Transition Risk under Uncertain Climate Policy

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Abstract: This paper analyzes the economic and financial implications of climate transition risk under policy uncertainty, with a particular emphasis on the energy sector. A stochastic modeling framework is developed to capture the dynamic evolution of climate policy regimes, calibrated on NGFS transition scenarios. The model incorporates both the probability of regime shifts and their financial consequences, highlighting how regulatory adjustments respond to the accumulation of physical climate stress and transmit shocks across energy sub-sectors. By employing Monte Carlo simulations, we estimate the likelihood of different transitions and derive climate-adjusted risk indicators., including Climate Value at Risk (VaR) and Climate Expected Shortfall (ES), for both fossil fuel and renewable energy sectors. Results show a clear structural division.: Once ambitious policy regimes come into play, transition trajectories find stability, leading to a reduction in transition probabilities as climate signals are mitigated.. The fossil-based electricity sector appears as highly vulnerable to adverse financial shocks, while renewable energy sector proves relative resilience, even in extreme scenarios. These findings highlight the crucial importance of considering policy uncertainty when making strategic investment decisions and managing financial risks.
The proposed framework offers a practical tool, beneficial for both investors and policymakers, to execute forward-looking stress tests and to reallocate assets in response to emerging climate commitments.

Key-Words: Climate transition risk; Policy uncertainty; Energy economics; Risk management; Stochastic modeling; Investment strategy; Sustainable economic development.

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1 Introduction

Transition risk has gained increasing attention among financial institutions, regulators, and sustainability-oriented stakeholders, as it is expected to materially affect investment portfolios over the medium term, particularly in light of anticipated tightening of climate policies [1]. However, the actual realization of such risks remains uncertain, primarily due to the political challenges involved in imposing and upholding strict regulation. [2], [3], [4].

Transition risks do not stem directly from climate change itself, but from the policies, technological developments, and market adjustments implemented to mitigate it. These measures include carbon pricing, emissions caps, clean energy subsidies, and shifting consumer preferences. Industries heavily reliant on fossil fuels, such as power generation and manufacturing, are particularly vulnerable to regulatory and demand changes that could render their business models obsolete. For example, an automaker that fails to decarbonize its fleet could suffer substantial losses if regulations or consumer choices shift rapidly toward zero-emission vehicles.

Assessing transition risk typically involves scenario-based analysis. The climate policy scenarios provided by the Network for Greening the Financial System (NGFS) are generated using Integrated Assessment Models (IAMs) and offer a set of plausible future trajectories for climate action, each defined by key control variables such as carbon prices and emissions pathways. Two main methodological approaches exist in the literature: top-down assessments using IAM-based pathways [5], [6] and bottom-up firm-level evaluations focused on carbon exposure and sensitivity [7]. Despite progress, much of the current modeling relies on deterministic representations of transition scenarios, assuming a known and fixed policy path—a premise that is increasingly unrealistic given the profound policy, technological, and physical uncertainties involved [8], [9], [10].

Recent research has highlighted the cascading effects of transition risk on financial markets and real economies [11], [12]. Even if direct exposures appear moderate, second-order effects via supply chains, market sentiment, and systemic feedback loops can amplify losses. Furthermore, theoretical advances in sustainable finance are now exploring how markets incorporate environmental sustainability signals [13], [14], and a small but growing body of work has begun to model transition risk as a stochastic process under uncertainty [15], [16], [17].

In this highly uncertain landscape, assuming full knowledge of the future policy scenario is not realistic [17]. Uncertainties stem not only from political choices, but also from socio-economic conditions, technological readiness, and even physical aspects of the climate system [18], [19], [20]. This calls for a new generation of financial risk models that integrate dynamic scenario switching and uncertainty.

This paper addresses that gap by proposing a dynamic probabilistic framework that captures transitions between climate policy regimes. Instead of assuming fixed narratives, we model climate scenarios—based on the six NGFS reference trajectories—as stochastic states in a Markovian system, with transitions driven by observed indicators of climate risk intensity (e.g., cumulative carbon emissions). This modeling approach reflects the idea that the probability of adopting or exiting a policy regime is not static, but evolves as environmental pressures accumulate. Our framework is tested in this paper on the Moroccan energy sector, which is significantly exposed to transition risk, with the aim of quantifying potential financial losses using forward-looking climate risk indicators

By directly integrating uncertainty into the evolution of climate policies and linking it to the financial impacts on the sectors studied, our contribution offers a more realistic and relevant tool for investors, regulators and planners seeking to understand the long-term implications of climate transition risk.

2 Literature Review

The assessment of risks associated with climate transition has become a major concern for financial and economic actors, given the multidimensional and systemic nature of these risks. Linked to efforts to reduce greenhouse gas emissions and achieve international climate goals, these risks require analytical frameworks capable of capturing their dynamic, uncertain, and cross-sectoral impacts. Several methodological approaches have appeared, each offering a distinct perspective for identifying, assessing, and quantifying the consequences of transition risks. Our work contributes to this body of literature by building upon and extending uncertainty-based approaches. In particular, a growing body of recent work adopts stochastic frameworks to reflect the unpredictable nature of climate policy pathways.

For instance, [15] developed a jump-diffusion framework in which climate policies are modeled as Poisson jumps with stochastic intensity, affecting asset prices in proportion to the carbon intensity of firms. This setup captures heavy-tailed financial loss distributions and enables the simulation of sudden repricing episodes due to regulatory changes. The model highlights how regulatory uncertainty, particularly for carbon-intensive firms, can translate into non-linear, asymmetric financial risks.

Similarly, [16] introduced a structural credit risk model that captures the effects of abrupt policy transitions and firms' decarbonization trajectories. Their framework introduces the notion of "green compatibility", which quantifies a firm's alignment with low-carbon pathways and links it to the pricing of green bonds and the likelihood of default. This model underscores the importance of forward-looking, climate-aligned metrics in risk assessment.

[17] advanced this line of research by introducing a Bayesian learning framework where investors revise their beliefs about future climate policy based on observable carbon price signals. Their model integrates belief updating into risk pricing, allowing credit spreads and asset valuations to adjust dynamically as new climate information emerges. This contributes to more responsive and forward-looking risk management tools.

While our work draws inspiration from these approaches, it diverges in a fundamental way. Rather than focusing on direct asset pricing models or forward-looking credit spreads, we adopt a higher-level systemic perspective that models the transition between climate policy regimes themselves. We treat climate pathways (as defined by NGFS scenarios) as stochastic regimes, with transitions governed by a stochastic process whose intensity reflects observable climate risk signals.

This approach introduces a dynamic and probabilistic layer directly at the scenario level, rather than embedding uncertainty within asset dynamics only. We simulate numerous potential policy trajectories, allowing for non-linear tipping behaviors, reversibility, and path dependence — features often absent from traditional, static scenario analyses.

Furthermore, rather than calibrating financial losses through standard asset pricing tools such as geometric Brownian motion, we approximate financial impacts using sectoral production data from IAM under each NGFS scenario. These production paths are then used to compute transition-induced financial shocks, making the modeling framework directly linked to NGFS data.

In doing so, our model bridges the gap between macro-level policy dynamics and sectoral financial exposure, offering a novel framework to simulate Climate VaR and Expected Shortfall metrics under deep and structural uncertainty. This methodological shift offers enhanced realism and operational relevance for institutional investors seeking to integrate climate risk into portfolio construction, especially in developing economies where data limitations preclude traditional asset-level calibration.

3 Materials and Methods

To evaluate climate transition risks under policy uncertainty, this study develops a stochastic modeling framework that integrates climate scenario dynamics, policy regime changes, and sector-level financial shocks. The methodology builds on previous contributions [11], [15], [16], while adapting their concepts to a discrete-time structure compatible with NGFS scenarios. Below, we present the methodological framework in four structured subsections.

3.1 Climate Regime Dynamics and Transition Modeling

In a situation where the future direction of climate policies is still quite uncertain, we assume that the typical decision-maker—like an investor or a sector planner—doesn't know beforehand which specific climate policy path will be taken. That said, they do have an understanding of a limited set of possible policy scenarios. These are captured by the six NGFS scenarios: Net Zero 2050, Below 2°C, Nationally Determined Contributions (NDCs), Delayed Transition, Current Policies, and Fragmented World. These scenarios are widely recognized and are designed in line with Integrated Assessment Models (IAMs). They provide clear narratives covering a wide range of climate ambitions and levels of political cooperation.Each combination of scenario S_j and IAM M_i defines a distinct climate regime, resulting in a total of 18 possible regimes $R(t) \in \{1,...,18\}$. We model the evolution of climate regimes as a discrete-time Markov process with transitions occurring every five years, consistent with typical policy planning cycles and data availability. This five-year time step is commonly used in the literature, including in references such as [11], where similar discretization is applied to align with the availability of data.

However, unlike standard exogenous transition models, we make the transition probabilities endogenous: the probability of switching from one regime to another depends on a measure of physical climate stress.

This stress is captured through a Poisson jump process whose intensity λ_t evolves with climate deterioration [15]. Specifically, according to the methodology proposed by [15], the transition intensity λ_t is a function of the intensity of physical climate risk, denoted λ_p, which increases with cumulative global CO_2 emissions E(t). Figure 1 illustrates the relationship between physical risk intensity and the transition risk intensity, based on the modeling of [15].

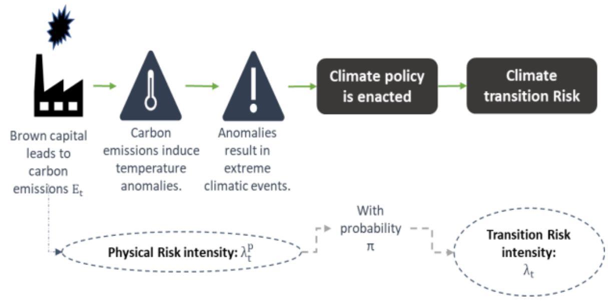

Fig. 1: Relationship between physical risk intensity and the transition risk intensity

Source: created by the authors

This modeling choice reflects the hypothesis that more visible and severe climate damage increases political pressure for stronger climate action. Following [15], the relationship is defined as:

$$\lambda_t = \pi \lambda_t^p \quad (1)$$

With,

$$\lambda_t^p = C + \xi \left(\frac{\Lambda}{\delta}\right) E(t) \ (2)$$

Where:

- C is the baseline probability of a disaster in the absence of emissions;
- ξ is a sensitivity coefficient ;
- Λ is the transient climate response (TCR) ;
- δ reflects radiative feedback (Planck effect);
- E(t) is the responsiveness of policy regimes to climate risk.

The numerical values assigned to the parameters are taken from the original literature [15] and are presented in Table 1.

Table 1. Parameters values

Parameter	Value
σ	0.12
C	0.003
ξ	0.096
Λ	0.00779
δ	0.1
π	0.6

Source: [15]

In this framework λ_t^p captures the escalating likelihood of extreme physical events as emissions accumulate, while λ_t models the induced pressure for climate policy shifts. Thus, policy transitions become more likely under high-emissions trajectories, integrating a causal link between physical climate risk and political change.

The simulation begins in 2025 with the "Current Policies" scenario under the GCAM5.3_NGFS model and proceeds in 5-year steps until 2050. Although the NGFS database offers projections across three distinct IAMs, we select a single model for the analysis to reduce complexity and maintain consistency in the interpretation of emissions, carbon pricing, and energy production dynamics. The selection of a single IAM (GCAM5.3_NGFS) is a deliberate methodological assumption. The objective of this study is not to compare structural differences across IAMs, but to analyze climate policy uncertainty conditional on a given techno-economic environment. By holding the IAM structure constant, we isolate uncertainty arising from policy regime transitions and avoid conflating model-driven variability with stochastic climate policy dynamics.

The climate regime process R(t) can be formally characterized as a discrete-time, finite-state, non-homogeneous Markov chain. Transition probabilities are time-dependent and evolve endogenously as a function of physical climate risk intensity, which itself is a function of cumulative emissions.

The model does not seek a closed-form stationary distribution in the classical Markovian sense. Instead, it exhibits quasi-absorbing states associated with ambitious climate regimes (such as Net Zero 2050 or Below 2°C), in which emission reductions dampen the physical risk signal driving further transitions. This endogenous feedback mechanism leads to a dynamic stabilization of trajectories.

3.2 Policy Signals and Transition Conditions

At each five-year interval, we evaluate whether the current climate policy regime R(t) persists or transitions toward a more ambitious one. This decision is governed by two key signals:

- A climate signal, captured by the transition intensity λ_t, derived from cumulative emissions as described in Section 3.1;
- A policy signal, based on the relative change in carbon pricing across regimes.

In this study, we employ a Poisson process to model the transitions between climate regimes. This choice is based on existing literature, particularly [15], who applied a similar approach to model discrete and random transitions between economic or environmental states. The Poisson process is well-suited for representing events occurring randomly over time, where the likelihood of a transition is independent of previous transitions. This approach is especially appropriate for modeling climate regime shifts, which are driven by physical climate risks, both of which evolve stochastically.

Given the transition intensity λ_t, we compute the probability of observing a regime shift over the 5-year time step as:

$$P_{Jump}(t) = 1 - \exp(-5\ \lambda_t) \quad (3)$$

This Poisson-based probability represents the likelihood of a regime change, triggered by physical climate risk. A random draw is used to determine whether a transition occurs, with the outcome decided by comparing a random number to $P_{Jump}(t)$. This process is carried out at every time step throughout the simulation.

Whenever a jump occurs, the model then figures out which regimes are eligible for a transition based on their carbon price trajectories.. For each candidate regime j, the difference in carbon pricing is evaluated:

$$\delta_\tau(t) = \tau_j(t+5) - \tau_{R(t)}(t) \quad (4)$$

Where:

- $\tau_j(t+5)$ is the projected carbon price in regime j five years ahead,
- $\tau_{R(t)}(t)$ is the carbon price in the current regime R at time t.
- A regime j is eligible for transition only if it reflects a tightening of climate policy, i.e.,
- $\delta_\tau(t) > 0$.

This reflects the assumption that climate transitions are asymmetrical: they are more likely to occur in response to mounting environmental pressure, and only in the direction of tightening climate policy.

The transition mechanism works as follows:

- If no jump happens—that is, if the Poisson process doesn't trigger a regime change—the current regime R(t) simply stays the same. If a jump occurs but no regime satisfies the policy condition ($\delta_\tau(t)$ >0), the regime also remains unchanged.

- If at least one eligible regime j satisfies the carbon price condition, a transition is simulated using the jump probability.

This logic combines climate-driven stochasticity with a structured filter based on carbon pricing policy signals. The model considers that climate shocks tend to boost the political chances of stricter regulations, but the transition only happens when there is a significant shift in policy ambition. This approach reflects how, in the real world, regulatory inertia usually prevails unless there's a clear and immediate environmental risk that sparks action.

3.3 Climate related Financial Shock Estimation

Once the stochastic climate regime trajectories R(t) have been simulated, the next step is to estimate the financial impact of regime transitions on specific energy sub-sectors. The goal is to quantify how changes in climate policy affect the valuation of related financial assets.

We follow the methodology proposed by [11], which interprets shifts in sectoral market share under different climate scenarios as proxies for asset revaluation. In this framework, changes in sectoral market shares under alternative climate policy scenarios are interpreted as proxies for relative asset revaluation, capturing structural shifts in revenues and expected profitability at the sectoral level, as originally proposed in [11].

Each climate regime R(t) includes projections of energy production by sub-sector. For each energy sub-sector i, we compute its market share $MS_i(\mathrm{R(t)})$, from NGFS database, as the proportion of energy production it represents within the total energy mix of regime R(t), as described in [11].

According to the modeling proposed in [11], The financial shock associated with a regime change between two-time steps t−5 and t is defined as the change in market share of sector i:

$$Shock_i(t) = MS_i(R(t)) - MS_i(\mathrm{R}(\mathrm{t}-5)) \quad (5)$$

This formulation captures the directional effect of climate policy shifts: fossil fuel sub-sectors typically see declining market shares under stricter regimes, while renewable energy sub-sectors experience increases. These market share variations serve as simplified but meaningful estimates of relative value loss or gain for financial exposures linked to each sector.

For each Monte Carlo simulation path of R(t), this calculation is repeated across time steps and across sub-sectors, allowing the construction of a distribution of financial shocks over the full policy uncertainty space. This distribution is then used in the next section to compute portfolio-level risk metrics such as Climate Value-at-Risk and Expected Shortfall.

By translating policy regime dynamics into sectoral financial outcomes, this approach connects climate uncertainty directly to asset-level vulnerabilities. It provides an operational framework for institutional investors to assess exposure to transition risk based on scenario-driven structural changes in energy markets.

3.4 Transition risk metrics

To quantify the financial exposure of energy sub-sectors to climate transition risk, we use two forward-looking and complementary risk measures widely used in climate finance: Climate Value-at-Risk (Climate VaR) and Climate Expected Shortfall (Climate ES).

These metrics are computed from the distribution of financial shocks $Shock_i(t)$ simulated for each sub-sector i, across all Monte Carlo trajectories of climate regime transitions.

The Climate VaR at confidence level C represents the maximum expected loss for sub-sector i under adverse climate transition scenarios, with probability C. It corresponds to the C-quantile of the empirical loss distribution derived from the simulated shocks:

$$\mathcal{P}(\mathrm{Shock_i(T)} < \mathrm{ClimateVaR}_i(\mathrm{T,C})) = C \quad (6)$$

In other words, there is a probability C that the loss in sub-sector i exceeds $\mathrm{ClimateVaR}_i(\mathrm{T,C})$ by the end of the horizon T. These metric captures tail risk due to unfavorable policy shifts or structural changes in market dynamics.

The Climate ES complements the VaR by measuring the average loss in extreme cases, i.e., conditional on losses exceeding the VaR threshold. It provides a more comprehensive view of downside risk:

$$\mathrm{ClimateES(T,C)} = \mathrm{E(Shock_i(T)|Shock_i(T)} < \mathrm{ClimateVaR(T,C))} \quad (7)$$

While VaR indicates the boundary of plausible losses under stressed scenarios, ES reflects the expected severity of such events. This is especially relevant in the context of transition risk, which is characterized by fat-tailed distributions due to non-linear market responses and policy jumps.

The joint use of Climate VaR and ES enables a more robust assessment of climate-related financial vulnerabilities. This framework captures both:

- Scenario-consistent shocks, reflecting structural losses under a given policy trajectory;

- Inter-scenario jumps, arising from regime switches driven by physical risk and political signals.

By relying on a large ensemble of stochastic climate regime simulations, this approach provides investors with a quantitative estimate of sectoral losses under deep uncertainty. It facilitates better-informed portfolio stress testing and supports alignment with emerging climate-related financial disclosure standards.

3.4 Implementation and Validation

The full framework is implemented using Monte Carlo simulation over a discrete time horizon spanning 2025 to 2050, with time steps of five years. At each time step, the model simulates the possible evolution of climate policy regimes R(t), determines whether a regime transition occurs, and computes the resulting financial shocks to energy sub-sectors.

All simulations start at $t_0 = 2025$ under the Current Policies scenario, using the IAM GCAM5.3_NGFS. 10,000 independent Monte Carlo trajectories are generated, each representing a plausible climate policy path.

For each regime, we extract projected values from the NGFS database including: Cumulative CO_2 emissions E(t), Carbon price trajectories τ(t), Sectoral energy production P(t).

At each step, the model computes the intensity of physical climate risk λ_t^p, derives the transition intensity λ_t, and uses this to simulate the occurrence of a policy regime jump. If a jump is triggered, the next regime is selected among those with a higher carbon price.

For each trajectory, the financial impact on energy sub-sectors is quantified based on changes in market share, which are used to compute Climate VaR and Expected Shortfall indicators as described in Section 3.4.

To ensure robustness, we conduct a sensitivity analysis on key parameters, particularly the transition intensity coefficient λ_t, which governs the responsiveness of policy shifts to physical risk. The results, including variation ranges and comparative metrics, are provided in Appendix A.

This step confirms that the model's outputs are stable under plausible parameter uncertainty and that the probabilistic structure effectively captures the influence of climate-related shocks on financial risk.

This framework is applied specifically to Morocco, with a focus on how the energy sector faces transition climate risk. This sector stands out because of its high carbon emissions, its key role in the economy, and its vulnerability to pressures to reduce emissions. The findings offer forward-looking estimates of potential financial losses amid climate policy uncertainties, helping to shape more resilient investment strategies and better climate-focused risk management.

4 Results

4.1 Probabilistic Dynamics of Climate Policy Transitions under Uncertainty

This section presents the results from our stochastic transition model, which simulates the evolution of climate policy regimes over time. Unlike deterministic pathways, our model accounts for the uncertainty and reversibility of policy decisions in response to climate stress signals.

Figure 2, Figure 3, Figure 4, Figure 5 and Figure 6 show transition probability matrices for successive five-year intervals. Each matrix shows the likelihood of moving from one NGFS scenario to another. In other words, each cell indicates the probability of shifting from a starting scenario (rows) to a target scenario (columns). These probabilities are based on the results of 10,000Monte Carlo simulations, where shifts between regimes are influenced by the transition intensity parameter λ_t, which in turn responds to cumulative emissions and climate anomalies.

The transition probability is found by counting how often a climate scenario at year N (the column) follows from a scenario at year N−1 (the row) across 10,000 Monte Carlo simulations. Because of how it's set up, the sum of transition probabilities in each row adds up to 1, since every row represents the same total number of simulations.This method ensures that the transition probabilities are conditional, meaning there's a clear certainty that each starting scenario leads to transitions into other possible scenarios.

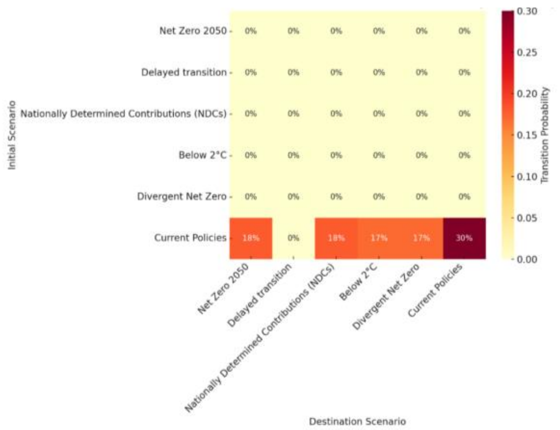

Fig. 2: Transition probability matrix between climate scenarios for 2025-2030.

Source: created by the authors

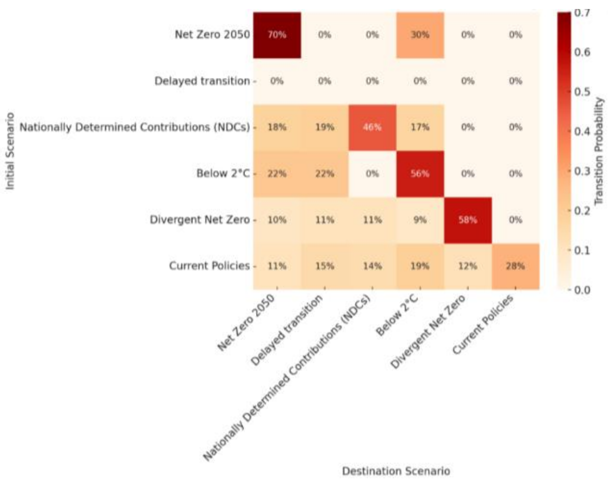

Fig. 3: Transition probability matrix between climate scenarios for 2025-2030.

Source: created by the authors

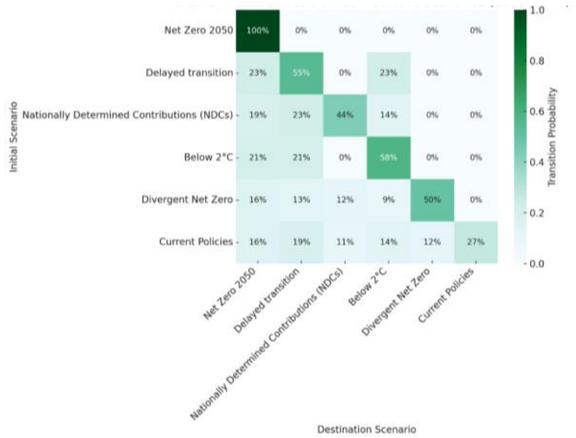

Fig. 4: Transition probability matrix between climate scenarios for 2035-2040.

Source: created by the authors

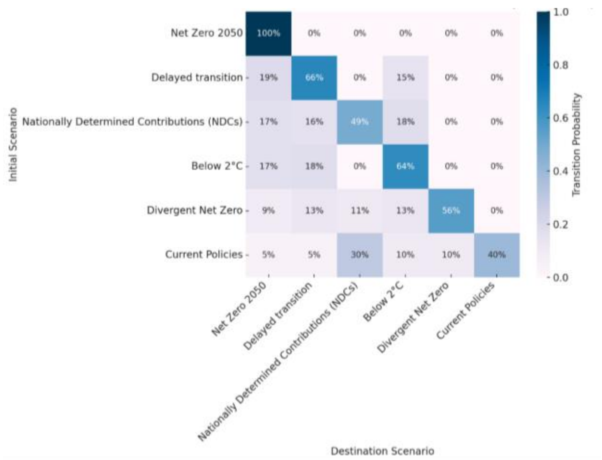

Fig. 5: Transition probability matrix between climate scenarios for 2040-2045.

Source: created by the authors

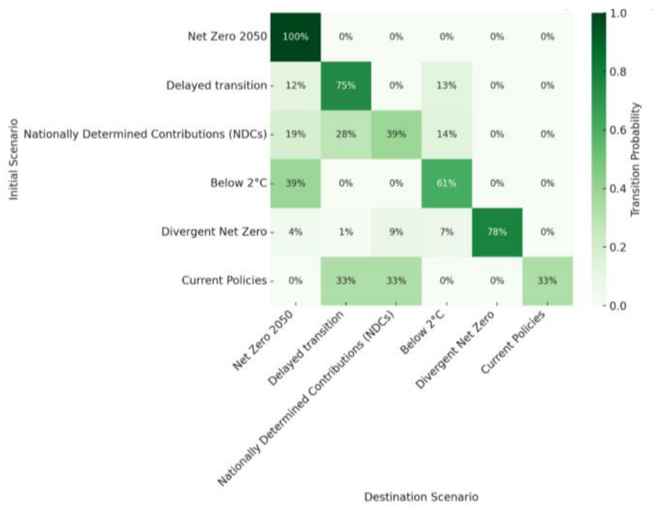

Fig. 6: Transition probability matrix between climate scenarios for 2045-2050.

Source: created by the authors

The results reveal a progressive convergence toward more ambitious scenarios.

From 2025 to 2030, the "Current Policies" scenario still dominates, sticking around about 30% of the time. However, we start to see early signs of change, with shifts toward "Net Zero 2050," "NDCs," and "Below 2°C" each showing up with roughly an 18% chance, highlighting some early uncertainty. Moving into 2030 to 2035, the landscape becomes more varied, the "Net Zero 2050" scenario gains solid ground, sticking around about 70% of the time, while the "Current Policies" path begins to lose traction, dropping to about 28%, intermediate scenarios become less stable, with around 50% intra-scenario transitions.

Between 2035 and 2040, the "Net Zero 2050" scenario becomes a solid, unwavering goal with full commitment. At the same time, other ambitious plans also start to take hold, while the "Current Policies" and "Delayed Transition" scenarios gradually lose momentum. Moving into 2040 to 2045, this pattern becomes even clearer.

Ambitious policy approaches take the lead between 2045 and 2050. Most pathways start to align closely with the goals set by the Paris Agreement, while scenarios like "Current Policies" and "Delayed Transition" are almost completely phased out.

This observed consolidation of ambitious climate regimes, particularly "Net Zero 2050" and "Below 2°C", has deeper implications within our probabilistic framework. As these scenarios become dominant, the probability of further regime switching decreases structurally. This phenomenon arises directly from how the model is designed, where the transition intensity depends on physical climate pressures, which are measured by cumulative emissions and temperature anomalies.

In practice, when strict mitigation policies like those in these scenarios are put into place, emissions growth slows down, physical risks build up more gradually, and eventually, the push for further policy changes becomes less urgent. This kind of self-regulating feedback loop aligns with sustainability goals: once climate action gains enough credibility and shows real impact, the need for more drastic shifts starts to fade. From a scientific and sustainability-oriented perspective, this result highlights how strong climate governance can have a stabilizing effect. It shows that if we adopt ambitious climate goals early and follow through effectively, we can not only lower the physical risks linked to climate change but also create a policy environment that's more predictable and less prone to sudden shifts. This really fits with the core ideas of sustainability, where building system resilience comes from being proactive and adaptive, rather than reacting to disruptions after they happen.Moreover, these dynamic shows the non-linearity of climate transition risk: delaying action or sticking with the status quo early on tends to increase the chances and impact of sudden, disruptive changes in the climate system. On the other hand, taking bold, proactive steps helps create a smoother path forward. These insights really highlight why it is important to commit early and ensure institutions work together—this way, we can avoid abrupt shocks and maintain consistency in both economic decisions and long-term policies.The convergence observed in the simulations, therefore reflects an emergent structural property of the stochastic system rather than a numerical or exogenous constraint.

These insights underscore the relevance of stochastic transition modeling in capturing the complex interplay between physical risk mitigation and policy stability, contributing to forward-looking tools for sustainable financial planning and public policy-related shocks on financial risk.

4.2 Sectoral Exposure to Transition Risk: The Case of the Moroccan Energy Sector

To illustrate the applicability of our framework, we assess the financial exposure of key Moroccan energy sub-sectors to transition risk. Specifically, we consider three representative segments: fossil-fuel, utility - Fossil-based electricity, and utility - Renewable-based electricity. Transition-induced financial shocks are derived from the stochastic climate policy pathways, and sectoral responses are simulated accordingly.

Figure 7, Figure 8 and Figure 9 present the empirical distributions of simulated financial shocks over a 5-year horizon for each sub-sector. These distributions reflect the range of potential asset value changes driven by shifts in policy regimes.

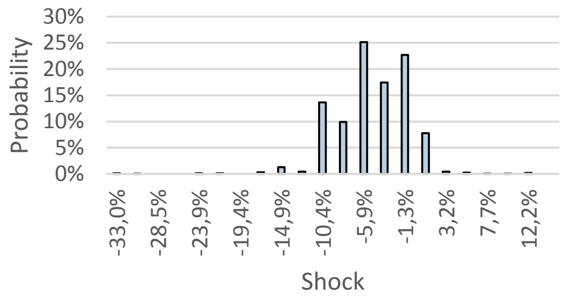

Fig. 7: Probabilistic shock distribution – Fossil-fuel.
Source: created by the authors

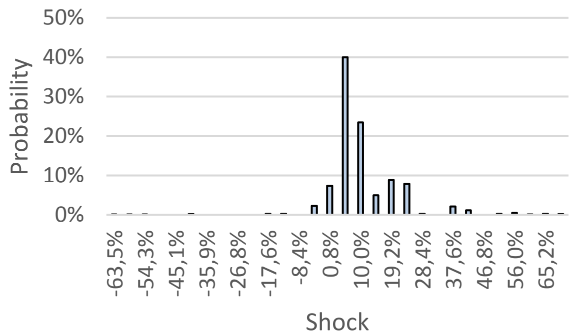

Fig. 8: Probabilistic shock distribution – utility - Renewable-based electricity.
Source: created by the authors

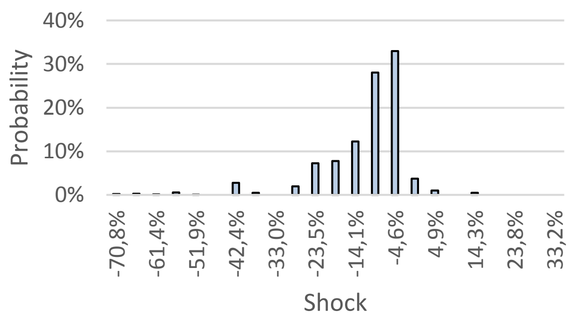

Fig. 9: Probabilistic shock distribution – utility - Fossil-based electricity.
Source: created by the authors

In addition, Figure 10 highlights forward-looking risk indicators. The Climate Value-at-Risk (VaR) and Expected Shortfall (ES) at a 95% confidence level provide a probabilistic estimates of the potential maximum and average losses under severe transition scenarios.

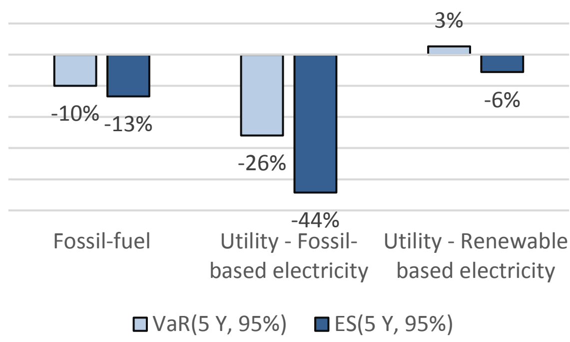

Fig. 10: Climate risk metrics (VaR and ES) across energy sub-sectors.

Source: created by the authors

The shock distribution for fossil-fuel assets points to a moderate to severe downside risk, with most losses falling between –1% and –5%, and in extreme cases, dropping as much as –10%. This highlights a clear vulnerability to carbon-heavy pathways and tightening policies. Interestingly, the risk is not symmetrical, with heavier tail losses, which suggests latent financial fragility under ambitious climate scenarios.

The fossil-based electricity sub-sector exhibits the highest exposure. Simulated shocks range widely from –20% to –45%, with extreme values exceeding –70%. These results are consistent with the concept of stranded assets, as fossil-based utilities are structurally exposed to decarbonization policies. The tail risks are particularly pronounced, making this sector the most sensitive to transition uncertainty.

In contrast, renewable-based electricity tends to show a distribution that's positively skewed, usually hovering around a 10% gain, with only a small chance of significant losses. Even in tough scenarios, any setbacks are minor, which highlights the sector's strategic strength and growth potential. moreover, its financial outlook gets better as policy goals become more ambitious, aligning well with investment strategies focused on sustainability.These results confirm that transition risk is highly heterogeneous across energy sub-sectors, with fossil-intensive segments facing disproportionate downside exposure. In contrast, low-carbon sectors demonstrate robust performance, both in terms of resilience and potential upside.

Such asymmetries are critical for investors, regulators, and policymakers seeking to align financial strategies with the Sustainable Development Goals (SDGs). Notably, the use of probabilistic metrics such as ClimateVaR and ClimateES offers a quantitative lens to support climate-resilient investment planning, risk mitigation, and the redirection of capital towards sustainable infrastructure.

5 Discussion and Conclusion

The probabilistic dynamics simulated in our framework offer valuable insights into how climate policies might evolve under structural uncertainty. By incorporating random shifts across different climate scenarios, our model provides a realistic—though still theoretical—picture of how political responses can change as climate risks grow. This dynamic setup helps us better grasp the circumstances under which ambitious policies take shape, hold steady, or end up stalling over time.

During the early simulation periods, the dominance of the “Current Policies” scenario reflects a typical pattern of institutional inertia often observed in the initial stages of transition. However, this inertia should not be interpreted as a sign of equilibrium. Rather, the model reveals a silent accumulation of latent systemic risk—driven by the absence of political response despite mounting physical climate signals. This latent risk materializes as a rising probability of regime change at each time step, suggesting a build-up of regulatory pressure that may eventually trigger abrupt policy shifts in response to extreme events, geopolitical pressures, or technological tipping points.

From 2030 onward—particularly beyond 2035—the simulations indicate a growing prevalence and stability of the “Net Zero 2050” and “Below 2°C” scenarios. This emergent lock-in behavior can be understood by looking at the structure of these NGFS pathways: once implemented, they significantly cut emissions,, which in turn lessens the physical risk signal (λ□) that influences policy transitions. As a result, the chances of another regime switch go down, creating a kind of self-reinforcing cycle. In other words, ambitious policy trajectories become auto-stabilizing, as they address the very conditions that triggered uncertainty and volatility.

This dual behavior, persistent instability under weak scenarios and rapid stabilization under ambitious ones, has direct implications for sustainability-oriented investment strategies:

- If ambitious scenarios aren’t put into action, the chances of policy tightening tend to increase over time.;
- However, once these ambitious paths are actually adopted, they gain credibility, become sustainable, and prove to be resilient, which in turn lowers the risk of sudden transitions..

Such asymmetry challenges any strategy based on the assumption of status quo persistence. Instead, our findings suggest that gradual portfolio alignment with ambitious climate trajectories is a rational risk-hedging approach. This supports the growing interest in:

- Dynamic stress testing tools that account for regime-switching probabilities,
- Probabilistic asset allocation frameworks over deterministic baselines,
- And proactive regulatory anticipation, even in the absence of enacted policies.

In contexts like Morocco, where climate policy direction remains open-ended, these results carry strong operational value. The model offers a forward-looking analytical framework for financial institutions seeking to integrate transition risks in alignment with international commitments and the Sustainable Development Goals (SDGs).

From a sectoral standpoint, our results corroborate and extend earlier findings [11], emphasizing that transition risk is not uniformly distributed across the energy system. Exposure depends on factors like carbon intensity, reliance on certain technologies, and how well a company's strategy lines up with long-term climate goals.s:

Fossil-based electricity seems to be the most vulnerable area, dealing with both high technological inflexibility—like the sunk costs tied up in hydrocarbon infrastructure—and regulatory uncertainties. Under strict policy scenarios, it faces immediate drops in value and long-term risks to its viability because of stranded assets and the costs involved in making adjustments.Traditional fossil sectors (excluding electricity) also face transition-related losses, albeit to a lesser extent. This is likely due to greater price elasticity, diversification of end-uses (e.g., industry, transport), and delayed policy transmission effects.

Renewable electricity, by contrast, shows a strong ability to withstand challenges. Even when faced with major policy changes, its risk remains steady and its performance stays reliable.. This confirms the economic and strategic rationale for reorienting capital flows towards sustainable energy assets.

Methodologically, this study underscores the relevance of probabilistic climate risk assessment models, capable of capturing policy variability, trajectory uncertainty, and heterogeneous sectoral responses. Unlike traditional stress tests that are deterministic, our framework captures a dynamic learning environment where policy paths and investor beliefs evolve together, influenced by the signals they observe.

This approach offers institutional investors and regulators a powerful tool to guide gradual decarbonization efforts while taking into account economic limitations and political uncertainties. By integrating climate risk into a wider system of feedback loops and potential regime changes, our model supports the principles of resilient financial planning and governance focused on sustainability..

These findings also have clear implications for public policy and investment strategies.To start with, they emphasize the importance of using dynamic stress testing tools that factor in changes between different scenarios, rather than sticking to fixed, one-off projections.Additionally, they suggest adopting a probabilistic approach to asset allocation—one that takes policy uncertainty into account and leans towards more resilient options like renewable energy. Also, they help anticipate regulations in advance, allowing portfolios to gradually adjust in line with ambitious climate goals before transition risks become fully apparent. In Morocco's case, this approach serves as a useful tool for making decisions that align financial strategies with the country's climate commitments (NDCs) and Sustainable Development Goals (SDGs). This not only strengthens the resilience of the financial system but also supports the shift toward a low-carbon future..

Finally, it should be emphasized that the proposed framework follows an exploratory and structural approach. The objective is not to deliver point forecasts, but to characterize the probabilistic distribution of transition risks under deep policy uncertainty. Model validation relies on internal consistency, parametric robustness, and the ability to reproduce plausible qualitative dynamics rather than ex post empirical calibration.

Appendix A

This appendix presents sensitivity analyses conducted on the key parameter of transition intensity λ, in order to assess the robustness of the stochastic framework used to simulate climate policy trajectories and their financial impacts. Through a series of parametric simulations and aggregated behavior analyses (average shocks and volatility), the appendix validates the structural consistency of the model in a probabilistic setting, accounting for political uncertainty.

In this study, the sensitivity analysis primarily focused on the parameter λ, which represents the transition intensity between climate regimes. This parameter is directly a function of cumulative emissions, which, in our model, captures the uncertainty of climate policies and emission scenarios. By construction, testing λ is sufficient to validate the robustness of the model, as this parameter already incorporates variations from other factors influencing transitions between regimes. By varying λ, we observe how uncertainties in the intensity of climate policies impact the model's outcomes, indirectly accounting for the effects of emission uncertainties. Therefore, the sensitivity analysis on λ captures the essence of the uncertainties related to transitions between climate scenarios, providing a robust overview without the need for additional tests on each individual parameter.

To assess the model's behavior, we constructed response curves under increasing values of λ, ranging from 0% to 100%, with 10% increments. Throughout the exercise, the initial policy state is held constant and corresponds to the "Current Policies" scenario. This assumption ensures that the dynamic effects observed in the simulations are purely the result of transition processes triggered by different intensities, rather than variations in initial conditions.

Two extreme values are used as reference bounds:

- λ=0%: No regime transitions occur. This case reflects a frozen political environment and allows observation of the system's baseline behavior under policy inertia.
- λ=100%: The probability of transition is maximized at every time step, simulating a scenario of rapid and systemic policy shifts in response to climate signals.

Instead of a granular analysis for each scenario, we employ two composite metrics to capture system-level responses:

- The mean value of financial shocks across all simulations, by sector;
- The volatility (standard deviation) of these shocks, as a proxy for uncertainty.

These metrics are computed for each of the three energy sub-sectors considered: (1) fossil fuels, (2) fossil-based electricity generation, and (3) renewable electricity generation. The results are displayed in Figure 11, Figure 12.

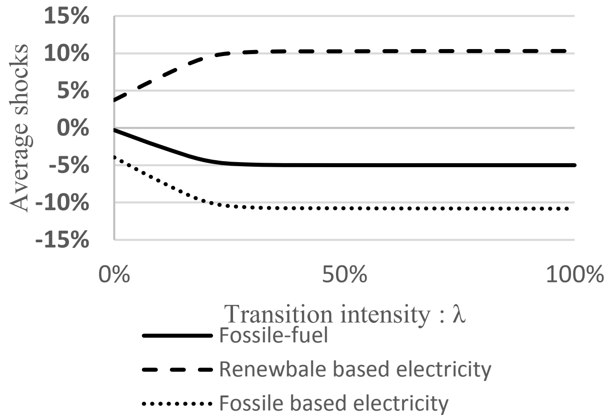

Fig. 11: Sensitivity Test of Average Shock to Transition Intensity
Source: created by the authors

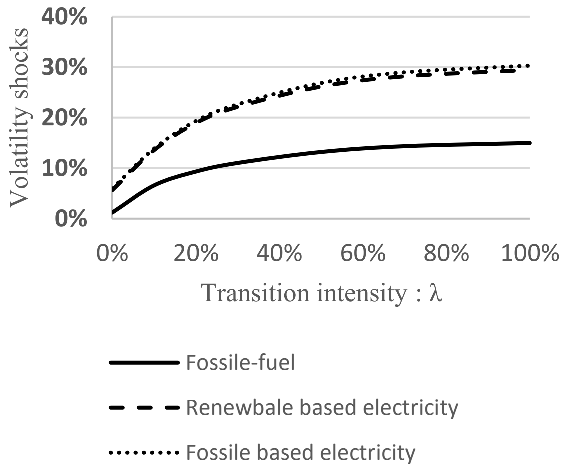

Fig. 12: Sensitivity Test of Shock Volatility to Transition Intensity.
Source: created by the authors

The analysis reveals that the absolute magnitude of shocks increases with the transition intensity parameter λ exceeds 25%, fossil-based sectors experience average losses nearing –5%, while transition-aligned sectors (renewables) register average gains of up to +10%. Simultaneously, the volatility of shocks increases with higher values of λ, peaking at around 30%. This trend reflects the heightened uncertainty associated with more dynamic climate policy environments and corresponding market adjustments.

Beyond the 25% threshold, both the average shock and its volatility tend to stabilize. This plateau effect can be attributed to the fact that the cumulative transition probability over a 5-year horizon reaches 100%, effectively saturating the system with regime switches. In such a context, additional increases in λ no longer produce marginal changes in transition outcomes.

The Monte Carlo sample size (10,000 trajectories) was selected to ensure empirical convergence of risk indicators. Preliminary tests indicate that tail quantiles (VaR and ES) stabilize beyond this threshold, with very limited sensitivity to initial conditions and random seeds. The observed convergence reflects the structural stability of the probabilistic framework rather than a numerical artifact.

In conclusion, these sensitivity tests confirm the internal consistency and robustness of the model. The stochastic structure responds progressively to variations in political uncertainty, offering a realistic simulation of financial risks across energy subsectors. This supports the framework's relevance for forward-looking assessments of climate transition risks in investment decision-making.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.