, calculated from the GARCH parameters omega, alpha, and beta.

The volatility of variance and the correlation between the metric's changes and its volatility were estimated using the variances derived from the GARCH model and the correlation of these variances with the log returns. This method allowed for an integrated analysis of volatility dynamics, capturing both the average tendencies and the unpredictability within the volatility itself.

Enel REC parameters. This time series covers the period from shows moderate initial volatility and drift, suggesting a relatively stable trend in REC changes with some uncertainty at the start. The low mean reversion level and high reversion speed indicate quick adjustments to a very low long-term volatility, suggesting that any fluctuations are short-lived and stabilize rapidly. The correlation of 0.402 between changes in the metric and its volatility indicates a significant linkage, where changes in REC metrics might predict shifts in volatility to some extent.

Chile NCRE parameters. The NCRE metrics for Chile display higher initial volatility and drift, indicating more pronounced fluctuations and a strong upward trend. A higher mean reversion level coupled with a slower reversion speed suggests that volatility takes longer to stabilize and does so at a higher level. The high correlation of 0.556 between metric changes and volatility suggests a strong predictive relationship between how metric values change and how volatile they are.

Chile GHG parameters. The changes in GHG emissions in Chile exhibit a negative drift since we considered only data from 2016 to reflect Chile's climate policy after the Paris Agreement. This indicates an expected decrease in GHG emissions over time. For the rest of the parameters, we considered data from 1990. Initial volatility is relatively higher, suggesting notable initial uncertainty in emission reductions. The extremely high mean reversion level and reversion speed indicate a strong and rapid pull towards a high baseline volatility, reflecting aggressive and dynamic adjustments in the metric. The negative correlation indicates that as GHG emissions decrease, volatility tends to decrease as well, albeit with a moderate inverse relationship.

Table C1. Parameters for the stochastic model implementation.

Parameter	Δ Enel REC	Δ Chile NCRE	ln (Δ Chile GHG)
Drift (μ)	0.016	0.047	-0.004
Initial Volatility (v_0)	0.021	0.043	0.043
Drift (μ) + Rank Effect	0.015	0.044	-0.004

Initial Volatility (v_0) + Score Effect	0.006	0.009	0.009
Mean reversion level (θ)	0.0001	0.014	0.183
Mean Reversion Speed (κ)	0.107	0.013	0.516
Volatility of Variance (ξ)	0.0001	0.003	0.183
Correlation between the Sustainability Metric Change and its Volatility ( )	0.402	0.556	-0.180

D: Model validation

Backtesting. Our backtesting approach splits the historical data of sustainability performance metrics into training and testing segments. This allows the model to be fitted on one subset of the data (training) and validated on another (testing). This approach enhances the robustness of our stochastic model. Two types of stochastic model simulations are run. These include a baseline model and a transition plan model. The two differ in the drift and volatility terms used, which reflect the effect of the transition plan (see Equations 8 and 9).

Using root mean square error (RMSE) and mean absolute error (MAE) to measure the accuracy of the predictions against the actual test data. These metrics provide quantitative insights into the model's predictive performance.

The comparative backtesting analysis of Enel's renewable energy capacity projections using the baseline and transition models reveals significant performance nuances amidst evolving geopolitical risks. The baseline model tends to slightly underestimate capacity, aligning with investor perceptions that increasingly view Enel at risk of missing its targets, particularly post-2022. Despite this bias, the model closely aligns with actual trends, underestimating only in the later stages. Conversely, the transition plan model subtly overestimates capacity, which is reflected by a more symmetric residual distribution indicating fewer extreme outliers. This model accurately tracks actual capacity in earlier quarters and effectively incorporates Enel's leadership in accelerating renewable energy infrastructure. By closely matching the level of REC at the series' end, it meets Enel's targets, countering investor scepticism. This model might be preferable in scenarios demanding minimal bias for effective capacity management and planning in a changing geopolitical context.

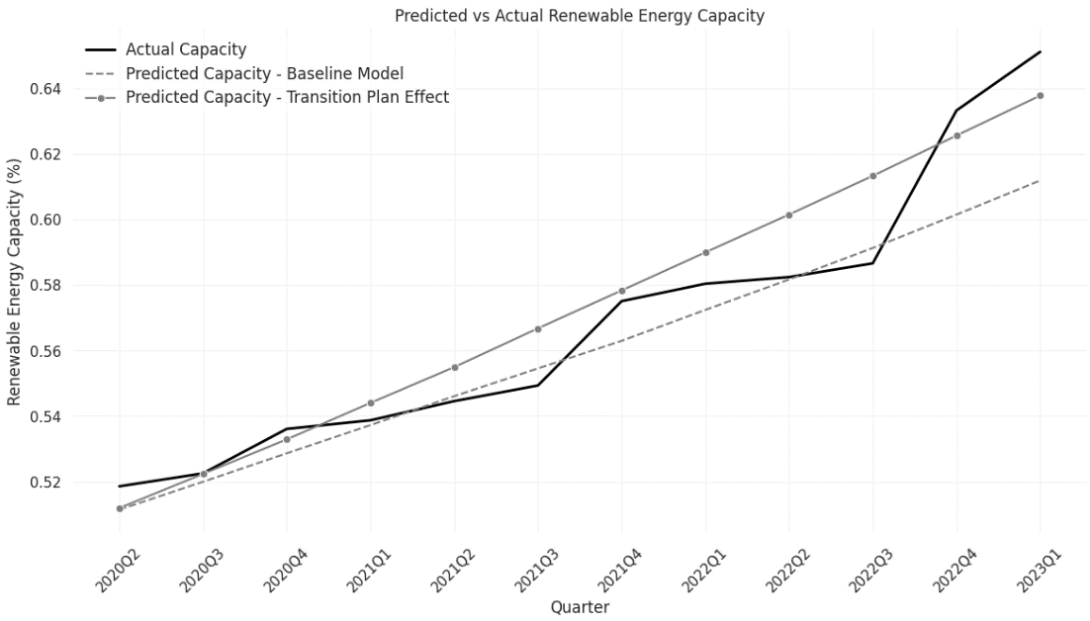


Figure D1. Longitudinal analysis of predicted vs. actual Enel's REC: Assessing stochastic model efficacy

The backtesting analysis of Chile's NCRE using the baseline and transition plan models reveals distinct differences in predictive accuracy and error characteristics. The transition model, which incorporates Chile's climate transition leadership and rapid deployment of NCRE captures the accelerated increase in renewable energy. This model's performance aligns with Chile's achievement of its 2025 NCRE goals five years early, a testament to the significant growth of renewable energy from 8% in 2015 to 20% in 2020 (Ministry of Finance (Chile), 2022). Although both models exhibit right skewness in their residuals, indicating a tendency to underestimate higher values, the Transition Model's residuals are characterised by a more pronounced negative mean and lower standard deviation, which aligns with its ability to capture more extreme increases in NCRE deployment not factored into the baseline model. This analysis underscores the transition model's effectiveness in scenarios requiring nuanced understanding and responsiveness to rapid policy and environmental changes.

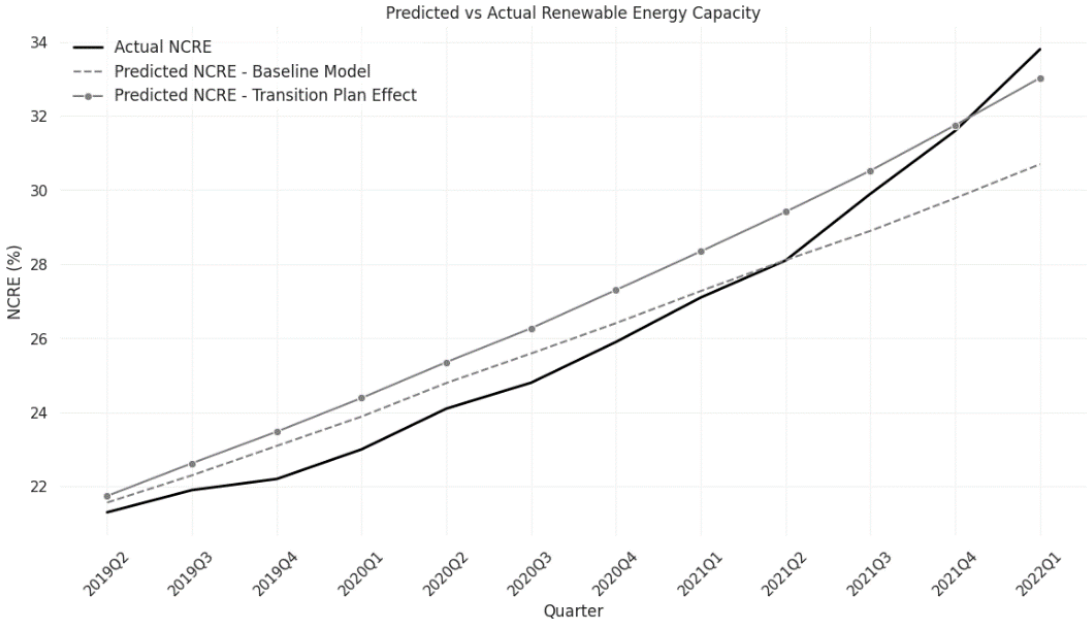


Figure D2. Longitudinal analysis of predicted vs. actual Chile's NCRE: Assessing stochastic model efficacy

The analysis of the baseline and transition plan models for predicting GHG in Chile reflects the nuanced dynamics of the country's climate policy and its impact on model performance. The baseline model, not incorporating Chile's latest climate policy breakthroughs, follows an upward trend, mirroring the historical data without accounting for recent policy shifts. Although it appears to overestimate GHG emissions, this does not necessarily indicate inaccuracy, given its context of non-adjusted policy conditions. In contrast, the transition plan model, aligning with Chile's updated NDC and its high ranking for net-zero commitments by Climate Action Tracker, shows an underestimation of GHG emissions. This model captures the actual decline in emissions, evident as it nearly converges with the actual GHG levels by 2020. The discrepancy between the models underscores the significance of integrating contemporary policy changes into modelling frameworks, suggesting that while the baseline model provides a consistent trend projection, the transition plan model offers a realistic reflection of Chile's ambitious climate targets, necessitating recalibration of both models to enhance alignment with current and projected GHG trajectories.

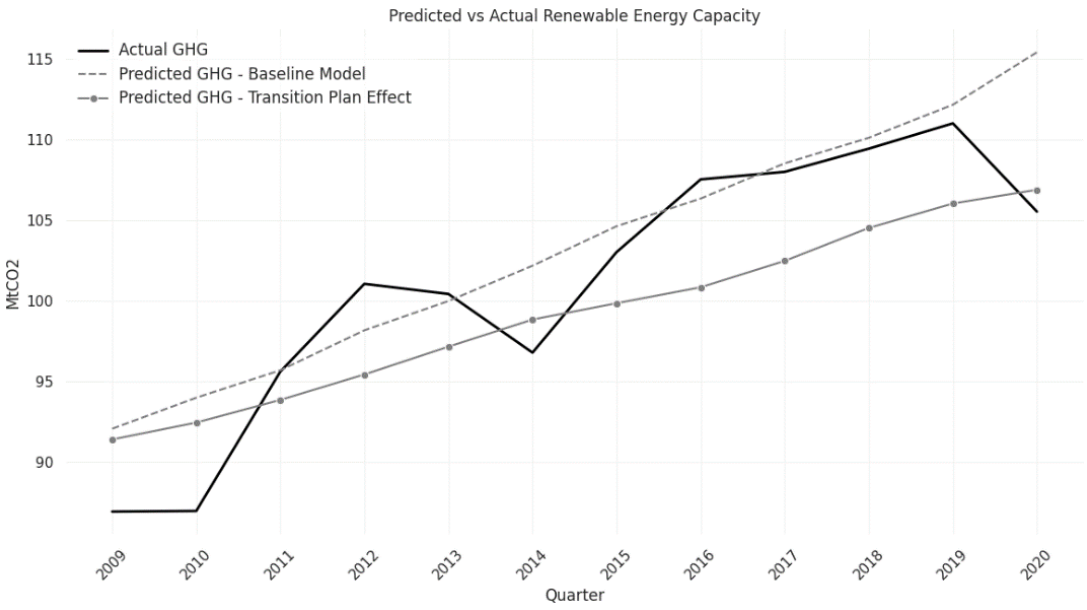


Figure D3. Longitudinal analysis of predicted vs. actual Chile's GHG: Assessing stochastic model efficacy

Table D1. Comparison of predictive performance and residual analysis for standard and transition plan models

	Enel REC		Chile NCRE		Chile GHG	
	Baseline	*Transition Plan*	*Baseline*	*Transition Plan*	*Baseline*	*Transition Plan*
RMSE	0.0156	0.0126	1.1949	1.0897	4.2567	4.4359
MAE	0.0101	0.0102	0.8778	1.0049	3.0020	4.1105
Mean Residual	0.0083	-0.0051	0.1095	-0.8761	-2.2495	1.8820
Std Dev of Residuals	0.0133	0.0116	1.1898	0.6480	3.6138	4.0169
Skewness	1.3015	-0.2379	1.4268	1.2956	-0.6969	-0.6132
Kurtosis	0.5222	-0.9092	0.8528	0.8196	-0.5424	-1.0709

Note: The table details various statistical metrics to evaluate the predictive performance and error distribution characteristics of the Standard and Transition Plan Models across different datasets. RMSE (Root Mean Square Error) quantifies the average magnitude of the prediction errors, with lower values indicating more accurate predictions. MAE (Mean Absolute Error) measures the average error magnitude, directly reflecting prediction accuracy. Mean Residual indicates the average deviation of predictions from actual values, with positive values showing overestimations and negative values showing underestimations. Standard Deviation of Residuals provides insight into the spread of errors around the mean, indicating the consistency of the model. Skewness assesses the asymmetry of the error distribution, with positive values suggesting a tail extending towards

higher errors, and negative values indicating a tail towards lower errors. Lastly, Kurtosis measures the heaviness of the tails of the distribution, with positive values indicating heavier tails (leptokurtic) and negative values lighter tails (platykurtic). Together, these metrics offer a comprehensive evaluation of each model's accuracy, consistency, and the nature of their prediction errors.

Monte Carlo convergence analysis. the Monte Carlo convergence test, which systematically explores how the model's outputs change with varying numbers of simulation paths. By evaluating the simulation at different scales (100, 1000, 5000, 10,000 paths), the analysis checks for convergence in the statistical properties (mean, standard deviation, minimum, maximum) of the final values across simulations. Such a test is crucial for validating the model's stability and reliability, as consistent convergence results suggest that increasing the number of paths stabilizes the output around a specific distribution, thus affirming the model's robustness in capturing the underlying stochastic process. The detailed recording of results for each set of paths helps in identifying any anomalies or patterns in the model's predictions as the number of simulations increases.

The results from the three models demonstrate varying degrees of stability and output variance as the number of simulation paths increases. For Enel's Renewable Energy Capacity, the model outputs remain stable, with mean values consistently around the low 40s and a slight decrease in standard deviation as the number of paths increases, indicating minor convergence. Chile's NCRE model shows increasing mean values and decreasing standard deviation with more simulation paths, suggesting improved stability and better convergence at higher simulation counts. Conversely, Chile's GHG Emissions model presents notable fluctuations in mean values and a significant increase in variance, particularly with a sharp rise in standard deviation as the number of paths grows. This variability could reflect the complex dynamics of modelling GHG emissions under varying policy scenarios, where recent changes potentially lead to the observed instability and high variability in the results.Top of Form

Table D2. Convergence analysis results.

Model	Paths	Mean	Std	Min	Max
Enel REC	100	43.94	19.05	16.13	100.
	1000	41.76	16.73	9.15	100.
	5000	42.15	16.94	9.56	100
	10000	42.16	16.84	7.64	100
Chile NCRE	100	63.00	29.99	6.37	100
	1000	64.94	28.49	1.60	100
	5000	65.13	28.53	2.29	100

Chile GHG	10000	65.75	28.37	1.93	100
	100	70.08	233.08	0.06	2148.82
	1000	88.59	337.45	0.01	5827.68
	5000	90.62	423.01	0.002	15066.35
	10000	84.47	343.18	0.00034	11271.70

E: Model for Enel SLB

The series of kernel density estimates from Monte Carlo simulations, shown in Figure E1, were used to estimate Enel's evolving probability of meeting its 60% REC target by 2023, the target set in 2020 (ISIN XS2244418609). These plots, illustrating variable spread and skewness across quarters from Q3 2020 to Q2 2022, reveal an initially high uncertainty that gradually narrows, indicating decreased unpredictability as the target date approaches and model parameters are updated with new data. Despite probabilities remaining consistently below 50%, the simulation showed an improving outlook in later quarters. This reflects the dynamic nature of our model as it responds to evolving operational strategies and changing external conditions. The shift in probability and the complexity of the simulated outcomes, coupled with the actual achievement of the target despite initial concerns, underscore the ambitious nature of Enel's sustainability targets.

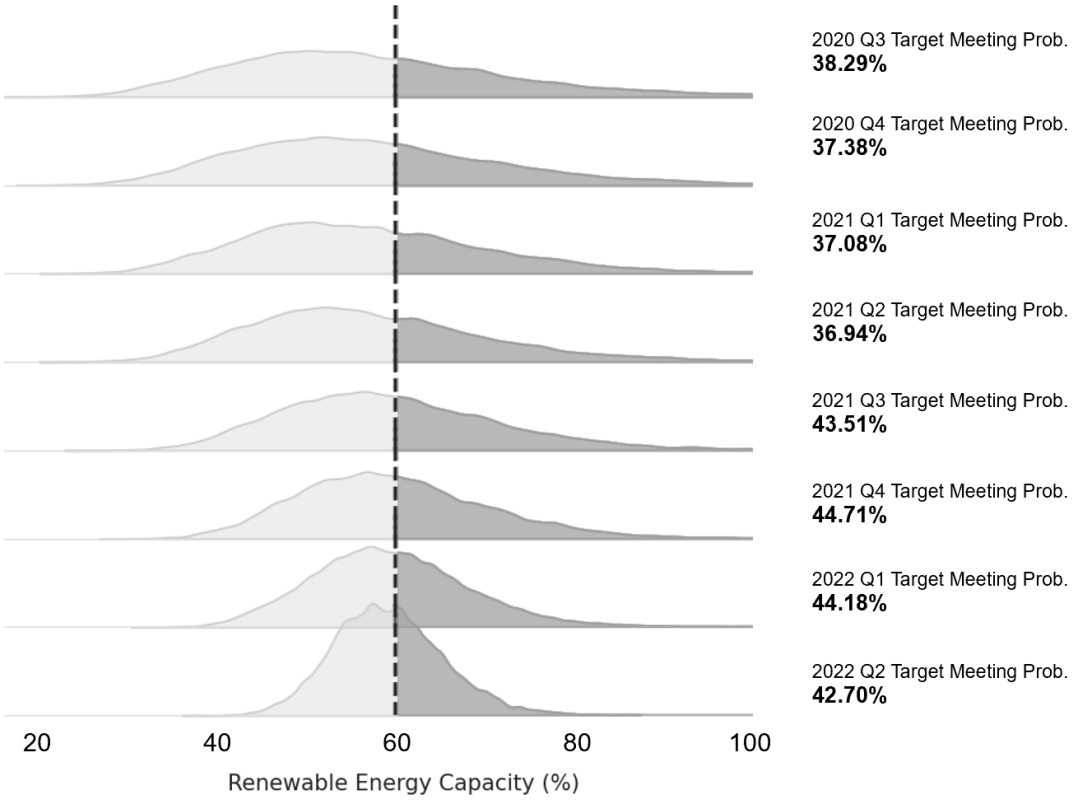


Figure E1. Probability distributions of renewable energy targets via Monte Carlo simulations

Note: Darker regions in the density plots represent a higher density of simulated paths exceeding the 0.6 REC target, indicating increased likelihood of achieving the renewable energy capacity goals.

References

Abdul Razak, L., M. H. Ibrahim, and A Ng (2020). *Which Sustainability Dimensions Affect Credit Risk? Evidence from Corporate and Country-Level Measures*. doi: 10.3390/jrfm13120316.

Abdullah, A., S. Yamak, A. Korzhenitskaya, R. Rahimi, and J McClellan (2024). *Sustainable development: The role of sustainability committees in achieving ESG targets*. doi: 10.1002/bse.3596.

Abram, S., E. Atkins, A. Dietzel, K. Jenkins, L. Kiamba, J. Kirshner, J. Kreienkamp, K. Parkhill, T. Pegram, and L. M Santos Ayllón (2022). *Just Transition: A whole-systems approach to decarbonisation*. doi: 10.1080/14693062.2022.2108365.

Acemoglu, D., P. Aghion, L. Bursztyn, and D Hemous (2012). *The Environment and Directed Technical Change*. Tech. rep. doi: 10.1257/aer.102.1.131.

ACT and WBA (2023). *Electric Utilities Benchmark. Assessing Low-Carbon Transition & World Benchmarking Alliance*. url: https://www.worldbenchmarkingalliance.org/publication/electric-utilities/eu/rankings/.

Adams, C. A., A. Alhamood, X. He, J. Tian, L. Wang, and Y Wang (2021). *The double-materiality concept*. Tech. rep. url: https://tinyurl.com/2s3eskmf.

Airbus (2023). *Sustainable aviation fuel: Advancing the ecosystem for a proven alternative fuel. Airbus*. url: https://www.airbus.com/.

Aklin, M (2025). *The political logic of just transition policies*. doi: 10.1080/14693062.2024.2378995.

Alghalith, M., C. Floros, and K Gkillas (2020). *Estimating Stochastic Volatility under the Assumption of Stochastic Volatility of Volatility*. doi: 10.3390/risks8020035.

Alonso-Robisco, A., J. M. Carbo, E. Kormanyos, and E Triebskorn (2025). *Houston, we have a problem: Can satellite information bridge the climate-related data gap? Latin American Journal of Central Banking, 100173*. doi: 10.1016/j.latcb.2025.100173.

Alonso-Robisco, A., J. M. Carbo, and J. M Marques (2023). *Machine learning methods in climate finance: A systematic review (Documentos de Trabajo No*. Tech. rep.

Amel-Zadeh, A. and G Serafeim (2018). *Why and How Investors Use ESG Information: Evidence from a Global Survey*. doi: 10.2469/faj.v74.n3.2.

Ameli, N., O. Dessens, M. Winning, J. Cronin, H. Chenet, P. Drummond, A. Calzadilla, G. Anandarajah, and M Grubb (2021). *Higher cost of finance exacerbates a climate investment trap in developing economies*. doi: 10.1038/s41467-021-24305-3.

Ante, L (2024). *The scope of green finance research: Research streams, influential works and future research paths*. doi: 10.1016/j.ecolecon.2024.108302.

Arthur, W. B (1989). *Competing Technologies, Increasing Returns, and Lock-In by Historical Events*. doi: 10.2307/2234208.

ASTM (2022). *Standard Specification for Aviation Turbine Fuel Containing Synthesized Hydrocarbons. Advancing Standards Transformation Markets*. doi: 10.1520/D7566-22.

ATAG (2021). *Waypoint 2050. Air Transport Action Group*. url: https://aviationbenefits.org/media/167417/w2050%5C_v2021%5C_27sept%5C_full.pdf.

Babcock, A., A. He, and V Ramani (2022). *Building Investor Trust in Net-Zero*. doi: 10.1111/jacf.12505.

Baldursson, F. M. and N.-H. M von der Fehr (2004). *Price volatility and risk exposure: On market-based environmental policy instruments*. doi: 10.1016/j.jeem.2003.06.004.

Bansal, R., M. Ochoa, and D Kiku (2016). *Climate Change and Growth Risks (NBER Working Paper No*. Tech. rep. doi: 10.3386/w23009.

Barnett, M., W. Brock, and L. P Hansen (2020). *Pricing Uncertainty Induced by Climate Change*. doi: 10.1093/rfs/hhz144.

Battiston, S., A. Mandel, I. Monasterolo, F. Schütze, and G Visentin (2017). *A climate stress-test of the financial system*. doi: 10.1038/nclimate3255.

Battiston, S. and I Monasterolo (2020). *The Climate Spread of Corporate and Sovereign Bonds*. doi: 10.2139/ssrn.3376218.

Bauer, M. D., E. A. Offner, and G. D Rudebusch (2023). *The Effect of U.S. Climate Policy on Financial Markets: An Event Study of the Inflation Reduction Act (Brookings Working Paper No*. Tech. rep. url: https://tinyurl.com/bde8cnu7.

Bazhair, A. H., S. F. A. Khatib, and H Al Amosh (2022). *Taking Stock of Carbon Disclosure Research While Looking to the Future: A Systematic Literature Review*. doi: 10.3390/su142013475.

Beirne, J., N. Renzhi, and U Volz (2021). *Bracing for the Typhoon: Climate change and sovereign risk in Southeast Asia*. doi: 10.1002/sd.2199.

Bender, J., T. A. Bridges, and K Shah (2019). *Reinventing climate investing: Building equity portfolios for climate risk mitigation and adaptation*. doi: 10.1080/20430795.2019.1579512.

Berg, F., J. F. Kölbel, and R Rigobon (2022). *Aggregate Confusion: The Divergence of ESG Ratings*. doi: 10.1093/rof/rfac033.

Berger-Schmitz, Z., D. George, C. Hindal, R. Perkins, and M Travaille (2023). *What explains firms' net zero adoption, strategy and response? Business Strategy and The Environment, 32(8), 5583–5601*. doi: 10.1002/bse.3437.

Bergero, C., G. Gosnell, D. Gielen, S. Kang, M. Bazilian, and S. J Davis (2023). *Pathways to net-zero emissions from aviation*. doi: 10.1038/s41893-022-01046-9.

Berrada, T., L. Engelhardt, R. Gibson, and P Krueger (2022). *The economics of sustainability-linked bonds*. doi: 10.2139/ssrn.4059299.

Bingler, J. A., C. Colesanti Senni, and P Monnin (2022). *Climate transition risk metrics: Investigating convergence and estimation drivers (Statistics for Sustainable Finance No.* url: https://www.bis.org/ifc/publ/ifcb56%5C_20.pdf.

BIS (2022). *Frequently asked questions on climate-related financial risks [Basel Committee on Banking Supervision]. Bank for International Settlements*. url: https://www.bis.org/bcbs/publ/d543.pdf.

Bjørn, A., S. M. Lloyd, M. Brander, and H. D Matthews (2022). *Renewable energy certificates threaten the integrity of corporate science-based targets*. doi: 10.1038/s41558-022-01379-5.

Black, F. and M Scholes (1973). *The Pricing of Options and Corporate Liabilities*.

Bockel, L. and L Vian (2016). *Towards Sustainable Impact Monitoring of Green Agriculture and Forestry Investments by NDBs: Adapting MRV Methodology*. url: https://tinyurl.com/456r5h6y.

Bolay, A.-F., A. Bjørn, L. Patouillard, O. Weber, and M Margni (2024). *What drives companies' progress on their emission reduction targets? Journal of Cleaner Production, 468, 143124*. doi: 10.1016/j.jclepro.2024.143124.

Bollerslev, T (1986). *Generalized Autoregressive Conditional Heteroskedasticity*. doi: 10.1016/0304-4076(86)90063-1.

Bolton, P. and M Kacperczyk (2020). *Do Investors Care about Carbon Risk? NBER*. url: http://dx.doi.org/10.2139/ssrn.3398441.

Bolton, P. and M Kacperczyk (2021). *Do investors care about carbon risk? Journal of Financial Economics, 142(2), 517–549*. doi: 10.1016/j.jfineco.2021.05.008.

Borges, J. L (1975). *El libro de arena*.

Brazzola, N., A. Patt, and J Wohland (2022). *Definitions and implications of climate-neutral aviation*. doi: 10.1038/s41558-022-01404-7.

Broadie, M. and Ö Kaya (2006). *Exact Simulation of Stochastic Volatility and Other Affine Jump Diffusion Processes*. doi: 10.1287/opre.1050.0247.

Brueckner, J. K. and C Abreu (2017). *Airline fuel usage and carbon emissions: Determining factors*. doi: 10.1016/j.jairtraman.2017.01.004.

Brutschin, E., F. Schenuit, B. Van Ruijven, and K Riahi (2022). *Exploring Enablers for an Ambitious Coal Phaseout*. doi: 10.17645/pag.v10i3.5535.

Busch, T., M. Johnson, and T Pioch (2022). *Corporate carbon performance data: Quo vadis? Journal of Industrial Ecology, 26(1), 350–363*. doi: 10.1111/jiec.13008.

Calcaterra, M., L. Aleluia Reis, P. Fragkos, T. Briera, H. S. De Boer, F. Egli, J. Emmerling, G. Iyer, S. Mittal, F. H. J. Polzin, M. W. J. L. Sanders, T. S. Schmidt, A. Serebriakova, B. Steffen, D. J. Van De Ven, D. P. Van Vuuren, P. Waidelich, and M Tavoni (2024). *Reducing the cost of capital to finance the energy transition in developing countries*. doi: 10.1038/s41560-024-01606-7.

Caldecott, B (2022a). *Climate risk management (CRM) and how it relates to achieving alignment with climate outcomes (ACO)*. doi: 10.1080/20430795.2020.1848142.

Caldecott, B (2022b). *Defining transition finance and embedding it in the post-Covid-19 recovery*. doi: 10.1080/20430795.2020.1813478.

Campiglio, E (2016). *Beyond carbon pricing: The role of banking and monetary policy in financing the transition to a low-carbon economy*. doi: 10.1016/j.ecolecon.2015.03.020.

CAPA and Envest (2024). *Global Airline Sustainability Benchmarking and Rating Report. CAPA-Centre For Aviation & Envest*. Tech. rep. url: https://centreforaviation.com/shop/capa-envest-airline-sustainability-benchmarking-report-2023.

Capasso, G., G. Gianfrate, and M Spinelli (2020). *Climate change and credit risk*. doi: 10.1016/j.jclepro.2020.121634.

Caramichael, J. and A. C Rapp (2024). *The green corporate bond issuance premium*.

CAT (2024). *Net Zero Targets. Climate Action Tracker*. url: https://climateactiontracker.org/methodology/net-zero-targets/.

Cavalett, O., M. D. B. Watanabe, M. Voldsund, S. Roussanaly, and F Cherubini (2024). *Paving the way for sustainable decarbonization of the European cement industry*. doi: 10.1038/s41893-024-01320-y.

CBI (2022). *Transition finance for transforming companies: Tools to assess companies' transitions and their SLBs. Climate Bonds Initiative*. url: https://www.climatebonds.net/files/documents/publications/Climate-Bonds%5C_Transition-Finance-for-Transforming-Companies%5C_EN%5C_Sep-2022.pdf.

CBI (2023). *Guidance to assess transition plans. Climate Bonds Initiative*. url: https://www.climatebonds.net/files/documents/publications/Guidance-to-Assess-Transition-Plans.pdf.

CBI and UN Global Compact (CFO Coalition for the SDGs) (2023). *The role of the Chief Financial Officer in driving low-carbon transition. Climate Bonds Initiative & UN Global Impact*. url: https://www.climatebonds.net/files/documents/publications/The-role-of-the-Chief-Financial-Officer-in-driving-low-carbon-transition.pdf.

CDP (2023a). *Are companies developing credible climate transition plans? CDP*. url: https://www.cdp.net/en/climate-transition-plans.

CDP (2023b). *CDP Climate Change 2023 Questionnaire*.

CEN (2024). *Reportes Energéticos Mensuales, 2015-2023. Coordinador Eléctrico Nacional*. Tech. rep. url: https://www.coordinador.cl/reportes/documentos/reporte-energetico/.

Cevik, S. and J. T Jalles (2022). *This changes everything: Climate shocks and sovereign bonds*. doi: 10.1016/j.eneco.2022.105856.

Chan, K. J. D., B. Cheung, and L Wilson Mok (2024). *Market Fragmentation or Market Failure? A Dilemma of Harmonizing Green Finance Taxonomy Designs*. doi: 10.2139/ssrn.4188304.

Chatterji, A. K., R. Durand, D. I. Levine, and S Touboul (2016). *Do ratings of firms converge? Implications for managers, investors, and strategy researchers*. doi: 10.1002/smj.2407.

Chatterji, A. K., D. I. Levine, and M. W Toffel (2009). *How Well Do Social Ratings Actually Measure Corporate Social Responsibility? Journal of Economics & Management Strategy, 18(1), 125–169*. doi: 10.1111/j.1530-9134.2009.00210.x.

Chekriy, K., R. Kiesel, and G Stahl (2023). *Probabilistic Assessment of Corporate Net-Zero Transition*. url: https://ssrn.com/abstract=5255705.

Chenet, Hugues, Josh Ryan-Collins, and Frank van Lerven (2021). "Finance, climate-change and radical uncertainty: Towards a precautionary approach to financial policy". In: *Ecological Economics* 183, p. 106957. doi: 10.1016/j.ecolecon.2021.106957.

Chiburis, R. and M Lokshin (2007). *Maximum Likelihood and Two-Step Estimation of an Ordered-Probit Selection Model*. doi: 10.1177/1536867X0700700202.

Christensen, D., G. Serafeim, and A Sikochi (2021). *Why is corporate virtue in the eye of the beholder? The case of ESG ratings (Nos*. url: https://www.hbs.edu/ris/Publication%5C%20Files/20-084%5C_6c5b0248-d117-4049-baad-c0e1877eb537.pdf.

CISL and Deloitte (2024). *The ClimateWise Principles Independent Review 2023. Cambridge Institute for Sustainability Leadership (CISL) & Deloitte*. url: https://www.cisl.cam.ac.uk/files/cisl%5C_climatewise%5C_principles%5C_2023.pdf.

Ciummo, S., F. Walch, and M Breitenstein (2022). *Disclosure of Climate Change Risk in Credit Ratings*. doi: 10.2139/ssrn.4218357.

Clark, G. L., A. Feiner, and M Viehs (2015). *From the stockholder to the stakeholder*. url: https://ssrn.com/abstract=2508281.

Climate TRACE (2025). *Climate TRACE [Dataset]*. url: https://climatetrace.org/.

Coen, D., K. Herman, and T Pegram (2022). *Are corporate climate efforts genuine? An empirical analysis of the climate 'talk–walk' hypothesis*. doi: 10.1002/bse.3063.

Cohen, S., I. Kadach, and G Ormazabal (2023). *Institutional investors, climate disclosure, and carbon emissions*. doi: 10.1016/j.jacceco.2023.101640.

Colesanti Senni, C., T. Schimanski, J. Bingler, J. Ni, and M Leippold (2025). *Using AI to assess corporate climate transition disclosures*. doi: 10.1088/2515-7620/ad9e88.

CPI (2023). *Global Landscape of Climate Finance 2023. Climate Policy Initiative*. url: https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-2023/.

CPI (2024a). *Global Landscape of Climate Finance 2024. Climate Policy Initiative*. url: https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-2024/.

CPI (2024b). *Managing Currency Risk to Catalyze Climate Finance*. url: https://www.climatepolicyinitiative.org/publication/managing-currency-risk-to-catalyze-climate-finance/.

Crenshaw, C. A (2025). *Statement on the Commission's Status Report in the Climate-Related Disclosure Rules Litigation [Statement]. U.S. Securities and Exchange Commission*. Tech. rep. url: https://www.sec.gov/newsroom/speeches-statements/crenshaw-statement-climate-related-disclosure-rules-litigation-072325.

Cvitani, J., B. Rozovskii, and I Zaliapin (2006). *Numerical estimation of volatility values from discretely observed diffusion data*. doi: 10.21314/JCF.2006.149.

Daly, H. E (1991). *Steady-State Economics (2nd ed.)*

Dana, J. D. and D. J Greenfield (2019). *The Impact of Passenger Mix on Load Factors in the Airline Industry*. doi: 10.1007/s11151-018-9631-2.

Danielsson, J (1994). *Stochastic volatility in asset prices estimation with simulated maximum likelihood*. doi: 10.1016/0304-4076(94)90070-1.

Delis, M. D., K. D. Greiff, M. Iosifidi, and S Ongena (2024). *Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans*. doi: 10.1111/fmii.12189.

Demirtas, H. and D Hedeker (2016). *Computing the Point-biserial Correlation under Any Underlying Continuous Distribution*. doi: 10.1080/03610918.2014.920883.

Demšar, J (2006). *Statistical comparisons of classifiers over multiple data sets*.

Dhayal, K. S., A. K. Giri, L. Esposito, and S Agrawal (2023). *Mapping the significance of green venture capital for sustainable development: A systematic review and future research agenda*. doi: 10.1016/j.jclepro.2023.136489.

Dickey, D. A. and W. A Fuller (1979). *Distribution of the Estimators for Autoregressive Time Series With a Unit Root*. doi: 10.1080/01621459.1979.10482531.

Dietz, S., A. Bowen, C. Dixon, and P Gradwell (2016). *'Climate value at risk' of global financial assets*. doi: 10.1038/nclimate2972.

Ding, D., B. Liu, and M Chang (2023). *Carbon Emissions and TCFD Aligned Climate-Related Information Disclosures*. doi: 10.1007/s10551-022-05292-x.

Dixit, Avinash K. and Robert S. Pindyck (1994). *Investment under Uncertainty*. Princeton, NJ: Princeton University Press.

Do, T. N. and P. J Burke (2023). *Phasing out coal power in a developing country context: Insights from Vietnam*. doi: 10.1016/j.enpol.2023.113512.

Dokuchaev, N (2014). *Volatility estimation from short time series of stock prices*. doi: 10.1080/10485252.2013.844805.

Dray, L., A. W. Schäfer, C. Grobler, C. Falter, F. Allroggen, M. E. J. Stettler, and S. R. H Barrett (2022). *Cost and emissions pathways towards net-zero climate impacts in aviation*. doi: 10.1038/s41558-022-01485-4.

Duchin, R., J. Gao, and Q Xu (2024). *Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution*. url: http://dx.doi.org/10.2139/ssrn.4095885.

Duffie, D. and D Lando (2001). *Term Structures of Credit Spreads with Incomplete Accounting Information*. doi: 10.1111/1468-0262.00208.

Duffie, D. and K. J Singleton (1999). *Modeling Term Structures of Defaultable Bonds*. doi: 10.1093/rfs/12.4.687.

Dutta, N. S., E. Gill, B. K. Arkhurst, M. Hallisey, K. Fu, and K Anderson (2023). *JUST-R metrics for considering energy justice in early-stage energy research*. doi: 10.1016/j.joule.2023.01.007.

EBA, ESMA and EIOPA (2024). *Principal Adverse Impact disclosures under the Sustainable Finance Disclosure Regulation (Joint Committee of the ESAs*. Tech. rep. url: https://www.esma.europa.eu/sites/default/files/2024-10/JC%5C_2024%5C_68%5C_Final%5C_Joint%5C_ESAs%5C_2024%5C_Final%5C_Report%5C_on%5C_PAI%5C_disclosures%5C_%5C_Article%5C_18%5C_SFDR%5C_.pdf.

ECB (2022). *2022 climate risk stress test. European Central Bank*. Tech. rep. url: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.climate%5C_stress%5C_test%5C_report.20220708%5Ctextasciitilde2e3cc0999f.en.pdf.

Eccles, R. G., I. Ioannou, and G Serafeim (2014). *The Impact of Corporate Sustainability on Organizational Processes and Performance*. doi: 10.1287/mnsc.2014.1984.

Eccles, R. G., M. D. Kastrapeli, and S. J Potter (2017). *How to Integrate ESG into Investment Decision-Making: Results of a Global Survey of Institutional Investors*. doi: 10.1111/jacf.12267.

Edmans, A (2023). *The end of ESG*. doi: 10.1111/fima.12413.

Edwards, W., R. Jain, C. Soehner, M.-C. Nadeau, and D Stephens (2023). *Green growth: Unlocking sustainability opportunities for retail banks [Article]. Mckinsey Sustainability*. url: https://www.mckinsey.com/capabilities/sustainability/our-insights/green-growth-unlocking-sustainability-opportunities-for-retail-banks.

Eisenhardt, K. M (1989). *Agency Theory: An Assessment and Review*. doi: 10.2307/258191.

Elliot, R., P. Fischer, and E Platen (1999). *Hidden Markov filtering for a mean-reverting interest rate model*. doi: 10.1109/CDC.1999.831354.

Enel (2024). *Financial information: Interim and annual reports (2014–2023) [Interim Financial Reports]. Enel*. Tech. rep. url: https://www.enel.com/investors/financials.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J Stroebel (2020). *Hedging climate change news*. doi: 10.1093/rfs/hhz072.

Environment (Chile), Ministry of (2022). *Quinto Informe Bienal de Actualización y del Informe del Inventario Nacional de Chile 1990-2020. Ministry of Environment, Chile*. url: https://cambioclimatico.mma.gob.cl/wp-content/uploads/2022/12/Informe%5C_5IBA%5C_2022.pdf.

EPRS (2020). *Sustainable Aviation Fuels. European Parliamentary Research Service*. url: https://www.europarl.europa.eu/RegData/etudes/BRIE/2020/659361/EPRS%5C_BRI(2020)659361%5C_EN.pdf.

EPRS (2022). *RefuelEU Aviation initiative*. url: https://www.europarl.europa.eu/RegData/etudes/BRIE/2022/698900/EPRS%5C_BRI(2022)698900%5C_EN.pdf.

Erb, I (2020). *Partial correlations in compositional data analysis*. doi: 10.1016/j.acags.2020.100026.

Eren, E., F. Merten, and N Verhoeven (2022). *Pricing of climate risks in financial markets: A summary of the literature (No.* url: https://www.bis.org/publ/bppdf/bispap130.htm.

Erickson, P., S. Kartha, M. Lazarus, and K Tempest (2015). *Assessing carbon lock-in*. doi: 10.1088/1748-9326/10/8/084023.

Erlandsson, U., S. Mielnik, J. Richardson, and C Rimaud (2022). *Notes on Risk-Neutral Pricing of SLBs and Step-down Structures*. doi: 10.2139/ssrn.4258897.

Escanciano, J. C. and J Olmo (2011). *Robust Backtesting Tests for Value-at-risk Models*. doi: 10.1093/jfinec/nbq021.

ETC (2023). *Financing the Transition: How to make the money flow for a net-zero economy. Energy Transition Commission*. Tech. rep. url: https://www.energy-transitions.org/wp-content/uploads/2023/08/ETC-Financing-the-Transition-MainReport%5C_update.pdf.

EU Platform on Sustainable Finance (2025). *Building trust in transition: Core elements for assessing corporate transition plans. European Commission*. Tech. rep. url: https://finance.ec.europa.eu/publications/platform-sustainable-finance-report-building-trust-transition-core-elements-assessing-corporate%5C_en.

European Commission (2020). *Updated analysis of the non-CO2 climate impacts of aviation and potential policy measures pursuant to EU Emissions Trading System*

Directive Article 30(4) (No. url: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0747.

European Commission (2023). *On facilitating finance for the transition to a sustainable economy (No.* url: http://data.europa.eu/eli/reco/2023/1425/oj.

European Commission (2024). *New monitoring rules agreed for the EU ETS, including non-CO₂ emissions from the aviation sector. European Commission, Directorate-General for Climate Action.* url: https://climate.ec.europa.eu/news-your-voice/news/new-monitoring-rules-agreed-eu-ets-including-non-co2-emissions-aviation-sector-2024-08-30%5C_en.

European Commission (2025). *Reducing emissions from aviation (Energy, Climate Change, Environment). European Commission.* url: https://climate.ec.europa.eu/eu-action/transport-decarbonisation/reducing-emissions-aviation%5C_en.

European Parliament and Council of the European Union (2022). *Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate sustainability reporting (No.* Tech. rep. url: http://data.europa.eu/eli/dir/2022/2464/oj.

European Parliament and Council of the European Union (2023). *On ensuring a level playing field for sustainable air transport (ReFuelEU Aviation) (No.* url: https://eur-lex.europa.eu/eli/reg/2023/2405/oj.

European Transport Workers' Federation (ETF) (2022). *Landing desirable jobs.* url: https://www.etf-europe.org/wp-content/uploads/2022/09/Sustainable-Aviation-Landing-Desirable-Jobs-ETF.pdf.

FAA (2021). *United States 2021 Aviation Climate Action Plan.*

Fankhauser, S., S. M. Smith, M. Allen, K. Axelsson, T. Hale, C. Hepburn, J. M. Kendall, R. Khosla, J. Lezaun, E. Mitchell-Larson, M. Obersteiner, L. Rajamani, R. Rickaby, N. Seddon, and T Wetzer (2022). *The meaning of net zero and how to get it right.* doi: 10.1038/s41558-021-01245-w.

FCA (2024). *Sustainability disclosure and labelling regime [Rules and guidance]. Financial Conduct Authority.* url: https://www.fca.org.uk/firms/sustainability-disclosure-requirements-investment-labels.

Feldhütter, P., K. Halskov, and A Krebbers (2024). *Pricing of sustainability-linked bonds.* doi: 10.1016/j.jfineco.2024.103944.

Fiedler, T., A. J. Pitman, K. Mackenzie, N. Wood, C. Jakob, and S. E Perkins-Kirkpatrick (2021). *Business risk and the emergence of climate analytics.* doi: 10.1038/s41558-020-00984-6.

Finance (Chile), Ministry of (2022). *Chile's Sustainability-Linked Bond Framework. Public Debt Office*. url: https://www.hacienda.cl/english/work-areas/international-finance/public-debt-office/esg-bonds/sustainability-linked-bonds.

Fiorentini, G., A. León, and G Rubio (2002). *Estimation and empirical performance of Heston's stochastic volatility model: The case of a thinly traded market*. doi: 10.1016/S0927-5398(01)00052-4.

Fisch-Romito, V., C. Guivarch, F. Creutzig, J. C. Minx, and M. W Callaghan (2021). *Systematic map of the literature on carbon lock-in induced by long-lived capital*. doi: 10.1088/1748-9326/aba660.

Fischer, C. and R. G Newell (2008). *Environmental and technology policies for climate mitigation*. doi: 10.1016/j.jeem.2007.11.001.

Flammer, Caroline (2021). *Corporate green bonds*. doi: 10.1016/j.jfineco.2021.01.010.

Flammer, Caroline, Thomas Giroux, and Geoffrey M. Heal (2025). *The Economics of Blended Finance*. doi: 10.1257/pandp.20251072.

Flint, E., E. Ochse, and D Polakow (2015). *Estimating long-term volatility parameters for market-consistent models*. doi: 10.4314/saaj.v14i1.2.

Flugge, M. L., R. C. K. Mok, and F. E Stewart (2021). *Striking the Right Note: Key Performance Indicators for Sovereign Sustainability-Linked Bonds. World Bank*. doi: 10.1596/36805.

FRC (2023). *CRR Thematic review of climate-related metrics and targets. Financial Reporting Council*. Tech. rep. url: https://www.frc.org.uk/library/supervision/corporate-reporting-review/corporate-reporting-thematic-reviews/.

Froot, K. A (2001). *The market for catastrophe risk: A clinical examination*. doi: 10.1016/S0304-405X(01)00052-6.

FSA, METI and ME (2021). *Basic Guidelines on Climate Transition Finance. Financial Services Agency; Ministry of Economy,Trade and Industry; and Ministry of the Environment, Japan*. url: https://www.fsa.go.jp/en/news/2021/20210524/04.pdf.

Fuenfschilling, L. and B Truffer (2016). *The interplay of institutions, actors and technologies in socio-technical systems—An analysis of transformations in the Australian urban water sector*. Tech. rep. doi: 10.1016/j.techfore.2015.11.023.

Furness, Hannah (2025). *Clustered Climate Extremes and Their Macroeconomic Impact in the Euro Area*. European Central Bank supervisory analysis.

Galanis, G., M. Napoletano, L. Popoyan, A. Sapio, and O Vardakoulias (2025). *Defining just transition*. doi: 10.1016/j.ecolecon.2024.108370.

Galitzine, C. and I. D Boyd (2015). *An analysis of the convergence of the direct simulation Monte Carlo method*. doi: 10.1016/j.jcp.2015.02.039.

Gasparini, M., M. C. Ives, B. Carr, S. Fry, and E Beinhocker (2024). *Model-based financial regulations impair the transition to net-zero carbon emissions*. doi: 10.1038/s41558-024-01972-w.

Gautam, A., Z. A. Khan, A. Gani, and M Asjad (2025). *Identification, ranking and prioritization of Key Performance Indicators for evaluating greenness of manufactured products*. doi: 10.1016/j.grets.2024.100114.

Geels, F. W., F. Berkhout, and D. P van Vuuren (2016). *Bridging analytical approaches for low-carbon transitions*. doi: 10.1038/nclimate2980.

Geels, F. W. and J Schot (2007). *Typology of sociotechnical transition pathways*. Tech. rep. doi: 10.1016/j.respol.2007.01.003.

Gez, M., S. Kerschner, S. Levi, T. Pullins, M. Rutta, M. Anderson, and D Herrick (2024). *SEC Voluntarily Stays Its Climate Rules Pending Judicial Review. White & Case*. url: https://www.whitecase.com/insight-our-thinking/sec-voluntarily-stays-its-climate-rules-pending-judicial-review.

GFANZ (2022a). *Expectations for Real-economy Transition Plans. Glasgow Financial Alliance for Net Zero*. url: https://www.gfanzero.com/press/gfanz-publishes-first-framework-for-net-zero-transition-plans/.

GFANZ (2022b). *Financial Institution Net-zero Transition Plans. Glasgow Financial Alliance for Net Zero*. url: https://assets.bbhub.io/company/sites/63/2022/10/Financial-Institutions-Net-zero-Transition-Plan-Executive-Summary.pdf.

GFANZ (2022c). *Guidance on use of sectoral pathways for financial institutions. Glasgow Financial Alliance for Net Zero*. url: https://assets.bbhub.io/company/sites/63/2022/06/GFANZ%5C_Guidance-on-Use-of-Sectoral-Pathways-for-Financial-Institutions%5C_June2022.pdf.

GFANZ (2022d). *Measuring Portfolio Alignment: Driving Enhancement, Convergence, and Adoption. Glasgow Financial Alliance for Net Zero*. url: https://www.gfanzero.com/press/gfanz-publishes-guidance-on-phase-ii-alignment-metrics/.

GFANZ (2023a). *AVIATION: Net-zero Pathways Analysis and Expectations for Transition Plans (Working Draft)*.

GFANZ (2023b). *Scaling Transition Finance and Real-economy Decarbonization [A GFANZ Secretariat Technical Review Note]. Glasgow Financial Alliance for Net Zero*. Tech. rep. url: https://www.gfanzero.com/press/gfanz-publishes-technical-note-on-transition-finance/.

Gibson Brandon, R., P. Krueger, and P. S Schmidt (2021). *ESG Rating Disagreement and Stock Returns*. doi: 10.1080/0015198X.2021.1963186.

Giglio, S., B. Kelly, and J Stroebel (2021). *Climate Finance*. doi: 10.1146/annurev-financial-102620103311.

Glasserman, P (2003). *Monte Carlo methods in financial engineering*.

Goodhart, C (1984). *Problems of Monetary Management: The UK Experience*. doi: 10.1007/978-1-349-17295-5_4.

Gössling, S. and A Humpe (2020). *The global scale, distribution and growth of aviation: Implications for climate change*. doi: 10.1016/j.gloenvcha.2020.102194.

Gözlügöl, A. A. and W.-G Ringe (2023). *Net-zero Transition and Divestments of Carbon-Intensive Assets (Working Paper No*. Tech. rep.

Grasselli, M (2017). *The 4/2 stochastic volatility model: A unified approach for the Heston and the 3/2 model*. doi: 10.1111/mafi.12124.

Grewe, V., A. Gangoli Rao, T. Grönstedt, C. Xisto, F. Linke, J. Melkert, J. Middel, B. Ohlenforst, S. Blakey, S. Christie, S. Matthes, and K Dahlmann (2021). *Evaluating the climate impact of aviation emission scenarios towards the Paris agreement including COVID-19 effects*. doi: 10.1038/s41467-021-24091-y.

Grubb, M., P. Drummond, A. Poncia, W. McDowall, D. Popp, S. Samadi, C. Penasco, K. T. Gillingham, S. Smulders, M. Glachant, G. Hassall, E. Mizuno, E. S. Rubin, A. Dechezleprêtre, and G Pavan (2021). *Induced innovation in energy technologies and systems: A review of evidence and potential implications for CO_2 mitigation*. doi: 10.1088/1748-9326/abde07.

Guagliano, C (2020). *Short-termism pressures from financial markets (pp*. Tech. rep. url: https://www.esma.europa.eu/press-news/esma-news/esma-publishes-trends-risks-and-vulnerabilities-report-1-2020.

Guevara, M., H. Petetin, O. Jorba, H. Denier van der Gon, J. Kuenen, I. Super, C. Granier, T. Doumbia, P. Ciais, Z. Liu, R. D. Lamboll, S. Schindlbacher, B. Matthews, and C Pérez García-Pando (2023). *Towards near-real-time air pollutant and greenhouse gas emissions: Lessons learned from multiple estimates during the COVID-19 pandemic*. doi: 10.5194/acp-23-8081-2023.

Haas, C., H. Jahns, K. Kempa, and U Moslener (2023). *Deep uncertainty and the transition to a low-carbon economy*. doi: 10.1016/j.erss.2023.103060.

Hadziosmanovic, M., K. Rahimi, and P Bhatia (2022). *Trends show companies are ready for Scope 3 reporting with U.S. climate disclosure rule. World Resources Institute*. Tech. rep. url: https://www.wri.org/insights/trends-show-companies-are-ready-scope-3-reporting-us-climate-disclosure-rule.

Hain, L. I., J. F. Kölbel, and M Leippold (2022). *Let's get physical: Comparing metrics of physical climate risk*. doi: 10.1016/j.frl.2021.102406.

Hameed, A (2023). *RAG-Solution [Computer software]*. url: https://github.com/ayhameed/RAG-Solution.

Haq, I. U. and D Doumbia (2022). *Structural loopholes in sustainability-linked bonds (Working Paper No.* Tech. rep. doi: 10.1596/1813-9450-10200.

Harnett, E., T. Holland, and L Kessler (2023). *Defining Transition Finance: Exploring Its Purpose, Scope, and Credibility.* url: https://rmi.org/defining-transition-finance-exploring-its-purpose-scope-and-credibility/.

He, Y., Q. Tang, and K Wang (2013). *Carbon disclosure, carbon performance, and cost of capital.* doi: 10.1080/21697221.2014.855976.

Heinkel, R., A. Kraus, and J Zechner (2001). *The Effect of Green Investment on Corporate Behavior.* doi: 10.2307/2676219.

Heston, S. L (1993). *A Closed-Form Solution for Options with Stochastic Volatility with Application to Bond and Currency Options.* doi: 10.1093/rfs/6.2.327.

Higham, D. J (2001). *An Algorithmic Introduction to Numerical Simulation of Stochastic Differential Equations.* doi: 10.1137/s0036144500378302.

Höck, A., C. Klein, A. Landau, and B Zwergel (2020). *The effect of environmental sustainability on credit risk.* doi: 10.1057/s41260-020-00155-4.

Holden, L., J. King, H. Richards, C. Siegert, and L Krebel (2024). *Measuring climate-related financial risks using scenario analysis [Quarterly Bulletin]. Bank of England.* url: https://www.bankofengland.co.uk/quarterly-bulletin/2024/2024/measuring-climate-related-financial-risks-using-scenario-analysis.

Huang, D., H. Wang, and Q Yao (2008). *Estimating GARCH models: When to use what? The Econometrics Journal, 11(1), 27–38.* doi: 10.1111/j.1368-423X.2008.00229.x.

Huang, Y. A., C. L. Weber, and H. S Matthews (2009). *Categorization of Scope 3 Emissions for Streamlined Enterprise Carbon Footprinting.* doi: 10.1021/es901643a.

Huij, J., L. Dries, P. A. Stork, and R. C. J Zwinkels (2024). *Carbon Beta: A Market-Based Measure of Climate Transition Risk Exposure.* url: http://dx.doi.org/10.2139/ssrn.3957900.

Hull, J. C (2022). *Options, futures, and other derivatives (11th ed.)*

Hunt, C. and O Weber (2019). *Fossil Fuel Divestment Strategies: Financial and Carbon-Related Consequences.* doi: 10.1177/1086026618773985.

Hyun, S. and H Lee (2025). *Assessing the progress and challenges in transition finance: Comparative insights from Japan and Europe for Korea.* doi: 10.1016/C2023-0-50749-9.

IATA (2022a). *IATA Recommended Practice—RP 1726.* url: https://www.iata.org/contentassets/139d686fa8f34c4ba7a41f7ba3e026e7/iata-rp-1726%5C_passenger-co2.pdf.

IATA (2022b). *Net zero 2050: Sustainable aviation fuels.*

IATA (2023a). *Aircraft technology net zero roadmap.*

IATA (2023b). *Finance Net Zero Roadmap*. url: https://www.iata.org/contentassets/8d19e716636a47c184e7221c77563c93/finance-net-zero-roadmap.pdf.

IATA (2024). *Disappointingly Slow Growth in SAF Production (Press Release No.* url: https://www.iata.org/en/pressroom/2024-releases/2024-12-10-03.

Ibe, O. C (2013). *Markov processes for stochastic modeling (Second)*.

ICAO (2022a). *ICAO document—CORSIA Sustainability Criteria for CORSIA Eligible Fuels*.

ICAO (2022b). *Report on the feasibility of a long-term aspirational goal (LTAG) for international civil aviation CO2 emission reductions. International Civil Aviation Organization*. Tech. rep. url: https://www.icao.int/environmental-protection/LTAG/Documents/REPORT%5C%20ON%5C%20THE%5C%20FEASIBILITY%5C%20OF%5C%20A%5C%20LONG-TERM%5C%20ASPIRATIONAL%5C%20GOAL%5C_en.pdf.

ICMA (2024). *Sustainability-Linked Bond Principles*.

IEA (2021). *Net Zero by 2050: A roadmap for the global energy sector*.

IEA (2022). *World Energy Outlook 2022*.

IFC (2023). *Social KPIs Matter*.

IFRS (2023). *IFRS S2 Climate-related Disclosures*.

IFRS (2025). *IFRS Foundation publishes jurisdictional profiles providing transparency and evidencing progress towards adoption of ISSB Standards [News]*. Tech. rep.

IFRS Foundation (2025). *Disclosing information about an entity's climate-related transition, including information about transition plans, in accordance with IFRS S2 [Guidance]. International Financial Reporting Standards*. Tech. rep. url: https://www.ifrs.org/news-and-events/news/2025/06/disclosing-information-in-accordance-with-ifrs-s2/.

IIGCC (2023). *Investor Expectations of Corporate Transition Plans: From A to Zero*.

IIGCC (2024). *Physical Climate Risk Divergence: PCRAM for investors*.

IIGCC, AIGCC, Ceres and IGCC (2024). *Net Zero Investment Framework 2.0*.

Ilhan, E., P. Krueger, Z. Sautner, and L. T Starks (2023). *Climate Risk Disclosure and Institutional Investors*. doi: 10.1093/rfs/hhad002.

Ilhan, E., Z. Sautner, and G Vilkov (2021). *Carbon Tail Risk*. doi: 10.1093/rfs/hhaa071.

Intelligence, SandP Global Market (2024). *The world's largest banks by assets, 2024*. url: https://www.spglobal.com/market-intelligence/en/news-insights/research/the-worlds-largest-banks-by-assets-2024.

IOSCO (2025a). *IOSCO Sustainable Bonds Report (No.* Tech. rep. url: https://www.iosco.org/library/pubdocs/?q=FR%5C%2F09%5C%2F2025%5C&sd=1.

IOSCO (2025b). *Work program 2025 (No.*

IPCC (1999). *Aviation and the Global Atmosphere*. url: https://www.ipcc.ch/site/assets/uploads/2018/03/av-en-1.pdf.

ISCC (2022). *ISCC Certification for Sustainable Aviation Fuels. International Sustainability and Carbon Certification*. url: https://www.iscc-system.org/markets/sustainable-transport-fuels/sustainable-aviation-fuels/.

ISDA (2021). *Sustainability-linked Derivatives: KPI Guidelines*.

ISDA (2024). *ISDA Sustainability-Linked Derivative Clause Library*.

ISO (2022). *Net Zero Guidelines*. url: https://www.iso.org/standard/85253.html.

ISSB (2022). *General Requirements for Disclosure of Sustainability-related Financial Information [Exposure draft]. International Sustainability Standards Board*. url: https://www.ifrs.org/content/dam/ifrs/project/general-sustainability-related-disclosures/exposure-draft-ifrs-s1-general-requirements-for-disclosure-of-sustainability-related-financial-information.pdf.

ISSB (2023). *IFRS S1 General Requirements for Disclosure of Sustainability-related Financial Information and IFRS S2 Climate-related Disclosures*. url: https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/.

Ivantsova, A., K. Kim, and X Lin (2021). *Climate Risk Disclosure and Institutional Investors: Evidence from the Insurance Industry*. url: http://dx.doi.org/10.2139/ssrn.3984467.

Jakob, M., F. J. Steckel, Benjamin K., S., L. Cornelsen, R. Chandra, O. Edenhofer, C. Holden, A. Löschel, T. Nace, N. Robins, J. Südekum, and J Urpelainen (2020). *The future of coal in a carbon-constrained climate*. doi: 10.1038/s41558-020-0829-6.

Japan, Government of (2023). *Basic policy for realization of green transformation: Roadmap for the next 10 years. Cabinet Secretariat*. url: https://www.cas.go.jp/jp/seisaku/gx%5C_jikkou%5C_kaigi/pdf/kihon.pdf.

Javadi, S. and A.-A Masum (2021). *The impact of climate change on the cost of bank loans*. doi: 10.1016/j.jcorpfin.2021.102019.

Jegarasasingam, A (2025). *Climate-aware investing (No*. url: https://www.bis.org/publ/bppdf/bispap155.htm.

Jessop, S (2024). *Insurers' climate alliance relaunches after member exodus. Reuters*. url: https://www.reuters.com/world/uk/insurers-climate-alliance-relaunches-after-member-exodus-2024-06-17/.

Jia, J., K. Axelsson, A. Chaudhury, and E Taylor (2023). *A Rapid Review of GHG Accounting Standards*. url: https://dx.doi.org/10.2139/ssrn.4523132.

Jiang, X., S. Kim, and S Lu (2025). *Limited accountability and awareness of corporate emissions target outcomes*. doi: 10.1038/s41558-024-02236-3.

Kathan, M. C., S. Utz, G. Dorfleitner, J. Eckberg, and L Chmel (2025). *What you see is not what you get: ESG scores and greenwashing risk*. doi: 10.1016/j.frl.2024.106710.

Khan, M., G. Serafeim, and A Yoon (2016). *Corporate Sustainability: First Evidence on Materiality*. doi: 10.2308/accr-51383.

Khosla, R., J. Lezaun, A. McGivern, and J Omukuti (2023). *Can 'Net Zero' still be an instrument of climate justice? Environmental Research Letters, 18(6), 061001*. doi: 10.1088/1748-9326/acd130.

Köhler, J., F. W. Geels, F. Kern, J. Markard, E. Onsongo, A. Wieczorek, F. Alkemade, F. Avelino, A. Bergek, F. Boons, L. Fünfschilling, D. Hess, G. Holtz, S. Hyysalo, K. Jenkins, P. Kivimaa, M. Martiskainen, A. McMeekin, M. S. Mühlemeier, and P. Wells (2019). *An agenda for sustainability transitions research: State of the art and future directions*. doi: 10.1016/j.eist.2019.01.004.

Kölbel, J. F., F. Heeb, F. Paetzold, and T Busch (2020). *Can Sustainable Investing Save the World? Reviewing the Mechanisms of Investor Impact*. doi: 10.1177/1086026620919202.

Kotchen, M. J (2005). *Impure public goods and the comparative statics of environmentally friendly consumption*. doi: 10.1016/j.jeem.2004.05.003.

Krabbe, O., G. Linthorst, K. Blok, W. Crijns-Graus, D. P. van Vuuren, N. Höhne, P. Faria, N. Aden, and A. C. Pineda (2015). *Aligning corporate greenhouse-gas emissions targets with climate goals*. doi: 10.1038/nclimate2770.

Krosnick, J. A (1999). *Survey Research*.

Krueger, P., Z. Sautner, and L. T Starks (2020). *The Importance of Climate Risks for Institutional Investors*. doi: 10.1093/rfs/hhz137.

L.P, Bloomberg (2024). *Sustainability-linked bonds (Version 2024) [Dataset]*.

Lantushenko, V. and C Schellhorn (2023). *The rising risks of fossil fuel lobbying*. doi: 10.1016/j.gfj.2023.100829.

Lee, D. S., D. W. Fahey, A. Skowron, M. R. Allen, U. Burkhardt, Q. Chen, S. J. Doherty, S. Freeman, P. M. Forster, J. Fuglestvedt, A. Gettelman, R. R. De León, L. L. Lim, M. T. Lund, R. J. Millar, B. Owen, J. E. Penner, G. Pitari, M. J. Prather, and L. J. Wilcox (2021). *The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018*. doi: 10.1016/j.atmosenv.2020.117834.

Lee, R. and M Zakota (2024). *Lenders' Environmental Monitoring: Evidence From Environmental Covenants in Private Loan Contracts*. doi: 10.1177/0148558X241257973.

Leiter, T., O. Anne, R. Al Alzar, V. Baramby, D. Bours, V. Wei Chen Clement, T. W. Dale, C. Davies, and H Jacobs (2019). *Adaptation metrics*. url: https://unepccc.org/wp-content/uploads/2019/09/adaptation-metrics-current-landscape-and-evolving-practices.pdf.

Li, J., X. Peng, and H Zhang (2025). *The role of science-based targets on carbon mitigation: Addressing the tension between net zero anxiety and economic growth*. doi: 10.1016/j.bar.2024.101491.

Li, M., G. Trencher, and J Asuka (2022). *The clean energy claims of BP, Chevron, ExxonMobil and Shell: A mismatch between discourse, actions and investments*. doi: 10.1371/journal.pone.0263596.

Lipton, A. and I Savescu (2014). *Pricing credit default swaps with bilateral value adjustments*. doi: 10.1080/14697688.2013.828239.

Lyon, T. P. and A. W Montgomery (2015). *The Means and End of Greenwash*. doi: 10.1177/1086026615575332.

Malek, G (2022). *Transferred Emissions: How Risks in Oil and Gas M&A Could Hamper the Energy Transition. Environmental Defense Fund*. url: https://business.edf.org/wp-content/blogs.dir/90/files/Transferred-Emissions-How-Oil-Gas-MA-Hamper-Energy-Transition.pdf.

Marobhe, M. I. and J. M Kansheba (2024). *Airlines and climate policy uncertainty: Are the sector's stocks soaring or stalling? Journal of Air Transport Management, 115, 102536*. doi: 10.1016/j.jairtraman.2024.102536.

Marsden, P. V. and J. D. (Eds.) Wright (2010). *Handbook of survey research (2nd ed.)*

Marupanthorn, P., C. S. Nikitopoulos, E. D. Ofosu-Hene, G. W. Peters, and K.-A Richards (2024). *Mechanisms for implementing fossil fuel divestment in portfolio management with impact on risk, return and carbon reduction*. doi: 10.1016/j.eneco.2024.107724.

Mathiesen, K (2018). *Rating climate risks to credit worthiness*. doi: 10.1038/s41558-018-0184-z.

Mayne, J (2015). *Useful Theory of Change Models*. doi: 10.3138/cjpe.230.

Meckling, J., J. E. Aldy, M. J. Kotchen, S. Carley, D. C. Esty, P. A. Raymond, B. Tonkonogy, C. Harper, G. Sawyer, and J Sweatman (2022). *Busting the myths around public investment in clean energy*. doi: 10.1038/s41560-022-01081-y.

Merton, R. C (1974). *On the Pricing of Corporate Debt: The Risk Structure of Interest Rates*. doi: 10.1111/j.1540-6261.1974.tb03058.x.

Michaelowa, A., L. Hermwille, W. Obergassel, and S Butzengeiger (2019). *Additionality revisited: Guarding the integrity of market mechanisms under the Paris Agreement*. doi: 10.1080/14693062.2019.1628695.

Mielnik, S. and U Erlandsson (2022). *An option pricing approach for sustainability-linked bonds*. url: http://dx.doi.org/10.2139/ssrn.4582574.

Moody's (2022). *Proposed Framework for Net Zero Assessments. Moody's Investors Service*. url: https://www.moodys.com/web/en/us/hosted-assets/esg-website-moodys-net-zero-assessments-request-for-feedback-07nov22.pdf.

Moody's (2023). *General Principles for Assessing Environmental, Social and Governance Risks Methodology Appendix H — Carbon Transition Indicators. Moody's Investor Service*. url: https://ratings.moodys.com/api/rmc-documents/408513.

Morgan, M. G (2014). *Use (and abuse) of expert elicitation in support of decision making for public policy*. doi: 10.1073/pnas.1319946111.

Morrison, E. A., D. A. Adu, G. Yongsheng, D. Kimani, and V. Y Saa (2025). *Assessing the Impact of Board Sustainability Committees on Greenhouse Gas Performance: Evidence From Industrialised European Countries*. doi: 10.1002/bse.4073.

MPP (2022). *Making Net-Zero Aviation Possible*. url: https://missionpossiblepartnership.org/wp-content/uploads/2023/01/Making-Net-Zero-Aviation-possible.pdf.

Mullan, M. and N Ranger (2022). *Climate-resilient finance and investment: Framing paper (OECD Environment Working Papers No*. Tech. rep. url: https://www.oecd-ilibrary.org/environment/climate-resilient-finance-and-investment%5C_223ad3b9-en.

Müller-Casseres, E., F. Leblanc, M. van den Berg, P. Fragkos, O. Dessens, H. Naghash, R. Draeger, T. Le Gallic, I. S. Tagomori, I. Tsiropoulos, J. Emmerling, L. B. Baptista, D. P. Van Vuuren, A. Giannousakis, L. Drouet, J. Portugal-Pereira, H.-S. De Boer, N. Tsanakas, P. R. R. Rochedo, and R. Schaeffer (2024). *International shipping in a world below 2 °C*. doi: 10.1038/s41558-024-01997-1.

Nacke, L., V. Vinichenko, A. Cherp, A. Jakhmola, and J Jewell (2024). *Compensating affected parties necessary for rapid coal phase-out but expensive if extended to major emitters*. doi: 10.1038/s41467-024-47667-w.

Naidu, R. and S Jessop (2024). *Companies walk ESG tightrope, under fire from all sides over disclosures. Reuters*. url: https://www.reuters.com/sustainability/boards-policy-regulation/companies-walk-esg-tightrope-under-fire-all-sides-over-disclosures-2024-02-29/.

NGFS (2023a). *Scaling Up Blended Finance for Climate Mitigation and Adaptation in Emerging Market and Developing Economies (EMDEs) [Technical document]. Network for Greening the Financial System*. Tech. rep. url: https://www.ngfs.net/en/scaling-blended-finance-climate-mitigation-and-adaptation-emerging-market-and-developing-economies-emdes.

NGFS (2023b). *Stocktake on financial institutions' transition plans and their relevance to micro-prudential authorities. Network for Greening the Financial System*. url: https://www.ngfs.net/en/stocktake-financial-institutions-transition-plans-and-their-relevance-micro-prudential-authorities.

NGFS (2024). *NGFS publishes latest long-term climate macro-financial scenarios for climate risks assessment [Press Release]. Network for Greening the Financial System*. url: https://www.ngfs.net/en/press-release/ngfs-publishes-latest-long-term-climate-macro-financial-scenarios-climate-risks-assessment.

Nguyen, Q., I. Diaz-Rainey, A. Kitto, B. I. McNeil, N. A. Pittman, and R Zhang (2023). *Scope 3 emissions: Data quality and machine learning prediction accuracy*. doi: 10.1371/journal.pclm.0000208.

NLR and SEO (2021). *Destination 2050. A Route to Net Zero European Aviation. Royal Netherlands Aerospace Centre and SEO Amsterdam Economics*. Tech. rep. url: https://www.destination2050.eu/wp-content/uploads/2021/02/Destination2050%5C_Report.pdf.

Noailly, J., L. Nowzohour, and M van den Heuvel (2022). *Does Environmental Policy Uncertainty Hinder Investments Towards a Low-Carbon Economy? (CIES Research Paper Nos*. url: https://ideas.repec.org/p/gii/ciesrp/cies%5C_rp%5C_74.html.

Norman, M. A. and W Schlenker (2024). *Empirical tests of the green paradox for climate legislation (NBER Working Paper No*. Tech. rep. doi: 10.3386/w32405.

O'Rourke, A (2003). *A new politics of engagement: Shareholder activism for corporate social responsibility*. doi: 10.1002/bse.364.

OECD (2023). *Improving the Landscape for Sustainable Infrastructure Financing. OECD Publishing*. doi: 10.1787/bc2757cd-en.

OECD (2024). *Towards more accurate, timely, and granular product-level carbon intensity metrics: Challenges and potential solutions: An IFCMA report. OECD Publishing*. Tech. rep. url: https://www.oecd-ilibrary.org/deliver/4a87e0fe-en.pdf.

OECD (2025). *Behind ESG Ratings*. url: https://www.oecd.org/finance/behind-esg-ratings-unpacking-sustainability-metrics.htm.

Ohta, H. and B. F. D Barrett (2023). *Politics of climate change and energy policy in Japan: Is green transformation likely? Earth System Governance, 17, 100187*. doi: 10.1016/j.esg.2023.100187.

Oude Lansink, A. and M Kapelko (2025). *Do Sustainability-Linked Bonds Pay Lower Interest Rates? Corporate Social Responsibility and Environmental Management, 1–11*. doi: 10.1002/csr.3246.

Owolabi, A., M. M. Mousavi, G. Gozgor, and J Li (2024). *The impact of carbon risk on the cost of debt in the listed firms in G7 economies: The role of the Paris agreement*. doi: 10.1016/j.eneco.2024.107925.

Pástor, L., R. F. Stambaugh, and L. A Taylor (2022). *Dissecting green returns*. doi: 10.1016/j.jfineco.2022.07.007.

Pástor, L. and P Veronesi (2012). *Uncertainty about Government Policy and Stock Prices*. doi: 10.1111/j.1540-6261.2012.01746.x.

Pástor, Ľ. and P Veronesi (2013). *Political uncertainty and risk premia*. doi: 10.1016/j.jfineco.2013.08.007.

Pindyck, R. S (2021). *What We Know and Don't Know about Climate Change, and Implications for Policy*. doi: 10.1086/711305.

Plantinga, A. and B Scholtens (2021). *The financial impact of fossil fuel divestment*. doi: 10.1080/14693062.2020.1806020.

Ploeg, F. van der and A Rezai (2020). *The risk of policy tipping and stranded carbon assets*. doi: 10.1016/j.jeem.2019.102258.

Polanyi, K (2024). *The great transformation: The political and economic origins of our time*.

PRI (2022). *Review of trends in ESG reporting requirements for investors. Principles for Responsible Investment*. Tech. rep. url: https://www.unpri.org/download?ac=16705.

Rahn, A., M. Schuch, K. Wicke, B. Sprecher, C. Dransfeld, and G Wende (2024). *Beyond flight operations: Assessing the environmental impact of aircraft maintenance through life cycle assessment*. doi: 10.1016/j.jclepro.2024.142195.

Reay, D (2024). *The uneven foundations of a just transition for workers: A UK perspective*. doi: 10.3389/fclim.2024.1498156.

Refinitiv (2024). *Sustainability-linked bonds [Dataset]*. url: https://www.lseg.com.

Richardson, J. and E Loh (2025). *A watershed year for the SLB market. Anthropocene Fixed Income Institute*. url: https://anthropocenefii.org/slb/a-watershed-year-for-the-slb-market.

Ritchie, G. and T Vossos (2024). *Enel's SLB target miss could cost it an additional USD 89 million in interest*.

Robeco (2024). *Navigating the climate transition with forward-looking analytics [White Paper]. Robeco*. url: https://www.robeco.com/en-us/insights/2024/01/navigating-the-climate-transition-with-forward-looking-analytics.

Robinson, J (1962). *Economic philosophy*.

Romanello, M., C. D. Napoli, C. Green, H. Kennard, P. Lampard, D. Scamman, M. Walawender, Z. Ali, N. Ameli, S. Ayeb-Karlsson, P. J. Beggs, K. Belesova, L. Berrang Ford, K. Bowen, W. Cai, M. Callaghan, D. Campbell-Lendrum, J. Chambers, T. J. Cross, and A. Costello (2023). *The 2023 report of the Lancet Countdown on health and climate change: The imperative for a health-centred response in a world facing irreversible harms*. Tech. rep. doi: 10.1016/S0140-6736(23)01859-7.

Romano, M. and N Touzi (1997). *Contingent Claims and Market Completeness in a Stochastic Volatility Model*. doi: 10.1111/1467-9965.00038.

Rosenbloom, D (2017). *Pathways: An emerging concept for the theory and governance of low-carbon transitions*. doi: 10.1016/j.gloenvcha.2016.12.011.

Rosenbloom, D (2018). *Framing low-carbon pathways: A discursive analysis of contending storylines surrounding the phase-out of coal-fired power in Ontario*. doi: 10.1016/j.eist.2017.11.003.

RSB (2023). *RSB CORSIA Certification*. url: https://rsb.org/programme/corsia-certification/.

Rumsa, M., M. John, and W Biswas (2025). *Global steel decarbonisation roadmaps: Near-zero by 2050*. doi: 10.1016/j.eiar.2025.107807.

Sanchez, F. and L Linde (2023). *Turning out the light: Criteria for determining the sequencing of countries phasing out oil extraction and the just transition implications*. doi: 10.1080/14693062.2023.2197854.

Sanchez, F. H. and J. S Palacio (2013). *Gaussian Estimation of One-Factor Mean Reversion Processes*. doi: 10.1155/2013/239384.

Santi, C (2023). *Investor climate sentiment and financial markets*. doi: 10.1016/j.irfa.2023.102490.

SASB (2018). *Airlines (SASB standard). Sustainability Accounting Standards Board*. url: https://www.sasb.org/wp-content/uploads/2018/11/Airlines%5C_Standard%5C_2018.pdf.

Sato, M., G. Gostlow, C. Higham, J. Setzer, and F Venmans (2024). *Impacts of climate litigation on firm value*. doi: 10.1038/s41893-024-01455-y.

SBTi (2021). *Science-based target setting for the aviation sector: Guidance for airlines. Science Based Targets initiative*. url: https://sciencebasedtargets.org/sectors/aviation.

SBTi (2024). *Financial Institutions Net-Zero Standard (Consultation Draft No*. url: https://sciencebasedtargets.org/standards/net-zero/financial-institutions-net-zero-standard.

Schlecht, I., C. Maurer, and L Hirth (2024). *Financial contracts for differences: The problems with conventional CfDs in electricity markets and how forward contracts can help solve them*. doi: 10.1016/j.enpol.2024.113981.

Schrage, M., D. Kiron, F. Candelon, S. Khodabandeh, and M Chu (2024). *The Future of Strategic Measurement: Enhancing KPIs With AI. MIT Sloan Management Review*. url: https://sloanreview.mit.edu/projects/the-future-of-strategic-measurement-enhancing-kpis-with-ai/?.

Schumacher, J. B (2023). *Transition Finance and its Relationship to Green Finance*.

Schumpeter, J. A (1939). *Business cycles: A theoretical, historical, and statistical analysis of the capitalist: Vol*.

Scott, M (2025). *Net-Zero Insurance Alliance relaunches with weaker commitments after antitrust scrutiny*.

Seltzer, L., L. T. Starks, and Q Zhu (2024). *Climate Regulatory Risks and Corporate Bonds (Staff Reports No.* Tech. rep. url: https://www.newyorkfed.org/medialibrary/media/research/staff%5C_reports/sr1014.pdf?sc%5C_lang=en.

Sendstad, L. H. and M Chronopoulos (2020). *Sequential investment in renewable energy technologies under policy uncertainty*. doi: 10.1016/j.enpol.2019.111152.

Shell (2023). *Greenhouse Gas Emissions Inventory Report*. Tech. rep.

Shen, P. and J Corning (2001). *Can TIPS Help Identify Long-Term Inflation Expectations? (Economic Review No.* url: https://www.kansascityfed.org/documents/976/2001-Can%5C%20TIPS%5C%20Help%5C%20Identify%5C%20Long-Term%5C%20Inflation%5C%20Expectations%5C%3F.pdf.

Sherif, Z., S. Sarfraz, M. Jolly, and K Salonitis (2022). *Identification of the Right Environmental KPIs for Manufacturing Operations: Towards a Continuous Sustainability Framework*. doi: 10.3390/ma15217690.

Shi, L. and J Fitzgerald (2023). *Introduction to the Special Issue: Planning for Climate Transformations*. doi: 10.1177/08854122231180216.

Shi, M (2024). *Do Climate Risks Increase Stock Volatility? SSRN*. url: https://dx.doi.org/10.2139/ssrn.4878181.

Simon, H. A (1955). *A Behavioral Model of Rational Choice*. doi: 10.2307/1884852.

Slovenia, Republic of (2025). *Sustainability-linked bond framework. Republic of Slovenia*. url: https://www.gov.si/assets/ministrstva/MF/Zakladnistvo/Trajnostna-obveznica-ang/Slovenia-SLB-Framework.pdf.

Smith, S., O. Geden, G. Nemet, M. Gidden, W. Lamb, C. Powis, R. Bellamy, M. Callaghan, A. Cowie, E. Cox, S. Fuss, T. Gasser, G. Grassi, J. Greene, S. Lueck, A. Mohan, F. Müller-Hansen, G. Peters, Y. Pratama, and J. Minx (2023). *State of Carbon Dioxide Removal—1st Edition*. doi: 10.17605/OSF.IO/W3B4Z.

StataCorp LLC (2023a). *heckoprobit—Ordered probit model with sample selection [Stata Base Reference Manual: Release 18]. Stata Press*. url: https://www.stata.com/manuals/rheckoprobit.pdf.

StataCorp LLC (2023b). *kappa—Interrater agreement [Stata Statistical Software: Release 17]*. url: https://www.stata.com/manuals/rkappa.pdf.

StataCorp LLC (2023c). *Spearman—Spearman's and Kendall's correlations [Stata Base Reference Manual: Release 18]*. url: https://www.stata.com/manuals/rspearman.pdf.

Steffen, B., T. Matsuo, D. Steinemann, and T. S Schmidt (2018). *Opening new markets for clean energy: The role of project developers in the global diffusion of renewable energy technologies*. doi: 10.1017/bap.2018.17.

Stern, N (2007). *The Economics of Climate Change The Stern Review. Cambridge University Press*. doi: 10.1017/CBO9780511817434.

Stiglitz, J. E. and A Weiss (1981). *Credit Rationing in Markets with Imperfect Information*.

Stoep, A. W. van der, L. A. Grzelak, and C. W Oosterlee (2014). *The Heston stochastic-local volatility model: Efficient Monte Carlo simulation*. doi: 10.1142/S0219024914500459.

Stroebel, J. and J Wurgler (2021). *What do you think about climate finance? Journal of Financial Economics, 142(2), 487–498*. doi: 10.1016/j.jfineco.2021.08.004.

Sun, X., S. Wandelt, and A Zhang (2022). *COVID-19 pandemic and air transportation: Summary of recent research, policy consideration and future research directions*. doi: 10.1016/j.trip.2022.100718.

Sustainable Fitch (2024). *Enel's Missed Targets Could Support Maturing SLB Market (Sustainable Insight). Sustainable Fitch*. url: https://www.sustainablefitch.com/research-and-insight/enel-s-missed-targets-could-support-maturing-slb-market.

SWFI (2024a). *Top 100 Asset Managers by Managed AUM. Sovereign Wealth Fund Institute*. url: https://www.swfinstitute.org/fund-rankings/asset-manager.

SWFI (2024b). *Top 100 largest insurance rankings by total assets. Sovereign Wealth Fund Institute*. url: https://www.swfinstitute.org/fund-rankings/insurance.

TAI (2023). *The Asset Owner 100 – 2023. Thinking Ahead Institute*. url: https://www.thinkingaheadinstitute.org/research-papers/the-asset-owner-100-2023/.

Tandon, A (2021). *Transition Finance: Investigating the State of Play—A Stocktake of Emerging Approaches and Financial Instruments (Environment Working Paper No.* Tech. rep.

Tayan, B., D. Larcker, E. Watts, and L Pomorski (2022). *ESG Ratings: A Compass without Direction*.

TCFD (2021). *Guidance on Metrics, Targets, and Transition Plans. Task Force on Climate-related Financial Disclosures*. url: https://www.fsb-tcfd.org/publications/.

Team, Portfolio Alignment (2021). *Measuring portfolio alignment [Technical Considerations]. Task Force on Climate-Related Financial Disclosures*. Tech. rep. url: https://www.tcfdhub.org/wp-content/uploads/2021/10/PAT%5C_Measuring%5C_Portfolio%5C_Alignment%5C_Technical%5C_Considerations.pdf.

Teske, S., S. Niklas, and S Talwar (2022). *Decarbonisation Pathways for Industries*. doi: 10.1007/978-3-030-99177-7_5.

Teske, S. (Ed.) (2019). *Achieving the Paris Climate Agreement Goals: Global and Regional 100% Renewable Energy Scenarios with Non-energy GHG Pathways for +1.5°C and +2°C. Springer International Publishing*. doi: 10.1007/978-3-030-05843-2.

TFMR (2024). *Scaling Transition Finance: Findings of the Transition Finance Market Review. Transition Finance Market Review*. url: https://www.theglobalcity.uk/insights/scaling-transition-finance.

Tichenor, M (2020). *Metrics*. url: http://doi.org/10.29164/20metrics.

Tiwari, S., M. J. Pekris, and J. J Doherty (2024). *A review of liquid hydrogen aircraft and propulsion technologies*. doi: 10.1016/j.ijhydene.2023.12.263.

Tollefson, J (2025). *Earth breaches 1.5 °C climate limit for the first time: What does it mean? [News]. Nature*. doi: 10.1038/d41586-025-00010-9.

TotalEnergies (2024). *First quarter 2024 results [Press Release]. TotalEnergies*. url: https://totalenergies.com/news/press-releases/first-quarter-2024-results.

Touboul, S., M. Glachant, A. Dechezleprêtre, S. Fankhauser, and J Stoever (2023). *Invention and Global Diffusion of Technologies for Climate Change Adaptation: A Patent Analysis*. doi: 10.1086/725365.

TPI (2021a). *Carbon Performance assessment of airlines: Note on methodology*.

TPI (2021b). *TPI's methodology report: Management Quality and Carbon Performance*. Tech. rep.

TPT (2022). *Consultation*. url: https://www.e3g.org/wp-content/uploads/TPT-Implementation-Guidance%5C_embargoed.pdf.

TPT (2023a). *Building momentum for transition plans: Status update from the Transition Plan Taskforce. Transition Plan Taskforce*. url: https://itpn.global/wp-content/uploads/2024/11/TransitionPlanTaskforce-Update-July2023-FINAL-1.pdf.

TPT (2023b). *Disclosure Framework*.

TPT (2023c). *The Transition Plan Taskforce Disclosure Framework (Consultation). IFRS Foundation Knowledge Hub*. url: https://www.ifrs.org/content/dam/ifrs/knowledge-hub/resources/tpt/disclosure-framework-oct-2023.pdf.

TPT (2024). *Progress achieved and the path ahead: The final report of the Transition Plan Taskforce. Transition Plan Taskforce*. Tech. rep. url: https://itpn.global/wp-content/uploads/2024/11/Final-Report-Progress-Achieved-and-the-Path-Ahead-TPT.pdf.

Tracker, Net Zero (2023). *New analysis: Half of world's largest companies are committed to net zero. Net Zero Tracker*. url: https://zerotracker.net/analysis/half-of-worlds-largest-companies-are-committed-to-net-zero/.

Tracker, Net Zero (2024). *Net Zero Stocktake 2024. NewClimate Institute; Oxford Net Zero; Energy & Climate Intelligence Unit; Data-Driven EnviroLab*. url: https://zerotracker.net/analysis/net-zero-stocktake-2024/.

Trinks, A., M. Mulder, and B Scholtens (2020). *An Efficiency Perspective on Carbon Emissions and Financial Performance*. doi: 10.1016/j.ecolecon.2020.106632.

Tuckman, B. and A Serrat (2022). *Fixed Income Securities: Tools for Today's Markets (4th ed.)*

UK DBT (2025). *Exposure draft of UK Sustainability Reporting Standards: UK SRS S1 and UK SRS S2 [Consultation]. Department for Business & Trade*. Tech. rep. url: https://www.gov.uk/government/consultations/exposure-drafts-uk-sustainability-reporting-standards.

UK DfT (2022). *Jet Zero Strategy: Delivering net zero aviation by 2050. UK Department for Transport*. url: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment%5C_data/file/1095952/jet-zero-strategy.pdf.

UNDRR and CGFI (2022). *Towards a climate-risk data architecture: Common and open risk metrics to align finance with climate-resilient development goals. UN Office for Disaster Risk Reduction & UK Centre for Greening Finance & Investment*. Tech. rep. url: https://www.cgfi.ac.uk/2022/11/grii-report-nov22/.

UNEP FI (2024). *Navigating Data Challenges: A Guide to Data Collection for Climate Stress Testing*.

UNEP-FI and PRI (2023). *Unlocking Investment in Net Zero*.

UNFCCC (2024a). *Climate Action Pathways. United Nations Framework Convention on Climate Change*. Tech. rep. url: https://unfccc.int/climate-action/marrakech-partnership/reporting-and-tracking/climate%5C_action%5C_pathways.

UNFCCC (2024b). *Integrating hard-to-abate industries in the process of preparing and implementing NDCs [Report]*. Tech. rep.

UNFCCC (2025). *Introduction to Climate Finance [Brief]. United Nations Framework Convention on Climate Change*. url: https://unfccc.int/topics/introduction-to-climate-finance.

Unruh, G. C (2000). *Understanding carbon lock-in*. doi: 10.1016/S0301-4215(00)00070-7.

US Department of Energy (2020). *Sustainable Aviation Fuel: Review of Technical Pathways. US Department of Energy: Office of Energy Efficiency & Renewable Energy*. Tech. rep. url: https://www.energy.gov/sites/default/files/2020/09/f78/beto-sust-aviation-fuel-sep-2020.pdf.

UTS (2022). *Limit global warming to 1.5^{o}C. Sectoral pathways and key performance indicators. University of Technology Sydney*. url: https://www.unepfi.org/wordpress/wp-content/uploads/2022/05/UTS%5C_Limit-global-warming%5C_Sectoral-Pathways-and-Key-KPIs.pdf.

Verdolini, E., L. D. Anadón, E. Baker, V. Bosetti, and L Aleluia Reis (2018). *Future prospects for energy technologies: Insights from expert elicitations*. doi: 10.1093/reep/rex028.

Vrontisi, Z., I. Charalampidis, K. Fragkiadakis, and A Florou (2024). *Towards a just transition: Identifying EU regions at a socioeconomic risk of the low-carbon transition*. doi: 10.1016/j.egycc.2024.100129.

Wang, B., Z. J. Ting, and M Zhao (2024). *Sustainable aviation fuels: Key opportunities and challenges in lowering carbon emissions for the aviation industry*. doi: 10.1016/j.ccst.2024.100263.

Wang, D., Y. Zhang, and J Li (2022). *Financing sustainability-linked bonds: A new approach to bond pricing*.

Wang, Y (2025). *Greenwashing or green evolution: Can transition finance empower green innovation in carbon-intensive enterprise? International Review of Financial Analysis, 97, 103826*. doi: 10.1016/j.irfa.2024.103826.

Wang, Y., S. Shen, J. Xie, H. Fujii, A. R. Keeley, and S Managi (2024). *How corporate climate change mitigation actions affect the cost of capital*. doi: 10.1002/csr.2853.

Watson, M. J., P. G. Machado, A. V. Da Silva, Y. Saltar, C. O. Ribeiro, C. A. O. Nascimento, and A. W Dowling (2024). *Sustainable aviation fuel technologies, costs, emissions, policies, and markets: A critical review*. doi: 10.1016/j.jclepro.2024.141472.

Weber, O., A. Hoque, and M Ayub Islam (2015). *Incorporating environmental criteria into credit risk management in Bangladeshi banks*. doi: 10.1080/20430795.2015.1008736.

Weber, O., R. W. Scholz, and G Michalik (2010). *Incorporating sustainability criteria into credit risk management*. doi: 10.1002/bse.636.

WEF (2020). *Clean Skies for Tomorrow: Sustainable Aviation Fuels as a Pathway to Net-Zero Aviation. World Economic Forum, McKinsey & Company*. url: https://www3.weforum.org/docs/WEF%5C_Clean%5C_Skies%5C_Tomorrow%5C_SAF%5C_Analytics%5C_2020.pdf.

WEF, RMI and PwC (2022). *Sustainable Aviation Fuel Certificate (SAFc) Emissions Accounting and Reporting Guidelines*. Tech. rep. url: https://www3.weforum.org/docs/WEF%5C_SAFc%5C_Accounting%5C_Guidelines%5C_2022.pdf.

Weitzman, M. L (2009). *On Modeling and Interpreting the Economics of Catastrophic Climate Change*. doi: 10.1162/rest.91.1.1.

White, S (2025). *Support for environmental shareholder proposals drops in 2025 US proxy season*.

WWF, World Bank and Global Canopy (2022). *Geospatial ESG. The emerging application of geospatial data for gaining "environmental" insights on the asset, corporate and sovereign level. WWF, World Bank & Global Canopy*. url: https://wwf-sight.org/geospatial-esg/.

Xie, J. J., M. Martin, J. Rogelj, and I Staffell (2023). *Distributional labour challenges and opportunities for decarbonizing the US power system*. doi: 10.1038/s41558-023-01802-5.

Xu, W., Z. Sun, and H Ni (2024). *Transparency pays: How carbon emission disclosure lowers cost of capital*. doi: 10.1016/j.eap.2024.05.020.

Yang, L., N. Z. Müller, and P Jinghong Liang (2021). *The Real Effects of Mandatory CSR Disclosure on Emissions: Evidence from the Greenhouse Gas Reporting Program (No.* Tech. rep.

Yang, X., Z. Zhang, S. Rao, B. Liu, and Y Li (2022). *How Does Environmental Information Disclosure Affect Pollution Emissions: Firm-Level Evidence from China*. doi: 10.3390/ijerph191912763.

Yuan, J., X. Yang, Y. Zhou, and J Zhang (2023). *The challenge of just transition in China's coal power sector: A city-level employment vulnerability assessment*. doi: 10.1080/14693062.2022.2149453.

El-Zein, A. H. and C Hedemann (2016). *Beyond problem solving: Engineering and the public good in the 21st century*. doi: 10.1016/j.jclepro.2016.07.129.

Zerbib, O. D (2019). *The effect of pro-environmental preferences on bond prices: Evidence from green bonds*. doi: 10.1016/j.jbankfin.2018.10.012.

Zhang, D (2023). *Does green finance really inhibit extreme hypocritical ESG risk? A greenwashing perspective exploration*. doi: 10.1016/j.eneco.2023.106688.

Zhao, Z., R. Huang, Y. Zhang, Y. Shiga, and R Shaw (2024). *Assessing the Role of Climate Transition Bonds in Advancing Green Transformations in Japan*. doi: 10.3390/cli12120201.

Zhou, K., Z. Qu, J. Liang, Y. Tao, and M Zhu (2024). *Threat or shield: Environmental administrative penalties and corporate greenwashing*. doi: 10.1016/j.frl.2024.105031.

Zhu, B., Z. Deng, X. Song, W. Zhao, D. Huo, T. Sun, P. Ke, D. Cui, C. Lu, H. Zhong, C. Hong, J. Qiu, S. J. Davis, P. Gentine, P. Ciais, and Z Liu (2023). *CarbonMonitor-Power near-real-time monitoring of global power generation on hourly to daily scales*. doi: 10.1038/s41597-023-02094-2.

Statement of Authorship

This statement sets out the independent research contributions of the candidate and co-authors in the publications included in the thesis.

University of Oxford

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Statement of Authorship – Paper A

PAPER TITLE

Climate Transition Plans' Assessment in Hard-to-Abate Sectors: Evidence from Airlines

PUBLICATION STATUS

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CONTRIBUTIONS (CREDIT: CREDIT.NISO.ORG)

The following contributions were made to the paper, following the Contributor Role Taxonomy:

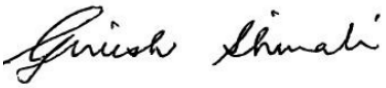
- José Luis Reséndiz García: Conceptualization; Formal analysis; Methodology; Investigation; Writing – original draft; Visualization; Writing – review & editing
- Gireesh Shrimali: Conceptualization; Supervision; Writing – review & editing

DECLARATION

Based on the contribution above, I declare that José Luis Reséndiz García has made a substantial contribution to this publication.

CO-AUTHOR SIGNATURE

Gireesh Shrimali Date: 04/09/25



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- Gireesh Shrimali: Conceptualization; Supervision; Writing – review & editing
- Johan Sulaeman: Writing – review & editing
- David Broadstock: Writing – review & editing

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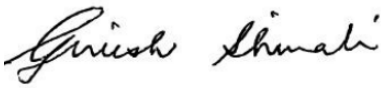

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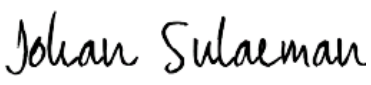

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- Gireesh Shrimali: Conceptualization; Supervision; Writing – review & editing

DECLARATION

Based on the contribution above, I declare that José Luis Reséndiz García has made a substantial contribution to this publication.

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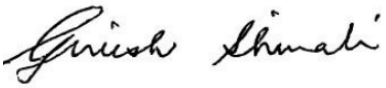
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