UNIVERSIDAD DE COSTA RICA
SISTEMA DE ESTUDIOS DE POSGRADO

ROBUST ENERGY SYSTEM PLANNING FOR DECARBONIZATION UNDER TECHNOLOGICAL UNCERTAINTY: FROM TRANSPORT ELECTRIFICATION TO POWER SYSTEM INVESTMENTS.

Tesis sometida a la consideración de la Comisión del Programa de Posgrado en Ingeniería Eléctrica para optar al grado y título de Maestría Académica en Ingeniería Eléctrica

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Ciudad Universitaria Rodrigo Facio, Costa Rica

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Dedication

For my Family,

Thank you

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I express my gratitude to my supervisor Prof. Jairo Quirós-Tortós. He has provided me with numerous learning opportunities at the Electric and Power Energy Research Laboratory at the University of Costa Rica.

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Abstract

This work develops energy system modeling tools that identify features of a robust energy policy: a policy that performs well relative to alternatives. The tools are based on the *Open Souce Modeling System* (OSeMOSYS), are named the *Multipurpose OSeMOSYS-based Framework* (MOMF), and are applied to Costa Rica´s energy transition through the lens of its National Decarbonization Plan (NDP). The MOMF can support energy decarbonization planning exercises, and it is suitable to address the uncertainty involved in a decades-long process. It compares possible NDP futures -quantitative combinations of uncertainties and sectoral policy objectives- to a business-as-usual (BAU) scenario without decarbonization. The MOMF also evaluates actors within a country, including the fiscal impacts of decarbonization, following the best practices of applied energy modeling for policy support.

This work finds that the NDP has high economic benefits (avoided costs relative to the BAU) in the long term, equivalent to 5.5% of GDP yearly in the 2041-2050 decade. In 2031-2040, the benefits are 0.8% of GDP yearly; in 2022-30, the NDP faces net costs (more costs than the BAU) of 0.9% of GDP yearly. These results are averages across futures and can be higher or lower. The government will have lower direct tax revenue of about 0.87% of GDP yearly in 2041-2050 and will need to redistribute benefits to compensate for this. It can use vehicle-kilometer taxes (VKT), property taxes, or energy taxes for the redistribution, mainly taxing private transport owners -who have the highest benefits-. However, to facilitate the decarbonization of freight firms in 2022-2030 and 2031-2040, the government could subsidize their zero-emission vehicles (ZEV) adoption.

High benefits, low emissions complying with net-zero targets, and low electricity and public transport prices are desirable policy outcomes. Low costs for ZEVs and energy infrastructure -including renewables and storage- are crucial uncertain conditions for desirable outcomes. The robust levers the government can adopt to achieve desirable outcomes must decouple economic growth from transport activity. The specific levers include public transport investments, digitalization, non-motorized transport, ride-sharing, logistics hubs, and city densification. Moreover, low electricity prices need a low cost of capital to finance investments in the power sector.

Resumen

Este trabajo desarrolla herramientas de modelado de sistemas energéticos que identifican las características de una política energética robusta: una política con buenas métricas de desempeño en relación con alternativas. Las herramientas se basan en el *Sistema de Modelado de Código Abierto* (OSeMOSYS, por sus siglas en inglés), se denominan *Multipurpose OSeMOSYS-based Framework* (MOMF) y se aplican a la transición energética de Costa Rica plasmada en su Plan Nacional de Descarbonización (PND). El MOMF puede respaldar ejercicios de planificación de descarbonización energética y es adecuado para abordar la incertidumbre que implica un proceso de décadas. También compara posibles futuros del PND -combinaciones cuantitativas de incertidumbres y objetivos de políticas sectoriales- con un escenario de negocio habitual (BAU, del inglés *business-as-usual*) equivalente sin descarbonización. El MOMF también evalúa a los actores dentro de un país, incluidos los impactos fiscales de la descarbonización, siguiendo las mejores prácticas de modelado energético aplicado para el apoyo de políticas.

Este trabajo encuentra que el NDP tiene altos beneficios económicos (costos evitados en relación con el BAU) en el largo plazo, equivalentes al 5,5 % del PIB anual en la década 2041-50. En 2031-2040, los beneficios son solo el 0,8 % del PIB anual; en 2022-2030, el NDP enfrenta costos netos del 0,9 % del PIB anual. Estos resultados son promedios de futuros y pueden ser mayores o menores. El gobierno tendrá ingresos fiscales directos más bajos de alrededor del 0,87 % del PIB anual en 2041-2050 y deberá redistribuir los beneficios para compensar esto. Puede utilizar impuestos por vehículo-kilómetro (VKT, por sus siglas en inglés), impuestos a la propiedad o impuestos a la energía para la redistribución, gravando principalmente a los propietarios de transporte privado -que tienen los mayores beneficios-. Sin embargo, para facilitar la descarbonización de las empresas de carga en 2022-2030 y 2031-2040, el gobierno podría subsidiar la adopción de vehículos de cero emisiones (ZEV, por sus siglas en inglés).

Altos beneficios, bajas emisiones que cumplen con los objetivos de cero emisiones netas y bajos precios de la electricidad y el transporte público son resultados de política deseables. Los bajos costos de los ZEV y la infraestructura energética, incluidas las energías renovables y el almacenamiento, son condiciones inciertas cruciales para obtener resultados deseables. Los objetivos de política robustos que el gobierno puede adoptar para lograr resultados deseables deben desvincular el crecimiento económico de la actividad de transporte. Los objetivos de política específicos incluyen inversiones que logren aumentar el transporte público, la digitalización, el transporte no motorizado, los viajes compartidos, los centros logísticos y la densificación de las ciudades. Además, alcanzar bajos precios de la electricidad requiere un bajo costo del capital para financiar las inversiones del sistema de eléctrico.

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Chapter 1

Introduction

The Paris Agreement, a legally binding international treaty on climate change, sets a global temperature increase target of 1.5°C above pre-industrial levels. The Intergovernmental Panel on Climate Change (IPCC), a United Nations body responsible for advancing knowledge on anthropogenic climate change (see IPCC, n.d.), recommends in IPCC, 2018a and IPCC, 2021 that world emissions reach net zero by 2050 to meet the goal. Net-zero emissions are equivalent to carbon neutrality: carbon dioxide equivalent (CO2e) emissions[1] put into the atmosphere equal the CO2 removed, e.g., by forests. Many countries have already pledged to reach important emission reduction or containment milestones by 2030, including Costa Rica in its Nationally Determined Contribution (NDC) Government of Costa Rica 2018-2022, 2020. To achieve the final state of net-zero emissions by 2050, the current policy instrument in Costa Rica is the National Decarbonization Plan (NDP), laying out a pathway of sectoral instruments and objectives that transform the economy.

While the adverse effects of climate change are already palpable IPCC, 2021, particularly in vulnerable communities exposed to extreme weather events like flooding and drought, only ten countries were responsible for 68.7% of global greenhouse gas (GHG) emissions in 2018, according to World Resources Institute, 2020. World Resources Institute, 2020 shows estimations for global emissions at 47,515.3 MTon in 2018, while Costa Rica's net emissions were 11.5 MTon in 2017 according to Instituto Meteorológico Nacional, 2019, the most recent GHG emissions inventory. The natural question arises: if Costa Rica's emissions are about 0.024% of global emissions, why does the country commit to ambitious emission reduction targets?

Out of the 11.5 Mton of CO2e, almost 8 Mton are emitted in the energy system (or energy sector). According to IPCC, 2014, an energy system comprises "*all components related to the production, conversion, delivery, and use of energy.*" In Costa Rica, the 2017 GHG inventory shows that 6 Mton of CO2e come from transport activities, followed by the manufacturing industry with 1.3 Mton. Moreover, according to SEPSE, 2021, the final secondary energy consumption was 56.7% gasoline and diesel in

[1] CO2e includes the global warming potential of carbon dioxide, methane, and nitrous oxide gases.

2018; transport consumed 93.2% of gasoline and diesel. Despite having a highly renewable electricity generation matrix, the final secondary energy consumption in the country was only 23.4% electrical energy. Therefore, it is clear that Costa Rica's emissions and energy demands orbit around gasoline and diesel consumption, both fossil fuel derivatives imported by the state-owned company RECOPE (from the Spanish, *Refinadora Costarricense de Petroleo*).

In 2018, Costa Rica imported US$1.28 billion in diesel and gasoline, according to RECOPE, n.d.-a. This magnitude comprises the Cost, Insurance, and Freight (CIF) value and is equivalent to 2% of its nominal GDP in the same year (see World Bank, 2019). Its total imports in that same year were about US$1.6 billion, considering jet fuel, liquified petroleum gas (LPG), fuel oil, asphalt, and other products. In 2014, the total *oil bill* -another term for fossil fuel derivative imports- surpassed US$2 billion. This statistic precedes the shale oil revolution, i.e., an increased oil and gas production in the United States as a result of fracking and horizontal drilling for extraction, as Center, n.d. explains. The higher production resulted in lower international crude oil prices after 2015, reducing Costa Rica's oil bill as shown in RECOPE, n.d.-a.

World Bank, 2021 mentions the trends of higher energy prices worldwide since the last quarter of 2021, which are related to supply chain constraints and will likely increase Costa Rica's oil bill. Other events can keep oil prices upward or downward, increasing volatility and impairing economic growth, as explained by van Eyden et al., 2019. The NDP, by Government of Costa Rica 2018-2022, 2019, is emphatic in defining decarbonization as a process of transforming the economy such that national emissions per unit of economic output decrease. This work adopts that decarbonization definition and justifies its importance for Costa Rica not because of climate change mitigation (Costa Rica's contribution to global emissions is 0.024%) but for energy security and affordability.

Decarbonization will drive governments, companies, and individuals worldwide to alter their collective energy management, transformation, and consumption. Low-emission electricity generation and energy use technologies can make the country avoid energy costs, decouple GHG emissions from economic growth, and reach climate mitigation commitments as a byproduct. Moreover, if developed economies reverse the historical tendency to outsource environmental harm to the Global South, as explained in Jorgenson et al., 2022, countries with decarbonized energy systems can become more attractive for foreign investment. Such a reversal can occur through increased international private sector responsibility or regulations in the European Union and the United States. Finally, a decarbonized energy system could be less vulnerable to oil price volatility, providing energy cost stability to private firms and households.

Considering the technological characteristics of vehicles[2], the trends of fuel costs projected by the International Energy Agency in International Energy Agency, 2019, and the cost reduction trajectory of batteries and renewables, Godínez-Zamora et al., 2020 found that decarbonizing the energy and transport sectors in Costa Rica by 2050 produce US$20 billion, discounted at 5%. Then, Groves et al., 2020 evaluated the NDP under deep uncertainties about the future, i.e., variables that cannot be known or agreed upon by stakeholders. They found vulnerabilities of decarbonizing in terms of emission targets and high costs, which would make the NDP unsuccessful: i) low adoption of electric private vehicles and buses, ii) high economic growth with cheap and efficient conventional vehicles, and iii) expensive vehicles and low adoption of electric trucks.

This work builds on these previous studies by developing tools that support robust energy system planning for Costa Rica. Planning results in policy, which produces outcomes measured in metrics. Marchau et al., 2019 define a robust policy as one that produces the most favorable outcomes across possible future scenarios. Moreover, there are policy objectives and policy instruments, as distinguished by van den Bergh et al., 2021. Victor-Gallardo, Roccard, et al., 2022 explain that plans such as the NDP propose mitigation measures like transport electrification, which have associated specific objectives (e.g., 95% of the private fleet in 2050) and instruments to achieve them (e.g., through tax subsidies for electric vehicles). The focus of this work is the understanding of robust mitigation measures, objectives, and instruments quantifiable through energy system modeling tools, which have internally consistent engineering and economic features.

The decarbonization of the energy system requires a pathway, often called the energy transition (see IRENA, n.d.), comprising technology adoption and policy objectives and instruments that should occur by mid-century. Pye and Bataille, 2016 and Bataille et al., 2016 explain that energy system modeling supports energy transition by estimating future costs, emissions, and energy requirements, gathering and providing insights from and to stakeholders. Lopion et al., 2018 mention that energy models provide insights for policy questions with varying methodologies, spatiotemporal resolutions, and bottom-up or top-down analytical approaches. In Costa Rica, Godínez-Zamora et al., 2020 developed OSeMOSYS-CR, which is an example of an energy system optimization model (ESOM).

This chapter presents the state of the art in the following fields:

- long-term strategies for the energy transition;

[2] For example, battery electric vehicles waste less energy than internal combustion vehicle counterparts.

- the applications, characteristics, and limitations of ESOMS;
- robustness for the energy transition.

It also presents a justification for the work, the problem statement, a hypothesis, and the research objectives. Chapter 2 develops this work's theoretical framework, covering the underpinning concepts of this research: ESOMs, Robust Decision Making (RDM), and transactions in energy systems (energy-related prices and taxes). Chapter 3 presents the methodological developments of the work, Chapter 4 presents and discusses the results, and Chapter 5 presents the conclusions, recommendations, and future work. Many of the developments of this work have been written in five original research articles submitted for peer review. This document compiles some elements from those articles to answer the research objectives, and they are cited accordingly.

1.1. State of the Art

IPCC, 2018b reports the need for carbon dioxide (CO2) emissions to fall 45% 2030 relative to 2010 and reach practically zero by 2050 to avoid harsh climate impacts. Therefore, the time for the 2030 emission reduction targets worldwide is relatively short. Costa Rica did not pledge GHG emission reductions by 2030 in its NDC Government of Costa Rica 2018-2022, 2020; instead, the country defined an emissions budget more or less equivalent to keeping emissions constant from 2018 onwards. The NDC and the NDP pledge to reach net-zero GHG emissions by 2050. This decade will give the country time to prepare for more aggressive transformations after 2030 and import low and zero-carbon technologies at competitive costs, which wealthy countries will most likely develop and pay for at early adoption. This state of the art will describe the existing research on how countries advance the energy transition in the 2022-50 horizon.

1.1.1. Strategies for the Long-term Energy Transition

Energy systems supply, transform and carry energy in different forms to satisfy the demands of society. Priesmann et al., 2019 state that ESOMs are the most popular tool to analyze energy systems. Sass et al., 2020 highlight the relevance of ESOMs to study decarbonization and decentralization in the design, operation, and control of sector-coupled energy systems. DeCarolis et al., 2017 explain that the solution of an ESOM is the selection of activity and capacity of technologies out of a pool of alternatives, based on differences in the relative cost of competing options, performance, fixed demands, and constraints (i.e., inputs). ESOMs deploy the technologies over a horizon with perfect foresight.

Energy system modelers can use diverse implementations of ESOMs to perform a cost-benefit analysis, as Xiang et al., 2020 have done to analyze demand response policies in an integrated system of electricity and gas. Schlachtberger et al., 2018 explain that, typically, ESOMs estimate a least-cost combination of technological options under physical, environmental, and societal boundaries. For example, OSeMOSYS-CR developed by Godínez-Zamora et al., 2020 minimizes cost in the long-term for a countrywide energy system, subject to emission and technological restrictions, and has a yearly temporal resolution. In contrast, Prina et al., 2020 present a multi-objective optimization method with an hourly temporal resolution and multi-node (or regional) approach to consider the spatial resolution.

ESOMs support decision-making but do not guarantee a perfect policy design since they can ignore social, economic, or engineering realities. To gain more insights, ESOMs and Computable General Equilibrium Models (CGEMs) have been integrated to explain demands through macroeconomic drivers, prices, elasticities, fiscal policies, and levels of income across the population, as mentioned by DeCarolis et al., 2017 and Helgesen, 2013. ITF, 2019 and Bhattacharyya and Timilsina, 2009 explain that the results of these models are not forecasts, but plausible scenarios about the future, i.e., stories describing how the future can unfold through illustrative pathways.

Generally, ESOMs have static demands and do not reflect the participation of multiple agents in the energy system. Some efforts have attempted to improve demand modeling. For example, Blanco et al., 2019 linked a behavioral transport model with an ESOM to study hydrogen options for the European Union (EU) by having both models exchange parameters describing the same scenario. Moreover, Zhang et al., 2020 used an agent-based model to determine the demand of an energy system by adding multiple stochastic individual demands of households.

Technical cost minimization should not be the only relevant objective of ESOMs. Algunaibet et al., 2019 show there are indirect costs or externalities of deploying technologies in the energy system, often not accounted for in ESOMs; they found that keeping the current mix of energy resources can cost the world up to 1.1 ± 0.2 trillion US$, including direct and indirect costs. Also, Zvingilaite, 2011 presents that planning for the future considering externalities is cheaper than paying for damages.

A decarbonized future energy system will have a larger power system based on renewable generation sources, substituting fossil fuel consumption. The trade-off between cost minimization and land requirements has been highlighted by kuang Chen et al., 2022, where costs 10% higher could reduce land requirements for renewable energy by 58% in the Northern European energy system. According to Dominković et al., 2022, research about individual technology has been declining, while recent literature has focused on energy system flexibility and integrated energy systems.

A specific line of research for integrated energy system analysis is the role of electrification in supporting the electrical grid, which can reduce implementation costs through vehicle-to-grid mechanisms (V2G) (see Aghajan-Eshkevari et al., 2022). Still, storage options that diversify the power system technology portfolio are of interest to enable highly renewable systems, like pumped hydropower, biogas, and heat pumps, as exemplified by Nadolny et al., 2022 and Mittelviefhaus et al., 2022.

1.1.2. Applications, Capabilities, and Limitations of ESOMs

ESOM approaches vary widely, from deterministic linear programming to stochastic optimization that considers uncertainties subject to partial equilibrium constraints. Besides the optimization, models vary in temporal and spatial desegregation and scope. Wei et al., 2020 showcase an example of a multi-planning problem (varying temporal scope) for the long and short terms, which in turn have corresponding uncertainties: e.g., technology costs and renewable energy availability. In terms of scope, there are two contrasting examples. Yang et al., 2019 optimize for the operation of a metro system, a specific energy system component. More broadly, Shen et al., 2020 optimize for investment and operation of industrial energy systems, and Ju et al., 2020 optimize for demand response schemes in power markets.

Schlachtberger et al., 2018 and Usher and Strachan, 2012 point out that solutions of ESOMs are sensitive to input parameters and have inherent uncertainty. For deterministic energy-economic models, such as OSeMOSYS-CR, Fais et al., 2016 mention that uncertainty can be addressed by analyzing the variation of outputs as a function of changing inputs. Pye et al., 2018 give notice of structural or qualitative uncertainty, which are related to biases in modeling choices. Ruhnau et al., 2022 have used different models to study the same problem using equal data inputs and have shown that models produce different results, evidencing model uncertainty.

Ju et al., 2020 propose flexible constraints in the optimization to reflect how decision-makers face risk. Tan et al., 2020 suggest an iterative two-stage optimization for an electricity and heating system considering different uncertain conditions that modify constraints, ensuring continuous operation despite worst-case wind power availability. Similarly, but for individual buildings, Wang et al., 2020 use bi-objective trade-off optimization, along with a posteriori analysis based on Monte Carlo simulations to verify performance between environmental and cost outcomes.

The above examples use stochastic optimization and complex models for specific systems. Nonetheless, although accuracy and detail are desirable in ESOMs, Priesmann et al., 2019 warn that the complexity must be balanced with acceptable use of computational resources and DeCarolis et al., 2017 recommend increasing the complexity if policy questions make it necessary. Nolting and Praktiknjo, 2022 notes that the complexity of models is increasing, which makes the management of uncertainty harder. In contrast to the stochastic optimization models, tools such as OSeMOSYS-CR trade complexity for flexibility and modularity. Howells et al., 2011 mention that tools such as OSeMOSYS-CR have useful prototyping and testing capabilities and Ringkjøb et al., 2018 state that the bottom-up setup of such tools enables a detailed technology characterization, suitable for a national energy system. Niet et al., 2021 mention the importance of communities of practice around open source models such as OSeMOSYS-CR, which contributes to increased use and model improvements.

Below are examples of countrywide ESOM applications. Fais et al., 2016 provide insights for the long-term low-carbon transition of the UK, considering uncertainty, using a national bottom-up ESOM and sensitivity analysis (SA). In Latin America, mostly regional studies have been developed to analyze climate policy: Kober et al., 2014 showed existing commitments would attain CO2e reductions of 40% relative to a baseline scenario in 2050. van der Zwaan et al., 2014 found carbon taxes and biomass resources will play a relevant role in decarbonizing the region. Marcucci et al., 2019 developed an assessment of decarbonization pathways for different regions of the world by treating uncertainties as random variables, e.g., economic growth, resources, and technology costs.

According to DeCarolis et al., 2017, the SA approach identifies the input parameters that have the largest influence on results and can strengthen policy insights. Yue et al., 2018 refer to this approach as Monte Carlo Analysis (MCA): to systematically perturb the inputs and then evaluate the outputs with statistical techniques. Wagener and Pianosi, 2019 highlight the relevance of SA because even base year data affects decision-related inputs, particularly in developing countries where data is sparsely available, if at all, as Yeh et al., 2017 reflect.

1.1.3. Robustness for the Energy Transition

ESOMs seek insights on what investments or operation schemes comply with an objective (e.g., minimal cost). How do modeling insights influence energy policy and vice-versa? On the one hand, according to Süsser et al., 2021, models help investigate policy options, define targets, and estimate impacts. On the other hand, policymaking also influences data sources, assumptions, the study scope, and how results are used. Fodstad et al., 2022 mentions that there is a lack of studies that models uncertainties of emerging technologies and consumer behavior. Therefore, there is an opportunity to connect ESOM capabilities with policy support processes aiming at finding robust policies, which are the ones that produce the most favorable outcome across multiple scenarios, according to Marchau et al., 2019. Marchau et al., 2019 also say that robust policies have the least regret, i.e., deviate least from the best possible policy provided perfect information was available.

To assess energy investment risks, Colla et al., 2020 recommend that decision-makers consider factors like resource availability, installation site, socioeconomic implications, and environmental impact of energy projects. The transition can present vulnerabilities, like the case of Uganda explored by Sridharan et al., 2019: hydropower dependency and future requirements compete with water allocation for human consumption. Ji et al., 2020 show another example of modeling for the robust planning of electricity systems, considering energy-water interactions. Zhu et al., 2022 show that policy instruments with low GHG abatement costs are more politically feasible, thus, increasing robustness.

The cost-benefit analysis of the energy transition will be subject to many debates in the coming decades. With that prospect, N. Kalra et al., 2014 indicate that stakeholders should engage together in a decision process rather than agreeing on assumptions about uncertain matters of the future. R. J. Lempert et al., 2011 introduce Robust Decision Making (RDM) as a methodological tool to help stakeholders improve their decisions under conditions of deep uncertainty. Deep uncertainty is an expression of self-recognized high uncertainty about the future outcome of a system, or in the context of a group of decision-makers, collectively not agreeing on a future outcome of a system. RAND, 2013 explains that RDM relies on computer models and data to explore outcomes of interest with many simulations instead of looking for predictions of the future. Hence, decision-makers change the question of "what will happen in the future?" to "what steps can be made today to shape the future?", as explained by RAND, 2013.

RAND, 2013 enlists some RDM applications: water management, management of energy resources, flood risk management, and national defense. In the water management field, with RDM methods, N. R. Kalra et al., 2015 found that the Master Plan for the water of Lima (Perú) was overdesigned and suggested specific policies (i.e., demand-side management, pricing, and soft-infrastructure) to save up to 25% of investment costs. Notably, RDM has been used in the United States by Groves and Lempert, 2007 for the 2005 California Water Plan, by Groves et al., 2013 for the Colorado River

Basin, and by Finucane et al., 2018 for the Patuxent River Basin.

Matrosov et al., 2015 sought robust strategies for London's water supply, using multi-objective optimization models and visualization tools to study key trade-offs. Callihan, 2013 used RDM to study the implications of climate variability on water management. Singh et al., 2015 studied ecosystem management with varying stakeholder preferences using RDM. Cervigni et al., 2015 address infrastructure decisions for climate adaptation, considering the trade-off of water availability for hydropower and irrigation in Africa. This issue is further explored by Taliotis et al., 2019 for Eastern Africa and the implications of climate on the resilience of the power sector, and how picking a dry climate future strategy contrasts with a wet future one.

In the energy sector, Guthrie et al., 2009 and Popper et al., 2009 used RDM to support planning in Israel, providing policy recommendations. Mahnovski, 2007 evaluated decisions of energy companies investing in hydrogen fuel cell technologies. R. Lempert and Trujillo, 2018 affirm that RDM can suitably adress decarbonization planning. Eker and Kwakkel, 2018 explain that RDM evaluates a discrete and pre-specified set of alternative policies, whereas Many-Objective Robust Decision Making (MORDM) generates a large set of alternatives with computational search. Sahlberg et al., 2021 presented the first application of the scenario discovery approach, which sustains RDM (see Section 2.2), in geospatial electrification modeling. Li et al., 2022, Liu et al., 2022, and Ding et al., 2022 took a different approach to find robustness; they embedded robustness within specific energy-related optimization problems to deal with uncertainty.

Fiscal policy is an instrument to implement decarbonization. Taylor et al., 2017 propose taxes to favor the reallocation of assets from fossil-based to renewable portfolios. Freire-González and Puig-Ventosa, 2019 suggest options to discourage polluting economic activities, making a case for taxing fossil-based electricity production instead of all options. Moreover, Lin and Jia, 2019 explored the impacts of taxes on energy demand, and OECD, 2019b comprehensively studied the effects of different carbon pricing policies. Finally, even though many countries rely on taxing fuels for government revenue, the literature on the post-decarbonization fiscal policy is not abundant. OECD, 2019a explores how taxes can adapt to declining fossil fuel use in Slovenia and Cesar et al., 2022 define a framework to analyze the fiscal impact of electromobility, i.e., the loss of tax revenue associated with fossil-based transport. Hence, energy system analysis efforts should aim at understanding transactions within it and the costs and benefits for the interacting players, all while seeking robustness in the policy recommendations, for which RDM is suitable.

1.2. Justification

Groves et al., 2020 and Quirós-Tortós et al., 2021 suggest that a low carbon future is beneficial for countries comparable to Costa Rica. Decarbonization will also produce jobs (see Saget et al., 2020) and advance achieving sustainable development goals (see Haines et al., 2017). J. H. Williams et al., 2021 argue that the sustained implementation of the transition remains a challenge. Each country's most suitable decarbonization options will depend on their uncertain specific conditions. Therefore, having tools to assess energy system planning that can adjust to national and regional conditions and cater to uncertainties will support the implementation of the energy transition in the oncoming years.

Government agencies that formulate energy policy and related policies can benefit from this research by continually performing scenario analysis and comparing the simulation outputs with measured indicators. These agencies will better understand the implications of their policy options regarding energy and investment requirements, CO2 emissions, overall system cost, and economic benefits per energy system actor. Through this understanding, policies could more easily comply with the public interest in minimizing regret of over or under-investing in energy sectors, having a coherent fiscal policy, and having affordable transport and energy services and products.

1.3. Problem Statement

The uncertainty of low or zero-carbon technological availability and cost-effectiveness can hinder effective planning of energy policies that seek energy transformations to accomplish socially-wide benefits, e.g., energy security and affordability. In the context of the worldwide energy transition, countries with firm commitments to reach a low-carbon energy system can face barriers caused by:

- intermittent political support at national and international levels;
- high investment requirements and cost and revenue changes for different economic actors;
- public sentiment about the threat of climate change or the available technologies for mitigation.

The impossibility of predicting the events of the oncoming decades urges energy policies to have a long-term perspective and adapt to adverse conditions. These policies should guide technology and infrastructure choice, level of investment, and pricing that maximize benefits for actors and minimize regret understood as a deviation from the best possible outcomes. The design of any tool that supports policies with those characteristics is itself a problem that can be stated as follows:

How is the energy system modeling tool that supports the planning of technology and infrastructure choice, investment, and pricing that aims at maximizing benefits and minimizing regret understood as a deviation from the best possible outcomes?

1.4. Hypothesis

Computational experiments applied to models that represent the energy system can stress-test policy objectives and instruments from a quantitative perspective. Policy objectives and instruments can be more costly than beneficial under certain conditions, i.e., risk conditions. Consequently, the energy system planning tool must shed light on specific technology adoption and investment targets and price changes through taxes, subsidies, or discount rates that avoid such risks. Hence:

Policies conceived with the support of energy system modeling tools can maximize their benefits by estimating robust technology adoption targets, investments, and market price modifications via computational experiments and statistical analysis of possible futures.

1.5. Objectives

1.5.1. Main Objective

To develop computational tools to support energy system planning by characterizing robust policy options that maximize benefits and minimize regrets -deviations from the best possible outcomes-.

1.5.2. Specific Objectives

1. To develop a computer experiment software tool to analyze uncertainties and the sensitivity of multiple policy options in the transport and energy sectors for long-term planning horizons.

2. To implement price estimations within an integrated software tool based on energy system models, including taxes, transport service and energy prices, and transactions amongst public transport operators, private and public transport users, energy companies, and the government.

3. To develop a methodology that estimates the investments, technology adoption rates, tax rates, service prices, and asset financing rates that cause robust economic outcomes despite uncertainty.

Chapter 2

Energy System Modeling and Robust Decision Making

This chapter assembles key concepts for the development of the work. Three major topics are joined in this research: ESOMs, RDM, and transfer estimation (taxes, electricity prices, and bus fares). Figure 2.1 shows how the topics are linked. The ESOM is the main energy system model because it enables the techno-economic representation of interacting technologies. Later in this work, a *Transaction Estimation Module* (TEM) is developed, referring to the modeling of the energy system from the perspective of interacting actors. The ESOM and TEM produce baseline scenarios established on reasonable assumptions, although subject to uncertainty about the future.

Since the ESOM and TEM scenarios reflect specific policies and exogenous conditions about the energy system (i.e., demand and technology cost), the RDM-inspired analysis and tools are relevant to evaluate the policies and find which are robust. First, the tools generate an experiment, i.e., a database with possible futures looking toward 2050. Then, the input and output datasets are analyzed to determine what are the robust policies: investments and adoption rates from the perspective of the ESOM and taxes and prices from the perspective of the TEM. This chapter presents Sections 2.1 and 2.2 to conceptually develop ESOMs and RDM, respectively. Section 2.3 lays the groundwork for the development of the TEM.

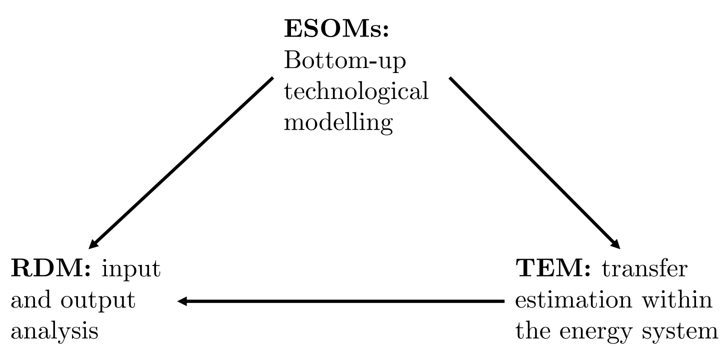

Figure 2.1: Connection of topics.

2.1. Energy System Optimization Models

Considering the complexity cautions by DeCarolis et al., 2017 and taking advantage of OSeMOSYS-CR (i.e., the model started by Godínez-Zamora et al., 2020), the ESOM scheme presented here is based on the Open Source Energy Modeling System (OSeMOSYS), i.e., a set of equations that describe an energy system following a parameterization. Howells et al., 2011 explain that OSeMOSYS models support long-run energy planning and are designed to generate insights based on flexible prototyping and testing capabilities. The open-source feature of OSeMOSYS allows advancement in understanding energy systems through the collaboration of researchers, provided adequate documentation of datasets, code sets, and analyses, according to Pfenninger et al., 2017 and Pfenninger et al., 2018. Groissböck, 2019 warn that for short and mid-term analyses, models that consider operational aspects of energy systems in depth may be more suitable than OSeMOSYS.

Models like OSeMOSYS-CR generally have perfect foresight, although there are alternative formulations that split solutions over time, according to DeCarolis et al., 2017. The models endogenously calculate the activity and capacity of technologies or processes, the cost of deploying and operating them, building and maintaining required infrastructure, importing energy, or extracting resources while satisfying demands linked to economic activities. Figure 2.2 shows how the energy system is structured in a Reference Energy System (RES).

The RES represents the flow of energy from primary or secondary sources to the final energy uses. It includes the processes that transform the energy in different stages. For instance, Figure 2.2 shows how renewable resources (e.g., water, geothermal, wind, solar, or waste) can be used as input to generate electrical power. The electrical power is then distributed to the users via the power distribution infrastructure, which comprises transmission and distribution systems. Electricity is then delivered to households and buildings that use energy in different economic activities. Distributed generation (DG) schemes can also be represented.

Electric transport is another demand that electrical power can supply. Traditionally, vehicle technologies are powered by fossil fuel derivatives (also reflected in the RES), which satisfy passenger and freight demands. The characteristics of these vehicles vary according to size, sophistication, and the fuel they use. Such characteristics are energy efficiency, operational life, number of technology units needed to satisfy a yearly demand or commodity output, unit capital costs, unit fixed operation and maintenance costs, and variable costs.

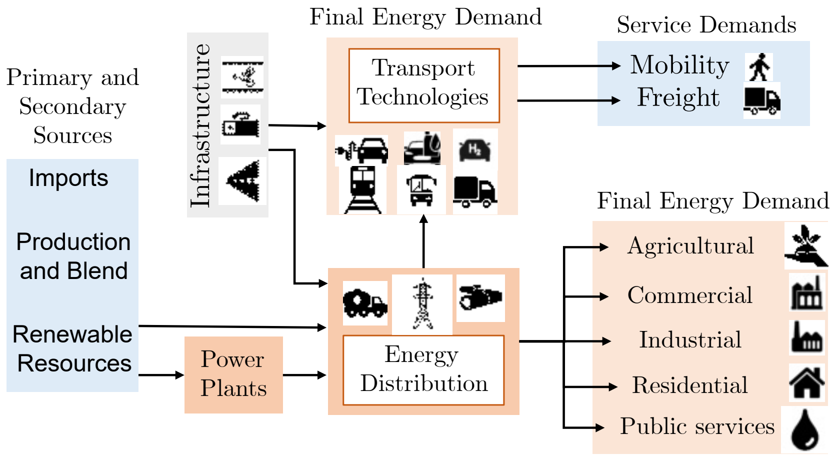

Figure 2.2: Reference Energy System (RES) of OSEMOSYS-CR.

The RES has interconnected blocks representing energy transformation processes to supply end-use devices with energy. The system's energy supply must be in equilibrium with the demand as a fundamental restriction to the optimization of the ESOM with the objective function in Equation 2.1; Equation 2.2 defines the total cost. The model estimates the output variables shown in Figure 2.3. Any block has two general characteristics referenced throughout ESOM analyses:

- **Capacity:** represents the quantity of technology in the unit defined by the modelers. For example, the capacity of power plants is defined in MW or GW.
- **Activity:** a technology's level of activity is the production of a commodity, i.e., a demand or another form of energy converted by a technology. Most activities are measured in Petajoules (PJ). In the case of transport demand, units are passenger or ton-kilometers (pkm or tkm).

$$min \sum_{(y,t,r)} (\text{Total Discounted Cost}_{(y,t,r)}), y : \text{year}, t : \text{technology}, r : \text{region} \tag{2.1}$$

$$\begin{aligned}\forall_{(y,r,t)} \text{Total Discounted Cost}_{(y,t,r)} &= \text{Discounted Operating Cost}_{(y,t,r)} \\ &+ \text{Discounted Capital Investment}_{(y,t,r)} + \text{Discounted Emissions Penalty}_{(y,t,r)} \\ &- \text{Discounted Salvage Value}_{(y,t,r)}\end{aligned} \tag{2.2}$$

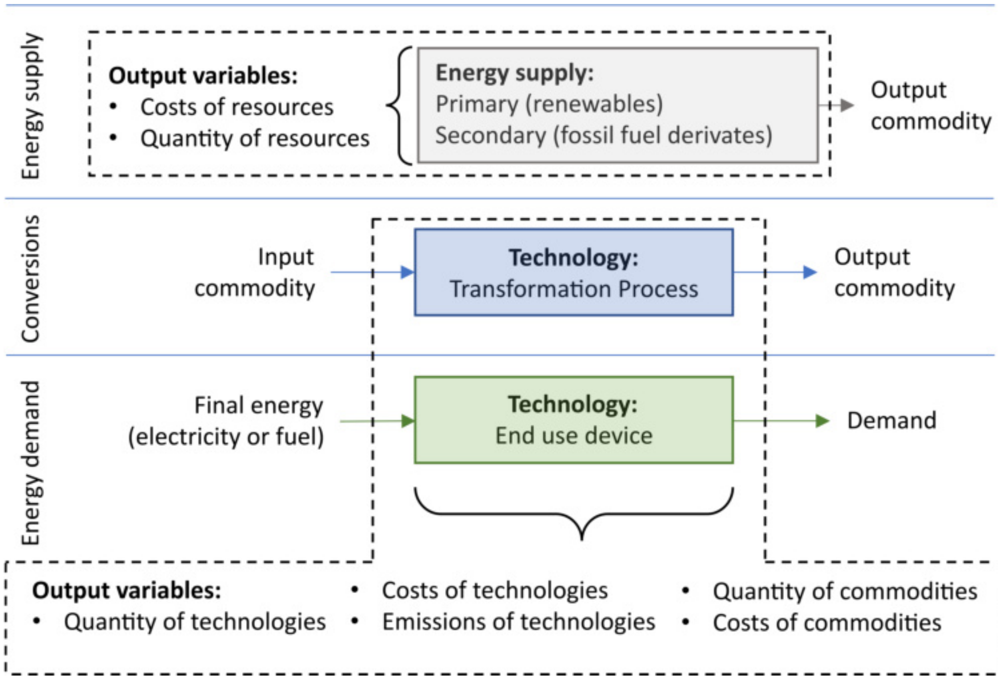

Figure 2.3: Outputs of RES elements.

Parameterizing the model blocks completes the modeling. Figure 2.4 shows the relationships between technologies and commodities in OSeMOSYS, as well as their respective inputs, listed below:

- **Energy efficiency:** transforming or transporting energy from the primary (e.g., renewable resource) or secondary (e.g., barrels of gasoline) sources to the end-use devices causes losses. Each block in the RES has an efficiency that considers the losses due to conversion or transport.
- **Operational lifetime:** the number of years the technology are used over the planning horizon.
- **Capital cost:** the capital cost of technology investments per unit of capacity.
- **Fixed O&M cost:** fixed operation and maintenance (O&M) technology costs per unit of capacity.
- **Variable O&M cost:** variable O&M technology costs per unit of activity.
- **Availability in a year:** the availability factor changes the time that technologies are functional in a year and the capacity factor defines the fraction of the installed capacity used in one year.
- **Emission factor:** emission factor of a technology per unit of activity.

- **Emissions penalty:** penalty per unit of emission used to include externalities. Shaw et al., 2014 say that using less emitting technologies can bring about health improvements associated with carbon reductions, which are monetized by Coady et al., 2019.

- **Conversion of output to capacity:** connects activity and capacity by defining the quantity (capacity) of technology per unit of commodity produced (activity).

- **Residual capacity:** the capacity (quantity of a technology) available from before the modelling period. This value allows calibrating the amount of existing technologies.

- **Maximum or minimum quantity of technology or commodity (constraint):** upper and lower limits, as well as fixed values, that can force levels of capacity. This parameter is applicable for commodities too. It allows modeling adoption rates of technologies.

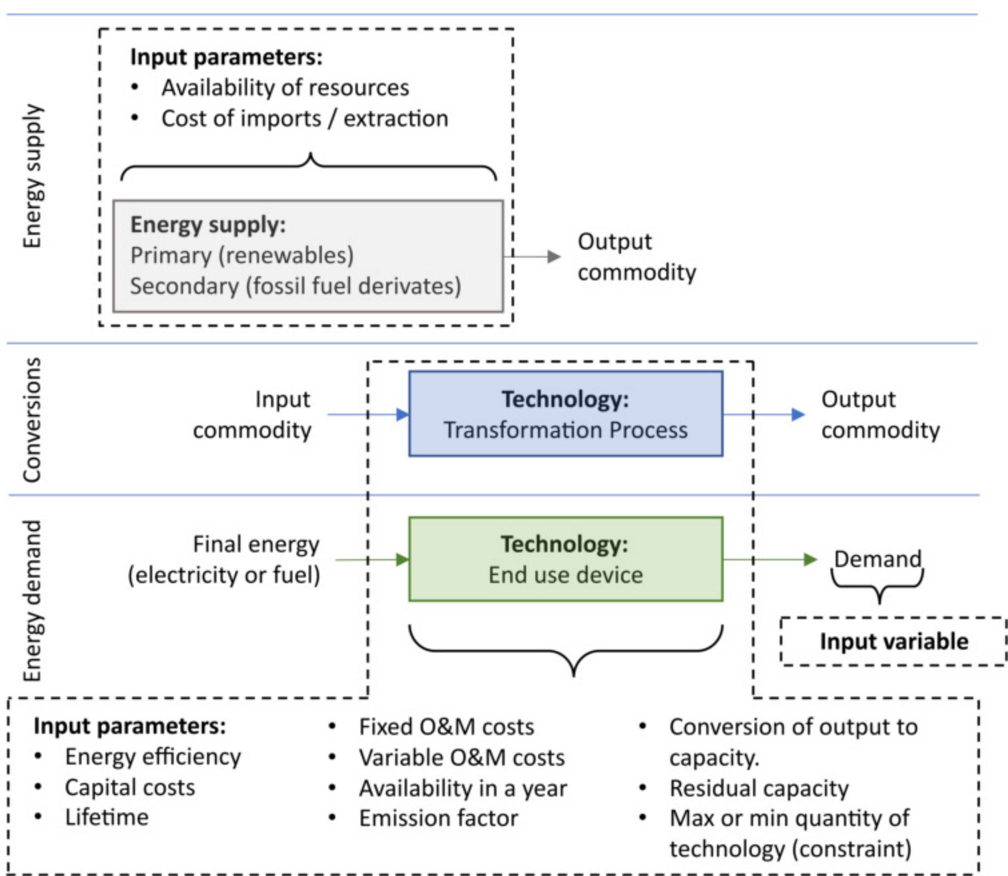

Figure 2.4: Inputs of RES elements.

2.1.1. Modeling Demand in ESOMs

The energy demands and adoption rates of technologies are also input variables. These are not technological inputs; they are related to people's behavior and economic activities. Defining energy demands is crucial for ESOM analyses and often one of the most debated inputs because of uncertainty. For transport, RAND, 2006 explains that uncertainty is linked to the variability of travel on a physical transportation network. Although there are engineering models that describe aggregate patterns in the use of transport (i.e., the peak time demand), RAND, 2006 mentions persistent uncertainties: i) which transport modes are used for trips, ii) differences in time of use, vehicle occupancy rates and purposes, iii) variability in origins and destinations, iv) cancellation or postponement of trips.

Fraser et al., 2018 say the effects of climate change on extreme weather conditions put the transportation systems around the globe at risk, showcasing a broader link between transport sector planning and climate change (e.g., adaptation of infrastructure in power, water, and communications systems). Lovrić et al., 2017 assess the infrastructure capacity utilization and its link to the energy system.

Emissions from transport are quantified with an emission factor proportional to driven distance or per gallon of fuel consumed. The latter approach is easier to implement and used in OSeMOSYS-CR. The IPCC Tier 1 methodology consists of multiplying emission factors per unit of energy times an activity level (i.e., consumption of fuels). The National GHG Inventory uses data from the National Energy Balance. Bhattacharyya and Timilsina, 2009 present transport demand methods based on fuel consumption econometric models, as well as the following mixed approaches:

- **Identity model:** fuel demand equals the product of vehicle utilization and stock.
- **Structural model:** derives energy demand of transport from the demand of transport services, which in turn are services used as inputs to minimize costs of production.
- **Market-share model:** considers inter-fuel substitution possibilities.

Bhattacharyya and Timilsina, 2009 explain that end-use approaches like the above consider the diversity of transport modes, types of vehicles, and efficiencies. According to these authors, the number of trips and modal distribution influence passenger traffic. In contrast, the production of goods, average distance, and characteristics of the traffic structure to move goods determine freight traffic. Yeh et al., 2017 concluded mobility demand is a function of population and Gross Domestic Product (GDP), with integrated modeling options using logit functions or least-cost optimization. They also explain that freight projections are generally dependent on GDP forecasts. However, Keshavarzian et al., 2012 signal non-linearities in the relationship between GDP and vehicle ownership. Sakamoto et al., 2016 warned that trends are faulty when systems undergo structural change. One alternative proposed by Keshavarzian et al., 2012 is using non-linear Gompertz or logistic curves to estimate vehicle ownership. Bhattacharyya and Timilsina, 2009 identified that simpler models are virtuous for insufficient data assumptions and have results similar to more complicated ones. Yeh et al., 2017 explain that passenger and freight demands, along with occupancy rates, yearly distance traveled, and vehicle survival rates, can estimate the number of vehicles on the road. Mobility demands are in passenger-kilometer units, i.e., the number of persons times their traveled distance in one year. Similarly, freight demand -in ton-kilometers units- represents the movement of goods instead of persons.

Figure 2.5 shows an example of how transport demand is managed in OSeMOSYS-CR. First, the modeled parameterizes an exogenous demand and the mode shift of the scenario. Second, the modeler computes the necessary vehicle capacity with distance and occupancy rates assumptions. Third, the efficiencies of vehicles in kilometers per liter (converted to PJ/km) convert mobility to energy. The modeling process is formalized in Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 and presented in Section 3.1. OSeMOSYS-CR only covers road transport, although other models such as ICCT, 2012 explore aircraft and marine vessels in-depth.

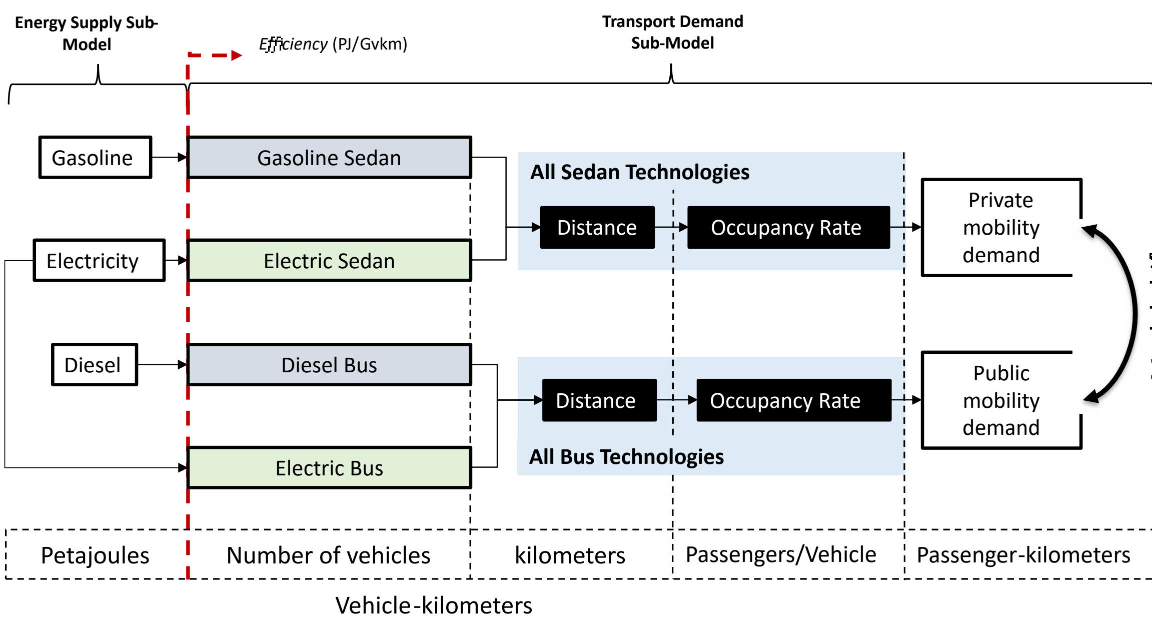

Figure 2.5: Transport modeling in OSEMOSYS-CR.

OSeMOSYS-CR characterizes vehicles and energy use devices but lacks similar technologies for other demand sectors like industry and buildings. For these cases, the demand was introduced in

PJ directly. Godínez-Zamora et al., 2020 recognize OSeMOSYS-CR uses an autoregressive integrated moving average (ARIMA) model to define demand projections based on historic energy balance data; the transport sector uses additional constants to reach mobility and freight demands. Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 adjusts these considerations to include the industry sector modeling based on data from Escuela de Ingeniería Eléctrica - Universidad de Costa Rica, 2020 and Escuela de Ingeniería Eléctrica - Universidad de Costa Rica, 2019.

Similar to transport, other sectors have demands projected with various features. For example, Edelenbosch et al., 2017 used a linear estimator for electric load data with a daily and hourly resolution with peak demand, temperature, GDP, population, industrial production, and day duration. Bhattacharyya and Timilsina, 2009 enlist demand alternatives: combinations of econometric and engineering-economy models, system dynamics models, scenario approaches, decomposition models, process models, input-output models, and artificial neural networks. Bhattacharyya and Timilsina, 2009 clarify that econometric methods are employed at a national level, whereas accounting methods (i.e., bottom-up technology-related descriptions) are used at sectoral or end-use levels.

The International Energy Agency, 2019 affirmed that worldwide energy demand has a 1% yearly growth projection by 2040, which is significantly lower than the historical 2.3% increase seen in 2018. If such energy demand increase worldwide continues, the strain on the global energy system would be considerable. According to J. Williams and Waisman, 2018, for decarbonization pathways such as the Decarbonization Plan, stakeholders are interested in defining physical transformations and subsequent investments that achieve socioeconomic and emissions objectives. The RES representation is a practical way to define where the investments occur and what technological options are available. The ESOM is relevant to inform investment decision making if translated to a cost-benefit analysis (CBA), which according to N. Kalra et al., 2014 consists of:

- calculating the value of financial and non-financial costs over a time period;
- translating future costs and benefits into present value using a discount rate;
- ranking each investment with a metric for later selection when compared to alternatives, and thus, the investments that bring the greatest benefit are chosen.

Energy systems are not, in practice, centrally planned. Thus, ESOMs are criticized for often modeling single decision-makers in the energy system. DeCarolis et al., 2017 present technology-specific discount rates as a solution to reflect agent preferences and other non-financial costs, although empirical evidence is often nonexistent for parameterization. Other solutions to ESOM criticisms, according to DeCarolis et al., 2017, are merging consumer utility and cost objectives and further endogenization (e.g., technological learning) to reduce the need for exogenous assumptions. Yue et al., 2018 explains that these modeling choices face trade-offs between data gaps, the ambition of the studies, level of effort, and thirst for more impactful insights.

2.2. Robust Decision Making

Groves et al., 2014 define RDM as a methodology that supports decision-making with the potential to identify policy alternatives that are desirable despite uncertainties, i.e., have good performance across many possible combinations of conditions. It uses statistical and software tools iteratively with the participatory engagement of stakeholders, as shown in Figure 2.6. RAND, 2014 explains that RDM involves deliberation by firstly meeting with stakeholders, planners, and decision-makers to define the scope of a policy study. At that stage, stakeholders help identify the policies' likely risks or relevant outcomes. Following Groves et al., 2014 and Figure 2.6, the evaluation starts with a large database of simulations, resulting in visualizations of strategies. Iterative consultation with stakeholders leads to refinement of the strategies, leading to fewer choices for further evaluation.

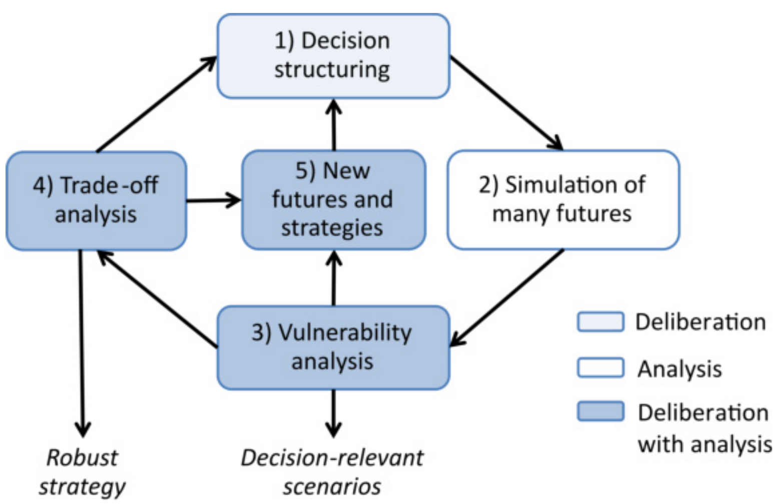

Figure 2.6: Iterative steps of a robust decision making analysis. Based on Groves et al., 2014.

Groves et al., 2014 explains that, when implementing RDM, there is an evaluation of policy options across multiple futures. Vulnerabilities linked to adopting an option are then identified. The following concepts are relevant to distinguish:

- **Cases:** run of a simulation model.
- **Future:** a specific set of assumptions about the future.
- **Condition:** set of futures that are similar along one or more dimensions of uncertainty.
- **Scenario:** set of cases that share a decision-relevant attribute.
- **Strategy:** amount, location, and timing of investments and programs (i.e., levers). Hence, there is a distinction when referring to ”policy”: i) synonym of strategy, or ii) it can be short for ”policy lever,” i.e., individual component of a strategy.

For *decision structuring*, stakeholders (e.g., decision-makers, experts, agency professionals) reunite and perform the following activities aiming to narrow down the analysis:

1. identify key goals for the policy;
2. define critical uncertain factors that could influence planning conditions or strategy success;
3. preliminary set of options (strategies) to evaluate;
4. define performance metrics to assess strategies across futures;
5. compile data and models to estimate performance.

According to RAND, 2014, one tool that facilitates the XLRM matrix facilitates decision structuring. It systematizes the following components:

- **Exogenous uncertainties (X):** factors outside the control of decision-makers that may affect the ability of actions to achieve the desired goals.
- **Policy levers (L):** actions that decision makers may consider.
- **Relationships (R):** describe how the policy levers perform, as measured by the metrics, under the various uncertainties. Simulation models are often used.
- **Metrics (M):** of performance to evaluate if a choice of policy levers achieves the desired goals.

Mahnovski, 2007 defines robustness as the relative insensitivity of a strategy (or policy) to the unknown probabilities of any state, i.e., the difference between the performance of a strategy in a future state of the world and the best performing strategy of the same future. More robustness metrics in diverse contexts are defined by Doumpos et al., 2016 and McPhail et al., 2018.

For the *simulation of many futures*, data and models evaluate future conditions across a wide range of future possibilities. This step generates a large database of quantitative information through computational experiments to explore the implications of varying assumptions and hypotheses. RAND, 2014 explain that the computational experiment explores uncertainties by sampling variations broadly and uniformly, unlike a Monte-Carlo probabilistic sampling approach requiring a probability distribution function per uncertainty. Thus, by defining broad and uniform samples, strategies are stress-tested without judging whether a future is more or less likely than another, according to RAND, 2014.

Experiments can be full factorial, i.e., including all combinations of uncertain factors and their assigned possible ranges. RAND, 2014 explains that this approach is computationally expensive, and thus, a Latin Hypercube Sampling (LHS) scheme is convenient to sample across the factor space without requiring all combinations uniformly. Experimental designs must weigh the computing time needed to simulate the management system for a single future and the number of futures developed to reflect uncertainty, strategies evaluated, and iterations of analysis to perform.

Groves and Lempert, 2007 explain the produced scenarios are linked to a story about how drivers affect the trend of variables of interest (e.g., GHG emissions) and how users of that scenario face decisions. Bryant and Lempert, 2010 addressed scenario quality and recommended carefully choosing the number of scenarios that explain key driving forces to avoid false expectations among users of the analysis. In an approach of many futures, the analytics to discard noisy scenarios and extract relevant information is a crucial step to comply with clarity, practicality, and credibility of an RDM project.

For the *vulnerability analysis*, the underlying concept is Scenario Discovery, i.e., an application of statistical and data-mining algorithms to databases generated with simulations, according to Bryant and Lempert, 2010. R. J. Lempert et al., 2008 describes the two general algorithms to choose:

- **Patient Rule Induction Method (PRIM):** identifies regions in an uncertain model input space that are highly predictive of model outcomes that are of interest (see Kwakkel and Cunningham, 2016 for a clear explanation of the PRIM algorithm).

- **Classification and regression trees (CART):** machine-learning methods for constructing prediction models from data. The models are obtained by recursively partitioning the data space and fitting a simple prediction model within each partition. As a result, Loh, 2011 explains that partitioning can be represented graphically as a decision tree.

Moreover, decision-makers and stakeholders work together to define a few key scenarios that tell a compelling story about its implications in evaluating the policy. Groves et al., 2014 explain that these actors do not need to agree on the results but rather provide information to refine them. RAND, 2014 explains two measures often used in the vulnerability analysis:

- **Coverage:** the ratio of the number of futures represented by the vulnerable conditions that do not meet goals to all futures that do not meet goals.

- **Density:** the ratio of futures that are represented by the vulnerable conditions and do not meet goals to all futures that are represented by the vulnerable conditions.

Uncertainties are then statistically evaluated across simulated cases with the variables of interest from the experiment. For example, a two-dimensional plot of two key performance measures can statistically evaluate cases, illuminating the importance of visualization tools. Then, clustering cases in the two-dimensional plot leads to finding a scenario: a centroid of a cluster of cases that gives similar interpretations and, thus, an associated narrative.

In the *trade-off analysis*, stakeholders engage in the analysis again through visualizations. In the previous step, a collection of static two-dimensional plots is useful to find scenarios. Interactive plots are required to discuss and analyze qualitative results. Groves et al., 2014 argues that the visualization must highlight key trade-offs and compare performance measures among strategies. RAND, 2014 explains that trade-offs are examined in terms of how alternative strategies perform in reducing vulnerabilities. According to Groves et al., 2014, the deliberation involves participating experts, gathering additional information, and providing context about the likelihood of scenarios. The discussions can lead to further inquiring about the results. As a result, more iterations across the RDM process can be necessary to reconcile the robustness criteria.

For *new futures and strategies*, the outcome of the RDM methodology is a robust strategy, i.e., policies that have good performance despite changing conditions over time developed with awareness of possible futures (see Walker et al., 2013). Gong et al., 2017 mention that robust scenario analysis allows stakeholders to understand worst-case futures. Different analysis types exist, such as Dynamic Adaptive Policy Pathways by Haasnoot et al., 2013. Kwakkel et al., 2016 found that RDM and Dynamic Adaptive Policy Pathways are complementary by offering an alternative to handling the vulnerabilities that RDM identifies. They also explain that an Adaptive Policy Pathways approach offers guidance to make choices by steering the adaptation of policies over time Kwakkel et al., 2016. Hermans et al., 2017 designed how observation of technical or political metrics trigger strategy adaptation actions.

Below are examples of available RDM toolkits. Kwakkel, 2017 developed the Exploratory Modeling Workbench to support the generation and execution of experiments and to support the visualization and analysis of the obtained results. More recently, Hadjimichael et al., 2020 develop a Python library for MORDM analysis. Although Dreier and Howells, 2019 presented an option to study OSeMOSYS models under uncertainty, this work develops a computational experiment framework as an extension of OSeMOSYS-CR, based on the Python programming language. This implementation enables uncertainty exploration, policy levers comparison, and coherent TEM modeling.

2.3. Transfers in Energy Systems

OSeMOSYS-CR includes exogenously established costs for power plants, energy infrastructure (including transmission and distribution systems), vehicles, and civil infrastructure. Moreover, fossil fuels have an import cost. All these costs are subject to uncertainty. Nonetheless, there are different types of costs in the energy system. The ESOM reflects costs from the country's or region's perspective, i.e., how much the imported vehicles and fuels would cost to the nation or region if it were a single agent. Zooming in on the energy system, the government taxes the imports and property of vehicles. It also applies a tax to the sales of gasoline, diesel, and other fuels. Electricity supply prices are subject to the power system investments, the cost of its operation, and the demand. The customer perceives the supply price plus a value-added tax (VAT). Hydrogen, one of the technological choices for transport decarbonization in the long term, will have a consumer price. Finally, the users of public transport pay a fare relative to the demand and investments made by the operators, similar to electricity.

Two objectives could have opposite effects: 1) tax policy can punish the use of fossil fuels and related technologies, 2) with uptake in electrification of transport and other energy system components, taxing clean electricity can support the government's finances. Pursuing either objective depends on the timing and the economic context of the country. If decarbonization is successful and benefits society, a government can tax a percentage of the benefits. Nonetheless, the benefits are not the same for every actor participating in the energy system. Thus, the proposed TEM in this work is an important complement to the ESOM that responds to the weaknesses identified by DeCarolis et al., 2017. The TEM was applied by Rodriguez et al., 2021 for the Costa Rican Ministry of Finance to inform the NDP's fiscal effects.

Chapter 3

Methodology

Figure 3.1 shows the framework that accomplishes the work's objectives and respond to the best energy modeling practices suggested by DeCarolis et al., 2017, here named the *Multipurpose OSeMOSYS-based Modeling Framework* (MOMF). Figure 3.1a shows the steps and principles of energy modeling that DeCarolis et al., 2017 formalized. Figure 3.1b shows the MOMF contributions, listed below:

- The block A in Figure 3.1b represents a tool to structure and parameterize a model efficiently, following the logic of Section 3.1. This tool was a component of the contribution in Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022, who developed OSeMOSYS-CR-v2. Its data sources and assumptions are in the online documentation[1]; complementary software programs are available in the open-source license repository[2]. This block responds to Principle IV (orange in Figure 3.1), offering flexibility to model technology variety, future performance and cost assumptions, and restrictions.

- The block B in Figure 3.1b builds multiple scenarios using the modeling tool described above. Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 developed scenarios for each possible NDP mitigation measure, with different levels of ambition (uncertainties of outcome), e.g., transport electrification magnitudes. Hence, this process responds to Principle VI (in purple) by evaluating different mitigation measures and implementation possibilities.

- The tools have Python-based processing of inputs and outputs that increase the model's transparency and communicate insights using data visualization tools, i.e., Principle VII (green in Figure 3.1). The results from block B offer *Tier 1* policy insights, i.e., costs, emissions, and technological capacity and activity per scenario.

- The block C in Figure 3.1b shows the TEM component (in Section 3.2). It expands the sectoral detail in the modeling and produces insights beyond those offered by Godínez-Zamora et al., 2020

[1] https://osemosys-cr-v2.readthedocs.io/en/latest/
[2] https://github.com/EPERLab/osemosys-cr-v2

because it considers actor disaggregation. Thus, it also contributes to Principle VI by dealing with uncertainty about actor-related questions, e.g., what is the change in government revenue.

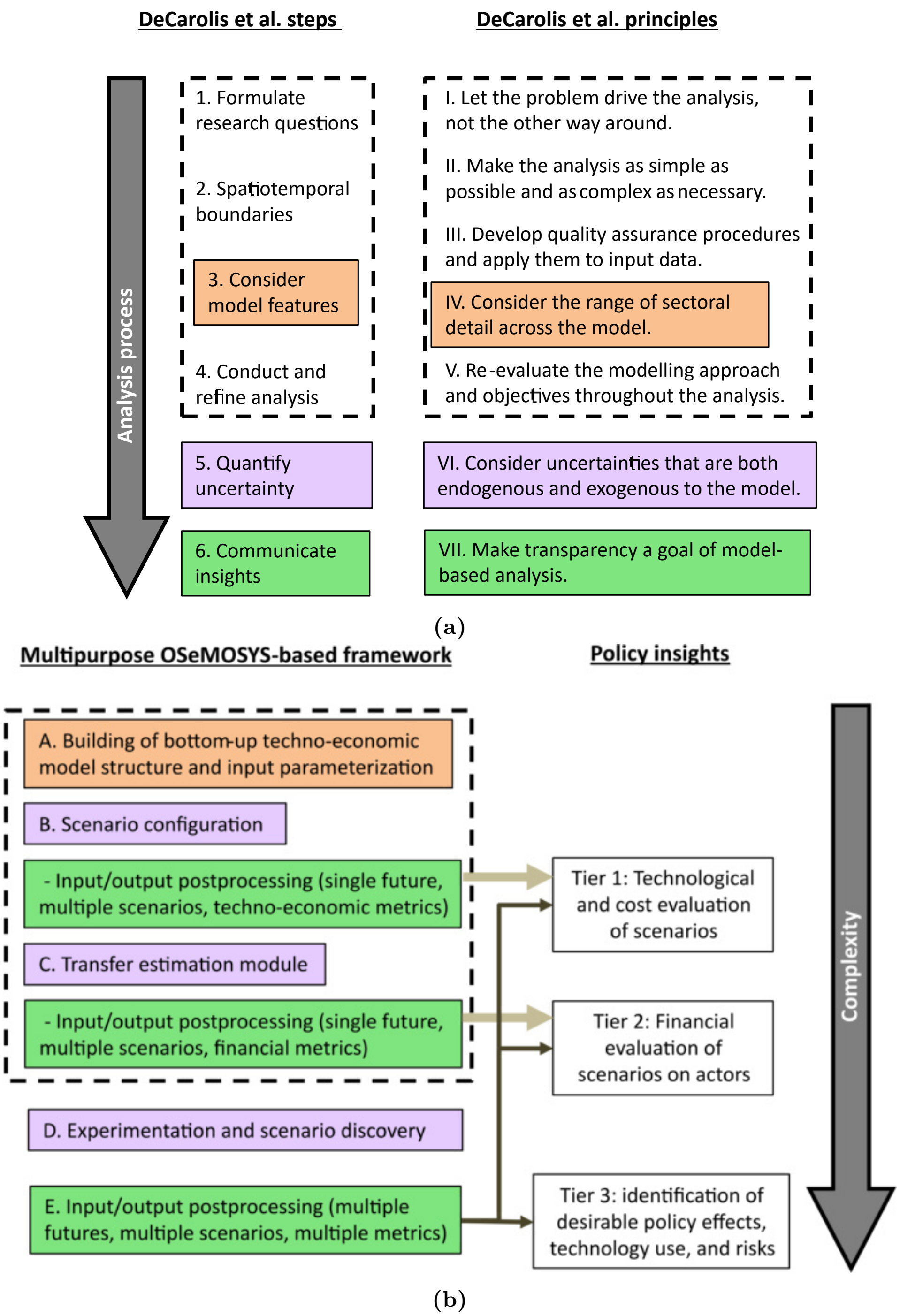

Figure 3.1: Overview of best practices and modeling framework for robust planning analysis. (a) Best practices according to DeCarolis et al., 2017. (b) MOMF developed in this work.

- The block C results offer *Tier 2* policy insights, i.e., a financial evaluation of scenarios on actors. Best practices suggest conducting and refining the analysis by re-evaluating the modeling approach according to the objectives of a specific study. The contributions listed above (boxed in a black dashed line) apply for that analysis and re-evaluation process.

- While the contributions above cover some aspects of uncertainty, block D in Figure 3.1b systematically addresses uncertainty-specific questions, covering Principle VI (green in Figure 3.1). This block identifies desirable policy effects, technology use, and risks (*Tier 3* results, Figure 3.1b). To achieve this, block E is necessary: it processes results and creates visualizations to interpret model input variations. Crucially, the modeling tools are deterministic, i.e., there are no specific probability distributions for any inputs in this work. Hence, the MOMF uses the RDM practice of sampling inputs with uniform distributions and defined intervals.

Figure 3.1 shows the evolution of the analysis process and the steps, which follow the alphabetical order logic described in Figure 3.1b and the list of contributions. Modelers should analyze uncertainties after the steps 1 to 4 have been advanced. The MOMF can address uncertainty without block D, although limitedly, which helps control the complexity of the analysis. When many parameters are moved simultaneously in experiments, deriving insights from the results can be challenging if previous specific questions have not been clearly defined. This methodological chapter is structured as follows:

Scenarios and Modeling (see Section 3.1): describes the scenarios, equations, model structure, and policy ranking process. It covers block A of the MOMF and is based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

Transaction Estimation Module (see Section 3.2): develops the equations and logic to model prices and prices between energy system actors. The TEM responds to Objective 2, increasing the complexity of the analysis. The specific policy questions addressed by the TEM are:

- <u>The fiscal impact of decarbonization</u>: the TEM served as the basis to estimate the fiscal impact of road transport decarbonization in Rodriguez et al., 2021.
- <u>Estimation of bus and electricity prices</u>: these are metrics of interest for the analysis developed in Section 3.4 and in Victor-Gallardo, Quirós-Tortós, et al., 2022.

- Evaluation of discount rates profit margins: the TEM was used by Victor-Gallardo and Quirós-Tortos, 2022 to estimate the effect of discount rates and profit margins in electricity prices, which affect the NPV benefits for transport actors caused by decarbonization.

Model Experiments (see Section 3.3): describes how model experiments are developed. This work shows three different experiments to address specific objectives:

- Wide experiment: it varies most OSeMOSYS-CR inputs to produce 2000 futures, which fundamentally responds to Objective 1. The results are then used to explore the magnitude and timing of investments, technology adoption rates, and service prices that produce robust performance metrics for future energy plans, responding to Objective 3.
- Narrow experiment: it varies some OSeMOSYS-CR inputs to produce 800 futures. It explores the electricity sector and the financial costs of new power investments. It responds to Objective 3 by searching for asset financing rates that are more convenient, enhancing the robustness of the policy recommendations.
- Tax adjustment evaluation: it varies the contribution to eliminating the fiscal impact per tax type for one specific future. The experiment allows exploring robustness criteria for tax rates, thus, responding to Objective 3.

Robustness Analysis (see Section 3.4): describes the approach to find *robust decarbonization pathways* defined in Victor-Gallardo, Quirós-Tortós, et al., 2022 as the combinations of levers and uncertainties that produce desirable and avoid risk outcomes. This methodological contribution responds to Objective 3 of this work and belongs to blocks D and E of the MOMF.

3.1. Scenarios and Modeling

This section describes the scenarios and model versions developed in different studies. Godínez-Zamora et al., 2020 developed the seminal model. Victor-Gallardo, Quirós-Tortós, et al., 2022 modified it to model the costs of additional energy system elements, e.g., distance variation, freight rail, electric fast-charging, and hydrogen refueling stations; the same version was used in Victor-Gallardo and Quirós-Tortos, 2022. Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 expanded the model to include the industrial sector. Finally, a policy objective ranking approach is presented.

3.1.1. Scenarios

There are two main types of scenarios, both developed for the 2018-2050 period:

i) A business-as-usual (BAU) scenario represents how the energy system could evolve if the current energy carrier use proportions remain constant under higher production -as GDP grows-. The BAU is used as a benchmark to compare other scenarios with decarbonization efforts.

ii) Alternative scenarios, one of which is the National Decarbonization Plan (NDP). They reflect mitigation measures: policy objectives in different subsectors within the energy system.

Table 3.1: Measures and interventions per parameter of the NDP scenario.

Measure	Parameter	Intervention
Mode shift and passenger rail transport	Public passenger transport demand	Increase its participation in motorized transport by 7.5% in 2035 and 20% in 2050
	Non-motorized transport demand	It reduces motorized transport by 4% in 2035 and 10% in 2050 relative to BAU
	Electric passenger rail demand	Transports 0.1 Gpkm and enables public passenger transport mode shift
Freight rail	Electric freight rail demand	Transport 10% of heavy freight demand in 2050, increasing linearly every year starting in 2024
Heavy freight ZEV penetration	Fleet composition	5% by 2030 and 50% by 2050 with electric and hydrogen technology
Light ZEV penetration		5% by 2030 and 50% by 2050 with electric technology. By 2030, 20% of the fleet uses LPG, and the restriction is removed afterward
Public ZEV penetration		30% by 2035 and 85% by 2050 with electric technology. 3%by 2035 and 10% by 2050 with hydrogen buses and minibusses.
Private ZEV penetration		35% by 2035 and 99% by 2050 with electric technologies
Biofuels	% of the fuel volume	Biodiesel: 1% by 2026 and 5% by 2030. Gasoline (ethanol): 8% by 2022.
Boilers in industry	thermal / electrical / mechanical kW composition	40% of biomass and 60% electric
Heat production in industry		90% by 2050 with electric technology and 10% with biomass
Heat production for glass		99% by 2050 with electric technology
Lift trucks		Entirely with electric technology
On-site power generation		60% by 2050 in battery storage. The rest with biomass
Power generation renewability	% of fossil fuel-based production	0% by 2050
Power generation characteristics	Considerations for model restrictions	Hydropower is not further developed. Only planned geothermal projects are simulated. It is assumed that wind and solar (with and without storage) supply the growth in demand, including transport electrification.
Commercial and residential LPG consumption	LPG substitution with electricity	The LPG phase-out occurs by 2050, gradually starting in 2024. The demand is substituted with electricity on a 1 to 1 basis.

Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

Table 3.1 shows the mitigation measures included in the NDP scenario. Each measure is modeled through a parameter than can be mapped into the previous equations. The quantitative assumption of the mitigation measure is in the intervention column, reflecting policy objectives per measure. Table 3.2 shows individual mitigation measures for the ranking exercise. Measures 4 and 12 are numbered to distinguish between options with or without hydrogen (H2) vehicle technologies.

Table 3.2: Description of energy sector mitigation measures for ranking.

	Measures	**Description**
1	Biofuels	Biodiesel: 1% by 2026 and 5% by 2030. Gasoline: 8% by 2022. We do not consider relative cost differences between biofuels and fossil fuels.
2	Mode shift and passenger rail*	50% of motorized passenger transport in 2050
		10% of passenger transport in 2050
3	Freight rail	20% of heavy freight transport in 2050
4.a	Public ZEV penetration	30% in 2035 and 85% in 2050
4.b	(include H2 for half of the participation)	
5	Private ZEV penetration	30% in 2035 and 95% in 2050.
6	Passenger elasticity to GDP reductions	Decrease the demand elasticity to GDP by 10% in 2030
7	Freight elasticity to GDP reductions	
8	Distances	Apply 0.9 in 2050 to passenger and freight distances
9	Renewable electricity	Keeps 100% renewable electricity production by 2050
10	Commercial and residential LPG removal	Removes LGP by 2050
11	Industry decarbonization	Substitutes oil for biomass and electricity in 2050
12.a	Freight ZEV penetration	30% in 2035 and 85% in 2050
12.b	(include H2 for half of the participation)	

Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.
* For reference, motorized passenger transport has 24% public and 76% private transport participation throughout the analysis period in the BAU.
** For reference, the demand elasticities to GDP of 1.015 for freight and 0.916 for passenger transport in the base year.

3.1.2. Versions

Figure 3.2 of the RES used in Victor-Gallardo, Quirós-Tortós, et al., 2022 and Victor-Gallardo and Quirós-Tortos, 2022. Imported fuels supply transport technologies, final energy demands, and diesel and fuel oil power plants. Ethanol and biodiesel are included as a blend with fossil fuels, only reducing the unit emission factor. Power plants produce electricity and electrolyzers powered by utility-scale photovoltaic (PV) solar produce hydrogen. Electricity and hydrogen are then distributed to transport technologies and energy demands. Finally, transport technologies use the energy to convert it into kilometers, mobilizing people or freight. Figure 3.3 shows an extended model version used in Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022. It includes biomass costs and industry technologies, which produce heat, force (e.g., for lifting objects with forklifts), onsite power generation, and other electricity demands.

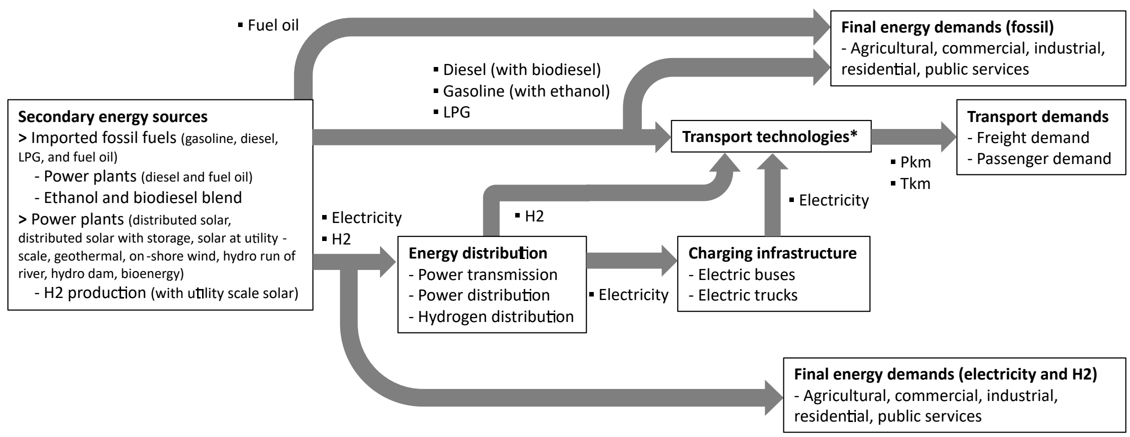

Figure 3.2: Reference energy system for the energy and transport sectors. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

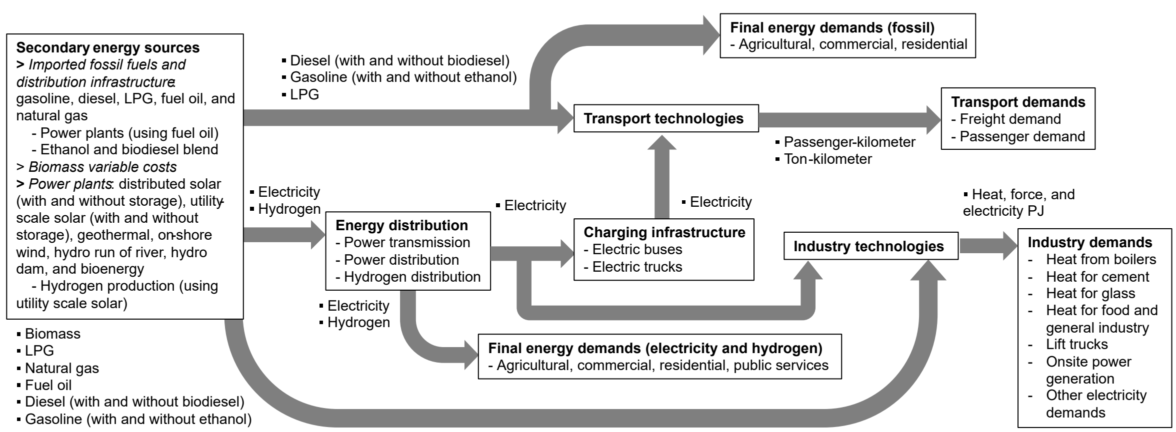

Figure 3.3: Reference energy system for the energy, transport, and industry sectors. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

3.1.3. Relationships

The equations here describe the modeling done outside of OSeMOSYS[3]. They support the pre and post-processing of OSeMOSYS inputs and outputs, following the logic described in Figure 2.5.

[3]See https://osemosys.readthedocs.io/en/latest/ for the general OSeMOSYS documentation

Equation 3.1 shows the number of vehicles V for every vehicle type k at any given year y. The demand for each vehicle type is in either passenger-kilometers (sedans, SUVs, motorcycles, buses, minibusses, and taxis) or ton-kilometers (light and heavy trucks). Each passenger vehicle type has an occupancy rate OR, reflecting the average number of occupants in a given year, and a representative yearly distance d. The OR for freight vehicles represents the tons transported per kilometer.

$$V_{k,y} = \frac{D_{k,y}}{d_{k,y} \times OR_{k,y}} \tag{3.1}$$

The transport demand is interfaced with energy consumption EC through the *energy consumption per unit of distance* $ECUD$, as shown in Equation 3.2. The $ECUD$ changes per vehicle type and propulsion technology, e.g., the values differ for a diesel SUV, a diesel bus, and an electric bus.

$$EC_{k,y} = ECUD_{k,y} \times V_{k,y} \times d_{k,y} \tag{3.2}$$

The GDP growth drives transport demands. These elasticities change their magnitude in percent for every 1% of GDP growth, which is considered a deep uncertainty in the long term. Equation 3.3 shows the demand before distance changes.

$$\sum_{k=1}^{K} D_{k,y,\text{without distance adjustments}} = \sum_{k=1}^{K} D_{k,y-1} \times (1 + \epsilon_{\Delta\%GDP}) \times \Delta\%GDP \tag{3.3}$$

The mode shift modeling depends on the BAU. Mode shift to public transit (MSPT) or non-motorized transport (MSNMT) can alter these distributions. With this modeling approach, MSNMT encompasses private transport demand reductions due to non-motorized transport uptake and digitalization of services like telework. Equations 3.4 and 3.5 represent the resulting private and public transport demands. The demands are related to the technology types K_{private} and K_{public} that produce private and public mobility[4]. Equation 3.6 adjusts the demand upon driven distance changes.

$$\sum_{k=1}^{K_{\text{private}}} D_{k,y,NDP} = \left(\sum_{k=1}^{K_{private}} D_{k,y,BAU} \right) \times (1 - \text{MSPT} - \text{MSNMT}) \tag{3.4}$$

$$\sum_{k=1}^{K_{\text{public}}} D_{k,y,NDP} = \left(\sum_{k=1}^{K_{public}} D_{k,y,BAU} \right) \times (1 + \text{MSPT}) \tag{3.5}$$

[4]Private transport includes sedans, SUVs, and motorcycles; public transport: buses, minibusses, taxis, and rail.

$$D_{k,y,\text{with distance adjustments}} = D_{k,y,\text{without distance adjustments}} \times \frac{d_{k,y}}{d_{k,\text{by}}} \tag{3.6}$$

OSeMOSYS-CR-v2 includes mode shift from heavy truck to rail through the Freight Mode Shift Rail (FMSR) coefficient and Equation 3.7. All mode shift coefficients MSPT, MSNMT, and FMSR are percentage points used to redistribute the total demands.

$$\sum_{k=1}^{K_{\text{heavy truck}}} D_{k,y,NDP} = \left(\sum_{k=1}^{K_{\text{heavy truck}}} D_{k,y,BAU} \right) \times (1 - \text{FMSR}) \tag{3.7}$$

Finally, for industry demands, Equation 3.8 estimates the energy demand (ED) of activity A (see industry demands in Figure 3.3), in a given year y, as the multiplication of the activity's energy intensity times the GDP.

$$ED_{A,y} = EI_{A,y} \times GDP_y \tag{3.8}$$

3.1.4. Ranking

This section shows an example application of the MOMF's *Scenario Confection* component, based on the measures described in Table 3.2: to define a prioritization criteria of the mitigation measures. Results are extracted from OSeMOSYS-CR-v2 for each mitigation measure per scenario. The scenario comparison is used in Equations 3.9 and 3.10 to estimate economic benefits (or avoided costs relative to the BAU) and emission reductions (or avoided emissions relative to the BAU). Another metric is the investment and fixed costs (IFC), which reflects the level of spending required to enable each mitigation measure that may require financing.

$$\begin{aligned} EB_{scen} = \text{Total CAPEX}_{\text{BAU}} + \text{Total OPEX}_{\text{BAU}} + \text{Total Externalities}_{\text{BAU}} - \\ \text{Total CAPEX}_{\text{scen}} - \text{Total OPEX}_{\text{scen}} - \text{Total Externalities}_{\text{scen}} \end{aligned} \tag{3.9}$$

$$ER_{scen} = \text{Cumulative Emissions}_{\text{BAU}} - \text{Cumulative Emissions}_{\text{scen}} \tag{3.10}$$

$$EB\_\text{norm}_{scen} = \frac{EB_{scen}}{EB_{\text{NDP}}} \tag{3.11}$$

$$ER\_\text{norm}_{scen} = \frac{ER_S}{ER_{\text{NDP}}} \tag{3.12}$$

$$IFC\_\text{norm}_{scen} = 1 - \frac{IFC_S}{IFC_{\text{NDP}}} \tag{3.13}$$

$$mm_{scen} = w_{EB} \times EB\_\text{norm}_{scen} + w_{ER} \times ER\_\text{norm}_{scen} + w_{IFC} \times IFC\_\text{norm}_{scen} \tag{3.14}$$

The ranking process consists of normalizing each metric relative to the NDP's result (i.e., compare each scenario with only one measure as per Table 3.2 with the scenario described in 3.1). The normalizations are in Equations 3.11, 3.12, and 3.13. Equation 3.13 differs from the other normalization equations because the lower the cost, the more affordable, and the higher the merit in a ranking. The other two normalized variables have proportional merit and magnitude. Equation 3.14 presents the combined metric of merit (mm), where a constant w weights each metric. In the results, the following configurations of metrics of merit are tested:

All metrics: $w_{EB} = 1/3, w_{ER} = 1/3, w_{IFC} = 1/3;$

Considering benefits and emissions: $w_{EB} = 1/2, w_{ER} = 1/2, w_{IFC} = 0;$

Considering emissions and IFCs: $w_{EB} = 0, w_{ER} = 1/2, w_{IFC} = 1/2$

3.2. Transfer Estimation Module

This section shows the relationships between actors and OSeMOSYS-CR-v2 to model the TEM. It includes private transport users, public transport operators, energy companies, and the government as general actor types or classes (see Table 3.3). The classes can be instantiated with similar methods but different parameters. 3.3 shows the instances, or actors, and the corresponding transactions (in each row, excepting elements with bullets).

Figure 3.4 shows the relationships among actors. Here, the association between technologies and actors is critical to estimating the actor costs and prices. Equation 3.15 presents the total costs (TC) of a technology t in a given year y, which are equivalent to the capital costs (CC), operational costs

(OC), and external costs (EC)[5].

Table 3.3: Actor classification and transactions.

Actor type (class)	Actor (instance)	Transactions (methods)
Government	Central government	Collect taxes (energy consumption, vehicle purchases, and use)
Energy firms	Electricity firms Hydrocarbon firms Hydrogen firms	Sell electricity using pricing equations Sell fossil fuels* according to predefined profit margins Sell hydrogen using using pricing equations
Public transport operators	• Bus • Taxi • Minibus	• Purchase vehicles • Purchase energy products • Pay taxes • Sell a service*
Private transport owners	Sedan, SUV, and motorcycle	• Purchase vehicles • Purchase energy products • Pay taxes
Freight firms	• Light freight • Heavy freight	
Public transport users		Purchase public transport services

* Fossil fuels include gasoline, diesel, LPG, and fuel oil.
** Sales of minibus services are not modeled.
The bullets represent a list of common instances of transactions.

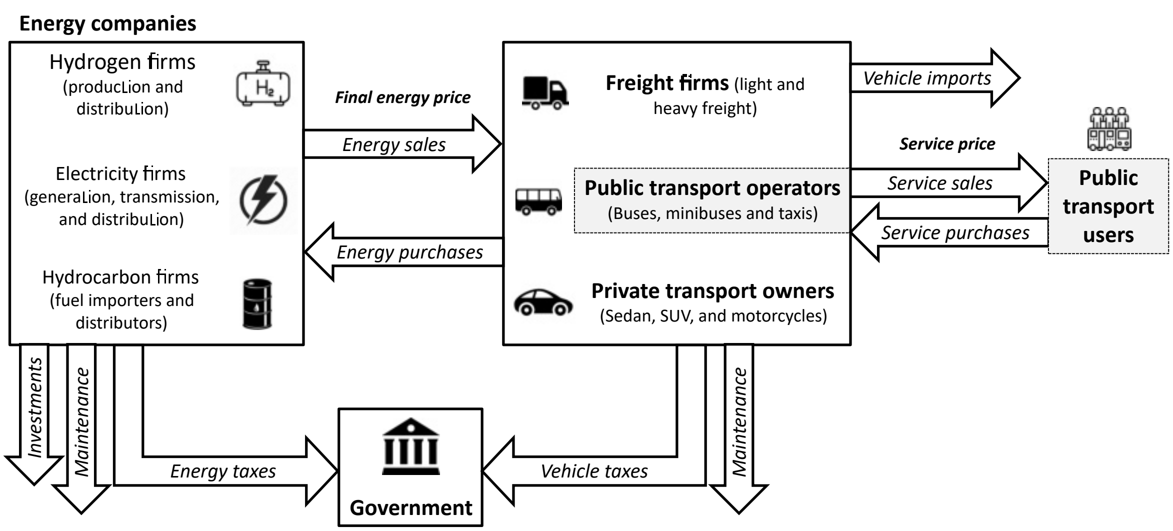

Figure 3.4: Relationships among actors in the transaction estimation module.

Equation 3.16 shows the national financial impacts (NFI) as defined by Victor-Gallardo, Quirós-Tortós, et al., 2022, simply expressing the excess costs of the reference scenario (rs) relative to the policy scenario (ps). Generally, the rs is the BAU, and the ps is the NDP or one of the scenarios defined for policy ranking. The financial impacts only include CC and OC, also named capital expenses (CAPEX) and operational expenses (OPEX). The greater the magnitude of the NFI, the greater the avoided costs

[5]Godínez-Zamora et al., 2020 defined how external costs, or externalities, are modeled within OSeMOSYS-CR. They included air pollution, accidents, and congestion costs. The latter is an expression of lost productivity.

by implementing a *ps*. Equation 3.16 expresses the national economic impacts (NEI), which include the effect of external costs in addition to the NFI.

$$TC_{t,y,scen} = CC_{t,y,scen} + OC_{t,y,scen} + EC_{t,y,scen} \tag{3.15}$$

$$NFI_{y,ps} = \sum_{t=1}^{T} CC_{t,y,rs} + OC_{t,y,rs} - CC_{t,y,ps} - OC_{t,y,ps} \tag{3.16}$$

$$NEI_{y,ps} = NFI_{y,ps} + \sum_{t=1}^{T} EC_{t,y,rs} - EC_{t,y,ps} \tag{3.17}$$

Equation 3.18 defines actor expenses and depend on capital (CE) and operation expenses (OE); all the terms depend on actor a. Expenses include the transactions between the actors. Every actor owns a group of technologies T_a, following the representation of Figure 3.4. Equation 3.19 shows the definition of financial impacts (FI) per actor, including the revenue (REV) of energy or transport service sellers. In the TEM, the energy firms' revenue contains the vehicle owners' energy expenses, and the public transport firms' revenue is equal to the expenses of public transport users.

$$TE_{y,scen,a} = \sum_{t_a=1}^{T_a} CE_{t_a,y,scen,a} + OE_{t_a,y,scen,a} \tag{3.18}$$

$$FI_{a,y} = (REV_{ps,a,y} - TE_{ps,a,y}) - (REV_{rs,a,y} - TE_{rs,a,y}) \tag{3.19}$$

The subsections below explain the energy and transport service price estimations. Some expenses have a reference cost defined in Equation 3.20 as *Reference Cost Expense* (RCE). The goods (g) associated with RCE have exogenous unit costs (UC), which are model inputs. They can have an associated unit tax (UT) and additional unit costs (AUC). Then, the total unit cost is multiplied by the quantity Q of a technology (e.g., a gasoline motorcycle) or a technology input (gasoline) to constitute a capital or operational expense.

$$RCE_{g,y,scen} = (UC_{g,y,scen} + UT_{g,y,scen} + AUC_{g,y,scen}) \times Q_{g,y,scen} \tag{3.20}$$

One of the subsections below also details taxes. In summary, vehicles pay taxes when purchased for the first time from an importer (local manufacturing is not modeled), then annually for the ownership (property taxes), and recurrently when purchasing energy. The taxes affect the final pricing other transport actors pay when purchasing fuel or electricity.

3.2.1. Electricity Prices

Equations 3.21 to 3.23 were defined by Victor-Gallardo, Quirós-Tortós, et al., 2022 to define endogenous pricing of electricity and hydrogen, i.e., energy services. First, Equation 3.21 is applied for a service s and the service technology st; each service has a total number of service technologies (TNST). It estimates the future annuity at a rate r and a period Y of new investments NI. Importantly, for each year y, the ANI must be accumulated in all years between y (the year where NI occurs) and all future years y_f such that $y + y_f \leq Y$.

$$ANI_{st_s,y+y_f,scen} = \frac{NI_{st_s,y,scen} \times r_{st_s,y,scen}}{1 - (1 + r_{st_s,y,scen})^{-Y}} \tag{3.21}$$

Equation 3.22 shows the new cost component (NCC) of the service s, which incorporates all the costs incorporated in OSeMOSYS-CR associated with delivering a quantity Q_s of service in a given year. It includes variable costs (VC), fixed maintenance costs (MC), and possible additional costs (AC). Equation 3.23 shows the residual cost component (RCC) of the service, which is equivalent to the cost of providing the service in the base year y_{base}. The price modeling assumes this cost remains constant and just becomes more diluted as $Q_{s,y}$ grows.

$$NCC_{s,y,scen} = \frac{\sum_{st_s=1}^{\text{TNST}_s} \left(VC_{st_s,y,scen} + MC_{st_s,y,scen} + ANI_{st_s,y,scen} + AC_{st_s,y,scen}\right)}{Q_{s,y,scen}} \tag{3.22}$$

$$RCC_{s,y,scen} = \frac{p_{s,y_{base},scen} \times Q_{s,y_{base},scen}}{Q_{s,y,scen}} \tag{3.23}$$

Equation 3.24 defines the price “at cost” (ac) of the service. This definition is suitable for Costa Rica’s existing regulatory framework and electricity system model. However, Victor-Gallardo and Quirós-Tortos, 2022 contributed by adding a profit margin (pm) to the price in Equation 3.25, as a percent of the price, for catering to possible additional earnings by investors.

$$p^{ac}_{s,y,scen} = RCC_{s,y,scen} + NCC_{s,y,scen} \tag{3.24}$$

$$p_{s,y,scen} = p^{ac}_{s,y,scen} \times (1 + pm/100) \tag{3.25}$$

3.2.2. Bus Prices

Victor-Gallardo, Quirós-Tortós, et al., 2022 defined an approach different to electricity for bus and taxi investments in Equation 3.26. In it, *df* and *pr* are depreciation factors and profit rates, respectively, established by the regulator. Hence, Equations 3.23 to 3.24 apply for buses and taxis[6] Table 3.4 shows TEM inputs applicable to Equations 3.21 to 3.26.

$$ANI_{st_s,y+y_f,scen} = NI_{st_s,y+y_f,scen} \times df_{st_s,y+y_f} \times pr_{st_s,y+y_f} \tag{3.26}$$

Table 3.4: TEM inputs.

Variable	Magnitude	Source
Residual cost component (RCC) of the bus service price or fare	6.6 ¢/km/passenger	ARESEP's (the public servie price regulator) historic data in ARESEP, n.d.-b.
Residual cost component (RCC) of the taxi service price or fare	1.16 $/km/passenger	ARESEP's historic data in ARESEP, n.d.-d.
Profit margin of energy firms that sell fossil fuels prices for end-users	35% over the import cost of gasoline, 19% from the cost of diesel, and 15% from fuel oil.	From RECOPE's fuel price structure website RECOPE, n.d.-b.
Residual cost component (RCC) of thed electricity price	15.46 ¢/kWh	ARESEP's historic data in ARESEP, n.d.-c.
Discount rate (r) for electricity and hydrogen firms	6%	Author's assumptions
Financing period (Y) for electricity and hydrogen firms	25 years	Author's assumptions
Bus and taxi* depreciation factors (df)	0.1143 for the first six years of the vehicle lifetime. After the seventh year, apply a df of 0.022	ARESEP's bus price methodology in ARESEP, n.d.-a.
Bus and taxi profit rates (pr)	0.1291	ARESEP's bus price methodology in ARESEP, n.d.-a.

Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.
* Future work can separate methodologies for buses and taxis.

3.2.3. Taxes

The tax equations below were applied in Rodriguez et al., 2021 (in Spanish) and formalized by Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. Import taxes depend on the CIF value and an *equivalent import tax rate* $EITR$ that summarizes multiple excises. The tax revenue TR from import taxes IT is defined in Equation 3.27, summing across all vehicle technologies k and considering

[6] In this work, it is assumed that transport services remain regulated public services with fixed earnings for public transport operators, already included in their cost structure.

their imported quantities Q_k^{imp}. This work defines TR as the sum of actor tax expenses; the TR is equal to the government revenue paid by the actors modeled in Figure 3.4.

$$TR_{IT,y} = \sum_{k=1}^{K} EITR_{k,y} \times CIF_{k,y} \times Q_{k,y}^{\text{imp}} \tag{3.27}$$

Equation 3.28 computes the TR from valued-added taxes (VAT), which include the profit margin of vehicle importers and commercializes PR. The PR varies per vehicle type k. Excises and VATs are levied on first-time sales, and the corresponding revenue is a function of imports. In contrast, property taxes defined in Equation 3.29 are recurrent and apply to the total fleet Q_k. Vehicles can have different market values as a function of brand, size, and age. As explained by Rodriguez et al., 2021, in Costa Rica, the Ministry of Finance estimates the fiscal value FV of vehicles in great detail, which reflects their market prices. Then, according to the FV, a specific property tax rate PT applies. The higher the FV, the higher the PT; the $PT(FV)$ function is non-linear. Rodriguez et al., 2021 defined the parameters of 3.29 and are used in this work.

$$TR_{\text{VAT},y} = \sum_{k=1}^{K} \text{VAT}_{k,y} \times (1 + EITR_{k,y} + PR_{k,y}) \times CIF_{k,y} \times Q_{k,y}^{\text{imp}} \tag{3.28}$$

$$TR_{PT,y} = \sum_{k=1}^{K} \sum_{age=0}^{age_max} PT_{k,y}(FV_{k,age,y}) \times FV_{k,age,y} \times Q_{k,age,y} \tag{3.29}$$

Taxes on fuel and electricity consumption also apply per vehicle type k. Equation 3.30 shows the TR for gasoline and depends on its fuel tax rate FT -a per unit tax- and the consumption C. The same logic applies to diesel and LPG. The parameter $1/\eta$ converts energy consumption C into energy volume, i.e., the usual denominator for fuel prices and taxes. Equation 3.31 shows the TR for electricity tax revenue, which is ad-valorem, i.e., depends on the price (defined on the sections above) a percent rate ET, and the electricity consumption. The same approach to electricity applies to hydrogen, with an initial tax rate of zero.

$$TR_{Gasoline,y} = FT_{Gasoline,y} \times (1/\eta_{Gasoline,y}) \times \sum_{k=1}^{K} C_{k,Gasoline,y} \tag{3.30}$$

$$TR_{Electricity,y} = ET_{Electricity,y} \times P_{Electricity,y} \times \sum_{k=1}^{K} C_{k,Electricity,y} \tag{3.31}$$

Equation 3.32 shows the TR for vehicle-kilometer traveled (VKT) taxes, which depend on the distance traveled D of each vehicle type k. They are not applied in Costa Rica yet but are an option to substitute fossil fuel taxes in the long-term according to Van Dender, 2019.

$$TR_{VKT,y} = \sum_{k=1}^{K} VKT_{(k,y} \times D_{k,y} \tag{3.32}$$

Equation 3.33 shows the government revenue GR from transport taxes per year.

$$\begin{gathered} GR_y = TR_{IT,y} + TR_{VAT,y} + TR_{PT,y} + \\ TR_{Gasoline,y} + TR_{Diesel,y} + TR_{LPG,y} + \\ TR_{Electricity,y} + TR_{Hydrogen,y} \end{gathered} \tag{3.33}$$

3.3. Model Experiments

This section describes how to create multiple futures using OSeMOSYS-CR following the developments of Victor-Gallardo, Quirós-Tortós, et al., 2022. The experimentation steps are:

1. Identify the number of exogenous inputs (V) necessary to reflect an XLRM story (see XLRM definition in Section 2.2). Also, define the sample (N) for the number of futures per scenario.

2. Apply LHS sampling (see Section 2.2); the sampling results in a matrix with dimensions $V \times N$ with random values between 0 and 1. Each row is a normalized input parameter type, and each column is a future. Each cell must be scaled according to an interval defined for each row (these are explained for each experiment).

3. The LHS cells must then be used to manipulate the OSeMOSYS-CR input parameter time series. The variable manipulation process has four layers: uncertainties, sets, parameters, and manipulation methods. Uncertainties are technological, social, and economic metrics that cannot be known in the future (see Section 2.2 for more theoretical background on uncertainties). The sets are technologies, technology inputs (fuels), or technology outputs (demands). The sets are grouped according to similarity to simplify the number of uncertainties. For example, electric sedans and trucks have an equal relative change since both depend on battery costs. Parameters are the types of model inputs: unit costs, demands, input-output ratios, and restrictions. The

combination of uncertainty, sets, and parameters has an associated normalized time series. The manipulation methods use the LHS results to modify the model inputs; there are three methods:

- **Method 1: final year.** It changes the final value of the time series relative to the final value of the base case by applying a rule of three. It then interpolates the whole time series starting from an initial exploration year. This method keeps the shape of the base case time series. The initial value can be adjusted before or after changing the final value[7].
- **Method 2: multiply.** It multiplies the entire time series with a constant.
- **Method 3: logistic.** It models logistic shapes for the adjusted time series using Equation 3.34. In it, x is the time series value, y is the year, L is the desired value in the final year (2050), C is the value in year M, and k is the growth rate defined in Equation 3.35. To fix the logisc curves in the 2021-50 horizon, Equation 3.35 uses $r2050 = 0.999$ as the proportion of L the time series reaches in 2050. Moreover, C must be equal or lower than C_{max}, defined in Equation 3.36, which is a function of L and M and k.

$$x(y) = \frac{L}{1 + ((L/C) - 1) \times e^{-k(y-M)}} \tag{3.34}$$

$$k = log_e \left(\frac{r2050 - 1}{(L/C) - 1} \times \frac{1}{M - 2050} \right) \tag{3.35}$$

$$\begin{aligned} C_{max} &= \frac{L}{e^{log_e(ae1/ae2)/ae3} + 1} \\ ae1 &= \left(\frac{1}{r2021_max} - 1 \right) \\ ae2 &= \left(\frac{1}{r2050} - 1 \right)^{\frac{M-2021}{M-2050}} \\ ae3 &= \left(1 - \frac{M - 2021}{M - 2050} \right) \end{aligned} \tag{3.36}$$

This step and the previous two are a Python process from block D in Figure 3.1.

4. Generate model input files, execute the simulations, store the outputs, and create results visualizations. This step is a process from block E in Figure 3.1.

[7] Changing the initial value of the time series can be useful for parameters whose assumed base case value might vary considerably (e.g., the cost of hydrogen trucks).

3.3.1. Wide Experiment

Table 3.5 shows the XLRM matrix for the *wide experiment*, including the metrics (M). The ranges of input values and time series manipulation methods for the experimentation of each uncertainty (X) or lever (L) are in Table 3.6; the Appendix A has an example of cost trajectories for renewables and other energy infrastructure generated with Table 3.6 (13th row). There are a total of 28 uncertainties and levers, i.e., drivers. GDP growth is a constant throughout the period, thus not having any manipulation method. It is used in the equations of Section 3.1 appropriately.

Table 3.5: XLRM matrix for the wide experiment.

Uncertainties (X)	Levers (L)
Economic: 1. GDP growth [%] 2. Passenger demand elasticity [%Gpkm/ %GDP] 3. Freight demand elasticity [%Gtkm/ %GDP] 4. Non-transport fossil energy intensity [MJ/USD] 5. Non-transport electricity energy intensity [MJ/USD] **Climate:** 6. Hydro capacity factor [adimensional] **Technological (transport):** 7. Internal combustion engine vehicle (ICEV) costs* [rel. 2018] 8. Battery electric vehicle (BEV) costs* [rel. 2018] 9. Fuel cell electric vehicle (FCV) costs* [rel. 2018] 10. Unit cost of freight rail [USD/ton-km] **Technological (energy supply):** 11. Unit costs of fossil fuels** [rel. 2018] 12. Residual grid capacity [rel. 2018] 13. Unit costs of renewable generation, storage, and other energy infrastructure [rel. 2018] **Social:** 14. Mode shift to public transit [% of trips] 15. Mode shift to non-motorized transport*** [% of trips] 16. Private transport occupancy rates [rel. 2018]	**Regulations:** 1. Share of battery-electric vehicle (BEV) in public transport fleet [%] 2. Share of fuel-cell electric vehicle (FCEV) in public transport fleet [%] 3. Share of BEV in private transport fleet [%] 4. Share of BEV in light freight fleet [%] 5. Share of BEV in heavy freight fleet [%] 6. Share of FCEV in heavy freight fleet [%] **Operations:** 7. Freight modal shift to rail [% of heavy ton-kilometers] 8. Public transport occupancy rates [rel. 2018] **Investments (transport):** 9. Passenger rail and urban investments [% of GDP] **Investments (energy supply):** 10. Utility-scale solar generation [% of generation] 11. Distributed solar generation [% of generation] 12. Wind farm investments [% of generation]
Relationships (R)	**Metrics (M)**
1. The Bottom-up energy system model OSeMOSYS-CR to compute technical results. 2. A relational model to link inputs, partial outputs, and metrics; it allows executing PRIM hierarchically.	1. National financial impacts [% of GDP, period average] 2. National emissions [MTon at the end of the period] 3. Capital expenses [% of GDP, period average] 4. Bus prices [price at the end of the year] 5. Electricity prices [price at the end of the year]

* Vehicle costs comprise unit import costs (i.e., the CIF value) and yearly maintenance costs. We consider the vehicle energy input to output ratio to be an uncertainty that varies proportionally to cost.
** Includes fossil fuel infrastructure costs for LPG supply.
*** Includes an avoided private transport demand component from the digitalization of activities, e.g., telework. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.

The uncertainty classifications in economic, climate, technological (transport and energy supply), and social categories simplifies the definition and interpretation of model drivers. The uncertainties out of any actor's direct control and apply to both the NDP and the BAU scenarios. For example, the residual capacity[8] of the transmission and distribution grids in the future can vary depending on the impacts of natural disasters and obsolescence of assets to operate a modern power system.

Table 3.6: Ranges of input values to produce the experiment from random value matrix.

Category	Variable	Min	Max	Method
Economic	GDP growth	2	4.5	Constant
	Non-transport electricity energy intensity	0.7	1.3	Final year
	Fossil fuel energy intensity	0.1	1	
	Passenger demand elasticity to GDP	0.5	1.5	
	Freight demand elasticity to GDP	0.5	1.5	
Climate	Hydro capacity factor	0.7	1	Final year
Technological (transport)	Battery-electric vehicle (BEV) unit costs	0.5	1.5	Final year
	Internal combustion engine vehicle (ICEV) unit costs	0.75	1.25	
	Fuel-cell vehicle (FCEV) unit costs	0.5	1	
	Unit cost of freight rail	1	2	Multiply
Technological (energy)	Fossil fuel prices and other costs	0.5	1.5	Final year
	Residual grid capacity	0.5	1	
	Renewables, storage, and other infrastructure unit costs	0.5	2	
Social	Modal shift to public transit (2050)	0%	25%	Logistic
	Modal shift to public transit (2034-36)	0%	12.5%	
	Non-motorized transport and digitalization (2050)	0%	12.5%	
	Non-motorized transport and digitalization (2034-36)	0%	7.5%	
	Public transport occupancy rate	1	1.5	Final year
Regulations	BEV penetration (public) (2050)	50%	85%	Logistic
	BEV penetration (public) (2034-36)	0%	50%	
	FCEV penetration (public) (2050)	10%	30%	
	FCEV penetration (public) (2034-36)	0%	10%	
	BEV penetration (private) (2050)	90%	99.9%	
	BEV penetration (private) (2034-36)	10%	50%	
	BEV penetration (heavy trucks) (2050)	30%	60%	
	BEV penetration (heavy trucks) (2034-36)	0%	30%	
	H2 penetration (heavy trucks) (2050)	30%	50%	
	H2 penetration (heavy trucks) (2034-36)	0%	30%	
	BEV penetration (light trucks) (2050)	70%	99.9%	
	BEV penetration (light trucks) (2034-36)	0%	70%	
Operations	Freight modal shift (2050)	0%	25%	Linear
	Private transport occupancy rate	1	1.5	Final year
Investments (transport)	Passenger rail and urban interventions	1	2	Final year
Investments (energy)	Max capacity of solar utility-scale	0.8	1.2	Final year
	Max capacity of distributed solar with storage	1	3	
	Max capacity of wind generation	0.8	1.2	

Lever classifications reflect possible actions by different actors. The government can set regulations on electrification rates or opt for policy objectives and support the private sector. Fright firms and public transport operators can change their operative parameters. Transport investments are part of

[8]The residual capacity is the capacity in the base year of a specific technology. In the case of grid capacity, it refers to how much of the capacity in the base year is still usable in the future.

government public works, financed directly or through a concession contract (or a similar mechanism). Finally, the investments in energy supply are decisions on power generation options. Importantly, the levers apply only to the NDP, and the BAU does not have any structural transformation.

3.3.2. Narrow Experiment

Table 3.7 shows the XLRM matrix for the *narrow experiment*, specifically aimed at studying the power sector and the effect of the discount rate and the profit margin. The uncertainty and lever classifications vary relative to the *wide experiment*. One of the levers is the share of ownership of charging infrastructure between incumbent energy firms and distributed generation (DG) owners. Incumbent firms own all utility-scale power plants and transmission and distribution networks. The DG owners only have distributed solar (with and without storage) in this work. The other new levers are the discount rate and profit margin, which policy influences.

Table 3.7: XLRM matrix for the narrow experiment.

Uncertainties (X)	**Levers (L)**
Demand: 1. *Share of battery-electric vehicles (BEV) in light-duty transport [fleet %]:* we apply a logistical curve that reaches 2035 and 2050 electrification levels in the intervals [10, 55] and [90, 99], respectively. 2. *Share of BEV in medium and heavy-duty fleets [%]:* reaches 2035 and 2050 electrification levels in the intervals [0, 40] and [55, 90], respectively. **Climate:** 3. *Hydro capacity factor [adimensional]:* the final value is multiplied by a constant between [0.6, 1]. Then, the variable's time series is interpolated. **Technological:** 4. *Unit costs of solar with and without storage:* the final value of the capital and fixed unit costs of all solar technologies is multiplied by a constant in the interval [0.5, 2]. Then, the variable's time series is interpolated. 5. *Unit costs of wind generation and other power infrastructure:* the same manipulation as above, but for wind generation, transmission and distribution system costs, and charging infrastructure for heavy-duty vehicles.	**Financial:** 1. *Discount rates [%]:* constant in the interval between 2% and 15% 2. *Profit margin [%]:* constant in the interval between 0% and 20% **Investments:** 3. *Utility-scale solar and wind generation [% of production]:* achieved by multiplying the maximum capacity of wind and utility-scale solar in 2050 by a constant in the interval [0.5, 1]. The ESOM selects the cost generation mix based on maximum capacity and cost minimization. **Business:** 4. *Share of charging infrastructure ownership [%]:* a constant share in an interval between 0% and 100%
Relationships (R)	**Metrics (M)**
1. The Bottom-up energy system model OSeMOSYS-CR. 2. Equations to estimate prices and revenue of energy firms.	1. Financial impacts per actor* 2. Electricity prices [¢/kWh]

* The financial impacts are estimated considering electricity prices with profits. Moreover, the units of financial impacts are in % of GDP (period average) and M USD (discounted to 2022 at the explored rate).
Taken from Victor-Gallardo and Quirós-Tortos, 2022.

The profit margin is explored between 0 and 20% of the final price. In this work, the discount rate serves two purposes: i) to discount future cash flows and ii) to put a value on the *cost of capital* (or debt) to finance power infrastructure. As explained by Gilbert, 2020, the discount rate reflects investors' confidence in future cash flows materializing: if confidence is low, the discount rate is high, and the net present value is low. If the confidence is low, investors will want more return for their capital (cost of capital) as a reward for their perceived risks.

This work assumes equivalence between the discount rate and the cost of capital. The weighted average cost of capital (WACC) reflects the risks borne by owners and investors when developing projects in a given industry, according to Franc-Dabrowska et al., 2021. The discount rate interval explored here is the extreme WACC values presented by Steffen, 2020 for solar and wind generation projects in multiple countries: between 2% and 15%.

3.3.3. Tax Adjustment Evaluation

Rodriguez et al., 2021 found that decarbonizing transport affects government revenue negatively, i.e., a fiscal impact occurs. Below is the method to analyze possible corrections to the fiscal impact employed in Rodriguez et al., 2021 and formalized by Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. The steps -applied yearly- are:

1. For every tax ψ (defined in the tax equations), generate a weight w_ψ between 0 and 100%. These parameters comply with Equation 3.37 and are a random combination of tax options to cover the fiscal impact in a given future.

$$\sum_{\psi,y} w_{\psi,y} = 1, \text{ where } 0 \leq w_{\psi,y} \leq 1 \tag{3.37}$$

2. Calculate the tax change according to Equation 3.38. It calculates the new unit tax UT' per tax ψ and vehicle type k for taxes existing before the adjustment. The activity data AD the tax ψ can be vehicles, energy, or distance traveled, depending on the tax.

$$UT'_{(k,\psi,y)} = \begin{cases} \frac{GR_y + (w_\psi \times FI_{\text{gov},y})}{GR_y} \times \frac{TR_{k,\psi,y}}{AD_{k,\psi,y}}, & \text{tax exists before adjustment} \\ \frac{w_\psi \times FI_{\text{gov},y}}{AD_{\psi,y}}, & \text{otherwise} \end{cases} \tag{3.38}$$

3. For the taxes that do not exist before the adjustment, also apply Equation 3.38 accordingly. In the case of the VKT, the total activity data is the total number of kilometers traveled, thus producing a flat tax per kilometer. A similar approach applies to taxes on hydrogen.

4. Calculate the fiscal cost per actor. To do this, recalculate all the expenses with the additional taxes. Then, quantify additional tax expenses. When the fiscal impact is not negative, the fiscal costs are negative, reflecting tax reductions or subsidies.

3.4. Robustness Analysis

Chapter 2 introduced the concept of *robust policy*: the ones that produce the most favorable outcome across multiple scenarios. However, in the light of the XLRM matrices defined above, another question arises: what are the values of uncertainties that produce favorable outcomes? Victor-Gallardo, Quirós-Tortós, et al., 2022 defines a robust pathway as the combination of drivers (uncertainties and levers) that produce desirable outcomes and avert risk outcomes. The methodology described below applies to the *wide experiment*, and thus to five metrics: national financial impacts, national emissions, gross capital expenses[9], bus prices, and electricity prices. Victor-Gallardo, Quirós-Tortós, et al., 2022 considered these five metrics, and this work finds the robust pathways for each actor based on the financial impact metric. When the financial impacts are positive, the country or actors benefit. The opposite means the country would spend more decarbonizing (with a *ps* scenario) than with the BAU.

The desirable outcomes are high benefits and low emissions, capital expenses, and prices. The converse is true for risk outcomes: high emissions would mean decarbonization goals are not met. More problematically, low benefits would mean there is no incentive to decarbonize. High capital expenses can make the transformations difficult because investment sources can be scarce. High bus prices can affect poor households, and high electricity prices can make the country less competitive.

The *wide experiment* produces 2000 time series for each metric. The metrics can be period averages or specific years of the time series. Victor-Gallardo, Quirós-Tortós, et al., 2022 use the following definitions: a high value belongs to the highest 25% values, and a low value belongs to the 25% lowest. They use the periods 2022-30 and 2031-50. The financial impacts and the capital expenses are period averages. Emissions and prices are studied for values corresponding to the last period year.

Finding the drivers that produce desirable and risk outcomes requires a systematic analysis of the inputs explored in the *wide experiment*. Victor-Gallardo, Quirós-Tortós, et al., 2022 use PRIM (see Section 2.2), based on the Python implementation of the Exploratory Modeling Workbench by Kwakkel, 2017. PRIM produces multiple boxes (or combinations of drivers) with varying coverages and densities (see Section 2.2 for definitions); the higher the coverage, the lower the density, and vice versa.

[9] Gross expenses, unlike net expenses, are not relative to the expenses in the BAU scenario.

The boxes can be obtained for one metric and a given number of drivers that can cause a metric to be high or low, i.e., the *metric space* MS. The boxes contain the value intervals of those drivers related to the metric; the futures within the driver intervals are the *pathway futures* PF. Hence, coverage and density can be defined in Equations 3.39 and 3.40, as proposed by Victor-Gallardo, Quirós-Tortós, et al., 2022, where the $size()$ function represents the counting of the futures of either set PF or MS.

$$coverage = \frac{size(PF \cap MS)}{size(MS)} \tag{3.39}$$

$$density = \frac{size(PF \cap MS)}{size(PF)} \tag{3.40}$$

According to Victor-Gallardo, Quirós-Tortós, et al., 2022, since the model is deterministic and the cause-effect relationships of the input parameters and the metrics are known apriori, systematic and hierarchical application of the PRIM algorithm on the experiment data can quantify the relationships amongst model outputs and drivers. The *hierarchical PRIM* is introduced by Victor-Gallardo, Quirós-Tortós, et al., 2022 and is described below.

3.4.1. Hierarchical Patient Rule Induction Method

Figures 3.5, 3.6, and 3.7[10] show the hierarchical PRIM application relationships per metric (see the captions per Figure for the specific metric). With this approach, PRIM is applied to related data on three levels. The first level contains the metric of interest, and the third contains the most uncertainty and lever drivers. The second level connects both through partial model outputs. PRIM produces the intervals of partial outputs and drivers that explain the region of interest of the main metric, i.e., high or low values. The partial outputs include:

i) the fleets, which depend on the demand elasticities and GDP;

ii) the zero-emission vehicle (ZEV) penetrations, measured as energy consumed by ZEV vehicles as a share of total transport energy consumption;

iii) the non-transport electricity and fossil fuel demands;

[10] The following abbreviations are used: i) *NT. elec* is non-transport electricity consumption; ii) *NT. fuel* is non-transport fossil fuel consumption; iii) $T\&D$ is transmission and distribution; *inv* means investment; *gen* means generation; *trans* means transport; $H2$ means hydrogen; inf means infrastructure; ZEV means zero-emission vehicles.

iv) electricity sector cost averages (per unit of sales), distinguishing generation, transmission, and distribution costs, including charging infrastructure for heavy-duty electric vehicles;

v) for financial impacts (net costs if negative and benefits if positive), the values grouped by passenger transport, freight transport, power and hydrogen production, energy distribution infrastructure, and fossil fuels.

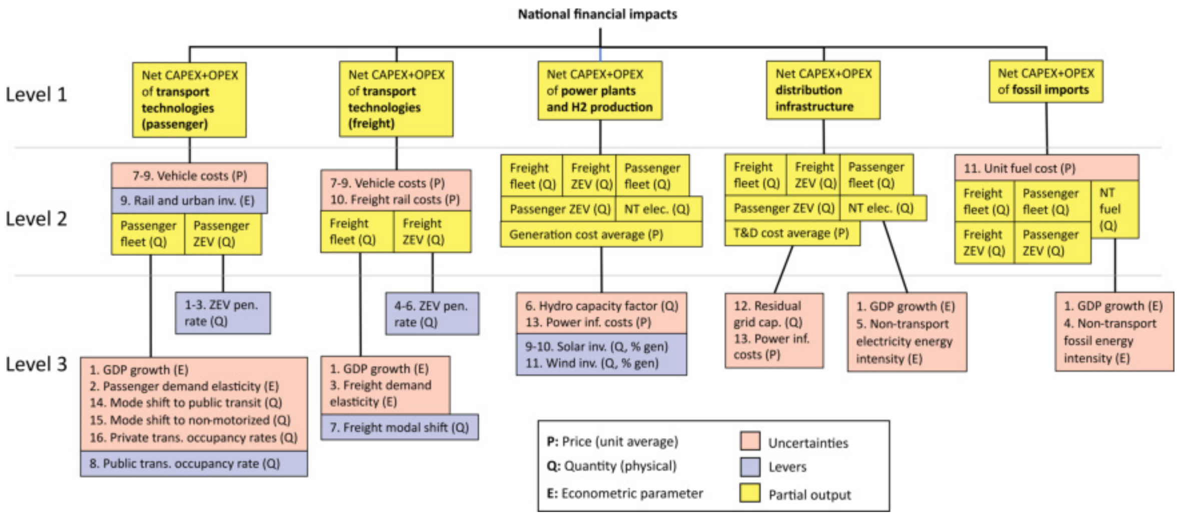

Figure 3.5: Hierarchical PRIM application for national financial impacts. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.

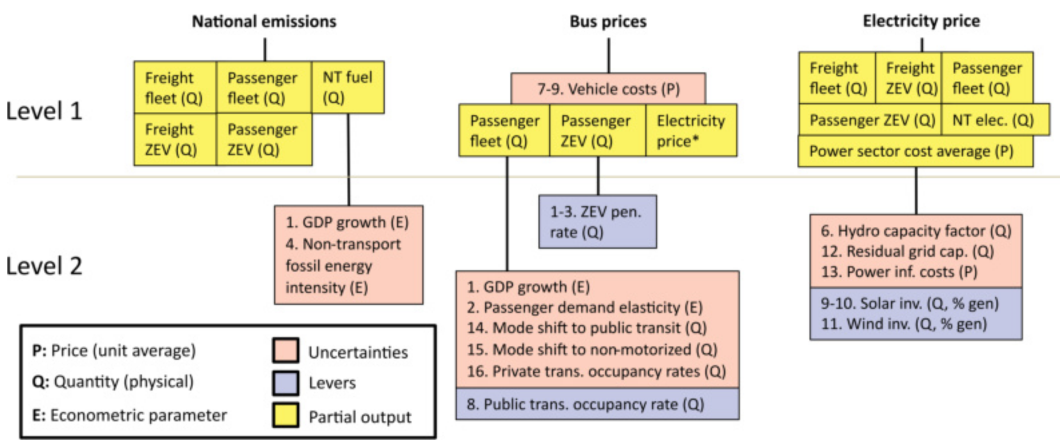

Figure 3.6: Hierarchical PRIM application for emissions, bus, and electricity prices. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.

The resulting intervals of partial outputs are thresholds (i.e., the interval endpoint that is not an absolute minimum or maximum) for the next levels to continue applying PRIM. The resulting driver combinations do not necessarily include all of the listed variables[11], only the ones identified by PRIM. Importantly, the PRIM box chosen for the next levels is the one with the highest dimensions with at least 70% coverage, which is a design rule.

A *direction* indicates whether the region identified by PRIM is lower than or higher than the threshold. Although the hierarchical PRIM is applied per metric and outcome, some drivers can repeat for the same outcome. If the drivers and their directions repeat, the used threshold is the mean of the thresholds. The most predominant direction and corresponding average threshold are chosen if the directions are different. Some drivers repeat across outcomes and can have diverging intervals. Victor-Gallardo, Quirós-Tortós, et al., 2022 provides an example: low emissions, high benefits, and low CAPEX (all desirable outcomes) need high, high, and low private electrification, respectively. Hence, high electrification is predominantly desirable, and would be the best driver for most metrics.

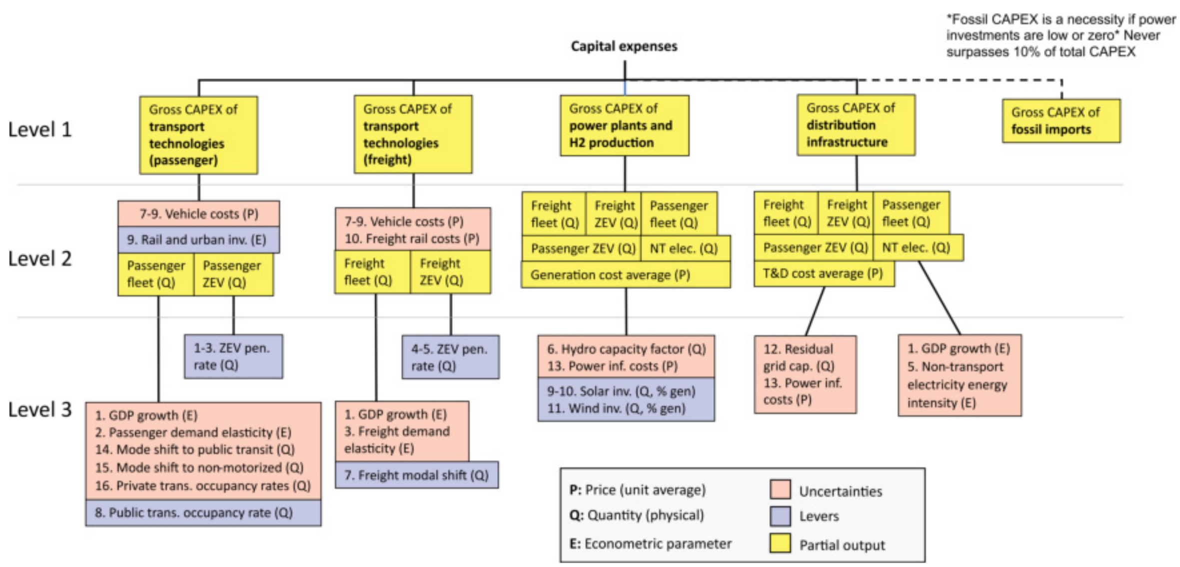

Figure 3.7: Hierarchical PRIM application for gross capital expenses. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. The dashed black line shows that the gross capital expenses of fossil imports are not considered in the box of capital expenses. The experiment results show that fossil capital expenses never surpass 10% of total capital expenses. Thus, these expenses are relatively small and can be excluded from the PRIM box for capital expenses.

In sum, to determine a single interval for a driver, the hierarchical PRIM iterates across all the intervals found per metric, picks the predominant direction, and picks the mean of the thresholds. The relationships for the financial impacts per actor are in Appendix B.

[11] The uncertainties and levers in Figures 3.5, 3.6, and 3.7 match the ones defined in Tables 3.5 and Table 3.6.

Chapter 4

Results and analysis

4.1. National Costs, Benefits, and Emissions

The results in this section show base case scenarios, i.e., before experiments. Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 developed the scenarios shown here. Figure 4.1 shows the financial expenses per scenario and their distribution per sector[1] for each one of the three decades between 2020 and 2050. The costs under the BAU remain more or less constant. In the NDP, costs are higher in the first decade, similar in the second decade, and lower in the third decade.

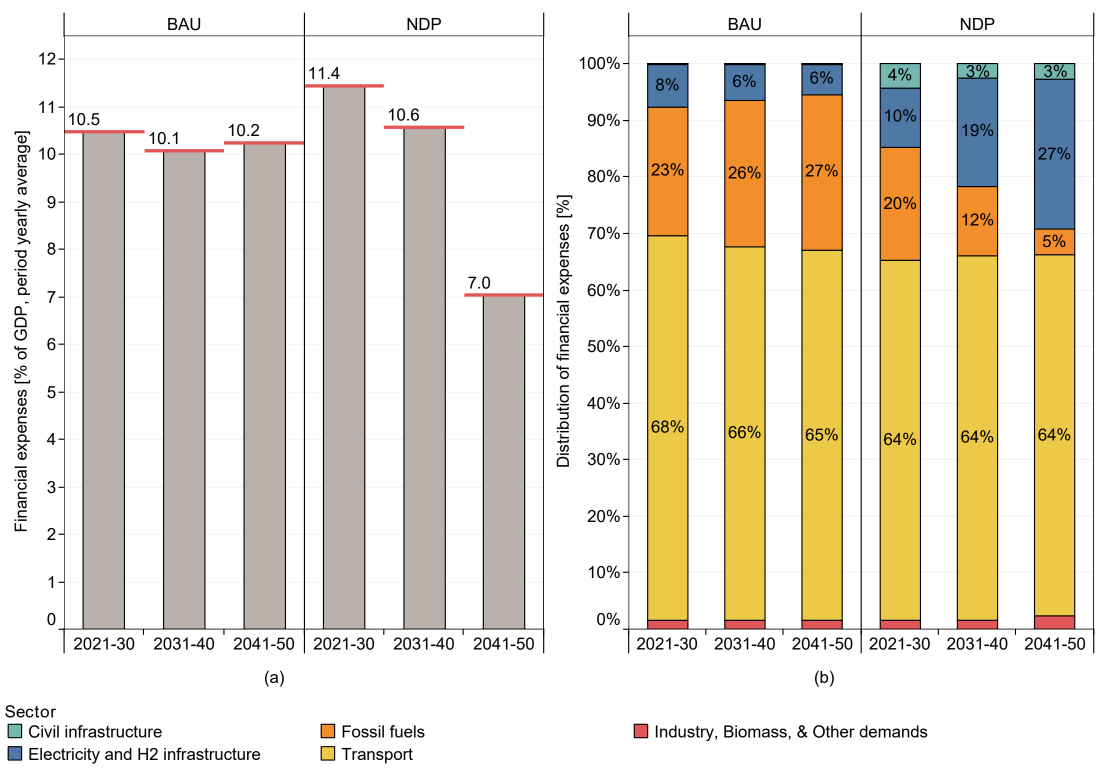

Figure 4.1: Financial expenses per sector of the BAU and NDP scenarios. (a) Total. (b) Distribution per sector. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

[1] Financial costs differ from economic costs in not considering externalities.

Considering the five sectors in Figure 4.1, the electricity and hydrogen (H2) infrastructure sector increase its share of the total expenses, while fossil fuels decrease. These sectors comprise the country's energy supply and associated costs. The transport sector has the highest share of financial expenses, comprising capital and operational and maintenance costs (excluding energy costs). In the NDP, necessary civil infrastructure expenses are 3-4% of total expenses, excluding other necessary expenses under the BAU, e.g., on roads. Other sectors, including industry, have the lowest share of expenses.

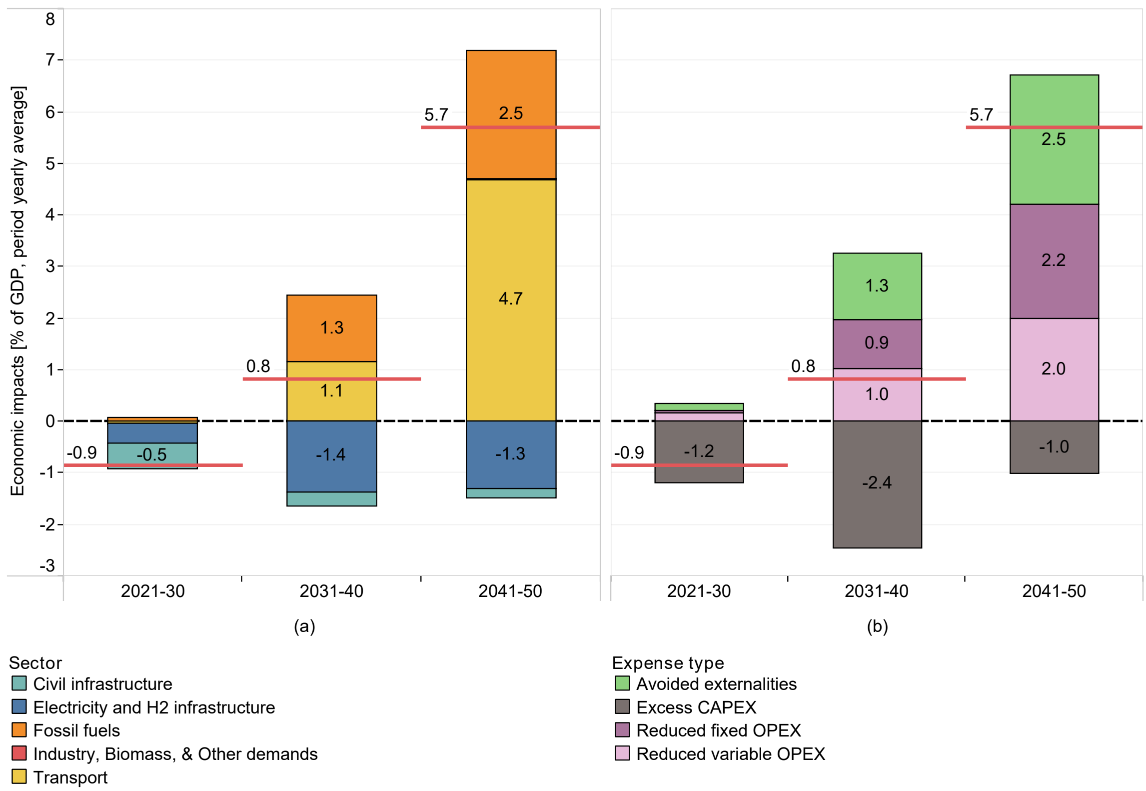

Figure 4.2: Economic benefits for the NDP scenario. (a) Per sector. (b) Per expense type. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022. Note: the horizontal red line shows the sum.

Figure 4.2 shows the national economic impacts per decade. The first decade has net costs (i.e., negative economic impacts). The NDP is more costly than the BAU, mainly because of additional electricity costs (0.4% of GDP) and civil infrastructure costs (0.5% of GDP). These additionals costs enable benefits in the next decades. The transport sector has the second-highest benefit in the second decade (1.1% of GDP) and the highest benefit in the third decade (4.7% of GDP). Fossil fuel savings increase from 1.2% of GDP in the second decade to 2.5% of GDP in the third decade. Fossil fuel savings in the first decade are negligible in the first case, partly because of the substitution from diesel and gasoline to LPG modeled for the first decade (see Table 3.1). The electricity sector has net costs higher in the last two decades than in the first decade.

Figure 4.2 also shows the economic impact disaggregation per expense type. The excess CAPEX is highest in the second decade, when the technological shift is fastest. Hence, the total benefits are lower in the second decade than in the third. The benefits from other expense types grow in time.

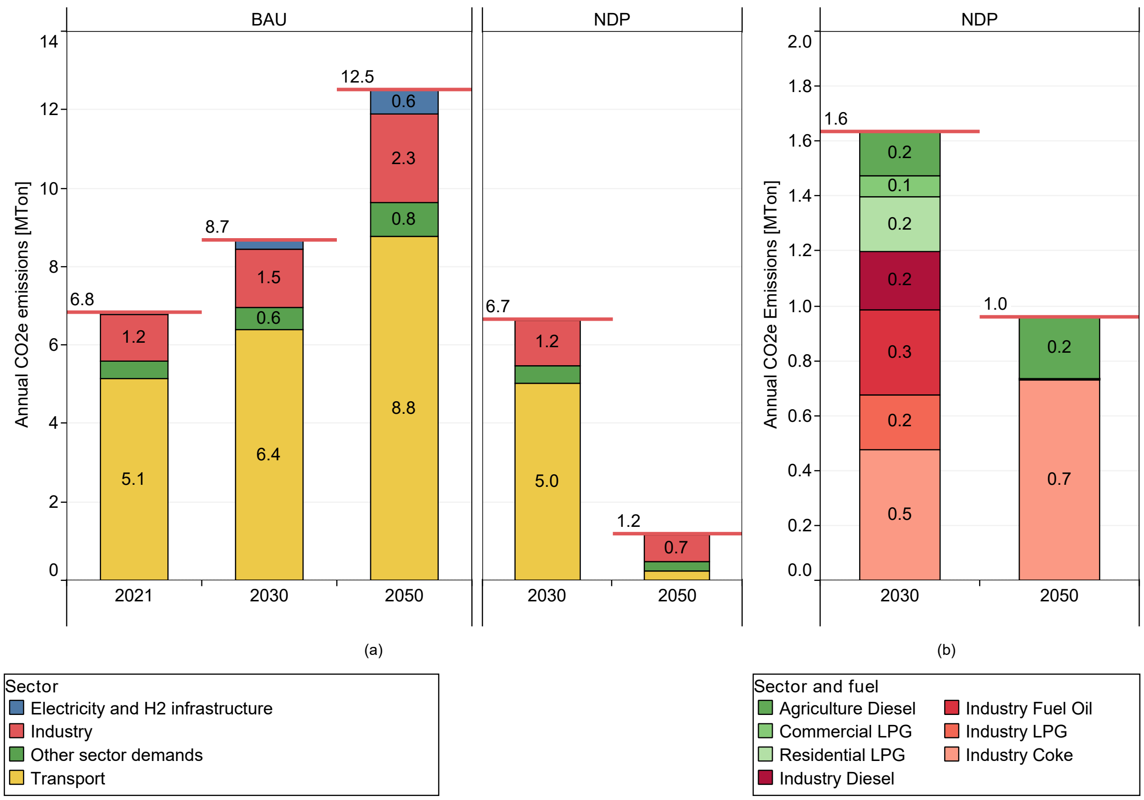

Figure 4.3: Emissions of carbon dioxide equivalent (CO2e). (a) For the BAU and NDP scenarios by sector. (b) For the NDP scenario by sector and fuel, excluding transport. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

Figure 4.3 shows emissions of CO2e. The NDP scenario practically keeps 2030 emissions equal to 2021[2][3]. The largest emission source is the transport sector, except for 2050 in the NDP, where the measures reduce them drastically to practically zero. By 2050 in the BAU, the industry sector can

[2]The model results in 2018 are 7.1 Mton of CO2e, which exclude off-road, maritime, and aviation transport. It also excludes kerosene and jet fuel consumption from industrial, residential, commercial, and public sectors. In the electricity sector, methane emissions from hydropower dams are not included. These exclusions result in an approximate 0.9 Mton difference between de 7.1 estimated Mton for 2018 and the reported 7.98 Mton reported by Instituto Meteorológico Nacional, 2019.

[3]There is an effect of demand reduction from the economic slowdown in 2020 due to the COVID-19 pandemic, which reduces emissions in 2021 relative to 2018 by 0.3 Mton or 4.2%.

potentially double its emissions, and not phasing out fossil fuel plants can increase electricity sector emissions[4]. Diesel and coke substitutes were not modeled for agriculture and industry, respectively. Thus, these residual emissions would remain prevalent in the NDP. Agriculture can opt for electricity-powered equipment, and the cement industry -where coke is primarily used- can become more efficient.

4.2. Ranking Policy Objectives

Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022 shows the relative importance of each measure in Table 3.2, also exploring how energy cost reductions increase the country's competitiveness. Here, a simpler comparison of metrics per measure is presented, following the ranking methodology from Section 3.1 and the RES of 3.3. Figures 4.4, 4.5, and 4.6 show the ranked scenarios for economic benefits, cumulative emission reductions, and excess CAPEX and fixed costs.

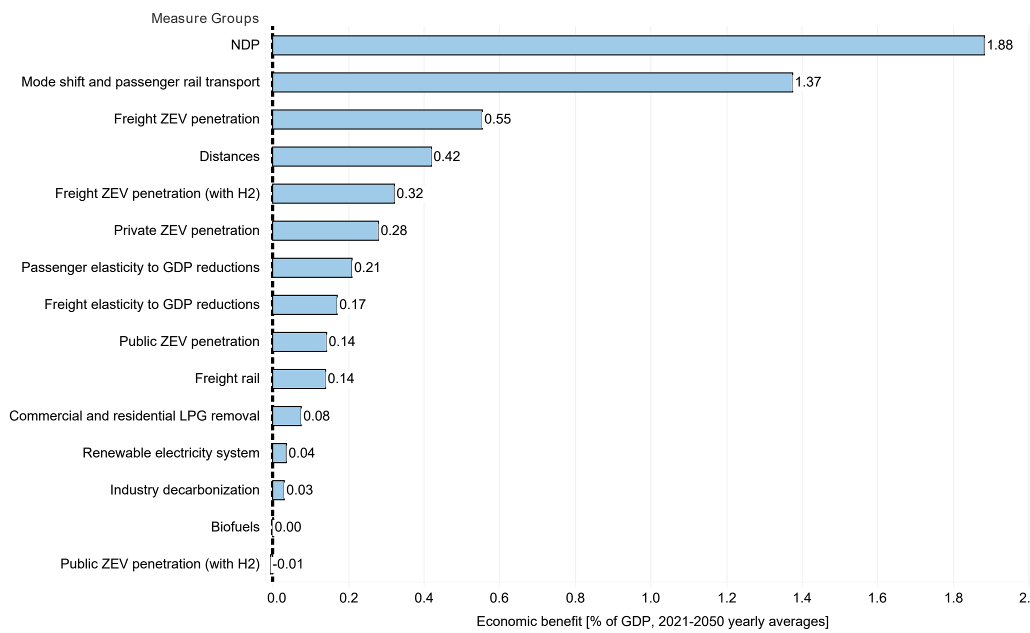

Figure 4.4: Economic benefits by mitigation measures. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

[4]For the BAU, non-renewable capacity remains installed. The optimization results imply that the least-cost system operates these plants and avoids idle capacity instead of investing in renewable alternatives that eliminate their emissions.

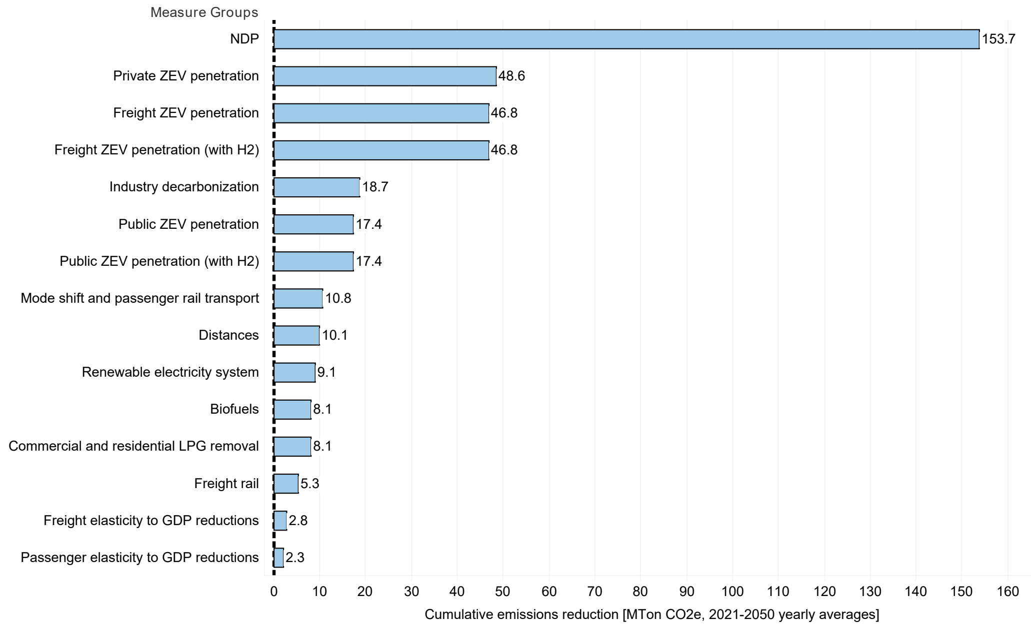

Figure 4.5: Cumulative emissions reduction by mitigation measures. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

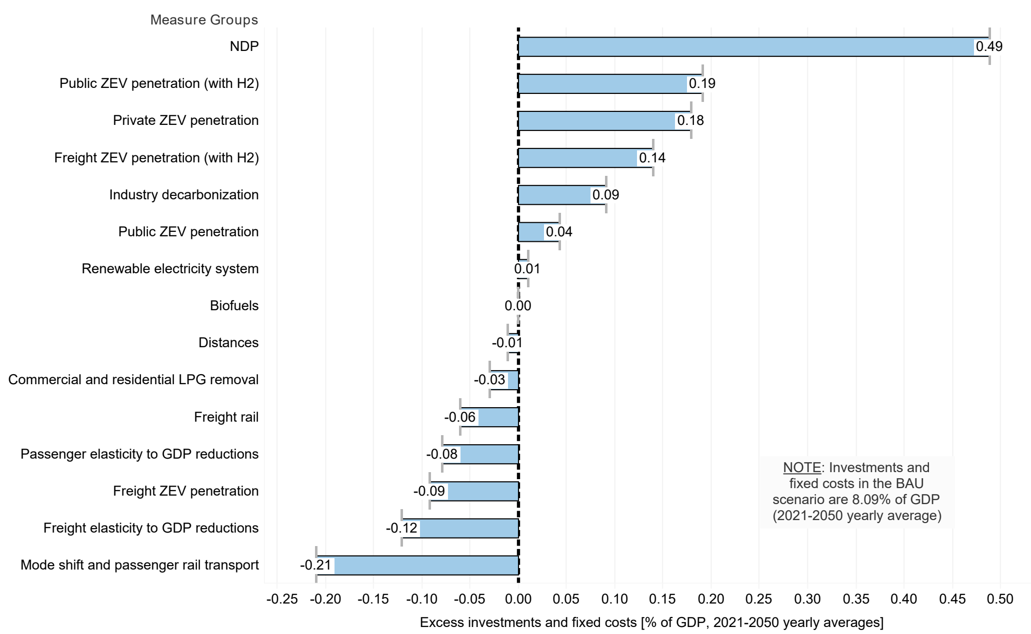

Figure 4.6: Excess CAPEX and fixed costs. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

Mode shift and passenger rail transport produce the highest benefits (second measure in Figure 4.4) because they reduce the number of vehicles and associated congestion and accident costs. However, that measure alone does not reduce emissions considerably (see Figure 4.5. ZEV penetrations in private and freight transport reduce emissions the most. ZEV penetrations in public transport are not just over a third of private or freight ZEV emission avoidance potential.

Figure 4.6 shows which sectors require more (positive values) or less (negative values) investment than the BAU. Mode shift and demand elasticity reductions reduce the capital requirements for the NDP. Shifting from truck to rail transport also avoids buying trucks and providing maintenance. In the case of freight ZEV, savings in fixed operational costs can be positive, thus appearing in the negative values from Figure 4.6.

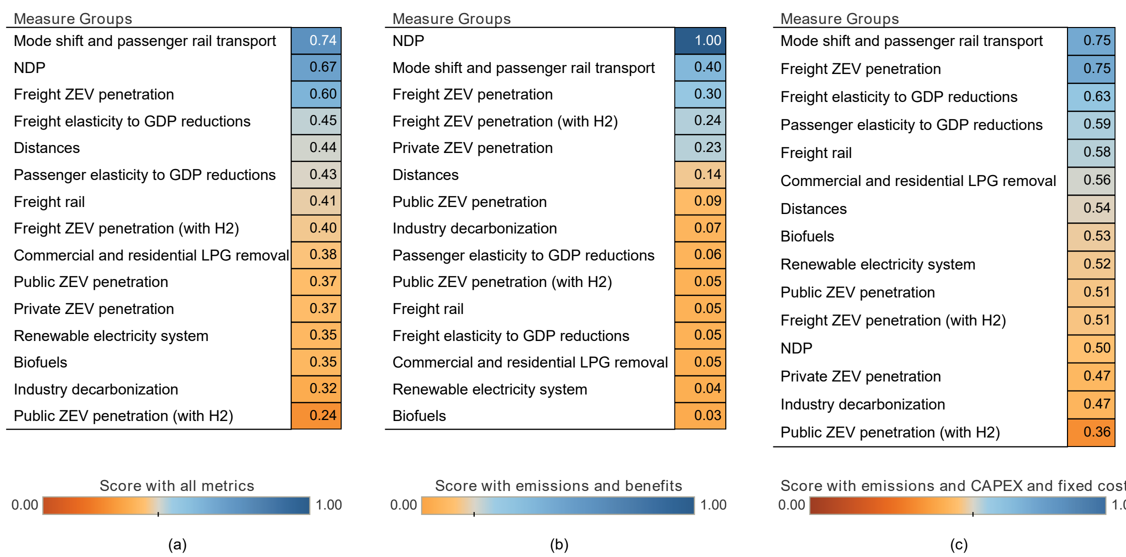

Figure 4.7: Ranking of mitigation measures. (a) Considering benefits, emissions, and excess CAPEX and fixed costs. (b) Considering emissions and benefit. (c) Considering emissions and CAPEX and fixed costs. (d) Considering benefits and CAPEX and fixed costs. Taken from Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce, et al., 2022.

Figure 4.7 shows the ranking of the measures for three different combinations scores. The results show how crucial providing public transport is to have lower costs than the BAU, thus, ranking first or second in all the three metrics. The low score of biofuels, industry, and public transport ZEV penetration with H2 suggests that, for the base case, the enabling technologies of these scenarios are not cheaper than alternatives and do not reduce emissions as much[5]. Freight ZEV is another measure

[5] Biofuels are modeled with equal costs as fossil fuels and their only effect is emission reductions.

that ranks among the top three measures across the scores. Importantly, these measures consider the entirety of the horizon. Hence, in smaller periods, the ranking could change. The other measures not mentioned above contribute to reducing emissions further and should be advanced. The prioritization exercise should give policymakers perspective on the dimension of challenge and opportunity in each sector to reduce energy-related costs and emissions.

4.3. Uncertainty Effects

Victor-Gallardo, Quirós-Tortós, et al., 2022, Victor-Gallardo and Quirós-Tortos, 2022, and Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022 used a model with the RES of Figure 3.2; the results below summarize the findings from those articles in what pertains to this work. Figure 4.8a shows the national economic impacts under the *wide experiment*. Comparing against Figure 4.2, the impacts have a lower magnitude under uncertainty, particularly in the second decade. That Figure also shows how benefits can be considerably higher or lower than the period averages.

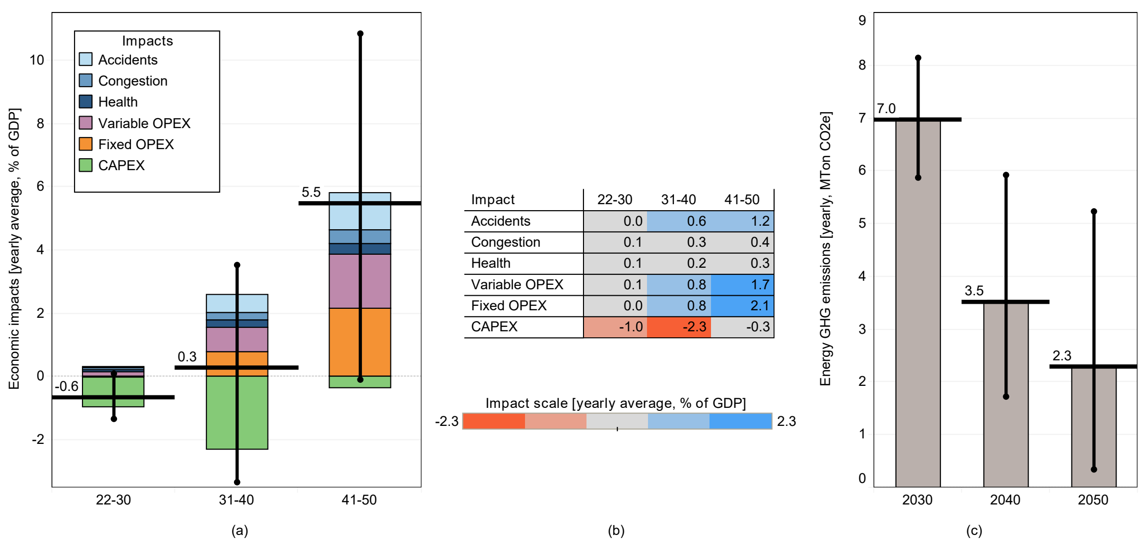

Figure 4.8: Overview of national metrics under uncertainty. (a) Average and range across futures of economic impacts. (b) Detail of economic impacts. (c) Average and range across futures of emissions. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. Notes: The black lines in (a) and (c) represent the range across futures. In (a), the horizontal line shows the sum across categories.

Figure 4.8 zooms into the disaggregation of the impacts on a scale of high and low impacts. The highest net cost occurs for the second decade CAPEX, while the highest benefits occur for fixed and variable OPEX and accidents in the last decade. Figure 4.8c also shows the yearly emissions per decade; the average across the *wide experiment* futures are higher than the base case results from Figure 4.3. This reflects how the experiment stresses the base case decarbonization ambition.

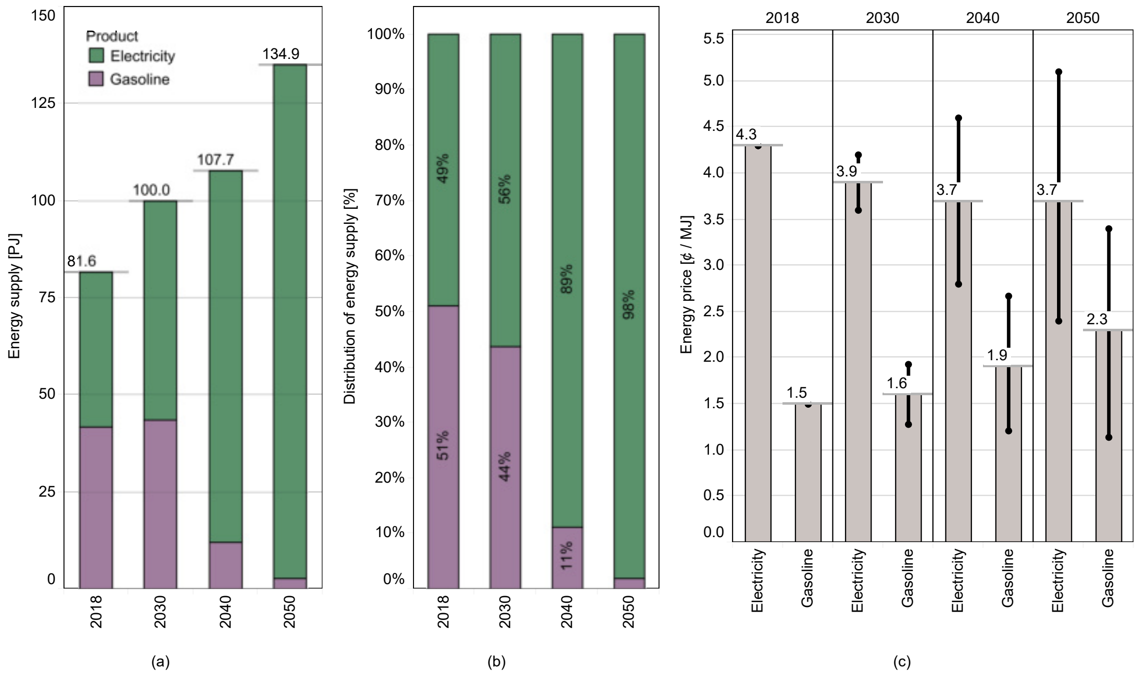

Figure 4.9: Context of electricity prices. (a) Average across futures of energy supply by energy products (not all products included). (b) Distribution of the average across futures of energy supply by energy products (not all products included). (c) Average and range of across futures of prices by energy product. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. Note: The black lines in (c) represent the range across futures.

Figure 4.9c shows electricity price results. Figure 4.9a and 4.9b show how, for the NDP, electricity has an increasing supply and gasoline has a decreasing supply[6]. In OSeMOSYS-CR-v2 and the TEM, supply gasoline prices are exogenous. This feature is consistent with Costa Rica being a tiny player in the international oil market, thus having no pricing effects by only importing fuel. Nonetheless, the electricity prices are a function of the country's natural resources and investment decisions and, thus, are correlated with the demand and supply of electricity.

In Figure 4.9a, only electricity and gasoline are compared. Between the two energy vectors, electricity grows from 49% in 2018 of the supply to 98% in 2050. The total supply of these two energy vectors would increase by 65% in 2050 relative to 2018. Despite this supply growth, the pricing mechanism at cost makes the prices 14% lower in 2050 relative to 2018, on average across

[6]In OSeMOSYS-CR-v2, supply is directly proportional to internal demand because there are no significant exports and inventories are not modeled.

futures (Author calculations based on 4.9c). In contrast, gasoline prices would become more expensive (average across futures), and gasoline consumption would become negligible by 2050. Some futures from the *wide experiment* keep the exogenous gasoline price more or less constant by 2050 relative to 2018, while others make it more than double in the same period.

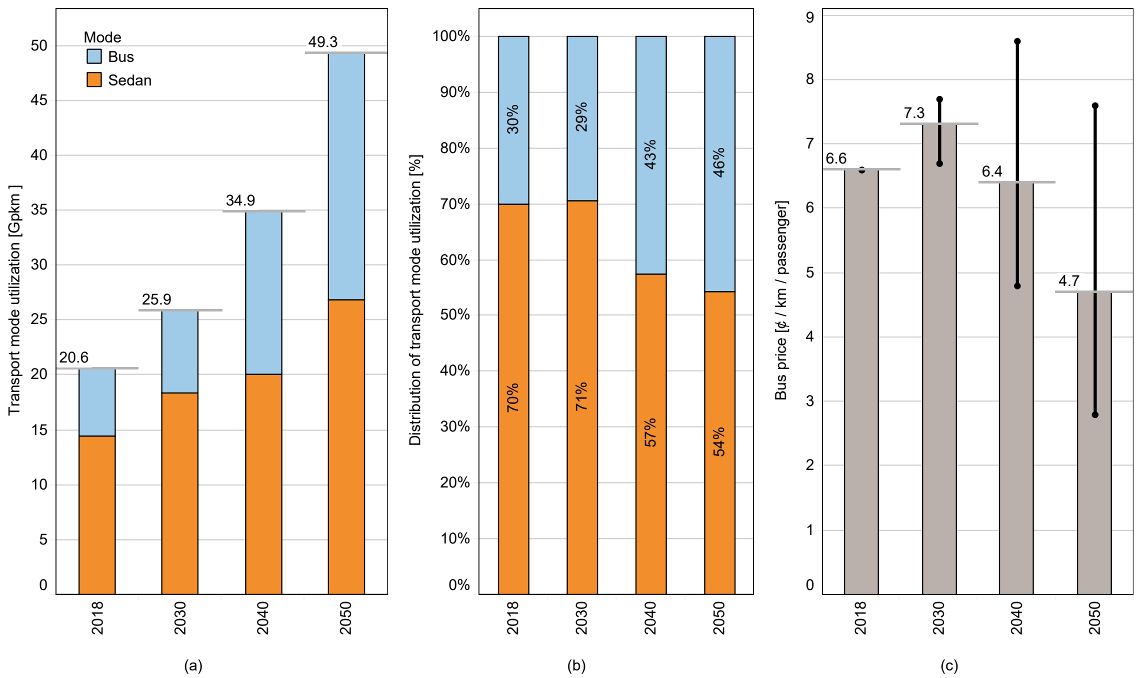

Figure 4.10: Context of bus prices. (a) Average across futures of transport mode utilization (not all modes included). (b) Distribution of the average across futures of transport mode utilization (not all modes included). (c) Average and range of across futures of bus prices. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. Note: The black lines in (c) represent the range across futures.

Figure 4.10 shows a similar story for transport modes as Figure 4.9 does for prices. According to Figure 4.10a, the bus and sedan passenger-kilometers increase 239% by 2050 relative to 2018 (on average, across futures). Between these two modes, bus prices increase their participation by 2050 to 46%, up from the 30% in 2019 (see Figure 4.10b). Despite the growth, bus prices decrease by 2050, although they increase by 2030 (on average, across futures).

Focusing on financial impacts, which show the difference between national technology ownership cost per scenario, Figure 4.11 shows the distribution of impacts in each future. About 20% of futures have negative financial impacts, with an average impact of -0.46% of GDP (yearly average of 2022-50); the lowest impact is -1.92% of GDP. These futures would make energy decarbonization undesirable, posing a risk for any policy aiming at objectives that would be more costly than beneficial. The other

80% of futures are the opposite: decarbonization is desirable in those futures because meeting energy needs would be cheaper relative to not doing so. The average financial impact of positive futures is 1% of GDP, i.e., 0.29 percentual points higher than the average across all futures; the highest impact is 3.16% of GDP.

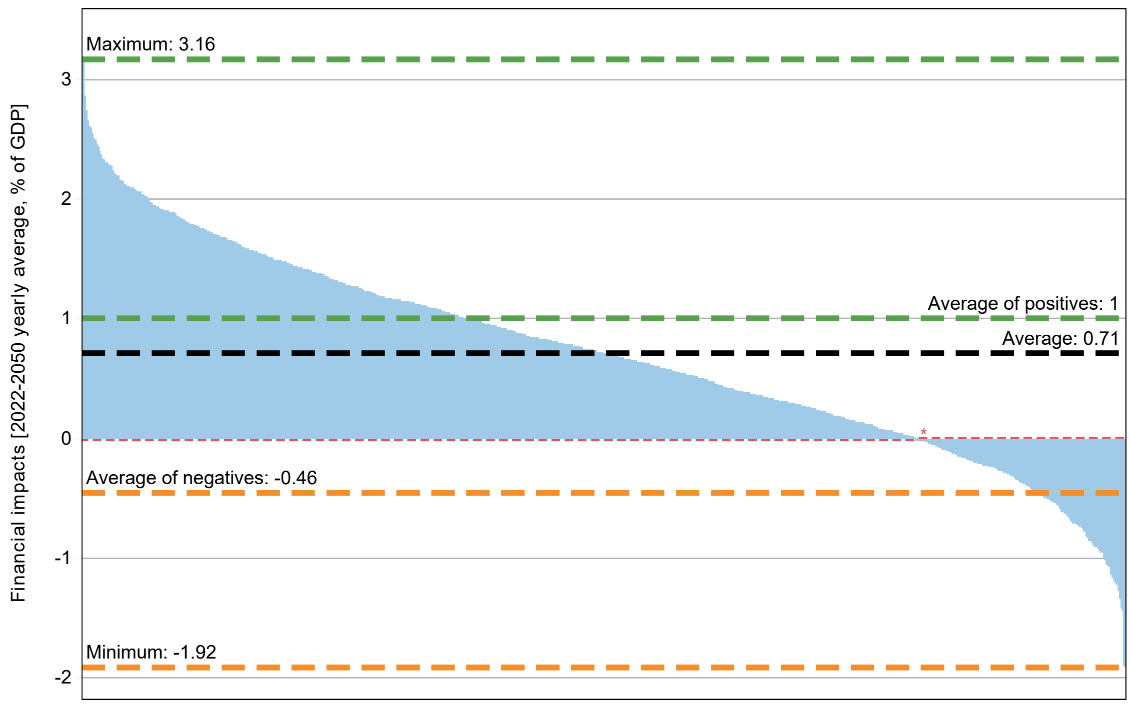

Figure 4.11: Financial impacts for the NDP in the 2022-50 period. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.

4.3.1. Power Sector Impacts

Here, the results from both the *narrow experiment* and *wide experiments* are presented. Figure 4.12 shows the relationship between four variables in the *narrow experiment*: i) transport financial benefits[7], ii) electricity prices, iii) discount rates, iv) and profit margin. The NPV for financial benefits and the discount rates have a high correlation of 0.89; the profit margin and the transport benefits are uncorrelated (see Figure 4.12a). The relationship between those two variables is inverse, i.e., the higher the discount rate, the lower the benefits. Discounting at high rates makes the cost of capital higher, which translates into lower benefits, as it offsets the OPEX savings.

[7]These financial benefits are national financial impacts filtered only for transport technologies, i.e., excluding the power sector.

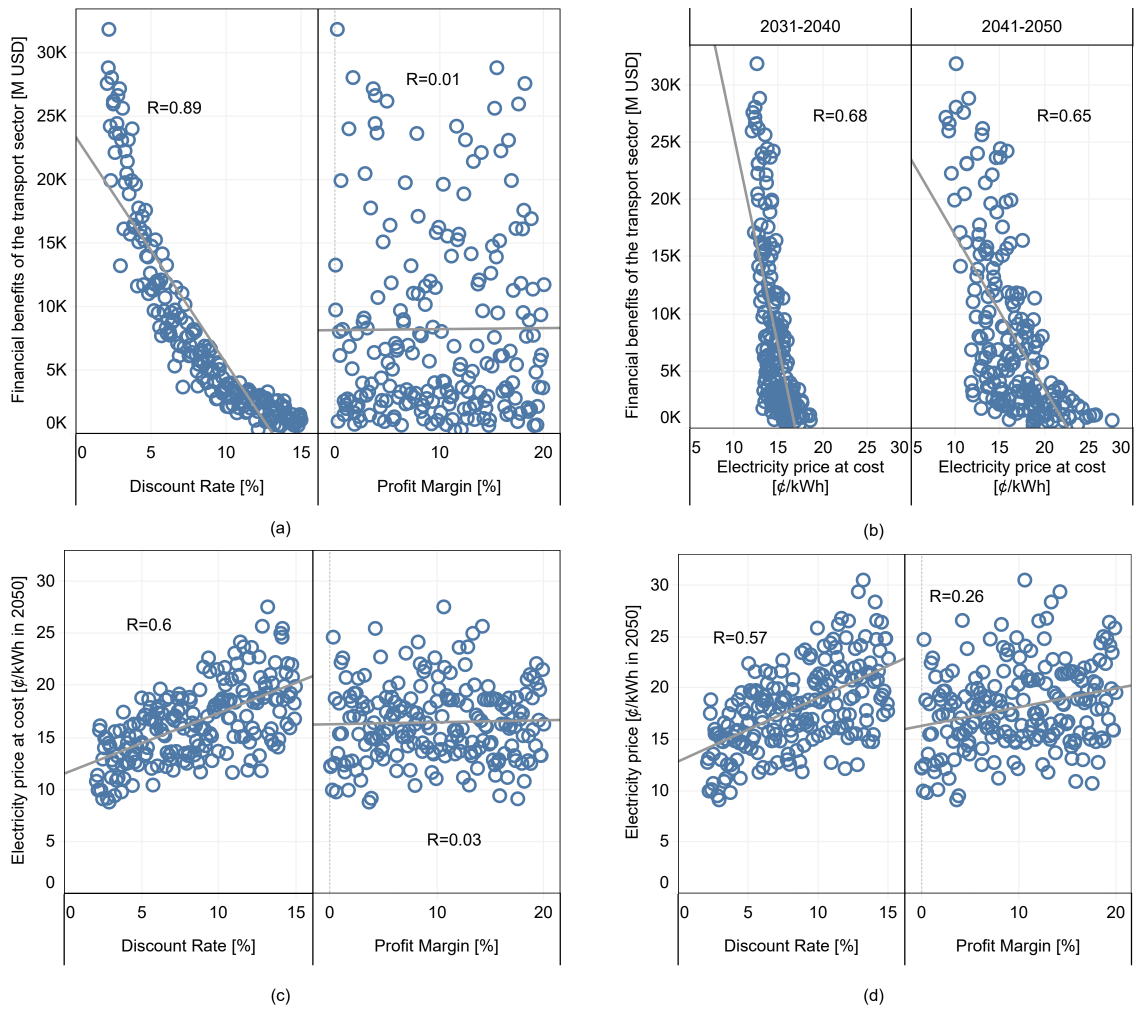

Figure 4.12: Relationship between the transport financial benefits, electricity prices, discount rates, and profit margin. (a) Financial benefits of the transport sector versus discount rates and profit margins. (b) Financial benefits of the transport sector versus electricity prices at cost per period. (c) Electricity prices at cost versus discount rates and profit margins. (d) Electricity prices versus discount rates and profit margins. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. Notes: i) R represents the Pearson Correlation Coefficient between the variables of each graph. ii) The benefits in MUSD units are net present values (NPV). iii) In (c), the prices for the 2031-40 period are yearly values for 2035; for the 2041-50 period, the prices are for 2050.

Figure 4.12b shows that electricity prices at cost and transport benefits have a correlation of 0.65 or higher in the long-term (when benefits are positive); the relationship is inverse. Hence, the higher the electricity price, the lower the transport benefits. In turn, electricity prices at cost are higher when discount rates are higher (see Figure 4.12c); the correlation between these two variables is 0.6, reflecting the higher cost of capital translating into higher consumer costs. According to Figures 4.12c and 4.12d, the profit margin only affects electricity prices (final values) and have a lower correlation than discount rates. Thus, policymakers must focus on finding affordable rates to finance electrical infrastructure. According to Monasterolo et al., 2022, this policy action can be achieved through carbon taxes or green sovereign bonds to subsidize green technology. It can have a more important effect than allowing reasonable profit rates for investors, i.e., not exceeding 20% of the price.

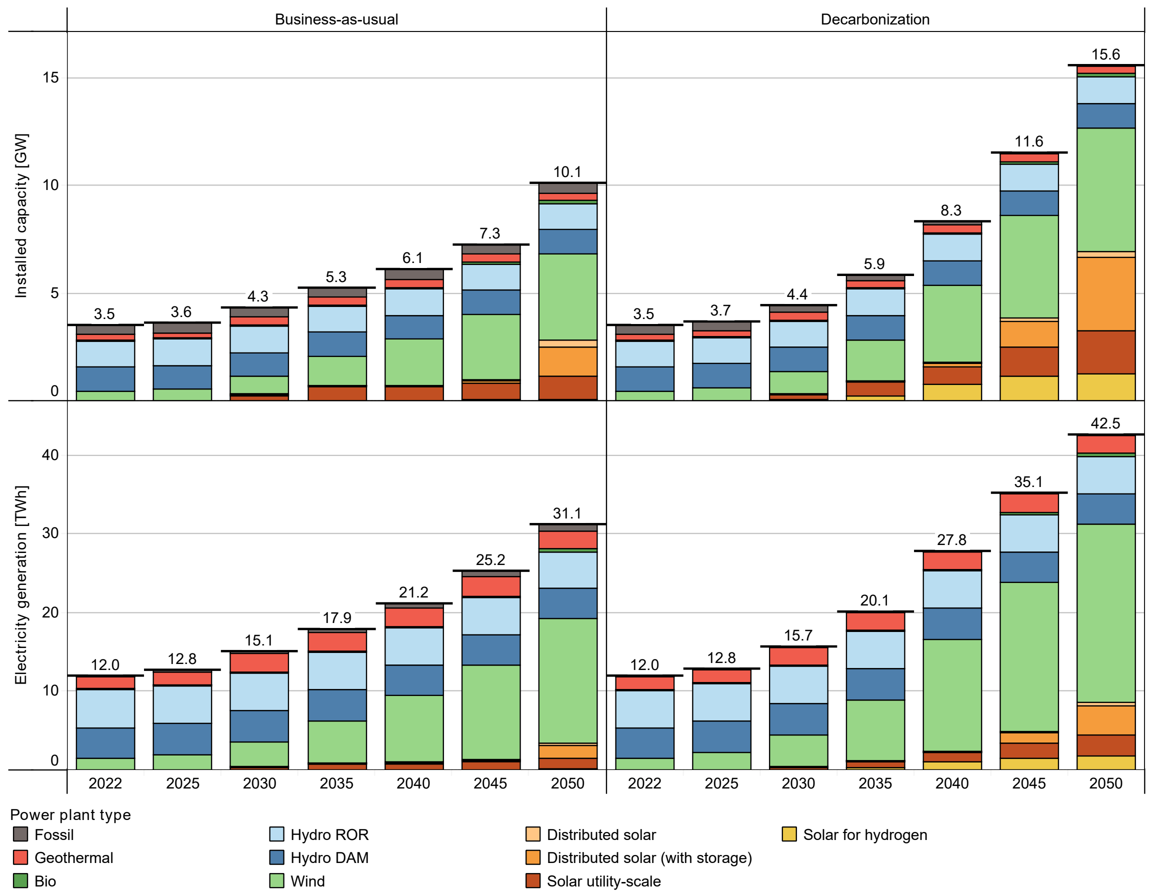

Figure 4.13: Yearly capacity and generation of BAU and NDP the power sectors. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022. Note: the results show the average across futures.

Figure 4.13 shows the power capacity and generation for both scenarios in the *wide experiment*. This metric contextualizes the scale of the transformation for the next 30 years. The NDP would need 50% more installed capacity than the BAU by 2050. Relative to 2018, the NDP needs almost 4.5 times more capacity in 2050. Since OSeMOSYS-CR-v2 has a yearly timescale, the capacities satisfy average power demands with the corresponding modeled capacity factors. Thus, the demand curves would have to be flattened for these results to be precise from a daily and monthly time resolution.

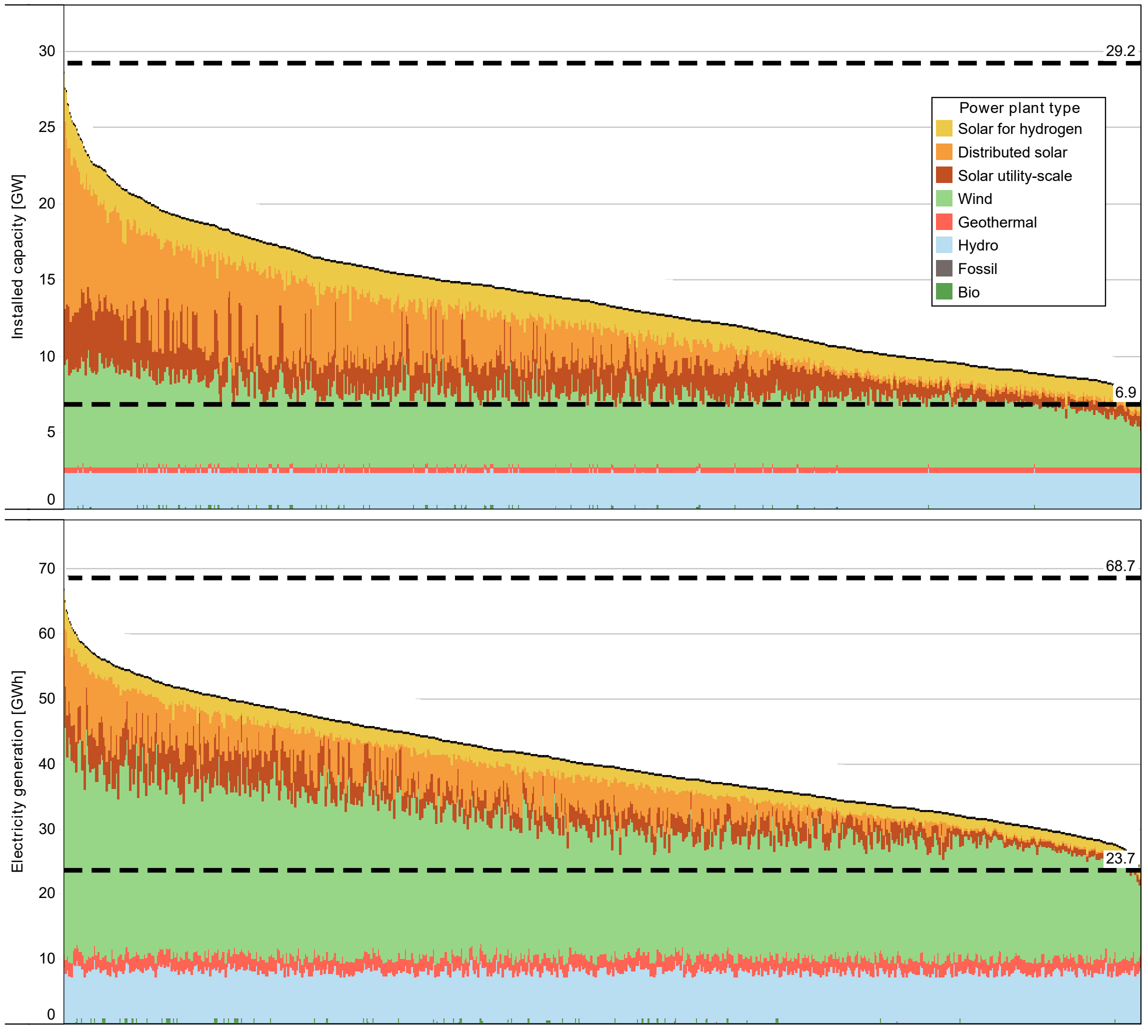

Figure 4.14: The capacity and generation of the power sector of the NDP in 2050 across futures. The black dotted lines represent the minimum and maximum values across futures. Taken from Victor-Gallardo, Quirós-Tortós, et al., 2022.

The *wide experiment* explores the production shares of utility-scale solar, distributed solar, and wind. These technologies have different capacity factors that affect the system's production to capacity ratio. The OSeMOSYS-CR-V2 modeling uses low capacity factors for solar (under 0.2) and high for wind (over 0.4, see documentation referenced in Section 3.1), making the equivalent capacity factor of the NDP lower than BAU in 2050[8]: 0.31 and 0.35, respectively. Figure 4.14 shows how distributed solar with storage is an option for higher productions related to higher demands. Hence, the OSeMOSYS-CR optimization picks wind over solar as a least-cost solution for low-demand futures; when demand

[8]The equivalent capacity factor is simply the electricity production divided by the potential production of the total installed capacity, both obtained from Figure.

increases, solar is necessary to supply the demands because of maximum capacity constraints for wind.

4.4. Actor Impacts

This section has multiple results not previously embodied in an article, resulting from the TEM component of the MOMF. Figure 4.15 shows the net revenue[9] for transport actors, i.e., the sector with the highest financial costs and benefits.

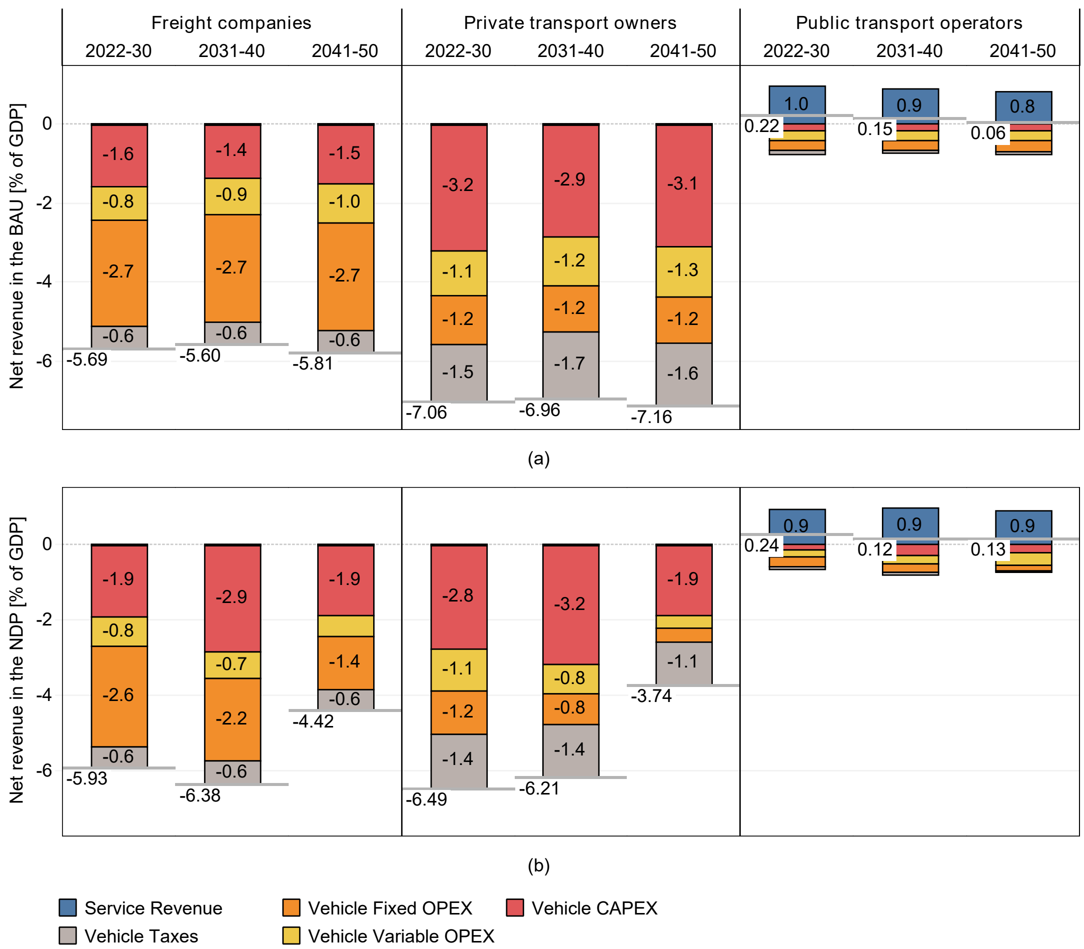

Figure 4.15: Net revenue of transport actors. (a) For the BAU scenario. (b) For the NDP scenario. Notes: the bars contain averages across futures. The horizontal line shows the sum.

Public transport operators have positive net revenue in both scenarios, i.e., the bus and taxi prices cover the corresponding expenses[10]. The TEM does not include revenue for freight firms and

[9]The net revenue refers to the term in Equation 3.19 having the revenue minus expenses per scenario.

[10]Although the bus and taxi price models are at cost, there are unaccounted costs and profits that make the revenue and total expenses not exactly match.

private transport owners, making their values in Figure 4.15 negative, only reflecting expenses. Under the BAU, private transport owners spend almost 1.5% of GDP more than freight firms each decade. Under the NDP, private transport owners have lower costs in all decades; the lowest cost is in the last decade. However, freight firms have lower costs in the NDP than in the BAU only in the last decade.

Under the BAU, fixed OPEX is the largest expense for freight firms, whereas, for private transport owners, the largest expense is CAPEX. The same occurs in the NDP for CAPEX, but CAPEX becomes the largest expense for freight firms. Thus, freight firms must increase their CAPEX considerably to save on fixed and variable OPEX. In the case of private transport owners, the CAPEX increase is not too high for the first two decades. CAPEX is lower in the last decade because the demand reduction measures apply (see the NDP measures in Table 3.1).

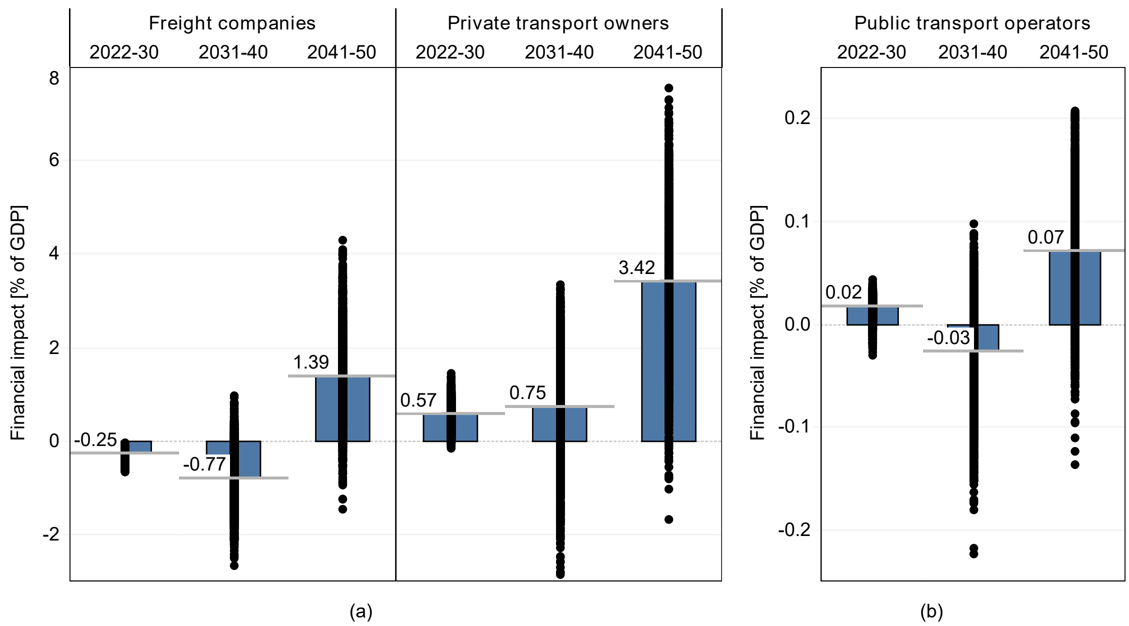

Figure 4.16: Financial impact for transport actors (a) For freight companies and private transport owners. (b) Public transport operators. Note: the black dots represent the futures and the bars are averages across futures.

Figure 4.16 shows the financial impacts (aggregated and as defined in Equation 3.19) for the *wide experiment*. The results averaged across futures are compatible with Figure 4.15: private transport owners have positive benefits in all decades, freight benefits occur only in the last decade, and public transport operators have a minor change in their net revenue (i.e., the magnitude of their financial impact is small). The black dots show that the magnitude of the impacts varies widely: in some cases, private transport can face net costs, and freight firms have more positive outcomes than the average.

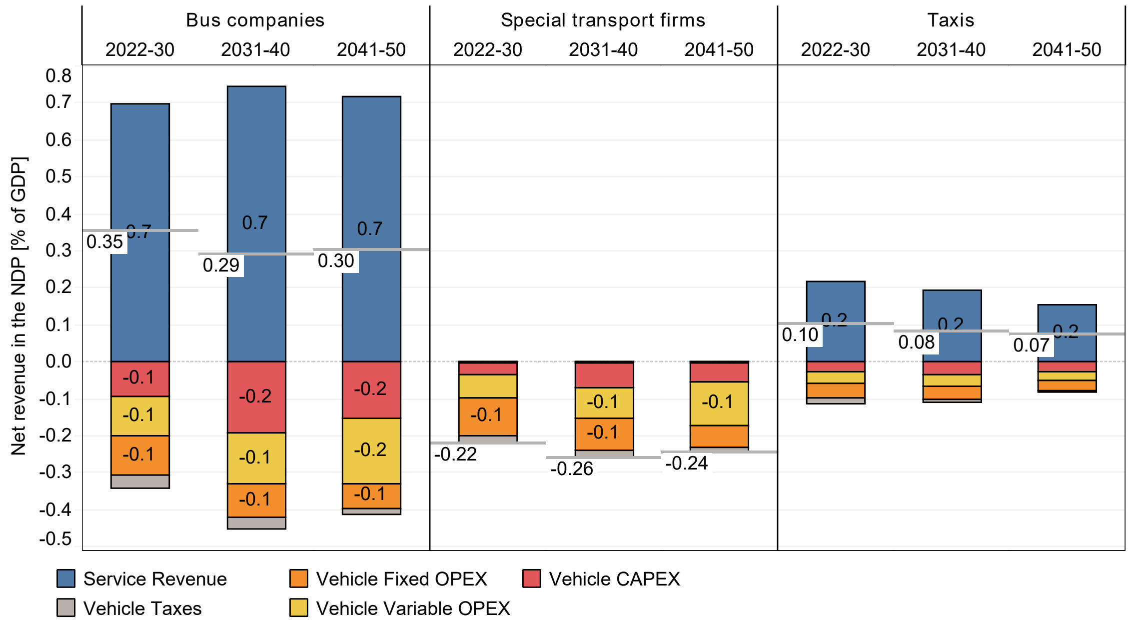

Figure 4.17: Net revenue of public transport operators. Notes: the bars contain averages across futures. The horizontal line shows the sum.

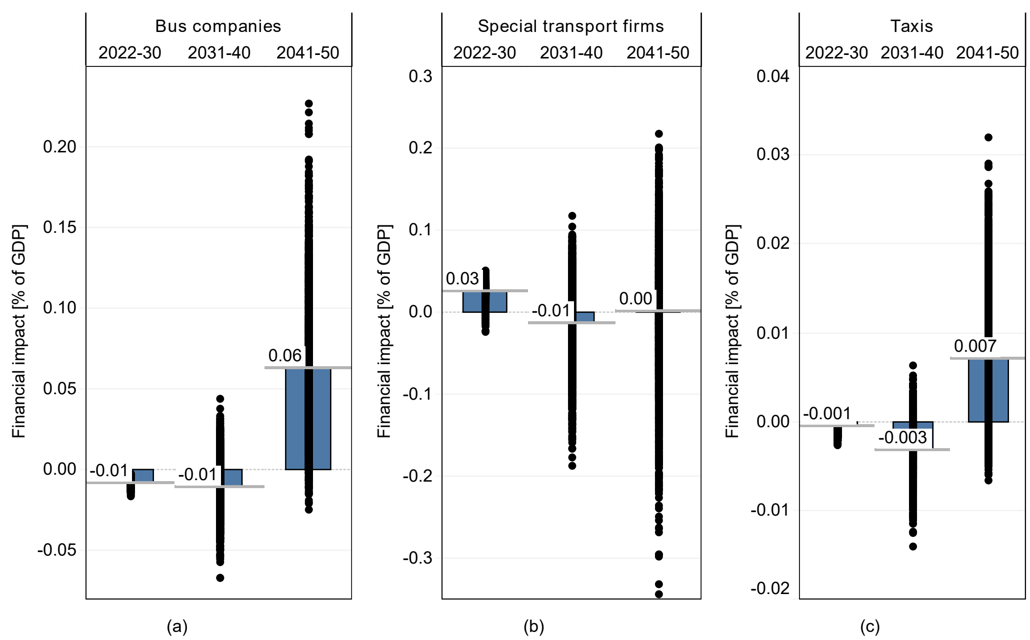

Figure 4.18: Net revenue of public transport operators. (a) Bus companies. (b) Special transport firms. (c) Taxis. Note: the black dots represent the futures and the bars are averages across futures.

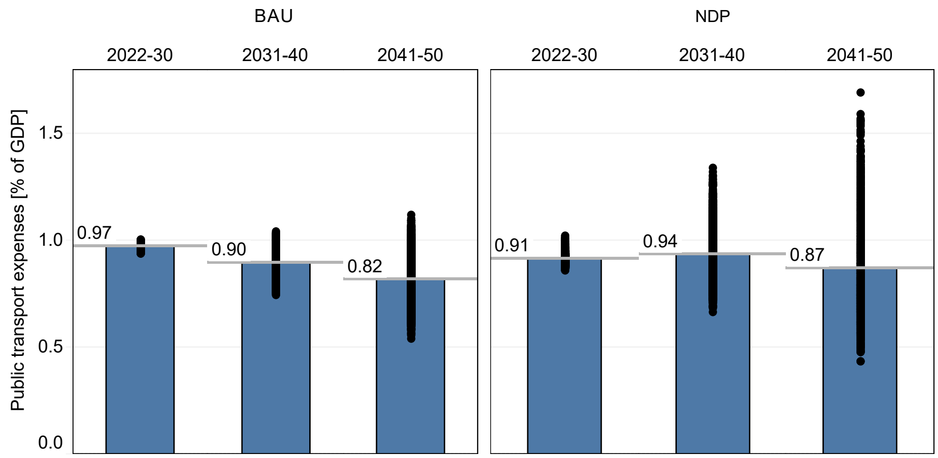

Figure 4.19: National public transport expenses. (a) For the BAU. (b) For the NDP. Note: the black dots represent the futures and the bars are averages across futures.

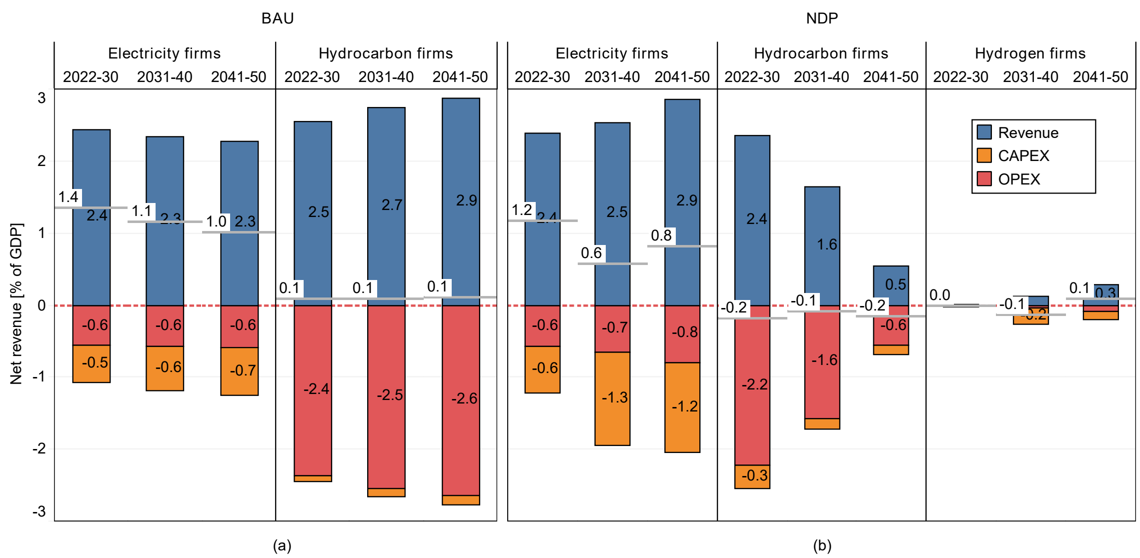

Figure 4.20: Net revenue of energy firms. (a) For the BAU scenario. (b). For the NDP scenario. Notes: the bars contain averages across futures. The horizontal line shows the sum.

Figure 4.17 shows a more detailed disaggregation of the net revenue of public transport operators under the NDP, i.e., per bus companies, special transport firms[11] (minibus owners) and taxis. Figure 4.18 shows the results averaged across futures (bars) and per future (dots). It shows that some futures, mainly for the second decade, have bus operators and taxi firms with negative impacts, reflecting a

[11]In Costa Rica, minibusses transport workers, tourists, and students, requiring special permits to operate. The TEM does not have an estimation for their revenue, thus, making the net revenue have a negative value in the Figure.

delay in their investment returns for the last decade. The pricing scheme makes public transport user spending similar between scenarios, as presented in Figure 4.19. However, the NDP has a range with higher values of public transport spending, associated with higher use and high prices.

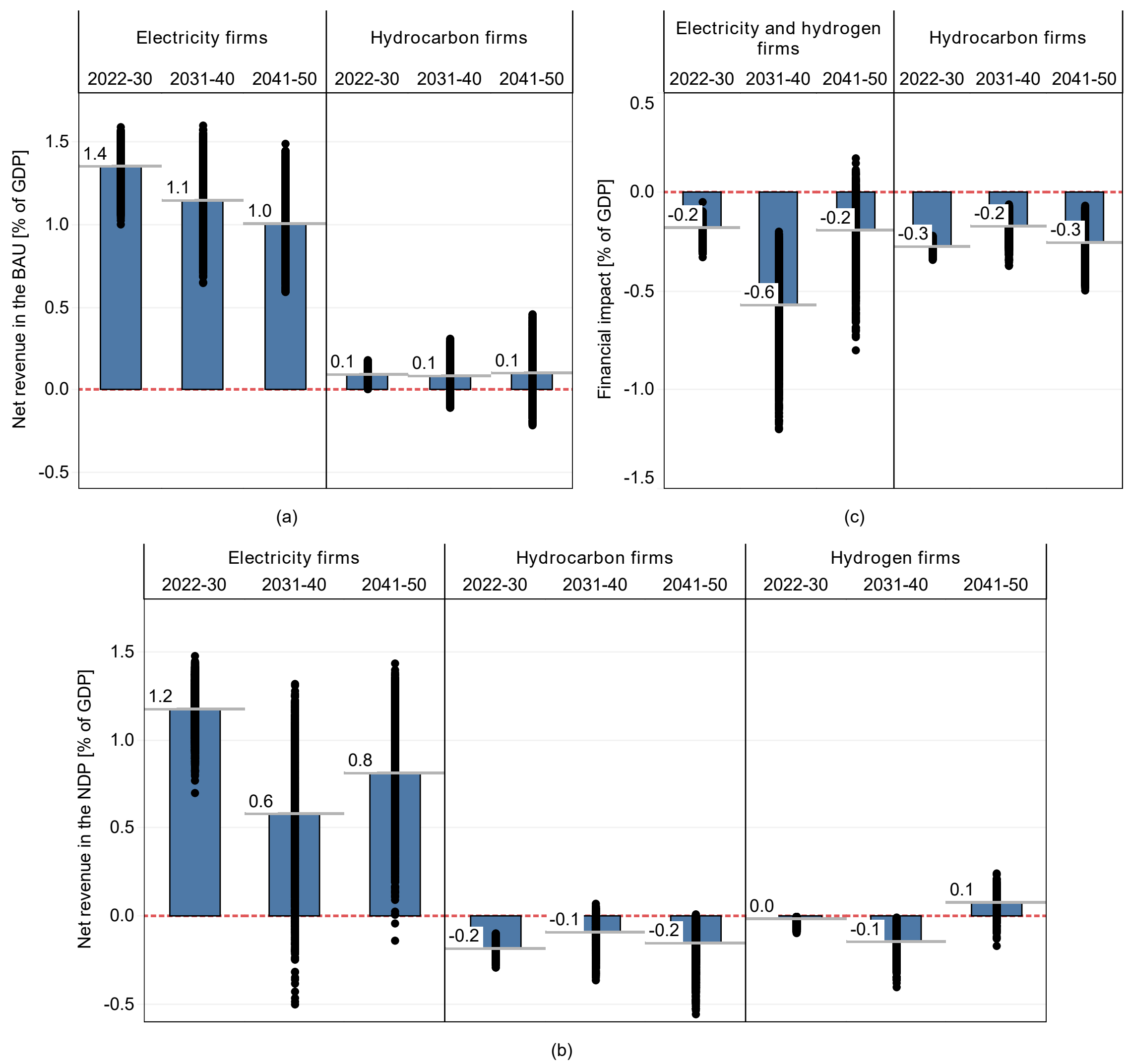

Figure 4.21: Net revenue and financial impact of energy firms under uncertainty. (a) Net revenue in the BAU. (b) Net revenue in the NDP. (c) Financial impact. <u>Note:</u> the black dots represent the futures and the bars are averages across futures.

Energy firms have similar results as public transport operators. Figure 4.20 shows the net revenue, averaged across futures, for each type of energy firm per scenario. Electricity firms have a lower net revenue under the NDP than under the BAU since it can take more years after 2050 to obtain the full return of investments in the last periods, considering that the discount period of the rate is approximately equal to the operational life of the technologies. For example, if energy firms invest one million USD in 2049 in a 25-year-lifetime technology, this capital expense would be recovered until 2074. In that case, the total revenue is out of the result's horizon but remains positive for all periods.

The same effect from electricity firms occurs for hydrogen firms at a lower scale: the final decade has a positive net revenue, while the second one has a negative one. The TEM did not include LPG CAPEX and fixed OPEX in the modeling, thus making the net revenue of hydrocarbon firms negative under the NDP, which requires LPG infrastructure. Figure 4.21 shows the BAU and NDP revenues and the financial impacts under uncertainty. The results suggest that energy firms will have to face lower net revenues in the NDP than in the BAU to maintain lower prices. However, eventually, they will recover their investments after 2050. Figure 4.20 shows that the gross revenue of electricity firms increases, but not as fast as investments, explaining the negative financial impacts from Figure 4.21.

4.4.1. Fiscal Impacts and Tax Reform

The government is another actor; its net revenue is presented in Figure 4.22. Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022 described the fiscal implications of transport decarbonization, but here the results are presented under uncertainty, i.e., under the *wide experiment*.

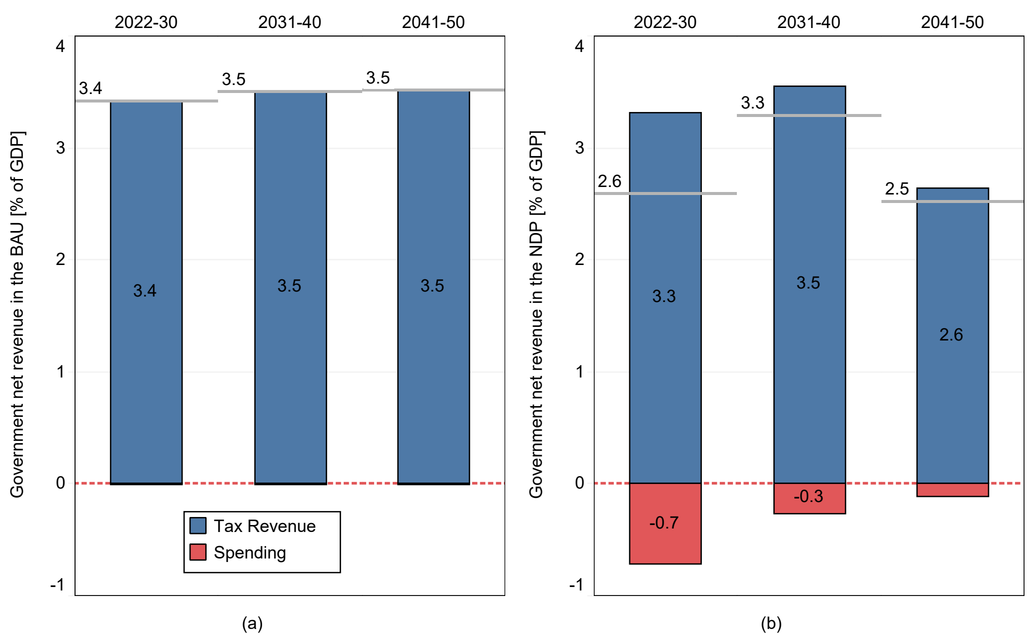

Figure 4.22: Government net revenue (a) In the BAU. (b) In the NDP. Notes: the bars contain averages across futures. The horizontal line shows the sum.

Figure 4.22a shows that transport tax revenue -averaged across futures- is practically constant in the BAU. However, in the NDP, the way the government will finance excess infrastructure to enable decarbonization matters. In this decade, the government will have to spend 0.7% of GDP on public transport infrastructure, averaged across futures (see Figure 4.22b).

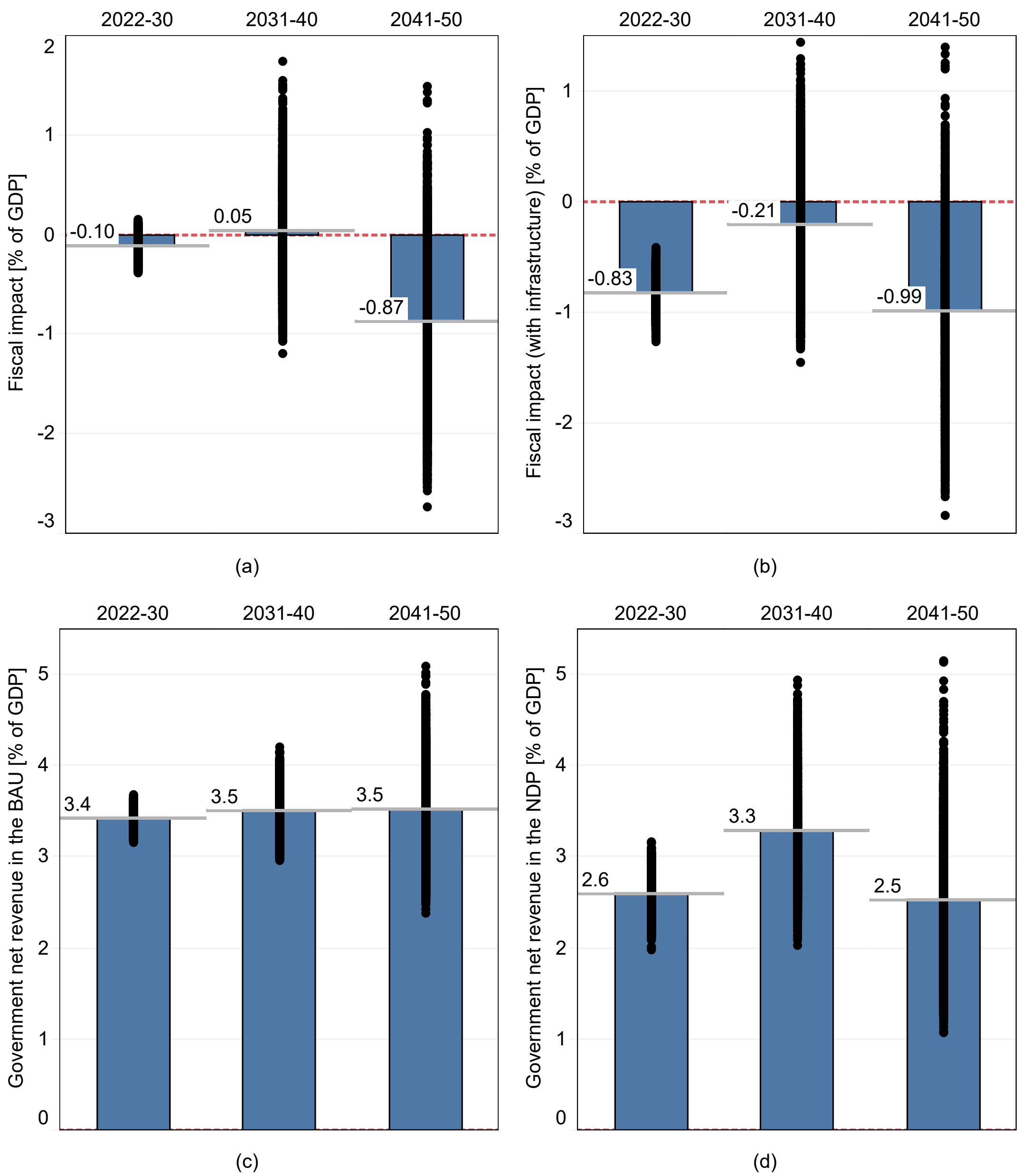

Figure 4.23: Government metrics under uncertainty. (a) Fiscal impact without infrastructure spending. (b) Fiscal impact with infrastructure spending. (c) Revenue in the BAU. (d) Revenue in the NDP. Note: the black dots represent the futures and the bar represents the average across futures.

The fiscal impact can vary significantly in the second and third decades, only considering tax revenue, as presented in Figure 4.23a. In the first decade, the fiscal impact is relatively small. Its magnitude increases if public transport spending is included, as in Figure 4.23b. The effect of government spending is highest in the first decade, posing one of the most significant challenges to advancing decarbonization. It will likely require debt, which will carry the fiscal impact into the future. The results also show another perspective: the fiscal impact is positive in some futures. In the last decade, there are NDP futures with higher net revenue than in the first decade of BAU futures (see Figures 4.23c and 4.23d). However, the findings from Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022 hold: the fiscal impact is highest when the overall transport benefits are also highest, i.e., in the last decade. Hence, there is an opportunity to redistribute the impacts with tax reforms.

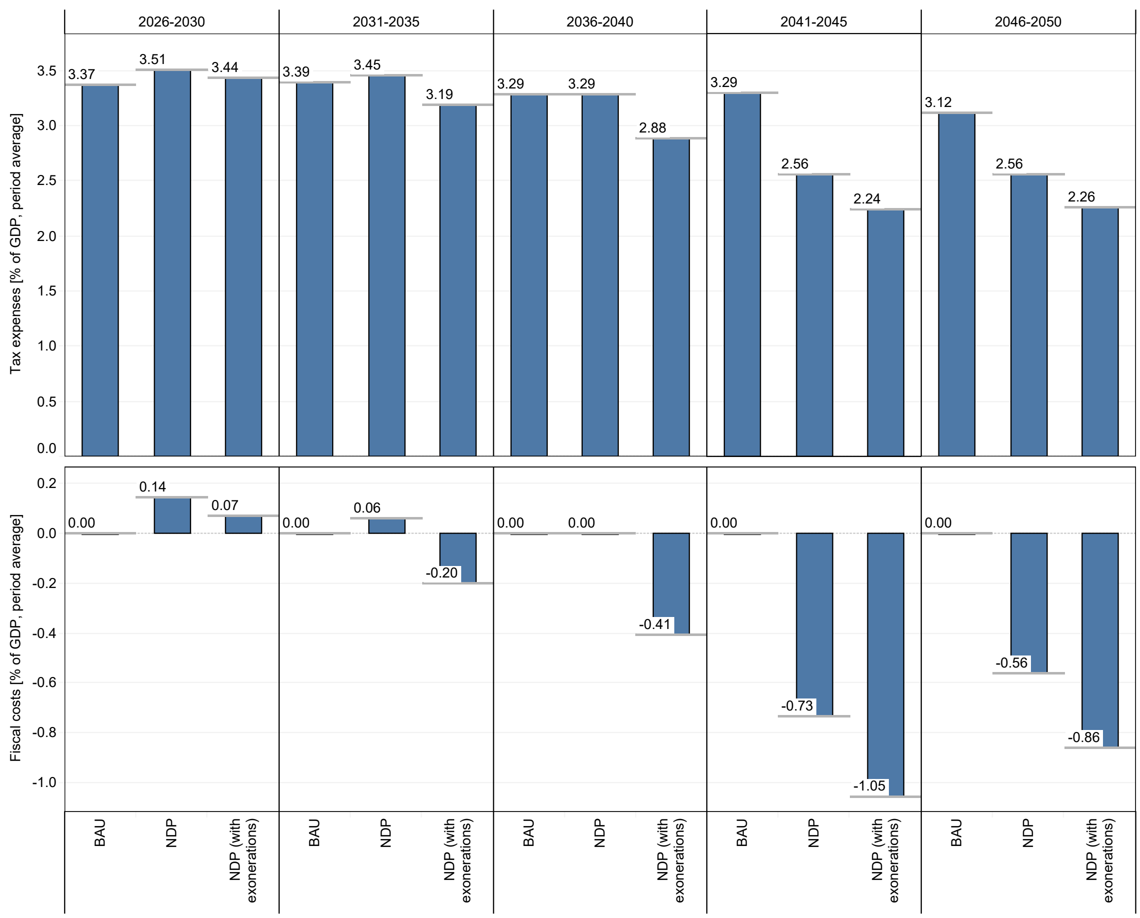

Figure 4.24: Tax expenses and fiscal costs per period and scenario. Based on Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. Note: results are presented for the base case.

Onwards, the analysis from Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022 is summarized, excluding regional and income distribution impacts of tax reforms. The methodological approach to the assessment below was explained as the *Tax Adjustment Evaluation* experiment in Section 3.3. First, Figure 4.24 shows quinquennial tax expenses (first row) and fiscal costs (second row) per scenario. The fiscal cost, measured relative to the BAU, is positive if actors need to pay more in tax and negative if the opposite occurs. Keeping the existing electric vehicle exonerations and the reduced transport activity makes actors save more than 0.8% of GDP in taxes in the last two quinquennials under the NDP[12]. These exonerations apply to property taxes, according to Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. The reduced tax revenue, averaged across futures, is slightly higher than the infrastructure spending on public infrastructure in the first decade (see Figure 4.22b). Eliminating the subsidies after 2030 increases the fiscal cost (see the NDP scenario in Figure 4.24), and thus, tax revenue.

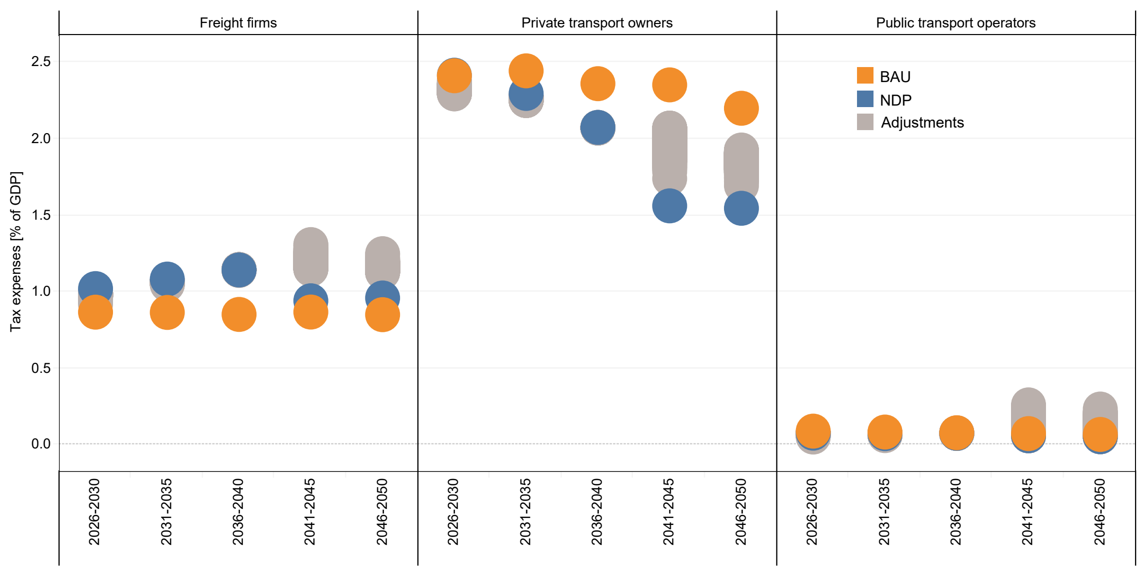

Figure 4.25: Comparison of tax expenses across scenarios. Based on Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. Note: results are presented for the base case.

Eliminating subsidies is insufficient to reach the constant 3.5% of GDP revenue from transport under the BAU scenario, i.e., the fiscal cost is still negative for the NDP scenario in Figure 4.24. Hence, the *Tax Adjustment Evaluation* is an approach to assess the fiscal cost effects of different tax options. Figure 4.25 shows that actors who spend more in taxes are, in descending order: private transport owners, freight firms, and public transport operators. The two latter have practically constant tax

[12]See the NDP (with exonerations) scenario in Figure 4.24.

expenses under the BAU, while private transport owners see theirs decrease. In the NDP, taxes on freight firms increase after 2035 but decrease after 2041 to similar BAU levels. For private transport owners, tax expenses are reduced by almost 1% of GDP in the last two quinquennials. The *Tax Adjustment Evaluation* increases the tax expenses of all actors relative to the NDP in the last decade.

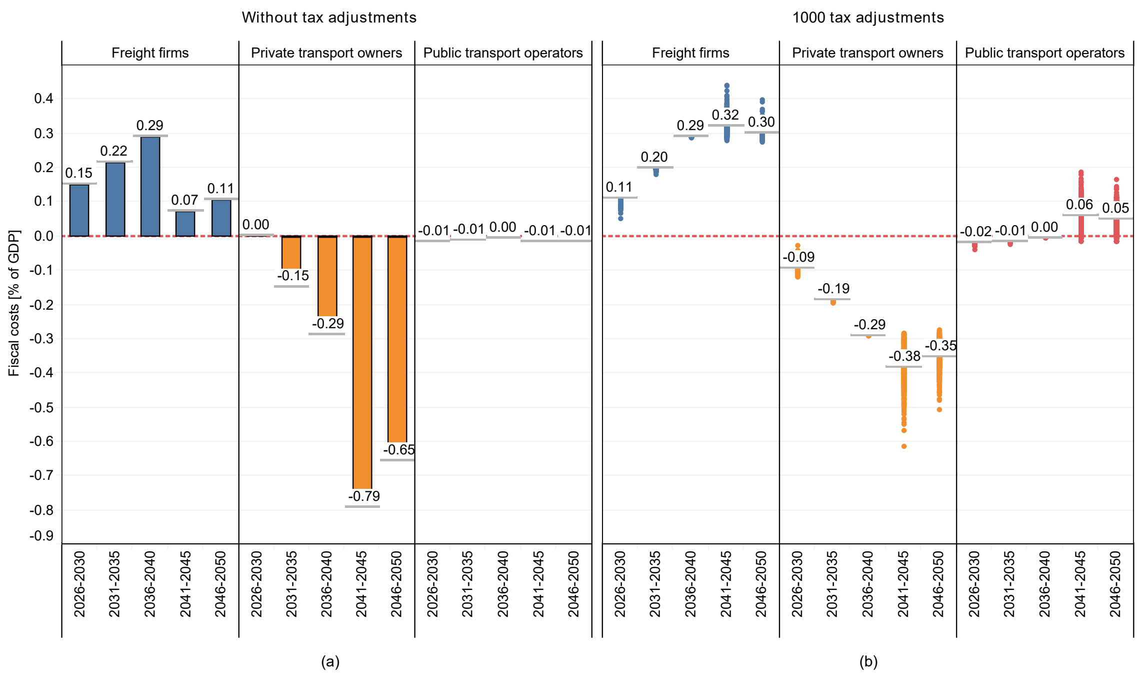

Figure 4.26: Fiscal costs per transport sector actor. (a) Without tax adjustments. (b) 1000 tax adjustments. Based on Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. Notes: results are for the base case. In (b), the dots represent the futures and the line represents the average.

Figure 4.26 shows the how the tax adjustment amplifies the effects of decarbonization in fiscal costs. Figure 4.26a shows that transferring fiscal costs from freight firms to private transport owners could be possible in the last decade: private transport owners have more than 0.5% of GDP in reduced fiscal costs, while freight firms have under 0.15%. For the first three quinquennials, the redistribution would be impossible because private transport owners have smaller fiscal savings[13].

The fiscal costs with adjustments have 1000 possible tax changes in Figure 4.26b. In the last decade, the adjustments increase the fiscal cost for all actors, including public transport operators, who practically remain with a zero fiscal cost without tax adjustments. Since the base case has higher revenue under the NDP than under the BAU (as in Rodriguez et al., 2021), the adjustments reduce

[13] The base case produces additional revenue for the government in the first decade from freight, but this is different from the results averaged across futures presented in Figure 4.23a.

the fiscal costs in the first decade.

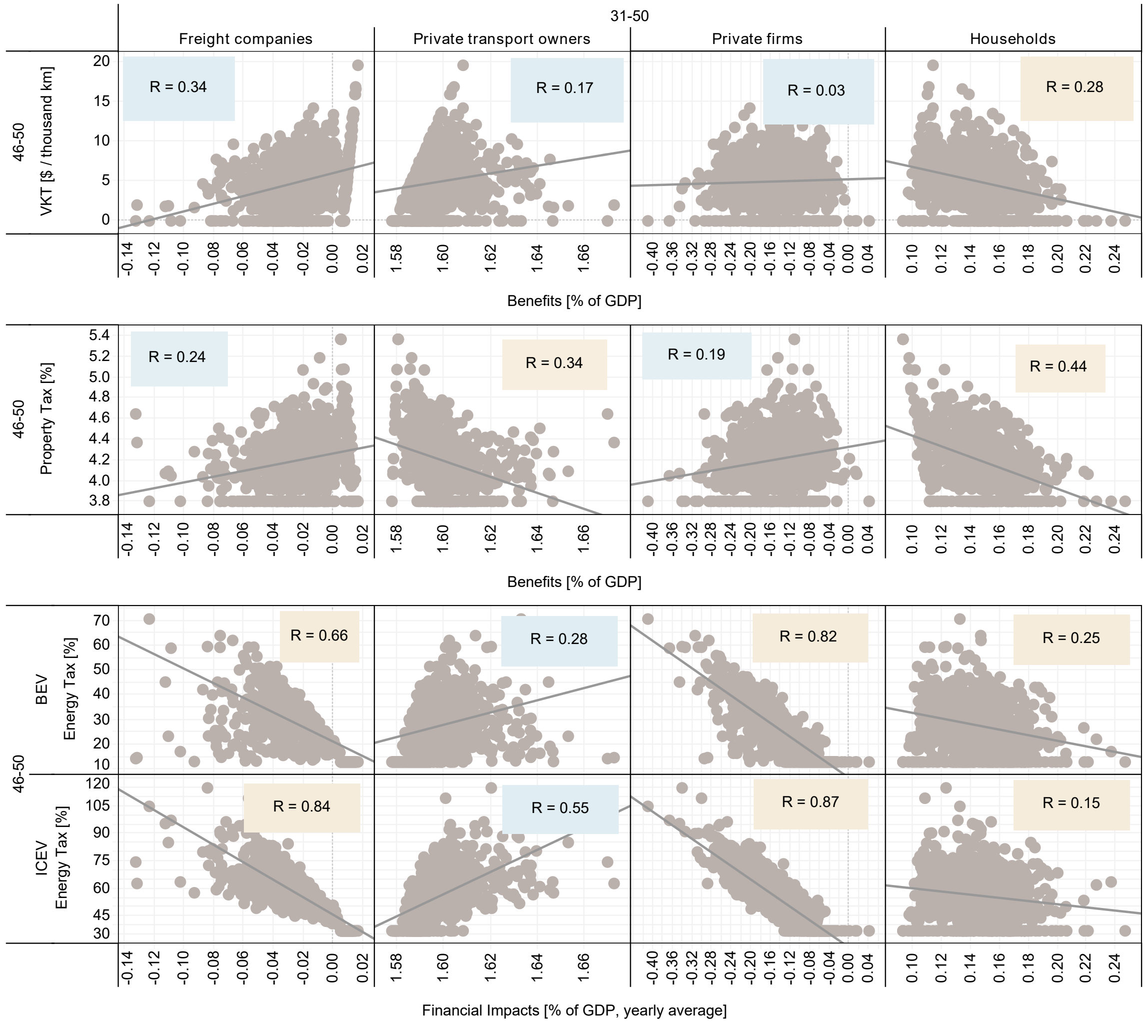

Figure 4.27: Tax rates versus financial impacts per actor. Based on Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022. Notes: i) R represents the Pearson Correlation Coefficient between the variables of each graph. ii) The tax rates are technology and period averages. Each dot represents a unique tax adjustment out the 1000 produced in the *Tax Adjustment Evaluation* experiment.

Figure 4.27 focuses on the long-term effects when fiscal costs increase, by correlating financial impacts per actor in 2031-50 with tax adjustments in 2046-50. The results consider, as in Rodriguez et al., 2021, that 75% of private transport owners are households and the rest are private firms, which also include freight firms; households also spend on public transport. The impacts per tax option are:

- **Vehicle Kiloments-Traveled (first row).** VKT taxes are positively correlated with freight firms and private transport owners, but they are negatively correlated with households. Positive correlations mean the higher the tax, the higher the financial impact, and a higher impact is beneficial, i.e., a more positive or a less negative impact. Negative correlations mean the opposite. Since public transport operators travel the longest distances, a flat VKT tax affects them more than other tax options. These results consider that the VKT is transferred to the bus and taxi prices, affecting households that consume public transportation directly.

- **Property Tax (second row).** They affect private transport and households the most (negative correlations). Since the adjustments have a proportional increase to the base tax structure, and freight vehicles pay very small property taxes (see Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022), high property taxes are beneficial for freight firms. Rodriguez et al., 2021 found that these taxes also affect the wealthiest households, who own more expensive vehicles, while the VKT affects the poorest ones since they rely more on public transport.

- **Energy tax for battery electric vehicles (third row).** Private firms and households are impacted negatively. Private firms are negatively impacted to a greater extent because the correlation is higher (0.82) for them than for households (0.25). Heavy-duty vehicles will consume more energy than light-duty vehicles (see Appendix C). Thus, since freight firms and public transport operators own such heavy-duty vehicles, they will face higher costs and have lower financial impacts. The operators will pass on the higher energy costs to households through bus prices similar to the VKT option.

- **Energy tax for internal combustion vehicles (fourth row).** They have the same effect as the previous option but have higher rates since they are consumed less in the long-term than electricity or hydrogen.

The results above produce insights for robustness criteria, i.e., policies that produce better outcomes than the alternatives. Taxing energy will produce more costs on production, potentially causing undesirable indirect impacts not quantified here. Moreover, differentiating energy taxes to charge private transport owners more can be costly and inefficient. Property taxes are a good way to substitute energy costs with a levy on wealth; nevertheless, these taxes are already unpopular and can be difficult to enforce through loopholes. A fairer tax is the VKT, as suggested by Van Dender, 2019, by using electronic tolls as a charging mechanism. However, a flat VKT tax is not convenient; public transport operators should be exonerated to lessen household impacts. The VKT has the implementation challenges of jurisdictional clarity and electronic toll costs (see Van Dender, 2019). In sum, all options have trade-offs, and other policy objectives will define adequate adjustments.

According to Figure 4.25, the tax adjustment increases tax expenses more than in the BAU except for private transport owners, i.e., freight firms and public transport operators are over-impacted. Future work can improve the *Tax Adjustment Evaluation* experiment so that all actors are affected relative to their benefits. The modification options include designing rules to tax externalities and transport wealth from private transport owners, e.g., road wear from heavy-duty vehicles and taxes on the most expensive vehicles through property taxes.

4.5. Decision Insights for Robust Energy Planning

This section finds desirable and risky pathways from the *wide experiment*. As explained in Section 3.4, the pathways are combinations of uncertainties and levers, or drivers, that explain an outcome. Knowing the combination of drivers can prepare policymakers to seek desirable outcomes and avoid risky ones, making their energy planning processes robust. Therefore, the *robust drivers* can inform what policies produce the most favorable outcomes compared to the alternatives. First, the pathways found by Victor-Gallardo, Quirós-Tortós, et al., 2022 for national metrics are presented. Then, the financial impacts per actor pathways are presented.

The robust drivers are presented as normalized values on a scale from 0 to 100; the discussion centers around whether policy objectives should be low, mid-low, mid, mid-high, or high, (separated by 20 points). Moreover, the drivers are presented for the 2022-30 (short term) and 2031-50 (long term) periods. The financial impacts and gross CAPEX are metrics in yearly period averages; prices and emissions are measured at the end of the period. Most drivers are also measured at the end of the period, except investments (they originally have percent of GDP units). Appendix D shows the validation process developed by Victor-Gallardo, Quirós-Tortós, et al., 2022 for the robust pathways. Also, Appendix E shows the unnormalized values for the nationwide results.

4.5.1. Robust Pathways for Nationwide Benefits

Figure 4.28 shows the robust rivers for national financial impacts. In the 2022-30 period, low and mid-low BEV penetrations in private and public transport are desirable (first column). However, low values of freight BEV or FCEV penetrations are desirable. This is expected since ZEVs change their costs only slightly in the first decade. Other concurrent[14] conditions include:

- passenger rail and urban intervention investments should be low (the scale is between 0 and 28, including low and mid-low values);
- wind electricity production should be low as a share of total production (the scale is between 0 and 71, including low to mid-high values);
- GDP values should be low (the scale is between 0 and 63, including low to mid-high values);
- energy infrastructure costs should be low (scale between 0 and 81, excluding most high values);
- vehicle occupancy rates should be high (scale between 5 and 100, avoiding only the lowest values).

			22-30				31-50			
			Desirable outcomes		Risk outcomes		Desirable outcomes		Risk outcomes	
			Min	Max	Min	Max	Min	Max	Min	Max
Levers	Regulations	Private Transport % of BEV	0	51	2	100				
		Public Transport % of BEV	0	43					36	100
		Public Transport % of FCEV							4	100
		Heavy Freight % of BEV	0	22			0	80	19	100
		Heavy Freight % of FCEV	0	27					15	100
		Light Freight % of BEV	0	29			0	86	5	100
	Investment (transport)	Passenger rail and urban interventions	0	38	60	100				
	Investments (energy supply)	Wind electricity production	0	71	29	100				
Uncertainties	Economic	GDP	0	63	40	100			30	100
		Passenger demand elasticity							5	100
	Technological (transport)	Capital costs of BEVs					0	47	45	100
		Capital costs of ICEVs			0	95	42	100	0	72
	Technology (energy supply)	Cost of energy infrastructure	0	81	27	100			23	100
		Unit cost of fossil fuels					14	100	0	57
	Social	Mode shift to public transport			0	55				
		Occupancy rates of private vehicles	5	100						

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.28: Drivers for desirable and risk outcomes for national financial impacts. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

As explained in 3.1, the GDP drives the energy and transport demands. The higher the demands, the higher the total costs to supply them. Since the transformation is relatively smooth, the NDP and the BAU are not so different in the first decade, and the technological costs do not diverge considerably either. Hence, high levels of GDP produce higher demands and higher transformation costs with technologies that are not the cheapest.

One interpretation from Figure 4.28 is that this decade's most beneficial strategy is to avoid over electrification and have low a GDP. Naturally, a low GDP is not desirable. In this decade, the

[14] In all the figures showing the robust drivers, the drivers (or rows) must be concurrent for each column. However, as explained in Appendix D, not all the driver combinations exist in the experiment, so at least most concurrent conditions should be met to produce the desirable or risk outcomes.

country should be more aggressive in ride-sharing and demand reduction policies to make high GDP compatible with desirable benefits. Hence, this is a limitation of the *wide experiment*: the variations of demand elasticity reductions and increasing passengers per trip are significant until 2050. However, the conclusion is clear: these mechanisms must decouple transport activity from GDP growth as soon as this decade if GDP growth is to be higher than 3.5%[15]. This finding is compatible with the high ranking of the mode shift and passenger rail scenario from Section 4.2.

Since energy supply investments pick up in the first decade, avoiding very high unit energy infrastructure costs[16] is desirable. Low wind energy generation participations reflect that the existing power grid supplies most of the existing demand, and few new units must be installed in this decade.

Risk outcomes in 2022-30 (second column) are the opposite of some of the previous drivers, e.g., expensive public transport investments. High wind energy generation participations reflect high demands (from high GDP and transport ZEV penetrations) and low hydropower capacity factors. These factors contribute to higher costs if unit costs are also high (see the *cost of energy infrastructure* row in the second column). Moreover, low values of mode shift to public transport also produce risks, increasing the need for a private fleet that starts to electrify in the first decade. Hence, low internal combustion engine vehicles (ICEV) costs produce risk for attaining the benefits of electrification.

In the long term, the clearest requirements for desirable financial impacts are low BEV capital costs and high ICEV capital costs (third column). Avoiding the lowest fossil fuels costs is also desirable for decarbonization. Moreover, the BEV penetrations in freight should not be high. The risk outcomes occur under the opposite conditions (fourth column): high ZEV penetrations, with high GDP (high demand and fleet requirements), expensive BEVs and energy infrastructure, and cheap ICEVs and fuels. Under such conditions, the financial benefits would be low or even negative, decreasing the likelihood of decarbonization benefits. Since high GDP is a vulnerability for benefits, reducing the need for countrywide investment by making the transport system more efficient will be the most robust lever, i.e., decoupling transport activity from higher production.

4.5.2. Robust Pathways for Nationwide Prices

Figure 4.29 shows the robust drivers for prices. Electricity prices in the 2022-30 period are desirable if the wind electricity production share is not very high, GDP growth is high, non-transport electricity

[15] The 60th percentile of the GDP growth is 3.5% according to Victor-Gallardo, Quirós-Tortós, et al., 2022.
[16] These include renewables and other power sector costs, as defined in Table 3.5.

intensity is high, and energy infrastructure costs are low. Hence, low electricity prices occur with high demands and low unit costs. The risk outcomes practically have the opposite conditions.

				22-30				31-50			
				Desirable outcomes		Risk outcomes		Desirable outcomes		Risk outcomes	
				Min	Max	Min	Max	Min	Max	Min	Max
Levers	Electricity price	Investments (energy supply)	Wind electricity production	0	81	44	100				
	Bus Price	Regulations	Private Transport % of BEV					17	100		
			Public Transport % of BEV					26	100	33	100
			Public Transport % of FCEV					0	100		
Uncertainties	Electricity price	Economic	GDP	46	100	0	64	19	100	0	95
			Non transport electrical intensity	65	100	0	89	61	100		
		Technology (energy supply)	Cost of energy infrastructure	0	54	34	100	0	17	75	100
		Climate	Capacity factor of hydropower							0	90
	Bus Price	Economic	GDP	30	100	0	54				
		Technological (transport)	Capital costs of BEVs					0	43	54	100
			Capital costs FCEVs					0	90	5	100
			Capital costs of ICEVs	0	57	30	100			5	100
		Social	Mode shift to public transport	0	55						

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.29: Drivers for desirable and risk outcomes for electricity and bus prices. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

For electricity prices, the GDP growth intervals for desirable and risk outcomes are more comprehensive in 2031-50 than 2022-30. However, the desirable outcomes depend on high electrical intensity. The lowest long-term energy prices are related to low energy infrastructure costs (third column). High costs cost with low hydropower capacity factors produce risk outcomes (fourth column).

In 2022-30, desirable bus prices depend on low ICEV capital costs and low mode shifts to public transport, transferring less CAPEX to users. In the same period, risk outcomes occur due to low demands (associated with low GDP) and high ICEV costs. Low demands reduce the number of users, bringing prices upward. In the long-term, desirable bus prices are compatible with high electrification and hydrogen penetration values, as long as BEVs and FCEVs have low costs (or not the very high values). High BEV penetrations are risky in the long term if BEV costs are high.

4.5.3. Robust Pathways for Nationwide Emissions

Figure 4.30 shows that low GDP growth (low transport demands) cause desirable emissions. More ambitious decoupling in the near term can allow for higher GDP growth, e.g., through high occupancy rates (see the first column). Low electrification and hydrogen penetrations, and high demands cause risk outcomes for emissions. Moreover, low non-transport fuel intensities also cause low emissions. In the 2031-50 period, high freight BEV penetrations produce desirable emissions, which is compatible with the ranking findings from Section 4.2. In the long term, the algorithm captures the effect of low passenger demand elasticities and high non-motorized transport and digitalization for desirable outcomes (third column). The risk outcomes for emissions are related to high GDP growth values, fuel intensities, and freight demand elasticities.

			22-30				31-50			
			Desirable outcomes		Risk outcomes		Desirable outcomes		Risk outcomes	
			Min	Max	Min	Max	Min	Max	Min	Max
Levers	Regulations	Private Transport % of BEV			0	36				
		Public Transport % of BEV			0	34				
		Heavy Freight % of BEV			0	33	31	100		
		Heavy Freight % of FCEV			0	34				
		Light Freight % of BEV			0	35	5	100		
	Operations	Freight mode shift	4	100						
Uncertainties	Economic	GDP	0	51	43	100	0	77	48	100
		Passenger demand elasticity					0	81		
		Freight demand elasticity					0	95	10	100
		Non transport fossil fuel intensity	0	48	44	100	0	34	66	100
	Social	Mode shift to public transport			0	40				
		Non-motorized and digitalization			0	60	5	100		
		Occupancy rates of private vehicles	18	100	0	87				

Driver value scale: 0 – 100 (Low, Mid-Low, Mid, Mid-High, High)

Figure 4.30: Drivers for desirable and risk outcomes for national emissions. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

4.5.4. Robust Pathways for Nationwide CAPEX

Figure 4.31 shows the drivers for national gross capital expenses (CAPEX). The results are similar to those from Figure 4.28 since high CAPEX requirements cause low financial benefits.

			22-30				31-50			
			Desirable outcomes		Risk outcomes		Desirable outcomes		Risk outcomes	
			Min	Max	Min	Max	Min	Max	Min	Max
Levers	Regulations	Heavy Freight % of BEV	0	24			0	80		
		Heavy Freight % of FCEV	0	28						
		Light Freight % of BEV	0	35			0	86		
	Investment (transport)	Passenger rail and urban interventions	0	58	53	100				
	Investments (energy supply)	Wind electricity production	0	69	51	100				
Uncertainties	Economic	GDP	0	53	38	100	0	61	34	100
		Passenger demand elasticity					0	95	19	100
		Freight demand elasticity					0	95	14	100
		Non transport electrical intensity			61	100			61	100
	Technological (transport)	Capital costs of BEVs	0	95			0	48	47	100
		Capital costs of ICEVs			5	100				
	Technology (energy supply)	Cost of energy infrastructure	0	46	48	100	0	50	68	100
		Residual capacity infrastructure			0	81				
	Social	Mode shift to public transport			0	55				
		Occupancy rates of private vehicles	10	100						
	Climate	Capacity factor of hydropower							0	95

Driver value scale: 0 – 100 (Low, Mid-Low, Mid, Mid-High, High)

Figure 4.31: Drivers for desirable and risk outcomes for national CAPEX. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

Additional drivers for CAPEX are: transport demand intensities, non-transport electrical intensity, the residual capacity infrastructure, and the capacity factor of hydropower. High non-transport electrical intensities produce high capital requirements for power sector investments for both periods. In the long term, high transport demand elasticities and low hydropower capacity factors, combined with high electrical unit costs, cause risk outcomes (fourth column).

4.5.5. Robust Pathways Nationwide

Figure 4.32 shows the combination of drivers for all metrics. In the 2022-30 period, there is a trade-off between desirable and risk outcomes. Reducing emissions considerably by 2030 produces higher net costs in the near term. A country with Costa Rica's small emission contributions should probably not over-invest in electrification to reach more ambitious goals unless an unforeseen situation like extraordinarily high fossil fuel prices were sustained for the entire decade. However, one of the keys to low emissions and high benefits in the near term is fast decoupling between transport demand and GDP, including higher passenger occupancy rates per vehicle (or ride-sharing). In the long term, high private and public BEV penetrations are desirable but also risky. If they are high, emissions are low. If they are low, financial impacts are low if unit BEV and energy infrastructure costs are high.

			22-30				31-50			
			Desirable outcomes		Risk outcomes		Desirable outcomes		Risk outcomes	
			Min	Max	Min	Max	Min	Max	Min	Max
Levers	Regulations	Private Transport % of BEV	0	51	0	36	17	100		
		Public Transport % of BEV	0	43	0	34	26	100	34	100
		Public Transport % of FCEV					0	100	4	100
		Heavy Freight % of BEV	0	23	0	33	0	80	19	100
		Heavy Freight % of FCEV	0	27	0	34			15	100
		Light Freight % of BEV	0	32	0	35	0	86	5	100
	Operations	Freight mode shift	4	100						
	Investment (transport)	Passenger rail and urban interventions	0	48	57	100				
	Investments (energy supply)	Wind electricity production	0	74	41	100				
Uncertainties	Economic	GDP	0	54	40	100	0	69	37	100
		Passenger demand elasticity					0	88	12	100
		Freight demand elasticity					0	95	12	100
		Non transport electrical intensity	65	100	61	100	61	100	61	100
		Non transport fossil fuel intensity	0	48	44	100	0	34	66	100
	Technological (transport)	Capital costs of BEVs	0	95			0	46	48	100
		Capital costs FCEVs					0	90	5	100
		Capital costs of ICEVs	0	57	18	100	42	100	0	72
	Technology (energy supply)	Cost of energy infrastructure	0	60	39	100	0	39	55	100
		Residual capacity infrastructure			0	81				
		Unit cost of fossil fuels					14	100	0	57
	Social	Mode shift to public transport	0	55	0	50				
		Non-motorized and digitalization			0	60	5	100		
		Occupancy rates of private vehicles	11	100	0	87				
	Climate	Capacity factor of hydropower							0	93

Driver value scale

0 — 100

Low Mid-Low Mid Mid-High High

Figure 4.32: Drivers for desirable and risk outcomes across national metrics. Based on Victor-Gallardo, Quirós-Tortós, et al., 2022.

4.5.6. Robust Pathways per Actor

Figure 4.33 shows the robust drivers for the private transport owners. The results are similar to the national financial impacts, which is expected since private transport owners have the highest financial benefits (see Section 4.4). High GDP growth in 2022-30 can produce higher costs and, thus, lower financial impacts. High GDP growth and elasticity can produce risk outcomes in the long term. Low BEV costs are also desirable for the long term; the opposite produces risk outcomes. ICEV and BEV costs have the opposite desirable and risk conditions. In 2022-30, low electrification can produce both desirable and risk outcomes. Low electrification and low mode shift in 2022-30 can reduce the potential OPEX savings that generate desirable outcomes.

		22-30				31-50			
		Desirable		Risk		Desirable		Risk	
Driver groups	Drivers	Min	Max	Min	Max	Min	Max	Min	Max
Economic	GDP	0	51	51	100			34	100
	Passenger demand elasticity							11	100
Technological (transport)	Costos of private ICEV	5	100	0	89	44	100	0	82
	Costs of private BEV					0	49	54	100
Technological (energy supply)	Unit cost of fossil fuels					54	100	0	51
Social	Mode shift to public transport			0	47				
	Occupancy rates of private vehicles	9	100						
Regulations	Private Transport % of BEV	0	40	0	45			16	100

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.33: Drivers for desirable and risky financial impacts for private transport owners.

		22-30				31-50			
		Desirable		Risk		Desirable		Risk	
Driver groups	Drivers	Min	Max	Min	Max	Min	Max	Min	Max
Economic	GDP	0	90						
Technological (transport)	Costs of freight BEV					0	39	60	100
	Costs of freight FCEV					0	94		
	Costs of freight ICEV					48	100	0	66
Technological (energy supply)	Cost of energy infrastructure			0	66				
	Unit cost of fossil fuels	5	100			49	100	0	49
Regulations	Heavy Freight % of BEV	0	16	1	100			19	100
	Heavy Freight % of FCEV	0	17	10	100			6	100
	Light Freight % of BEV	0	24					24	100

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.34: Drivers for desirable and risky financial impacts for freight firms.

Figure 4.34 shows the robust drivers for freight firms. In this case, vehicle costs that produce desirable outcomes must be relatively lower than for private transport owners in 2031-50: the driver value scale is [0, 39] for freight, and it is [0, 49] for private transport owners (see Figure 4.33). For risk outcomes, the interval also contemplates a higher threshold for freight firms than for private transport owners, which shows the importance of CAPEX affordability for positive freight financial impacts. In the long term, high BEV and FCEV capital costs are harmful if their penetrations are also high. Meanwhile, additional requirements for desirable outcomes are high ICEV and fossil fuel costs.

Although small in magnitude, the financial impacts of public transport operators (see Figure 4.18) are determined by the drivers in Figure 4.35. First, high demands cause risk outcomes, and low demands cause desirable outcomes, i.e., with more demand, more capital is required, and the returns of investment for operators are delayed under the "price at cost" scheme. The demand's impact is also observed in mode shift to public transport: the lower it is, the more desirable. Those capital requirements will be low and produce desirable outcomes if BEV costs in 2031-50 are also low (third column); the converse is true (fourth column).

		22-30				31-50			
		Desirable		Risk		Desirable		Risk	
Driver groups	**Drivers**	Min	Max	Min	Max	Min	Max	Min	Max
Economic	GDP	0	59	35	100	0	73	14	100
	Passenger demand elasticity					0	95		
Technological (transport)	Costos of public ICEV	11	100			10	100	0	90
	Costs of public BEV					0	78	38	100
Technological (energy supply)	Cost of energy infrastructure	0	81			0	76	27	100
	Unit cost of fossil fuels	23	100			43	100	0	70
Social	Mode shift to public transport	0	22	10	100	0	77	37	100
Regulations	Public Transport % of BEV			0	24	31	100	56	56
	Public Transport % of FCEV			0	38	5	100	5	100
Operations	Occupancy rates of public transport	19	100	0	86				
Investments (energy supply)	Distribution solar electricity production					0	62		
	Wind electricity production	0	72						

Driver value scale

0 — 100

High | Mid-Low | Mid | Mid-High | High

Figure 4.35: Drivers for desirable and risky financial impacts for public transport operators.

Energy supply drivers also affect public transport operators: high energy costs get transferred to public transport operators, whose expense would also be higher, thus reducing the net financial impact. Moreover, the more efficient the existing power grid in supplying electrical demands, the lower the electricity prices; this is reflected by low renewable production as desirable conditions for both periods. Finally, one short-term lever that public transport operators can enforce for higher financial benefits is investing in vehicles and schemes with high occupancy rates, thus, reducing the number of vehicles necessary to supply ever higher demands.

		22-30				31-50			
		Desirable		Risk		Desirable		Risk	
Driver groups	Drivers	Min	Max	Min	Max	Min	Max	Min	Max
Economic	GDP	5	100	0	95				
Climate	Capacity factor of hydropower							0	95
Technological (energy supply)	Cost of energy infrastructure	0	51	50	100	0	21	74	100
	Residual capacity infrastructure	16	100	0	84				
Regulations	Heavy Freight % of BEV	0	26	2	100			19	100
	Heavy Freight % of FCEV	0	23	1	100			13	100
	Light Freight % of BEV	0	31					5	100
	Private Transport % of BEV	0	51	2	100				
	Public Transport % of BEV	0	43					33	100
Investments (energy supply)	Distribution solar electricity production					0	59		
	Wind electricity production	0	65	51	100				

Driver value scale

0 100

Low Mid-Low Mid Mid-High High

Figure 4.36: Drivers for desirable and risky financial impacts for electricity firms.

The cost of energy infrastructure is relevant for both electricity prices and the financial impacts of electricity firms in the long term, and to a lesser extent, in the short term (see Figures 4.29 and 4.36). The intervals of energy infrastructure cost for desirable and risk outcomes in 2022-30 have the common threshold of 0.5 with opposite endpoints observed in Figure 4.36 (third row). The intervals for the long term are small, covering only low and high values. In the long term, limiting transport electricity demands also avoids investing in renewables at early transition stages, thus producing desirable outcomes (first column). While GDP and hydropower capacity factors influence some outcomes, their thresholds are close to 0 or 100. The last two rows offer insights into the power sector. High wind production values reflect high CAPEX requirements in the near term. Also, low levels of solar generation are desirable in the long term since wind generation has a higher capacity factor.

Figure 4.37 shows what drivers affect the financial impacts of hydrocarbon firms -essentially equal to the opportunity cost of decarbonizing-. Low demands and fossil fuel prices are desirable in the near term since the BAU's net revenues would not be so high. In contrast, decarbonizing affects hydrocarbon firms under high demands and high prices, thus producing risk outcomes. The same logic applies long-term but for freight ZEV penetration levels as proxies of lost fossil fuel consumption.

Driver groups	Drivers	22-30 Desirable Min	22-30 Desirable Max	22-30 Risk Min	22-30 Risk Max	31-50 Desirable Min	31-50 Desirable Max	31-50 Risk Min	31-50 Risk Max
Economic	Freight demand elasticity	0	95						
	GDP	0	70	19	100				
Technological (energy supply)	Unit cost of fossil fuels	0	34	68	100	0	21	77	100
Regulations	Heavy Freight % of BEV					23	100	0	80
	Heavy Freight % of FCEV					10	100		
	Light Freight % of BEV							0	86

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.37: Drivers for desirable and risky financial impacts for hydrocarbon firms.

Figure 4.38 shows the drivers for government impacts. The government would have positive fiscal impacts if GDP were high, vehicle costs were high, mode shift was low, and electrification levels were low in 2030. These conditions would keep vehicle-related revenue high and maintain high levels of fossil fuel revenue. While high transport electrification in 2030 also produces costs, the government has opposing drivers to the ones for beneficial financial impacts, e.g., low BEV costs. The same logic applies to the 2031-50 period, except the fiscal impacts are less sensitive to ZEV penetration variations (almost not appearing in columns three and four).

Driver groups	Drivers	22-30 Desirable Min	22-30 Desirable Max	22-30 Risk Min	22-30 Risk Max	31-50 Desirable Min	31-50 Desirable Max	31-50 Risk Min	31-50 Risk Max
Economic	GDP	45	100	0	57	27	100		
	Passenger demand elasticity					5	100		
Technological (transport)	Costs of BEV	23	100	5	100	53	100	0	51
	Costs of FCEV	0	95	5	100			5	100
	Costs of ICEV	0	95	10	100	0	64	37	100
Social	Mode shift to public transport	0	47						
	Occupancy rates of private vehicles			19	100				
Regulations	Heavy Freight % of BEV	0	21	0	33				
	Heavy Freight % of FCEV	0	23	0	44				
	Light Freight % of BEV	0	50	0	40				
	Private Transport % of BEV	0	36	2	100				
	Public Transport % of BEV	0	34			36	100		

Driver value scale

0 — 100

Low | Mid-Low | Mid | Mid-High | High

Figure 4.38: Drivers for desirable and risky financial impacts for the government. Note: the financial impacts of the government are equivalent to the fiscal impacts.

Chapter 5

Conclusions, recommendations, and future work

5.1. Conclusions

Whether private firms and households adopt decarbonization measures depends largely on final technological costs. If low-carbon technologies are affordable and have the same or better functionality as their fossil-based options, the technological transition can happen. However, the transition must be fast: world GHG emissions should peak by 2025 to limit the temperature increase above pre-industrial levels to 1.5°C (IPCC, 2022). Still, according to IPCC, 2022, reaching the target is unlikely, but efforts must be high to at least keep the temperature increase below 2°C. Large countries will drive these transformations, with smaller countries adapting to the new technological trends and opportunities. Through taxes, subsidies, and financial rates, governments can shape final technological costs faster, and through investments, they can enable behavioral change and energy system improvements. This work concludes with Costa Rica's opportunities, challenges, and options to navigate the world's energy transition, comparing the National Decarbonization Plan (NDP) and Business-as-Usual (BAU) scenarios, depicting futures with and without decarbonization, respectively.

This work provides methodological innovations with the potential to inform energy policy in other countries or regions, extending the capabilities of ESOMs by analyzing parametric uncertainty through experiments and structural uncertainty through the modeling of energy system actors (i.e., electricity companies, hydrocarbon companies, public transport operators, freight companies, firms with a private transport fleet, households, and the Government) and transactions between them. The overarching methodology, called the *Multipurpose OSeMOSYS-based Modeling Framework* (MOMF) and presented in Chapter 3, tries to respond to some of the limitations of energy models highlighted by DeCarolis et al., 2017 while also following its best practice recommendations. The methodology can be adapted to different contexts and policy questions. By doing so, the tools developed in this work comply with the main objective established in Section 1.5.

The possibilities of the MOMF analysis can suit multiple energy policy exercises, particularly the identification of drivers (adoption targets, investments, and taxes) that cause desirable and risk outcomes. The conclusions are presented for each of the following topics:

1. national costs, benefits, and emissions;
2. ranking of policy objectives;
3. fiscal impacts and tax reform;
4. power sector impacts;
5. actor impacts;
6. robust drivers nationwide and per actor.

From the conclusions, this work provides nine specific policy recommendations to shape future energy planning in Costa Rica, seeking the most desirable outcomes and avoiding undesirable ones that cause economic risks, e.g., very high costs.

5.1.1. National Costs, Benefits, and Emissions

In Costa Rica, with the base assumptions[1] about the future and with the NDP's ambition, the transport sector has and will have the highest share of energy system expenses with or without decarbonization. Energy decarbonization is beneficial because the transport and energy system costs will decrease in the last decade relative to the first decade. However, under base assumptions, this cost reduction requires spending on the electricity system: 1.1% of GDP in 2021-2030 (yearly[2]), 2% of GDP in 2031-2040, and 1.9% of GDP in 2041-2050. Without decarbonization, the electricity system requires about 0.8% of GDP in the first decade, dropping to 0.6% in the next two. Decarbonization spending also includes about 0.5% of GDP in public transport infrastructure in the first decade, followed by 0.2-0.3% of GDP in the next two.

The energy system total cost will be 0.9% of GDP higher with decarbonization than without it in the first decade. In the next two decades there are benefits: the NDP's energy system is cheaper than the BAU's by 0.8% of GDP in 2031-2040 and 5.7% of GDP in 2041-2050. The reasons for high benefits in the last decade are that, by 2050, fossil fuels may become more expensive, zero-emission vehicles become cheaper, and renewables cheaper than in the earlier decades. Moreover, public transit will increase significantly, and private transport use and expenses will decrease. As a result, 2041-

[1] These assumptions are based on the expected cost trajectories, adoption of technologies, and demands defined from the literature or expert criteria. These expected values are then modified systematically to explore uncertainty.

[2] All the values with a unit as a percentage of GDP in a period are yearly period averages.

2050 avoided costs contemplate 2.5% of GDP in externalities, i.e., under the BAU, congestion, health problems, and accidents would have that additional economic value than under the NDP.

The NDP is very clear about transport sector mitigation measures but less clear about industry sector measures. Most sectors have decarbonization options, but remanent coke emissions for cement production could be remanent in 2050, with a total magnitude of about 0.7 Mton of equivalent carbon dioxide (CO2e). In the case of the industry sector, the costs and benefits are mainly at an energy consumption level: industry technologies (e.g., boilers) have smaller total cost differences between scenarios than transport, fossil fuels, or electricity.

One limitation of this work is that the industrial sector analysis was not developed with the participation of the sector, but rather, as an academic exercise. Future work should assess a roadmap for industry decarbonization because it will impact they country's economic competitiveness and the achievement of GHG emission targets. The roadmap should be developed with those actors, since there are structural or parametric uncertainties not explored in this work.

5.1.2. Ranking Policy Objectives

The measure that produces the highest benefits is mode shift to public transport and passenger rail transport: 1.37% of GDP in 2022-2050. This measure has the highest avoided capital and fixed costs, at about 0.21% of GDP in 2022-2050. Section 4.2 shows and discusses the ranking for all measures; the ranking is for the total period, but could be lower or higher in different decades. While mode shift ranks the highest in economic metrics, it alone does not decrease emissions by a large magnitude. Zero-emission vehicle (ZEV) penetration in private and freight transport avoided emissions the most and considerable economic benefits, ranking in the top half of the measures with the highest benefits.

The top three measures weighing benefits and emissions equally are mode shift, ZEV penetration in freight, and ZEV penetration in private transport. Then, when considering the investment and fixed costs required, demand reduction measures appear in the top half of the ranking. These include: reducing the distances traveled, demand elasticities for passenger and freight transport, and introducing freight rail. The first three measures do not have specific costs modeled and are associated with behavioral and business operation shifts. Beyond the importance of cost, the challenge for these demand reduction measures is organizational. The measures themselves can reduce costs or have equal costs to the BAU alternative. However, they are not enforced because of lacking policy instruments that facilitate their implementation, as noted by Victor-Gallardo, Roccard, et al., 2022. Improving these organizational barriers are possible government interventions resulting in better city planning and technological transfer to the private sector.

5.1.3. Power Sector Impacts

All else being equal, electricity prices[3] can significantly affect the benefits of transport sector actors. In large part, electricity prices will depend on low-cost renewable energy generation, which will require 4.5 times more capacity in 2050 than in 2018. How infrastructure is financed will affect prices: if interest rates are high, paying back investments will be more expensive (see Section 3.3.2).

Keeping discount rates low will make the net present value of benefits higher and maintain the future value of prices low. The low discount rates can result from government policy aimed at de-risking investments in energy. According to Monasterolo et al., 2022, the de-risking can occur with carbon taxes (i.e., increasing the risk of carbon alternatives) and sovereign green bonds for subsidies. Industry coalitions, or having membership in a group of firms with decarbonization objectives as defined by Green et al., 2021, may increase the leverage of a group of businesses and, perhaps, reduce risks associated with supply chains. A consistent government strategy to electrify can also reduce risks. If investors trust that the future energy system will be electricity-based, they can be more confident about the future cash flows from sustained electricity sales to the transport sector. Not doing so can cause high prices and low benefits, hindering decarbonization progress and failing to meet sustainability criteria for future energy systems, i.e., affordability (Sustainable Development Goal 7).

Governments must strive to de-risk energy infrastructure investments in the NDP to succeed. The *robust drivers* section below does not explore this conclusion. However, it offers insight on necessary actions for the government to prioritize, resulting in positive economic impacts of other decarbonization measures. Future work should quantify precisely how much subsidies will be necessary to de-risk investments, considering the fiscal impacts explained next. Also, the analysis showed the reliance on wind power generation investments in the future. Hence, de-risking the future power system implies developing more detailed technical planning on the implications of wind power development in the country and how storage can be coupled to increase its reliability.

[3] This work assessed the electricity price by considering future power system investments and operational costs. The price estimation uses the levelized cost of electricity (LCOE) of new generation, storage, transmission, and distribution infrastructure and equipment to approximate the future yearly average electricity price. The estimation assumes that the current expenses are constant throughout the 2018-2050 period and are estimated using the average price in 2018 times the total electricity sales. Future work can model the electricity prices in more detail if the research question merits further modeling, e.g., including differentiated rates.

5.1.4. Fiscal Impacts and Tax Reform

Across possible futures, on average, the government will receive less revenue by following an NDP pathway than a BAU, at least in terms of direct tax revenue and additional public works investments. The average magnitude of this *fiscal impact* (sacrificed revenue) in 2041-50 would be -0.87% of GDP (yearly period average), the period when it is highest. The fiscal impact in 2022-30 would be only -0.1% of GDP. In 2031-40, the government could enjoy a slightly higher revenue due to the import taxes from all the vehicles that replace the fleet from fossil to electric. When considering public transport investments, the fiscal impacts are negative (higher in the BAU than in the NDP): -0.83% of GDP in 2022-30, -0.21% of GDP in 2031-40, and -0.99% of GDP in 2041-50.

The results from the fiscal impact analysis show the revenue will be almost unchanged in the near term; governments will have to think about fiscal reforms to recover revenue after 2030, and more likely after 2040. However, financing the public transport infrastructure can considerably increase the magnitude of those impacts. Since public transport infrastructure enables long-term benefits, it could be financed separately from the near-term transport-related revenues. For example, if it is financed using debt, it could be paid for using part of the economic benefits (avoided costs) from transport, which are 5.5% of GDP in 2041-2050, on average across futures.

As explained by Van Dender, 2019, transport taxes should price transport externalities. This work presented what Rodriguez et al., 2021 and Victor-Gallardo, Rodríguez-Zúñiga, Quirós-Tortos, et al., 2022 defined as a relevant fiscal problem to solve: increase taxes or define new ones to make up for the lost revenue in the long-term. This work finds the following insights about future fiscal impacts:

- Reductions in revenue are equivalent to reduced fiscal costs on actors (private transport owners, freight firms, and public transport operators), causing higher positive financial impacts.
- Exonerations on property taxes are not trivial: they will reduce fiscal costs and tax revenue.
- Under the NDP relative to the BAU, the fiscal costs increase for freight firms and decrease for private transport owners. The effect is neutral for public transport operators. This information is important to consider a smart design of fiscal adjustments.
- All actors increase their fiscal costs with a proportional tax adjustment approach, i.e., increasing the tax rates of each option (vehicle-kilometer traveled, property, energy taxes). The increase is marked in 2041-2050 when the fiscal impact is the highest.

- Tax adjustments increase fiscal costs; higher fiscal costs reduce financial impacts (i.e., reduce decarbonization benefits). On the upside, the tax adjustments eliminate the fiscal impact, i.e., the NDP's fiscal revenue is equal to the BAU's.

- A vehicle-kilometer traveled tax (VKT) increases household costs: since buses travel the longest distances, they would spend on VKT the most if the tax is flat, i.e., considers a single VKT rate per kilometer. The consequence of this simplistic approach would be higher household fiscal costs since the VKT would be passed onto users through rates. The VKT is desirable because it prices the externalities of driving, according to Van Dender, 2019. However, a flat design will affect public transport users, who are likley low-income household users according to Rodriguez et al., 2021. Excluding public transport vehicles from this tax can be enough, in which case, the actor with the following highest distance traveled are freight firms (see Appendix C), who have high fiscal costs before tax adjustments.

- Property taxes make private transport owners carry the fiscal cost; mostly on households. Since property taxes on vehicles are progressive in Costa Rica, it can move the fiscal cost toward the wealthiest households.

- Energy taxes -on electricity or fossil fuels- affect heavy-duty vehicles, i.e., trucks and buses. The latter would pass the additional energy taxes onto the price, affecting households similarly to the VKT. Hence, energy taxes can potentially affect competitiveness, and according to Van Dender, 2019, not price driving externalities. On the upside, fossil energy taxes prices the negative carbon emissions effects. A significant drawback of energy taxes is the high rates necessary to eliminate the fiscal impacts: on the scale of 10-70% for electricity taxes and 30-120% for fossil prices. These rates can distort prices, causing elasticity-price effects not analyzed with ESOMs or TEM.

5.1.5. Actor Impacts

From a national perspective, decarbonizing the energy sector in Costa Rica will require 2.2% of GDP in CAPEX in 2031-2040. This magnitude and timing is the highest economic cost. The highest economic benefit will be 1.7% of GDP in avoided variable OPEX and 2.1% of GDP in avoided fixed OPEX, both in 2041-2050. Another important source of benefits in 2041-2050: 1.2% of GDP from avoided accidents caused by a lower transport activity in the NDP relative to the BAU. Electricity and bus prices can also be lower, provided new investments are recovered during the assets' lifetime.

One of the main MOMF contributions is the *Transaction Estimation Module* or TEM. It breaks down the costs from national impacts to actor impacts, including the government and energy sales and purchases. With a *price at cost* scheme, public transport operators and energy firms (electricity companies and hydrocarbon companies) generally have a positive net revenue, i.e., they can cover their costs. In the case of electricity companies, they must invest and then pass on those costs to consumers in the form of electricity prices. The electricity expenses substitute fuel expenses for vehicle owners, including public transport operators. The change in energy expenses would be reflected in bus prices directly. The changes in overall energy expenses (financial impacts per actor) would affect other economic metrics, e.g., food prices, but this is not explored in the TEM.

The financial impacts (net revenue costs in the NDP minus the BAU) are more varied for freight firms and private transport owners, i.e., net energy consumers. In every decade, private transport owners have positive financial impacts (benefits): 0.57% in 2022-2030, 0.75% in 2031-2040, and 3.42% of GDP yearly in 2041-2050, on average across futures. In some cases, they can face net costs (more costs in the NDP than in the BAU). Freight firms face net costs in 2022-2030 and 2031-2040, i.e., -0.25% and -0.77% of GDP yearly, on average across futures. These results are after taxes, which means there is an opportunity to adjust the tax structure so that freight firms have favorable financial impacts in the first two decades. Freight firms have financial benefits of 1.39% of GDP yearly in 2041-2050, on average across futures, which shows the opportunities to avoid OPEX in the long term.

Under the current paradigm, freight firms face fiscal costs in the first two decades due to all the technology imports they must incur to transform their fleets. While exonerating freight vehicles from import duties and value-added taxes can facilitate the transformation for these firms and will likely be necessary, it will increase the fiscal impact's magnitude. However, as long as the economic benefits are higher than the fiscal impact, the different tax options explored in the previous conclusion are instruments at the government's disposal to correct imbalances in the distribution of energy costs and benefits. Future work should address this redistribution with awareness of the fiscal burden on each actor, which is a function of the tax base and quantity of consumed goods.

5.1.6. Robust Drivers Nationwide and per Actor

Costa Rica's desirable outcomes depend on very affordable BEVs and energy infrastructure unit costs, including renewables, charging stations, and electrical grid reinforcements. While out of the government's control, any international efforts to keep these costs down will be helpful for very positive economic outcomes: financial impacts, electricity prices, and bus prices. The challenge at a global scale will be keeping the costs of energy infrastructure low, e.g., commodity prices, while also incentivizing a scaled-up production, e.g., mining of metals for BEVs or renewables.

Since Costa Rica imports its fuel, carbon taxes on fuel production abroad can increase the unit cost of fossil fuels. Higher unit fossil fuel prices are another condition for desirable financial impacts, particularly in the long term. On the contrary, if fossil fuels are cheap in the long term, decarbonizing will be less advantageous.

On policy levers, high electrification is desirable if unit costs are low but undesirable if the opposite becomes true. Hence, any future mandatory regulations on fleet electrification must consider the unit costs of vehicles. Moreover, some degree of freight mode shift is desirable in the 2022-30 period.

If wind electricity production is too high in the near term, it is a proxy of high electricity demands that can cause low financial impacts and high CAPEX requirements. High electricity demands are associated with high GDP and high non-transport electrical energy intensity. Low infrastructure costs are a condition to enable high electricity demands cost-effectively because more electricity sales can dilute electricity costs. In the opposite case, high unit energy infrastructure costs combined with high electricity demands can cause high CAPEX requirements and low benefits. Other aspects that can pose a risk to power CAPEX and prices are: i) replacing existing distribution and transmission infrastructure in 2030 and ii) low hydropower capacity factors in 2050. Hence, inexpensive infrastructure (including storage) can hedge against these risks but is not entirely within government control.

Expensive internal combustion engine vehicles (ICEVs) in the 2022-30 period can affect bus prices regardless of BEVs costs since buses will not all transform to electric this decade, and some fleet units will still be fossil-based. Moreover, high mode shift levels produce a trade-off:

- high mode shift levels from private to public transport increases investments, affecting prices;
- low mode shift levels produce low national financial benefits because private transport owners would not reduce their costs. Therefore, the government can consider subsidizing the bus price to enable national benefits without affecting the bus prices.

Low GDP growth is associated with desirable outcomes because of low CAPEX requirements. High GDP causes the risk of high CAPEX. This condition can be associated with higher employment and overall economic activity, thus making high CAPEX not entirely problematic. However, the robust strategy is to accelerate the decoupling of transport activity from GDP growth. The decoupling can be done with the following levers:

- increase telework and non-motorized transport;
- increase ridesharing (the occupancy rates of vehicles);
- increase city densification to reduce demands, enabled by public transport investments;
- use logistics hubs to transport industrial output and consumer goods;
- use 3D printing to reduce the need to transport goods between facilities in industrial centers.

The last three points are possible levers that change the passenger and freight demand elasticities, which are uncertainties in the analysis. These levers cause desirable benefits and emissions in 2030 and 2050. Therefore, these are also the most robust policies the government should advance since they enable benefits, avoid costs, and are independent of other uncertainties. Only high spending on public transport infrastructure can cause risks to these levers, so picking up effective projects will be necessary to achieve desirable outcomes.

The actor analysis suggests that the drivers of desirable government impacts produce risks for other actors' benefits. Hence, the government will have to change the tax structure to maximize national benefits. Another finding is that freight firms will need very affordable ZEV trucks to achieve the highest possible financial benefits, which will require significant technological innovations and subsidies. Failing to produce affordable trucks will make emission reductions harder.

Finally, infrastructure investments should be conceived with climate change adaptation targets. There can be premiums to these investments, increasing their overall costs and increasing the vulnerability of the NDP, i.e., increasing the likelihood of risk outcomes and decreasing the likelihood of desirable outcomes. Future cost-benefit assessments and robust policy identification exercises should consider quantifying the potential losses from not paying climate adaptation premiums. Futures with high CAPEX can produce desirable economic impacts if the risk of losing electrical services or rebuilding destroyed transport infrastructure is minimized.

5.2. Recommendations

5.2.1. Invest in this Decade

Public transport investments are the most robust levers. They decrease private transport needs, reduce emissions, CAPEX requirements and increase financial benefits for the country. Early adopters of ZEVs must also invest and pave the way for rapid uptake soon after 2030; this applies to private transport owners, public transport operators, and freight firms. The power system should also prepare by studying the future power grid expansion that will support large-scale electrification.

5.2.2. Make Transport Electrification a Priority

Without large-scale ZEV penetration in the long term, emissions and transport OPEX will be high. Certainty about the future adoption of ZEVs will give investors and energy firms confidence about the investments they must carry out. In turn, the high confidence in future electrification will provide the pricing stability for the electricity they sell, benefiting the whole economy. Transport electrification should be a sustained effort linked to energy independence and investment-seeking opportunities for other development goals, e.g., job creation and avoiding international indirect carbon prices.

5.2.3. Decouple Transport from Economic Growth Soon

High GDP growth can cause high emissions and CAPEX requirements, also hampering the prospect of high financial benefits. It is necessary to have a structural decoupling between transport and GDP to enjoy high economic growth without elevated energy costs. This can be achieved by maximizing the possibilities of telework and other digitalization efforts that reduce private transport demand. Simultaneously, non-motorized transport and ridesharing are concrete measures the government can promote. Crucially, improving the urban layout of Costa Rican cities will be necessary to enable higher activity at low transport costs, which goes on par with public transport investments and the development of logistics hubs that efficiently move materials within the country.

5.2.4. Develop and International Strategy for Freight Transport

Freight firms have significant OPEX savings opportunities in the long-term by substituting their fleets for ZEVs. Substantial emission reductions require a ZEV transformation as well. Advancing on a regional fleet substitution will be necessary, mainly because of the transnational use of the trucks and the trade component. The ZEV adoption will likely start in the second decade under the necessary conditions, i.e., low technological costs helped by tax modifications that reduce fiscal costs on freight firms. The strategy must also aim to reduce transport costs in the long term, increase potential job creation in the region, enable energy independence across countries, and reduce their vulnerability to international fuel or carbon prices.

5.2.5. Design a Reform with Progressive Taxes and Externality Pricing

Property taxes are a good option to substitute lost energy taxes. Vehicle-kilometer taxes (VKT) are good at pricing the externalities of driving. However, the VKT should consider exonerations for public transport and freight firms because they can have regressive impacts and hinder competitiveness. Energy taxes have the disadvantage of requiring high rates, thus, distorting prices. Reforms will be necessary to cover the long-term fiscal impacts with the economic benefits.

5.2.6. Take Advantage of Existing Power Assets

Increasing electricity demand with transport electrification and other industries and using the existing installed capacity to supply it will provide cost sustainability to the overall energy system. For example, consider using night-time charging for electric vehicles strictly. The undesirable alternative would be the triggering of investments that increase the national production capacity, thus, pushing final consumer costs upward.

5.2.7. Finance Assets at Low Rates

The electricity sector in the country must be de-risked. Actions like technology investment subsidies, clear electrification goals, and carbon taxes can send signals to financiers that generation, transmission, and distribution investments can be financed at low rates in the country. Failing to financially de-risk the sector can significantly reduce the magnitude of transport sector benefits due to elevated electricity prices, containing a high cost of capital.

5.2.8. Price Services with Lifetime Perspective

The "at cost" approach to establishing final prices allows moving the cost to the future without sudden spikes in energy prices due to necessary investments. The regulations and incentives must be enough such that final users enjoy affordable energy. New electricity market formulations should keep the spirit of "at cost" pricing while also enabling the incentives for investment and efficiency. Notably, allowing profit margins is not too impactful on final prices. Governments should maintain a "big-picture" of the energy system when enacting new regulations and laws, understanding how the electricity sector will impact the transport sector and vice versa.

5.2.9. Search for (or Develop) Assets with Low Unit Costs

The unit costs of ZEVs and energy infrastructure (including renewables and storage) determine how good decarbonization will be. There must be an active effort to reduce the costs of these technologies, even by using new low-cost vehicle paradigms, which ultimately will be adopted by the public. The government actions to find these low-cost solutions are:

i) participating in international efforts with the same objective;

ii) supporting research and development that could translate into business opportunities in the energy sector, e.g., competitively manufacturing parts of ZEVs, renewables, and storage.

5.3. Future Work

The findings point towards the following avenues for future research:

- Link models of high technical resolution with the robust techno-economic modeling developed here. Particularly, focus on how electric vehicle charging and discharging management affects the investment options of power sector assets. Additionally, include the effects of the seasonal availability and intermittency of power generation from renewable sources.

- Study the interaction of climate mitigation and climate adaptation measures to increase the robustness and resilience of energy systems. This work found the mitigation measures that achieve desirable economic outputs and the uncertainties associated with desirable outcomes, which have been denominated *robust policies*. However, resiliency has not been developed here and is associated with how well the energy system will recover from economic or nature-related shocks.

- Compare each tax option -on fuels, electricity, VKT, property, and excises- on four dimensions: external cost pricing, administration cost, price distortion, and progressivity.

- Find how subsidies or taxes can shape the final cost of technologies under uncertainty, i.e., if drivers reach a particular value, then a given combination of tax instruments should be enforced to maximize financial impacts. These fiscal instruments can mitigate risk outcomes.

Chapter 6

Bibliography

Aghajan-Eshkevari, S., Azad, S., Nazari-Heris, M., Ameli, M. T. & Asadi, S. (2022). *Charging and Discharging of Electric Vehicles in Power Systems: An Updated and Detailed Review of Methods, Control Structures, Objectives, and Optimization Methodologies*. MDPI. https://doi.org/10.3390/su14042137

Algunaibet, I. M., Pozo, C., Galán-Martín, Á. & Guillén-Gosálbez, G. (2019). Quantifying the cost of leaving the Paris Agreement via the integration of life cycle assessment, energy systems modeling and monetization. *Applied Energy*, *242*(March), 588-601. https://doi.org/10.1016/j.apenergy.2019.03.081

ARESEP. (s.f.-a). *Modelo de fijación ordinaria buses (hoja de calculo)*. https://aresep.go.cr/autobus/metodologias/3333-modelo-fijacion-ordinaria-buses-1-setiembre-2021

ARESEP. (s.f.-b). *Pasajeros movilizados e ingresos percibidos autobuses*. https://aresep.go.cr/transparencia/datos-abiertos/pasajeros-movilizados-autobuses

ARESEP. (s.f.-c). *Tarifas de electricidad del sistema de distribución*. https://aresep.go.cr/transparencia/datos-abiertos/tarifas-electricidad-sistema-distribucion

ARESEP. (s.f.-d). *Tarifas históricas de Taxi*. https://aresep.go.cr/transparencia/datos-abiertos/tarifas-historicas-taxi

Bataille, C., Waisman, H., Colombier, M., Segafredo, L., Williams, J. & Jotzo, F. (2016). The need for national deep decarbonization pathways for effective climate policy. *Climate Policy*, *16*, S7-S26. https://doi.org/10.1080/14693062.2016.1173005

Bhattacharyya, S. C. & Timilsina, G. R. (2009). *Energy Demand Models for Policy Formulation A Comparative Study of Energy Demand Models*, The World Bank. https://doi.org/10.1596/1813-9450-4866

Blanco, H., Gómez Vilchez, J. J., Nijs, W., Thiel, C. & Faaij, A. (2019). Soft-linking of a behavioral model for transport with energy system cost optimization applied to hydrogen in EU. *Rene-*

wable and Sustainable Energy Reviews, *115*(August), 109349. https://doi.org/10.1016/j.rser.2019.109349

Bryant, B. P. & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, *77*(1), 34-49. https://doi.org/10.1016/j.techfore.2009.08.002

Callihan, L. M. (2013). A robust decision-making technique for water management under decadal scale climate variability. *University of Colorado Boulder Dissertation*.

Center, T. S. (s.f.). *The U.S. Shale Revolution*. https://www.strausscenter.org/energy-and-security-project/the-u-s-shale-revolution/

Cervigni, R., Liden, R., Neumann, J. E. & Strzepek M., K. (Eds.). (2015). *Enhancing the Climate Resilience of Africa's Infrastructure*. Th e World Bank.

Cesar, A., Teixeira, B., Benavides, J., Rasteletti, A. G., Leonardo, I., Rios, U. & Madrigal, M. (2022). *A Framework for the Fiscal Impact of Electromobility*. Inter-American Development Bank. http://www.iadb.org

Coady, D., Parry, I., Le, N.-P. & Shang, B. (2019). Global Fossil Fuel Subsidies Remain Large: An Update Based on Country-Level Estimates IMF Working Paper Fiscal Affairs Department Global Fossil Fuel Subsidies Remain Large: An Update Based on Country-Level Estimates Prepared by. *IMF Working Papers*, *19*(89), 39. https://www.imf.org/en/Publications/WP/Issues/2019/05/02/Global-Fossil-Fuel-Subsidies-Remain-Large-An-Update-Based-on-Country-Level-Estimates-46509

Colla, M., Ioannou, A. & Falcone, G. (2020). Critical review of competitiveness indicators for energy projects. *Renewable and Sustainable Energy Reviews*, *125*(December 2019), 109794. https://doi.org/10.1016/j.rser.2020.109794

DeCarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., Yeh, S. & Zeyringer, M. (2017). Formalizing best practice for energy system optimization modelling. Elsevier Ltd. https://doi.org/10.1016/j.apenergy.2017.03.001

Ding, L., Gao, J., Shi, G. & Ni, Z. (2022). Robust optimal dispatch of integrated energy system considering with coupled wind and hydrogen system. *Journal of Physics: Conference Series*, *2215*, 012001. https://doi.org/10.1088/1742-6596/2215/1/012001

Dominković, D. F., Weinand, J. M., Scheller, F., D'Andrea, M. & McKenna, R. (2022). *Reviewing two decades of energy system analysis with bibliometrics.* Elsevier Ltd. https://doi.org/10.1016/j.rser.2021.111749

Doumpos, M., Zopounidis, C. & Grigoroudis, E. (Eds.). (2016). *Robustness Analysis in Decision Aiding, Optimization, and Analytics.*

Dreier, D. & Howells, M. (2019). Osemosys-pulp: A stochastic modeling framework for long-term energy systems modeling. *Energies*, *12*(7). https://doi.org/10.3390/en12071382

Edelenbosch, O. Y., Kermeli, K., Crijns-Graus, W., Worrell, E., Bibas, R., Fais, B., Fujimori, S., Kyle, P., Sano, F. & van Vuuren, D. P. (2017). Comparing projections of industrial energy demand and greenhouse gas emissions in long-term energy models. *Energy*, *122*, 701-710. https://doi.org/10.1016/j.energy.2017.01.017

Eker, S. & Kwakkel, J. H. (2018). Including robustness considerations in the search phase of Many-Objective Robust Decision Making. *Environmental Modelling and Software*, *105*, 201-216. https://doi.org/10.1016/j.envsoft.2018.03.029

Escuela de Ingeniería Eléctrica - Universidad de Costa Rica. (2019). *Estudio para la caracterización del consumo energético en el sector industrial.*

Escuela de Ingeniería Eléctrica - Universidad de Costa Rica. (2020). *Opciones de descarbonización del consumo energético en el sector industrial.*

Fais, B., Keppo, I., Zeyringer, M., Usher, W. & Daly, H. (2016). Impact of technology uncertainty on future low-carbon pathways in the UK. *Energy Strategy Reviews*, *13-14*, 154-168. https://doi.org/10.1016/j.esr.2016.09.005

Finucane, M., Tariq, A., Lempert, R., Molina-Perez, E., Hoss, F. & Fischbach, J. (2018). *Managing Water Quality in the Face of Uncertainty: A Robust Decision Making Demonstration for EPA's National Water Program.* https://doi.org/10.7249/rr720

Fodstad, M., del Granado, P. C., Hellemo, L., Knudsen, B. R., Pisciella, P., Silvast, A., Bordin, C., Schmidt, S. & Straus, J. (2022). Next frontiers in energy system modelling: A review on challenges and the state of the art. *Renewable and Sustainable Energy Reviews*, *160*, 112246. https://doi.org/10.1016/j.rser.2022.112246

Franc-Dabrowska, J., Madra-Sawicka, M. & Milewska, A. (2021). Energy sector risk and cost of capital assessment—companies and investors perspective. *Energies*, *14*. https://doi.org/10.3390/en14061613

Fraser, A., Chester, M. V., Hoehne, C., Markolf, S. A. & Underwood, B. S. (2018). Transportation resilience to climate change and extreme weather events – Beyond risk and robustness. *Transport Policy*, *74*(July 2017), 174-186. https://doi.org/10.1016/j.tranpol.2018.11.003

Freire-González, J. & Puig-Ventosa, I. (2019). Reformulating taxes for an energy transition. *Energy Economics*, *78*, 312-323. https://doi.org/10.1016/j.eneco.2018.11.027

Gilbert, P. R. (2020). Making critical materials valuable: Decarbonization, investment, and "political risk". *The Material Basis of Energy Transitions*, 91-108. https://doi.org/10.1016/b978-0-12-819534-5.00006-4

Godínez-Zamora, G., Victor-Gallardo, L., Angulo-Paniagua, J., Ramos, E., Howells, M., Usher, W., León, F. D., Meza, A. & Quirós-Tortós, J. (2020). Decarbonising the transport and energy sectors: Technical feasibility and socioeconomic impacts in Costa Rica. *Energy Strategy Reviews*, *32*. https://doi.org/10.1016/j.esr.2020.100573

Gong, M., Lempert, R., Parker, A., Mayer, L. A., Fischbach, J., Sisco, M., Mao, Z., Krantz, D. H. & Kunreuther, H. (2017). Testing the scenario hypothesis: An experimental comparison of scenarios and forecasts for decision support in a complex decision environment. *Environmental Modelling and Software*, *91*, 135-155. https://doi.org/10.1016/j.envsoft.2017.02.002

Government of Costa Rica 2018-2022. (2019). *Plan Nacional de Descarbonización 2018-2050* (inf. téc.). Ministerio de Ambiente y Energía. San José, Costa Rica. https://cambioclimatico.go.cr/wp-content/uploads/2019/02/PLAN.pdf

Government of Costa Rica 2018-2022. (2020). Contribución Nacionalmente Determinada 2020. https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/Costa%20Rica%20First/Contribuci%C3%B3n%20Nacionalmente%20Determinada%20de%20Costa%20Rica%202020%20-%20Versi%C3%B3n%20Completa.pdf

Green, J., Hadden, J., Hale, T. & Mahdavi, P. (2021). Transition, hedge, or resist? Understanding political and economic behavior toward decarbonization in the oil and gas industry. *Review of International Political Economy*. https://doi.org/10.1080/09692290.2021.1946708

Groissböck, M. (2019). Are open source energy system optimization tools mature enough for serious use? https://doi.org/10.1016/j.rser.2018.11.020

Groves, D. G., Fischbach, J. R., Bloom, E., Knopman, D. & Keefe, R. (2013). *Adapting to a Changing Colorado River: Making Future Water Deliveries More Reliable Through Robust Management Strategies*. https://doi.org/10.1214/07-EJS057

Groves, D. G., Fischbach, J. R., Knopman, D., Johnson, D. R. & Giglio, K. (2014). APPENDIX A Brief Description of Robust Decision Making, En *Strengthening Coastal Planning: How Coastal Regions Could Benefit from Louisiana's Planning and Analysis Framework*. RAND Corporation Chapter. https://doi.org/10.4135/9781412950558.n465

Groves, D. G. & Lempert, R. J. (2007). A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, *17*(1), 73-85. https://doi.org/10.1016/j.gloenvcha.2006.11.006

Groves, D. G., Syme, J., Molina-Pérez, E., Calvo, C., Víctor-Gallardo, L., Godínez-Zamora, G., Quirós-Tortós, J., Saavedra-Gómez, V. & Vogt-Schilb, A. (2020). *The Benefits and Costs Of Decarbonizing Costa Rica's Economy: Informing the Implementation of Costa Rica's National Decarbonization Plan under Uncertainty*. Interamerican Development Bank. https://doi.org/http://dx.doi.org/10.18235/0002867

Guthrie, S., Watu, W., Diepeveen, S., Wooding, S. & Grant, J. (2009). *Natural Gas and Israel's Energy Future: A Strategic Analysis Under Conditions of Deep Uncertainty* (inf. téc.). RAND. http://www.rand.org/content/dam/rand/pubs/monographs/MG1200/MG1217/RAND%7B%5C_%7DMG1217.pdf

Haasnoot, M., Kwakkel, J. H., Walker, W. E. & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, *23*(2), 485-498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Hadjimichael, A., Gold, D., Hadka, D. & Reed, P. (2020). Rhodium : Python Library for Many-Objective Robust Decision Making and Exploratory Modeling. *Journal of Open Research Software*, (8), 12. https://doi.org/http://doi.org/10.5334/jors.293

Haines, A., Amann, M., Borgford-Parnell, N., Leonard, S., Kuylenstierna, J. & Shindell, D. (2017). *Short-lived climate pollutant mitigation and the Sustainable Development Goals*. Nature Publishing Group. https://doi.org/10.1038/s41558-017-0012-x

Helgesen, P. I. (2013). Top-down and Bottom-up : Combining energy system models and macroeconomic general equilibrium models. *Centre for Sustainable Energy Studies (CenSES) working paper*, 30.

Hermans, L. M., Haasnoot, M., ter Maat, J. & Kwakkel, J. H. (2017). Designing monitoring arrangements for collaborative learning about adaptation pathways. *Environmental Science and Policy*, *69*, 29-38. https://doi.org/10.1016/j.envsci.2016.12.005

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M. & Roehrl, A. (2011). OSeMOSYS: The Open Source Energy Modeling System. *Energy Policy*, *39*(10), 5850-5870. https://doi.org/10.1016/j.enpol.2011.06.033

ICCT. (2012). *Global Transportation Roadmap Model* (inf. téc. December). http://www.theicct.org/info/assets/RoadmapV1/ICCT%20Roadmap%20Model%20Version%201-0%20Documentation.pdf

Instituto Meteorológico Nacional. (2019). Inventario nacional de emisiones por fuentes y absorción por sumideros de gases de efecto invernadero en Costa Rica 2017. http://cglobal.imn.ac.cr/documentos/publicaciones/InventariosGEI/InventarioGEI-2017/offline/InventarioGEI2017.pdf

International Energy Agency. (2019). World Energy Outlook 2019. *Oecd/Iea*, arXiv arXiv:1011.1669v3. https://doi.org/DOE/EIA-0383(2012)U.S.

IPCC. (s.f.). *About the IPCC*. https://www.ipcc.ch/about/

IPCC. (2014). *Fifth Assessment Report*.

IPCC. (2018a). *Special Report on Global Warming of 1.5°C*.

IPCC. (2018b). Summary for Policymakers [In Press.]. *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.*

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Full_Report_smaller.pdf

IPCC. (2022). *Climate Change 2022: Mitigation of Climate Change*. https://www.ipcc.ch/report/ar6/wg3/

IRENA. (s.f.). *Energy Transition*. https://www.irena.org/energytransition

ITF. (2019). *ITF Transport Outlook 2019* (inf. téc.). https://doi.org/10.1787/9789282103937-en

Ji, L., Zhang, B., Huang, G., Cai, Y. & Yin, J. (2020). Robust regional low-carbon electricity system planning with energy-water nexus under uncertainties and complex policy guidelines. *Journal of Cleaner Production*, *252*, 119800. https://doi.org/10.1016/j.jclepro.2019.119800

Jorgenson, A., Clark, R., Kentor, J. & Rieger, A. (2022). *Networks, stocks, and climate change: A new approach to the study of foreign investment and the environment*. Elsevier Ltd. https://doi.org/10.1016/j.erss.2021.102461

Ju, L., Wu, J., Lin, H., Tan, Q., Li, G., Tan, Z. & Li, J. (2020). Robust purchase and sale transactions optimization strategy for electricity retailers with energy storage system considering two-stage demand response. *Applied Energy*, *271*(April), 115155. https://doi.org/10.1016/j.apenergy.2020.115155

Kalra, N. R., Groves, D. G., Bonzanigo, L., Perez, E. M., Ramos Taipe, C. L., Cabanillas, I. R. & Brandon, C. J. (2015). Robust decision-making in the water sector : a strategy for implementing Lima's long-term water resources master plan. *World Bank*, (October), 1-51. https://doi.org/10.1111/scs.12268

Kalra, N., Hallegatte, S. S., Lempert, R., Brown, C., Fozzard, A., Gill, S. & Shah, A. (2014). Agreeing on Robust Decisions New Processes for Decision Making Under Deep Uncertainty. *World Bank Policy Research Working Paper*, *No. 6906*(June). https://doi.org/10.1596/1813-9450-6906

Keshavarzian, M., Kamali Anaraki, S., Zamani, M. & Erfanifard, A. (2012). Projections of oil demand in road transportation sector on the basis of vehicle ownership projections, worldwide: 1972-2020. *Economic Modelling*, *29*(5), 1979-1985. https://doi.org/10.1016/j.econmod.2012.06.009

Kober, T., Falzon, J., van der Zwaan, B., Calvin, K., Kanudia, A., Kitous, A. & Labriet, M. (2014). A multi-model study of energy supply investments in Latin America under climate control policy. *Energy Economics*, *56*, 543-551. https://doi.org/10.1016/j.eneco.2016.01.005

kuang Chen, Y., Kirkerud, J. G. & Bolkesjø, T. F. (2022). Balancing GHG mitigation and land-use conflicts: Alternative Northern European energy system scenarios. *Applied Energy*, *310*. https://doi.org/10.1016/j.apenergy.2022.118557

Kwakkel, J. H. & Cunningham, S. C. (2016). Improving scenario discovery by bagging random boxes. *Technological Forecasting and Social Change*, *111*, 124-134. https://doi.org/10.1016/j.techfore.2016.06.014

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling and Software*, *96*, 239-250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., Haasnoot, M. & Walker, W. E. (2016). Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty.

Environmental Modelling and Software, *86*, 168-183. https://doi.org/10.1016/j.envsoft.2016.09.017

Lempert, R. J., Bryant, B. P. & Bankes, S. C. (2008). *Comparing Algorithms for Scenario Discovery* (inf. téc.).

Lempert, R. J., Popper, S. W. & Bankes, S. C. (2011). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis.* (Vol. 4). https://doi.org/10.5465/amle.2005.19086797

Lempert, R. & Trujillo, H. (2018). Deep Decarbonization as a Risk Management Challenge. *Deep Decarbonization as a Risk Management Challenge*, (October). https://doi.org/10.7249/pe303

Li, D., Gao, C., Guo, X. & Han, S. (2022). Peak Shaving Effect of Power-to-Gas in Robust Energy Dispatching, IEEE. https://doi.org/10.1109/CPEEE54404.2022.9738669

Lin, B. & Jia, Z. (2019). How does tax system on energy industries affect energy demand, CO2 emissions, and economy in China? *Energy Economics*, *84*, 104496. https://doi.org/10.1016/j.eneco.2019.104496

Liu, G., Qin, Z., Diao, T., Wang, X., Wang, P. & Bai, X. (2022). Low carbon economic dispatch of biogas-wind-solar renewable energy system based on robust stochastic optimization. *International Journal of Electrical Power Energy Systems*, *139*, 108069. https://doi.org/10.1016/j.ijepes.2022.108069

Loh, W.-Y. (2011). Classification and Regression Trees. *Wiley_Interdisciplinary_Reviews*, *1*(February), 1-358. https://doi.org/10.1201/9781315139470

Lopion, P., Markewitz, P., Robinius, M. & Stolten, D. (2018). A review of current challenges and trends in energy systems modeling. *Renewable and Sustainable Energy Reviews*, *96*(August), 156-166. https://doi.org/10.1016/j.rser.2018.07.045

Lovrić, M., Blainey, S. & Preston, J. (2017). A conceptual design for a national transport model with cross-sectoral interdependencies, En *Transportation Research Procedia*. https://doi.org/10.1016/j.trpro.2017.12.150

Mahnovski, S. (2007). Robust Decisions and Deep Uncetainty - An Application of Real Options to Public and Private Investment in Hydrogen and Fuel Cell Technologies. *Pardee Rand Graduate School*, 1-130.

Marchau, V. A. J., Walker, W. E., Bloemen, P. J. & Pooper, S. W. (2019). *Decision Making Under Deep Uncertainty*. Springer. https://doi.org/https://doi.org/10.1007/978-3-030-05252-2

Marcucci, A., Panos, E., Kypreos, S. & Fragkos, P. (2019). Probabilistic assessment of realizing the 1.5 °C climate target. *Applied Energy*, *239*(January), 239-251. https://doi.org/10.1016/j.apenergy.2019.01.190

Matrosov, E. S., Reed, P. M., Lambert, C., Huskova, I., Harou, J. J. & Kasprzyk, J. R. (2015). Many-objective optimization and visual analytics reveal key trade-offs for London's water supply. *Journal of Hydrology*, *531*, 1040-1053. https://doi.org/10.1016/j.jhydrol.2015.11.003

McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A. & Westra, S. (2018). Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? *Earth's Future*, *6*, 169-191. https://doi.org/10.1002/2017EF000649

Mittelviefhaus, M., Georges, G. & Boulouchos, K. (2022). Electrification of multi-energy hubs under limited electricity supply: De-/centralized investment and operation for cost-effective greenhouse gas mitigation. *Advances in Applied Energy*, *5*. https://doi.org/10.1016/j.adapen.2022.100083

Monasterolo, I., Dunz, N., Mazzocchetti, A. & Gourdel, R. (2022). Derisking the low-carbon transition: investors' reaction to climate policies, decarbonization and distributive effects. *Review of Evolutionary Political Economy*. https://doi.org/10.1007/s43253-021-00062-3

Nadolny, A., Cheng, C., Lu, B., Blakers, A. & Stocks, M. (2022). Fully electrified land transport in 100 % renewable electricity networks dominated by variable generation. *Renewable Energy*, *182*, 562-577. https://doi.org/10.1016/j.renene.2021.10.039

Niet, T., Shivakumar, A., Gardumi, F., Usher, W., Williams, E. & Howells, M. (2021). Developing a community of practice around an open source energy modelling tool. *Energy Strategy Reviews*, *35*. https://doi.org/10.1016/j.esr.2021.100650

Nolting, L. & Praktiknjo, A. (2022). The complexity dilemma – Insights from security of electricity supply assessments. *Energy*, *241*. https://doi.org/10.1016/j.energy.2021.122522

OECD. (2019a). *Tax Revenue Implications of Decarbonising Road Transport: Scenarios for Slovenia*. https://doi.org/10.1787/87b39a2f-en

OECD. (2019b). *Taxing Energy Use 2019: Using Taxes for Climate Action*. https://doi.org/10.1787/058ca239-en

Pfenninger, S., DeCarolis, J., Hirth, L., Quoilin, S. & Staffell, I. (2017). The importance of open data and software: Is energy research lagging behind? *Energy Policy*, *101*(October 2016), 211-215. https://doi.org/10.1016/j.enpol.2016.11.046

Pfenninger, S., Hirth, L., Schlecht, I., Schmid, E., Wiese, F., Brown, T., Davis, C., Gidden, M., Heinrichs, H., Heuberger, C., Hilpert, S., Krien, U., Matke, C., Nebel, A., Morrison, R., Müller, B., Pleßmann, G., Reeg, M., Richstein, J. C., … Wingenbach, C. (2018). Opening the black box of energy modelling: Strategies and lessons learned. *Energy Strategy Reviews*, *19*arXiv 1707.08164, 63-71. https://doi.org/10.1016/j.esr.2017.12.002

Popper, S. W., Berrebi, C., Griffin, J., Light, T., Min, E. Y. & Crane, K. (2009). *Natural Gas and Israel's Energy Future: Near Term Decisions from a Strategic Perspective* (inf. téc.). RAND.

Priesmann, J., Nolting, L. & Praktiknjo, A. (2019). Are complex energy system models more accurate? An intra-model comparison of power system optimization models. *Applied Energy*, *255*(March), 113783. https://doi.org/10.1016/j.apenergy.2019.113783

Prina, M. G., Casalicchio, V., Kaldemeyer, C., Manzolini, G., Moser, D., Wanitschke, A. & Sparber, W. (2020). Multi-objective investment optimization for energy system models in high temporal and spatial resolution. *Applied Energy*, *264*(September 2019), 114728. https://doi.org/10.1016/j.apenergy.2020.114728

Pye, S. & Bataille, C. (2016). Improving deep decarbonization modelling capacity for developed and developing country contexts. *Climate Policy*, *16*, S27-S46. https://doi.org/10.1080/14693062.2016.1173004

Pye, S., Li, F. G., Petersen, A., Broad, O., McDowall, W., Price, J. & Usher, W. (2018). Assessing qualitative and quantitative dimensions of uncertainty in energy modelling for policy support in the United Kingdom. *Energy Research and Social Science*, *46*(March), 332-344. https://doi.org/10.1016/j.erss.2018.07.028

Quirós-Tortós, J., Godínez-Zamora, G., Ugarte, D. G. D. L. T., Heros, C., Lazo, J. L., Ruiz, E., Quispe, B., Canseco, D. D., Garro, F., Mora, J., Eguren, L., Sandoval, M., Campos, S., Salmeri, M., Baron, R., Fernandez-Baca, J., Fukushima, A. S. I., Saavedra, V. & Vogt-Schilb, A. (2021). *Costos y beneficios de la carbono neutralidad en Perú: una evaluación robusta*. https://doi.org/http://dx.doi.org/10.18235/0003286

RAND. (2006). Transportation Planning, Climate Change, and Decisionmaking Under Uncertainty, 1-26.

RAND. (2013). Making Good Decisions Without Predictions: Robust decision making for planning under deep uncertainty, 1-7.

RAND. (2014). The Robust Decision Making Framework, En *Developing Robust Strategies for Climate Change and Other Risks: A Water Utility Framework*. https://www.jstor.org/stable/10.7249/j.ctt14bs4mg.9

RECOPE. (s.f.-a). *Datos Estadísticos Anuales de Importación - RECOPE*. https://www.recope.go.cr/productos/estadisticas-de-importacion-y-exportacion/

RECOPE. (s.f.-b). *Estructura de Precios de los Combustibles*. https://www.recope.go.cr/productos/precios-nacionales/estructura-de-precios/

Ringkjøb, H. K., Haugan, P. M. & Solbrekke, I. M. (2018). A review of modelling tools for energy and electricity systems with large shares of variable renewables. Elsevier Ltd. https://doi.org/10.1016/j.rser.2018.08.002

Rodriguez, M., Victor-Gallardo, L., Quirós-Tortós, J., Jaramillo, M. & Vogt-Schilb, A. (2021). *Impacto fiscal de la descarbonización del transporte en Costa Rica y opciones de política para manejarlo*. Inter-American Development Bank. https://doi.org/10.18235/0003402

Ruhnau, O., Bucksteeg, M., Ritter, D., Schmitz, R., Böttger, D., Koch, M., Pöstges, A., Wiedmann, M. & Hirth, L. (2022). Why electricity market models yield different results: Carbon pricing in a model-comparison experiment. *Renewable and Sustainable Energy Reviews*, *153*. https://doi.org/10.1016/j.rser.2021.111701

Saget, C., Vogt-Schilb, A. & Luu, T. (2020). El empleo en un futuro de cero emisiones netas en América Latina y el Caribe. https://doi.org/10.18235/0002509

Sahlberg, A., Khavari, B., Korkovelos, A., Nerini, F. F. & Howells, M. (2021). A scenario discovery approach to least-cost electrification modelling in Burkina Faso. *Energy Strategy Reviews*, *38*. https://doi.org/10.1016/j.esr.2021.100714

Sakamoto, T., Takase, K., Matsuhashi, R. & Managi, S. (2016). Baseline of the projection under a structural change in energy demand. *Energy Policy*, (98), 274-289. https://doi.org/10.1016/j.enpol.2016.08.035

Sass, S., Faulwasser, T., Hollermann, D. E., Kappatou, C. D., Sauer, D., Schütz, T., Shu, D. Y., Bardow, A., Gröll, L., Hagenmeyer, V., Müller, D. & Mitsos, A. (2020). Model compendium, data, and optimization benchmarks for sector-coupled energy systems. *Computers and Chemical Engineering*, *135*. https://doi.org/10.1016/j.compchemeng.2020.106760

Schlachtberger, D. P., Brown, T., Schäfer, M., Schramm, S. & Greiner, M. (2018). Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints. *Energy*, *163*arXiv 1803.09711, 100-114. https://doi.org/10.1016/j.energy.2018.08.070

SEPSE. (2021). *Balances Energéticos de Costa Rica 2012-2019*. https://sepse.go.cr/ciena/balances-energeticos/

Shaw, C., Hales, S., Howden-Chapman, P. & Edwards, R. (2014). Health co-benefits of climate change mitigation policies in the transport sector. *Nature Climate Change*, *4*(6), 427-433. https://doi.org/10.1038/nclimate2247

Shen, F., Zhao, L., Du, W., Zhong, W. & Qian, F. (2020). Large-scale industrial energy systems optimization under uncertainty: A data-driven robust optimization approach. *Applied Energy*, *259*(August 2019), 114199. https://doi.org/10.1016/j.apenergy.2019.114199

Singh, R., Reed, P. M. & Keller, K. (2015). Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. *Ecology and Society*, *20*(3). https://doi.org/10.5751/ES-07687-200312

Sridharan, V., Ramos, E. P., Taliotis, C., Howells, M., Basudde, P. & Kinhonhi, I. V. (2019). Vulnerability of Uganda's Electricity Sector to Climate Change: An Integrated Systems Analysis. *Handbook of Climate Change Resilience*, 1-30. https://doi.org/10.1007/978-3-319-71025-9_45-2

Steffen, B. (2020). Estimating the cost of capital for renewable energy projects. *Energy Economics*, *88*. https://doi.org/10.1016/j.eneco.2020.104783

Süsser, D., Ceglarz, A., Gaschnig, H., Stavrakas, V., Flamos, A., Giannakidis, G. & Lilliestam, J. (2021). Model-based policymaking or policy-based modelling? How energy models and energy policy interact. *Energy Research and Social Science*, *75*. https://doi.org/10.1016/j.erss.2021.101984

Taliotis, C., Shivakumar, A., Boehlert, B., Huber-Lee, A., Strzepek, K. M., Howells, M., Lempert, R., Neumann, J. E., Groves, D. G., Broad, O., Sridharan, V., Cervigni, R., Rogner, H.-H. & Joyce, B. (2019). Resilience of the Eastern African electricity sector to climate driven changes in hydropower generation. *Nature Communications*, *10*(1), 1-9. https://doi.org/10.1038/s41467-018-08275-7

Tan, J., Wu, Q., Hu, Q., Wei, W. & Liu, F. (2020). Adaptive robust energy and reserve co-optimization of integrated electricity and heating system considering wind uncertainty. *Applied Energy*, *260*(October 2019), 114230. https://doi.org/10.1016/j.apenergy.2019.114230

Taylor, D. D., Paiva, S. & Slocum, A. H. (2017). An alternative to carbon taxes to finance renewable energy systems and offset hydrocarbon based greenhouse gas emissions. *Sustainable Energy Technologies and Assessments*, *19*, 136-145. https://doi.org/10.1016/j.seta.2017.01.003

Usher, W. & Strachan, N. (2012). Critical mid-term uncertainties in long-term decarbonisation pathways. *Energy Policy*, *41*, 433-444. https://doi.org/10.1016/j.enpol.2011.11.004

van den Bergh, J., Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T. & Savin, I. (2021). Designing an effective climate-policy mix: accounting for instrument synergy. *Climate Policy*, *21*, 745-764. https://doi.org/10.1080/14693062.2021.1907276

Van Dender, K. (2019). Taxing vehicles, fuels, and road use: Opportunities for improving transport tax practice, 59. https://doi.org/10.1787/e7f1d771-en

van der Zwaan, B., Kober, T., Calderon, S., Clarke, L., Daenzer, K., Kitous, A., Labriet, M., Lucena, A. F., Octaviano, C. & Di Sbroiavacca, N. (2014). Energy technology roll-out for climate change mitigation: A multi-model study for Latin America. *Energy Economics*, *56*, 526-542. https://doi.org/10.1016/j.eneco.2015.11.019

van Eyden, R., Difeto, M., Gupta, R. & Wohar, M. E. (2019). Oil price volatility and economic growth: Evidence from advanced economies using more than a century's data. *Applied Energy*, *233-234*, 612-621. https://doi.org/10.1016/j.apenergy.2018.10.049

Victor-Gallardo, L. & Quirós-Tortos, J. (2022). Techno-economic Comparison of Centralized and Distributed Power Systems to Support Large-Scale Transport Electrification. *Manuscript submitted for publication.*

Victor-Gallardo, L., Roccard, J., Campos, P., Malley, C., Lefevre, E. & Quirós-Tortos, J. (2022). Identifying cross-sectoral policy synergies for decarbonization: towards short-lived climate pollutant mitigation action in Costa Rica. *Manuscript submitted for publication.*

Victor-Gallardo, L., Rodríguez-Zúñiga, M., Rodríguez-Arce, M., Alfaro-Corrales, I. & Quirós-Tortos, J. (2022). Prioritizing policy options in the net-zero energy transition considering economic complexity. *Manuscript submitted for publication.*

Victor-Gallardo, L., Quirós-Tortós, J., Syme, J., Groves, D., Molina, E., De León, F., Meza, A., Saavedra, V. & Vogt-Schilb, A. (2022). Identifying Robust Energy Decarbonization Pathways under Multi-Objective Criteria: the Case of Transport in Costa Rica. *Manuscript in preparation.*

Victor-Gallardo, L., Rodríguez-Zúñiga, M., Quirós-Tortos, J., Jaramillo, M. & Vogt-Schilb, A. (2022). Policy options to mitigate the fiscal impact of road transport decarbonization: the case of Costa Rica. *Manuscript submitted for publication.*

Wagener, T. & Pianosi, F. (2019). What has Global Sensitivity Analysis ever done for us? A systematic review to support scientific advancement and to inform policy-making in earth system modelling. *Earth-Science Reviews*, *194*(February 2018), 1-18. https://doi.org/10.1016/j.earscirev.2019.04.006

Walker, W. E., Lempert, R. J. & Kwakkel, J. H. (2013). Deep Uncertainty: Uncertainty in Model-Based Decision Support. *Encyclopedia of operations research and management science*, *1*(1), 395-402.

Wang, M., Yu, H., Jing, R., Liu, H., Chen, P. & Li, C. (2020). Combined multi-objective optimization and robustness analysis framework for building integrated energy system under uncertainty. *Energy Conversion and Management*, *208*(February), 112589. https://doi.org/10.1016/j.enconman.2020.112589

Wei, J., Zhang, Y., Wang, J., Cao, X. & Khan, M. A. (2020). Multi-period planning of multi-energy microgrid with multi-type uncertainties using chance constrained information gap decision method. *Applied Energy*, *260*(August 2019), 114188. https://doi.org/10.1016/j.apenergy.2019.114188

Williams, J. H., Jones, R. A. & Torn, M. S. (2021). Observations on the transition to a net-zero energy system in the United States. *Energy and Climate Change*, *2*, 100050. https://doi.org/10.1016/j.egycc.2021.100050

Williams, J. & Waisman, H. (2018). *2050 Pathways: A Handbook* (inf. téc. July). https://www.2050pathways.org/

World Bank. (2019). *Costa Rica | Data*. https://data.worldbank.org/country/CR

World Bank. (2021). *Commodity Markets Outlook*. https://www.worldbank.org/en/news/press-release/2021/10/21/soaring-energy-prices-pose-inflation-risks-as-supply-constraints-persist

World Resources Institute. (2020). *World's Top Emitters Interactive Chart*. https://www.wri.org/insights/interactive-chart-shows-changes-worlds-top-10-emitters

Xiang, Y., Cai, H., Gu, C. & Shen, X. (2020). Cost-benefit analysis of integrated energy system planning considering demand response. *Energy*, *192*, 116632. https://doi.org/10.1016/j.energy.2019.116632

Yang, X., Wu, J., Sun, H., Gao, Z., Yin, H. & Qu, Y. (2019). Performance improvement of energy consumption, passenger time and robustness in metro systems: A multi-objective timetable optimization approach. *Computers and Industrial Engineering*, *137*(September), 106076. https://doi.org/10.1016/j.cie.2019.106076

Yeh, S., Mishra, G. S., Fulton, L., Kyle, P., McCollum, D. L., Miller, J., Cazzola, P. & Teter, J. (2017). Detailed assessment of global transport-energy models' structures and projections. *Transportation Research Part D: Transport and Environment*, *55*, 294-309. https://doi.org/10.1016/j.trd.2016.11.001

Yue, X., Pye, S., DeCarolis, J., Li, F. G., Rogan, F. & Gallachóir, B. (2018). A review of approaches to uncertainty assessment in energy system optimization models. *Energy Strategy Reviews*, *21*(May), 204-217. https://doi.org/10.1016/j.esr.2018.06.003

Zhang, Z., Jing, R., Lin, J., Wang, X., van Dam, K. H., Wang, M., Meng, C., Xie, S. & Zhao, Y. (2020). Combining agent-based residential demand modeling with design optimization for integrated energy systems planning and operation. *Applied Energy*, *263*(January), 114623. https://doi.org/10.1016/j.apenergy.2020.114623

Zhu, Q., Leibowicz, B. D., Busby, J. W., Shidore, S., Adelman, D. E. & Olmstead, S. M. (2022). Enhancing policy realism in energy system optimization models: Politically feasible decarbonization pathways for the United States. *Energy Policy*, *161*. https://doi.org/10.1016/j.enpol.2021.112754

Zvingilaite, E. (2011). Human health-related externalities in energy system modelling the case of the Danish heat and power sector. *Applied Energy*, *88*(2), 535-544. https://doi.org/10.1016/j.apenergy.2010.08.007

Appendix

Appendix A

Cost Trajectories of Energy Infrastructure

Figures A.1 and A.2 show the cost trajectories for energy infrastructure. The cost trajectories in Figure A.1 are for renewable power generation technologies and in Figure A.2 for electricity distribution technologies, including chargers. The unit costs in the first row present the 2018 values and are the reference for the next two rows, which show the relative values in 2050.

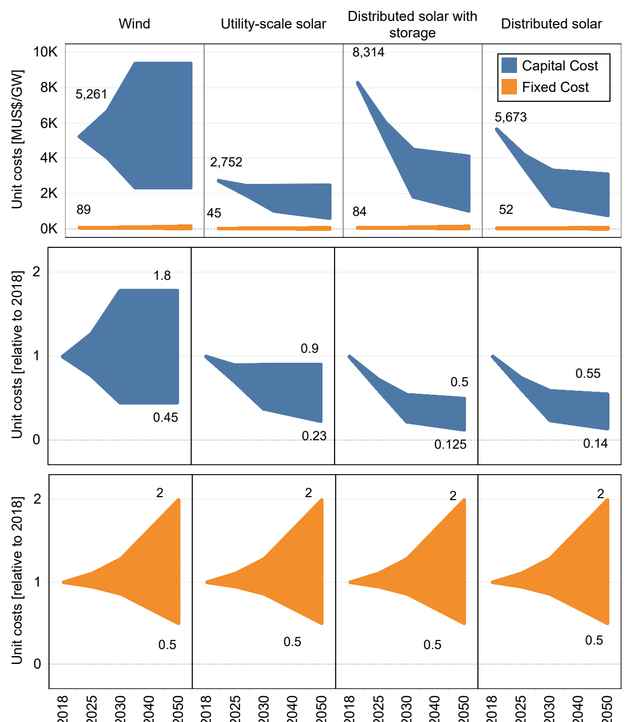

Figure A.1: Cost trajectories of renewable power generation. Taken from Victor-Gallardo, Quirós-Tortós et al. 2022.

From Table 3.6, the interval of minimum and maximum values for renewables, storage, and other infrastructure is [0.5, 2] with a *final year* method. The 2050 values in Figures A.1 and A.2 (rows two and three) are not exactly equal to the interval because of the cost trajectory in the base case; one exception is the cost of transmission and distribution (see Figure A.2, last column), which remains constant in the base case.

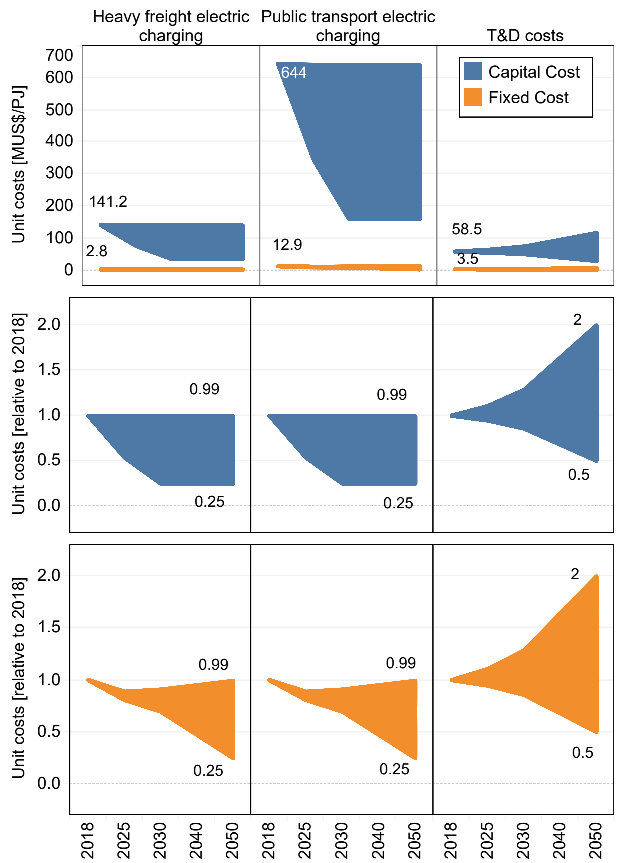

Figure A.2: Cost trajectories of electricity distribution technologies. Taken from Victor-Gallardo, Quirós-Tortós et al. 2022.

Appendix B

Patient Rule Induction Method per Actor

Figures B.1 to B.5 show the hierarchical PRIM application (or relationships) for the financial impacts per actor. Figures B.1, B.2, and B.3 show the relationships for private transport firms, public transport operators, and freight firms, respectively.

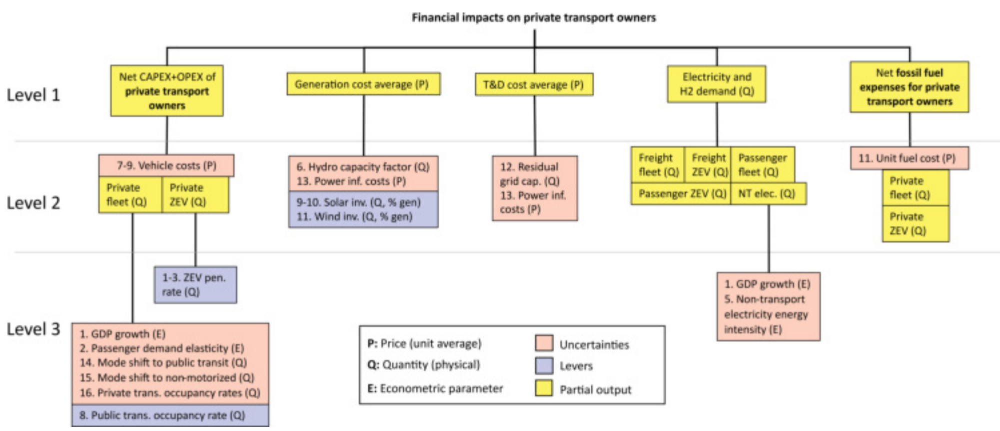

Figure B.1: Hierarchical PRIM application for private transport owners.

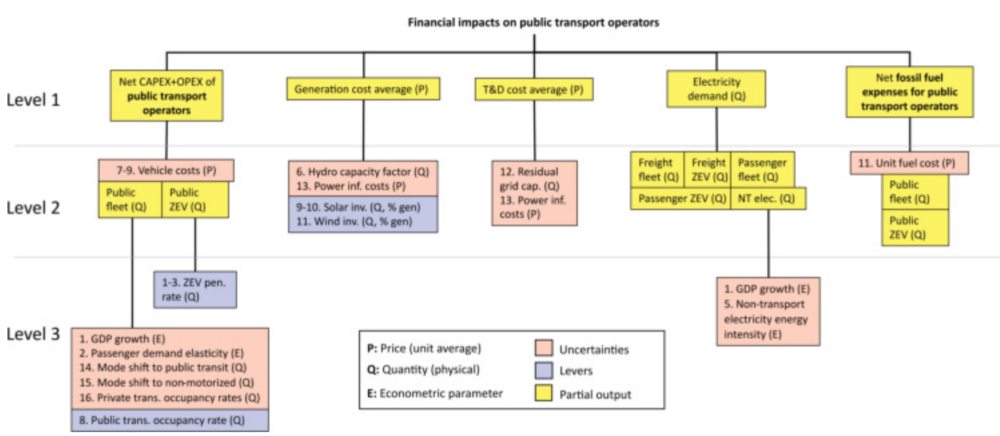

Figure B.2: Hierarchical PRIM application for public transport operators.

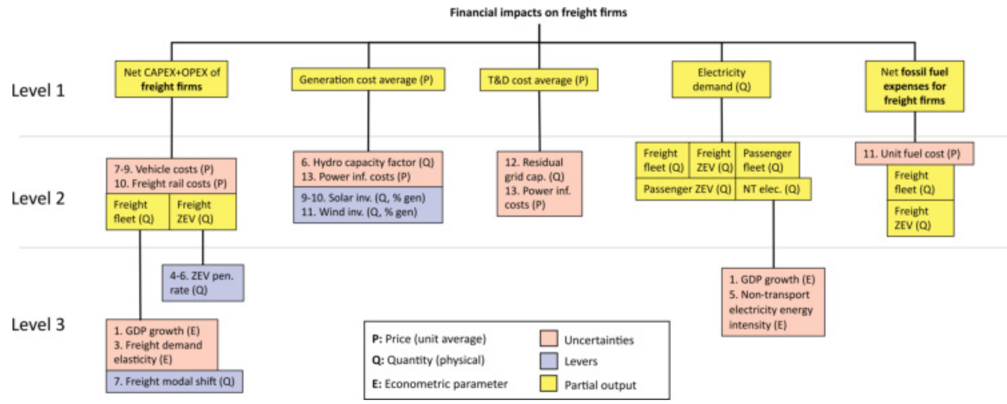

Figure B.3: Hierarchical PRIM application for freight firms.

Each diagram has the costs of specific technology types, whereas the national impacts use broad zero-emission vehicles (ZEV) or internal combustion engine vehicle (ICEV) categories. Figure B.4 shows the relationships for energy firms, which are concerned with their energy sales and average unit cost of supplying energy. Finally, Figure B.5 shows the impact on the government, related the activity data explained under the tax equations and tax adjustment evaluation experiment in Sections 3.2 and 3.3, respectively. These activity data include: fuel consumption, vehicle imports, and vehicle fleet.

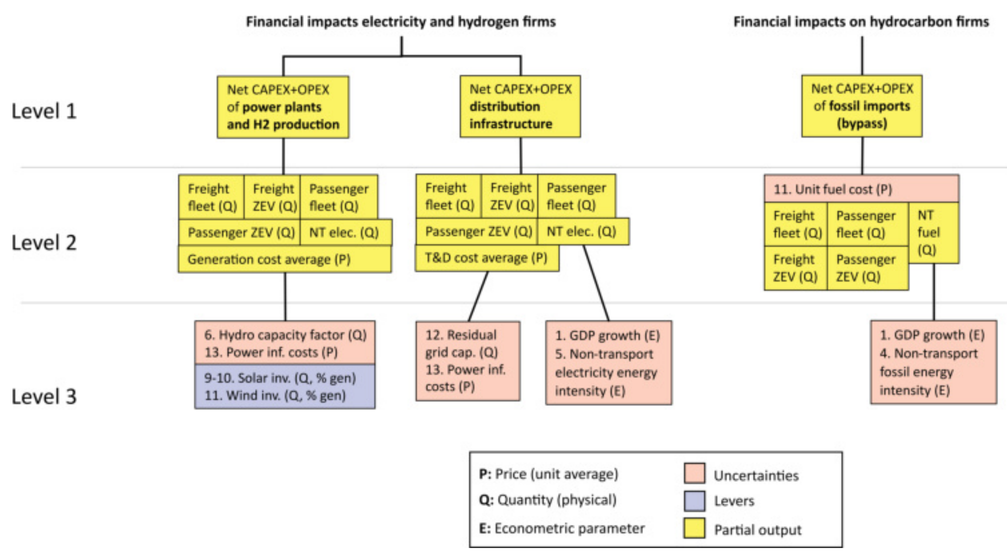

Figure B.4: Hierarchical PRIM application for energy firms.

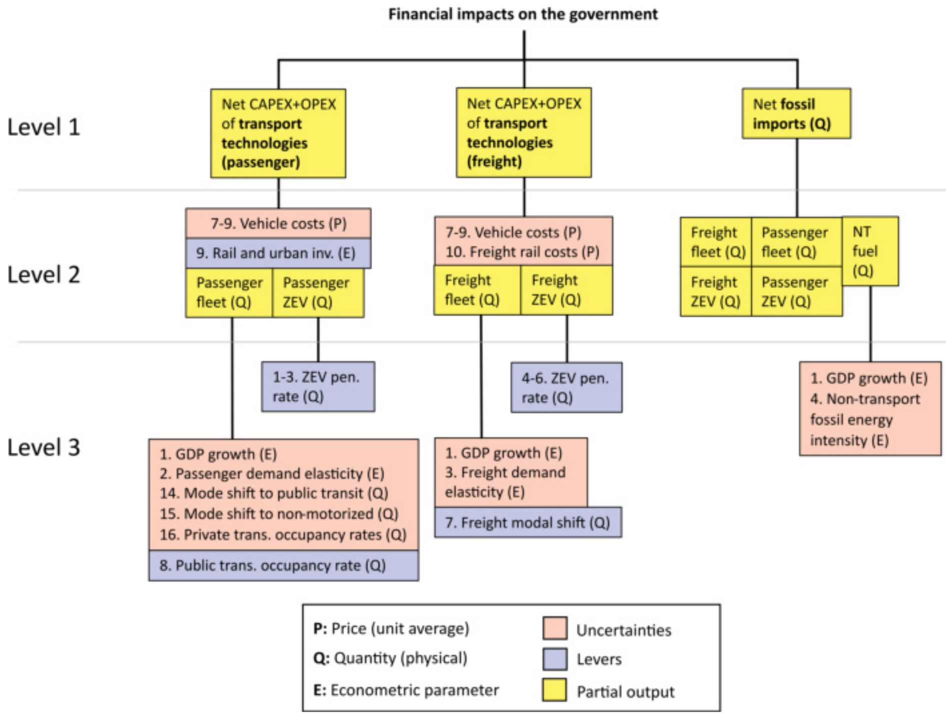

Figure B.5: Hierarchical PRIM application for the government.

Appendix C

Transport Energy Consumption and Fleet

This Appendix presents energy and transport sector physical variables *for the base case*. Figure C.1 shows the evolution of energy consumption for the National Decarbonization Plan (NDP) scenario. Energy consumption is kept more or less constant before 2030 and decreases 42 % relative to 2022 by 2050. This energy consumption drop occurs despite the higher passenger-kilometer and ton-kilometer demands due to higher GDP growth. The change in energy consumption can be rapid: in five years, between 2030 and 2035, transport energy consumption decreases by 14.6 %.

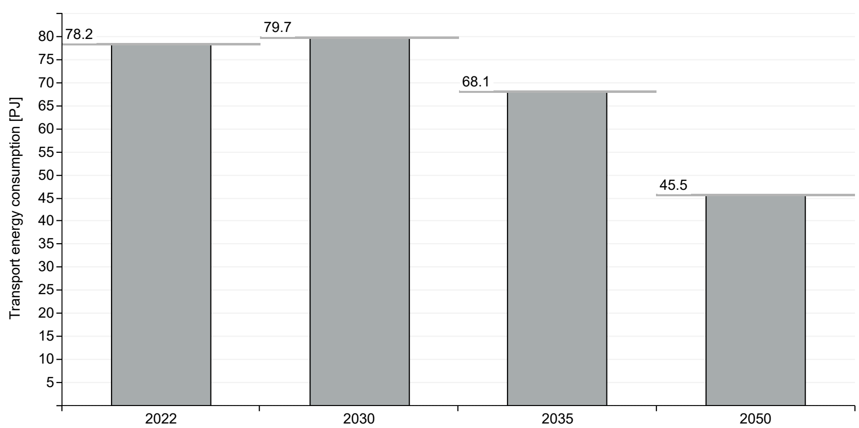

Figure C.1: Transport energy consumption for the NDP scenario. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

Figure C.2 shows the distribution of energy consumption by subsector (i.e., freight, private transport, and public transport) and fuel. Private transport has the highest share of energy consumption in 2022, but it becomes the smallest in 2050. Public passenger transport has the highest growth: from 11 % to 32 %. Freight transport has the highest energy consumption share but increases slightly relative to 2022: only three percentual points. Fossil fuels supply all[1] of energy for transport, but only 5 % in 2050. Liquified Petroleum Gas (LPG) is a transition option in the NDP, reaching 8 % of consumption

[1] In practice, some ZEV vehicles exist in the Costa Rican fleet but still do not appear in the national energy balance statistics. Moreover, OSeMOSYS-CR-v2 does not contemplate ZEVs in the near term.

in 2030. In 2050, electricity and hydrogen supply 92 % of the transport sector's energy consumption.

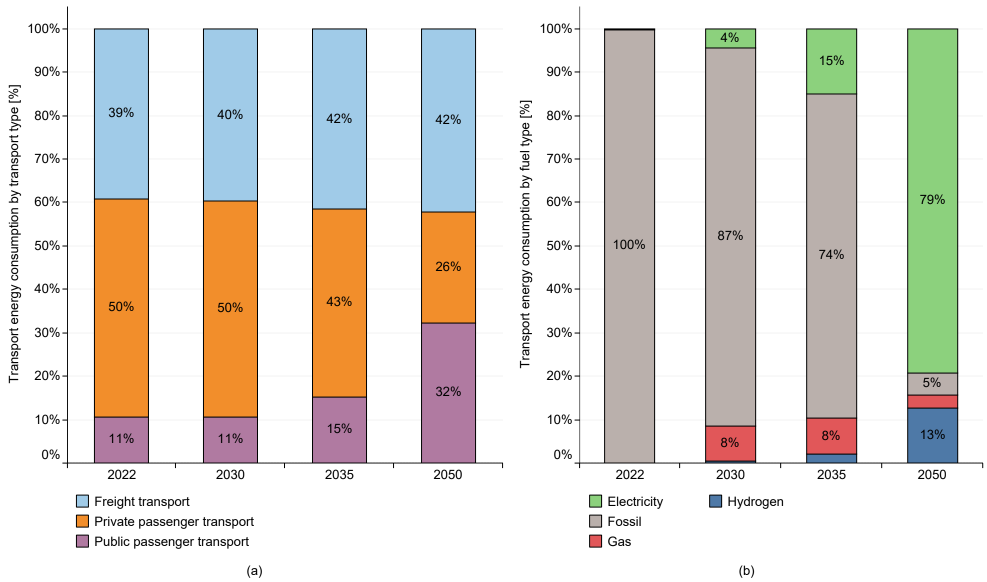

Figure C.2: Distribution of energy consumption in the NDP scenario. (a) By transport type. (b) By fuel type. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

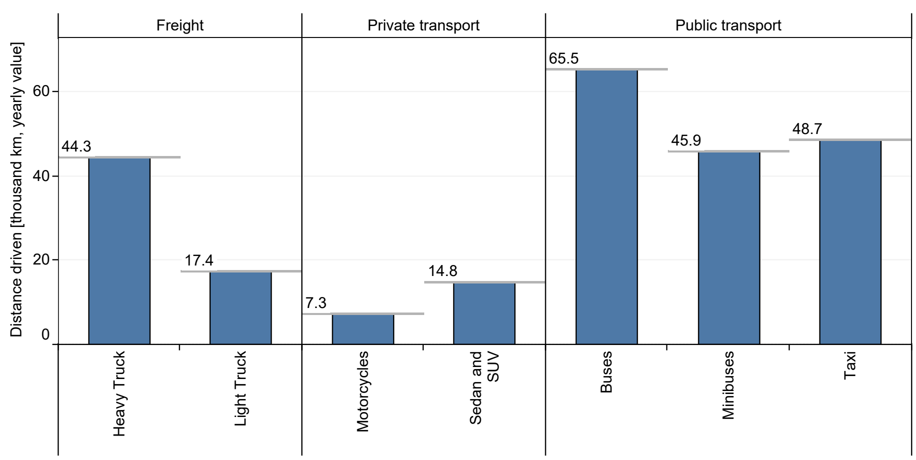

Figure C.3: Distance driven by transport mode. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

Figure C.3 shows the driven distances per vehicle classes in each subsector. Then, Figures C.4 to C.7 show transport metrics for each group of vehicle classes, reuslting in the following characteristics:

- Light-duty vehicles include motorcycles, sedans, SUVs, and taxis; Figure C.4 shows their energy and transport metrics. Figure C.4a shows this category's energy consumption in 2050 becomes about a third of its 2022 value, composed of electricity in 97 % (see Figure C.4b).

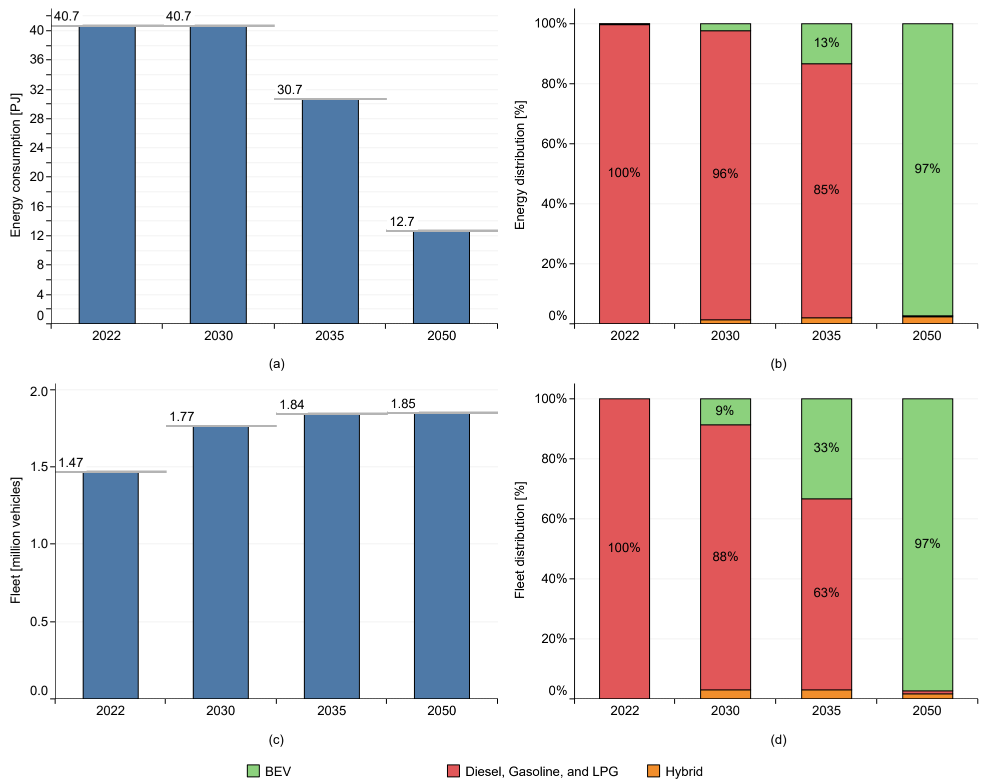

Figure C.4: Light duty transport metrics. (a) Energy consumption. (b) Energy consumption shares. (c) Fleet. (d) Fleet shares. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

The drop in energy demand occurs despite a larger fleet, increasing 25 % in 2035 relative to 2022 (see Figure C.4c). The 2050 fleet is practically the same as in 2035, but with a different composition: only 33 % of vehicles are battery-electric (BEV) in 2035 compared to 97 % in 2050 (see Figure C.4d). Mode shift to public and non-motorized transport can limit the growth of the fleet[2]. The 33 % of BEVs in 2035 only consume 13 % of their respective energy, illustrating the higher efficiency of BEVs relative to internal combustion vehicles based on fossil fuels.

- Light freight (transported with light trucks) metrics, presented in Figure C.5, show a similar transformation as light-duty vehicles. One key difference is the growth of the fleet: it more than doubles by 2050 relative to 2022. Unlike light-duty vehicles, mainly containing private transport classes, no mode shift measures decrease light freight ton-kilometers or limit their growth.

[2]Fleet digitalization can avoid private vehicle demand, which Section 3.1 explains.

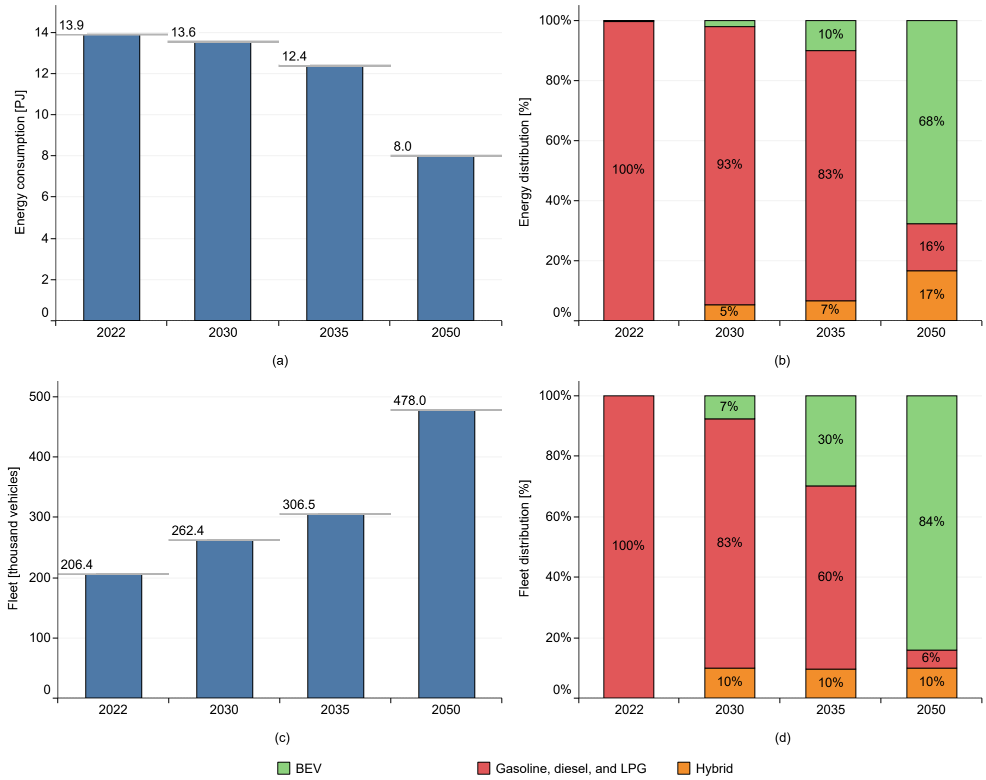

Figure C.5: Light freight transport metrics. (a) Energy consumption. (b) Energy consumption shares. (c) Fleet. (d) Fleet shares. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

- Figure C.6 shows the transport metric for heavy freight driven by heavy trucks. Fuel-cell electric vehicles (FCEV) and BEVs will be present in heavy truck fleets by 2050, assuming that hydrogen vehicles will be available only for heavy freight transport. The National Decarbonization Plan is not explicit about the role of either technology and is open to the adoption of the most suitable for Costa Rica. In the model experimentation developed in this work (see Section 3.3), the shares of the vehicle fleet that are FCEV or BEV can vary.

- Figure C.7 shows the metric for bus and minibus classes, which also have FCEVs in 2050 (i.e., hydrogen vehicles). Although the fleet is lower than heavy trucks, the energy consumption in 2050 is 42 % higher for buses and minibusses than for heavy trucks (compare Figures Figure C.6a and C.7a). The distances from Figure C.3 explain the difference: heavy trucks are driven fewer kilometers than buses or minibusses in a year. Another difference is the change of energy consumption by 2050 relative to 2022: buses and minibusses increase (see Figure C.7a), while heavy trucks decrease (see Figure C.6a) their respective energy consumption.

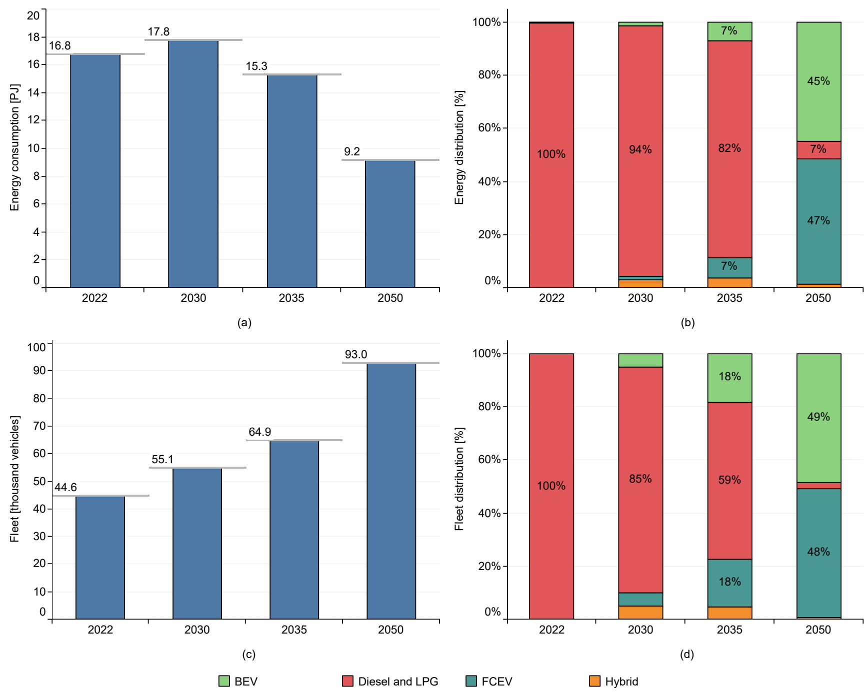

Figure C.6: Heavy freight transport metrics. (a) Energy consumption. (b) Energy consumption shares. (c) Fleet. (d) Fleet shares. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

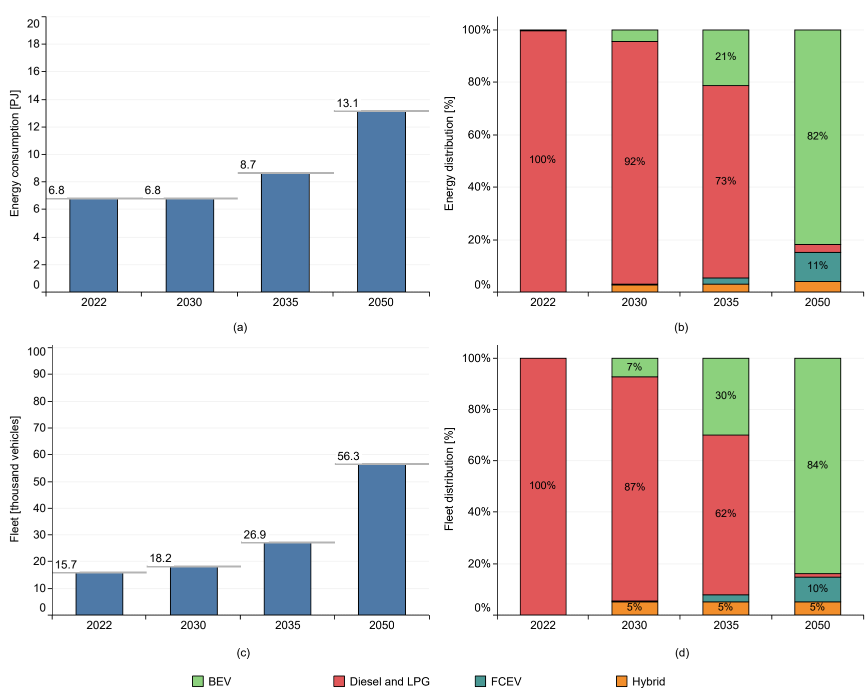

Figure C.7: Bus and minibus metrics (a) Energy consumption. (b) Energy consumption shares. (c) Fleet. (d) Fleet shares. Based on Victor-Gallardo, Rodríguez-Zúñiga, Rodríguez-Arce et al. 2022.

Appendix D

Validation of the Hierarchical PRIM

This Appendix presents a validation process developed by Victor-Gallardo, Quirós-Tortós et al. 2022, which describes how effective the hierarchical PRIM is at finding the robust drivers:

1. Select the futures that simultaneously meet *at least* a given percentage of the drivers, starting from 75 % until 95 % in steps of 5 %, called here sensitivity. Since few futures have 100 % simultaneous drivers, sensitivity across drivers is necessary.

2. Find the intersection between the pathway futures PF and the metric space MS for every sensitivity and outcome of interest. The pathway futures set comprises the futures collected in step 1. The metric space is the set comprised of the futures complying with a given outcome; this is the focus space in Figure D.1. The opposite metric space $\widehat{MS}$ has the futures that have the opposite results, e.g., for desirable benefits, $\widehat{MS}$ has bottom 25 % of benefits

3. For every sensitivity and outcome of interest, compute coverage and density.

4. Compute the opposite coverages and densities by replacing MS with $\widehat{MS}$.

Figure D.1 shows that the pathways predict the outcome of interest (a), and they also do not predict the opposite outcome (b). Figure D.1a shows that high coverages occur with lower sensitivities, i.e., the fewer concurrent parameters, the more likely it is to find a future within the pathways that meet the criteria of desirable and risk outcomes, per metric, for either period. However, it is also possible that the future does not meet the criteria to be desirable or risk, but is within the pathway drivers. The higher the sensitivity (i.e., more selective futures with concurrent pathway conditions), the lower the coverage and the higher the density. The selected futures are more likely to have desirable or risk outcomes only but cover fewer futures that belong to those metrics of interest. Figure D.1a shows that coverages and densities are generally high, with high sensitivities favoring high density and low sensitivities favoring high coverage. On the flip side, Figure D.1b confirms that the pathways do not predict the opposite outcome since coverages and densities are very low. Only bus prices have slightly high coverage in Figure D.1b, but not as high as Figure D.1a.

Outcome Type / Period

		Desirable				Risk			
		22-30		31-50		22-30		31-50	
Metrics	Sensitivity	Coverage	Density	Coverage	Density	Coverage	Density	Coverage	Density
Benefit	75%	90	36	89	68	89	33	93	44
	90%	40	81	40	92	48	68	34	93
Electricity price	75%	79	71	74	95	86	37	92	85
	90%	55	80	51	100	31	45	62	96
Bus price	75%	87	28	91	33	84	33	86	30
	90%	58	40	61	58	62	42	46	45
CAPEX	75%	95	56	97	52	91	55	88	61
	90%	46	91	50	92	48	89	45	93
Emissions	75%	74	64	89	46	95	46	75	90
	90%	43	77	68	84	58	76	54	96
All	75%	100	0	100	2	100	1	100	7
	90%	50	1	67	13	67	2	62	25

Focus space

(a)

Benefit	75%	37	15	0	0	45	17	11	5
	90%	0	0	0	0	1	2	0	0
Electricity price	75%	0	0	0	0	29	12	0	0
	90%	0	0	0	0	1	1	0	0
Bus price	75%	62	20	48	17	44	17	64	22
	90%	16	11	3	3	16	11	5	5
CAPEX	75%	0	0	5	3	2	1	1	1
	90%	0	0	0	0	0	0	0	0
Emissions	75%	0	0	13	7	11	5	0	0
	90%	0	0	0	0	0	0	0	0
All	75%	0	0	0	0	0	0	0	0
	90%	0	0	0	0	0	0	0	0

Opposite space

Coverage and density scale

0 Low Mid-Low Mid Mid-High High 100

(b)

Figure D.1: Validation of the hierarchical PRIM analysis for national metrics. Taken from Victor-Gallardo, Quirós-Tortós et al. 2022

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Appendix E

Wide Experiment Values

This Appendix presents the values of the variables in the *wide experiment* (see Section 3.3) for the nationwide robust pathway identification analysis presented in Section 4.5. Figure E.1 and Figure E.2 show the values for the 2022-2030 and 2031-2050 periods, respectively. The columns are the percentiles of the variables (in the rows) across futures. The percentiles can be compared against the normalized results presented from Figure 4.28 to 4.32 because the distribution of the experiment is uniform.

			Min value	P15	P25	P40	Median	P60	P75	P85	Max value	
Metrics	Metrics	Benefit	-1.41	-1.04	-0.96	-0.87	-0.82	-0.76	-0.68	-0.60	-0.23	% of GDP
		Electricity price	12.58	13.48	13.71	13.95	14.12	14.28	14.53	14.70	15.33	¢/kWh
		Bus price	6.34	6.95	7.05	7.18	7.27	7.35	7.48	7.60	8.23	¢/km/passenger
		Emissions	5.88	6.53	6.69	6.86	6.97	7.09	7.27	7.43	8.15	MTon
		CAPEX	3.60	4.15	4.26	4.41	4.50	4.60	4.76	4.90	5.57	% of GDP
Intermediary	General	Passenger transport fleet	1,425.72	1,640.58	1,674.66	1,715.73	1,740.20	1,769.28	1,815.08	1,856.93	2,003.11	thousand vehicles
		Freight fleet	292.16	303.51	308.46	316.53	322.40	327.81	336.01	341.64	357.50	thousand vehicles
		Passenger transport % of ZEV	0.04	0.33	0.47	0.69	0.84	1.02	1.33	1.67	4.45	% of GDP
		Heavy and light freight % of ZEV	0.03	0.34	0.49	0.68	0.84	1.01	1.37	1.73	5.38	% of GDP
		Non transport electrical demand	42.91	45.97	46.72	47.92	48.73	49.65	50.85	51.71	54.14	PJ
		Non transport fossil fuel demand	15.79	17.59	18.13	18.84	19.27	19.68	20.41	21.15	23.17	PJ
Levers	Regulations	Private Transport % of BEV	0.15	0.61	0.92	1.50	1.97	2.56	3.70	4.82	10.69	%
		Public Transport % of BEV	0.00	0.23	0.50	1.25	2.02	3.10	5.62	8.40	25.86	%
		Public Transport % of FCEV	0.00	0.00	0.00	0.00	0.26	0.39	0.64	0.95	4.86	%
		Light Freight % of BEV	0.15	0.66	1.00	1.66	2.25	2.96	4.45	6.03	17.21	%
		Heavy Freight % of BEV	0.00	0.13	0.29	0.68	1.05	1.55	2.76	4.10	16.26	%
		Heavy Freight % of FCEV	0.00	0.14	0.31	0.76	1.21	1.82	3.24	5.01	15.50	%
	Operations	Freight mode shift	0.00	1.16	1.94	3.10	3.88	4.65	5.82	6.59	7.76	%
		Occupancy rates of public vehicles	14.30	14.61	14.81	15.12	15.32	15.53	15.83	16.04	16.34	passengers/trip
	Investments (transport)	Passenger rail and urban interventions	0.41	0.47	0.52	0.58	0.62	0.66	0.72	0.76	0.84	% of GDP
	Investments (energy supply)	Distributed solar electricity production	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	%
		Utility-scale solar electricity production	1.87	2.38	2.45	2.55	2.61	2.68	2.84	3.04	4.54	%
		Wind electricity production	14.20	21.25	22.71	24.58	25.83	27.08	28.87	30.27	35.26	%
Uncertainty	Economic	GDP direct	2.00	2.38	2.63	3.00	3.25	3.50	3.87	4.12	4.50	% of growth
		Passenger demand elasticity	0.82	0.86	0.88	0.91	0.94	0.96	0.99	1.02	1.05	Δ%Gpkm/Δ%GDP
		Freight demand elasticity	0.90	0.93	0.96	0.99	1.01	1.04	1.07	1.09	1.13	Δ%Gtkm/Δ%GDP
		Non transport electrical intensity	524.65	577.56	580.60	584.95	587.73	590.50	594.25	597.37	608.33	kJ/USD
		Non transport fossil fuel intensity	204.04	213.92	219.35	227.26	232.49	237.91	246.18	251.12	261.48	kJ/USD
	Technological (transport)	Capital costs of BEVs	60.77	67.24	71.55	78.00	82.30	86.62	93.09	97.40	103.86	rel. 2018
		Capital costs of FCEVs	81.09	82.80	83.95	85.67	86.81	87.96	89.67	90.81	92.53	rel. 2018
		Capital costs of ICEVs	92.86	95.01	96.43	98.58	99.99	101.42	103.57	104.99	107.14	rel. 2018
		Unit freight rail costs	20.06	23.06	25.07	28.08	30.08	32.09	35.10	37.11	40.12	MUS$/Gtkm
	Technological (energy supply)	Cost of energy infrastructure	44.77	64.87	78.28	98.38	111.77	125.21	145.33	158.76	178.87	rel. 2018
		Residual capacity infrastructure	85.72	87.86	89.29	91.43	92.86	94.29	96.43	97.86	100.00	rel. 2018
		Unit cost of fossil fuels	80.42	86.53	90.60	96.69	100.74	104.82	110.92	114.98	121.09	rel. 2018
	Social	Mode shift to public transport	24.41	24.48	24.58	24.82	25.02	25.35	26.05	26.85	32.01	%
		Non-motorized and digitalization	0.00	0.04	0.10	0.23	0.36	0.55	1.04	1.57	4.50	%
		Occupancy rates of private vehicles	15.00	15.32	15.54	15.86	16.07	16.29	16.61	16.82	17.14	passengers/10 trips
	Climate	Capacity factor of hydropower	47.29	48.03	48.52	49.25	49.74	50.22	50.96	51.45	55.56	%

Figure E.1: Wide experiment values for the 2022-2030 period. Based on Victor-Gallardo, Quirós-Tortós et al. 2022. The last column shows the units, including values relative to 2018 (rel. 2018).

The variables are divided in metrics and drivers (intermediary, levers, and uncertainties). The levers and uncertainties are in the Figures discussed in Section 4.5, while the intermediary drivers are part of the hierarchical Patient Rule Induction Method (PRIM) application explained in Section 3.4. Importantly, the variables with percent of GDP units are period yearly averages, whereas the rest have values indicated for the end of the period.

			Min value	P15	P25	P40	Median	P60	P75	P85	Max value	
Metrics	Metrics	Benefit	-2.28	0.15	0.59	1.08	1.41	1.72	2.21	2.67	4.91	% of GDP
		Electricity price	7.45	9.92	10.91	12.33	13.21	14.21	15.57	16.48	19.29	¢/kWh
		Bus price	2.35	3.76	4.03	4.37	4.58	4.81	5.20	5.58	8.10	¢/km/passenger
		Emissions	0.35	1.31	1.57	1.97	2.19	2.45	2.89	3.31	5.24	MTon
		CAPEX	2.51	3.74	4.05	4.45	4.70	5.00	5.45	5.82	8.26	% of GDP
Intermediary	General	Passenger transport fleet	1,126.17	1,719.06	1,873.93	2,091.56	2,262.95	2,448.56	2,768.72	3,055.34	5,452.04	thousand vehicles
		Freight fleet	376.06	471.95	504.58	552.64	592.71	633.03	705.24	778.02	1,082.63	thousand vehicles
		Passenger transport % of ZEV	54.67	77.27	80.15	83.66	85.80	87.80	90.82	93.33	99.04	% of GDP
		Heavy and light freight % of ZEV	27.00	51.00	55.54	61.22	65.03	68.72	75.09	79.82	99.29	% of GDP
		Non transport electrical demand	52.70	74.63	79.42	87.44	93.50	100.24	109.98	117.59	141.30	PJ
		Non transport fossil fuel demand	3.28	9.43	12.92	18.32	21.84	25.43	31.06	35.87	53.75	PJ
Levers	Regulations	Private Transport % of BEV	89.51	92.33	93.34	94.68	95.51	96.43	97.83	98.73	99.93	%
		Public Transport % of BEV	50.02	56.13	59.73	65.08	68.48	72.03	77.08	80.32	89.43	%
		Public Transport % of FCEV	9.85	12.98	14.84	17.18	18.65	20.43	23.44	25.66	30.47	%
		Light Freight % of BEV	70.66	75.14	78.17	82.69	85.69	88.71	93.10	95.87	100.00	%
		Heavy Freight % of BEV	29.92	34.74	37.77	42.26	45.21	48.19	52.57	55.53	60.55	%
		Heavy Freight % of FCEV	29.88	33.15	35.17	38.13	40.14	41.67	44.31	46.33	50.41	%
	Operations	Freight mode shift	0.00	3.74	6.25	10.00	12.50	15.00	18.75	21.24	25.00	%
		Occupancy rates of public vehicles	14.30	15.37	16.09	17.16	17.87	18.59	19.66	20.38	21.45	passengers/trip
	Investments (transport)	Passenger rail and urban interventions	0.03	0.04	0.04	0.05	0.05	0.06	0.06	0.07	0.08	% of GDP
	Investments (energy supply)	Distributed solar electricity production	0.53	0.77	0.93	1.06	1.18	3.43	8.06	11.30	25.73	%
		Utility-scale solar electricity production	4.19	6.98	7.96	9.71	10.74	11.59	13.03	14.18	20.59	%
		Wind electricity production	39.85	48.65	50.97	53.72	55.37	57.09	59.87	62.84	77.56	%
Uncertainty	Economic	GDP direct	2.00	2.38	2.63	3.00	3.25	3.50	3.87	4.12	4.50	% of growth
		Passenger demand elasticity	0.50	0.65	0.75	0.90	1.00	1.10	1.25	1.35	1.50	Δ%Gpkm/Δ%GDP
		Freight demand elasticity	0.50	0.65	0.75	0.90	1.00	1.10	1.25	1.35	1.50	Δ%Gtkm/Δ%GDP
		Non transport electrical intensity	356.77	554.59	566.27	584.62	596.43	608.00	625.73	637.92	663.26	kJ/USD
		Non transport fossil fuel intensity	25.88	60.79	84.61	119.42	142.52	165.26	200.54	223.61	260.45	kJ/USD
	Technological (transport)	Capital costs of BEVs	39.82	51.75	59.71	71.62	79.55	87.51	99.46	107.40	119.32	rel. 2018
		Capital costs of FCEVs	40.07	46.08	50.09	56.11	60.12	64.12	70.13	74.13	80.13	rel. 2018
		Capital costs of ICEVs	75.06	82.58	87.58	95.09	100.05	105.05	112.56	117.56	125.07	rel. 2018
		Unit freight rail costs	20.06	23.06	25.07	28.08	30.08	32.09	35.10	37.11	40.12	MUS$/Gtkm
	Technological (energy supply)	Cost of energy infrastructure	44.77	64.87	78.28	98.38	111.77	125.21	145.33	158.76	178.87	rel. 2018
		Residual capacity infrastructure	50.01	57.52	62.52	70.01	75.02	80.02	87.52	92.50	100.00	rel. 2018
		Unit cost of fossil fuels	71.26	92.63	106.88	128.22	142.42	156.65	178.00	192.22	213.62	rel. 2018
	Social	Mode shift to public transport	24.42	28.17	30.67	34.41	36.91	39.40	43.15	45.64	49.38	%
		Non-motorized and digitalization	0.01	1.88	3.13	5.00	6.25	7.50	9.37	10.61	12.49	%
		Occupancy rates of private vehicles	15.00	16.13	16.87	18.00	18.75	19.50	20.62	21.38	22.50	passengers/10 trips
	Climate	Capacity factor of hydropower	39.91	42.47	44.18	46.74	48.46	50.16	52.73	54.44	57.00	%

Figure E.2: Wide experiment values for the 2031-2050 period. Based on Victor-Gallardo, Quirós-Tortós et al. 2022. The last column shows the units, including values relative to 2018 (rel. 2018).