Rethinking Climate Investment Targets: From Static Funding Gaps to Data-Driven Dynamic Modelling

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Static Climate Finance Goals vs. Evolving Investments

Prevailing narratives on climate finance emphasize a persistent funding gap between actual investments and the ambitious targets set by international agreements (e.g., \$100B/year from COP15, \$1.3T/year by COP29). However, these static targets often overlook the dynamic trajectories through which investments scale over time.

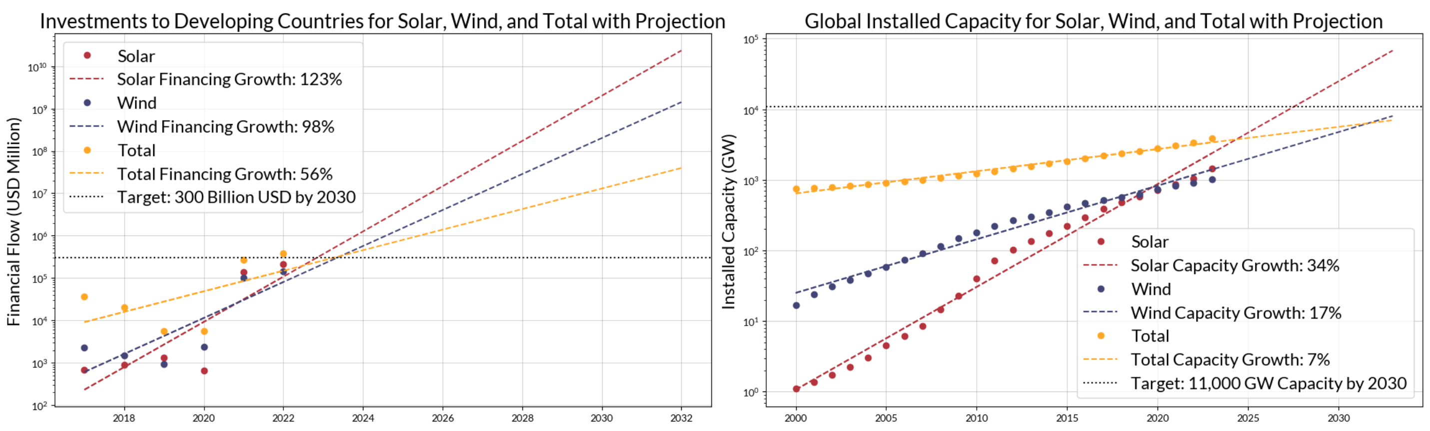


Figure 1. The left figure shows the financing flows going into developing countries with exponential projection and the COP29 NCQG target; The right figure shows the global capacity growth and the COP28 target.

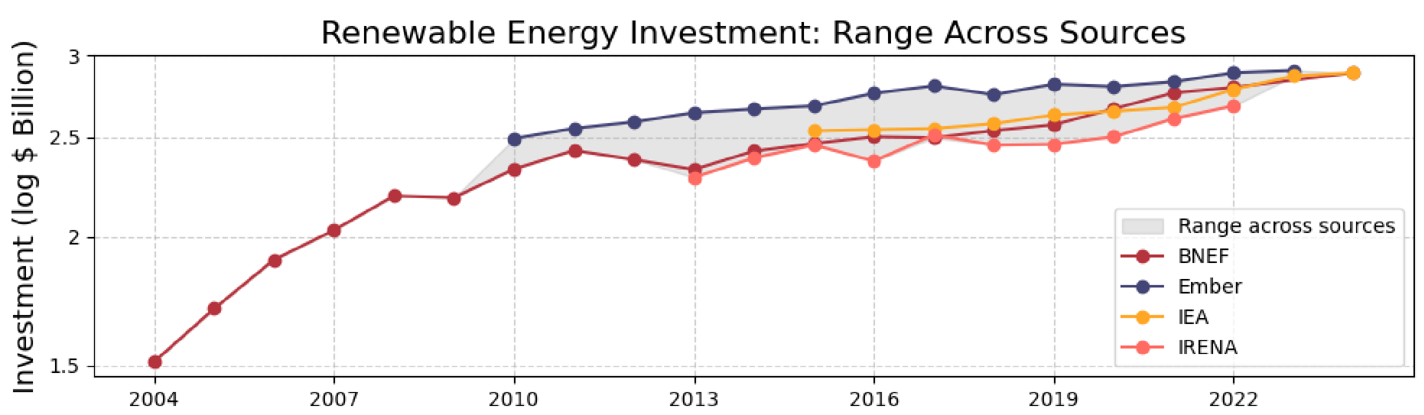
Investment in the energy system—the most critical component of the transition—is growing at an annual rate of 14%. Within this, mitigation-related investments, which account for over 94.5% of total energy transition spending, are increasing more slowly at 13% per year, while adaptation investments are growing at 21% annually. Notably, investments targeting the energy system itself are expanding at an exceptional 60% per year.

In absolute terms, the energy system received roughly \$1.74 trillion, averaging 30% of total annual energy transition investments. Of this, \$0.79 trillion (46.4%) went to solar and \$0.67 trillion (40.2%) to wind. Renewable energy capacity, particularly in solar and wind, continues to rise exponentially, reflecting both rapid deployment and scale.

Given that capacity has historically followed exponential growth patterns, assuming a constant annual investment is unrealistic. Capturing the evolving dynamics of the energy transition requires modeling approaches that account for time-varying investment trajectories, growth rates, and technology deployment [1, 3]. Such models are especially important for analyzing policy interactions, which can significantly influence investment behavior and capital allocation across technologies [2]. Explicitly modeling these dynamics enables a clearer understanding of how firms respond to changing market and policy conditions and how these responses shape the long-term evolution of the energy system. In particular, technology adoption typically follows an S-shaped path, which directly shapes investment trajectories.

Data Gaps & Inconsistencies

Tracking global energy investment is challenging because multiple organizations collect data using different scopes, methodologies, and definitions. Major sources include the IEA *World Energy Investment reports*, CPI's *Global Landscape of Climate Finance*, IRENA's *Renewable Energy Statistics* and *Renewable Power Generation Cost Database*, BloombergNEF *Energy Transition Investment Trends*, REN21's *Renewables Global Status Report*, Ember, and OWID. While these datasets provide valuable insights, they are often not directly comparable.



A key challenge is the measurement of private finance, which accounts for about 70% of global energy investment but remains opaque. Limited disclosure leads to underreporting and inconsistent aggregation. For example, CPI estimated renewable power investment at \$553 billion in 2022, while IEA reported \$608 billion, reflecting differences between tracking financial commitments (CPI) and capital expenditures (IEA).

Further inconsistencies arise from inclusion rules: some sources report only renewables, while others include nuclear or classify technologies differently. These divergences create gaps and discrepancies that obscure a coherent picture of global energy finance.

What is required for dynamic investment modelling?

Implementing the ABM requires integrating data from three key domains:

- **Power Plants:** Annual costs (CapEx and OpEx), annual capacity factors, location, ownership, lifetime, commissioning year, and retirement year.
- **Firms:** Portfolio composition and evolution over time, including the number and types of assets held, as well as investment strategies across different technologies.
- **Electricity Markets:** Market demand, regulatory structure (regulated vs. liberalized), and dispatch rules that allocate demand across generation assets.

Sources: IEA (2025), World Energy Investment 2025, IEA, Paris https://www.iea.org/reports/world-energy-investment-2025, Licence: CC BY 4.0; Climate Policy Initiative. 2025. Global Landscape of Climate Finance 2025. https://www.climatepolicyinitiative.org/publication/global-landscape-of- climate-finance-2025; IRENA (2025), Renewable energy statistics 2025, International Renewable Energy Agency, Abu Dhabi; IRENA (2025), Renewable power generation costs in 2024, International Renewable Energy Agency, Abu Dhabi; REN21. 2024. Renewables 2024 Global Status Report Collection, Global Overview.

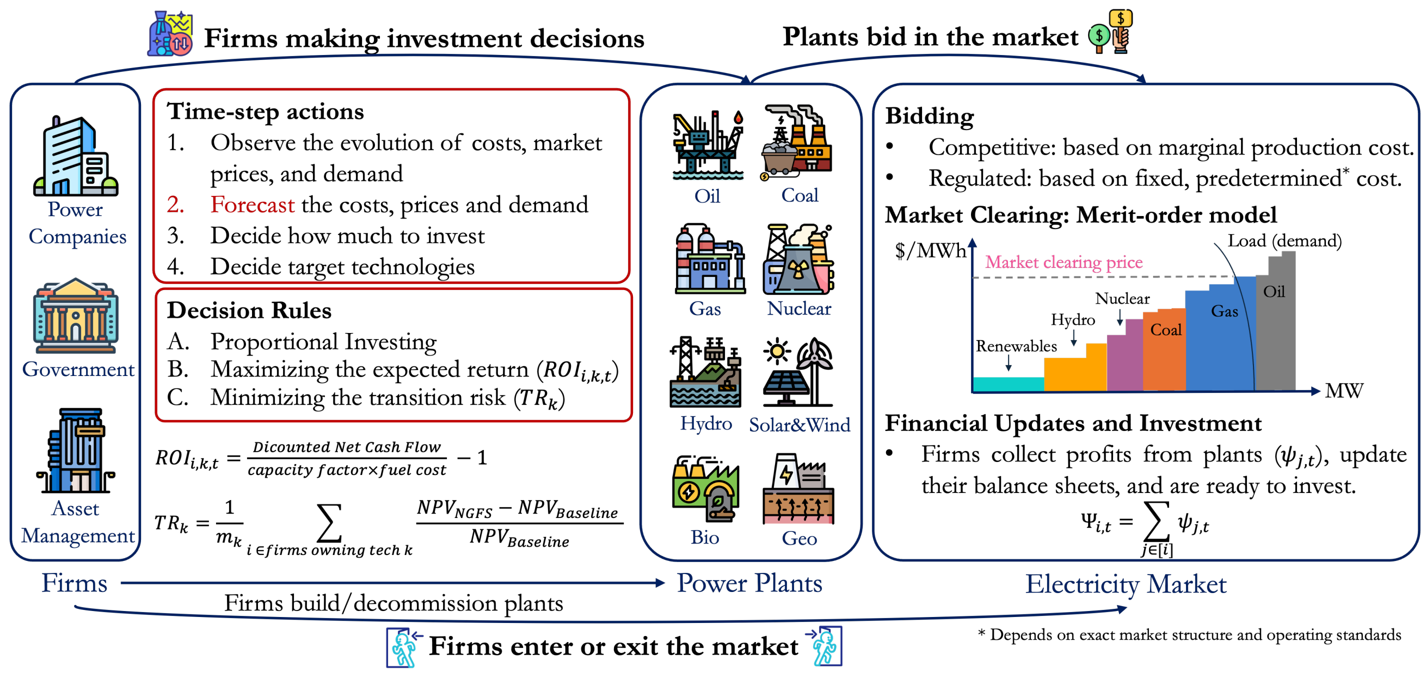
Firm- and Asset-Level Data for Dynamic Investment Modeling

To address these inconsistencies and requirements, we shift to firm- and asset-level data from S&P Capital IQ and Rystad Energy. The proposed agent-based model (ABM) relies on one-to-one matching with real firms and projects, capturing financing structures and investment decisions at a granular level. This provides a more reliable foundation for representing how investment dynamics evolve over time, beyond what aggregated figures can offer. Below is a summary table of two main data sources we rely on for the energy ABM.

	Firms	Assets	Power Plants	Tech. Categories
Capital IQ	28,461	136,454	72,739	12
Rystad	23,514	210,854	201,231	15

Table 1. Overview of firm- and asset-level data from Capital IQ and Rystad Energy used for the ABM. Due to the data quality and availability, we restricted the data from 2001 to 2023.

Agent-Based Model of Energy Investment Decisions



The model captures firms' investment in energy assets. Firms own power plants that operate in energy markets, generating profits or losses. Investment decisions depend on past performance, expectations about demand, prices, technology costs, and policy, making them responsive to energy policies [4].

Model Outputs: Technology Shifts and Investment

The figures illustrate how an output-based pricing system alters firms' technology portfolios and long-term investment trajectories. In the no-policy case (upper panels), firms maintain a relatively stable reliance on fossil fuels (coal and gas), with only modest growth in renewables. This inertia in investment behavior results in continued capital flows to carbon-intensive technologies, which even increase toward the latter half of the forecast horizon.

By contrast, under the policy scenario (lower panels), firms shift investment more decisively toward low-carbon technologies, particularly wind and solar PV. This structural change in the fuel mix is mirrored by a significant and sustained redirection of cumulative investment toward renewables. While some diversification reappears in later years, overall investment remains markedly more concentrated in clean energy compared to the no-policy trajectory.

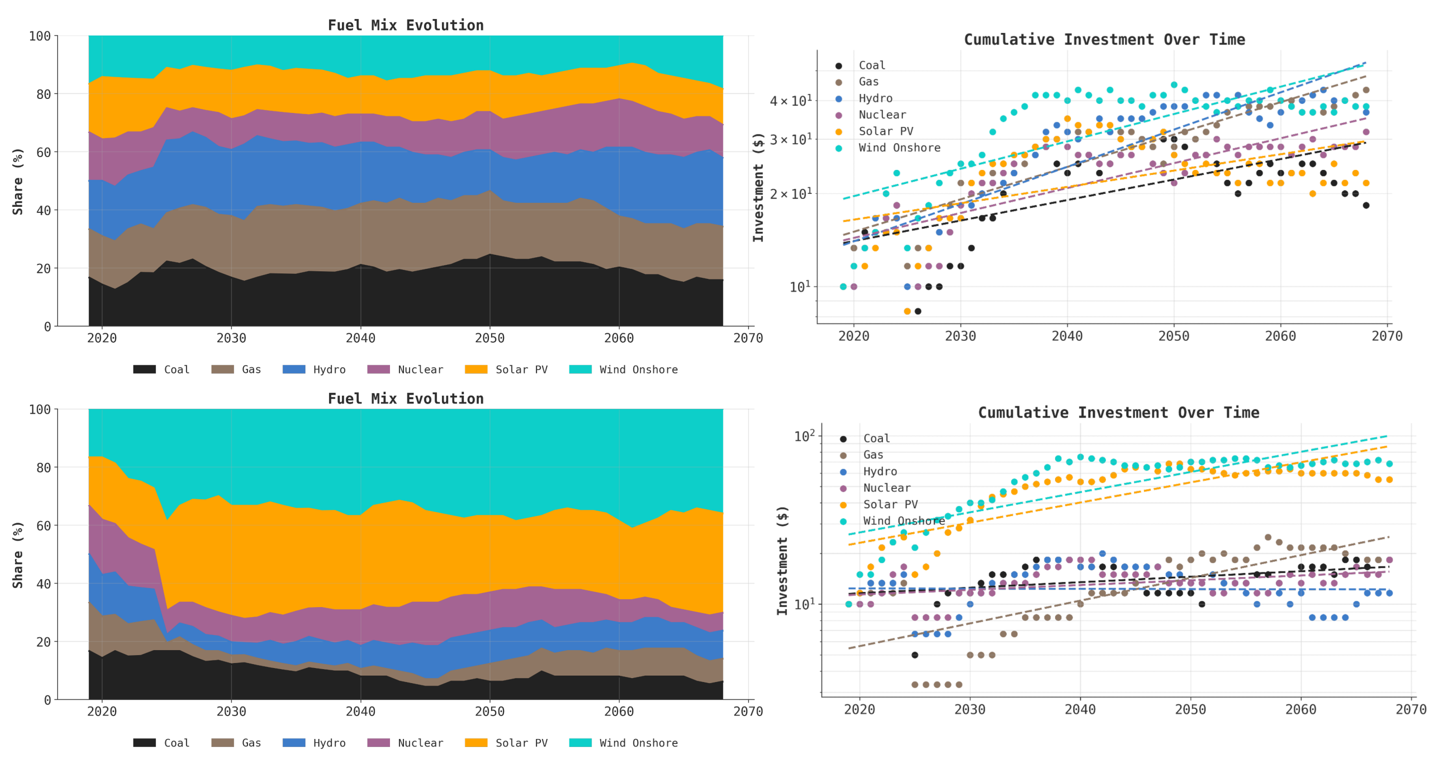


Figure 2. Projected evolution of firms' investment behavior over the next 50 years under two scenarios with sample data. Left panels depict the fuel mix composition, with the top panel showing the baseline without policy intervention and the bottom panel illustrating the scenario with policy intervention. Right panels show the corresponding trajectories of cumulative billion-dollar investments for each scenario.

References

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