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FTT-FLEX

Flexible Technology Diffusion Analysis Tool for Data Poor Countries

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Abstract

To achieve substantial emission reductions, widespread low-carbon technology adoption is vital. The process by which new technologies are developed and adopted and how their costs evolve is critical to understanding decarbonization. Modeling of this process requires a tool that realistically describes several phenomena related to technology adoption in different sectors, including technology diffusion, investment decisions, evolution of technology costs, and technology lock-in, among others. This paper introduces FTT-FLEX, a simplification of the Future Technology Transformation model. FTT-FLEX is suitable for application as a single-country, standalone tool or in connection with a macroeconomic model. FTT-FLEX captures the core country-level of features of Future Technology Transformation (knowledge spillovers as the driver of technology cost and inertia in the adoption of new technologies) as they pertain to an individual country and greatly reduces the data required as compared with the global Future Technology Transformation model. As presented, FTT-FLEX is a natural complement to country-specific macroeconomic models that analyze the decarbonization of key emitting sectors in small developing countries. The utility of FTT-FLEX is demonstrated by a decarbonization analysis for the power sector in Guinea-Bissau.

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FTT-FLEX: Flexible Technology Diffusion Analysis Tool for Data Poor Countries

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1. Introduction and objective

In their pursuit of a sustainable future, and given the urgent need to address climate change, countries worldwide are actively pursuing decarbonization strategies (United Nations, 2015). These strategies require the formulation of policies that facilitate the reduction of carbon emissions in the day-to-day operations of an economy, including in the power sector. An effective policy must take into consideration economic incentives but should also consider the complex dynamics by which low-carbon technologies are adopted to meet increasing power demand.

Data-rich high-income countries often have access to analytical tools to evaluate low-carbon policies and their implications for emission reductions, energy uses, government budgets, and overall macroeconomic impacts. However, many developing countries face significant hurdles, due in part to limited data availability. While the World Bank's MFMod (Burns et al, 2019) and MANAGE (Beyene et al, 2023) models lend themselves to analyzing the economic incentives and consequences of climate change policies, they lack features related to how the diffusion of new technologies might endogenously affect the cost and therefore uptake of different technologies.

This paper introduces FTT-FLEX, a model designed to bridge that gap in a developing country context. Applied to the power sector, FTT-FLEX can be used to help design policies to decarbonize the power sector in a small open economy context. FTT-FLEX can also be used in smaller high-income countries whose actions are sufficiently small on a global scale as not to affect global prices significantly.

2. The FTT-FLEX model

FTT-FLEX is a simplification of on an already established global modeling framework of technology diffusion called Future Technology Transformation-FTT (Mercure, 2012). The framework is applicable to the supply of different goods for which there is a menu of technologies including energy, transport, steel, or heating (Mercure, 2012; Mercure et al., 2014; Mercure et al., 2018; Knobloch et al., 2018, Vercoulen et al., 2018).

This paper focuses on the application of FTT-FLEX in the supply of electrical power. However, the approach laid out can be extended to the choice of technology in other sectors as well. FTT-FLEX reduces the data requirements of the global FTT model, allowing it to be used in countries with limited data. It focusses on the process embedded in the Global FTT model by which small developing economies adopt and diffuse power generation technologies available at the global level but incorporates the impact that external decisions might have on the global technology-cost frontier faced by the smaller economy.

In FTT, the technology diffusion process of a given technology depends both on its cost structure and the extent to which it is already used (its share in total generation capacity) both at the global and local level. Technology cost is assumed to be a declining function of global cumulative past investments in the technology. Experience with a new technology, proxied by its share in total output, constitutes a global knowledge externality. As the world installs more capacity in emergent technologies the cost of these technologies for new investors comes down. In FTT-FLEX, the reduction in costs from the diffusion and installation of technologies in the rest of the world are an exogenous input. Nevertheless, domestic diffusion is affected (as in the larger FTT model) by the extent to which different technologies are used in the domestic economy.

In contrast, standard "least-cost" energy systems models propose an efficient path in which the menu of cheapest technologies is chosen to satisfy a given path for energy demand – but those costs are not affected by the extent of take-up of a technology. In FTT, lower cost technologies also have a pro tanto advantage. But increasing market share generates an incumbency advantage that can either reinforce or mute the cost advantages. A technology with plenty of installed capacity in the domestic market will have several advantages over an incipient technology that are unrelated to costs. For instance, investors having seen the technology applied elsewhere will exhibit greater confidence in established technologies, reducing uncertainty around projects and perception of risks. This introduces hysteresis into the evolution of costs and the diffusion of technologies, helping to explain why older well-established technologies may persist even though new technologies may have lower costs.

FTT-FLEX can be used alone or in combination with a macro-economic model. Used alone, FTT-FLEX for the power sector takes as an exogenous input an electricity demand path and models the composition of technologies that are chosen over time to meet that demand. The user can modify parameters to implement most policies typically considered by governments in their decarbonization strategies (carbon tax, energy tax, subsidies, kick-start policies, and regulations), and evaluate the implications of those policies on the trajectories of cost, investment, technology mix, and emissions.

When used in conjunction with a macroeconomic model, the electricity demand path is determined by the macroeconomic model (as a function of prices, growth and other economic factors) and passed to FTT-FLEX, which determines the electricity price and power sector investment pathways that are then passed back to the macroeconomic model. Allowing electricity demand to adjust to prices and vice versa, improves the realism of the combined model as compared to the partial-equilibrium outputs derived from a least-cost model or FTT-FLEX operating in isolation.

Section 3, below, describes in more detail the intuition and main features of FTT-FLEX. It is followed by section 4, which describes how FTT-FLEX can be coupled with a macroeconomic model (in this instance, the World Bank's Macro-Fiscal Model for Climate Analytics (MFMod-CC)). Finally, section 5 presents a case study that illustrates some of the advantages of establishing the economic impacts of transition policies by jointly modeling power demand, technological diffusion, and macroeconomics.

While this paper focuses on the use of FTT-FLEX in the analysis of the decarbonization of the power sector, it can also be applied to other problems (such as heating and transportation), where future costs are likely to depend on the extent to which new technologies have been adopted.

3. FTT-FLEX features (power sector application)

The bulk of this section describes FTT-FLEX as applied to the power sector. It concludes with a short overview of alternative applications. The complete list of model equations is provided in Annex I at the end of the paper.

3.1 Diffusion and share dynamics

FTT-FLEX is a dynamic model that calculates the technological distribution in the supply of electrical power as a function of an electricity demand path provided to it. In any given period, electricity, a flow, is provided by the installed stock of generation capacity and various intermediate inputs (coal, oil, sun, wind, and hydro). Different feasible technologies are embodied in this capital stock, so that the total electricity supply is distributed into shares corresponding to the technologies used. As the capital stock is retired or electricity demand is increased, new capital stock must be built to meet the demand shortfall. The essential question answered by the model is, how does the composition of this capital stock, and thus the distribution of supplied electricity, change over time. The model incorporates a trajectory of the *technology diffusion process* (as first proposed by Rogers 1962) to help answer the question. This subsection describes the diffusion process.

Two time constants play a crucial role for the dynamics of the composition of the capital stock: the time required to build new generation capacity and the longevity of the capital associated with each technology. The shorter the construction time, the more quickly a technology will gain share once the unit economics are favorable to it. The longer the lifespan (or the slower the depreciation), the slower the transition away from an existing technology even after unit costs have turned against it.

Let the diffusion rate $\mathrm{A}_{i,j}$ measure the ease (speed) with which durable capital of type *j* is replaced by durable capital of type *i:* the greater its magnitude, the quicker the transition. Let $\lambda_i$denote the construction time of a given technology *i* and τ_j the corresponding lifespan of the technology *j.* Then the *diffusion rate* from technology *j* to *i* ($\mathrm{A}_{i,j}$) can then be written as the reciprocal of the product of the two times a constant:

$$\mathrm{A}_{i,j} = \frac{constant}{\lambda_i \ \cdot \tau_j}$$

The cost of a given project using technology *i* in FTT-FLEX is determined probabilistically. For each technology there is a distribution of costs around an average value $\overline{Cost_i}$. Under suitable distributional assumptions,[1] the probability that technology *i* is cheaper than technology *j* is given by

$$\mathrm{F_{ij}} = \frac{1}{1 + exp\left(\frac{\left(\overline{Cost_i} - \overline{Cost_j}\right)}{\sigma_{ij}}\right)}$$

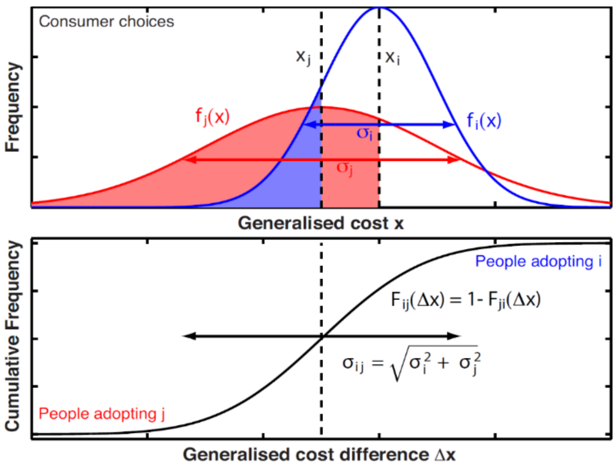
The interpretation is the following. If the average cost of technology *i* is greater than that of technology *j* then the denominator is larger and the probability that the cost of any given project using technology *i* is cheaper than some project using technology *j* is low. But is it not zero, because in some instances (in the tails of the distribution some projects *i* will be cheaper than some projects using technology *j*). The spread of the distributions of projects *i* and *j* is measured by σ_{ij}, the product of the standard deviations (see Annex I for full equations). The larger this value the more overlap in the costs of individual projects *i* and *j*, and therefore smaller the advantage of a technology with a given lower *average* cost. This is because even when on average projects using technology *i* are more expensive there will be a larger number of such projects that are lower cost than the more expensive part of the tail of the technology *j* distribution.

Figure 1 illustrates this in action. The average cost of technology *i* is given as X_i and its distribution of costs by the blue line $f_i(x)$, and similarly the average cost of technology *j* is given by X_j and the distribution of costs by the red line $f_j(x)$. For any individual project, pairing drawn from these distributions, the cost of each technology can be compared. Project pairings in the blue shaded area are ones where the project cost of technology *i* is lower than the average cost of technology *j* and in these cases an investor would

[1] The cost perceptions are assumed to be Gumbel distributed and have a single peak, so that the binary logit becomes a logistic curve. For more information see supplementary materials from Mercure et al., 2018.

choose technology *i* because for this project its costs is lower than the paired *j* project even though on average technology *i* technology is more expensive. In the red shaded space to the left and above the blue shaded space, investors would choose technology *j*. The bottom graph of Figure 1 shows the smooth cumulative distribution of choices between technology *j* and technology *i*.

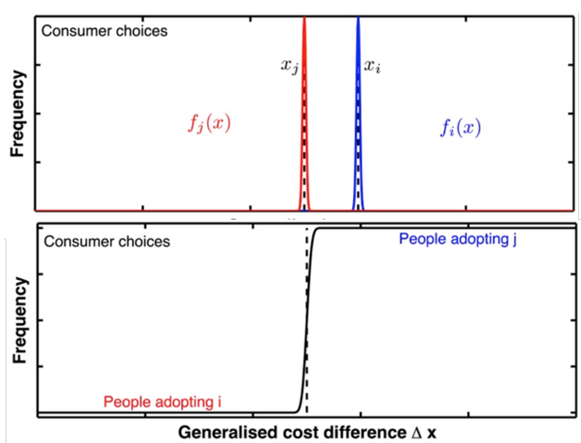
Figure 1: Binary discrete choice of technology adoption based on cost distributions (taken from Mercure, 2012)



In Figure 1 technology *j* has the average cost advantage (*X_j*) and a relatively wide distribution of costs across individual projects (σ_j) – some very expensive some very inexpensive. Because of the wide distribution there is a relatively large number of technology *j* projects where the cost of a particular installation or project is very high (and indeed higher than the more expensive, on average, technology *i*). Though few, such high-cost technology *j* projects drawn from the distribution will be costlier than most, if not all, draws from the distribution of technology *i* (the project pairings shaded white under the red distribution curve). It is this pairwise comparison over the whole distribution that is being measured by F_{ij}. The idea is that when costs are uncertain (and spread rather widely), multiple types of technology will be built at the same time, and F_{ij} measures the comparative advantage of *i* over *j.*

In extremis (Figure 2*)*, when the costs of the technologies are certain (and the probability curves are very narrow and very high, there will be no overlap across the curves and only one the technology with low average cost will be implemented (technology *j* in the figure below).

Figure 2: Technology adoption based on cost certainty.



Given the distribution of technologies, we can derive the dynamic of technological diffusion.

Let S_i^t be the share of technology *i* in period *t* (the sum over all technologies in each period is equal to 1), then the change in the share of technology *i* over time *t* (ΔS_i^t) is given by:

$$\Delta S_i^t \ = \ S_i^{t-1} \cdot \sum\nolimits_{j=1}^{N} S_j^{t-1} \left[A_{ij}^{t-1} F_{ij}^{t-1} \ - \ A_{ji}^{t-1} F_{ji}^{t-1} \right]$$

Focusing on the term in brackets, we can see that technology *i* grows more quickly when its diffusion rates and probabilities of lower cost ($A_{ij} F_{ij}$) are high in the pairwise comparisons with the other technologies. Growth in the use of technology *i* is penalized when the reverse comparisons are high ($A_{ji} F_{ij}$).

An essential feature of the model is the S_i^{t-1} term outside the sum. It captures the incumbency advantage discussed in the introduction. Say there are two technologies, *COAL* and *SOLAR,* for which the cost and diffusion comparisons (the entire term inside the sum) are, for the sake of argument, identical. From the perspective of a standard least cost model the technologies would be equivalent. But if the historical process has resulted in the current share of *COAL* being significantly greater than that of *SOLAR,* ($S_{COAL}^t \gg S_{SOLAR}^t$), then the incumbency advantage will tilt new investments towards coal and there will be much more new *COAL* capacity than *SOLAR* capacity in the immediate future. This incumbency advantage captures network effects in the supply chains, such as the existence of technology-specific skilled labor, and the non-pecuniary influence of familiarity on the risk perceptions of investors that new technologies cannot overcome immediately, even if the new technology has lower "average costs".

This incumbency advantage imposes friction on the adjustment process, with the important implication that the usual equivalence between price- and quantity-based policies is broken. In a frictionless model (such as a least cost optimization model), a carbon price policy and a policy of technology share mandates that achieve the same energy mix will have the same cost. In FTT the carbon price needed to overcome the friction *and* achieve the same energy mix as the direct mandate would be significantly higher. By the same token, policies that accelerate the transition in the direction of new low-cost technologies – by forcing increases in their share through demonstration projects or plant lifetime regulation mandates (which would speed the retirement of old technologies)– generate significant value for the economy by increasing their share in the installed capital stock, and thereby speeding up the transition toward them.[2] In practice, quantity and price policies target distinct market failures in the technology diffusion process—network effects and carbon emissions, respectively. By utilizing both policies in tandem, the deployment of low carbon technologies can be synergistically accelerated.

3.2 Cost dynamics

Another important feature of FTT-FLEX relates to the dynamics of average costs $\overline{Cost\_\iota}$ (the average cost of technology *i*). This variable measures the levelized cost of electricity (LCOE) for technology *i.* This can be split into the unit cost by factor: capital cost, operations and maintenance cost (O&M), fuel cost, and carbon cost. As briefly discussed in the introduction, FTT and FTT-FLEX implement a *learning curve* for

[2] In a global model (such as FTT-power) such policies have a further effect of bringing down the average cost through the cumulative global supply channel, and thus generate distinct long run equilibria. However, this feature is not present in FTT-FLEX. Since FTT-FLEX is specifically designed for small emitters and data-poor countries, their technology profiles are unlikely to significantly impact global outcomes.

the capital and O&M cost components. This learning curve translates into a fixed percentage cost reduction for each percent increase in global cumulative installed capacity of a technology, a relationship known as Wright's law. In practice, for solar energy it is assumed that for every percent increase in global cumulative production there is a 0.25% reduction in cost, in line with historical trends (IRENA 2023).

The learning curve feature allows assumptions about global decarbonization trajectories to be easily converted into domestic cost trajectories. If the world decarbonizes more quickly, solar in the modeled country will become more competitive with time, making a domestic solar-based net zero policy cheaper. Conversely, a slower global expansion of solar would have an adverse effect on the domestic cost of decarbonization.

3.3 Reduced data requirements

In addition to implementing the technology diffusion process described above, FTT-FLEX substantially reduces the data requirements as compared with FTT or other global energy systems models. Table 1 summarizes data requirements in FTT-FLEX (power sector).

Table 1: Summary of FTT-FLEX data requirement

Country specific data requirement	Country specific policy variables (default = zero)	Global data assumptions (provided)
Starting share of power generation by technology	Carbon tax rate and carbon tax rate exemptions by fuel	LCOE (means and standard deviation) by technology broken down to • Capital • O&M • Fuel (Assumed 7% discount rate and zero carbon tax). Source: IEA
Total electricity demand projections	Fuel tax by fuel-type	CO_2 intensity by power generation technology. Source: IEA
	Investment subsidy by technology	Global baseline cumulative power production by technology Source: Our World In Data (history) and IEA three future scenarios, World Energy Outlook 2022
	Minimum and maximum generation potential by technology (default 0 Gwh and 3000 Gwh)	Lifetime of different kinds of power plant (years) Source: IEA
		Lead construction time of different power plant types (years) Source: IEA
		Learning rate by technology Source: Main FTT
		International fuel price assumptions based on IEA three future scenarios. Source: World Energy Outlook 2022, IEA

FTT-FLEX utilizes technology-specific cost data from the IEA's Projected Costs of Generating Electricity (2020) database, which includes capital, operating and maintenance, and fuel costs. Average costs and standard deviations are calculated from this database. The default assumptions in the cost data include a 7% discount rate and zero carbon tax rate. The model also incorporates other global assumptions such as average lifetime and lead construction time of different power generation technologies (IEA), CO_2 emission coefficient per GWh (IEA), learning rate for renewable technologies (IRENA), and international energy price (IEA). While these global data sets are provided as defaults, users have the flexibility to revise them or use alternative data sources according to their preferences.

Regarding cumulative global power production, the model implements projections from the IEA. Users can select from three scenarios for cumulative global power production and future fossil fuel prices, sourced from the IEA's World Energy Outlook (2022): the Stated Policies Scenario (STEPS), Announced Pledges Scenario (APS), and Net Zero Emissions (NZE). According to the IEA, these scenarios are linked to global temperature increases of approximately 2.5˚C, 1.7˚C, and 1.5˚C, respectively. Coupled with the learning rate assumptions from IRENA, the global production data in these scenarios are sufficient to describe the dynamics of each technology's average LCOE in the FTT-FLEX model.

Where available, domestically sourced technology <u>cost</u> data are preferred to the global estimates, as these sources tend to better reflect local attributes like labor costs, logistic expenses, and production costs. In cases where a country intends to import equipment and external capacity, utilizing a global cost database becomes an acceptable option. The FTT-FLEX database offers pre-collected global average cost data, serving as an initial reference point for a readily accessible tool. In the next version of FTT-FLEX, users will be able to set their own discount rate to reflect local financing conditions or connect the discount rate to interest rates in a macroeconomic model (see the Discussion section).

In summary, the country specific data required to run FTT-FLEX are:

- Historical data for the production shares of each technology
- Total electricity demand projections
- Production maxima for physically limited technologies like hydroelectricity, wind, and solar

Since the future share dynamics depend on the shares today (this is an important feature of the model dynamics), the historical production shares by technology are the main country specific initial condition of setting up the model.

For some technologies geography places a hard physical limit on the potential for domestic capacity. This is most clearly the case for hydroelectric power, for which potential sites are easily enumerated, but it is also a factor for wind and solar, for which the scope for adding capacity is not boundless. If such data can be obtained, the model implements a cost penalty to the technology as its specific capacity limit is approached.

In the absence of more detailed data, the dynamics of the underlying diffusion theory does most of the heavy lifting. The analysis and conclusions that can be drawn are thus strongly contingent on how appropriate the theory is to the domestic setting (see Limitations section in this paper). The robust empirical support that has been found for these dynamics in Mercure et al., 2021, Mercure et al., 2018b and Semieniuk et al., 2022 in the context of the FTT model suggests that incorporating these dynamics even in low-data contexts is likely preferable to the alternative of assuming static costs.

Box 1: FTT-FLEX and FTT-Power comparison

The full FTT-Power model, on which FTT-FLEX is based on, implements additional features with greater data requirements.

FTT-Power implements dispatch and storage modules, which account for the cost of intermittency of new renewable energy capacity (cloudy days or days with now wind). This requires significant detail on the distributions of load and demand.

Instead of the capacity limit that we implement for certain technologies, FTT-Power implements natural resource cost curves, whereby the quality of suitable sites declines with the amount of locally installed capacity, thus reducing the energy yield of additional installations.

Both of these features could be integrated into FTT-FLEX but require large amounts of data that may be difficult to acquire in a developing country context.

Table below summarizes the features of the full FTT model and those of FTT-FLEX.

Model features	FTT	FTT-FLEX
Technology diffusion theory	✓	✓
Global learning rate	✓	✓ based on exogenous global cumulative production
Breakdown of LCOEs	✓	✓
Global resource cost curve	✓	X simpler treatment for diminishing return to renewables investment and exogenous cap on maximum and minimum generation
Dispatching submodule (Power)	✓	X (this could be added where relevant without increasing data requirements but at the expense of an additional complexity.)
Many policy instruments	✓	✓

3.4 FTT-FLEX model relationships

FTT-FLEX incorporates the core FTT preference, diffusion rate, and share equations outlined in Section 3. While retaining the essence of the main FTT equations, other equations within FTT-FLEX have undergone simplification by eliminating explicit references to predefined FTT regions, technologies, or sectors. In this study, we have employed FTT-FLEX within the context of the power sector, and several equations have been tailored to this sector's unique characteristics.

Table 2: Summary of FTT-FLEX equations

	FTT FLEX-Equations
Technology-specific equation	
Core FTT equations	• Investor preferences • Diffusion rate • Technology shares dynamic
Learning rate	• Investment learning rate (global exogenous technology cumulation) • Operation &Maintenance (O&M) learning rate (global exogenous technology cumulation)
LCOEs (mean and standard deviation)	• Investment costs subject to global learning rate • O&M costs subject to domestic learning rate • Fuel costs grow with international fuel price projections. • Policy options: investment subsidies, fuel tax and carbon tax • Total LCOE is the sum of investment, O&M, fuel costs and policy costs
Max and Min	• Penalties equations when share breaches exogenous maximum or minimum limit. • Total augmented cost is total cost LCOE plus penalties (this is the cost that get used in the preference equation)
Production	• Production by technology
Aggregated equations	
Electricity price	• Weighted average LCOEs (without penalties) • Weighted average LCOEs (with penalties)
Emissions	• Aggregate CO_2 emissions
Investment	• Total capital stock (delta = new investment less depreciation)
Fiscal	• Carbon tax revenues • Energy tax revenues • Total subsidy spending

The full detail of the FTT-FLEX equations is given in Annex I.

FTT-FLEX model is implemented in two versions: one coded in EViews and the other in Python using ModelFlow, a Python-based business logic programming language (Hansen, 2023). Both versions are available to users upon request.

3.5 FTT-FLEX application in other sectors

The FTT-FLEX model has been deliberately designed to be adaptable to a variety of sectors. This study focusses on its application in the power sector given its status as a major polluter and the well-defined nature of its technologies. The FTT-FLEX framework can also be applied in other sectors that have clearly defined competing technologies and comprehensive technology information (including lead time, lifetime, costs, energy type per production unit, and existing shares), for instance:

- Passenger or freight transport: diesel, petrol, hybrid, hydrogen, and electric vehicles, with total demand assessed in terms of passenger kilometers.
- Heating: gas boilers, oil boilers, electric heaters, solar options, and heat pumps, with total demand measured in heating units.

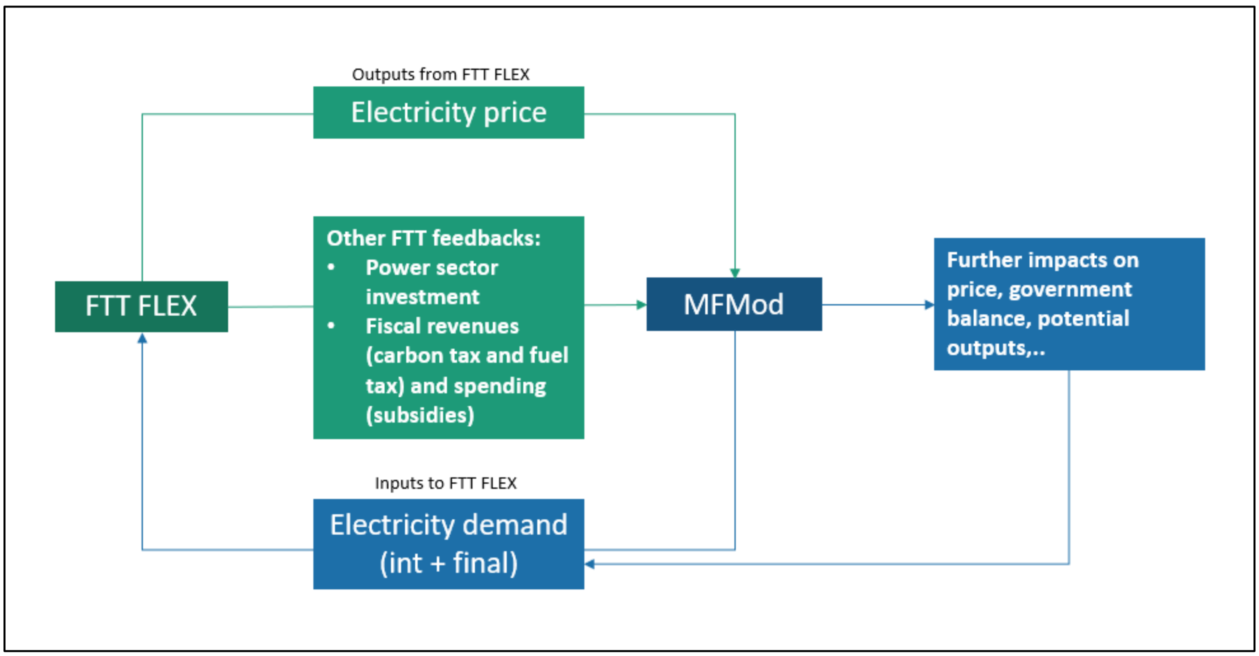
- Steel production: blast furnace, electric arc furnace, and recycled steel, with total demand expressed in tons of steel.
- Other sectors of technological change relevant for climate policies such as aviation, shipping, industry (for as long as data can be found).

These specific examples can be run as standalone analyses in FTT-FLEX or can be integrated into a macroeconomic model, enabling a comprehensive evaluation of broader economic and policy impacts, akin to the approach presented for the power sector in the following section.

4. MFMod (macrostructural economic model) and FTT-FLEX (power sector) linkages

The figure below illustrates the key connections between the MFMod macroeconomic model and the FTT-FLEX model in the context of the power sector. The FTT-FLEX model takes as inputs the total domestic electricity demand from MFMod, which in turn depends on GDP, prices, and other macroeconomic variables. Based on the logic outlined in section 2, FTT-FLEX calculates the power generation mix required to meet this demand, as well as the technology specific LCOE. The MFMod model receives feedback from the FTT-FLEX model on electricity prices (calculated as the share weighted average LCOE across technology), power sector capital investment and any fiscal adjustments resulting from decarbonization policy.

Figure 3: Summary of linkages between MFMod and FTT-FLEX



These in turn will impact power demand and the nature for economic activity as power intensive sectors shrink (expand) in the face of rising (falling) costs and resources are re-allocated in the economy.

5. Case example: Guinea-Bissau's power sector

This section reports results from efforts to apply FTT-FLEX and the MFMod framework to assess the effects of power sector decarbonization policies in Guinea-Bissau. The aim is not to deliver a complete assessment of decarbonization of the power sector, but rather to showcase the strengths and weakness of using FTT-FLEX for such an exercise.

5.1 Background on the power sector in Guinea-Bissau

Guinea-Bissau is a small coastal country, situated in West Africa. It is one of the world's poorest and most fragile countries. Only 35% of its population has access to electricity (World Bank, 2021) and the country contributed to less than 0.01% of global emissions (UNDP, 2022). Given its modest size, limited energy consumption, and lack of data, it is not surprising that most global energy-economic models, including the main FTT model, do not include Guinea-Bissau.

Historically, Guinea-Bissau has depended heavily on fuel oil for electricity generation. However, since 2020, solar power has emerged as a significant player in the market, experiencing rapid growth from a 1% share in total power generation in 2020 to 7% in 2021.[3] The remaining oil-based electricity generation is supplied by a floating power station docked near its capital city, Bissau, and operated by the Turkish company Karpowership.[4] The country plans to build its first hydropower plant in 2024, which is expected to contribute approximately 9% to the country's power mix. Currently, a 20MW solar PV power project is in the permitting stage and, if approved, is expected to come online in 2025,[5] nearly doubling its current total electric power generation capacity. Guinea-Bissau boasts significant solar potential, with the International Renewable Energy Agency (IRENA) indicating that 100% of the country's land area is suitable for an annual PV output of 1.6-1.8 (MWh/kWp[6]), compared to a global average of 20%.

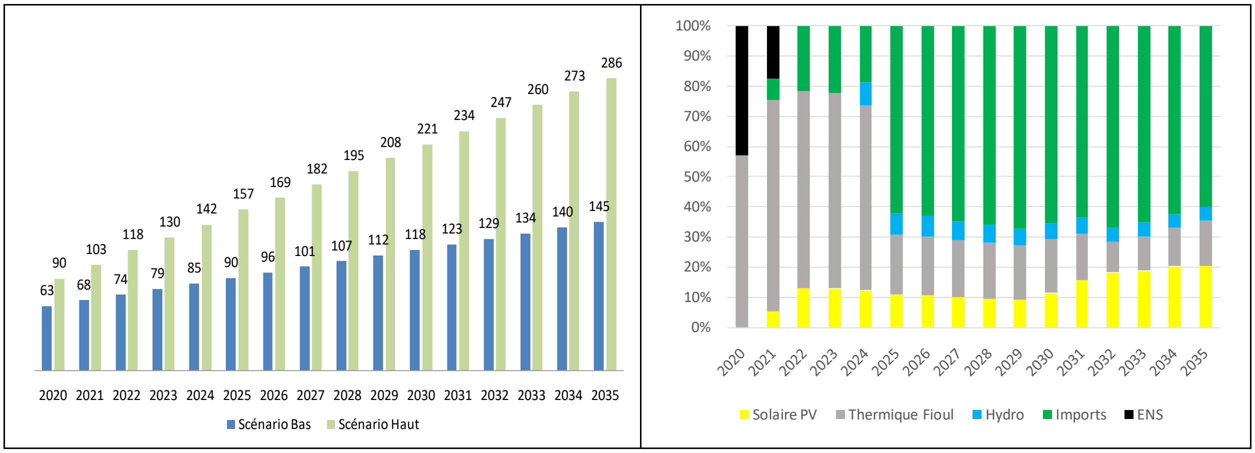
Unfortunately, the planned hydro plant as well as other energy infrastructure projects to enable power imports from its neighboring countries are facing severe delays,[7] suggesting that reliance on Karpowership will persist in the short to medium term.

5.2 The Guinea-Bissau 2020 least cost generation expansion plan

The World Bank's 2020 Power Sector Policy Note, using the least cost approach, recommended Guinea-Bissau move away from heavy-fuel oil for power generation towards low-cost electricity imports from the neighboring country of Guinea.

[3] https://www.irena.org/-/media/Files/IRENA/Agency/Statistics/Statistical_Profiles/Africa/Guinea-Bissau_Africa_RE_SP.pdf
[4] https://www.karpowership.com/
[5] https://www.power-technology.com/data-insights/power-plant-profile-bissau-solar-pv-park-1-guinea-bissau/
[6] kWp = kilowatt peak power output.
[7] Guinea-Bissau Public Policy Notes 2023:Energy, World Bank, forthcoming.

Figure 4 Guinea-Bissau's projected electricity demand (MW) and the optimal least-cost energy mix 2020-2035, Least Cost Generation Expansion Plan, 2020.



Source(s) Figure taken from Guinea-Bissau: Power Sector Policy Note 2020, World Bank.
Note(s): Solaire PV = Solar PV, Thermique Fioul = heavy-fuel oil, ENS = suppressed demand.

The least-cost approach employed in that study calculates the lowest cost energy mix for a specified level of electricity demand, based on assumptions regarding future technology costs (LCOEs) and a set of constraints, such as decarbonization goals or storage options. However, as discussed above, such approaches overlook the path dependency of technology diffusion and the role that endogenous cost reduction may play.

5.3 FTT-FLEX baseline for Guinea-Bissau's power sector

Based on historical power sector share data in 2020 and short-term projections up to 2025 that reflect the latest power sector developments mentioned above, FTT-FLEX calculates the power generation mix from 2026 onward to meet the projected electricity demand (growing at around 5% pa) coming from the Guinea-Bissau MFMod macroeconomic model. Due to a lack of data for cost, cost distribution, lifetime, and lead time, the FTT-FLEX analysis reported below excludes electricity imports from neighboring countries as competing technologies. With more data, these could be included.

The projected power sector baseline assumes that the rest of the world's energy transition is limited, consistent with the IEA's World Energy Outlook 2022 Stated Policies Scenario (STEPS). However, within the global power sector, solar is anticipated to expand even when there are limitations on energy transitions in other areas. In FTT-FLEX, this manifests as a significant reduction in solar costs over time due to exogenous global learning – with the result that the projected levelized cost of electricity (LCOE) for solar in Guinea-Bissau is estimated to decrease from $62 per MWh in 2030 to $37.5 per MWh in 2050 in the baseline without any additional policies (all prices presented in real 2020 price terms).

The resulting baseline projections using FTT-FLEX show a notable increase in the share of solar in Guinea-Bissau, rising from just over 30% in 2025 to 56% in 2050. While diminished, oil generation is expected to retain a significant share at 36% in 2050 in this baseline scenario.