Income Inequality and Climate Change

A Theory-Based System Dynamics Analysis for Canada

by Laila Youssifou

TU Delft

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to obtain the degree of Master of Science

at the Delft University of Technology,

to be defended in public on Tuesday June 10th, 2025

Student number: 4312309

Master Engineering and Policy Analysis

Faculty of Technology, Policy and Management

Delft University of Technology

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<u>And with special thanks to</u>

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Executive Summary

Climate change and income inequality are intertwined global challenges. Between 1990 and 2015, the wealthiest 10% of the global population were responsible for approximately half of all greenhouse gas emissions, with the top 1% alone accounting for 15%. Both climate change and income inequality have worsened in recent years, highlighting the urgent need for coordinated action. Rising inequality is associated with adverse social outcomes, including worsening public health and social cohesion, while climate change continues to impose long-lasting and irreversible effects on both ecosystems and human well-being.

This thesis explores the relationship between income inequality and carbon emissions, focusing on how changes in income distribution influence consumption patterns, and subsequently affect GDP and emissions over time. A theory-based System Dynamics (SD) modelling approach is used to examine these macroeconomic and environmental dynamics in the Canadian context.

This research addresses the following research question (RQ):

RQ: What are the underlying mechanisms linking income inequality and carbon emissions from consumption, and how do they influence economic growth and carbon emissions over time?

To answer this question, the study is structured around two sub-questions (SQ):

SQ1: What does the extant literature say about the relationship between income inequality and carbon emissions from consumption?

SQ2: How does income inequality influence economic behaviour and carbon emissions from consumption within the LowGrow SFC model of the Canadian economy?

To address SQ1, a literature review was conducted. This literature review reveals a fragmented academic landscape in which empirical findings contradict each other. While some studies argue that income inequality increases emissions due to the carbon-intensive lifestyles of the wealthy, others argue that income inequality lowers overall consumption and emissions by constraining demand among low-income groups. Many of these studies rely on highly aggregated, cross-country data, often overlooking heterogeneity across nations. From the literature, three uncertainties are identified:

1) The effect of income inequality on GDP
2) The effect of Marginal Propensity to Consume (MPC)
3) The effect of Marginal Propensity to Emit (MPE) and Carbon Intensity of Consumption (CIC)

Because many studies fail to capture the underlying dynamics between income inequality and carbon emissions, and since a country-specific context is expected to yield more meaningful results, this study applies a System Dynamics modelling approach applied to the Canadian economy.

This research builds on the LowGrow SFC model as developed by Jackson and Victor (2019), which simulates the Canadian economy from 2012 to 2073 exploring multiple post-growth scenarios. By evaluating the original LowGrow SFC model, it becomes clear that income inequality is only superficially modelled, resulting in the addition of a sub-model that incorporates income inequality as an input variable.

A conceptual model, grounded in the literature, was constructed and translated into a sub-model. This sub-model disaggregates household consumption by income group, assigning different shares of disposable income and distinct MPCs to each group. Data from Statistics Canada was used and interpolated to fit the model's 13 income groups.

The extended LowGrow SFC model combines the original LowGrow SFC model with the newly developed sub-model. To assess if the extended model is fit for purpose, four validation steps are applied: face validation with economic experts (including one of the model's developers), a behavioural comparison between the output of the original LowGrow SFC model and that of the sub-model, extreme condition tests, and both univariate and multivariate sensitivity analyses. These validation steps confirm that the extended model is fit for purpose.

Next, four scenarios are simulated, reflecting two levels of income inequality (equal and. unequal) and two MPC levels for lower-income groups (high and low). The performance of each scenario is evaluated using three indicators: total consumption, GDP, and the Environmental Burden Index (EBI).

The results show that more equal income distributions lead to higher total consumption due to increased aggregate demand. However, counterintuitively, these same scenarios produce lower GDP and EBI values. This occurs because rising consumption leads to a decline in both government spending and business investment, ultimately reducing GDP. Because EBI is closely linked to GDP in the model, it follows a similar trajectory.

These findings yield three important insights: (1) income inequality strongly influences consumption, (2) increased consumption does not necessarily lead to economic growth, and (3) increased consumption does not automatically lead to increased environmental pressure. Taken together, these results challenge the *equity-pollution dilemma* and suggest that improving income equality may be compatible with achieving climate goals. This insight offers a hopeful and compelling argument for integrating social equity with environmental sustainability in future policy design.

The discussion critically evaluates the modelling approach, highlighting limitations such as the exclusive focus on consumption-based emissions and the difficulty of generalising the findings. The reflection broadens this evaluation by examining the choice of inequality measures and exploring how system dynamics and econometric approaches can complement each other in macroeconomic modelling.

Future research is encouraged to extend the model's scope by integrating the Marginal Propensity to Emit or the Carbon Intensity of Consumption, and by accounting for emissions from investments and production across income groups. Additionally, incorporating alternative inequality measures beyond the Gini coefficient could provide an improved insight in income inequality. Policy recommendations include adopting broader indicators of progress beyond GDP to capture human well-being, shifting climate policy focus from individuals to industries, and fostering international cooperation on climate action.

Acknowledgements

First and foremost, I would like to thank Professors Peter Victor and Tim Jackson for generously sharing the LowGrow SFC model with me. It’s an impressive and sophisticated piece of work and, I'll admit, a bit intimidating to work with at first. It’s clear that a tremendous amount of time, dedication, and expertise has gone into its development. The fact that you were willing to share such a valuable academic model with a student you'd never met says a lot about your openness and willingness to share your knowledge. I’m also very grateful to Professor Victor for the thoughtful and honest feedback throughout the process. Our conversations were not only insightful but also motivating, and I truly appreciated your willingness to take the time to discuss the model in depth.

I would also like to thank Andrew Reeves, who was my go-to person for any questions related to the model. Over time, I ended up asking not only modelling questions, but also general economics questions and even software-related issues and you always made time to help. I’m incredibly thankful for your help, even from across the ocean.

To my supervisors: Servaas and Floortje, thank you both for being so supportive from the start. Your understanding of my background in sports was such a relief since not every professor has been supportive with this during my studies. Where Servaas would even compliment me on a rowing result after an exam, Floortje followed my tournament in Paris, which was very special to me. Servaas, your commitment and enthusiasm for the topic were evident from the beginning and your sincere interest in students is evident. Floortje, you have the ability to read people very well and with that, you always seemed to know exactly what I needed. Your structured guidance helped me a lot in finish this thesis.

Mama, thank you for your endless love and for always being there to listen. You're constantly reminding me to take breaks and to be satisfied with the things I’ve achieved and, even if I don’t always listen, that’s very valuable to me. Faraaz, thank you for sharing your own graduation journey with me and for being the kind of brother who can make me laugh no matter what. I can’t wait for the adventure that lies ahead of us! And Francesco, thank you for walking this path with me, for celebrating every small and big victory, for keeping me grounded, and for reminding me that graduation is a marathon, not a sprint. Golden chicken just crossed the finish line.

Daan and Maaike, thank you for being the best fellow students I could have hoped for. Maaike, your sense of perspective, perfectionism, and diplomacy (every bad cop needs a good one) motivated me to be a better student. Daan, your openness, sincerity, and dad-jokes at a questionable age brought humour and honesty to the journey. I'm proud of how far we’ve come: from wanting to make money to wanting to make a difference. I can only dream of future colleagues who’ll bring as much joy in working hard as you two have.

Laila Youssifou
Amsterdam, June 2025

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List of Abbreviations

2SLS	Two-stage Least Squares [regression]
ADF	Augmented Dickey-Fuller [test]
BRICS	Brazil, Russia, India, China, and South Africa
DCCE	Dynamic Common Correlated Effects [estimate]
(D)OLS	(Dynamic) Ordinary Least Squares [estimate]
EBI	Environmental Burden Index
ECM	Error Correction Model
FE	Fixed Effect [regression]
FMOLS	Fully Modified Ordinary Least Squares [estimate]
G7	Group of 7 countries: Canada, Germany, France, Italy, Japan, United Kingdom, and the United States of America
G20	Group of 19 countries and two regional bodies: Argentina, Austria, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Republic of Korea, Mexico, Russia, Saudia Arabia, South Africa, Turkey, United Kingdom, United States, the European Union, and the African Union
GLS	Generalized Least Squares [estimate]
GMM	Generalised Method of Moments [estimate]
HHNW	Household Net Worth
KPI	Key Performance Indicator
KPSS	Kwiatkowski Philips Schmidt Shin [test]
LAE	Least Absolute Errors [regression]
LLDVE	Local Linear Dummy Variable Estimation
MPC	Marginal Propensity to Consume
MPE	Marginal Propensity to Emit
(N)ARDL	(Non-Linear) Autoregressive Distributive Lag [model]
N-P test	Non-Parametric test
OECD	Organisation for Economic Co-operation and Development
PMG	Pooled Mean-Group [estimate]
POLS	Pooled Ordinary Least Squares [estimate]
PP	Philips-Perron [test]
SD	System Dynamics
SFC	Stock-flow consistent
SPI	Sustainable Prosperity Index
STIRPAT	Stochastic Impacts by Regression Population, Affluence and Technology [model]
Yd	Disposable Income

Chapter 1. Introduction

Climate change and economic inequalities represent two of the most pressing challenges of our era, and they are closely connected: the wealthiest 10% of the global population contributed around 50% of the greenhouse gas emissions released into the atmosphere between 1990 and 2015, while the top 1% alone accounted for 15% of total emissions during this period (Akenji et al., 2021). The United Nations has integrated both inequality and climate change into the Sustainable Development Goals (SDGs), recognizing them as urgent global challenges that demand coordinated international action (United Nations, 2023). Addressing inequality is essential for fostering inclusive societies. Widening disparities call for effective policies that empower individuals with lower incomes and promote their economic inclusion. At the same time, climate change continues to exert long-lasting and irreversible effects on the global climate system. Climate-related disasters not only incur economic losses but also lead to profound human suffering, as the majority of geo-physical disasters are climate-related (United Nations, 2023).

In recent years, both income inequality and climate change have worsened. Over the past two decades, regional income disparities have widened in more than half of the 27 OECD countries (Tsvetkova et al., 2020). Chrisendo et al. (2024) further highlight that while gross national income has risen for most individuals globally, income inequality has increased for approximately 68% of the global population between 1990 and 2021. Rising inequality poses significant societal challenges, as it causes health and social damages (Pickett & Wilkinson, 2015; Wilkinson & Pickett, 2010). Moreover, inequality can hinder economic growth, obstruct poverty reduction efforts, and increase societal vulnerability (Hübler, 2017; Ostry, 2014; Persson & Tabellini, 1994). Additionally, economic disparities have been shown to impede the implementation of climate policies by intensifying political polarization, making it more difficult to reach consensus on environmental initiatives (Chancel, 2020; United Nations Development Programme, 2019).

At the same time, the urgency of implementing climate policies continues to grow due to the increasing pressures of climate change on global populations (European Commission, 2024). The consequences of climate change – such as increased exposure to heatwaves, storms, floods, and droughts – pose risks to communities worldwide. To mitigate climate change, the Paris Agreement was signed by 175 countries at COP21 in 2015, emphasizing the need to limit global warming to below 1.5°C to significantly reduce climate-related risks and impacts (United Nations, 2015). However, if current emission trends persist, the remaining carbon budget – the amount of CO_2 that can be emitted without surpassing the 1.5°C threshold – will be exhausted within approximately four years (Oxfam Novib, 2024). Without interference, further accelerations of global warming, loss of capacity to grow crops, and multi-meter sea level rise could arise (Trust et al., 2025). Furthermore, beyond the impact of inequality on climate change, research has shown that climate change itself exacerbates income inequality within countries (Cevik & Jalles, 2023).

Despite a shared recognition that both inequality and climate change must be addressed, there is no academic consensus on the relationship between these two phenomena. Differences in study contexts – including the (number of) countries analysed, time frames considered, pollutants examined, econometric methods applied, and inequality measures used – have led to varying conclusions. As a result, despite extensive research, the causal and indirect relationships between income inequality and carbon emissions remain unclear, and a comprehensive understanding of their interactions is still lacking.

This lack of consensus in scientific findings presents a challenge for policymakers. The uncertainty surrounding this issue increases the risk of implementing ineffective or even counterproductive policies. Developing effective policies requires a thorough understanding of the direct and indirect interactions between climate change and inequality. To address this issue, this study poses the following research question (RQ):

RQ: What are the underlying mechanisms linking income inequality and carbon emissions from consumption, and how do they influence economic growth and carbon emissions over time?

To answer this question, this study employs a theory-based System Dynamics (SD) approach. Unlike the econometric methods frequently used in this field, SD is a methodology used to enhance the understanding of the structure and plausible behaviour of complex systems (Auping et al., 2024; Meadows, 2008; Sterman, 2000). SD allows for the design, implementation and evaluation of policies by incorporating feedback mechanisms, accumulations, and time delays (Auping et al., 2024; Forrester, 1994; Sterman, 2000). An example of such a feedback loop is inequality, which both is a driver and a consequence of environmental degradation (Chancel, 2020). Additionally, applying SD to macroeconomic issues provides insights not only into conventional economic aggregates such as GDP but also into the underlying financial flows and balance sheets, allowing for exploration of uncertainties (Jackson et al., 2016).

The remainder of this report is structured as follows. Chapter 2 refines the overarching research question into two sub-questions and outlines the methodological approach adopted to address them. Chapter 3 answers the first sub-question through a literature review on the relationship between income inequality, economic growth, and carbon emissions, highlighting conflicting hypotheses in the academic discourse. These contradictions reveal a knowledge gap that is addressed using the LowGrow SFC model, a macroeconomic system dynamics model developed by Jackson and Victor (2019), which is introduced in Chapter 4. This stock-flow consistent model simulates the Canadian economy from 2012 to 2073 under various policy scenarios. Chapter 5 details the development of a sub-model that extends the original LowGrow SFC model by incorporating income distribution, involving steps such as conceptualisation, formulation, and validation. This sub-model enables the investigation of the second sub-question. Chapter 6 presents the research findings and addresses the main research question by comparing the performance of the extended model across four different scenarios. Chapter 7 provides a discussion and reflection on the research process, addressing its limitations regarding assumptions, data, and the applied methodology. Finally, Chapter 8 synthesizes the main findings, presents the overall conclusions of the study, and offers recommendations for both future research and policymakers.

Chapter 2. Research Approach

In this chapter, the research question is sub-divided into two sub-questions. Afterwards, the research approach is outlined, linking each sub-question to an appropriate research method.

The overarching research question (RQ) of this study is:

RQ: What are the underlying mechanisms linking income inequality and carbon emissions from consumption, and how do they influence economic growth and carbon emissions over time?

This thesis focuses on carbon emissions from consumption, because income inequality affects the pattern and level of consumption, which, in turn, determine carbon emissions, directly – through the act of consuming – and indirectly – since the production of the goods and services that are consumed, requires energy, resources and transportation.

To address the main research question, the thesis answers two sub-questions (SQs):

SQ1: What does the extant literature say about the relationship between income inequality and carbon emissions from consumption?

SQ2: How does income inequality influence economic behaviour and carbon emissions from consumption within the LowGrow SFC model of the Canadian economy?

2.1. Theoretical Approach

To address SQ1, a literature review is conducted to examine the relationship between income inequality and climate change. By synthesizing prior research, this literature review aims to identify the sources of ambiguity underlying the relationship between income inequality and carbon emissions. Relevant literature is searched using the search terms: income inequality, economic growth, climate change, and carbon emissions. The review starts with a brief overview of the field of study, defining important terms and concepts. Next, various (ecological) macroeconomic theories are reviewed, beginning with traditional frameworks such as the Kuznets Curve and the Environmental Kuznets Curve, and progressing toward theories on the Marginal Propensity to Consume and the Marginal Propensity to Emit across different income groups. This analysis aims to identify both direct and indirect relationships between GDP, income inequality, consumption, and carbon emissions. Additionally, recent empirical findings and ongoing debates are examined, with particular attention to conflicting perspectives on the inequality-climate nexus.

To systematically compare previous studies, two summary tables are presented. These tables provide a structured overview of the reviewed literature by summarizing the geographical regions, time periods, pollutant indicators, research methods and conclusions of each article.

The literature review highlights the complexity of capturing the dynamic and feedback-driven relationship between income inequality and climate change. It emphasizes the need for an integrated, dynamic modelling approach capable of representing long-term systemic behaviour and identifying underlying causal mechanisms.

The theoretical framework that is derived from the review deepens the understanding of the dynamics involved, and thus, forms the basis for a conceptual model of the system, which is further developed during the modelling phase of the research.

2.2. Modelling Approach

Building on the insights gained from the literature review and the identified knowledge gap, the modelling phase starts by the introduction of the LowGrow SFC model, developed by Jackson and Victor (2019). This system dynamics model of the Canadian economy simulates the evolution of economic, social, and environmental indicators from 2012 to 2073, offering a comprehensive representation of real and financial flows. The evaluation of the model reveals that income inequality is superficially modelled in the LowGrow SFC model. Therefore, a conceptual model, grounded in the literature, is developed and subsequently translated into a sub-model. This sub-model is then incorporated into the original LowGrow SFC model. The resulting extended LowGrow SFC model is used to further explore the relationship between income inequality and carbon emissions.

2.2.1. Case Study Research

By using the LowGrow SFC model as a foundation of this research, the modelling component of this study focuses on the Canadian economy as a representative case study of a developed Western nation. We choose to focus on a single country so as to avoid the ambiguity often introduced by cross-country panel studies, where data are aggregated across structurally different economies at varying stages of development. Such studies frequently fail to yield consistent, country-specific insights into the mechanisms linking income inequality, economic growth, and carbon emissions.

Demir et al. (2019) stress the importance of country-specific analysis due to varying emission profiles and climate vulnerabilities among countries. For example, agricultural economies typically emit less carbon but are more sensitive to climate variability, whereas industrialized countries produce higher emissions yet experience less direct impact (Dogan & Inglesi-Lotz, 2020). Grigoryev et al. (2020) further argue that global climate governance primarily relies on aggregate national emissions, thereby overlooking disparities in development and emissions between countries. Additionally, while much of the existing research has examined the effects of climate change on inequality between countries, its impact on within-country inequality remains underexplored (Paglialunga et al., 2022).

Given that national governments often prioritize other socio-economic goals over climate change mitigation (Grigoryev et al., 2020), a single-country approach offers clear advantages. It highlights a nation’s specific responsibilities regarding emissions and enhances the feasibility of implementing effective climate and inequality-related policies at a national or regional level.

Case Study Selection: Canada

Canada is selected as a case study for several reasons. First, income inequality is particularly high in OECD countries that are also major greenhouse gas emitters, such as Canada, the United States, Japan, Germany, and Australia (Andersson & Atkinson, 2020).

Second, high-income and emerging economies contribute disproportionately to global emissions, while low- and middle-income countries bear the greatest consequences (Chancel et al., 2023). In 2020, Canada ranked tenth globally in total emissions and ninth in per capita emissions (Jorgenson et al., 2024), reinforcing its relevance as a representative case of high-income, high-emission economy. Addressing global equality and climate goals requires high-income nations to reduce resource consumption, creating space for sustainable development in lower-income countries (Akenji et al., 2021; Victor, 2008).

Finally, Canada is chosen for practical reasons: its national economic and environmental data are publicly available, and the LowGrow SFC model is already tailored to the Canadian economy.

2.2.2. System Dynamics

The LowGrow SFC model is a System Dynamics (SD) model. SD is an approach that aims to enhance the understanding of the structure and plausible behaviour of complex systems. SD facilitates the identification, implementation and evaluation of effective policies by incorporating feedback mechanisms, accumulations – represented by stocks – and delays – which arise from the interaction of stocks and flows (Auping et al., 2024; Forrester, 1994; Sterman, 2000).

This research employs SD for three reasons. First, feedback loops and delays that occur due to income inequality and carbon emissions are central to the study. For instance, inequality is both a driver and a consequence of environmental degradation (Chancel, 2020). Similarly, carbon emissions, as a byproduct of economic growth, exacerbate climate damage, while climate-related impacts – such as extreme weather events and resource scarcity – reduce profitability and, in turn, influence economic performance (Rezai et al., 2018). Time delays also play an important role; for example, an increase in aggregate demand for carbon-intensive goods and services does not immediately translate into higher greenhouse gas emissions but will likely take several weeks or months. Likewise, the effects of climate policies may take multiple decades to become visible (Rezai et al., 2018).

Second, applying SD to macroeconomic issues facilitates transparent modelling of dynamic relationships and ensures adherence to the stock-flow consistency that underlies macroeconomic analysis (Jackson & Victor, 2019).

Third, SD enables rigorous scenario analysis and policy testing under varying assumptions, making it an effective tool for assessing the long-term implications of economic and environmental policies and for exploring the uncertainties regarding the contradicting hypotheses among scientists (Auping et al., 2024).

The LowGrow SFC model is developed using *Stella Architect*, a widely used software for constructing, simulating, and analysing dynamic systems. It provides an interface for developing stock-flow diagrams, causal loop diagrams, and interactive simulations (Isee Systems, 2024).

2.2.3. Stock-Flow Consistency

The LowGrow SFC model is a Stock-Flow Consistent (SFC) model. Building on the foundational work of Kalecki (1971) and Goldey and Lavoie (2007), SFC modelling ensures that all monetary flows within and between financial sectors are consistently accounted for. This approach captures the circular flow of income and reflects the underlying monetary structure of the economy (Bezemer, 2010; Jackson & Victor, 2019; Nikiforos & Zezza, 2017). SFC models distinguish between balance sheet stocks and financial flows, and avoid excessive aggregation by incorporating sectoral interactions and multiple asset classes (Bezemer, 2010). This approach gained recognition for its ability to anticipate the Great Recession of 2007 to 2009, underscoring its practical relevance (Nikiforos & Zezza, 2017).

The LowGrow SFC model comprises six financial sectors: households, non-financial firms, financial firms, the central bank, government, and the rest of the world. Since each sector's expenditures are another's income and each sector's financial assets are another's liabilities, the model allows for a meaningful interpretation of the financial positions of all six economic sectors. Furthermore, the integration of system dynamics with SFC modelling enhances the model's transparency and its capacity to capture complex, dynamic relationships while preserving the accounting consistency fundamental to macroeconomic analysis (Jackson & Victor, 2019).

2.2.4. Sub-Model Development

This research builds upon the original LowGrow SFC model by incorporating an additional sub-model. The approach to model development as presented by Auping et al. (2024), consists of the following, iterative steps: problem articulation, conceptualisation, formulation, evaluation, policy testing, and returning to problem articulation. However, the approach taken here – developing a sub-model within an existing framework – asks for a modification of this modelling cycle, as illustrated in Figure 2.1.

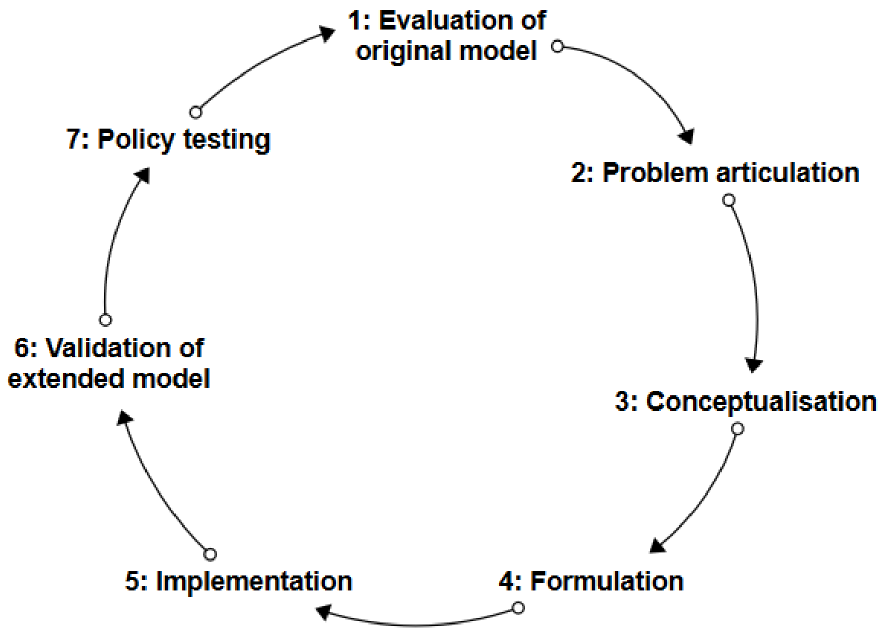

Figure 2.1: Modelling Cycle Applied in This Research (adapted from Auping et al. (2024))

Unlike the modelling cycle as presented by Auping et al. (2024), this research starts with an evaluation of the original LowGrow SFC model. Since the sub-model is integrated into an existing framework, this phase involves a detailed analysis of the LowGrow SFC model's structure, assumptions, and interdependencies to identify areas for extension and improvement.

The problem articulation phase then defines the purpose of the sub-model. Informed by insights from the literature review and the evaluation of the original model, the research problem is formulated. Given that aspects such as the model's scope – the Canadian economy – and its time horizon – 2012 to 2073 – are predefined within the LowGrow SFC model, these elements typically addressed in the problem articulation phase are predetermined.

In the conceptualisation phase, a qualitative representation of the sub-model is developed to capture the relationship between income inequality and consumption. Two iterations of the conceptual model are presented as Causal Loop Diagrams (CLDs), depicting relevant variables such as GDP, disposable income, and carbon emissions, as well as the polarity and feedback loops connecting them. These diagrams support the development of a dynamic hypothesis – a description of the hypothesised behaviour derived from the system's structure (Auping et al., 2024; Forrester, 1994; Sterman, 2000).

The formulation phase involves translating the qualitative conceptual model into a quantitative model. This includes writing mathematical equations, sourcing input data, and implementing the sub-model into the original LowGrow SFC model. Variables from the existing model are connected to newly introduced parameters and existing variable equations are adapted. The sub-model's structure is intentionally designed to align closely with that of the LowGrow SFC model to facilitate compatibility and future usability.

During the formulation phase, relevant data are also incorporated into the sub-model, which are sourced from Statistics Canada. As this data is typically grouped by deciles or quintiles, interpolation is required to match the 13 income groups used in the LowGrow SFC model. A Python script is written to perform this interpolation, after which the data is integrated into the sub-model.

The goal of validating the extended LowGrow SFC model is to determine whether it is fit for purpose. A model is considered fit for purpose if it can fulfil the purpose defined during the problem formulation phase (Auping et al., 2024). Ensuring this is essential for establishing the model's credibility, relevance, and practical utility. A fit-for-purpose model has a structure that accurately describes the relationships between variables and reflects the real-world system it aims to represent. Moreover, it should produce behaviour that responds plausibly to changes in inputs and assumptions (Auping et al., 2024; Forrester, 1994). Accurate representation is particularly important when the model is used to inform policy decisions, as incorrect modes outputs can lead to misleading conclusions and potentially harmful policy outcomes. Validating a model's fitness for purpose also helps build trust among future users, enhancing their confidence in its quality and reliability (Senge & Forrester, 1980).

To validate the extended LowGrow SFC mode, multiple validation techniques are employed:

- Face validation: consulting experts in the field of economics to verify the sub-model's assumptions, structure and behaviour.
- Behavioural comparison to original LowGrow SFC model: a comparison between the original and extended model to ensure similar outputs under equivalent assumptions.
- Sensitivity analysis: performing univariate and multivariate tests to discover how variations in parameters affect model behaviour.
- Extreme value tests: examination of the model's robustness under extreme conditions.

For the latter three validation techniques, multiple graphs are plotted to compare behaviour under different circumstances.

Following this, the policy testing phase compares important performance indicators such as GDP and the Environmental Burden Index (EBI) across four scenarios, each reflecting different assumptions about income inequality and the marginal propensity to consume.

Finally, another evaluation phase starts that discusses the extended model's performance, limitations, and areas for future research. These reflections and recommendations can be found in Chapter 7 and Chapter 8 of this report.

2.3 Conclusion Research Approach

In this chapter, the research structure is outlined by formulating two sub-questions and linking them to a methodological approach. To answer SQ1, a literature review is conducted to explore the theoretical and empirical foundations of the relationship between income inequality and carbon emissions from consumption. To answer SQ2, the LowGrow SFC model of the Canadian economy is extended with a sub-model to capture the effects of income inequality on economic behaviour and emissions. The choice of a single-country focus enhances policy relevance, while the system dynamics approach enables the analysis of complex, feedback-driven processes. The next chapter reviews the existing academic literature to clarify the complexities underlying the relationship between income inequality and carbon emissions, thereby addressing SQ1.

Chapter 3. Income inequality and Climate Change: A Literature Review

Ecological macroeconomics is the field of economics in which climate change, inequality and economic growth intersect. As is shown in Figure 3.1, economic growth has an impact on climate change (effect A) – mostly through carbon emissions associated with the increase of production, consumption and international trade – as well as on (income) inequality (effect C) (Rezai et al., 2018). The higher temperatures and more frequent extreme weather events associated with climate change, in turn, have an effect on economic growth (effect B) – mostly through rising climate damages; according to a report of the British Institute and Faculty of Actuaries (Trust et al., 2025), the global economy could face a 50% loss in GDP between 2070 and 2090. Higher (or lower) income inequality also feeds back into economic growth (effect D), as will be further explained below. Climate change affects inequality (effect F), because climate risks disproportionately affect the poorest countries and people, who are more exposed and more vulnerable to their impacts (Chancel, 2022). Changes in inequality, in turn, influence the speed of climate change (effect E), but, as will be discussed below, the sign (+/-) of this impact is still under debate.

The objective of ecological macroeconomics is to analyse the interconnections between ecological, economic, and social crises, identify their overlapping root causes, and develop sustainable and equitable solutions (Rezai & Stagl, 2016). The interconnections between economic growth, inequality, and climate change have been extensively studied in the academic literature. To fully understand the relationship between inequality and climate change, it is first necessary to understand the links between climate change and the economy, as well as between inequality and the economy. The following sections will provide a detailed elaboration on each of these mutual relationships.

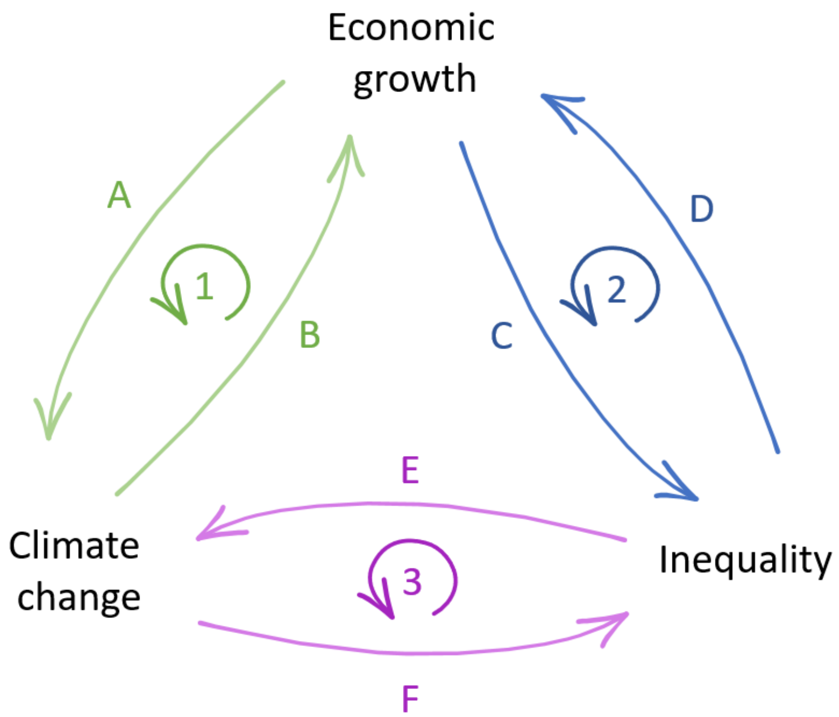

Figure 3.1: Fields of Interest of Ecological Macroeconomics with Feedbacks Between 1) Climate Change and Economic Growth, 2) Inequality and Economic Growth, and 3) Inequality and Climate Change (Image Constructed by the Author)

3.1. Climate Change and Economic Growth

The tension between climate change and economic growth has become more pronounced in recent years, as indicated by the rising accumulation of waste, increased air pollution, and the growing threat of global warming (Luo et al., 2017). According to the Keynesian perspective on macroeconomics, the driving force behind economic activity is aggregate demand. Based on this assumption, the effect of economic growth on carbon emissions – effect A in Figure 3.1 – can be explained as follows: as living standards improve, aggregate demand for (carbon-intensive) goods and services rises, leading to increased production and, consequently, greater economic growth. This, in turn, results in higher energy consumption, which is accompanied by the emission of greenhouse gases (Rezai et al., 2018). This suggests that as economies grow, greenhouse gas emissions will rise, a hypothesis that is supported by a significant body of literature. Jackson et al. (2016) argue that, assuming all other factors remain constant, an increase in economic growth leads to an increase in environmental impact. Schröder and Storm (2020) provide empirical evidence for this theory by demonstrating that emissions – production-based and consumption-based – increase monotonically with income in OECD countries.

While several other scholars also support this view (Hill & Magnani, 2002; Katircioğlu & Katircioğlu, 2018; Sarkodie & Strezov, 2018; Shafik, 1992; Zoundi, 2017), the relationship between economic growth and environmental pollution remains widely debated. Depending on the research methods used, the types of pollutants considered, and the nations studied, various scholars have identified not only monotonically increasing relationships but also U-shaped, inverted U-shaped, N-shaped, , monotonically decreasing, and statistically insignificant relationships between economic growth and pollution (Ching et al., 2022).

3.1.1. Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC), named after and derived from the work of Kuznets (1955), depicts an inverted U-shaped relationship between real GDP per capita and environmental degradation (see Figure 3.2).

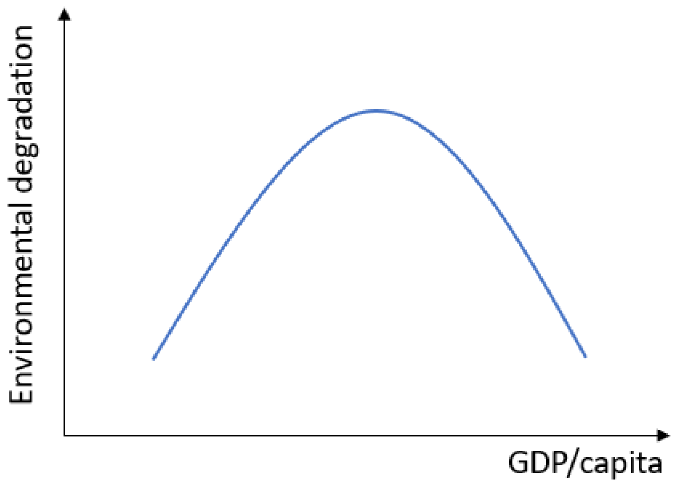

Figure 3.2: Environmental Kuznets Curve (Image Constructed by the Author)

The EKC theory is based on the assumption that countries follow a specific development pattern: transitioning from an agricultural to an industrial and eventually to a post-industrial, service oriented stage (Dinda et al., 2000; Stern, 2004). In the early stages of development, as the economy is industrialising, environmental degradation increases with economic growth. However, once a certain threshold is reached, further economic development is expected to lead to a reduction in environmental degradation. This turning point is attributed to structural and technological changes that replace conventional (carbon-intensive) technologies. These innovations, which tend to emerge in the later stages of economic development, are more likely to reduce polluting emissions (Ching et al., 2022). According to Wan et al. (2022), the key to reducing carbon emissions is economic growth, a theory that corresponds with the right-hand side of the EKC because higher living standards allow producers and consumers to switch to more energy-efficient, less CO_2-intensive technologies.

Although the EKC theory emerged in the early 1990s (Stern, 2004), it continues to find support in recent empirical literature. For instance, Ching et al. (2022) and Demir et al. (2019) provide evidence of the EKC in 64 countries globally and in Turkey, respectively. Similarly, Luo et al. (2017) demonstrate evidence for the existence of the EKC using data for a panel of 19 countries, however, they emphasize that the theory is not universally applicable to all countries or pollutants.

Despite evidence supporting the Environmental Kuznets Curve (EKC), numerous critiques exist. For instance, the assumption that the service sector is less polluting than the industrial sector has been challenged by several scholars (Kaika & Zervas, 2013). Moreover, Stern (2004) argues that there is no robust empirical evidence to support the existence of the EKC if one considers the actual (historical) change of real GDP per capita and per capita carbon emissions for one specific country over time, instead of considering a large panel of developed and industrialising countries. For the EKC to exist in the case of an individual economy, the income elasticity of CO_2 emissions has to become negative at the threshold; this means that an increase in real income (per capita) is associated with a decrease in per capita emissions. Stern (2004) suggests that while the income elasticity of emissions is likely to be less than one, it is not negative, as the EKC implies. Luo et al. (2017) further refines this debate by emphasizing the lack of strong evidence for the EKC's existence in developed countries between 1990 and 2010.

Furthermore, Grigoryev et al. (2020) highlight that most estimates of the Environmental Kuznets Curve (EKC) focus on production-based emissions. However, assessing the curve in the context of consumption-based emissions offers another insightful perspective. Findings indicate that, unlike production-based emissions, consumption-based emissions do not follow an inverted U-shape; instead, they increase consistently with rising incomes (Schröder & Storm, 2020).

Even if the assumption of a tipping point beyond which environmental degradation (per capita) decreases with higher real GDP per capita holds true, the critical question that remains is: is this effect substantial enough to achieve global climate goals? Figure 3.3 presents a world map illustrating that developed countries emit significantly more CO_2 per capita than less developed nations. So, if the existence of the EKC – and in particular its right-hand side – is invalid, the assumption that economic growth alone will reduce emissions does not hold. Consequently, alternative solutions must be found to mitigate environmental degradation.

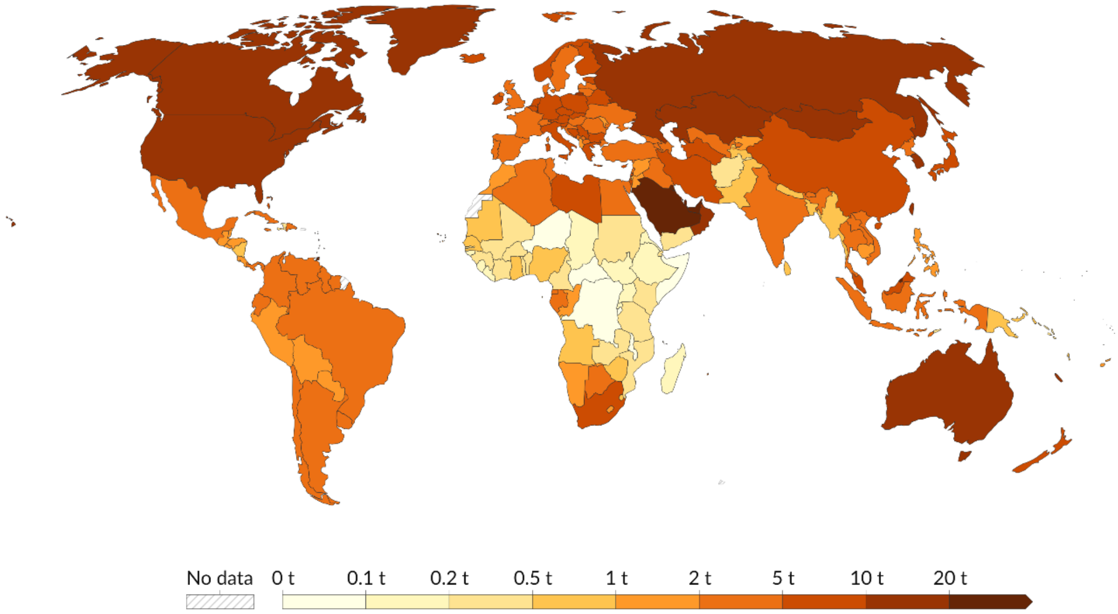

Figure 3.3: Per Capita CO_2 Emissions in 2023 (Our World in Data, 2024)

3.1.2. Decoupling

Decoupling refers to the process of disconnecting economic growth from carbon emissions, as described in the right-hand segment of the EKC. If growth can be successfully decoupled from emissions, limiting future global warming to 1.5 °C would be technically feasible (Schröder & Storm, 2020). Rogelj et al. (2022) argue that absolute decoupling is possible for the economic growth-energy trajectories of wealthy, deindustrializing nations; it could, for example, be achieved by generating electricity by means of solar, wind and geothermal energy plants (and nuclear power plants), which will be more costly but affordable for affluent countries. However, its practical feasibility is questioned by Jackson (2009), who emphasizes that technological improvements in resource efficiency appear insufficient to offset the scale of global economic activity. Similarly, Schröder & Storm (2020), based on their analysis of 58 OECD countries, find no evidence supporting the possibility of decoupling greenhouse gas emissions from economic growth, whether in terms of production- or consumption-based emissions. For their estimations, they use the Kaya identity (Kaya & Yokobori, 1997), an identity that calculates global CO2 emissions as a product of global population, global per-capita income, carbon intensity of primary energy supply, and energy intensity of GDP (Schröder & Storm, 2020).

3.1.3. Alternative Hypotheses

In addition to the hypotheses regarding monotonically increasing emissions, inverted U-shaped emission curves and the notion of decoupling, several other effects of economic growth on greenhouse gas emissions have also been identified. Among these relationships are U-shaped curves (Chakravarty & Mandal, 2016; Dogan et al., 2017; Dogan & Inglesi-Lotz, 2020; Jebli & Youssef, 2015; Omisakin, 2009; Ozturk & Al-Mulali, 2015), N-shaped curves (Aljadani et al., 2021; Bekhet & Othman, 2018; Chang et al., 2014; Dinda et al., 2000; Friedl & Getzner, 2003; Özokcu & Özdemir, 2017; Shahbaz et al., 2019), and monotonically decreasing relationships (Focacci, 2003; Liu et al., 2017; Narayan & Narayan, 2010). Table 3.1 provides an overview of these studies, highlighting their conclusions as well as the geographical regions, time periods, and indicators examined. This summary illustrates the considerable variation – and resulting uncertainty – in empirical findings on the relationship between economic growth and climate change.

Table 3.1: Literature Concerning the Relationship Between Climate Change and Economic Growth

Author(s) (year of publication)	Geographical area	Time frame	Pollutant	Method	Conclusion on relationship between economic growth and emissions
Katircioğlu and Katircioğlu (2018)	Turkey	1960 - 2013	energy use, CO_2	Time series data, ARDL, GLS, cointegration tests	Monotonically increasing emissions with GDP
Schröder and Storm (2020)	58 OECD countries	2007-2015	CO_2	Panel data analysis	Monotonically increasing emissions with GDP
Sarkodie and Strezov (2018)	Australia, Ghana, China, U.S.A.	1971-2013	CO_2	Panel data, unit root, co-integration and causality tests	Monotonically increasing emissions with GDP
Zoundi (2017)	25 African countries	1980-2012	CO_2	Panel data, unit Root tests, co-integration analysis, ECM	Monotonically increasing emissions with GDP
Chen et al. (2020)	G20 countries	1988-2015	CO_2	Simultaneous quantile regression analysis	Inverted U-shape relationship (confirmation of EKC)
Ching et al. (2022)	64 countries worldwide	1990 - 2016	CO_2	Unit root and cointegration tests, PMG and DCCE estimates	Inverted U-shape relationship (confirmation of EKC)
Demir et al. (2019)	Turkey	1963 - 2011	CO_2	Panel data, ARDL, OLS	Inverted U-shape relationship (confirmation of EKC)
Hailemariam et al. (2020)	17 OECD countries	1945-2010	CO_2	Panel cointegration analysis, DCCE estimates	Inverted U-shape relationship (confirmation of EKC)
Luo et al. (2017)	G20 countries	1960-2010	CO_2	Panel data, FE regressions, GMM estimations	Inverted U-shape (confirmation of EKC) for developing countries, not for developed countries
Chakravarty and Mandal (2016)	BRICS countries	1997-2011	CO_2	Panel data, FE regressions, GMM estimations	U-shaped relationship
Dogan and Inglesi-Lotz (2020)	7 European countries	1980-2014	CO_2	Panel data, STIRPAT, FMOLS estimations, co-integration tests	U-shaped relationship
Dogan et al. (2017)	45 OECD countries	1995-2010	CO_2	Panel data, unit root and co-integration tests, DOLS estimation	U-shaped relationship
Jebli and Youssef (2015)	Tunisia	1980-2009	CO_2	ARDL, Granger causality	U-shaped relationship
Omisakin (2009)	Nigeria	1970-2005	CO_2	Unit root tests, co-integration analysis, ECM	U-shaped relationship
Ozturk and Al-Mulali (2015)	Cambodia	1996-2012	CO_2	GMM and 2SLS estimations	U-shaped relationship

Aljadani et al. (2021)	Saudi Arabia	1970-2020	CO_2	ARDL, NARDL	N-shaped relationship
Bekhet and Othman (2018)	Malaysia	1971-2015	CO_2	ADF, PP, KPSS and N-P tests	N-shaped relationship
Chang et al. (2014)	98 countries worldwide	1990-2007	CO_2	LAE and OLS	N-shaped relationship
Dinda et al. (2000)	33 countries worldwide	1988-1990	SO_2 and spm	Panel data, OLS and LAE analysis	N-shaped relationship
Friedl and Getzner (2003)	Austria	1960-1999	CO_2	Time-series, co-integration and structural break analysis	N-shaped relationship
Özokcu and Özdemir (2017)	26 high-income OECD countries.	1980-2010	CO_2	Panel data analysis, Driscoll-Kraay standard errors	N-shaped relationship
Shahbaz et al. (2019)	Vietnam	1974-2016	CO_2	Unit root tests, ARDL, Granger causality	N-shaped relationship
Focacci (2003)	Australia, USA, UK, France, Italy, Japan	1960-1997	CO_2	Comparative statistical analysis	Monotonically decreasing emissions with GDP
Liu et al. (2017)	Indonesia, Malaysia, Philippines, Thailand	1970 - 2013	CO_2	Granger causality, panel data unit root and co-integration test	Monotonically decreasing emissions with GDP
Narayan and Narayan (2010)	43 developing countries	1980-2004	CO_2	Panel unit root and co-integration tests	Monotonically decreasing emissions with GDP

3.1.4. Climate Damage Function

In addition to the impact of economic growth on greenhouse gas emissions, a feedback effect – effect B in Figure 3.1 – also exists whereby greenhouse gas emissions influence economic growth. Environmental degradation, resource constraints, and rising mitigation costs are examples of external limitations imposed by climate change on economic growth (Rezai et al., 2018). These factors reduce investment and suppress economic output and, in the long run, diminish productivity growth and lower potential income levels (Rezai et al., 2018).

In their post-Keynesian model, driven by aggregate demand, Rezai et al. (2018) estimate the impact of climate damage on the long-term evolution of the economy. They argue that as climate damage intensifies, profits decline, leading to reduced investment. Consequently, aggregate demand decreases, resulting in higher unemployment. Figure 3.4 illustrates their projection of global GDP development over time under three scenarios: business as usual (BAU), a temperature increase limited to 2°C, and full mitigation with a temperature increase capped at 1.3°C.

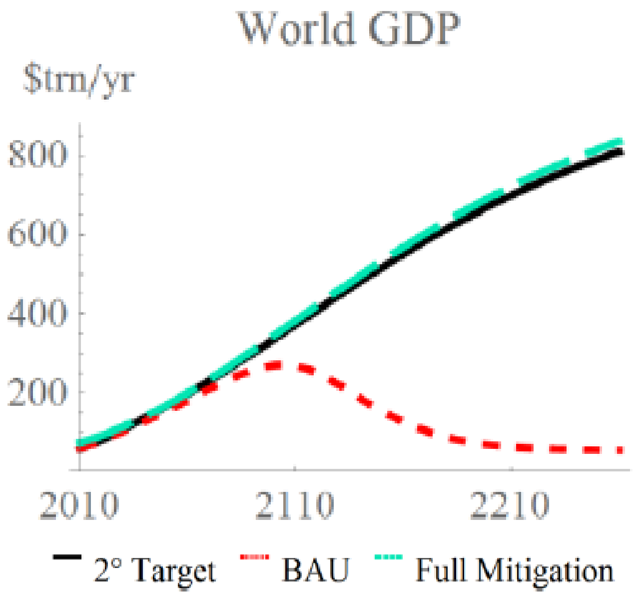

Figure 3.4: Estimated World GDP Loss in Three Scenarios (Rezai et al., 2018)

Trust et al. (2025) offer an alternative perspective on climate damage functions, emphasizing that many climate change risk assessments significantly underestimate risk. They argue that real-world impacts – such as tipping points, sea level rise, extreme weather events, human health effects, and migration – are often excluded from these assessments. In their study, they reference the Network for Greening the Financial System (Network for Greening the Financial System, 2025), which provides a range of estimates for climate damage functions. They compare projections of climate change's negative impact on GDP under a scenario in which global warming reaches 3°C by 2100, with damage estimates ranging from 2% of GDP (Nordhaus & Boyer, 2003) to 44% of GDP (Bilal & Känzig, 2024).

Trust et al. (2025) critique policymakers who do not prioritize mitigating climate change, often relying on outdated and seemingly negligible damage estimates, such as the 2% GDP loss projected by Nordhaus. They stress that climate damage estimates are the result of complex models, whose outcomes are highly sensitive to underlying assumptions and methodologies. Without a proper understanding of these factors, policymakers may unknowingly accept significantly higher levels of risk than they perceive.

Figure 3.5 illustrates the wide variation in GDP damage projections under the NGFS current policies scenario. This range highlights the increasing severity of estimated economic losses when comparing older climate damage assessments with more recent projections (Network for Greening the Financial System, 2025).

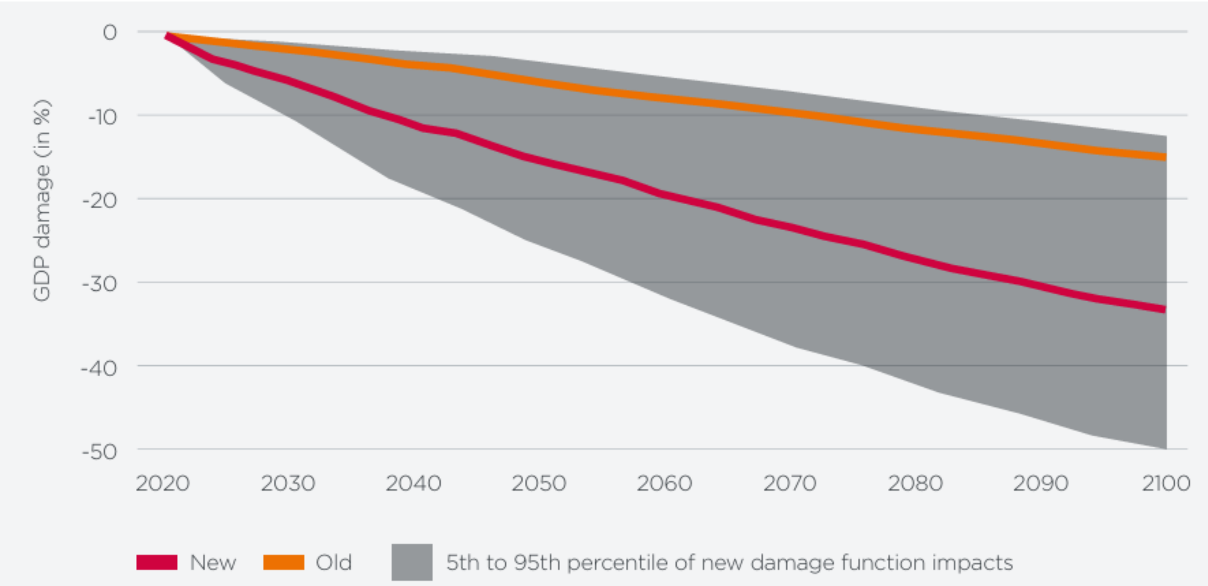

Figure 3.5: Global GDP Loss Projections Under NGFS Current Policies Scenario (Network for Greening the Financial System, 2025)

Kotz et al. (2024) present climate damage projections for two scenarios: a low-emission scenario aligned with the 2°C warming target by 2100 ($RCP_{2.6}$, represented by the purple line in Figure 3.6) and a high-emission scenario ($RCP_{8.5}$, represented by the orange line in Figure 3.6). Their most severe projection exceeds even that of Bilal and Känzig (2024); under the high-emission scenario, GDP is expected to decline by 63% by 2100.

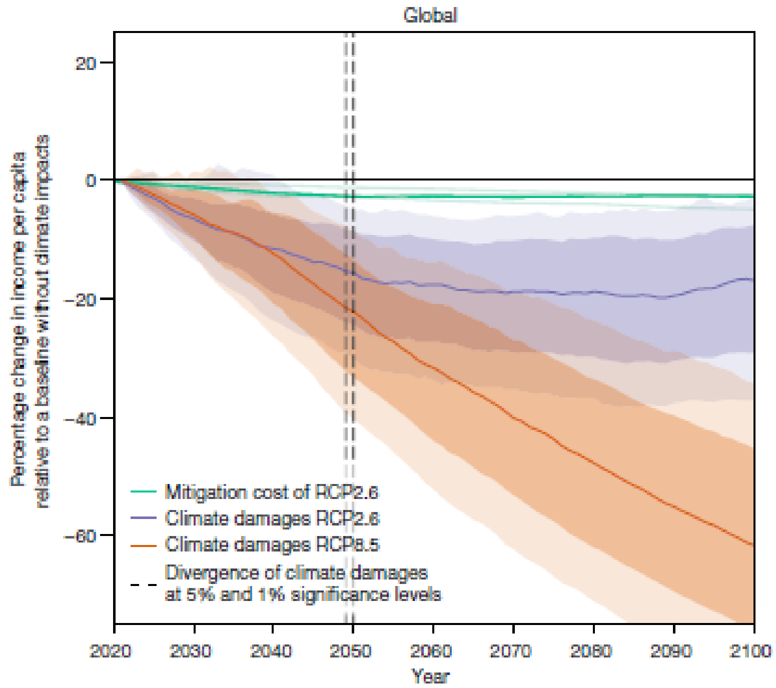

Figure 3.6: Estimated World GDP Loss in Two Scenarios (Kotz et al., 2024)

3.2. Inequality and Economic Growth

The effect of economic growth on income inequality – effect C in Figure 3.1 – has been extensively studied over a long period. Taylor and Bacha (1976) theorized that as economies develop, income distribution tends to worsen, with the poor receiving a smaller share of economic gains than the rich. Kaika and Zervas (2013) support this finding by demonstrating that, throughout economic history, income inequality has significantly widened despite rapid income growth. In the same way, Palley (2011) and Blanchet et al. (2019) have documented rising income inequality over the past few decades in the United States and across 38 European countries, respectively. Given that these economies have experienced sustained growth over the past six decades (World Bank, 2025), their findings provide empirical support for Taylor's theory.

3.2.1. Kuznets Curve

Another prominent theory on the relationship between inequality and economic growth is derived from Kuznets' (1955) hypothesis. According to the original Kuznets Curve (KC), income inequality initially rises during the early stages of economic growth as resources shift from agriculture to industry, leading to disparities between rural and urban populations. However, as development progresses, inequality begins to decline after reaching a tipping point, driven by improved governance and redistributive policies (see Figure 3.7).

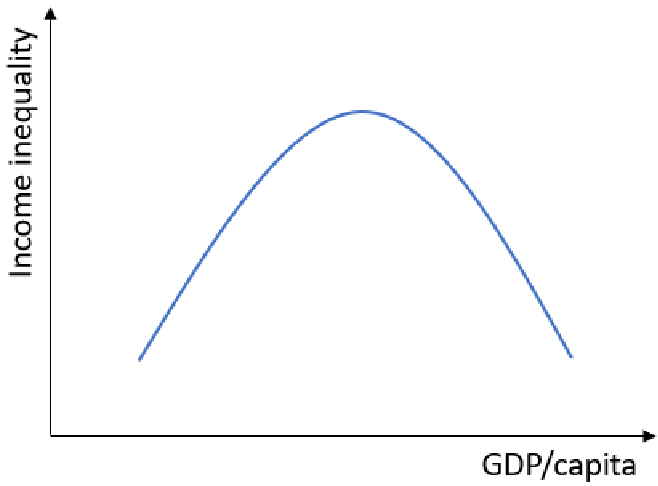

Figure 3.7: Kuznets Curve (Image Constructed by the Author)

Aligning with the right-hand side of the Kuznets Curve, Taylor (2009) argues that economic growth is essential for addressing poverty and inequality.

However, despite the support the Kuznets Curve has received, it has also been subject to significant criticism. Similar to the Environmental Kuznets Curve (EKC), the Kuznets Curve is based on data from developed countries such as the United States, the United Kingdom, and Germany, assuming that other nations will follow a similar urbanization trajectory. This assumption implies that economic growth will "naturally" lead to a more equitable income distribution. However, while rapid economic growth has contributed to reduced income inequality in some countries, this pattern cannot be universally applied as a prescriptive policy for others (Kaika & Zervas, 2013; Kanbur, 2000). Kanbur (2000) and Lindert (2000) show that even despite economic growth, income inequality can increase. Kuznets himself (1955) acknowledged that his conclusions were specific to certain developed nations and did not necessarily apply to all developing economies. Furthermore, Lakner et al. (2022) highlight that empirical support for the left side of the curve – where low-income countries experience economic growth – is weak.

3.2.2. Piketty's Hypothesis

Yet another perspective on the relationship between inequality and economic growth is presented by Piketty (2014). In his book *Capital in the Twenty-First Century*, he argues that the increasing inequality observed in recent decades in modern capitalist economies is a direct consequence of secular stagnation; the slowing economic growth. Piketty further contends that if growth rates continue to decline, income inequality will intensify (Jackson et al., 2016).

In contrast, Storm (2017) reverses the causality. He argues that the root cause of secular stagnation lies in inadequate demand, which may itself be driven by income inequality. Insufficient aggregate demand constrains labour productivity. Regarding labour productivity, Jackson and Victor (2016) suggest that in a context of secular stagnation, low labour productivity can also serve as a mechanism to maintain low unemployment levels.

3.2.3. Aggregate Demand

The impact of inequality on economic growth – effect D in Figure 3.1 – also is a subject of significant interest among scholars. Inequality and economic growth are interconnected through the principle of aggregate demand, which represents the total demand for goods and services within an economy. The distribution of income between wages and profits plays a crucial role in shaping aggregate demand and investment. While higher wages generally stimulate consumption, increased profits tend to drive savings and investment, creating a potential trade-off between short-term demand and long-term growth (Taylor et al., 2016).

Consistent with Taylor's findings, Rezai and Stagl (2016) identify two ways in which rising income inequality affects aggregate demand: by reducing consumption and increasing investment. This hypothesis is derived from the Neo-Kaleckian perspective, which assumes that profit earners save all their income while workers spend their entire earnings (Kalecki, 1942). Similarly, Persson and Tabellini (1994) argue that high income inequality hinders economic growth by diminishing the purchasing power of the middle and lower classes, thereby constraining consumer spending and weakening aggregate demand.

3.2.4. Marginal Propensity to Consume

Another concept closely related to aggregate demand and income inequality is the Marginal Propensity to Consume (MPC), which represents the proportion of an income increase that is spent on consumption. According to the Permanent Income Hypothesis – a theory suggesting that only permanent and unexpected income shocks lead to significant changes in consumption – the MPC should be close to zero. However, Canbary and Grant (2019) find that the MPC is statistically significant and positive, with notable differences across socio-economic groups. Their findings indicate that professional and skilled households exhibit a lower MPC compared to unskilled and unemployed households, with MPC values ranging between 0.32 and 0.71. In Keynesian macroeconomics, it is assumed that the MPC declines as household income grows (Jorgenson et al., 2017). The MPC can be calculated as follows:

$MPC = \frac{\Delta C}{\Delta Y}$ where ΔC = change in consumption and ΔY = change in income.

Wan et al. (2022) argue that the economic mechanism through which income inequality influences the economy can be explained by the law of Diminishing Marginal Propensity to Consume (DMPC), which suggests that reducing income inequality leads to higher overall consumption and thus to higher emissions under the assumption that the rich and the poor consume products and services with the same energy-intensities.

3.3. Inequality and Climate Change

The impact of income inequality on carbon emissions – effect E in Figure 3.1 – is far from consistent and is inconclusive (Huang & Duan, 2020). The literature primarily presents two opposing hypotheses. On one side, some scholars argue that greater income inequality leads to lower carbon emissions, while others contend the opposite, asserting that rising inequality exacerbates emissions. The nature of this relationship varies across studies, with findings describing it as monotonically increasing or monotonically decreasing, but also as U-shaped, inverted U-shaped, N-shaped, or statistically insignificant. These discrepancies stem from differences in research methods, the types of pollutants analysed, and the countries examined (Ching et al., 2022). Ehigiamusoe et al. (2022) emphasize that the reported outcomes are highly sensitive to the choice of country, environmental indicators, and estimation techniques. This section provides an overview of the diverse perspectives presented in the literature.

3.3.1. More Inequality, More Emissions

The first hypothesis to be examined suggests a positive relationship between inequality and carbon emissions – meaning that an increase in inequality leads to more emissions and vice versa. If true, this hypothesis would imply that there exists no trade-off between addressing income inequality and mitigating environmental harm.

Chancel (2020) argues that higher inequality exacerbates environmental degradation by enabling overconsumption among the rich and wealthy while limiting access to sustainable alternatives for the poor. The rich have disproportionately large ecological footprints due to luxury consumption and resource-intensive lifestyles. Wealthier individuals are more likely to own polluting firms and consume high-emission goods and services (Boyce, 1994). Additionally, the 'Veblen effect' suggests that as income inequality widens, the wealthy increase their consumption of luxury goods, further driving carbon emissions (Jorgenson et al., 2017). Meanwhile, financial constraints limit poorer communities' access to green technologies and sustainable infrastructure, sustaining low-cost, but environmentally harmful practices.

Ehigiamusoe et al. (2022) further refine the hypothesis of a positive relationship between inequality and emissions, arguing that higher income inequality globally contributes to higher carbon emissions. However, they find that this effect varies by a country's GDP level. In high-income countries, higher income inequality appears to mitigate environmental degradation, possibly due to wealthier populations investing in cleaner technologies. In contrast, in middle-income countries, higher inequality exacerbates pollution, reflecting disparities in access to environmentally friendly resources. This would be consistent with the EKC. In accordance with these findings, Chen et al. (2020) argue that reducing income inequality in developing countries leads to lower carbon emissions. However, in developed countries, they find no significant relationship between income inequality and carbon emissions.

Distinguishing between GDP levels across countries is a common approach in the literature. Grunewald et al. (2017), for instance, categorize countries into low-, middle-, upper-middle-, and high-income groups but reach the opposite conclusion of Ehigiamusoe et al. (2022). They find that in upper-middle-, and high-income countries, greater income inequality leads to increased environmental degradation, whereas in low- and middle-income countries, higher inequality is associated with lower environmental harm.

3.3.2. Equity-pollution Dilemma

The alternative hypothesis – that greater inequality reduces emissions – suggests a trade-off between social equity and environmental sustainability. Ravallion et al. (2000) find that higher inequality, both within and between countries, is associated with lower carbon emissions, supporting this trade-off. It is argued that reducing inequality may worsen global warming, as it typically involves improving the living standards of poorer populations, leading to a rise in mass consumerism, energy use, and carbon emissions. (Ravallion et al., 2000; Uddin et al., 2020). Rezai et al. (2018) refine this argument, noting that while reducing inequality fosters inclusive growth, it can temporarily increase emissions as lower-income households consume more per unit of income.

Sager (2019) describes this trade-off as the *equity-pollution dilemma* and provides an example for the U.S. to illustrate: a $1,000 transfer from a wealthier household to a poorer one in 2009 could increase the CO_2 emissions associated with that income by 5.1%. This example highlights that low-income groups have a higher carbon intensity of consumption than high-income groups. The London School of Economics and Political Science (2017) further explains this by noting that, despite having a smaller overall carbon footprint, poorer households spend a larger share of their income on carbon-intensive goods and services, such as fossil-fuel-based energy. For instance, the poorest 10% of households spend 7% of their income on utilities (accounting for 42% of their carbon footprint), whereas the richest 10% spend 4% on utilities (accounting for 29% of their footprint). This statement is further supported by Bruckner et al. (2022), who study 116 countries worldwide and draw the conclusion that alleviating global poverty will increase carbon emissions. Theine et al. (2022) comes to the same conclusion for Austria.

3.3.3. Marginal Propensity to Emit

Wan et al. (2022) also acknowledge the equity-pollution dilemma and argue that rising wages among high-income groups can contribute to reducing carbon emissions. They argue that higher income inequality induces greater investment in research and development (R&D), which drives technological advancements that lowers emissions. To support this, they apply the Marginal Propensity to Emit (MPE) approach, which quantifies the additional emissions resulting from additional income and is calculated as follows:

$MPE = \frac{\Delta E}{\Delta Y}$ where ΔE = change in emissions and ΔY = change in income.

This concept suggests that as income distribution becomes more equal, lower-income groups will increase their consumption of energy and other carbon-intensive products as they transition to the middle class (Jorgenson et al., 2017). In their study of 217 countries, Wan et al. (2022) find that the bottom 40% of the population has the highest MPE, while the richest 20% has the lowest. The high MPE among lower-income groups results from their higher MPC and limited access to environmentally friendly, low-emissions commodities or renewable electricity (Chen et al., 2020; Ravallion et al., 2000; Uddin et al., 2020; Wan et al., 2022).

Heerink et al. (2001), Berthe and Elie (2015), and Hailemariam et al. (2020) refer to this as the law of Diminishing Marginal Propensity to Emit (DMPE), which states that MPE declines as income rises. Consequently, worsening income distribution may reduce emissions. Similarly, the diminishing marginal propensity to consume (DMPC) suggests that income transfers to the poor lead to increased consumption and emissions if the MPE for the rich is no higher than for the poor.

Both DMPC and DMPE imply a trade-off between reducing income inequality and lowering carbon emissions (Wan et al., 2022). If both MPE and MPC are higher for low-income groups, income redistribution in their favour is likely to increase emissions (Uddin et al., 2020). Due to this mechanism, poverty reduction and income redistribution cannot simply be pursued as policies for improving environmental outcomes (Demir et al., 2019).

While (Sager, 2019) and Ravallion et al. (2000) support the equity-pollution dilemma, they also offer a more nuanced perspective. Ravallion et al. (2000) present a thought experiment: if reducing inequality initially leads to higher emissions due to the poor's higher MPE, it may also result in greater long-term economic gains for lower-income groups, ultimately reducing their MPE. This is illustrated with Figure 3.8, which projects carbon emissions in a high-growth economy under different inequality scenarios. Additionally, they argue that in developed countries, where energy systems are more advanced, reducing inequality may not significantly increase emissions if energy sources are already low-carbon or if consumption growth occurs in less energy-intensive sectors.

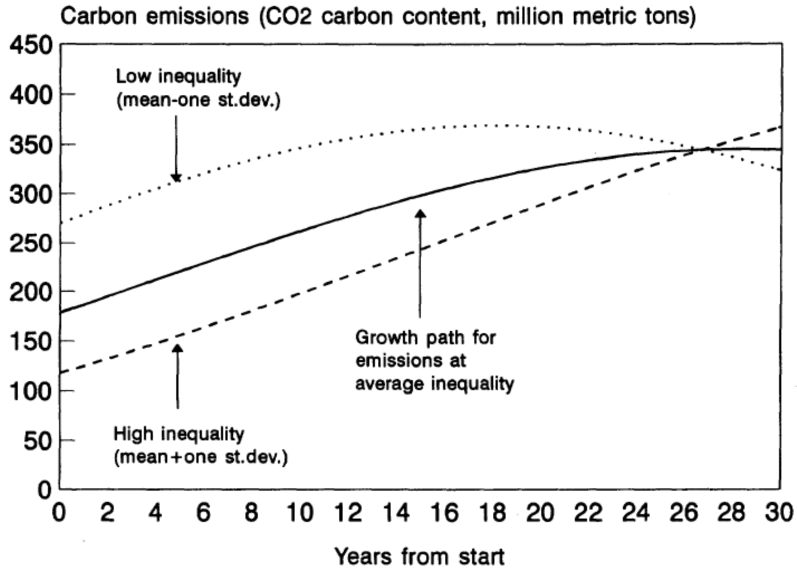

Figure 3.8: Forecast for Carbon Emissions in a High Growth Economy (Ravallion et al., 2000)

Sager (2019) argues that pollution increases with income. To demonstrate this, he calculates the impact of household income on pollution and finds that consumption-based greenhouse gas emissions rise with income, though the relationship may not be linear. Baležentis et al. (2020) find a U-shaped relationship between GDP per capita and consumption-based carbon footprint per capita.

3.3.4. Carbon Inequality

The findings of Ravallion et al. (2000) and Sager (2019) relate to the notion of carbon inequality. Carbon inequality refers to disparities in carbon emissions across income groups. The primary drivers of carbon inequality are the disproportionate consumption and investment patterns of the world's wealthiest individuals (Gore, 2021; Grigoryev et al., 2020). Figure 3.9 illustrates carbon inequality based on per capita, consumption-based, energy-related carbon emissions by income decile in 2021 for the United States, European Union, China, and India (International Energy Agency, 2022). The leftmost bar represents the lowest income decile, while the rightmost bar represents the highest.

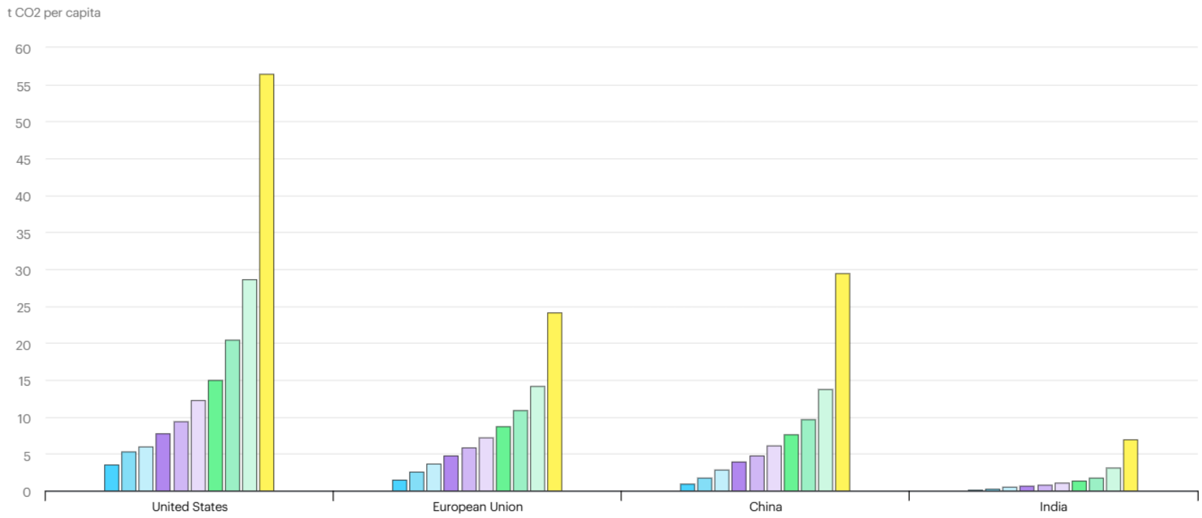

Figure 3.9: Energy-related CO_2 Emissions per Capita by Income Decile in 2021 (International Energy Agency, 2022)

This figure clearly illustrates that the highest income decile is associated with the highest per capita CO_2 emissions, with the relationship appearing to follow an exponential rather than a linear trend. Moreover, the figure highlights that carbon inequality is existent both within and between countries. Chancel (2022) analyses global trends in emissions inequality and shows that, over time, within-country emissions inequality has become a more significant determinant of global emissions inequality than between-country emissions inequality, as is visualised in Figure 3.10. He also emphasizes that although high-income and emerging economies are responsible for a substantial share of global greenhouse gas emissions, low- and middle-income countries suffer the largest consequences. This underscores the unequal contributions to, and impacts of, climate change, drawing attention to the critical role of income and wealth inequality (Chancel, 2022; Chancel et al., 2023). These findings are supported by Sauter et al. (2016), who report that within-country emissions inequality currently accounts for approximately two-thirds of total global emissions inequality.

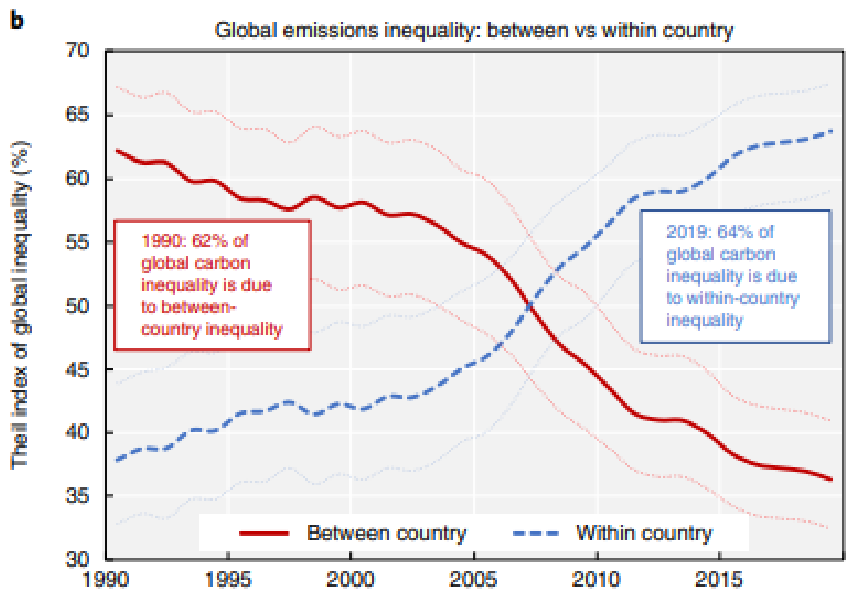

Figure 3.10: Global Emissions Inequality: Between versus Within Country (Chancel, 2022)

Recent studies on carbon inequality highlight the significant role that investments of the wealthy play in their carbon emissions (Chancel, 2022; Gore, 2021). Hebous and Vernon-Lin (2024) demonstrate that carbon emissions from sectors such as crypto mining and data centres already account for 1% of global emissions. Investments by the wealthy in these areas would therefore contribute substantially to global carbon emissions, contradicting the argument made by Wan et al. (2022), who suggest that the investments of the wealthy foster technological R&D advancements that reduce emissions.

Feng et al. (2021) confirm the presence of carbon inequality among U.S. households. In their study, they divide the U.S. population in nine income groups. They find that the per capita footprint of the highest income groups is 2.6 times larger than that of the lowest income group. Although the carbon intensity per dollar spent is lower for higher income groups compared to lower income groups, the substantial gap in consumption volume results in the wealthiest individuals being responsible for greater emissions.

The carbon intensity per dollar spent closely relates to the notion of the carbon intensity of consumption (CIC), which can be calculated as follows:

$CIC = \frac{E}{C}$ where E = emissions and C = total consumption expenditure.

Although the (CIC) is higher for low-income households than for high-income households, the substantial gap in per capita carbon footprints between these groups is primarily driven by differences in overall consumption levels. Higher-income households tend to spend more on everything (Feng et al., 2021).

The MPC, MPE, and CIC on the one hand and carbon inequality on the other, offer very distinct perspectives on the same issue. Table 3.2. summarizes these varying perspectives on the effect of income inequality on carbon emissions in the literature, providing an overview of the geographical areas studied, time frames, inequality measures, pollutants, methods, and conclusions.

Table 3.2: Literature Concerning the Relationship Between Inequality and Climate Change

Author(s) (year of publication)	Geographical area under study	Time frame	Inequality measure	Pollutant	Method	Relationship between inequality and carbon emissions
Baek and Gweisah (2013)	U.S.A.	1967 - 2008	Gini coefficient	CO_2	ARDL	Income inequality increases carbon emissions
Baloch et al. (2020)	40 Sub-Saharan African countries	2010 - 2016.	Gini coefficient	CO_2	Driscoll Kray regression estimates	Income inequality increases carbon emissions
Chen et al. (2020)	G20 countries	1988-2015	Gini coefficient	CO_2	Simultaneous quantile regression analysis	Income inequality increases carbon emissions
Ehigiamusoe et al. (2022)	70 countries worldwide	2000-2018	Gini coefficient	CO_2	GMM and Granger causality	Income inequality increases carbon emissions
Hailemariam et al. (2020)	17 OECD countries	1945-2010	Top income decile and Gini coefficient	CO_2	Panel cointegration analysis, DCCE estimates	Income inequality increases carbon emissions
Jorgenson et al. (2017)	U.S.A.	1997-2012	Gini and income deciles	CO_2	FE regressions	Income inequality increases carbon emissions
Rasheed et al. (2024)	17 Asian countries	2011-2022	Gini coefficient	CO_2	Quantile regressions, 2SLS estimates	Income inequality increase carbon emissions
Uzar and Eyuboglu (2019)	Turkey	1984-2014	Gini coefficient	CO_2	ARDL	Income inequality increases carbon emissions
Zhou and Li (2020)	China	1998-2017	Gini coefficient	CO_2	Stationarity and cointegration tests	Income inequality increases carbon emissions
Knight et al. (2017)	26 high-income countries	2000-2010	Top wealth decile	CO_2	Panel regression analysis, FE regressions	Wealth inequality increases carbon emissions
Ching et al. (2022)	64 countries worldwide	1990 - 2016	Gini coefficient	CO_2	PMG and DCCE estimates	Income inequality reduces carbon emissions
Demir et al. (2019)	Turkey	1963-2011	Gini coefficient	CO_2	Panel data analysis, ARDL, OLS	Income inequality reduces carbon emissions
Huang and Duan (2020)	92 countries worldwide	1991-2015	Gini coefficient	CO_2	GMM estimates	Income inequality reduces carbon emissions
Hübler (2017)	149 countries worldwide	1985-2012	Gini coefficient	CO_2	FE regressions, quantile regression analysis	Income inequality reduces carbon emissions
Ravallion et al. (2000)	42 countries worldwide	1975-1992	Gini coefficient	CO_2	OLS, POLS, FE regressions	Income inequality reduces carbon emissions

Remuzgo and Sarabia (2015)	131 countries worldwide	1990-2010	Theil index	CO_2	Factorial decomposition analysis	Income inequality reduces carbon emissions
Sager (2019)	U.S.A.	1996-2009	Gini coefficient	CO_2	Input-output analysis	Income inequality reduces carbon emissions
Wan et al. (2022)	217 countries worldwide	1960-2022	Gini, income deciles and quintiles	CO_2	Panel data analysis	Income inequality reduces carbon emissions
Masud et al. (2020)	ASEAN-5	1985-2015	Gini coefficient	Adjusted Net Savings	Panel data analysis, Granger causality	Inconsistent relationship
Uddin et al. (2020)	G7 countries	1870-2014	Gini coefficient	CO_2	LLDVE	Inconsistent relationship
Bhattacharya (2020)	India	1981-2008	Gini coefficient	CO_2	Panel data analysis, FE regressions	Insignificant relationship
Ota (2017)	20 Asian countries	2000-2010	Gini coefficient	CO_2	Cross-country data analysis	Insignificant relationship

3.3.5. Carbon Tax

To address carbon inequality, a commonly discussed economic instrument is the carbon tax (Andersson & Atkinson, 2020; Grigoryev et al., 2020; Wang et al., 2016). According to Andersson and Atkinson (2020) economists are recommending the implementation of carbon taxes as the most environmentally and economically efficient way to reach emission abatement targets.

However, the effectiveness of carbon taxes is contested among several scholars. According to Chancel (2022), carbon tax policies implemented in recent decades have primarily affected low-income, low-emitting parts of the population, while largely failing to impact the high emitters. These taxes have placed a disproportionate burden on lower-emitting groups, while they have not been able to alter the consumption behaviour of wealthier households. Starr et al. (2023) further argue that consumer-oriented approaches – such as consumer carbon taxes – rest on the assumption that consumers possess the knowledge, financial resources, and agency to shift their spending habits, as well as the power to influence corporate decisions regarding the greenhouse gas intensity of supply chains and operations.

3.3.6. Degrowth

Economic growth has long been associated with material progress, technological innovation, and improved living standards (Foley, 2012). Many economists – including proponents of the Kuznets Curve and the Environmental Kuznets Curve – consider growth as a solution to both income inequality and environmental degradation. However, this perspective often assumes economic processes are reversible, neglecting the irreversible nature of resource depletion and climate change. Rezai and Stagl (2016) argue that traditional macroeconomic models, grounded in neoclassical assumptions, fail to adequately address ecological limits and societal well-being.

The *Limits to Growth* report (Meadows et al., 1972) already stressed that indefinite economic expansion is incompatible with the planet's finite resources. Foley (2012) outlines three core dilemmas of growth:

1. Environmental degradation through resource depletion and climate change
2. Social inequalities due to uneven distribution of benefits
3. Resource limits due to the finite nature of resources

In response to these dilemmas, a growing amount of scholars advocates for a paradigm shift from maximizing growth to achieving sustainability. In *Prosperity Without Growth*, Jackson (2009) critiques the growth-centred model, arguing that further expansion undermines well-being and ecological stability. Rezai and Stagl (2016) propose adopting post-Keynesian principles focused on demand-led dynamics, equitable income distribution, and employment. Their policy recommendations include reduced working hours, sustainable consumption, and green investment. They also emphasize the transformative potential of the degrowth movement.

Supporting this perspective, Jackson and Victor (2019) demonstrate through their *LowGrow SFC* model that improved environmental and social outcomes are possible even with zero economic growth. Their findings challenge conventional economic paradigms and highlight the need for reorienting economic policy towards well-being, equity, and ecological sustainability.

3.3.7. More Emissions, More Inequality

In addition to the effect of inequality on climate change, a feedback effect – effect F in Figure 3.1 – of climate change on inequality can also be found.

Paglialunga et al. (2022) find that climate change exacerbates existing socio-economic inequalities within countries, disproportionately affecting low-income populations, particularly in rural areas that rely on agriculture and natural resources. This finding is confirmed by Ashenafi (2022), who shows that for 49, mostly rural, African countries an increase in greenhouse gas emissions widens income inequality. Chancel (2020) further emphasizes that marginalized groups are more vulnerab2700le to climate-related risks such as extreme weather, displacement, and food insecurity, with disparities in resilience and adaptive capacity intensifying social inequalities. Consequently, increasing environmental degradation contributes to the deepening of social inequalities.

Cevik and Jalles (2023) examine the effects of temperature increases due to climate change and find evidence that global warming contributes to rising global income inequality, as cooler countries in the north benefit from temperature increase, while warmer countries in the south suffer. They argue that poorer countries, being more vulnerable to climate shocks, experience greater losses in income and wealth, creating a negative feedback loop. Similarly, Dell et al. (2012), Gallup et al. (1999) and Nordhaus (2006) find that higher temperatures significantly reduce economic growth in developing countries.

3.4. Conclusion Literature Review

This literature review has examined the complex dynamics between income inequality and climate change, demonstrating that inequality is not only a social and economic concern but also an environmental matter.

In the context of this relationship, consumption plays an important role. Some scholars hypothesize that increasing income inequality affects aggregate demand by reducing overall consumption and increasing investment (Rezai & Stagl, 2016). This aligns with the theories of the Marginal Propensity to Consume (MPC) and the Marginal Propensity to Emit (MPE), which suggest that lower-income households spend a larger share of their income on consumption and that their consumption is more closely linked to emissions. These concepts give rise to the *equity-pollution dilemma* – a theory that highlights the potential trade-off between promoting income equality and achieving environmental sustainability.

On the other hand, empirical evidence shows that high-income households have significantly higher carbon footprints, despite their lower MPC and MPE. This carbon inequality, visible both between and within countries, can be attributed to the substantially higher consumption volumes of wealthier parts of the population, as well as emissions resulting from their investments.

A possible solution for combining economic growth with environmental preservation is offered by 'decoupling': the potential to detach economic growth from carbon emissions. Although some scholars are optimistic about decoupling, others question whether it can occur at a scale sufficient to meet the 1.5°C global warming target, or whether it is feasible at all. Climate damage functions attempt to estimate the monetary impacts of environmental degradation, resource depletion, and rising mitigation costs, but different models produce widely divergent outcomes.

Several empirical studies emphasize the importance of considering country-specific characteristics in understanding these dynamics – for example, the greater vulnerability of agricultural economies to climate variability compared to highly industrialized nations. However, many studies rely on highly aggregated cross-country samples, which overlook heterogeneity across nations. While some scholars adopt a global perspective, others focus on specific regions, or on particular country groupings such as the G7, G20, OECD, or BRICS.

Although the reviewed empirical literature offers valuable insights into the relationship between income inequality and carbon emissions, it often fails to capture the complex, dynamic, and feedback-driven nature of this relationship. Many studies rely on cross-sectional or panel data, limiting their capacity to capture long-term systemic behaviour or identify causality. The wide variation in findings contributes to an incomplete understanding and highlights several main uncertainties:

1) The effect of income inequality on GDP

It is hypothesized that rising income inequality reduces overall consumption while increasing investment. However, it remains unclear which of these effects is dominant in terms of GDP impact: the dampening effect of reduced consumption, which lowers GDP, or the stimulating effect of increased investment, which raises it.

2) The effect of Marginal Propensity to Consume (MPC)

There is apparent uncertainty regarding the value and statistical significance of the MPC. While the MPC is generally higher among low-income households – who spend a greater proportion of their income on consumption – estimates vary widely. Some theories suggest it is close to zero, while other empirical studies report values ranging from 0.32 to 0.71, reflecting diverging views on its magnitude and impact.

3) The effect of Marginal Propensity to Emit (MPE) and Carbon Intensity of Consumption (CIC)

The MPE and CIC indicate the emissions resulting from increased consumption and are typically higher among low-income households, whose consumption is more directly linked to emissions. This underpins the "equity-pollution dilemma": the idea that a more equitable income distribution comes at the cost of environmental degradation because it will raise emissions among lower-income groups. In contrast, the concept of carbon inequality suggests a different perspective – that increasing the income of high-income groups, who have higher absolute emissions, may lead to a greater rise in total emissions.

Due to these uncertainties, the insights required for effective climate and inequality policy remain underdeveloped. This highlights a critical knowledge gap and underscores the need for a more integrated and systemic research approach.

In summary, this literature review provides both theoretical and empirical support for integrating income inequality into ecological macroeconomic modelling. It underscores the need for a dynamic modelling approach to address the intertwined challenges of inequality and climate change. By extending the LowGrow SFC model to incorporate the effects of income inequality on carbon emissions via consumption behaviour, this research seeks to bridge the identified knowledge gap.

Chapter 4. The LowGrow SFC Model

In this chapter, the modelling phase of the research begins with an introduction to the LowGrow SFC model. Developed by Jackson and Victor (2019), this stock-flow consistent system dynamics model simulates the evolution of the Canadian economy from 2012 to 2073 under various policy scenarios. The model, which is based on post-Keynesian assumptions and consists out of 1782 variables, divides the economy into six interrelated financial sectors: households, financial firms, non-financial firms, the government, the central bank, and the rest of the world.

This chapter provides a concise overview of the model's structure and guiding principles. For a more comprehensive technical explanation, readers are referred to Jackson and Victor (2019). Together with presenting the model, this chapter also addresses the evaluation of the original LowGrow SFC model – step one of the modelling cycle outlined in Figure 2.1. In the conclusion of the chapter, the problem articulation can be found, forming the second step of the modelling cycle and laying the basis for the development of the sub-model in the next phase of the research.

4.1. Model Structure

Figure 4.1. presents an overview of the model structure of the LowGrow SFC model.

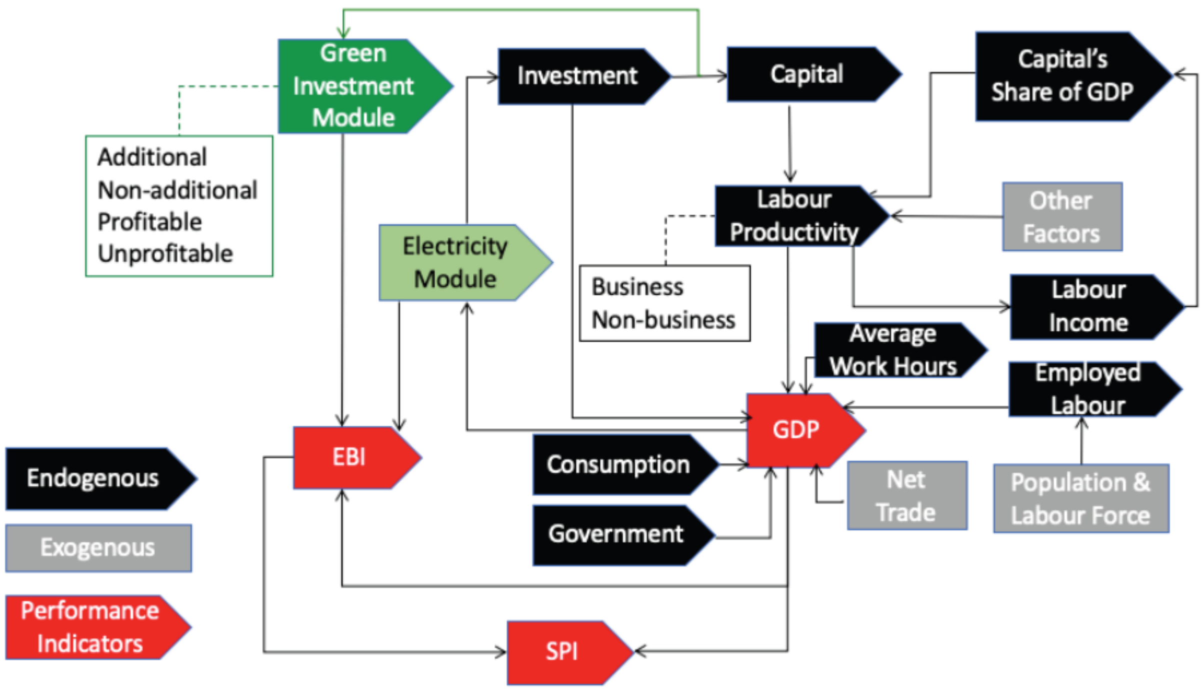

Figure 4.1: Structure of LowGrow SFC Model (Jackson & Victor, 2019)

In the schematic overview, the *Green Investment Module* and the *Electricity Module* are visible. These are two of the five interconnected modules that are present in the model setup in the *Stella Architect* environment. Next to the *Green Investment* and the *Electricity Module*, the model contains a *Real Economy*, a *SFC*, and a *Material Flow Module*. Figure 4.2 illustrates the full architecture and interrelations among these five modules.

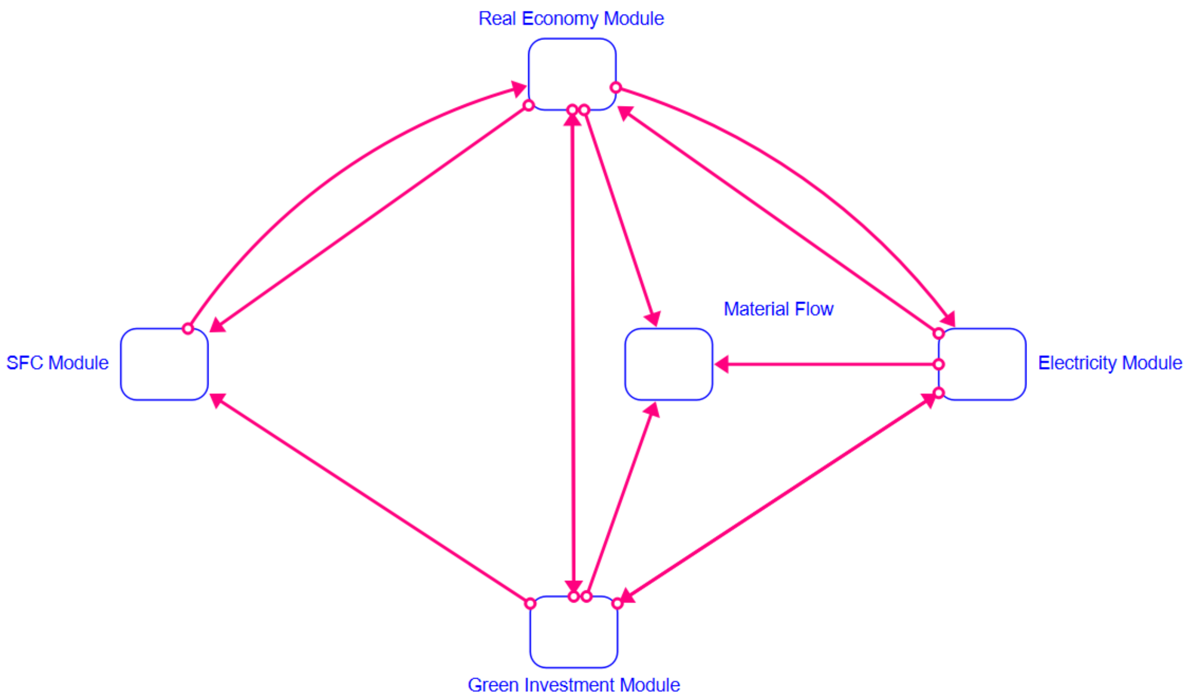

Figure 4.2: Overview of Modules of LowGrow SFC Model (Jackson & Victor, 2019)

Within the SFC module, all financial flows converge, and stock-flow consistency is maintained.

4.2. Green Investment

Within the LowGrow SFC model, firms' investment is divided into two categories: conventional and green investment. Conventional investment refers to expenditures aimed at reproducing or expanding the productive capital stock of the economy. In contrast, green investment is directed toward environmental protection or reducing ecological impacts. Firms' green investment plays a crucial role in the model's exploration of the transition to sustainable prosperity and is further classified along two dimensions: productivity and additionality.

Productive green investment enhances the economy's productive capacity, similar to conventional investment. However, some forms of green investment yield low or no financial return and cannot compete with other investments based on profitability. These are categorized as non-productive green investment and do not directly contribute to the productive capital stock. Examples of productive green investments include biofuel technologies, hybrid vehicles, wastewater treatment systems, and waste recycling infrastructure. Non-productive examples include green roofs, stormwater management systems, and investments in protected natural areas.

Green investment is also assessed in terms of additionality. When it adds to rather than replaces conventional investment, it is considered additional. Conversely, if it substitutes for conventional investment, it is considered non-additional. For example, decarbonization investments such as road and rail electrification are considered non-additional in the LowGrow SFC model.

While all green investment supports environmental sustainability, only those that are both productive and additional contribute to long-term GDP growth. As the set of productive and additional green investment opportunities becomes exhausted, future green investment is expected to become increasingly non-productive. This expected development underscores the importance of financing mechanisms and policy support to sustain both environmental and economic goals.

In addition to firms' green investment, the LowGrow SFC model also incorporates public sector green investment. The government can invest directly in environmental protection but can also impose green taxes on firms to reduce carbon emissions.

4.3. Consumption

In the LowGrow SFC model, household consumption is modelled as a linear sum of disposable income and household net worth and can be described by the following equation:

$$C = \alpha_1 y^{hde} + \alpha_2 nw^h_{-1} \tag{1}$$

with:

- α_1 is the marginal propensity to consume out of real expected disposable income (y^{hde}). This value is set to 0.79 in the model.
- α_2 is the marginal propensity to consume out of real net household worth of the previous period (nw^h_{-1}). This value is set to 0.01 in the model.

Both alpha values are constant, exogenous variables and represent an average value for the entire Canadian population.

Real expected disposable income is calculated as follows:

$$y^{hde} = y^{hd}_{-1}\left(1 + \frac{y^{hd}_{-1} - y^{hd}_{-2}}{y^{hd}_{-1}}\right) \tag{2}$$

with y^{hd}_{-1} = real disposable income of the previous year, y^{hd}_{-2} = real disposable income of two years ago.

Real price-adjusted disposable income is calculated as follows:

$$y^{hd} = \frac{Y^{hd}}{p} \tag{3}$$

with Y^{hd} = household disposable income, p = price level.

Household disposable income is calculated as follows:

$$Y^{hd} = Y^h - T^h + Z^h \tag{4}$$

with Y^h = total household income, T^h = household taxes, Z^h = government transfers or subsidies.

Real net household worth is calculated as follows:

$$nw^h = \frac{NW^h}{\tilde{p}} \tag{5}$$

with NW^h = nominal household net worth, $\tilde{p}$ = compound price level.

Nominal household net worth is calculated as follows:

$$NW^h = H + NFW^h \tag{6}$$

with H = market value of residential fixed assets, NFW^h = net financial worth of households.

Both real expected disposable income and real household net worth are endogenous variables, computed within the model's SFC module.

4.4. Scenarios

The LowGrow SFC model assesses the performance of the Canadian economy under several potential future scenarios. These scenarios represent a spectrum of policy pathways – from business-as-usual to ambitious sustainability transitions – offering valuable insights into their respective implications for economic performance, social equity, and environmental impact.

- Base Case Scenario

The Base Case Scenario describes a continuation of historical trends, assuming that the Canadian economy follows a trajectory similar to that of previous decades. This scenario serves as a benchmark against which the alternative scenarios can be tested.

- Carbon Reduction Scenario

The Carbon Reduction Scenario introduces policy measures aimed at mitigating greenhouse gas emissions. A carbon pricing mechanism is introduced in this scenario, which increases the cost of carbon-intensive electricity generation and incentivizes the use of renewable energy sources. Additionally, it assumes a gradual electrification of road and rail transport at a rate of 2% per year.[1]

- Sustainable Prosperity Scenario

The Sustainable Prosperity Scenario builds upon the Carbon Reduction Scenario by implementing a broader set of environmental policies and accelerating the transition to net-zero emissions. For instance, the electrification rate of transportation infrastructure is increased to 5% per year.

Moreover, this scenario includes policies aimed at achieving beneficial social outcomes. An important measure is the introduction of a redistributive fiscal policy whereby transfer payments are progressively increased to reduce income inequality. Furthermore, it assumes a deceleration in population growth and a reduction in average working hours to help maintain employment levels within a context of lower economic growth.[2]

- Escape Scenario

In more recent versions of the LowGrow SFC model, the number of scenarios has been reduced to two: the Base Case Scenario and the Escape Scenario. The latter closely resembles the earlier Sustainable Prosperity Scenario.

The Escape Scenario outlines a pathway for transitioning from ecological overshoot to a sustainable, post-growth economy. It emphasizes the importance of planned economic contraction particularly in industrialized nations. This scenario highlights the need for intentional policy interventions to reduce material and energy throughput, aligning economic activity with planetary ecological boundaries (Victor, 2023). Main assumptions include achieving net-zero emissions by 2045, lower population and labour force growth, a 10% reduction in work hours, and a gradual reallocation of 50% of non-green depreciation toward green investment over 50 years.

[1] In later versions of the LowGrow SFC model, the Carbon Reduction Scenario was not used any longer. Instead, alternative scenarios were used for scenario analysis.
[2] In later versions of the LowGrow SFC model, the Sustainable Prosperity Scenario was not used any longer. Instead, alternative scenarios were used for scenario analysis.

4.5. Performance Indicators

To evaluate the outcomes of different scenarios, the LowGrow SFC model incorporates a set of performance indicators. These indicators enable a comparative analysis of economic, environmental, and social dimensions across scenarios. In addition to conventional measures of economic success such as GDP, the debt-to-GDP ratio, and GDP per capita, the model also includes indicators of environmental impact and social equity, such as carbon emissions and income distribution (Jackson & Victor, 2019).

4.5.1. Gross Domestic Product

Gross Domestic Product (GDP) is a widely used indicator of economic performance. In the LowGrow SFC model, the calculation of GDP varies depending on the selected scenario. GDP may be determined either exogenously or endogenously. In the exogenous case, GDP is initialized with a predefined value for the year 2012 and subsequently grows at a constant, predefined exogenous growth rate over time. In the endogenous case, GDP is calculated within the model based on internal economic interactions. It is computed in two ways to ensure stock-flow consistency and model validation:

1. Expenditure approach (demand side):

$$GDP_d = C + G + I + \bar{X} \tag{7}$$

where C = sum of household consumption expenditures, G = government expenditure, I = fixed capital investment and $\bar{X}$ = net trade.

2. Income approach (sum of incomes):

$$GDP_i = W + F + \bar{T}^f + \bar{\iota}^f + \delta \tag{8}$$

where W = total wages or labour compensation to households, F = net profits from firms and banks distributed to households, $\bar{T}^f$ = net taxes paid by firms to government, $\bar{\iota}^f$ = net interest paid by firms, δ = depreciation of capital stock.

If the model is stock-flow consistent, the two approaches should yield identical results:

$$GDP = GDP_d = GDP_i \tag{9}$$

Despite its limitations in reflecting societal progress or environmental sustainability, GDP remains a popular metric in economic analysis (Jackson & Victor, 2019). Critics argue that GDP is not intended to measure well-being and that GDP growth may mask rising inequality and environmental degradation (Victor, 2019). Jackson (2016) calls for a redefinition of prosperity that emphasizes well-being, social cohesion, and ecological resilience. Whereas traditional economic models often consider growth to be equal to progress, ecological macroeconomic perspectives – such as post-growth and steady-state theories – advocate shifting policy objectives toward equity, well-being, and sustainability. Reflecting this perspective, the LowGrow SFC model adds two additional performance indicators: the Environmental Burden Index and the Sustainable Prosperity Index.

4.5.2. Environmental Burden Index

The Environmental Burden Index (EBI) is a composite indicator that captures the cumulative environmental impact of economic activity. The initial value of the EBI is 100, and a decrease in the index value indicates an improvement in environmental conditions. The EBI combines multiple dimensions of environmental change by combining the following three components:

- Carbon emissions over time, representing direct contributions to climate change.
- Co-benefits from decarbonisation, recognizing that reductions in carbon emissions often coincide with decreases in other harmful pollutants, thus generating additional health and environmental benefits.
- A generalised environmental burden measure, which represents a variety of different influences on the environment imposed by the economy. This component increases with GDP – under the assumption that greater economic output typically intensifies environmental pressure – and decreases with gains in energy efficiency, advancements in decarbonisation technologies, and higher levels of green investment.

By including both direct emissions and broader ecological dynamics, the EBI provides a holistic indicator for evaluating environmental performance. It enables comparisons across scenarios and supports policymakers in assessing trade-offs between economic growth and environmental sustainability.

In more recent versions of the LowGrow SFC model that implement the Escape Scenario, the EBI is no longer used as a primary performance indicator. Although the variable remains part of the model, it has been supplemented by an ecological footprint measure, which provides an improved representation of environmental pressure.

4.5.3. Sustainable Prosperity Index

The Sustainable Prosperity Index (SPI) is a composite indicator designed to provide a comprehensive assessment of economic and social performance. The initial value of the SPI is 100, with increases in the SPI indicating improving conditions and decreases indicating worsening conditions. The SPI is calculated as a weighted sum of the following indicators:

- GDP per capita
- The Gini coefficient on household incomes
- Average hours worked in the economy
- The Environmental Burden Index
- The unemployment rate
- The government debt-to-GDP ratio
- The ratio of unsecured household debt to income

Figure 4.3 provides an overview of the components and illustrates how changes in each variable affect the SPI.

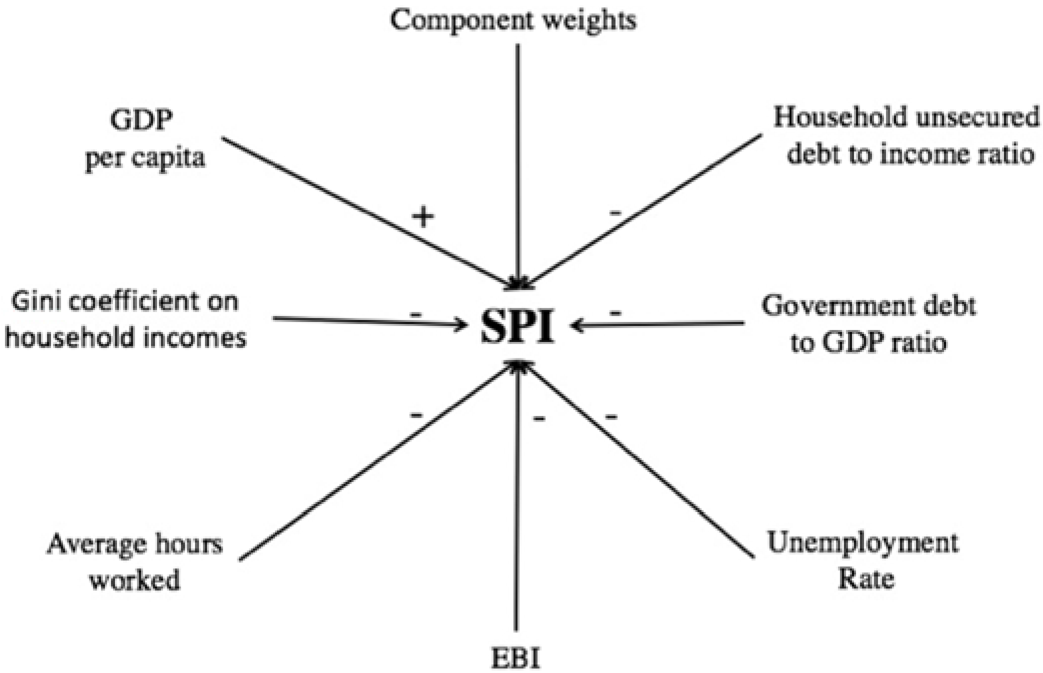

Figure 4.3: Overview of the Sustainable Prosperity Index (Jackson & Victor, 2019)

In later versions of the LowGrow SFC model incorporating the Escape Scenario, the Sustainable Prosperity Index (SPI) is no longer used as a principal performance indicator. Instead, social performance is measured through indicators such as average hours worked, the household loan-to-value ratio, and the Gini coefficient.

4.6. Inequality

Income inequality in the LowGrow SFC model is quantified using the Gini coefficient, a widely accepted statistical measure of inequality. The Gini coefficient is derived from the Lorenz curve, which illustrates the cumulative share of income received by cumulative segments of the population. A value of 0 reflects total equality, while a value of 1 indicates total inequality.

The LowGrow SFC model contains a distribution based on income groups that divides the population with income into 13 segments as described in Table 4.1.

Table 4.1: Income Groups in LowGrow SFC Model

Income group	Mean income [$/year]	Initial number of people in group
Under $5.000	2.500	2033390
To $10.000	7.500	1883510
To $15.000	12.500	2422490
To $20.000	17.500	2592250
To $25.000	22.500	2076900
To $35.000	30.000	3341200
To $50.000	42.500	4065630
To $75.000	62.500	3777860
To $100.000	87.500	1790360
To $150.000	125.000	1055280
To $200.000	175.000	271370
To $250.000	225.000	108580
Above $250.000	420.000	180470

The assumption is made that the mean income of each group lies exactly at the midpoint between the lower and upper bounds of its income bracket. For the highest income group, a mean income of $420,000 is assumed. The table further reveals substantial variation in group sizes. Based on these initial conditions, the Gini coefficient is constant at 0.47 in both the Base Case and the Carbon Reduction Scenario. In contrast, the Sustainable Prosperity Scenario sees a decline in the Gini coefficient from 0.47 in 2012 to 0.19 in 2073, due to a redistributive fiscal policy that progressively increases transfer payments from 2020 onward, particularly targeting the lowest income groups.

Within the LowGrow SFC model, the Gini coefficient functions as a performance indicator. While this allows the model to evaluate how redistributive policies influence income inequality, it does not permit income inequality to be used as an input to examine its effects on other performance indicators. Enhancing the model to treat income inequality as an input variable would enable analysis of its influence on economic growth and carbon emissions.

4.7. Conclusion LowGrow SFC Model

The LowGrow SFC model offers a comprehensive macroeconomic framework of the Canadian economy. Although constantly developing, it yields valuable insights into economic, social, and environmental performance under different policy scenarios.

While the model computes income inequality as one of the indicators for social performance, it cannot currently explore the reverse: how changes in income inequality affect other variables. Introducing income inequality as an input parameter – particularly by disaggregating the currently aggregated consumption function – could offer new insights into the links between income distribution, consumption behaviour, and carbon emissions.

Chapter 5. Sub-Model Development

To implement the possibility to explore the effects of income inequality on economic behaviour and carbon emissions with the LowGrow SFC model, this chapter presents the development of a sub-model that incorporates income inequality as an input to calculate consumption by income group. Building on the evaluation and problem articulation outlined in Chapter 4, the sub-model is developed following the modelling cycle presented in Figure 2.1. This chapter details the conceptualisation, formulation, implementation, and validation phases of the sub-model development.

5.1. Conceptualisation and Dynamic Hypothesis

This section addresses the conceptualisation phase of the modelling cycle as outlined in Figure 2.1. With the literature discussed in Chapter 3 serving as a foundation for understanding the interactions between macroeconomics, inequality, and environmental sustainability, the abstract system described in Figure 3.1 is further specified in Figure 5.1.

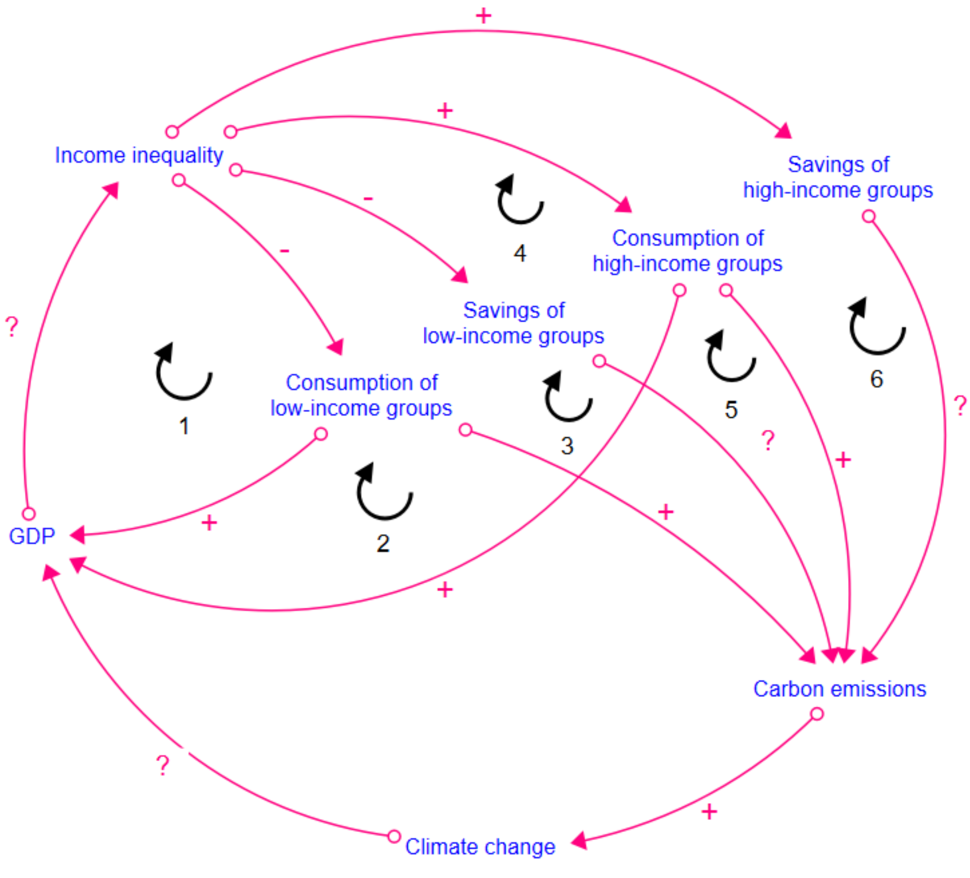

Figure 5.1: Conceptual Model of Connections Between Elements Within the System Concluding from the Literature Review in Which Positive Causal Relationships are Denoted by a Plus (+) and Negative Relationships by a Minus (-) (Image Constructed by the Author)

Figure 5.1 depicts a first conceptual model of the hypothesised behaviour of the system. This conceptual model connects the three core concepts of ecological macroeconomics: carbon emissions, economic performance (GDP), and income inequality. These elements form interconnected feedback loops that drive systemic behaviour. As living standards improve, aggregate demand for goods and services increases, leading to higher levels of production and energy use, and consequently, increased carbon emissions (Rezai et al., 2018).

However, increasing income inequality tends to suppress overall consumption and aggregate demand (Persson & Tabellini, 1994; Rezai & Stagl, 2016). Since aggregate demand drives production, and thus emissions, inequality indirectly influences environmental impact. Furthermore, environmental degradation is expected to feedback into and exacerbate existing inequalities.

The identified feedback loops in Figure 5.1 are:

1. Consumption by low-income groups
2. Emissions from consumption by low-income groups
3. Emissions from investments by low-income groups[3]
4. Consumption by high-income groups
5. Emissions from consumption by high-income groups
6. Emissions from investments by high-income groups

In Figure 5.1, most positive causal relationships are denoted by a plus (+) and negative relationships by a minus (-). The sign of certain relationships is ambiguous and therefore some effects remain undefined (?). Due to several uncertain relationships (e.g., the effect of GDP on inequality, the impact of savings on emissions, and the influence of climate change on GDP), the polarity of the loops cannot yet be determined.

Drawing on insights from the literature review, the initial conceptual model, and the evaluation of the LowGrow SFC model, a revised conceptual model is developed and presented in Figure 5.2. This updated model is specifically designed to align with the structure of the LowGrow SFC framework, enabling its integration as a sub-model extension. In the figure, dark blue arrows denote relationships already embedded in the original LowGrow SFC model, while pink arrows indicate the additional connections introduced by the sub-model.

[3] Emissions resulting from investments by low-income groups are considered negligible relative to those from high-income groups, due to substantial disparities in asset ownership. In 2012, the bottom income quintile in Canada held 4% of total asset shares, whereas the top quintile accounted for 46% (Statistics Canada, 2015). By 2024, this inequality had widened further: the lowest quintile owned 2.8% of total assets, while the highest quintile held 67.7% (Statistics Canada, 2024b).

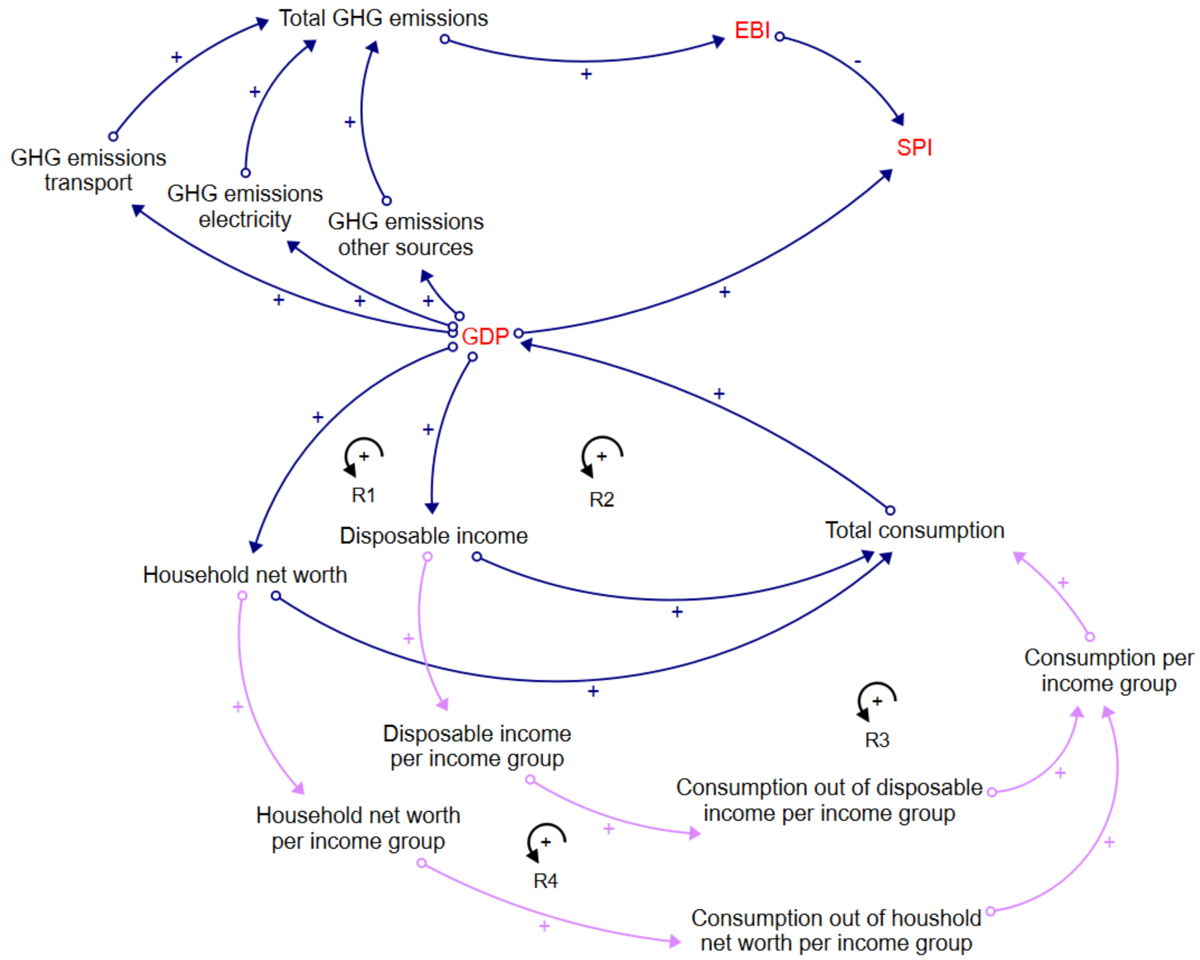

Figure 5.2: Conceptual Alterations to Adapt the LowGrow SFC Model in Which Positive Causal Relationships are Denoted by a Plus (+), Negative Relationships by a Minus (-), and in Which a Distinction is Made Between Connections Already Present in the LowGrow SFC Model (Dark Blue Arrows) and Connections Added by the Sub-model (Pink Arrows) (Image Constructed by the Author)

The pink elements illustrate the disaggregation of the population into income groups, for which consumption will be modelled separately. The LowGrow SFC model already incorporates a division of the Canadian population into 13 income groups, each characterized by a distinct mean income and a distinct group size. The introduction of the sub-model will allow for the calculation of varied consumption behaviour across these 13 groups. As a result, shifts in income inequality are expected to affect aggregate demand and, as a consequence, carbon emissions.

In the updated conceptual model, four reinforcing loops can be found:

- R1: Consumption out of household net worth
- R2: Consumption out of disposable income
- R3: Consumption out of disposable income per income group
- R4: Consumption out of household net worth per income group

Following the sub-model's integration, loops R3 and R4 will replace loops R1 and R2. Since all loops are reinforcing, growth is expected to be visible in the systemic behaviour. As the economy grows, accumulation of income and wealth is expected to become more pronounced, particularly among higher-income groups. Literature suggests that this concentration may constrain aggregate demand and lead to a self-reinforcing cycle of inequality and environmental harm (Foley, 2012; Islam & Winkel, 2017; Taylor & Bacha, 1976).

Both conceptual models support the development of a dynamic hypothesis – a description of the hypothesised behaviour derived from the system's structure (Auping et al., 2024; Forrester, 1994; Sterman, 2000). By testing a dynamic hypothesis, a study generates insights that can inform interventions aimed at changing systemic behaviour (Auping et al., 2024; Kwakkel & Pruyt, 2015; Lane, 2000).

For this research, the dynamic hypothesis anticipates the following systemic behaviour:

- In case of increasing income inequality, aggregate demand will decrease and so will consumption, leading to a decrease in GDP and a decrease in carbon emissions
- In case of decreasing income inequality, aggregate demand will increase and so will consumption, leading to an increase in GDP and an increase in carbon emissions

5.2. Formulation and Implementation

This section addresses the formulation and implementation phase of the modelling cycle as outlined in Figure 2.1. In the formulation phase, the conceptual model is translated into a quantitative model through the specification of mathematical equations and the assignment of parameter values (Auping et al., 2024). Since the formulation phase is closely integrated with the implementation phase, this section also explains the integration of the developed sub-model into the existing LowGrow SFC model. The formulation process is discussed in three steps: (1) an overview of the sub-model's structure is provided, (2) the disaggregated consumption function is specified, and (3) the procedures for data sourcing and processing are elaborated.

5.2.1. Model Structure

The LowGrow SFC model, constructed using Stella Architect software, consists of five modules (as was shown in Figure 4.2 in Section 4.1). Consumption is computed in the 'Real Economy Module', within the *Consumption* sector. To incorporate differentiated consumption across income groups, a new sector titled *Consumption per Income Group* was created. To enhance usability of the sub-model – both for current and future model developers – this sub-model closely resembles the structure of the original *Consumption* sector. Where possible, existing variables were reused to maintain internal consistency. Figure 5.3 presents an overview of the sub-model. A detailed description of the variables used in the sub-model can be found in Appendix A.

To integrate the sub-model with the original LowGrow SFC model, a switch – the *Income Group Effect Switch* – was introduced within the *Consumption* sector. When this switch is set to 1, the sub-model overrides the original consumption calculation, allowing the disaggregated consumption calculation to operate. When set to 0, the model reverts to the original, aggregated consumption calculation.

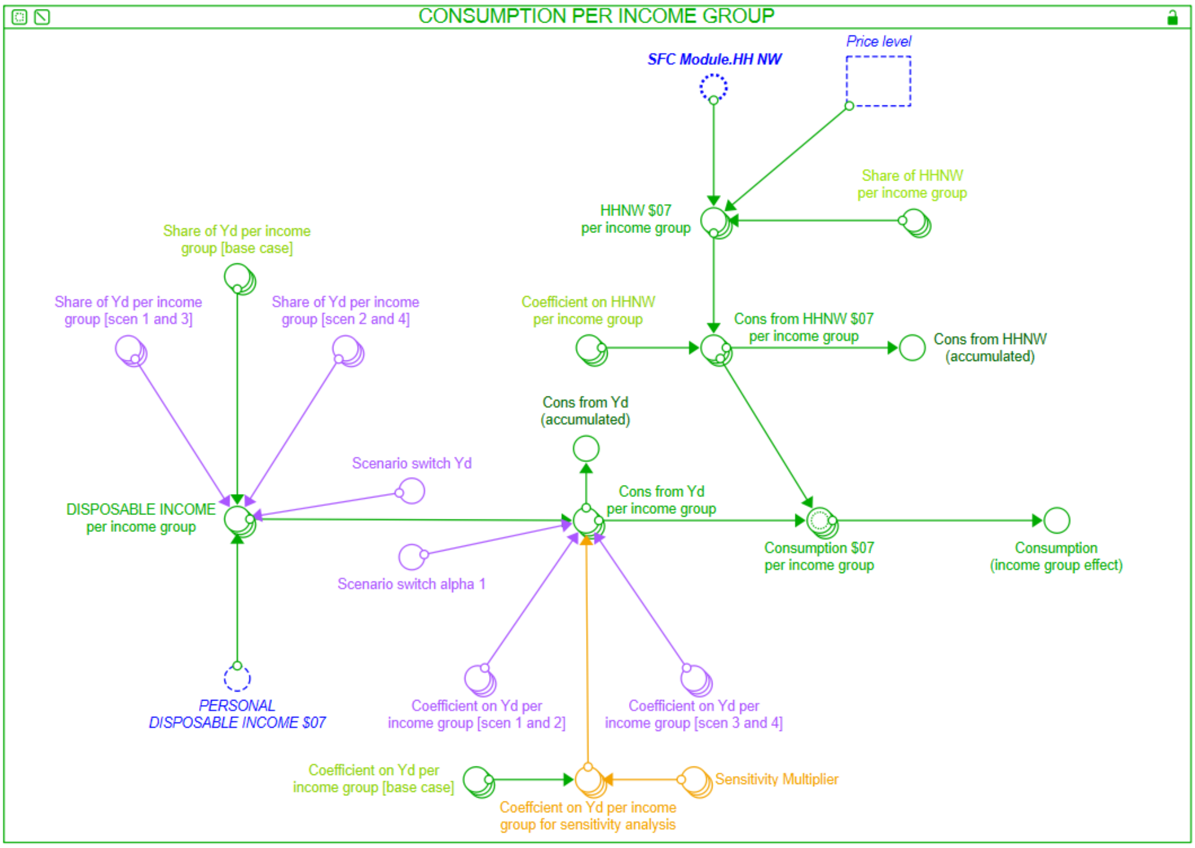

Figure 5.3: Structure of the Sub-model for Calculating Consumption per Income Group; Light Green Variables Denote Added Variables Requiring Input Data; Dark Green Variables are Added Variables Requiring Functional Specification; Blue Variables are Pre-existing Elements of the Original LowGrow SFC Model; Orange Variables are Used for Sensitivity Analysis; Purple Variables are Used for Scenario Development

5.2.2. Consumption Function

To incorporate consumption by income group into the LowGrow SFC model, the original consumption function, Equation (1) in Section 4.3, is disaggregated. This disaggregation implies that each variable in the original function becomes income-group specific, resulting in the following adjusted consumption function:

$$C_n = \alpha_{1,n} y_n^{hde} + \alpha_{2,n} nw_{-1,n}^{h} \tag{10}$$

with:

- $\alpha_{1,n}$ = marginal propensity to consume from real expected disposable income per income group
- y_n^{hde} = real expected disposable income per income group
- $\alpha_{2,n}$ = marginal propensity to consume from real household net worth of the previous period per income group
- $nw_{-1,n}^{h}$ = real household net worth of the previous period per income group
- n = 13

The disaggregated consumption function remains a linear combination of consumption out of disposable income and consumption out of household net worth. Within the sub-model, this disaggregation is operationalized through the use of arrayed variables – variables with multiple dimensions (13, because that is the number of income groups in this case), each of which can take distinct values. The four variables described in Equation (10), correspond to the light green variables in Figure 5.3 and each require input data for their specification.

Marginal Propensity to Consume from Disposable Income[4] ($\alpha_{1,n}$)

The *Marginal Propensity to Consume from Disposable Income* indicates which part of disposable income is used for consumption per income group. In the original LowGrow SFC model, the marginal propensity to consume from disposable income is defined as an aggregate value of 0.79 for the entire Canadian population. To disaggregate this parameter across income groups, data from Statistics Canada is used. These data are further refined through interpolation using a Python script, which is further explained in section 5.2.3.

Disposable Income per Income Group[5] (y_n^{hde})

Disposable income per income group is calculated using existing data within the LowGrow SFC model. The Gini coefficient sector of the model provides both the initial mean income and the population size for each of the 13 income groups. These values are used to derive the income distribution, which is used as input for the disposable income per group. To ensure consistency within the model, the sum of income shares across all groups adds up to 100% of total disposable income.

Marginal Propensity to Consume from Household Net Worth[6] ($\alpha_{2,n}$)

The *Marginal Propensity to Consume from Household Net Worth* indicates which part of household net worth is used for consumption per income group. In the original model, the marginal propensity to consume from household net worth is set at 0.01. For the sub-model, this value is held constant across all income groups. This decision is based on two considerations: first, the scarcity of reliable data on consumption out of household net worth disaggregated by income group; second, the relatively small contribution of this component to total consumption – as shown in Figure 5.4. Furthermore, despite applying a uniform marginal propensity to consume from household net worth across income groups, variations in household net worth across income groups will still result in different consumption levels.

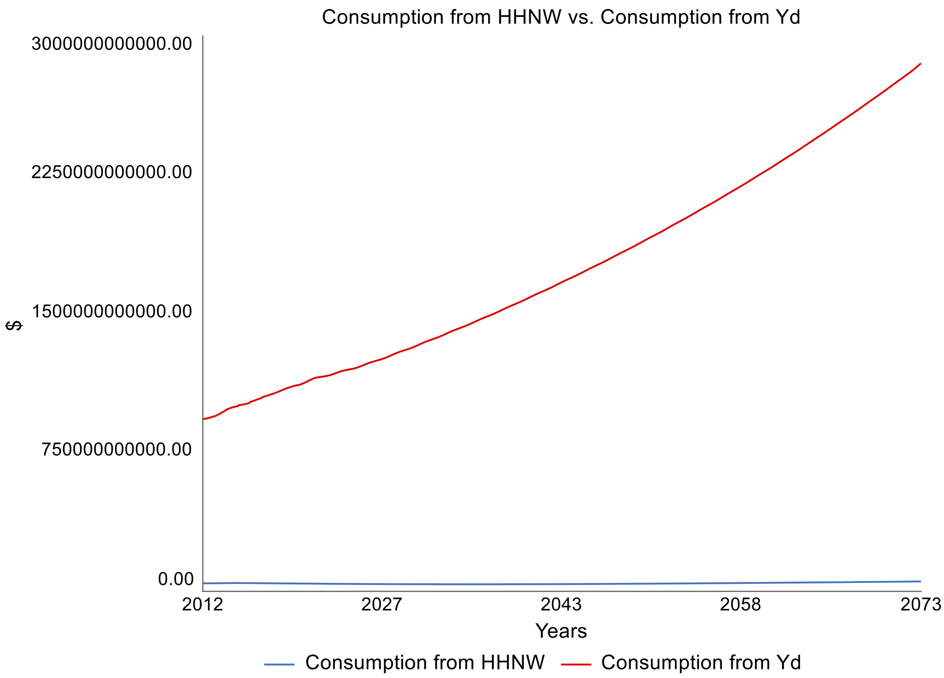

Figure 5.4: Difference in Consumption from Household Net Worth (Blue) and Consumption from Disposable Income (Red)

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[4] In the sub-model, this variable is called *Coefficient on Yd per income group*
[5] In the sub-model, this variable is called *Share of Yd per income group*
[6] In the sub-model, this variable is called *Coefficient on HHNW per income group*

Household Net Worth per Income Group[7] ($nw^{h}_{-1,n}$)

To disaggregate the household net worth per income group, input data from Statistics Canada is used. These data are further refined through interpolation, conducted via a Python script, as detailed in Section 5.2.3. To ensure consistency within the model, the sum of income shares across all groups adds up to 100% of total household net worth.

5.2.3. Data Sourcing and Processing

To assign values to the two variables requiring input from Statistics Canada ($\alpha_{1,n}$ and $nw^{h}_{-1,n}$), relevant datasets were sourced directly from the Statistics Cananda website. Ideally, data from 2011 – the base year used in the LowGrow SFC model – is applied. However, due to unavailability of certain 2011 datasets, the most appropriate alternatives were selected. For the *Coefficient on Yd per income group* ($\alpha_{1,n}$), 2019 data is used as a proxy for 2011 (Statistics Canada, 2024a). For the *Share of HHNW per income group* ($nw^{h}_{-1,n}$), data from 2012 is applied (Statistics Canada, 2015).

Because Statistics Canada reports income group data in income quintiles, and the LowGrow SFC model uses 13 heterogeneous income groups, interpolation was required to align these data. A Python script – as provided in Appendix B – was developed to perform this conversion.

The script begins by defining population quintile boundaries and translating the 13 income groups defined in the LowGrow SFC model into corresponding population shares. Weights are assigned to each group to facilitate interpolation.

After this, variable-specific computations begin. For both variables, the script imports the quintile data from Statistics Canada and fits a linear trendline through the points. A function is then defined to compute integrals over this trendline: the trendline is used to calculate the share from any lower to any upper boundary of the income groups. By looping through all the groups, this function computes the corresponding shares for each population segment. A normalization step ensures that for the *Share of HHNW per income group*, the aggregated shares across all income groups sum to 100% of the total.

After interpolation, all four input-dependent variables can be assigned values for each income group. These values are implemented into the sub-model, enabling the extended LowGrow SFC model (the LowGrow SFC model with the addition of the sub-model) to run simulations. An overview of the input values used in the sub-model is presented in Table 5.1.

[7] In the sub-model, this variable is called *Share of HHNW per income group*

Table 5.1: Overview of Input Values Used in Sub-Model

Income Group	Coefficient on Yd per income group ($\alpha_{1,n}$) [%]	Share of Yd per income group (y_n^{hde}) [%]	Coefficient on HHNW per income group ($\alpha_{2,n}$) [%]	Share of HHNW per income group ($nw_{-1,n}^{h}$) [%]
Under $5.000	199.37	0.47	1	1.54
To $10.000	164.83	1.30	1	2.02
To $15.000	131.28	2.79	1	3.47
To $20.000	118.89	4.17	1	4.98
To $25.000	111.43	4.30	1	4.96
To $35.000	103.69	9.22	1	9.88
To $50.000	91.80	15.90	1	17.21
To $75.000	75.73	21.72	1	25.29
To $100.000	64.20	14.41	1	15.18
To $150.000	58.31	12.14	1	9.91
To $200.000	55.56	4.37	1	2.66
To $250.000	54.77	2.25	1	1.08
Above $250.000	54.17	6.97	1	1.81

5.3. Validation

This section addresses the validation of the extended LowGrow SFC model, as outlined in the modelling cycle in Figure 2.1. Validation assesses whether a model is fit for purpose by evaluating its ability to accurately represent the real-world system and, with that, its effectiveness as a decision-making tool (Auping et al., 2024; Forrester, 1994). For the sub-model, the validation process consists of four steps: face validation, behavioural comparison, an extreme condition test and a sensitivity analysis.

Before discussing these validation steps, the process of verification is briefly addressed. Verification ensures the internal consistency of the model by confirming that all equations, parameter values, and dimensions are correctly implemented. In the case of the sub-model, verification involved checking whether all variables produced plausible outputs and whether dimensional consistency was maintained throughout the entire model structure. Although an automated dimensional consistency check was not feasible due to the absence of predefined units, a manual dimensional consistency check was performed. This included plotting sub-model variables against corresponding variables from the original model to ensure they were of equal magnitude. If this was not the case, the original LowGrow SFC model variable was studied further to check whether the units of this variable were expressed in thousands or millions.

Furthermore, model settings, including the simulation time frame, time step, and integration method, were inherited from the original model to maintain internal consistency. The model simulation runs from 2012 to 2073, with a time step of 0.0125 years. The Euler integration method is used, since it is suitable for discontinuous models that contain logical constructs such as 'IF THEN ELSE', 'MIN', and 'MAX' functions, which all are present in the LowGrow SFC model.

The objective of extending the LowGrow SFC model is to deepen the understanding of how income inequality influences economic growth and carbon emissions, as well as to evaluate the potential consequences of policy interventions with respect to income inequality under uncertainty. Consequently, a validation process is conducted to assess whether the extended model can accurately describe the effects of income inequality on economic growth and to determine its usefulness as a decision-making tool for policymakers in this field. The four previously mentioned validation steps, along with their outcomes, are described below.

1) Face validation

Face validation is a qualitative method used to assess whether a model's structure and behaviour appear reasonable to experts familiar with the real-world system it represents (Auping et al., 2024). The process begins with the modeller's review and is then extended to experts, who evaluate the plausibility of the model's assumptions, feedback loops, and input–output relationships (Sargent, 2013). Face validation was conducted with Professor Emeritus Peter Victor, Professor Servaas Storm, and Post-doctoral Fellow Andrew Reeves.

These economic experts were interviewed using a set of questions provided in Appendix C. They assessed the structural validity of the sub-model by evaluating the relationships between variables, feedback mechanisms, underlying assumptions, use of input data, and the integration of the sub-model with the original LowGrow SFC model. The sub-model did not conflict with the experts' understanding of the real-world system, thereby supporting its structural validity and enhancing the credibility of its outputs.

2) Behavioural comparison

In this step, the sub-model's behaviour is compared to that of the original LowGrow SFC model to verify whether it produces similar results under identical assumptions. This behavioural comparison is an essential part of the validation process, as it evaluates the accuracy of the sub-model's calculations compared to the original.

The results of the behavioural comparison (presented in Appendix D) reveal a small discrepancy between the total consumption calculated by the sub-model and that of the original LowGrow SFC model under identical assumptions. The largest deviation, occurring in 2073, is 1% and is attributed to differences in input data, which are further discussed in Chapter 7. As this discrepancy does not compromise the stock-flow consistency of the extended model, it is considered sufficiently small to not hinder the validation of the sub-model.

Moreover, the shapes and values of the consumption graphs produced by the sub-model closely match those of the original model, reinforcing its behavioural validity and its ability to generate plausible consumption outcomes.

3) Extreme condition test

The extreme condition test involves assigning extreme values to relevant input parameters to evaluate the model's robustness. By assessing if the model's behaviour under these conditions still falls within realistic bounds, the behavioural validity of the model is further examined (Auping et al., 2024; Forrester, 1994).

The results of the extreme condition tests (presented in Appendix E) indicate that the extended LowGrow SFC model generally produces plausible and explainable outcomes under extreme input values, supporting the model's robustness.

While total consumption behaves as expected in these scenarios, GDP occasionally shows counterintuitive behaviour. For example, it does not always increase in response to higher consumption, which appears to contradict the *Paradox of Thrift* – an economic theory suggesting that lower consumption and higher savings lead to reduced economic growth (Godley & Lavoie, 2012). This issue is discussed further in Section 6.3. The strong correlation between the EBI curve and GDP is expected, given that GDP partially determines EBI. However, in extreme consumption scenarios – such as when consumption from disposable income is reduced ten times or consumption from household net worth increases fifty times – the EBI displays unexpected outcomes. As these conditions are highly unlikely, such behaviour does not undermine the model's reliability under normal conditions. However, if the model is used in scenarios with extreme consumption inputs, the EBI variable should be interpreted with caution.

4) Sensitivity analysis

Sensitivity analysis is used to identify which parameters significantly influence model behaviour when subject to plausible changes (Auping et al., 2024). By systematically varying input parameters by ±10% the sensitivity of model outcomes to uncertainties in input data can be assessed (Senge & Forrester, 1980). Since this study involves an adaptation of an existing model, first a univariate sensitivity analysis with the original LowGrow SFC model is performed, which can be found in Appendix F. For the extended LowGrow SFC model, both univariate and multivariate sensitivity analyses are conducted. Univariate sensitivity analysis is used to test the variation of uncertain variables while multivariate analysis is particularly valuable for revealing effects that only occur due to simultaneous changes in different parameters (Auping et al., 2024).

The sensitivity analysis of the extended LowGrow SFC model (presented in Appendix G) reveals that the model is mainly numerically sensitive to changes in the *Coefficient on Yd per income group*. This finding is supported by both the univariate and multivariate analyses, as the behaviour of Key Performance Indicators (KPIs) in the multivariate tests closely aligns with the patterns observed in the univariate analysis of this variable. While minor behavioural changes, such as small oscillations, are visible in response to changes in this variable, no significant behavioural sensitivity – such as changes in curve shapes that would substantially alter model outputs – is observed for any of the tested parameters. The absence of structural behavioural shifts strengthens confidence in the robustness of the model's behaviour.

In conclusion, the integration of the sub-model into the LowGrow SFC model successfully incorporates the effects of income distribution. The four validation steps outlined above demonstrate that the extended model is capable of generating credible results. Its structure, underlying assumptions, integration with the original model, and relevance have been endorsed by economic experts. Furthermore, the sub-model closely replicates the outputs of the original LowGrow SFC model, confirming its computational accuracy and integration. The extended model also demonstrates plausible behaviour under extreme input values, and no structural behavioural changes are observed under multivariate sensitivity testing. Together, these findings confirm that the extended LowGrow SFC model is fit for purpose: it represents the real-world system in a reliable way, enhances understanding of how income inequality affects economic growth and carbon emissions, and thus can serves as a valuable tool for policymakers to evaluate the potential impacts of inequality-related policy interventions under uncertainty.

In the next chapter, the validated extended LowGrow SFC model will be used to explore future scenarios under different assumptions.

Chapter 6. Results

This chapter discusses the policy testing phase, as outlined in the modelling cycle shown in Figure 2.1. System dynamics models are often used for scenario development, a process in which different parameter values are selected simultaneously to construct alternative future scenarios. Through these scenarios, experiments can be conducted to evaluate a policy's robustness: its ability to function effectively regardless of how the future unfolds (Auping et al., 2024).

By testing the performance of the extended LowGrow SFC model under various conditions, the dynamic hypothesis can be assessed which provides insights into the relationship between income inequality, economic performance, and environmental harm.

6.1. Scenario Variables

For the scenario development in this research, two uncertainties identified in the literature review are selected as the basis for constructing scenarios:

- The Share of Disposable Income (Yd) per income group (y_n^{hde})
- The Coefficient on Disposable Income (Yd) per income group ($\alpha_{1,n}$)

By altering the *Share of Yd per income group*, the overall income distribution is adjusted – resulting in either a more equal or a more unequal scenario and, consequently, shifts in the Gini coefficient. Modifying the *Coefficient on Yd per income group* affects the marginal propensity to consume from disposable income, varying consumption behaviour across income groups.

Adjusting these two input variables enables the exploration of potential future developments and their implications for both economic and environmental outcomes. The possible scenario combinations resulting from this are outlined in the scenario logic diagram in Figure 6.1.

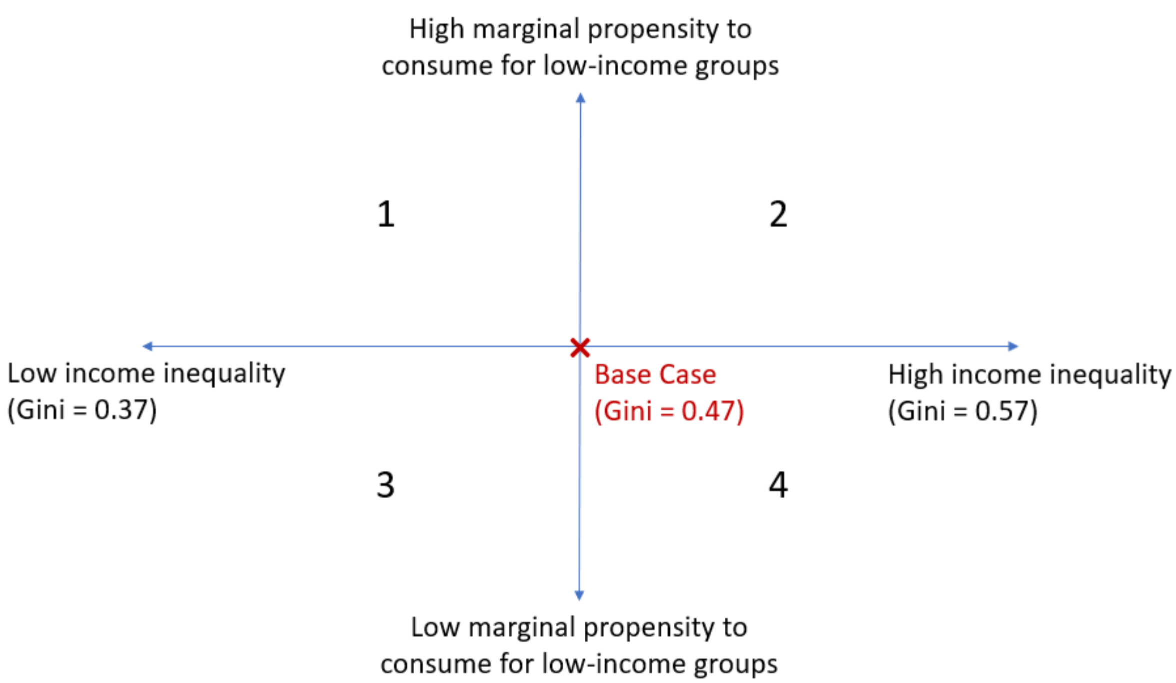

Figure 6.1: Scenario Logic Diagram for Experiments (Image Constructed by the Author)

In this figure, four different scenarios can be distinguished, each representing a possible future.

6.1.1. Income Inequality

The x-axis of the scenario logic diagram in Figure 6.1 represents the degree of income inequality, which is modelled using the *Share of Yd per income group* variable in the extended LowGrow SFC model. The Base Case Scenario has a Gini coefficient of 0.47, calculated using the original income distribution defined in the LowGrow SFC model.

In Scenarios 1 and 3, income is redistributed toward a more equal distribution, resulting in a Gini coefficient of 0.37. In these scenarios, the mean income of lower-income groups is increased, while the mean income of higher-income groups is decreased, ensuring that total income remains unchanged. The number of people per income group is held constant.

In Scenarios 2 and 4, the income distribution is adjusted toward a more unequal distribution, resulting in a Gini coefficient of 0.57. Here, the mean income of lower-income groups is decreased, while that of higher-income groups is increased. Also in this case, total income and the number of people in each group remains constant.

Figure 6.2 provides a graphical representation of the income distributions used in these scenarios.

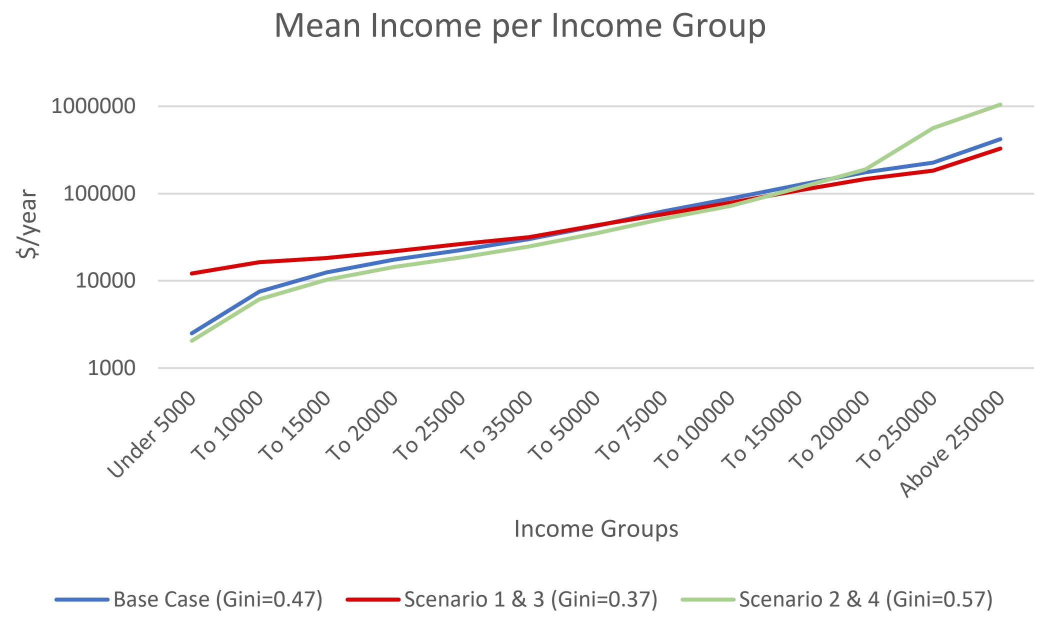

Figure 6.2: Mean Income per Income Group for Base Case Scenario (Blue), Scenario 1 and 2 (Red) and Scenario 3 and 4 (Green) (Image Constructed by the Author)

In the figure, the Base Case Scenario lies between the more equal scenarios (1 and 3) and more unequal scenarios (2 and 4). The most substantial changes in mean income occur at the lower and upper ends of the income spectrum. Note that the y-axis uses a logarithmic scale. A more detailed breakdown of the mean income per income group and the *Share of Yd per income group* across the scenarios can be found in Appendix H in Table H.1.

6.1.2. Marginal Propensity to Consume

The y-axis of the scenario logic in Figure 6.1 reflects differences in the Marginal Propensity to Consume (MPC) among lower-income groups, represented in the model by the *Coefficient on Yd per income group*. Altering this variable in the scenario development allows for the exploration of both the uncertainty highlighted in the literature and the numerical sensitivity demonstrated by the model.

For the Base Case Scenario, the values for this variable (as are presented in Table 5.1) were sourced from Statistics Canada. In Scenarios 1 and 2, the MPC for lower-income groups is increased relative to the Base Case. The MPC of the lowest income group is raised by 10%, and this adjustment decreases progressively for higher-income groups, reaching 0% change for the highest groups.

In Scenarios 3 and 4, the opposite occurs – the MPC for lower-income groups is decreased. The lowest income group's MPC is reduced by 10%, with smaller reductions applied to higher groups, again reaching 0% change for the richest income groups.

Figure 6.3 illustrates these adjustments in MPC across income groups.

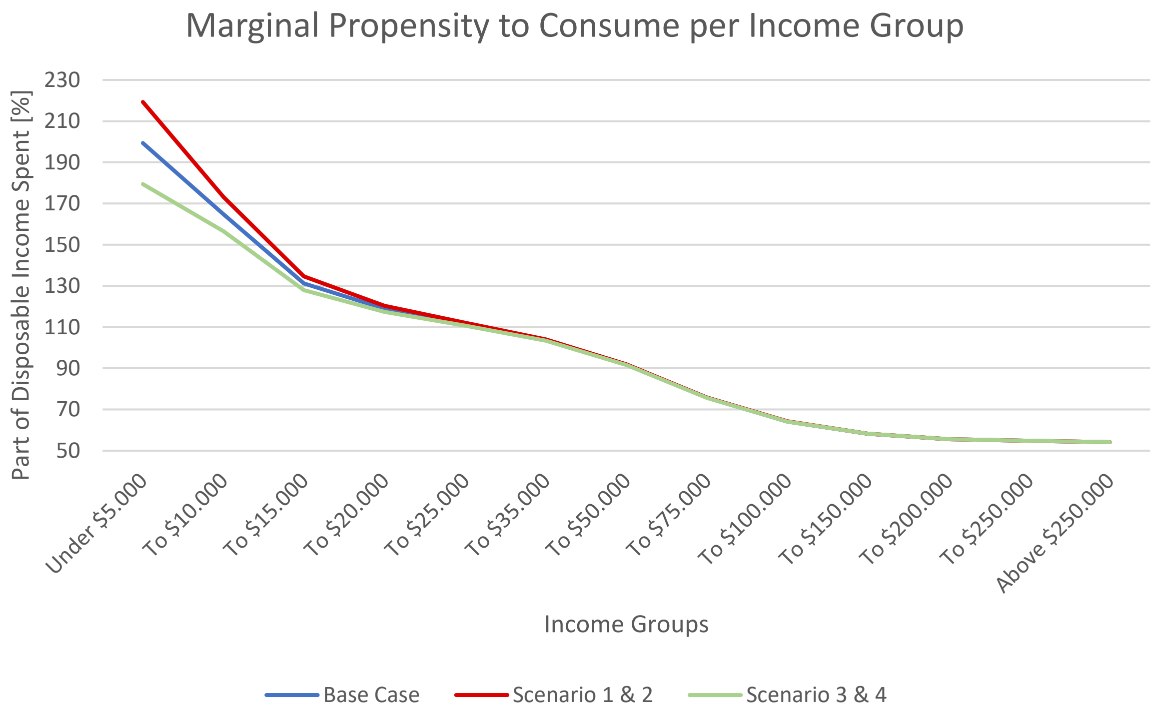

Figure 6.3: Marginal Propensity to Consume per Income Group for Base Case Scenario (Blue), Scenario 1 and 2 (Red) and Scenario 3 and 4 (Green) (Image Constructed by the Author)

As shown in the figure, the Base Case MPC values for low-income groups lie between the higher MPC scenarios (1 and 2) and the lower MPC scenarios (3 and 4). A more detailed explanation on MPC values per income group for each scenario is provided in Appendix H in Table H.2.

6.2. Scenarios

The four scenarios tested in the extended LowGrow SFC model are described below.

6.2.1. Scenario 1: Egalitarian Expansion

In this scenario, income inequality is reduced to a Gini coefficient of 0.37 by bringing the mean incomes of the 13 income groups significantly closer together. This represents a more equal income distribution than is currently the case in Canada, where the Gini coefficient stood at 0.50 in 2023 and 0.47 when the model development started in 2011. The income distribution in Scenario 1 is comparable to that of countries like the Netherlands and Sweden, which both reported Gini coefficients of 0.39 in 2023 (Our World in Data, 2024).

As outlined in the dynamic hypothesis, the combination of an increase in mean income and a higher MPC among lower-income groups is expected to result in high overall consumption, even with reduced income among wealthier groups.

This scenario reflects a potential future in which the Canadian government chooses to actively address persistent income inequality, which has hovered around a Gini coefficient of 0.50 for the past three decades (Our World in Data, 2024). Achieving this more egalitarian distribution would require substantial redistributive policy interventions, such as progressive taxation and expanded social transfers.

6.2.2. Scenario 2: The Core of Capitalism

In this scenario, income inequality increases to a Gini coefficient of 0.57, as the lower income groups earn less and the higher income groups earn more. This scenario presents an income distribution similar to that of the United States, where the Gini coefficient has risen from 0.56 in 2005 to 0.59 in 2023 (Our World in Data, 2024).

In Scenario 2, the MPC of lower-income groups increases compared to the Base Case Scenario. While this could imply an increase in absolute consumption, it can also indicate their absolute consumption remaining equal since their mean income has decreased. In contrast, high-income groups see a substantial rise in earnings, resulting in a significant increase in their absolute consumption because of their unchanged MPC. As outlined in the dynamic hypothesis, the increase in income inequality is expected to decrease overall consumption.

This scenario could emerge from a political shift in Canada toward economic liberalism, marked by minimal government intervention in economic markets. In such a context, progressive taxation and social transfer systems might be significantly reduced or entirely eliminated, leading to a more unequal income distribution. In this scenario, lower-income groups would face increasing difficulty making ends meet and become increasingly susceptible to debt accumulation.

6.2.3. Scenario 3: Gradual Growth

As in Scenario 1, this scenario features a more equal income distribution, with a Gini coefficient of 0.37. However, unlike Scenario 1, the MPC of lower-income groups is reduced compared to the Base Case. This means that while lower-income groups receive higher incomes due to redistribution, they spend a smaller percentage of their income compared to the Base Case Scenario. As a result, their absolute consumption could remain approximately unchanged, despite earning more.

This scenario envisions a future where the Canadian government combines strong redistributive policies with measures aimed at curbing consumerism, potentially as part of a post-growth agenda. It reflects a society focused not only on equality but also on environmental sustainability and reduced consumerism.

6.2.4. Scenario 4: Impeding Inequality

Like Scenario 2, this scenario features an increase in income inequality, reaching a Gini coefficient of 0.57. However, in this case, the MPC of lower-income groups decreases compared to the Base Case.

This implies that the poorest earn less and simultaneously spend a smaller share of their income, leading to a sharp drop in absolute consumption for these groups. From both an economic and social perspective, this scenario is highly unlikely to occur in reality, as lower-income households typically spend a larger proportion of their income on consumption – a tendency that becomes even more pronounced when their income decreases. Nevertheless, this scenario is included as a theoretical case.

6.3. Scenario Analysis

In this section, the four scenarios described above, along with the Base Case Scenario, are evaluated based on their performance across the following Key Performance Indicators (KPIs):

- Total Consumption
- Gross Domestic Product (GDP)
- Environmental Burden Index (EBI)

Figure 6.4 presents the results for Total Consumption across the different scenarios.

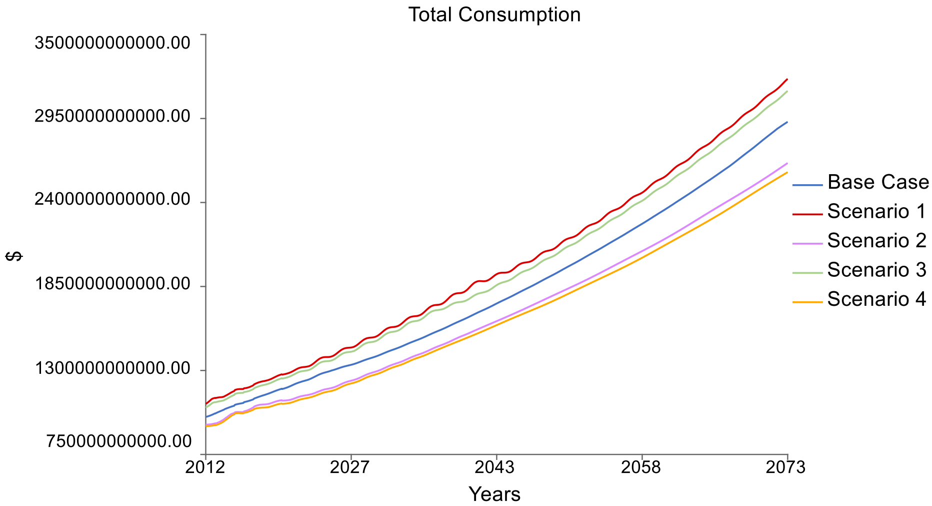

Figure 6.4: Development of Total Consumption in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

Figure 6.4 illustrates clear differences in total consumption across the various scenarios. Consumption is highest in the two scenarios featuring a more equal income distribution – Scenario 1: Egalitarian Expansion and Scenario 3: Gradual Growth. This outcome aligns with the economic theories found in the literature review: a more equal income distribution leads to higher aggregate demand, which in turn stimulates overall consumption. Conversely, the scenarios characterized by greater income inequality – Scenario 2: The Core of Capitalism and Scenario 4: Impeding Inequality – show lower levels of total consumption. This can be attributed to the reduced aggregate demand typically associated with high income inequality. These observed effects of income inequality on total consumption are consistent with the dynamic hypothesis.

Another expected pattern emerges when comparing the scenarios based on the MPC among lower-income groups. Scenarios with a higher MPC for these groups (Scenarios 1 and 2) result in higher total consumption than their counterparts with the same level of income inequality but a lower MPC (Scenarios 3 and 4, respectively).

As a result, Scenario 1 yields the highest total consumption, driven by the combined effect of increased incomes and higher MPC among lower-income groups. In Scenario 2, a lower consumption level compared to the Base Case is observed due to the negative impact of income inequality on aggregate demand. Scenario 3 exhibits a steady growth in consumption, just under that of Scenario 1 due to the MPC among poorer groups being lower in this scenario. This finding shows that the more equal income distribution still boosts aggregate demand, despite the effect of a reduced MPC. Finally, the unlikely Scenario 4, which combines high inequality with a low MPC for lower-income groups, results in the lowest total consumption among all scenarios.

Next, the results for GDP across the different scenarios are presented in Figure 6.5.

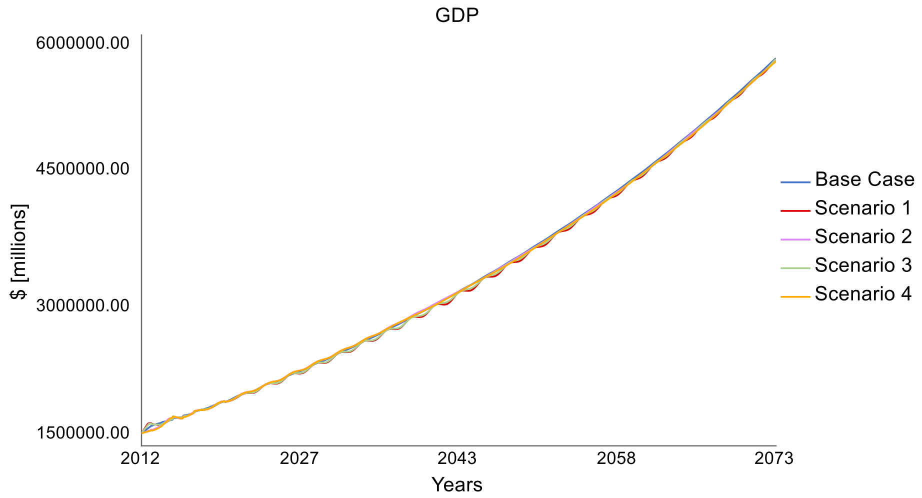

Figure 6.5: Development of GDP in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

Initially, the various scenarios appear to have no effect on GDP, given the small magnitude of the changes. However, a closer examination of Figure 6.5 reveals a more nuanced picture. Throughout the model run, GDP in Scenarios 2 and 4 – characterized by higher income inequality and lower total consumption – remains close to the Base Case. In contrast, GDP in Scenarios 1 and 3 – marked by lower income inequality and higher total consumption – tends to oscillate slightly below the Base Case.

This outcome can be better understood by analysing the dynamics of the extended LowGrow SFC model. As shown in Equation (7), GDP is calculated as the sum of consumption, government expenditure, business investment, and net trade. While the more equal scenarios (1 and 3) result in increased household consumption, they simultaneously lead to a reduction in government expenditure. This occurs because the model assumes countercyclical government spending, where the government increases expenditure in the case of low public spending and reduces it when public spending is high. Government expenditure itself is the sum of government investment and government consumption, both of which decline in scenarios with increased household consumption.

The development of Government Expenditure, Government Consumption and Government investment across the different scenarios is illustrated in Appendix I, Figures I.1, I.2, and I.3, respectively.

Another factor contributing to the lower GDP in scenarios with higher consumption is the decline in business investment. Business investment, composed of a residential and a non-residential component, decreases in Scenarios 1 and 3. This decline can be attributed to a drop in the house price index, which is influenced by housing wealth. In scenarios with higher consumption, households allocate more of their income to spending, leaving less for saving and investment and reducing household wealth.

The development of Business Investment, House Price Index, and Housing Wealth across the different scenarios are depicted in Figures I.4, I.5, and I.6 in Appendix I respectively.

This finding – that higher consumption correlates with lower GDP – was also observed in the extreme conditions test of the *Coefficient on Yd per income group* variable, discussed in Section 5.3 and in Appendix E. As highlighted there, this dynamic reflects a deviation from the *Paradox of Thrift*, a Keynesian theory that suggests higher savings lead to lower economic growth. In contrast, Godley and Lavoie (2012) present a framework where, in the long run, a higher propensity to consume can reduce the steady-state level of income, ultimately lowering GDP. The behaviour observed in the LowGrow SFC model aligns with this alternative view.

Figure 6.6 presents the results for EBI across the different scenarios.

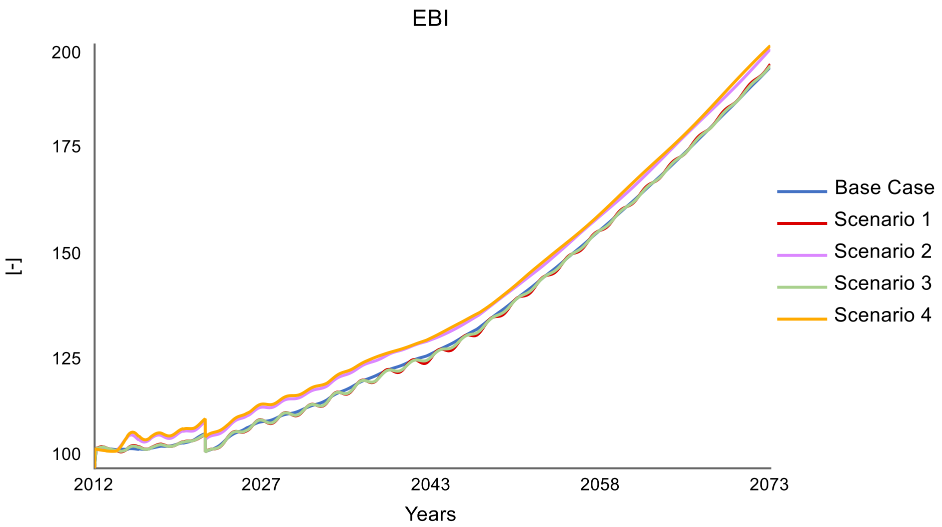

Figure 6.6: Development of the Environmental Burden Index in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

An analysis of Figure 6.6 reveals that the EBI values for Scenarios 2 and 4 are consistently higher than those of Scenarios 1 and 3. Given that the EBI is partially dependent on GDP, and that both of their curves often align (as noted in Section 5.3), this outcome logically follows from the patterns observed for GDP in Figure 6.5.

Scenarios 2 and 4, which feature higher income inequality, show similar trajectories in this figure. For both scenarios, the EBI remains above the Base Case value throughout the simulation. However, Scenario 2 performs slightly better than Scenario 4, suggesting that it imposes a slightly lower environmental burden, though the difference between them remains minimal.

On the contrary, Scenarios 1 and 3 – with more equal income distributions – display lower EBI values, oscillating around or below the Base Case value. Their GDP values were also lower than those of Scenarios 2 and 4, further reinforcing the parallel between economic output and environmental burden. In Figure 6.6, Scenarios 1 and 3 are difficult to distinguish due to their similar behaviour.

The drop in the EBI observed around 2022 is due to the implementation of a floor price on greenhouse gas emissions by the Canadian government. The policy was initially announced in 2017, with the intention to establish a minimum price for greenhouse gas emissions (Jackson & Victor, 2019). In the model, this measure is introduced in 2022, with the floor price set at $50 per tonne. This policy results in a noticeable dip in the EBI, reflecting the increased cost of emissions.

6.3.1. Conclusion Scenario Analysis

By comparing the outcomes of the four scenarios and the Base Case Scenario across *Total Consumption*, *GDP*, and *EBI*, a conclusion can be drawn about their performance and a reflection on the dynamic hypothesis introduced in Section 5.1 can be made.

Scenarios 1 and 3, featuring a more equal income distribution, lead to higher aggregate demand and, consequently, higher total consumption. Scenario 1 results in slightly higher consumption than Scenario 3 due to its higher MPC among low-income groups. In contrast, the more unequal scenarios (2 and 4) show lower aggregate demand and reduced total consumption. Among them, Scenario 2 achieves slightly higher consumption than Scenario 4, again due to a higher MPC.

Despite higher total consumption, Scenarios 1 and 3 result in lower GDP, offering an interesting insight: a more equal income distribution and increased aggregate demand do not necessarily translate into higher GDP. On the contrary, the more unequal scenarios (2 and 4), with lower consumption, yield higher GDP levels.

A similar pattern emerges for EBI. The more equal, high-consumption scenarios show lower environmental burdens, while the more unequal, low-consumption scenarios show higher EBI values. This contradicts the assumption that higher consumption automatically leads to increased environmental pressure.

In summary, the dynamic hypothesis is partially confirmed under varying levels of income inequality and marginal propensity to consume among lower-income groups. The results support the first part of the hypothesis: a more equal income distribution leads to higher total consumption, while greater inequality suppresses it. However, the second part – suggesting that increased consumption results in higher GDP and greater emissions – is not supported by the findings. Likewise, the expectation that a more unequal society would lead to lower GDP and emissions is not validated by the model outcomes.

Chapter 7. Discussion and Reflection

This chapter presents a critical discussion of the research approach taken in this study. In doing so, it marks the beginning of a second iteration of the modelling cycle, as illustrated in Figure 2.1, serving as an evaluation of the extended LowGrow SFC model. Following the discussion, a broader reflection is offered on the overall research approach.

7.1. Discussion

This discussion is divided in three parts: the examination of the scope of the research, the discussion of the original LowGrow SFC model, and finally the discussion of the extended LowGrow SFC model. For both versions of the model, attention is given to the model structure, underlying assumptions, and generalizability.

Research Scope

In defining the scope of this study, the focus was put on carbon emissions from household consumption. However, as shown in Chapter 6, despite the variation in total consumption across the simulated scenarios, GDP remains close to the values of the Base Case Scenario. This suggests that other macroeconomic components – such as government expenditure, business investment, and net trade – play a more substantial role in determining GDP.

Similarly, with respect to emissions, focusing solely on the emissions from household consumption produced only small changes in the EBI. This finding aligns with literature emphasizing that the carbon footprints of high-income individuals often are driven less by consumption and more by investments and capital ownership (Chancel, 2022; Gore, 2021). Moreover, production-related emissions could also be included in such research, as studies have shown these to increase with income levels in OECD countries (Schröder & Storm, 2020).

Another scoping decision was to focus on a single country – Canada – rather than adopting a multi-country perspective. This approach allowed for greater modelling detail, use of country-specific data, and generation of more relevant and actionable policy insights. However, it also introduces limitations. In today's interconnected world, no country operates in isolation, especially within the context of global trade and international climate agreements. A nation pursuing policies that limit economic growth could place itself at a competitive disadvantage relative to other countries, reducing the political feasibility of such strategies. Thus, while national models produce policy recommendations that are more actionable, achieving systemic change ultimately requires coordinated international efforts.

Finally, the scenario analysis in Chapter 6 was based on two uncertainties identified in the literature: income inequality and the marginal propensity to consume. Although a third uncertainty – the marginal propensity to emit or the carbon intensity of consumption – was initially intended to be included, this was unfeasible. In the original LowGrow SFC model, emissions are calculated based on GDP rather than being tied to household consumption. As a result, it was not possible to meaningfully represent carbon inequality due to differences in MPE among income groups within the extended model structure.

The Original LowGrow SFC Model

The original LowGrow SFC model, consisting of 1,782 variables, provides a highly detailed representation of the Canadian economy. While this level of detail enhances the model's comprehensiveness, it also poses challenges in terms of understandability, manageability, and generalizability. Within modelling, many assumptions must be made because models are simplified representations of reality. Although they are powerful tools for exploring complex dynamics and evaluating policy scenarios, their results must be interpreted with caution. Without a clear understanding of the underlying assumptions, model users – such as policymakers – risk drawing incorrect conclusions and implementing ineffective or even counterproductive strategies (Trust et al., 2025). Transparency about these assumptions is therefore critical, enabling future users to assess whether the model is fit for their intended purpose.

Jackson and Victor (2019) note that although the LowGrow SFC model was developed for Canada, its structure could be applied to other high-income countries. In practice, however, the model's complexity makes such generalization difficult. Documenting every assumption across these many variables is virtually impossible. Despite the availability of a detailed model explanation (Jackson & Victor, 2019) and descriptive notes within the model, additional clarification and feedback from the model developers was essential to understanding the system's internal dynamics.

To apply the original LowGrow SFC model to another country, extensive recalibration would be required. Examples of challenges that would occur in generalising the model to, for example, a European country would involve currency conversion and the institutional differences in monetary policy. In Canada, the central bank operates at the national level, with full autonomy over interest rates and other monetary instruments. In contrast, in eurozone countries the European Central Bank (ECB) formulates monetary policy at the continental level.

Nevertheless, the LowGrow SFC model serves as a valuable exploratory framework, capable of revealing trade-offs and interactions that might otherwise remain unseen. For instance, this research demonstrated that rising income inequality and higher consumption do not necessarily result in increased GDP or environmental harm – an insight that could inform sustainable growth strategies in other high-income countries.

The Extended LowGrow SFC Model

Extending the LowGrow SFC model with a sub-model that introduces income inequality as an input variable enabled the simulation and comparison of economic and environmental impacts across more equal and more unequal scenarios. However, by treating income inequality as an input variable, the model does not capture how inequality evolves from interactions among other economic variables. Instead, income distribution has to be calculated externally and manually entered into the extended model, limiting its adaptability for scenario analysis.

Several assumptions were required when implementing data for the sub-model, each carrying implications for the results. First, data interpolation was necessary to convert Statistics Canada data – originally divided into five income groups – into thirteen income groups compatible with the model. While this allowed integration, it may have compromised data accuracy. Second, the use of data from 2012 and 2019, rather than data consistent with LowGrow SFC's base year (2011) may have introduced inconsistencies in the input-data used for the sub-model. Although necessary due to limited data availability, this choice affects the precision of results, as was shown in Figure D.1 and D.2 in Appendix D.

Two main assumptions were also made in the scenario construction presented in Chapter 6. The first relates to how the Gini coefficient was modified. Only the mean income of each income group was adjusted, while the population distribution across those groups remained unchanged. In reality, in a more equal society, individuals would not only earn more or less but also shift between income groups. The second assumption concerns the Marginal Propensity to Consume (MPC). Although the mean income of each group changes across scenarios, the MPC remains fixed. For instance, in Scenario 1, the lowest income group has a mean income of $12,122 per year and in Scenario 2, this amounts to $2,051 per year. Yet both groups are assigned an MPC of 219.31%. Arguably, the group with the higher income in Scenario 1 should have a lower MPC, as the MPC tends to decrease with income.

Finally, the generalizability of this method is discussed. Integrating a sub-model into an existing framework has clear advantages: it avoids the need to develop a model from scratch and enables a focused contribution. However, the time investment required to understand and work with a complex model like LowGrow SFC should not be underestimated. Because the sub-model had to connect to the existing model and feed results back into it, I developed a deep understanding of the system and was ultimately able to contribute to it within a relatively short timeframe. Still, it took considerable effort before I fully understood the (specific part of the) model I was working with. Because of this, some of the features I had hoped to implement turned out to be unfeasible within the project's timeframe. Overall, this approach can be applied to other models and research projects, but it is essential to assess the model structure and complexity before planning any additions. This is especially important when working with a comprehensive model like the LowGrow SFC model.

7.2. Reflection

This reflection offers a broader evaluation of the research by considering the choice of inequality measures and assessing the value of combining macroeconomics with both econometrics and system dynamics.

Measures of Inequality

The choice of inequality metric can significantly influence research outcomes. For instance, Hailemariam et al. (2020), in their study on the relationship between income inequality and carbon emissions across 17 OECD countries, find that top income share ratios are positively correlated with carbon emissions, whereas the Gini coefficient shows a negative correlation.

In the LowGrow SFC model, the Gini coefficient is used to measure income inequality. This metric is widely accepted and commonly applied, making it useful for international comparisons. However, it also has its limitations. The Gini coefficient is less sensitive to changes at the extremes of the income distribution and may therefore underestimate inequality in societies where income or wealth is highly concentrated at the top (Sauter et al., 2016).

Macroeconomics and Econometrics

As highlighted in the literature review, econometric methods are widely used in macroeconomics to quantify relationships between variables and test hypotheses. A strength of econometrics is that it is based on empirical data. By applying statistical techniques to historical datasets, econometrics enables the estimation of both the magnitude and statistical significance of relationships among macroeconomic variables.

However, econometric approaches have limitations. Macroeconomic systems are complex, dynamic, and often influenced by factors that are difficult to observe or quantify. This became evident in the reviewed literature, where relationships – such as that between income inequality and carbon emissions – were estimated statistically, but without addressing the underlying behavioural mechanisms. Failing to examine these processes can blur important cause-and-effect relationships. In some cases, such as with inequality and emissions, it may even lead to contradictory results that lack a clear explanation of the underlying dynamics involved.

Additionally, econometrics is highly dependent on data quality and availability. Its effectiveness may be constrained by the number of countries included in an analysis, the length of the time series, or inconsistencies in how data is collected.

Macroeconomics and System Dynamics

System dynamics (SD) is a modelling approach that is particularly well-suited for modelling the complex, feedback-driven systems typical of macroeconomics. One of its core strengths is its ability to capture dynamic behaviour over time. Unlike econometric models, SD models emphasize feedback loops, accumulations, and time delays, allowing researchers to uncover long-term patterns and dependencies (Auping et al., 2024; Forrester, 1994; Sterman, 2000).

System dynamics is especially valuable for exploring policy scenarios under uncertainty. It can facilitate the examination of structural transformations in the economy and provides insights not only into traditional aggregates like GDP but also into financial flows and balance sheets (Jackson et al., 2016). Through scenario simulation, policymakers can better understand the systemic implications of their decisions.

However, system dynamics has its own limitations. SD models often rely on qualitative relationships and expert judgment rather than empirical data, which can reduce their statistical rigor. Parameter calibration can be subjective, and model validation is particularly challenging when historical data is limited or when abstract concepts are involved.

Future macroeconomic research could benefit from the integration of both econometric and SD modelling approaches. This combination allows researchers to leverage the empirical, statistical, and quantitative strengths of econometrics together with the causal, feedback-oriented perspective offered by system dynamics.

Chapter 8. Conclusion

In this chapter, the results of this study are presented by answering the main research question and its two sub-questions. Subsequently, reflections are provided for future research and for policy makers.

8.1. Answer to the Research Question

This section revisits and answers the main research question, followed by the sub-questions.

The central research question of this study was:

RQ: What are the underlying mechanisms linking income inequality and carbon emissions from consumption, and how do they influence economic growth and carbon emissions over time?

First, the results demonstrate that income inequality affects aggregate demand through its influence on household consumption. In scenarios with a more equal income distribution, total consumption is significantly higher. This is due to increased disposable income for lower-income households, who typically have a higher marginal propensity to consume (MPC). When the MPC is also varied across income groups, scenarios with a higher MPC unsurprisingly yield higher levels of consumption compared to their lower MPC counterparts.

Second, consumption impacts GDP, though the effect is smaller than initially expected. This can be explained by the fact that household consumption is only one component of GDP, alongside government expenditure, business investment, and net trade. Interestingly, scenarios with lower income inequality and higher consumption result in lower GDP values compared to more unequal, lower-consumption scenarios. This counterintuitive outcome occurs because in the model increased consumption is accompanied by reductions in both government spending and business investment, while the opposite happens when consumption decreases.

The link between income inequality and carbon emissions is captured through the Environmental Burden Index (EBI). The model shows a positive relationship between GDP and EBI: higher GDP correlates with greater environmental pressure. Therefore, the more equal, high-consumption scenarios (which produce lower GDP) result in lower environmental burdens, while the more unequal, low-consumption scenarios (which produce higher GDP) lead to higher EBI values. This finding challenges the assumption that higher consumption necessarily leads to greater environmental harm.

This seemingly paradoxical result leads to an important insight: a more equal income distribution and higher consumption do not automatically translate into higher GDP or greater environmental pressure. In fact, the model suggests that a more unequal society – despite lower overall consumption – may result in higher GDP and emissions. This finding suggests that the *equity-pollution dilemma* may not hold, indicating that greater income equality can potentially be achieved without compromising environmental goals.

It is important to emphasize that these conclusions are based on a model representing the Canadian economy. While the developers of the LowGrow SFC model argue that its structure is transferable to other high-income countries, caution is required when generalizing these results. The findings may be relevant for countries with similar economic structures and policy environments but should not be uncritically applied to economies with different institutional, social, or developmental contexts.

To answer the main research question, two sub-questions were formulated and addressed.

SQ1: What does the extant literature say about the relationship between income inequality and carbon emissions from consumption?

Chapter 3 presented a literature review exploring the complex dynamics between income inequality and climate change. The review revealed a lack of consensus regarding the signs of the relationships between income inequality, carbon emissions, and economic growth.

In the connection between income inequality and carbon emissions, consumption plays an important role. However, differing schools of thought offer conflicting perspectives. Some studies suggest that inequality increases emissions due to the carbon-intensive consumption of high-income groups, while others argue that high inequality suppresses total consumption and emissions by limiting the purchasing power of lower-income households.

Despite offering valuable insights, much of the literature falls short in capturing the dynamic, feedback-driven nature of these interactions. The reliance on cross-country or panel data often limits the ability to reflect long-term systemic behaviour or to establish causality. The wide variation in findings highlights three key uncertainties:

1. The impact of income inequality on GDP
2. The effect of the Marginal Propensity to Consume (MPC)
3. The effect of the Marginal Propensity to Emit (MPE) and the Carbon Intensity of Consumption (CIC)

These uncertainties hinder the development of effective policies, underscoring a knowledge gap and the need for a country-specific, system-based modelling approach.

In summary, the literature provides both theoretical and empirical justification for integrating income inequality into ecological macroeconomic models and highlights the necessity of using a dynamic, context-sensitive approach.

SQ2: How does income inequality influence economic behaviour and carbon emissions from consumption within the LowGrow SFC model of the Canadian economy?

This sub-question was addressed through the development of a sub-model that extended the original LowGrow SFC model to incorporate income inequality. Using four scenarios with varying income distributions and MPC values, the analysis revealed that more equal income distributions led to higher total consumption but were associated with lower GDP and EBI levels. Conversely, more unequal scenarios resulted in lower consumption but higher GDP and EBI values.

This dynamic stems from the model's internal mechanisms: increased household consumption leads to reduced business investment and reduced government spending due to countercyclical spending by the government. As a result, GDP decreases when consumption rises and increases when consumption falls. Since EBI is strongly correlated with GDP in the model, it mirrors this dynamic.

These findings suggest that income inequality has macroeconomic and environmental implications. More importantly, they offer a hopeful insight: it may be possible to achieve greater income equality without compromising environmental goals. This challenges conventional assumptions and provides a convincing argument for integrating social and environmental objectives in future policy design.

8.2. Recommendations for Future Research

Based on the findings, discussion, and reflection presented in this study, several options for further research are proposed.

Expanding the Research Scope

To complete this study within the available timeframe, the research scope was deliberately limited. However, expanding beyond this scope presents meaningful opportunities for future exploration.

First, the Marginal Propensity to Emit (MPE) and the Carbon Intensity of Consumption (CIC) were identified as uncertainty in the literature review, alongside the effects of income inequality on GDP and the Marginal Propensity to Consume (MPC). Due to the current structure of the LowGrow SFC model, it was not feasible to implement MPE or CIC within the project timeframe. Nevertheless, incorporating these metrics would enhance the model by allowing for a more precise analysis of carbon inequality across income groups. While technically possible, this extension would require a substantial redesign of the emissions calculation throughout the model.

Additionally, future research could explore incorporating emissions from investment and production activities by income group. The literature suggests these sources represent significant shares of total emissions. Including them alongside consumption-based emissions would allow for a more comprehensive assessment of emissions by income group, facilitating a more accurate estimation of carbon inequality within Canada.

Another valuable extension would involve exploring the generalisability of the model. Due to its complexity, direct application to other countries is challenging. Developing an overview of country-specific variables, assumptions, and institutional dynamics – such as population size, GDP, debt-to-GDP ratio, minimum wage, and net trade - would support researchers aiming to recalibrate the model for use in other national contexts.

Income Inequality

Income inequality was central to this research and extending the LowGrow SFC model to include inequality as an input variable was a meaningful addition to the original model. However, inequality has now become an input variable to the model as it must be manually defined and does not evolve from within the system. A promising direction for future research is to endogenize income inequality, allowing the income distribution and Gini coefficient to be recalculated annually, adjusting aggregate demand, MPC, and consumption per income group for each year accordingly. Ideally, such calculations would also integrate the MPE, enabling the estimation of annual emissions per income group and further explaining the relationship between income inequality and carbon emissions.

Moreover, incorporating alternative income inequality metrics would enrich the model. While the Gini coefficient is widely used, it is less sensitive to changes at the extremes of the income distribution, particularly in economies with high top-end wealth concentration. Alternative measures – such as the Theil index, Atkinson index, median income, and income share ratios – could offer complementary perspectives and improve the model's ability to represent inequality-related dynamics more accurately.

Broader Scenario Testing

This study evaluated the extended LowGrow SFC model under four distinct scenarios, focused on variations in income distribution and MPC. Future research could broaden the scope of scenario testing by incorporating for example the Carbon Reduction, Sustainable Prosperity, and Escape scenarios developed by Jackson and Victor (2019) to test how the extended LowGrow SFC model would behave in a post-growth or degrowth context. Testing a wider range of potential futures would allow for a more comprehensive understanding of the economic, social, and environmental implications of different policy pathways, thereby increasing the model's policy relevance and robustness.

8.3. Recommendations for Policy Makers

The findings of this study hold important implications for policymakers addressing income inequality, economic resilience, and climate mitigation.

Rethinking Measures of Progress

As discussed in the literature review, GDP remains the predominant indicator of progress in mainstream economic analyses (Jackson & Victor, 2019). However, while GDP effectively captures economic progress, it does not reflect societal well-being or account for environmental degradation. Relying solely on GDP can mask worsening social conditions and environmental degradation.

Policymakers are therefore encouraged to adopt a broader conception of prosperity – one that incorporates equity, sustainability, and well-being alongside economic performance. This shift aligns with ecological macroeconomic perspectives, which advocate a shift away from the growth centred mindset toward a more sustainable system.

Integrating complementary indicators such as the Gini coefficient for income inequality and carbon emissions metrics into policy considerations and evaluations would provide a more holistic understanding of societal progress. These measures would enable better-informed decisions that support equitable and sustainable outcomes in the long term.

Focus on Industries

While individual consumption is frequently targeted in climate narratives, the findings of this study indicate that, in a high-income economy such as Canada, household consumption only accounts for a modest share of total GDP and greenhouse gas emissions. Consumer-focused policy instruments – such as carbon taxes – are typically based on the assumption that individuals have sufficient knowledge, financial resources, and agency to alter their spending patterns and influence the carbon intensity of supply chains.

However, the literature also highlights that lower-income groups often face limited access to more sustainable – and typically more expensive – consumption options, as reflected in their higher Marginal Propensity to Emit. As a result, placing the burden of emissions reduction solely on consumers may not produce the intended outcomes.

This insight underscores the need to shift policy focus away from individual consumer behaviour and toward systemic, structural interventions. Regulatory measures at the industrial level are likely to be more effective in reducing emissions and in assigning responsibility to the sectors most accountable for environmental harm. Moreover, such an approach would also address emissions from investment and production activities – two major sources of pollution identified in Section 8.2 as important areas in current climate policy.

Global Cooperation

Although this study focuses on Canada, international cooperation with respect to climate change is essential. As discussed in Section 7.1, a country that independently implements policies to limit economic growth may place itself at a competitive disadvantage relative to others. Without international alignment, such actions are unlikely to be politically or economically sustainable. For instance, introducing strict regulations on polluting industries – such as discussed above – may prompt firms to relocate to countries with more tolerant environmental standards. This relocation would not only result in economic losses for the regulating country, such as job losses and reduced industrial output, but would also fail to reduce global emissions, as the pollution is merely displaced rather than eliminated.

This example underscores the critical need for coordinated international climate action. Effectively addressing climate change requires global corporation to ensure that environmental and social policies reinforce, rather than undermine, one another across borders.

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Appendix A: Overview of Variables used in Sub-Model

This Appendix provides an overview of all the variables used in the sub-model. Table A.1. lists the sector in which the variables are used, the variable names, their function or their initial value, the variable status (if the variable is added to the model, if the variable is an adjusted variable that was already present in the model or if the variable is unchanged), if the variable is arrayed or not, the variable type, and the variable unit.

Table A.1: Overview of Variables used in Sub-Model

Sector	Variable name	Function/Initial value	Status	Arrayed	Type	Unit
Consumption per income group	Consumption (income group effect)	SUM(Consumption_$07_per_income_group)	Added	No	Converter	$/year
	Consumption $07 per income group	Cons_from_Yd_$07_per_income_group+ Cons_from_HHNW_$07_per_income_group	Added	Yes	Converter	$/year
	Cons from Yd $07 per income group	IF Scenario_switch_alpha_1 = 0 THEN Coefficient_on_Yd_per_income_group_for_sensitivity_analysis* DISPOSABLE_INCOME_per_income_group[Income_Classes] ELSE IF Scenario_switch_alpha_1 = 1 THEN "Coefficient_on_Yd_per_income_group_[scen_1_and_2]" [Income_Classes]*DISPOSABLE_INCOME_per_income_group ELSE "Coefficient_on_Yd_per_income_group_[scen_3_and_4]" [Income_Classes]*DISPOSABLE_INCOME_per_income_group	Added	Yes	Converter	$/year
	Scenario switch alpha 1	*0 OR 1 OR 2*	Added	No	Converter	[-]
	Coefficient on Yd per income group for sensitivity analysis	"Coefficient_on_Yd_per_income_group_[base_case]"* Sensitivity_Multiplier	Added	Yes	Converter	[-]
	Coefficient on Yd per income group [base case]	*<Input data from Python>*	Added	Yes	Converter	[-]
	Sensitivity Multiplier	*1*	Added	Yes	Converter	[-]
	Coefficient on Yd per income group [scen 1 and 2]	*<Input data from Excel>*	Added	Yes	Converter	[-]
	Coefficient on Yd per income group [scen 3 and 4]	*<Input data from Excel>*	Added	Yes	Converter	[-]
	Cons from Yd (accumulated)	SUM(Cons_from_Yd_$07_per_income_group)	Added	No	Converter	$/year

	DISPOSABLE INCOME per income group	IF Scenario_switch_Yd = 0 THEN
		"Share_of_Yd_per_income_group_[base_case]"*
		PERSONAL_DISPOSABLE_INCOME_$07
		ELSE IF Scenario_switch_Yd = 1 THEN
		"Share_of_Yd_per_income_group_[scen_1_and_3]"*
		PERSONAL_DISPOSABLE_INCOME_$07
		ELSE
		"Share_of_Yd_per_income_group_[scen_2_and_4]"*
		PERSONAL_DISPOSABLE_INCOME_$07
			Added	Yes	Converter	$/year

	Scenario switch Yd	*0 OR 1 OR 2*	Added	No	Converter	[-]
	Share of Yd per income group [base case]	*<Input data from LowGrow SFC>*	Added	Yes	Converter	[-]
	PERSONAL DISPOSABLE INCOME $07	SFC_Module.Yd_$07m*10^6/MaxReal_GDP_Limiter	Unchanged	No	Converter	$/year
	Share of Yd per income group [scen 1 and 3]	*<Input data from Excel>*	Added	Yes	Converter	[-]
	Share of Yd per income group [scen 2 and 4]	*<Input data from Excel>*	Added	Yes	Converter	[-]
	Cons from HHNW $07 per income group	Coefficient_on_HHNW_per_income_group* HHNW_$07_per_income_group	Added	Yes	Converter	$/year
	Coefficient on HHNW per income group	*0.01*	Added	Yes	Converter	[-]
	HHNW $07 per income group	(SFC_Module.HH_NW*10^6/Price_level)* Share_of_HHNW_per_income_group	Added	Yes	Converter	$/year
	Share of HHNW per income group	*<Input data from Python>*	Added	Yes	Converter	[-]
	HH_NW	Housing_wealth+HH_net_financial_worth	Unchanged	No	Converter	10^6 $/year
	Price level	*1 <Initial value>*	Unchanged	No	Stock	[-]
	Cons from HHNW (accumulated)	SUM(Cons_from_HHNW_$07_per_income_group)	Added	No	Converter	$/year

Consumption	Consumption $07	IF Income_group_effect_switch=0 THEN Consumption_$07m*10^6 - Additional_Electricity_Costs_for_HHs_$b*10^9 - Green_Investment_Module.Consumption_Reduction_from_GHG_ Non_Electricity_Abatement_$b*10^9 ELSE "Consumption_(income_group_effect)" - Additional_Electricity_Costs_for_HHs_$b*10^9 - Green_Investment_Module.Consumption_Reduction_from_GHG_ Non_Electricity_Abatement_$b*10^9	Adjusted	No	Converter	$/year
	Income group effect switch	*0 OR 1*	Added	No	Converter	[-]
	Consumption (income group effect)	*see Consumption (income group effect) sector Consumption per Income Group*	Added	No	Converter	$/year
	Consumption $07m	(Consumption_per_Capita_$07 * POPULATION)/10^6	Unchanged	No	Converter	10^6 $/year

Appendix B: Data Interpolation with Python

This Appendix provides an overview of the Python script that was used to perform the data interpolation to obtain input values for the *Coefficient on Yd per income group* ($\alpha_{1,n}$) and the *Share of HHNW per income group* ($nw^h_{-1,n}$). Figure B.1. shows the general part of the script, Figure B.2. the calculation of the values for the *Coefficient on Yd per income group* and Figure B.3 shows the calculation of the values for the *Share of HHNW per income group*. A further explanation of the code is provided in Section 5.2.3.

```
In [1]: import numpy as np
        from scipy.interpolate import interp1d
        from scipy.integrate import quad

In [2]: # Percentages of population quintiles
        quintiles = np.array([0, 20, 40, 60, 80, 100])

In [3]: # Size of 13 income groups as defined in LowGrow
        income_group_size = np.array([2033390, 1883510, 2422490, 2592250, 2076900, 3341200, 4065630,
            3777860, 1790360, 1055280, 271370, 108580, 180470])

        # Total population with income in the year 2011 as defined in LowGrow
        pop_with_income_2011 = 25599290

        # Income group sizes as percentage of total population
        cumulative_pop = (np.cumsum(income_group_size)/pop_with_income_2011) * 100
        cumulative_pop = np.insert(cumulative_pop, 0, 0)  # Include starting point (0%)

        # Check for myself to see if percentages make sense
        print(cumulative_pop)

        [  0.           7.94314999  15.30081498  24.763929    34.89018641
          43.00330204  56.05522653  71.93703419  86.69470911  93.68849683
          97.81079866  98.87086712  99.29501951 100.        ]
```

Figure B.1: General Part of Python Script

Calculation Coefficient on Yd per income group (alpha1)

```
In [4]: # Insert input data from StatCan: percentage of income spent on consumption per income quintile [2019 data]
        cons_expenses = np.array([217.3, 127, 110.5, 96.2, 75])

        # Interpolation function for consumption from disposable income
        cons_interp = interp1d(quintiles[:-1], cons_expenses, kind='linear', fill_value='extrapolate')

In [5]: # Function that uses interpolation function to integrate over income ranges from 'lower' to 'upper'
        def cons_function(lower, upper):
            result, _ = quad(cons_interp, lower, upper)
            return result / (upper - lower)

        # Filling in the 13 income groups defined by the LowGrow SFC model as income ranges
        new_cons_expenses = []
        for i in range(len(income_group_size)):
            share = cons_function(cumulative_pop[i], cumulative_pop[i+1])
            new_cons_expenses.append(share)

        # Print results
        for i, share in enumerate(new_cons_expenses):
            print(f"Income Group {i+1}: {share:.2f}% of Yd spent on consumption")

        Income Group 1: 199.37% of Yd spent on consumption
        Income Group 2: 164.83% of Yd spent on consumption
        Income Group 3: 131.28% of Yd spent on consumption
        Income Group 4: 118.89% of Yd spent on consumption
        Income Group 5: 111.43% of Yd spent on consumption
        Income Group 6: 103.69% of Yd spent on consumption
        Income Group 7: 91.80% of Yd spent on consumption
        Income Group 8: 75.73% of Yd spent on consumption
        Income Group 9: 64.20% of Yd spent on consumption
        Income Group 10: 58.31% of Yd spent on consumption
        Income Group 11: 55.56% of Yd spent on consumption
        Income Group 12: 54.77% of Yd spent on consumption
        Income Group 13: 54.17% of Yd spent on consumption
```

Figure B.2: Interpolation of Coefficient on Yd per Income Group

Calculation Share of HHNW per income group

In [6]:
```
# Insert input data from StatCan: percentage of HHNW per income quintile [2012 data]
HHNW_shares = np.array([4.0, 9.6, 16.5, 23.8, 46.0])

# Interpolation function for HHNW
HHNW_interp = interp1d(quintiles[:-1], HHNW_shares, kind='linear', fill_value='extrapolate')
```

In [7]:
```
# Function that uses interpolation function to integrate over income ranges from 'lower' to 'upper'
def HHNW_function(lower, upper):
    result, _ = quad(HHNW_interp, lower, upper)
    return result

# Filling in the 13 income groups defined by the LowGrow SFC model as income ranges
new_HHNW_shares = []
for i in range(len(income_group_size)):
    share = HHNW_function(cumulative_pop[i], cumulative_pop[i+1])
    new_HHNW_shares.append(share)

# Normalize values to ensure they sum up to 100%
new_HHNW_shares = np.array(new_HHNW_shares)
new_HHNW_shares = new_HHNW_shares * (100 / np.sum(new_HHNW_shares))

# Print the results
for i, share in enumerate(new_HHNW_shares):
    print(f"Income Group {i+1}: {share:.2f}% of total HHNW")
```

```
Income Group 1: 1.54% of total HHNW
Income Group 2: 2.02% of total HHNW
Income Group 3: 3.47% of total HHNW
Income Group 4: 4.98% of total HHNW
Income Group 5: 4.96% of total HHNW
Income Group 6: 9.88% of total HHNW
Income Group 7: 17.21% of total HHNW
Income Group 8: 25.29% of total HHNW
Income Group 9: 15.18% of total HHNW
Income Group 10: 9.91% of total HHNW
Income Group 11: 2.66% of total HHNW
Income Group 12: 1.08% of total HHNW
Income Group 13: 1.81% of total HHNW
```

In [8]:
```
# Check for myself to see if sum of HHNW shares is indeed 100%
print("Sum of total HHNW shares", np.sum(new_HHNW_shares))
```

```
Sum of total HHNW shares 100.0
```

Figure B.3: Interpolation of Share of HHNW per Income Group

Appendix C: Face Validation

This appendix presents an overview of the face validation conducted as part of the validation of the extended LowGrow SFC model. As this research involved developing a sub-model as an addition to an existing model, the face validation was carried out iteratively and served three main purposes:

1. Evaluation of general understanding of the relationship between income inequality and carbon emissions.
2. Evaluation of the researcher's comprehension of the original LowGrow SFC model, including its structure and underlying assumptions.
3. Structural validation of the set-up, internal consistency and assumptions on which the sub-model is based by comparing it to the expert's knowledge of the real-world system

The following three experts in the field of economics were consulted for the face-validation:

- Peter Victor, economist and Professor Emeritus at the Faculty of Environmental and Urban Change at York University, co-developer of LowGrow SFC model
- Andrew Reeves, post-doctoral fellow in ecological macroeconomics and metrics at the Faculty of Environmental and Urban Change at York University.
- Servaas Storm, economist and Professor at the Faculty of Technology, Policy and Management at Delft University of Technology, first supervisor

The questions asked to the experts were divided in four categories:

1. General questions:
    a) What do you think is the relationship between GDP growth and income inequality…
        i. … in general?
        ii. … in Canada?
        iii. … in Western countries?
    b) What do you think about the Gini coefficient as a measure of inequality?
    c) What is your opinion about climate damage functions?

2. Questions about the LowGrow SFC model:
    a) In which ways is climate damage incorporated in the model?
    b) In which way is the carbon footprint integrated in the model?
    c) How is the relationship between household consumption and household lending modelled?

3. Questions about the structural validity of the sub-model:
    a) Do you think that the modelled connections and polarity are correct?
    b) Do you think that the underlying assumptions are correct?
    c) Are there any missing feedback loops in the sub-model? Do the feedbacks have the right polarity?
    d) How do you look at the implementation of a carbon footprint within this model?
    e) Do you think that this is useful addition to the LowGrow SFC model?
    f) What do you think are the limitations of this sub-model?

4. Specific data/variable related questions:
    a) Is data interpolation with Statistics Canada data a suitable way to make the data fitting?
    b) Which data would be suitable to use if Canadian data is not available?
    c) How do the coefficients on disposable income per capita and household net worth per capita relate back to the SFC module?
    d) For the calculation of disposable income per income group, would it be better to use the sum of the number of people in income groups or the total Canadian population?

The most important feedback received by these experts was:
- Under the same assumptions, the sub-model and the original LowGrow SFC model should produce the same results
- The climate impact of consumption is already captured within the existing model and does not require the addition of a separate climate damage function
- The climate impact of consumption at the national level is relatively small compared to emissions from sectors such as industry
- If the consumption in the sub-model changes, the model should still be stock-slow consistent

Feedback sessions on the sub-model with the experts took place between February and April 2025.

Appendix D: Behavioural Comparison

This appendix compares the behaviour of the sub-model to that of the original LowGrow SFC model as part of the validation process. Specifically, the sum of disaggregated consumption across all income groups in the sub-model should equal the aggregate consumption as calculated by the original model.

To verify this consistency, the outputs for *Total Consumption*, *Consumption from Yd*, and *Consumption from HHNW* are compared between the two models. Figure D.1 shows Total Consumption as calculated by both.

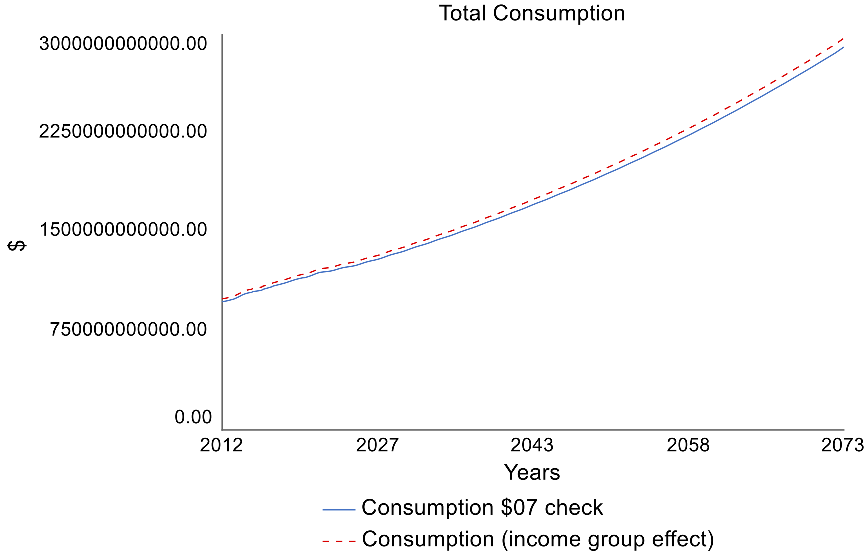

*Figure D.1: Comparison of Total Consumption Calculated by the Original LowGrow SFC Model (*Consumption $07 check*, Blue) and the Sub-Model (*Consumption (income group effect)*, Dashed Red)*

The figure shows a minor discrepancy between the total consumption calculated by the original LowGrow SFC model and that produced by the sub-model. To identify the source of this difference, total consumption is disaggregated into consumption from disposable income (Figure D.2) and consumption from household net worth (Figure D.3).

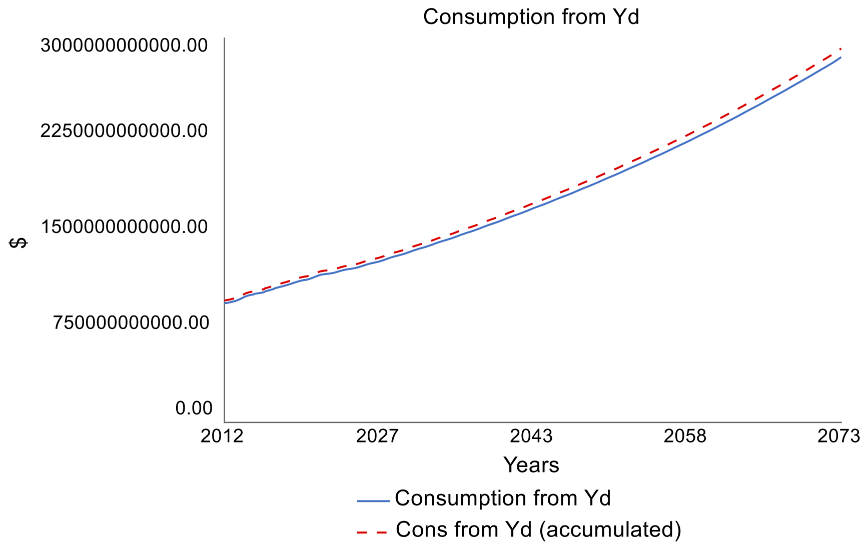

*Figure D.2: Comparison of Consumption from Disposable Income Calculated by the Original LowGrow SFC Model (*Consumption from Yd*, Blue) and the Sub-Model (*Cons from Yd (accumulated)*, Dashed Red)*

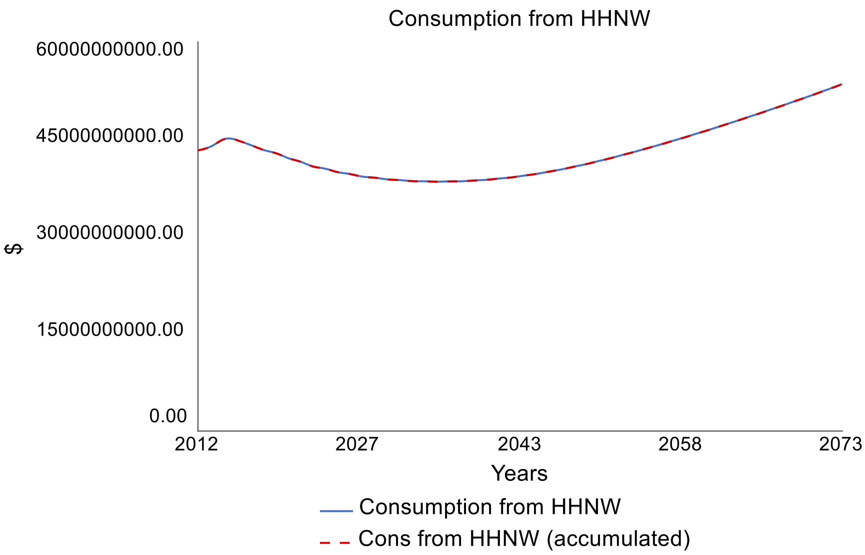

*Figure D.3: Comparison of Consumption from Household Net Worth Calculated by the Original LowGrow SFC Model (*Consumption from HHNW*, Blue) and the Sub-Model (*Cons from HHNW (accumulated)*, Dashed Red)*

As shown in Figure D.2, the discrepancy observed in Figure D.1 originates from the calculation of consumption from disposable income, as a similar deviation appears in this figure. In contrast, Figure D.3 shows that consumption from household net worth is identical in both models. The difference in consumption from disposable income can be attributed to a variation in input data: the original LowGrow SFC model uses 2011 data, whereas the sub-model's *Coefficient on Yd per income group* is based on 2019 data, as 2011 input data for this parameter were unavailable.

Appendix E: Extreme Conditions Test

This appendix presents the extreme condition tests conducted as part of the validation of the extended LowGrow SFC model. In these tests, relevant model parameters are set to extreme values to assess the model's robustness. The input parameters tested are:

- Coefficient on disposable income (Yd) per income group
- Coefficient on household net worth (HHNW) per income group
- Initial consumption

The first two variables originate from the sub-model, while the third originates from the original LowGrow SFC model but also affects calculations within the sub-model. Table E.1 summarizes the input parameters and their extreme values applied in these tests.

Table E.1: Input Variables and Their Extreme Values for Extreme Condition Test

Variable name	Extreme value – Low	Original value (Base Case)	Extreme value – High
Coefficient on Yd per income group ($\alpha_{1,n}$)	10% of values	13 values as defined in Table 5.1, section 5.2.3	120% of values
Coefficient on HHNW per income group ($\alpha_{2,n}$)	0.0001	0.01	0.5
Initial consumption	$10.000.000.000	$938.739.000.000	$1.500.000.000.000

The output of the following Key Performance Indicators (KPIs) will be tested under extreme conditions:

- Total Consumption
- GDP
- Environmental Burden Index (EBI)

Coefficient on Disposable Income per Income Group ($\alpha_{1,n}$)

Figure E.1 presents the development of the Total Consumption for extreme values of the *Coefficient on Yd per income group*, an input value of the sub-model.

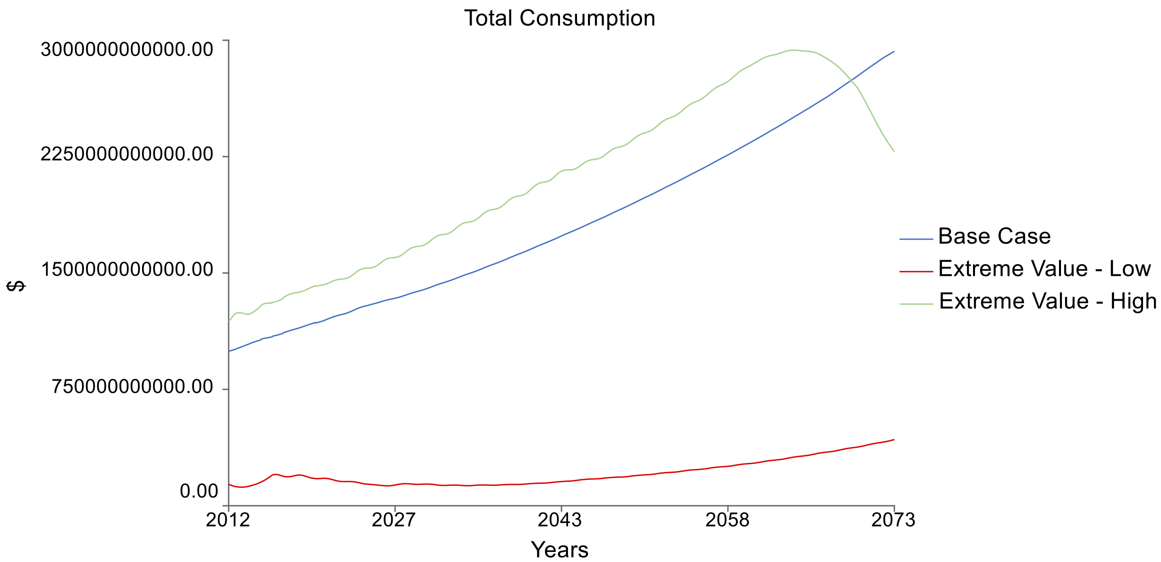

Figure E.1: Development of Total Consumption for Coefficient on Yd per income group *with its Original Values (Base Case, Blue), 10% of its Original Values (Extreme Value – Low, Red) and 120% of its Original Values (Extreme Value – High, Green)*

When all income groups reduce their consumption from disposable income to 10% of their original levels, total consumption behaves as expected: it drops sharply and then remains consistently low. For the opposite extreme – where all groups consume 120% of their original levels – total consumption again follows expectations. A pronounced peak around 2063 may reflect a "limits-to-growth" dynamic, where demand begins to exceed supply and production can no longer keep pace.

Figure E.2 presents the development of GDP for extreme values of the *Coefficient on Yd per income group*.

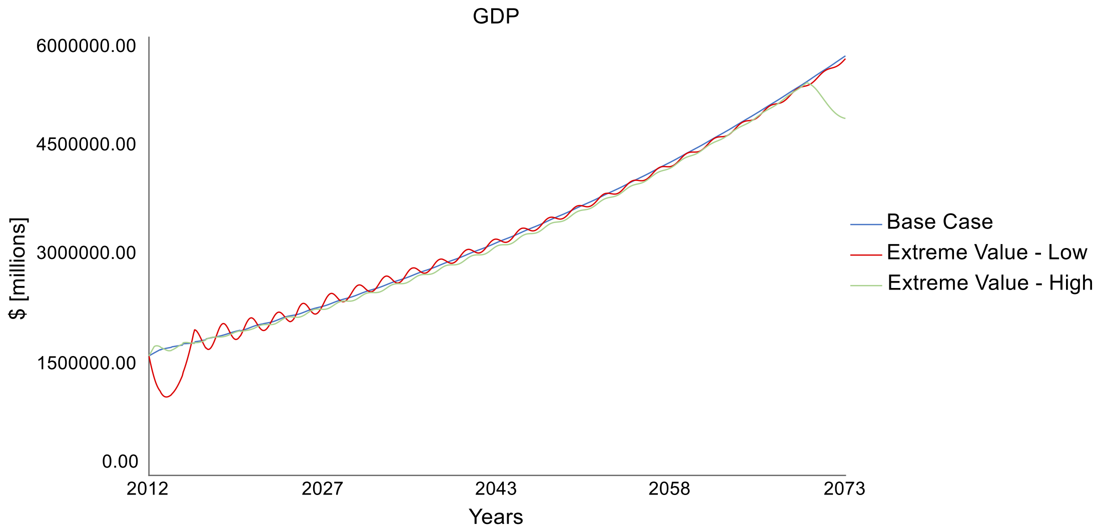

Figure E.2: Development of GDP for Coefficient on Yd per income group with its Original Values (Base Case, Blue), 10% of its Original Values (Extreme Value – Low, Red) and 120% of its Original Values (Extreme Value – High, Green)

GDP, however, displays a less expected pattern. Although it initially declines in the low-consumption scenario and initially increases in the high-consumption one, GDP eventually oscillates around slightly higher values in the low-consumption case compared to the high-consumption case. This contradicts the *Paradox of Thrift*, which posits that a higher propensity to save (i.e., lower consumption) leads to lower economic growth (Godley & Lavoie, 2012) while in this case, a higher marginal propensity to consume appears to be associated with lower economic growth.

Figure E.3 presents the development of the EBI for extreme values of the *Coefficient on Yd per income group*.

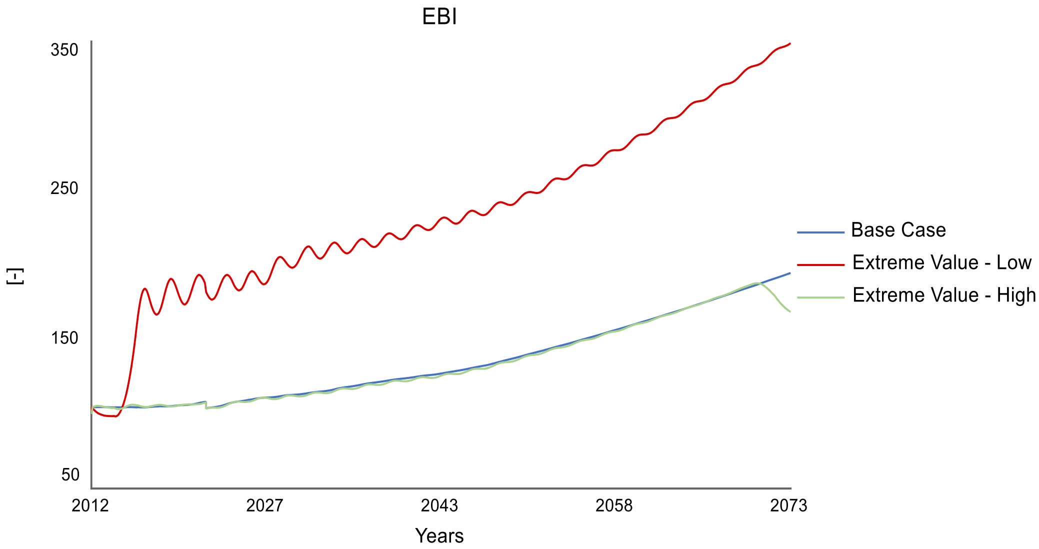

Figure E.3 Development of the Environmental Burden Index for Coefficient on Yd per income group *with its Original Values (Base Case, Blue), 10% of its Original Values (Extreme Value – Low, Red) and 120% of its Original Values (Extreme Value – High, Green)*

The EBI also shows somewhat unexpected behaviour. Under low-consumption conditions, it rises sharply at first and continues increasing with damped oscillations. In contrast, under high consumption, the EBI stays close to its Base Case levels. This may be explained by the fact that GDP also remains near its Base Case levels in the high-consumption scenario, indicating a close linkage between these two variables. Overall, the EBI curve appears to track the GDP curve closely, as evidenced by a noticeable decline in both variables around the year 2068, corresponding with a drop in total consumption for the high extreme value.

Coefficient on Household Net Worth per Income Group ($\alpha_{2,n}$)

Figure E.4 presents the development of the Total Consumption for extreme values of the *Coefficient on HHNW per income group*, an input value of the sub-model.

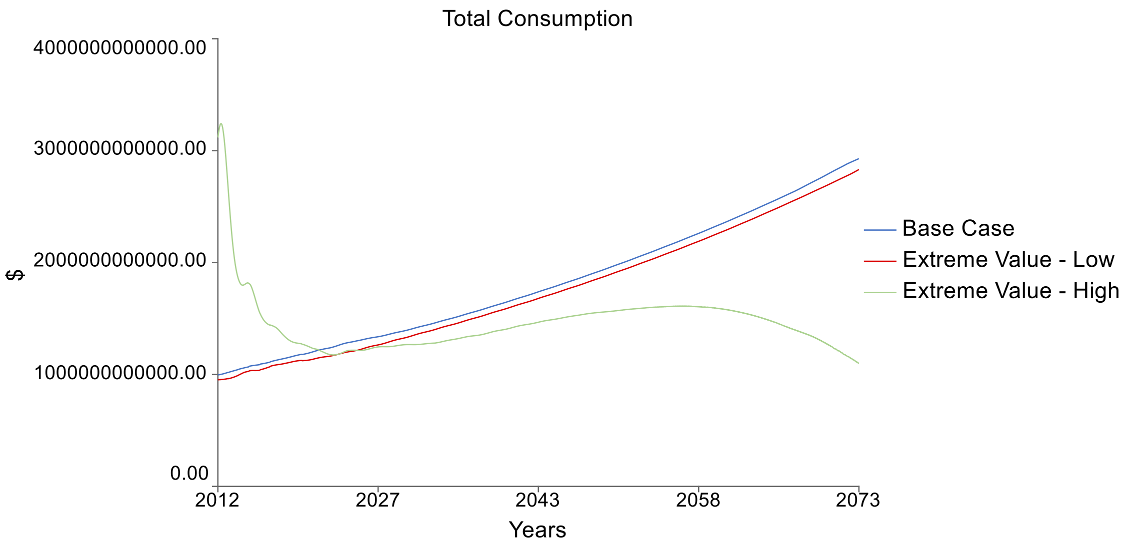

Figure E.4: Development of Total Consumption for Coefficient on HHNW per income group *with a Value of 0.01 (Base Case, Blue), a Value of 0.0001 (Extreme Value – Low, Red) and a Value of 0.50 (Extreme value – High, Green)*

When the consumption rate from household net worth is reduced from 1% to 0.01%, a slight decline in total consumption is observed. This modest change is expected, as consumption from household net worth already constitutes a small share of total consumption; consumption from disposable income remains the dominant source. In the opposite scenario, where the consumption rate from household net worth is increased from 1% to 50%, total consumption experiences a sharp initial spike. This is followed by a steep decline, likely due to demand exceeding the system's productive capacity. It appears that the economy cannot sustain such elevated demand levels, causing total consumption to fall rapidly and stabilize well below base case values – indicating an imbalance occurring in the system.

Figure E.5 presents the development of GDP for extreme values of the *Coefficient on HHNW per income group*.

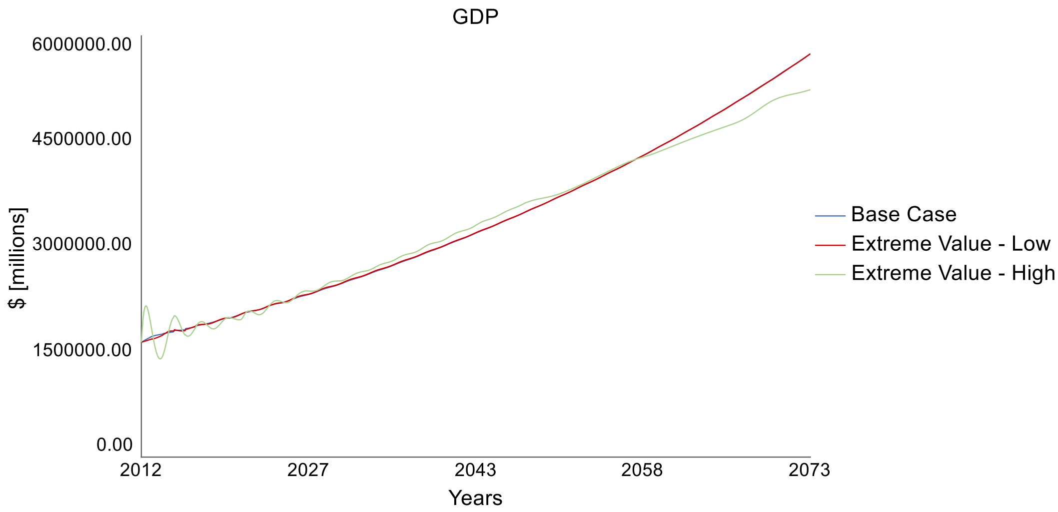

Figure E.5: Development of GDP for Coefficient on HHNW per income group with a Value of 0.01 (Base Case, Blue), a Value of 0.0001 (Extreme Value – Low, Red) and a Value of 0.50 (Extreme value – High, Green)

For the low value of consumption from household net worth, GDP shows no significant deviation, which aligns with expectations given the limited impact of this component on overall consumption. In contrast, for the high value GDP clearly responds to changes in total consumption. Following an initial rise, GDP begins to oscillate around its Base Case value. As total consumption declines, GDP growth slows – an outcome that is consistent with expectations.

Figure E.6 presents the development of the EBI for extreme values of the *Coefficient on HHNW per income group*.

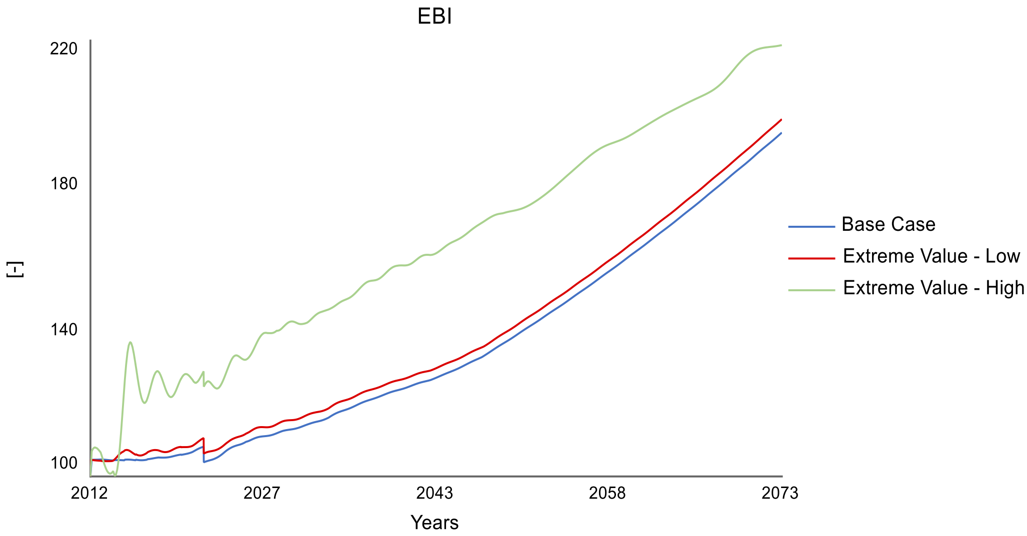

Figure E.6: Development of the Environmental Burden Index for Coefficient on HHNW per income group *with a Value of 0.01 (Base Case, Blue), a Value of 0.0001 (Extreme Value – Low, Red) and a Value of 0.50 (Extreme value – High, Green)*

In the low-consumption scenario, the EBI displays somewhat counterintuitive behaviour, increasing slightly despite reduced consumption. This may be explained by the fact that the EBI includes factors beyond GDP and emissions, and the rise could reflect changes in those other parameters. In the high-consumption scenario, the EBI behaves more intuitively: the spikes in total consumption and GDP are mirrored by an initial increase in EBI, which then remains substantially above the Base Case level throughout the simulation.

Initial Consumption

Figure E.7 presents the development of the Total Consumption for extreme values of the *Initial Consumption*, an input variable of the original LowGrow SFC model.

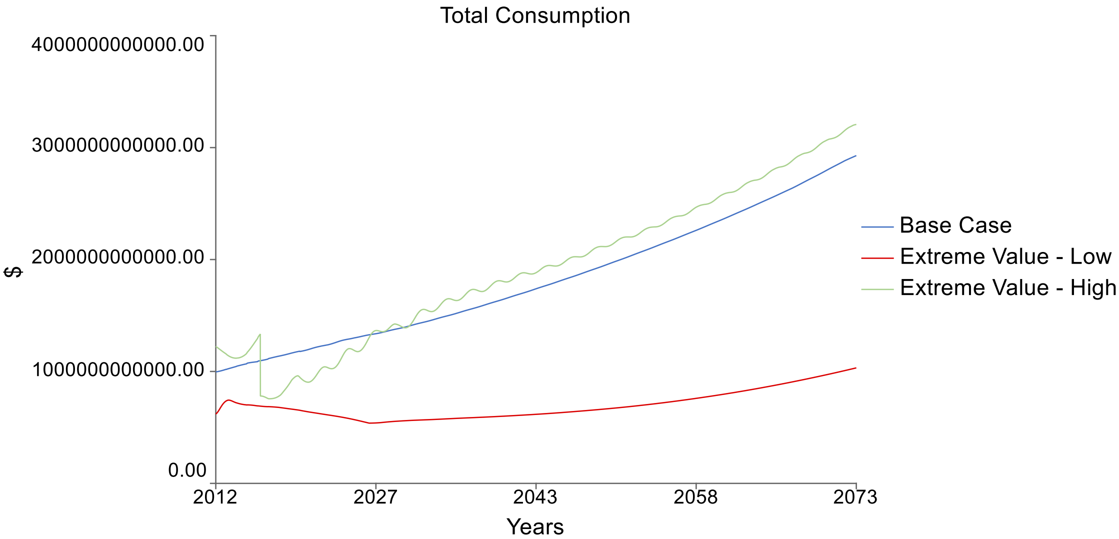

Figure E.7: Development of Total Consumption for Initial Consumption 2011 $07 *with a Value of $938.739.000.000 (Base Case, Blue), a Value of $10.000.000.000 (Extreme Value – Low, Red) and a Value of $1.500.000.000.000 (Extreme value – High, Green)* n the scenario where initial consumption is reduced to approximately 1% of its base case value, total consumption behaves as expected. It begins at a much lower level and remains significantly below the base case throughout the simulation. In the scenario where initial consumption is set to approximately 150% of its base case value an initial spike in total consumption is followed by a dip that brings it below the base case level. This is succeeded by damped oscillations, during which total consumption gradually begins to rise again.

Figure E.8 presents the development of GDP for extreme values of the *Initial Consumption*.

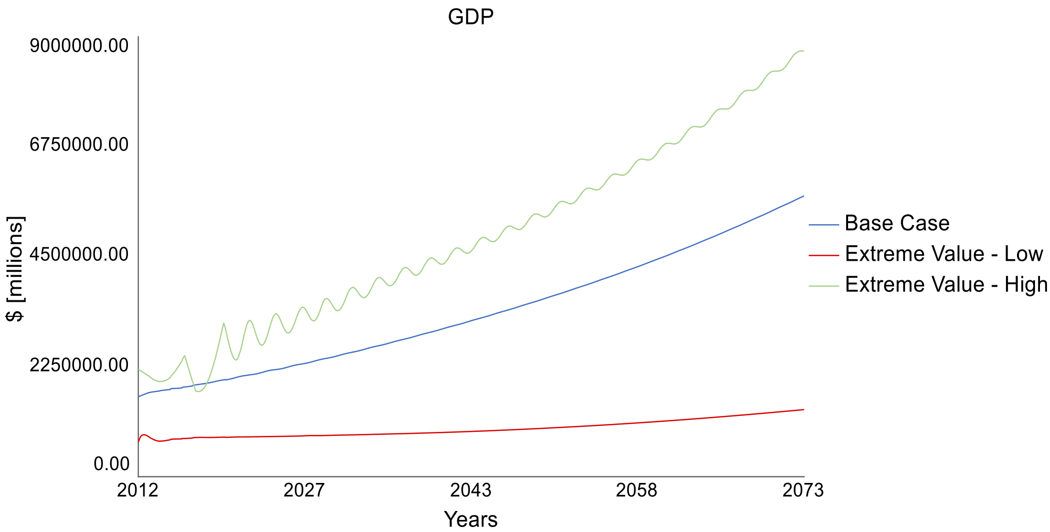

Figure E.8: Development of GDP for Initial Consumption 2011 $07 with a Value of $938.739.000.000 (Base Case, Blue), a Value of $10.000.000.000 (Extreme Value – Low, Red) and a Value of $1.500.000.000.000 (Extreme value – High, Green)

GDP exhibits expected behaviour across both extreme scenarios. In the low initial consumption case, GDP starts at a much lower level and remains significantly below the Base Case throughout the simulation – mirroring the pattern observed in total consumption. In the high initial consumption scenario, oscillatory behaviour is again visible. GDP briefly dips below the Base Case value around the year 2020 before it starts to oscillate around a higher level than the Base Case.

Figure E.9 presents the development of the EBI for extreme values of the *Initial Consumption*.

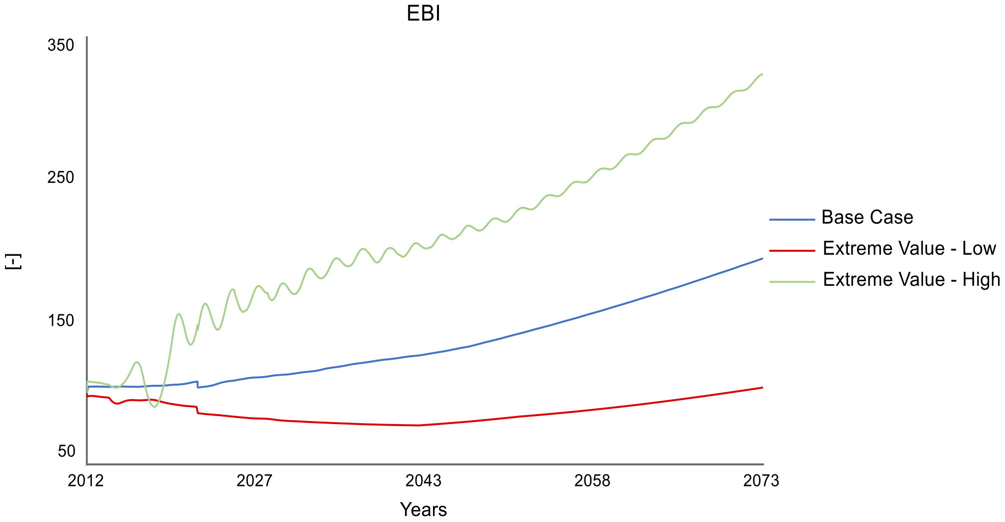

Figure E.9: Development of the Environmental Burden Index for Initial Consumption 2011 $07 *with a Value of $938.739.000.000 (Base Case, Blue), a Value of $10.000.000.000 (Extreme Value – Low, Red) and a Value of $1.500.000.000.000 (Extreme value – High, Green)*

The EBI follows a pattern similar to GDP in both scenarios, highlighting their relationship. In the low-consumption case, the EBI remains well below its Base Case values throughout the time frame. In the high-consumption case, the EBI oscillates above the Base Case, with a dip around 2020 before rising again.

Appendix F: Sensitivity Analysis of the Original LowGrow SFC Model

Before conducting a sensitivity analysis on the extended LowGrow SFC model, a univariate sensitivity analysis is first performed on the original model, as presented in this appendix. The purpose of this analysis is twofold: it provides insight into the behaviour of relevant variables in the model's original configuration, and it provides a baseline for comparison with the extended version of the model.

The input variables included in the sensitivity analysis are:

- Coefficient on disposable income (Yd) per capita
- Coefficient on household net worth (HHNW) per capita
- Initial rate of household tax and transfer (HH TAX & TRANSFER)

The first two variables originate from the Consumption sector in the original LowGrow SFC model and influence consumption directly, while the third variable is an initial value that affects consumption behaviour indirectly. Each variable is tested within a ±10% range from its original value. Table F.1 provides an overview of the original values of the input variables, along with their corresponding lower and upper bounds.

Table F.1: Variables for Sensitivity Analysis of Original LowGrow SFC Model

Variable name	Original value	Lower bound	Upper bound
Coefficient on Yd per capita	0.79	0.711	0.869
Coefficient on HHNW per capita	0.01	0.009	0.011
Initial rate HH TAX & TRANSFER	0.15	0.135	0.165

For each variable, the model is run 50 times, with 50 evenly spaced samples between the lower and upper bounds.

The sensitivity of the following KPI's will be tested:

- Total Consumption
- GDP
- Environmental Burden Index (EBI)

Sensitivity Analysis for Coefficient on Yd per capita (α_1)

Figures F.1, F.2, and F.3 show the results of the sensitivity analysis of the *Coefficient on Yd per capita*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively.

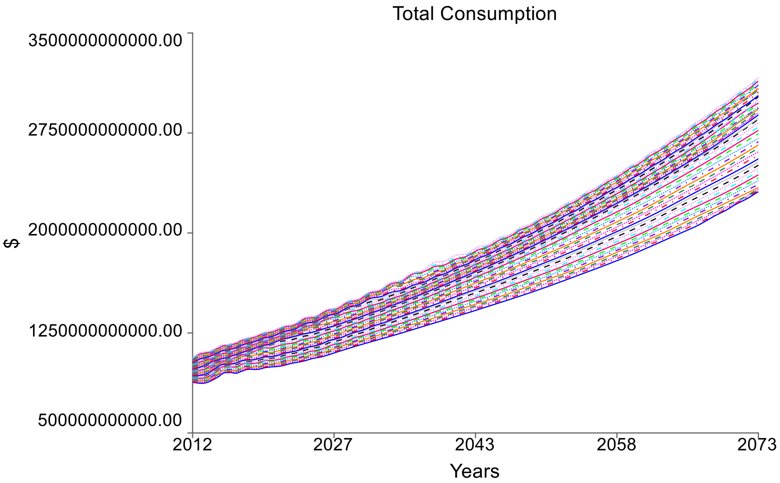

Figure F.1: Development of the Total Consumption for Coefficient on Yd per capita *Between 0.711 and 0.869 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

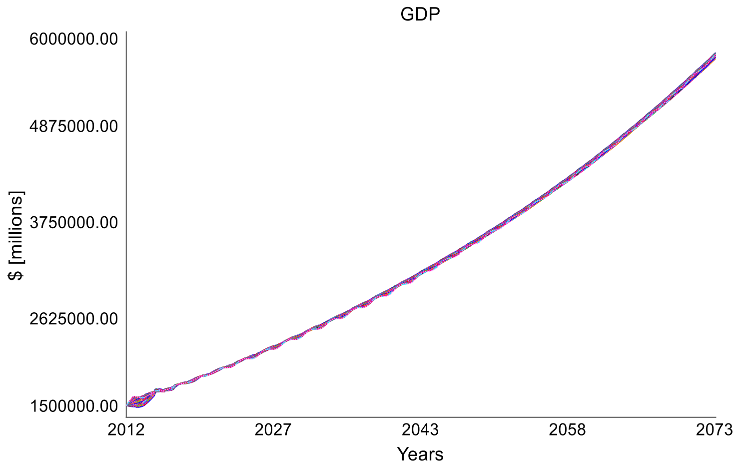

Figure F.2: Development of GDP for Coefficient on Yd per capita *Between 0.711 and 0.869 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

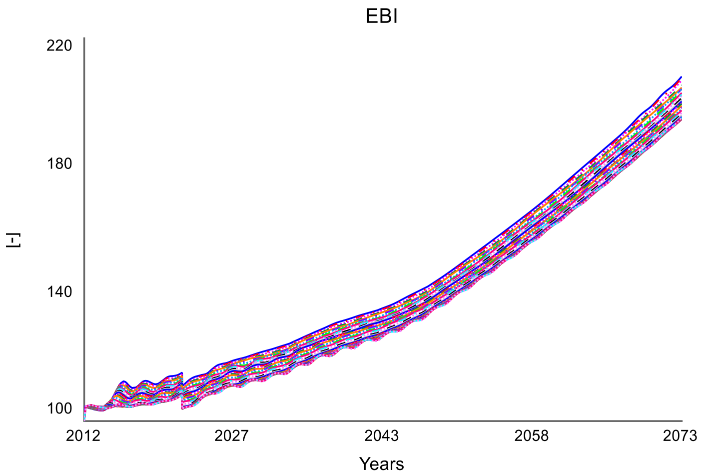

Figure F.3: Development of the Environmental Burden Index for Coefficient on Yd per capita *Between 0.711 and 0.869 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

The sensitivity analysis of the *Coefficient on Yd per capita* on *Total Consumption* reveals a clear numerical sensitivity. This outcome is expected, as consumption from disposable income constitutes the largest component of total consumption. While *GDP* and *EBI* also exhibit numerical sensitivity to changes in this coefficient, their responses are less pronounced than that of total consumption.

Additionally, some behavioural sensitivity is observed in the form of oscillations near the upper and lower bounds of the sensitivity range. For *Total Consumption*, these fluctuations may be caused by increased demand outpacing supply, causing a temporary imbalance. In the cases of *GDP* and *EBI*, the oscillations likely represent secondary effects stemming from the oscillations in total consumption.

Sensitivity Analysis for Coefficient on HHNW per capita (α_2)

Figures F.4, F.5, and F.6 show the results of the sensitivity analysis of the *Coefficient on HHNW per capita*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively

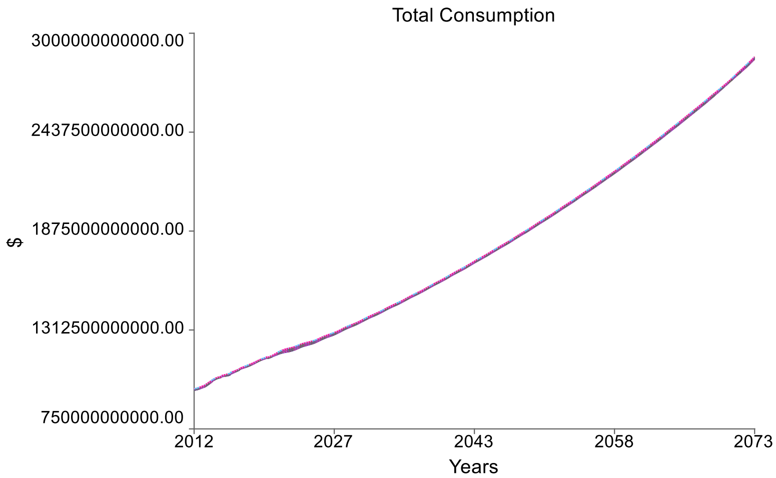

Figure F.4: Development of Total Consumption for Coefficient on HHNW per capita *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

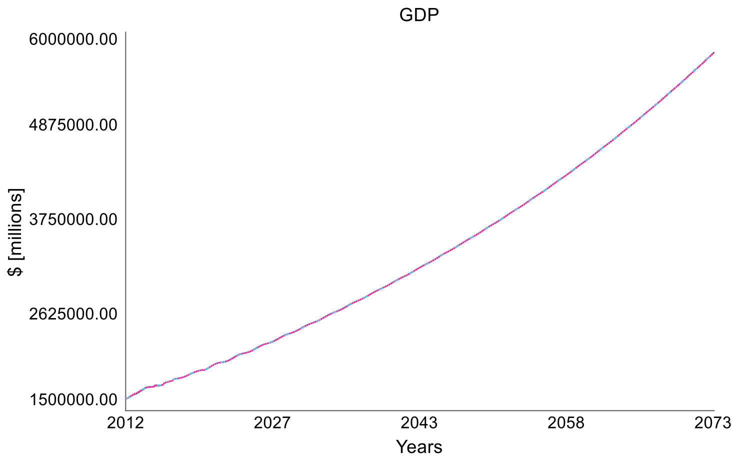

Figure F.5: Development of GDP for Coefficient on HHNW per capita *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

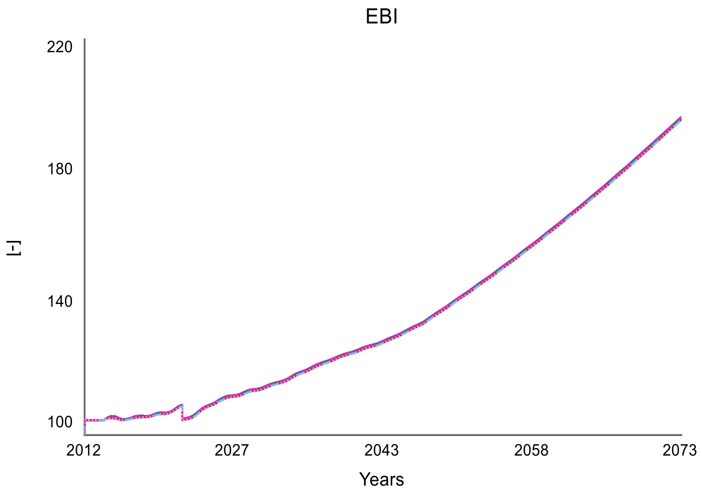

Figure F.6: Development of the Environmental Burden Index for Coefficient on HHNW per capita *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

Variations in the *Coefficient on HHNW per capita* exhibit minimal numerical and behavioural sensitivity in *Total Consumption*, *GDP*, and *EBI*, as shown in the three figures above. This outcome is expected, since consumption from household net worth represents only a small fraction of the total consumption.

Sensitivity Analysis for Initial rate HH TAX & TRANSFER

Figures F.7, F.8, and F.9 show the results of the sensitivity analysis of the *Initial rate HH TAX & TRANSFER*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively

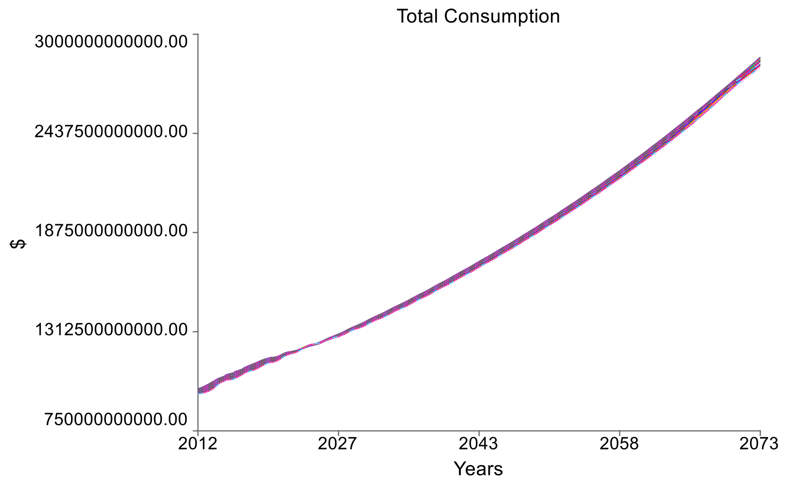

Figure F.7: Development of Total Consumption *for an* Initial rate HH TAX & TRANSFER *Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

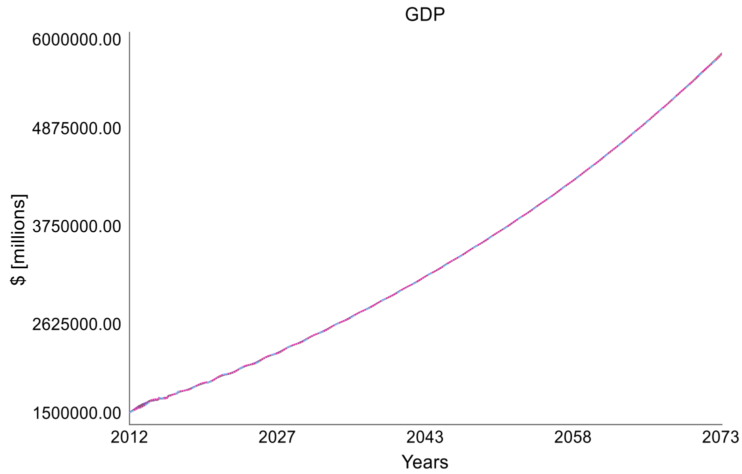

Figure F.8: Development of GDP *for* Initial rate HH TAX & TRANSFER *Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

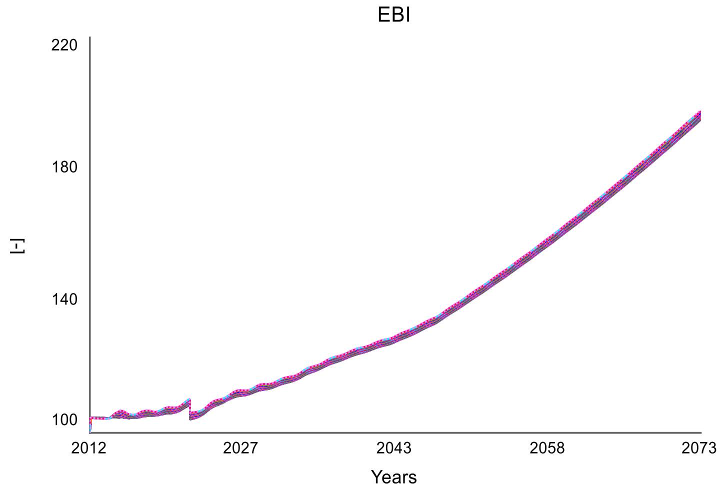

Figure F.9: Development of the Environmental Burden Index *for* Initial rate HH TAX & TRANSFER *Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

In the original LowGrow SFC model, variations in the *Initial rate HH TAX & TRANSFER* show some numerical sensitivity in *Total Consumption* and *EBI*, although the change in magnitude of values remains relatively small. The overall shape of these curves remains similar to their respective base case scenarios. The minor oscillations appearing during the first half of the time horizon, indicate behavioural sensitivity for these two KPI's. In contrast, *GDP* shows no sensitivity to changes in the *Initial rate HH TAX & TRANSFER*, neither numerical nor behavioural.

To conclude, the original LowGrow SFC model appears most sensitive to variations in the *Coefficient on Yd per capita*. For this input, both numerical and behavioural sensitivity are observed, which aligns with expectations, given its strong influence on the total consumption. The observed behavioural oscillations may stem from cyclical imbalances between supply and demand. In contrast, the model is largely insensitive to changes in the *Coefficient on HHNW per capita*, as this variable contributes only marginally to total consumption. Meanwhile, changes in the *Initial rate HH TAX & TRANSFER* produce only modest numerical and behavioural effects.

Appendix G: Sensitivity Analysis of the Extended LowGrow SFC Model

This appendix presents a sensitivity analysis of the extended LowGrow SFC model as part of the validation process. First, a univariate sensitivity analysis is performed, after which a multivariate sensitivity analysis is conducted.

The input variables included in the sensitivity analysis are:

- Coefficient on disposable income (Yd) per income group
- Coefficient on household net wealth (HHNW) per income group
- Initial household tax and transfer rate (HH TAX & TRANSFER)

The first two variables originate from the sub-model, while the third is part of the original LowGrow SFC model. The inclusion of both sub-model and original model variables in the sensitivity analysis ensures that the integrated model yields plausible and coherent results, given that the sub-model must function in harmony with the original framework.

The sensitivity of the following KPI's will be tested:

- Total Consumption
- GDP
- Environmental Burden Index

Univariate Sensitivity Analysis

In a univariate sensitivity analysis, each variable is tested individually to assess its impact on model outcomes. For each analysis, the model is run 50 times, with the number of samples – representing the incremental steps between the lower and upper bounds – set to 50 for each tested variable.

Coefficient on Yd per Income Group ($\alpha_{1,n}$)

The *Coefficient on Yd per income group* contains distinct values for each of the 13 income groups, which requires a modified approach to the sensitivity analysis. Since Stella Architect does not have a built-in functionality to directly perform sensitivity analysis on arrayed variables with varying values, two additional variables (both highlighted in orange in Figure 5.3) are introduced into the sub-model:

1. *Coefficient on Yd per income group for sensitivity analysis*
2. *Sensitivity Multiplier*

The *Coefficient on Yd per income group for sensitivity analysis* is calculated by multiplying the original *Coefficient on Yd per income group* by the *Sensitivity Multiplier*. The *Sensitivity Multiplier* is an arrayed variable with the 13 income groups as dimensions and takes value of 1 for every dimension.

By applying a sensitivity analysis ranging from 0.9 to 1.1 on the *Sensitivity Multiplier*, the corresponding values for each income group of the *Coefficient on Yd per income group* are multiplied by –10% to +10% of their original levels. By applying this approach, the sensitivity analysis for *Coefficient on Yd per income group* can be executed. In normal model runs, these additional variables have no impact, as each value of *Coefficient on Yd per income group* is simply multiplied by 1.

Table G.1 summarizes the original values of the *Coefficient on Yd per income group* alongside the lower and upper bounds used in the sensitivity analysis.

Table G.1: Sensitivity Analysis values for Coefficient on Yd per income group ($\alpha_{1.n}$)

Income group	Original value	Lower bound	Upper bound
Under $5.000	1.9937	1.7943	2.1931
To $10.000	1.6483	1.4835	1.8131
To $15.000	1.3128	1.1815	1.4441
To $20.000	1.1889	1.0700	1.3078
To $25.000	1.1143	1.0029	1.2257
To $35.000	1.0369	0.9332	1.1406
To $50.000	0.9180	0.8262	1.0098
To $75.000	0.7573	0.6816	0.8330
To $100.000	0.6420	0.5778	0.7062
To $150.000	0.5831	0.5248	0.6414
To $200.000	0.5556	0.5000	0.6112
To $250.000	0.5477	0.4929	0.6025
Above $250.000	0.5417	0.4875	0.5959

Figures G.1, G.2, and G.3 present the results of the sensitivity analysis of the *Coefficient on Yd per income group*, depicting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively.

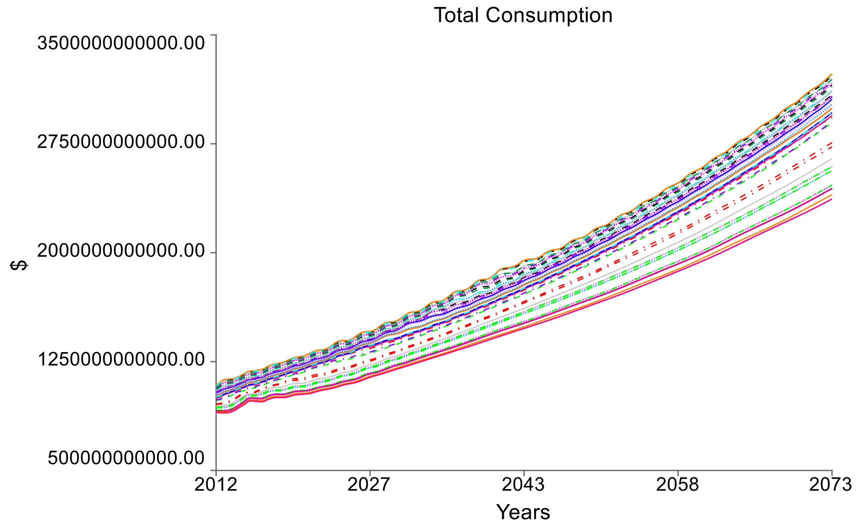

Figure G.1: Development of Total Consumption for Coefficient on Yd per income group *Between -10% and +10% of Every Individual Income Group Value (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

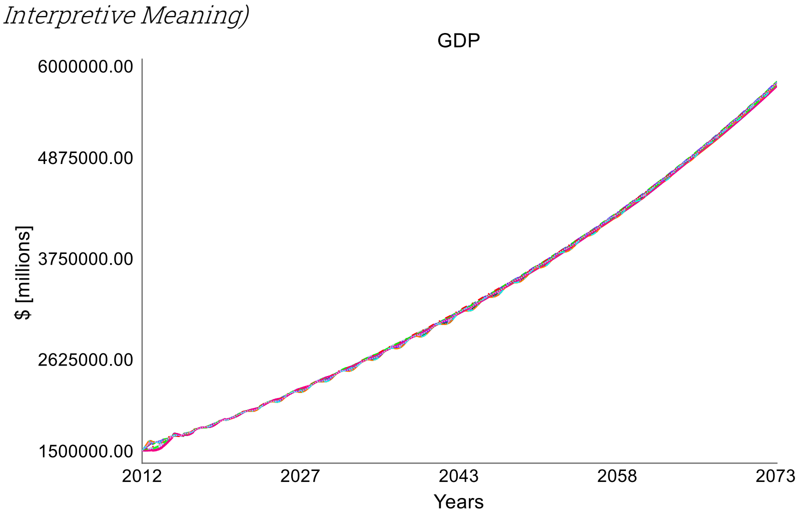

Figure G.2: Development of GDP *for* Coefficient on Yd per income group *Between -10% and +10% of Every Individual Income Group Value (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

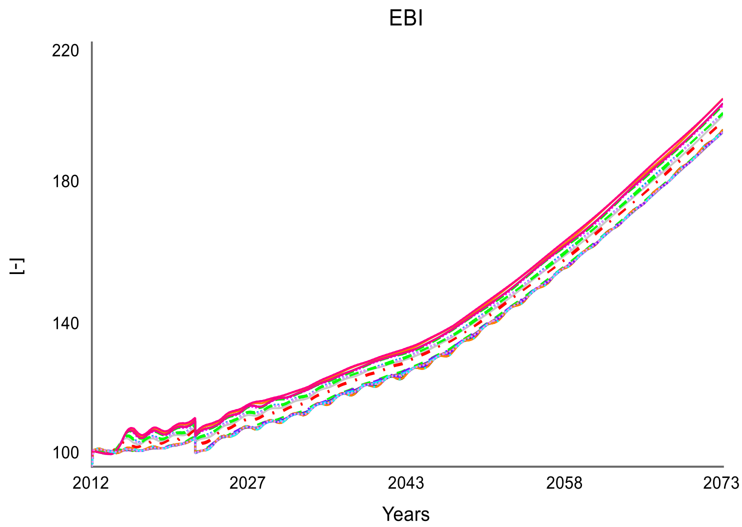

Figure G.3: Development of the Environmental Burden Index *for* Coefficient on Yd per income group *Between -10% and +10% of Every Individual Income Group Value (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

The sensitivity analysis of the *Coefficient on Yd per Income Group* reveals a noticeable change in the magnitude of *Total Consumption*, indicating numerical sensitivity. This result is expected, as consumption from disposable income constitutes the largest share of total consumption. *GDP* and *EBI* also exhibit numerical sensitivity, although the variations are less pronounced compared to *Total Consumption*. This is understandable, as *GDP* is influenced by multiple components beyond consumption, and *EBI* depends on more than just *GDP*.

Across all three KPIs, the overall shape of the curves remains consistent, but small oscillations are visible – particularly near the upper and lower bounds of the sensitivity range during the first 40 years of the model run. These fluctuations indicate behavioural sensitivity. In the case of *Total Consumption*, the oscillations may be caused by a lag in supply response due to abrupt shifts in demand. For *GDP* and *EBI*, the fluctuations are likely a secondary effect of the oscillations in *Total Consumption*. In later stages of the simulation, these oscillations taper off.

The results of this analysis closely align with those obtained for the sensitivity analysis of the *Coefficient on Yd per capita* in the original LowGrow SFC model (see Appendix F), suggesting consistent sensitivity behaviour between the original and the extended model.

Coefficient on HHNW per Income Group ($\alpha_{2,n}$)

The *Coefficient on HHNW per income group* is an arrayed variable with a constant value of 0.01 across all income groups. In this sensitivity analysis, this variable will range between 0.009 and 0.011 (±10%).

Figures G.4, G.5, and G.6 illustrate the effects of this variation on *Total Consumption*, *GDP*, and *EBI*, respectively.

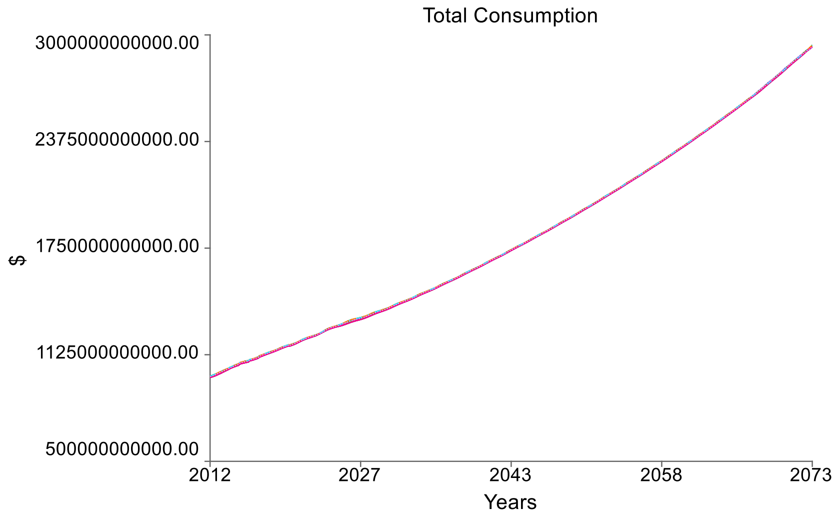

Figure G.4: Development of Total Consumption for a Coefficient on HHNW per income group *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

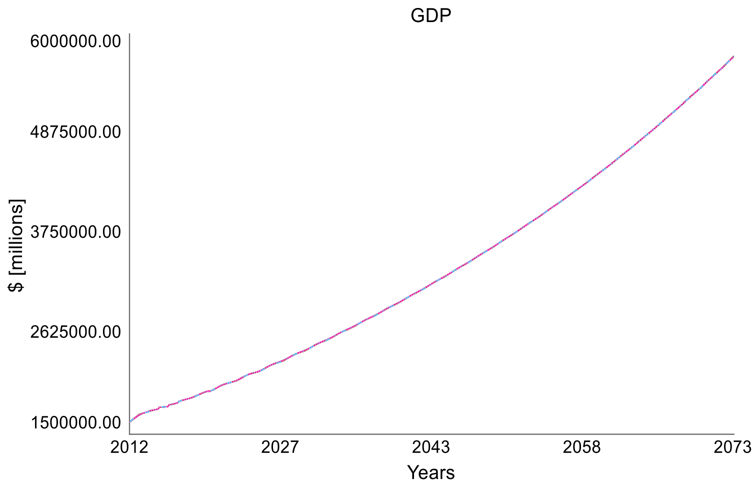

Figure G.5: Development of GDP for a Coefficient on HHNW per income group *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

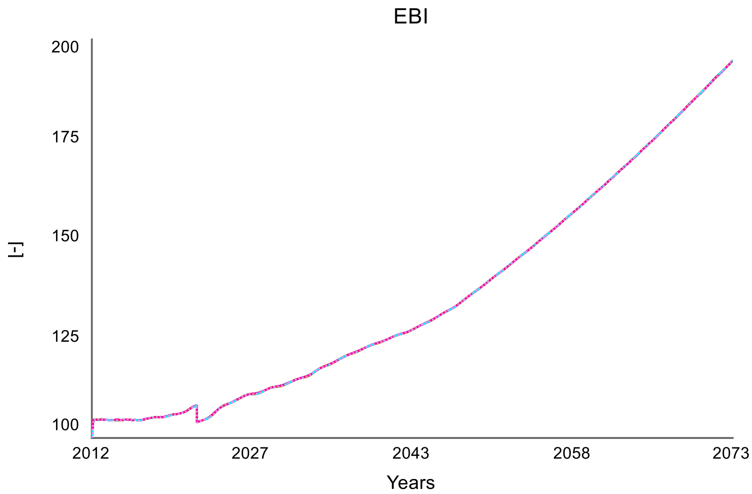

Figure G.6: Development of the Environmental Burden Index for a Coefficient on HHNW per income group *Between 0.009 and 0.011 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

As illustrated in the three figures above, variations in the *Coefficient on HHNW per income group* show almost no numerical or behavioural sensitivity for *Total Consumption*, *GDP*, or the *EBI*. This outcome is expected, as consumption from household net worth constitutes only a small fraction of total consumption compared to consumption from disposable income – an observation already noted in Section 5.2.2 and visualized in Figure 5.4. Because the impact of changes in this coefficient on total consumption is minimal, the resulting effects on *GDP* and *EBI* are barely noticeable.

The outcomes of this analysis closely mirror those from the sensitivity analysis of the *Coefficient on HHNW per capita* in the original LowGrow SFC model (see Appendix F), suggesting consistent sensitivity behaviour between the original and the extended model.

Initial Rate Household Tax and Transfer

The *Initial rate HH TAX & TRANSFER* is a parameter from the original LowGrow SFC model, initially set at 0.15. For this sensitivity analysis, its value is varied between 0.135 and 0.165 (±10%). This variable is included because it directly influences disposable income – an essential component of the extended model and a main focus of this research.

Figures G.7, G.8, and G.9 show the results of the sensitivity analysis on the *Coefficient on HHNW per income group*, depicting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively.

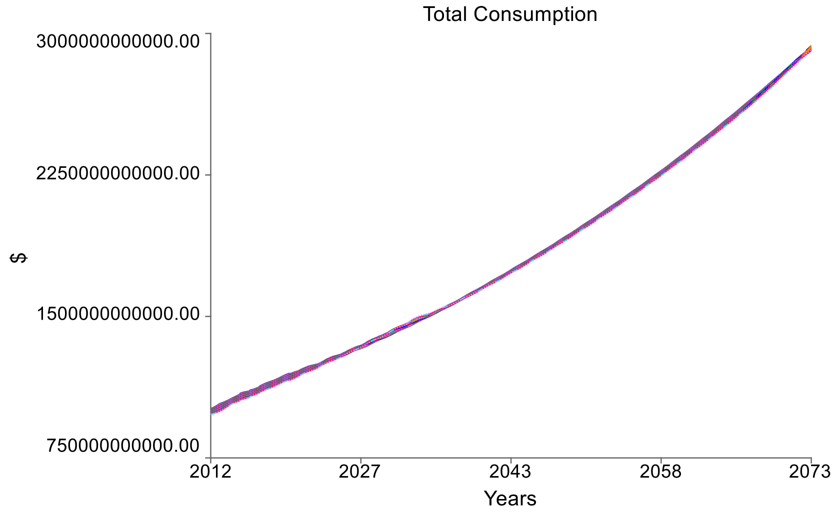

Figure G.7: Development of Total Consumption *for Initial rate HH TAX & TRANSFER Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

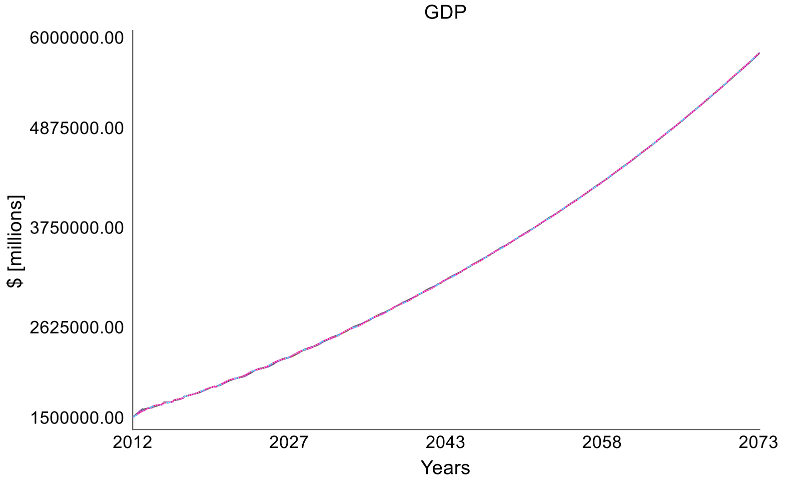

Figure G.8: Development of GDP for Initial rate HH TAX & TRANSFER Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)

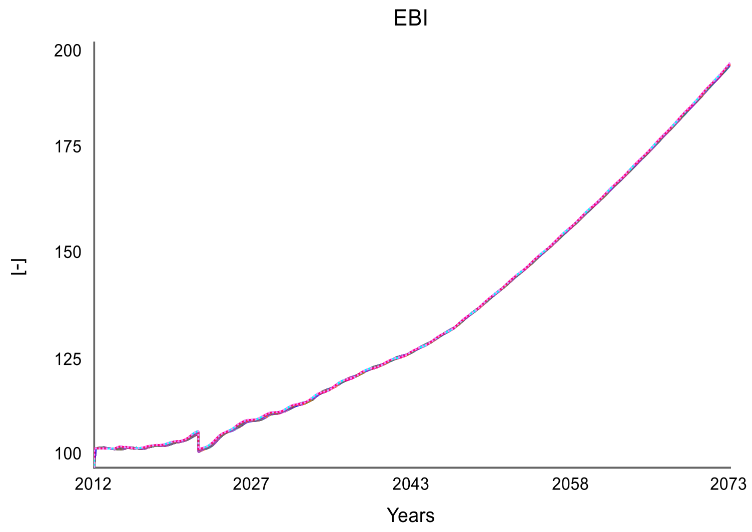

Figure G.9: Development of the Environmental Burden Index *for* Initial rate HH TAX & TRANSFER *Between 0.135 and 0.165 (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

The sensitivity analysis of the *Initial rate HH TAX & TRANSFER* in the extended LowGrow SFC model leads to a conclusion similar to that of the *Coefficient on HHNW per income group* in the previous section. Variations in this parameter result in minimal numerical sensitivity in *Total Consumption*, *GDP*, and the *EBI*. Although the numerical impact is slightly greater than that observed for the *Coefficient on HHNW per income group*, it remains very limited. No signs of behavioural sensitivity are evident in the results.

The results of this analysis closely resemble those from the sensitivity analysis of the *Initial rate HH TAX & TRANSFER* in the original LowGrow SFC model (see Appendix F). However, the EBI in the original model shows slightly more sensitivity to changes in the *Initial rate HH TAX & TRANSFER*.

Multivariate Sensitivity Analysis with Two Variables

The multivariate sensitivity analysis builds on the same three input variables examined in the univariate analysis in the previous section. Each variable is varied within a ±10% range of its original value. For each multivariate analysis, the model is run 200 times, with 50 samples per variable.

The first set of multivariate sensitivity analyses will test variables in pairs of two to observe the effects of simultaneous sensitivity analysis. The following combinations are evaluated:

- *Coefficient on Yd per income group* and *Coefficient on HHNW per income group*
- *Coefficient on Yd per income group* and *Initial rate HH TAX & TRANSFER*
- *Coefficient on HHNW per income group* and *Initial rate HH TAX & TRANSFER*

Coefficient on Yd per Income Group and Coefficient on HHNW per Income Group

Figures G.10, G.11, and G.12 show the results of the multivariate sensitivity analysis of the *Coefficient on Yd per income group* and the *Coefficient on HHNW per income group*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively

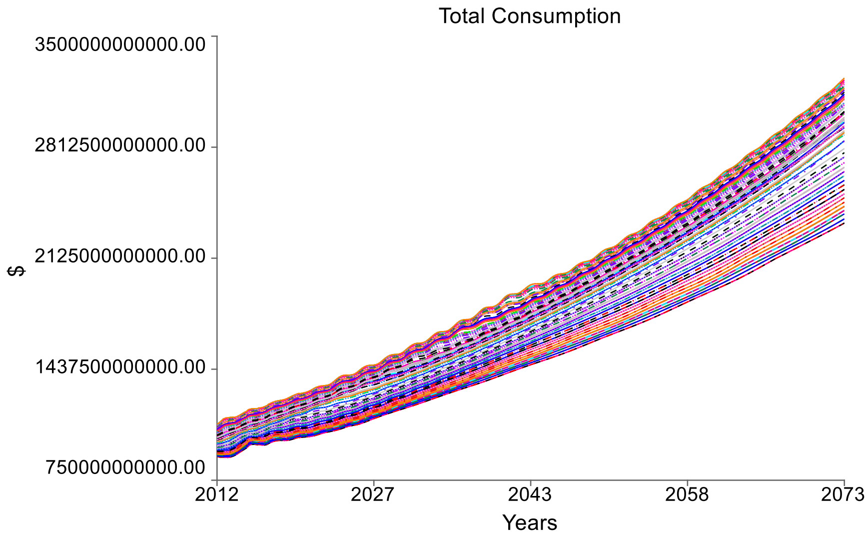

Figure G.10: Development of Total Consumption for Coefficient on Yd per income group *and* Coefficient on HHNW per income group *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

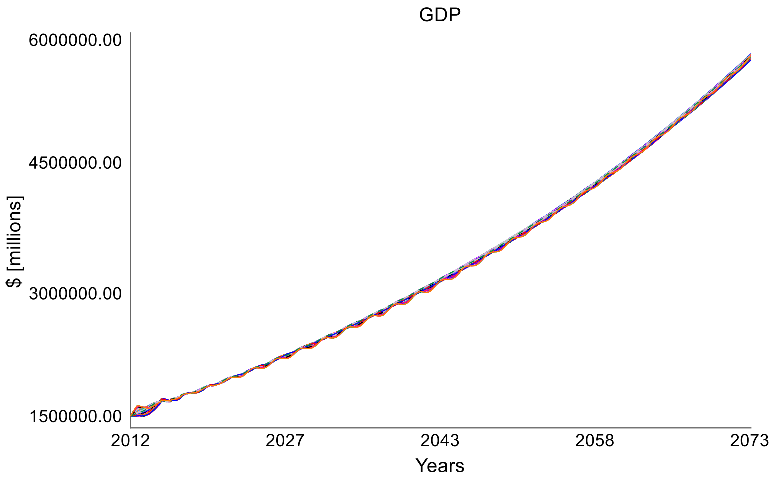

Figure G.11: Development of GDP for Coefficient on Yd per income group and Coefficient on HHNW per income group Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)

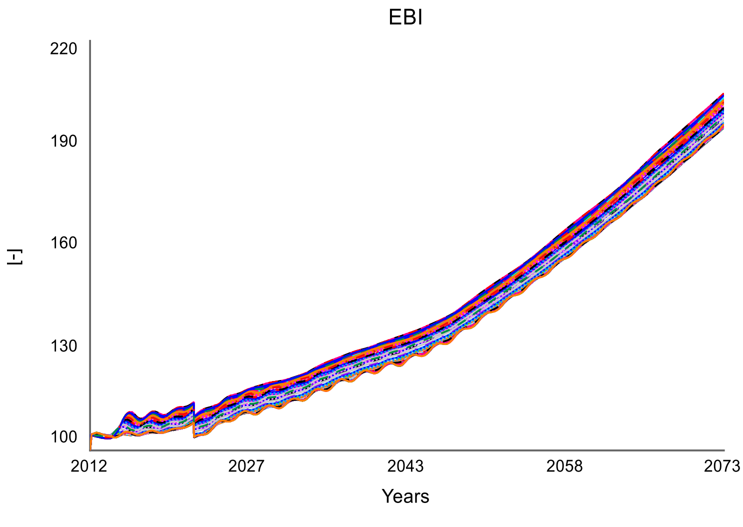

Figure G.12: Development of the Environmental Burden Index for Coefficient on Yd per income group *and* Coefficient on HHNW per income group *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

This multivariate sensitivity analysis reveals no additional behavioural patterns beyond those already observed in the univariate sensitivity analysis of the *Coefficient on Yd per income group*. This outcome is consistent with expectations, given that the extended LowGrow SFC model exhibited very limited sensitivity in the univariate analysis of the *Coefficient on HHNW per income group*.

Coefficient on Yd per Income Group and Initial Rate HH TAX & TRANSFER

Figures G.13, G.14, and G.15 show the results of the multivariate sensitivity analysis of the *Coefficient on Yd per income group* and the *Initial rate HH TAX & TRANSFER*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively

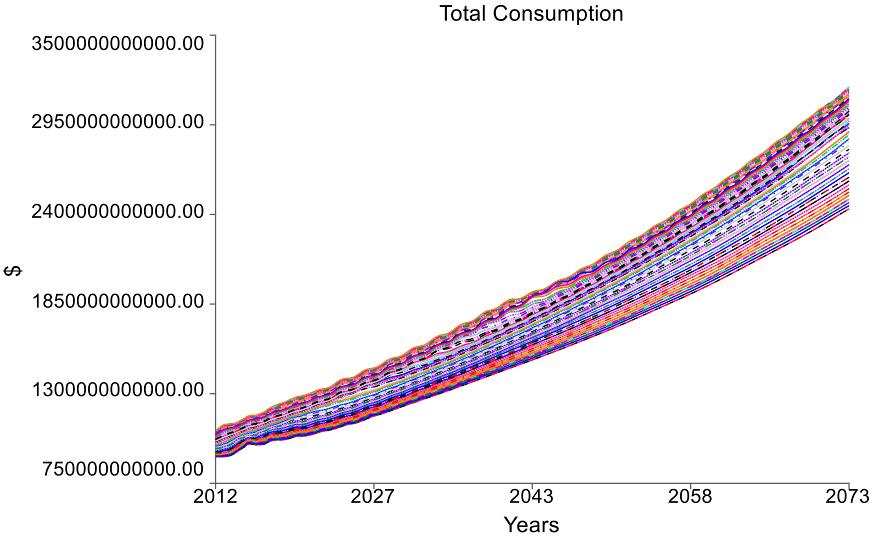

Figure G.13: Development of Total Consumption *for* Coefficient on Yd per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

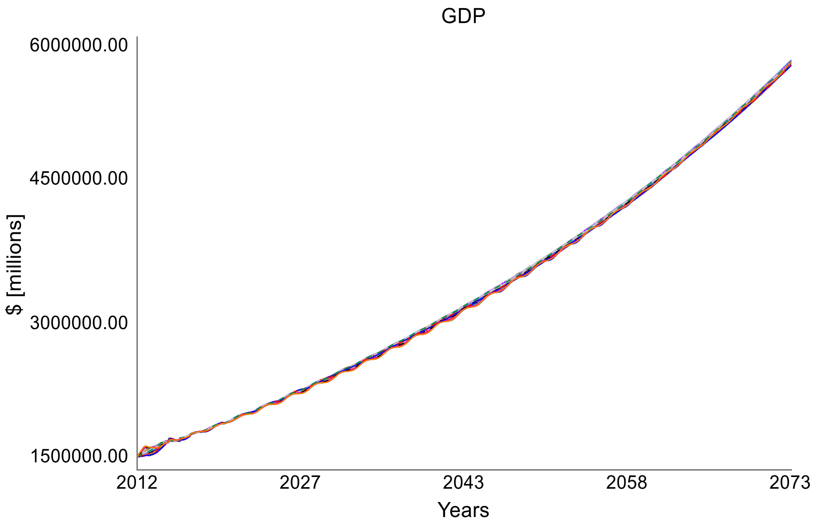

Figure G.14: Development of GDP *for* Coefficient on Yd per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

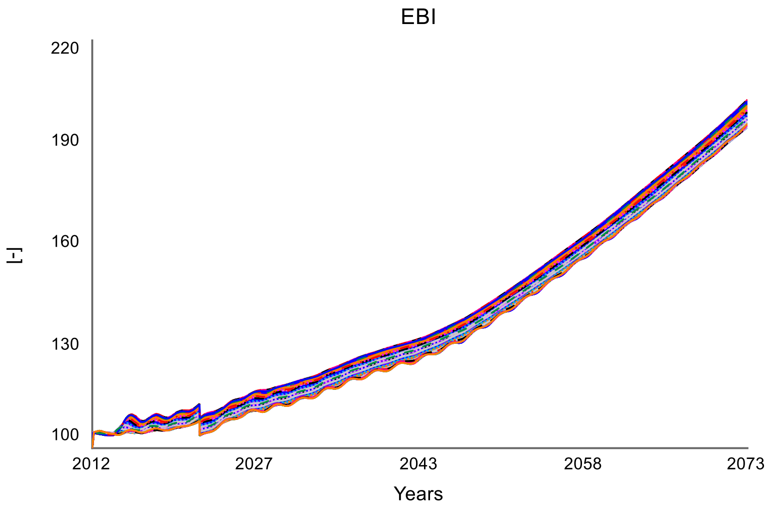

Figure G.15: Development of the Environmental Burden Index *for* Coefficient on Yd per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

Similarly, this multivariate sensitivity analysis does not reveal any new behavioural patterns beyond those identified in the univariate sensitivity analysis of the *Coefficient on Yd per income group*. This result aligns with expectations, as the extended LowGrow SFC model demonstrated very limited sensitivity in the univariate analysis of the *Initial rate HH TAX & TRANSFER*.

Coefficient on HHNW per Income Group and Initial Rate HH TAX & TRANSFER

Figures G.16, G.17, and G.18 show the results of the multivariate sensitivity analysis of the *Coefficient on HHNW per income group* and the *Initial rate HH TAX & TRANSFER*, presenting the effects on *Total Consumption*, *GDP*, and *EBI*, respectively

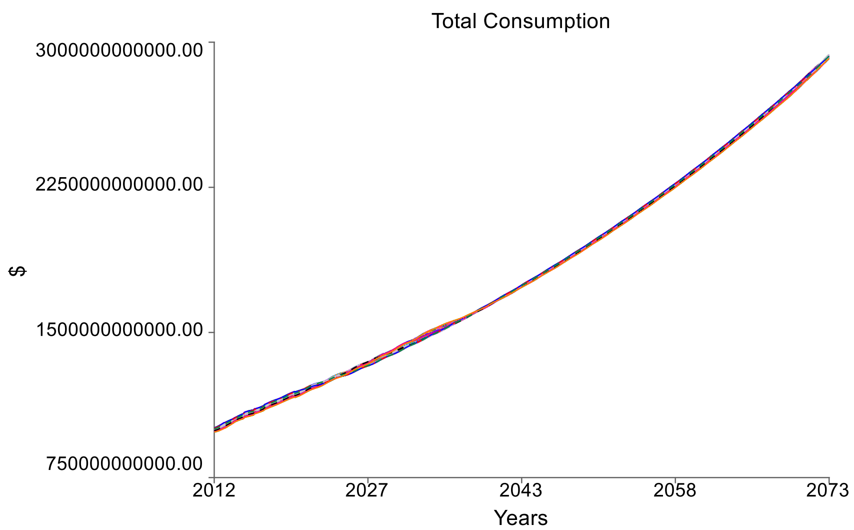

Figure G.16: Development of Total Consumption *for* Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

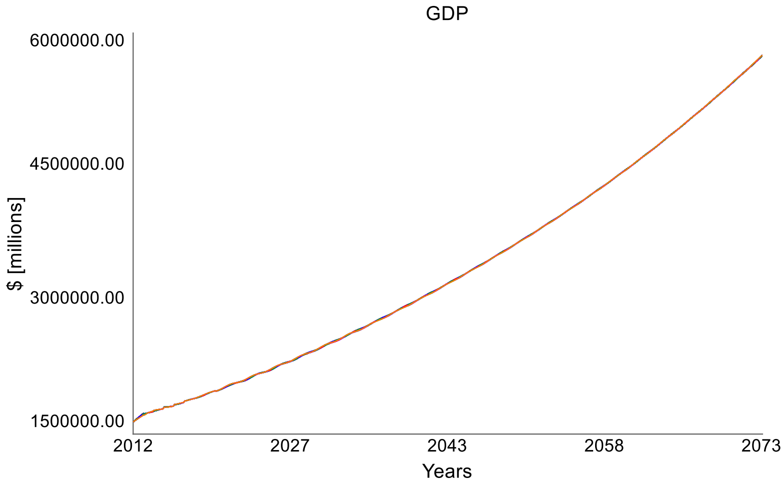

Figure G.17: Development of GDP *for* Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

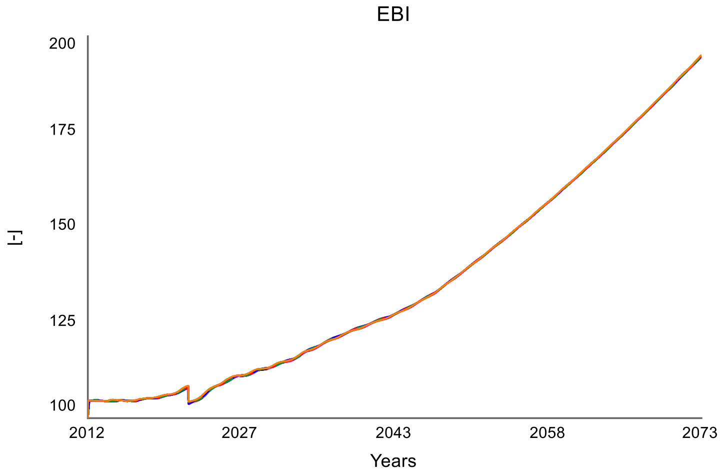

Figure G.18: Development of the Environmental Burden Index *for* Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

The multivariate sensitivity analysis of the *Coefficient on HHNW per income group* and the *Initial rate HH TAX & TRANSFER* shows minimal numerical and behavioural sensitivity across all three KPIs. This outcome is consistent with the limited sensitivity observed in the univariate sensitivity tests for these input variables.

Multivariate Sensitivity Analysis with Three Variables

In addition to the multivariate analyses with two variables, a multivariate sensitivity analysis with all three input variables varying simultaneously is also conducted. Each variable is varied within a ±10% range of its original value and the model is run 200 times, with 50 samples per variable. The outcomes for *Total Consumption*, *GDP*, and *EBI* are shown in Figures G.19, G.20, and G.21 respectively.

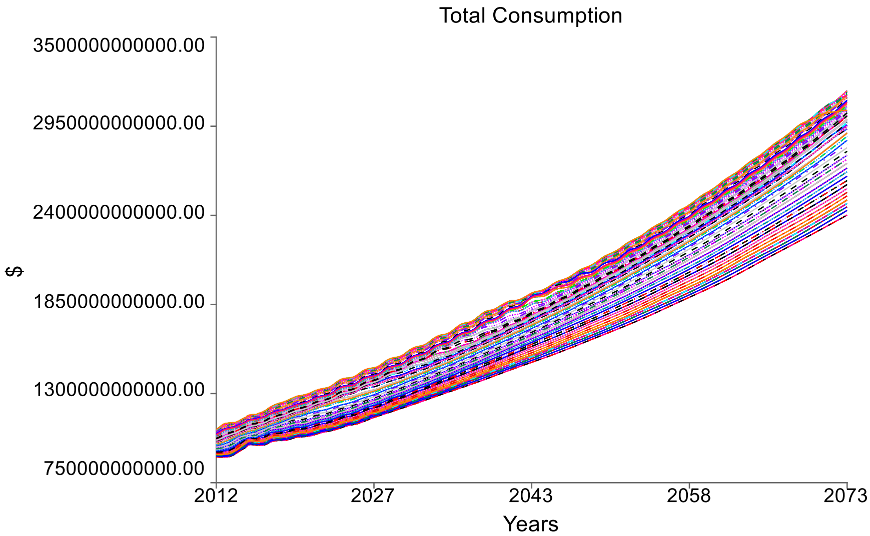

Figure G.19: Development of Total Consumption *for* Coefficient on Yd per income group, Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

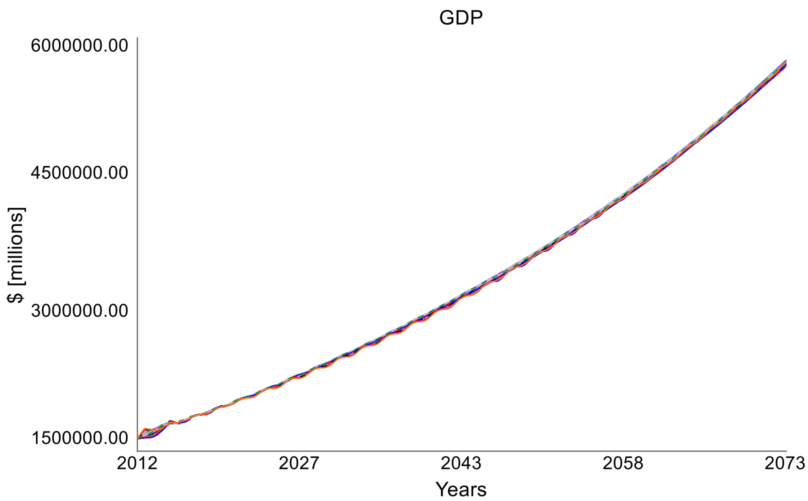

Figure G.20: Development of GDP *for* Coefficient on Yd per income group, Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

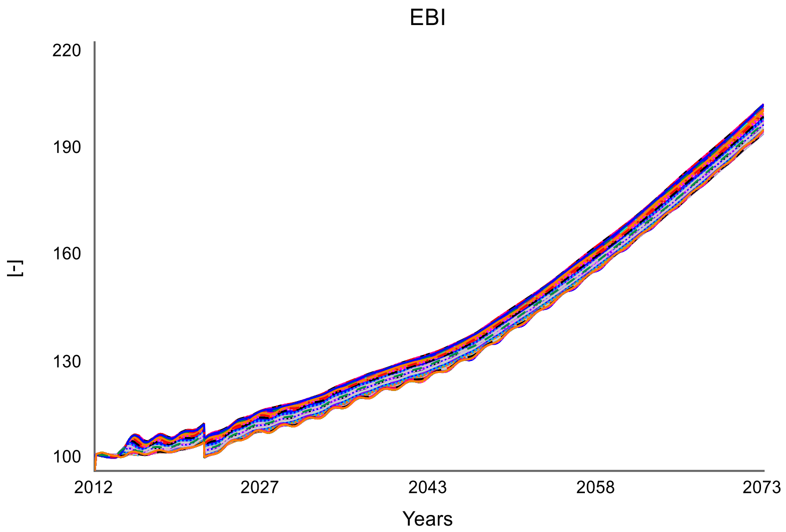

Figure G.21: Development of Environmental Burden Index *for* Coefficient on Yd per income group*,* Coefficient on HHNW per income group *and* Initial rate HH TAX & TRANSFER *Between -10% and +10% of Their Originial Value(s) (Note: Individual Lines Represent Model Runs and do Not Have a Specific Interpretive Meaning)*

Also, this multivariate analysis reveals no additional behavioural patterns beyond those observed in the univariate sensitivity analysis of the *Coefficient on Yd per income group*. This result is consistent with expectations, given the extended LowGrow SFC model demonstrated minimal sensitivity in the univariate analyses of both the *Coefficient on HHNW per income group* and the *Initial rate of HH TAX & TRANSFER*.

Appendix H: Scenario Definition

This appendix provides an overview of the input variables that define the four different scenarios as presented in Chapter 6.

Table H.1 displays the mean disposable income per income group and the corresponding values for the *Share of Yd per Income Group*, as implemented in each scenario.

Table H.1: Mean Disposable Income per Income Group and Share of Yd per Income Group *(y_n^{hde}) for the Base Case Scenario and Scenario 1 to 4*

	Base Case (Gini = 0.47)		Scenario 1 and 3 (Gini = 0.37)		Scenario 2 and 4 (Gini = 0.57)	
Income group	Mean income [$/year]	Yd share [%]	Mean income [$/year]	Yd share [%]	Mean income [$/year]	Yd share [%]
Under $5.000	2500	0.47	12122	2.27	2051	0.38
To $10.000	7500	1.30	16403	2.84	6156	1.07
To $15.000	12500	2.79	18269	0..07	10264	2.29
To $20.000	17500	4.17	21813	5.20	14375	3.43
To $25.000	22500	4.30	26537	5.07	18490	3.53
To $35.000	30000	9.22	31673	9.74	24662	7.58
To $50.000	42500	15.90	43187	16.15	34951	13.07
To $75.000	62500	21.72	58125	20.20	51419	17.87
To $100.000	87500	14.41	78750	12.97	72013	11.86
To $150.000	125000	12.14	108750	10.56	115490	11.21
To $200.000	175000	4.37	147000	3.67	189735	4..74
To $250.000	225000	2.25	182250	1.82	560415	5.60
Above $250.000	420000	6.97	327600	5.44	1046254	17.37

It is important to note that, in both the lower and higher Gini scenarios, some of the newly calculated mean incomes no longer fall within their original income group ranges. In Scenario 1 and 3, where the Gini coefficient decreases, the mean incomes of the five lowest income groups rise above their original ranges, while the mean incomes of the second and third richest groups fall below theirs. This occurs because these scenarios involve a significant redistribution of income in which a large part of the income of the rich is redistributed to the poorer income groups, resulting in a more equal distribution compared to the baseline. In contrast, in Scenario 2 and 4, where the Gini coefficient increases, the opposite pattern emerges. The mean incomes of several middle-income groups fall below their original ranges, while the second richest group's mean income exceeds its original range. This reflects a more unequal income distribution in these scenarios. Although the group names no longer align with the new mean income levels, this misalignment does not create any issues within the model.

It should also be noted that the income distributions shown in Table F.1 represent just one possible configuration for achieving the target Gini coefficients. In this analysis, the decision was made to keep the number of people per income group similar to the numbers that were defined in the LowGrow SFC model. Under this assumption, substantial changes in mean income per group are required to achieve a 0.1 increase or decrease in the Gini coefficient. Alternative approaches to modifying the Gini coefficient could include changing the population distribution across income groups or simultaneously adjusting both group sizes and mean incomes. The latter approach is more representative of how inequality would typically evolve in real-world situations.

Table H.2 presents the values for the *Coefficient on Yd per income group* across scenarios, along with the percentage increase or decrease relative to the Base Case Scenario.

Table H.2: Coefficient on Yd per income group ($\alpha_{1,n}$) for Base Case Scenario, Scenario 1 and 2, Scenario 3 and 4 and the Percentage Increase or Decrease Compared to the Base Case Scenario

	Base Case [%]	Scenario 1 and 2 (higher MPC for low-income groups) [%]	Scenario 3 and 4 (lower MPC for low-income groups) [%]	Increase (scen 1 & 2) or decrease (scen 3 & 4) compared to Base Case [%]
Under $5.000	199.37	219.31	179.43	10
To $10.000	164.83	173.07	156.59	5
To $15.000	131.28	134.56	128.00	2.5
To $20.000	118.89	120.38	117.40	1.25
To $25.000	111.43	112.13	110.73	0.625
To $35.000	103.69	104.01	103.37	0.313
To $50.000	91.80	91.94	91.66	0.156
To $75.000	75.73	75.79	75.67	0.0781
To $100.000	64.20	64.23	64.17	0.0390
To $150.000	58.31	58.31	58.31	0
To $200.000	55.56	55.56	55.56	0
To $250.000	54.77	54.77	54.77	0
Above $250.000	54.17	54.17	54.17	0

To simulate scenarios in which lower-income groups have a higher or lower marginal propensity to consume (MPC), the Base Case MPC is increased or decreased by 10% for the lowest income group. Afterwards, for each subsequent group, the adjustment percentage is divided by two. In this way, the second group received a ±5% change, the third group a ±2.5% change and so on. The highest four income groups maintain the same MPC values across all scenarios, as the focus of this analysis is on the consumption behaviour of lower-income groups. Additionally, these top four income groups represent a much smaller portion of the population compared to the other nine groups. Collectively, they account for approximately 1,615,700 individuals, whereas each of the remaining nine groups includes between 1,790,360 and 4,065,630 people. The percentage changes applied to the MPC values are presented in the final column of Table H.2.

Finally, Table H.3 presents the input values for the sub-model variables *Scenario switch Yd* and *Scenario switch alpha 1*, which are used to construct the different scenarios in the LowGrow SFC model.

Table H.3: Scenario Selection for Variables Scenario switch Yd *and* Scenario switch alpha 1 *in Extended LowGrow SFC Model*

Scenario	Scenario switch Yd	Scenario switch alpha 1
Base Case	0	0
Scenario 1	1	1
Scenario 2	2	1
Scenario 3	1	2
Scenario 4	2	2

Appendix I: Explanation of Model output

This appendix presents additional model variables to provide a more detailed explanation and visualisation of the dynamics observed in the scenario analysis for government expenditure and business investment as discussed in Chapter 6.

Government Expenditure

Figure I.1 shows the development of Government Expenditure across the Base Case Scenario and Scenarios 1 through 4.

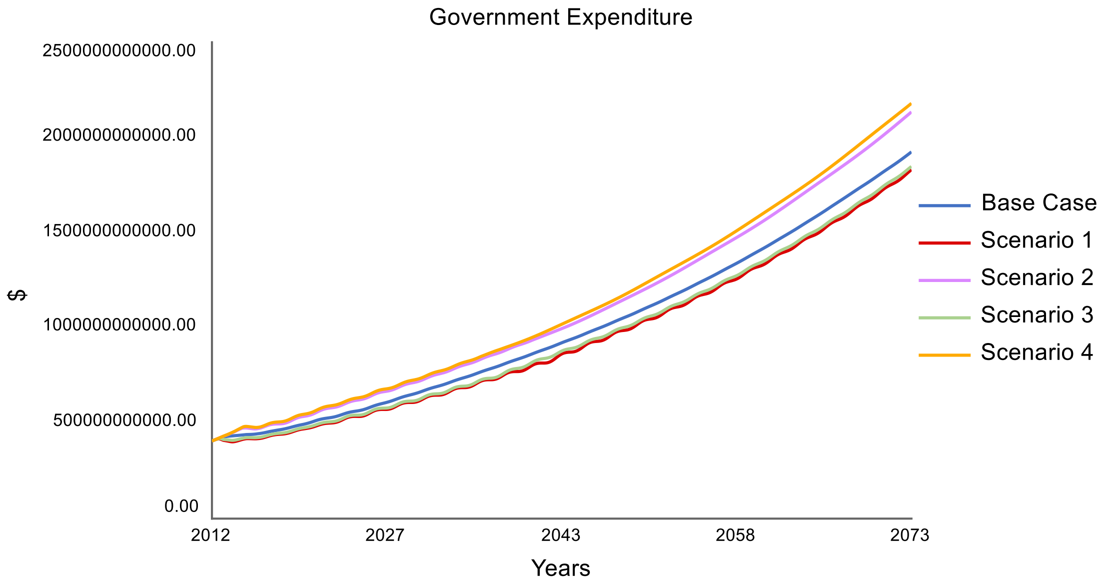

Figure I.1: Development of Government Expenditure in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

The figure reveals that Government Expenditure is lower in Scenarios 1 and 3 (the high-consumption scenarios) and higher in Scenarios 2 and 4 (the low-consumption scenarios). Government Expenditure consists of two components: Government Consumption (Figure I.2) and Government Investment (Figure I.3). Both components follow a similar pattern – lower in the high-consumption scenarios and higher in the low-consumption scenarios.

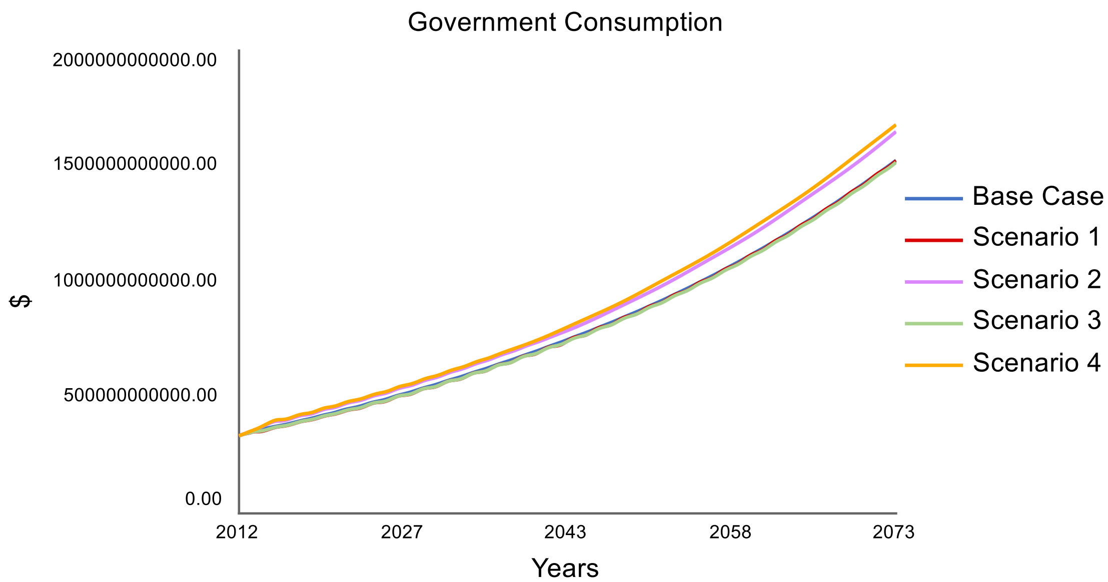

Figure I.2: Development of Government Consumption in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

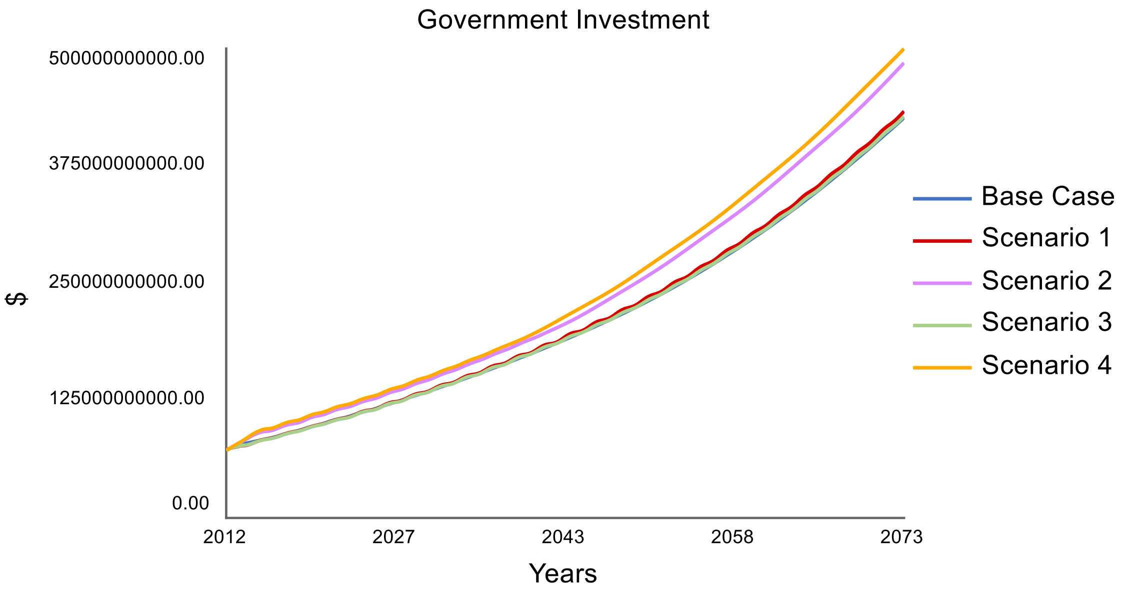

Figure I.3: Development of Government Investment in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

Business Investment

Figure I.4 illustrates the development of Business Investment across the Base Case Scenario and Scenarios 1 through 4.

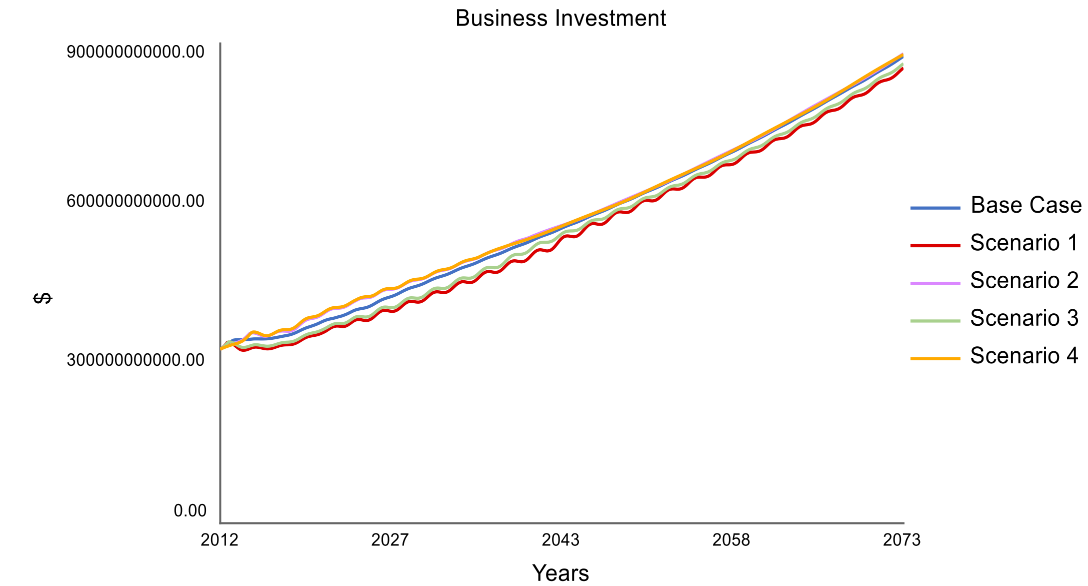

Figure I.4: Development of Business Investment in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

In this case Business Investment also is lower in the high-consumption scenarios (Scenarios 1 and 3) compared to the low-consumption scenarios. Business Investment is influenced by the House Price Index (Figure I.5), which in turn is affected by Housing Wealth (Figure I.6). These figures show that higher consumption is associated with lower house prices and housing wealth, while lower consumption results in higher values for both.

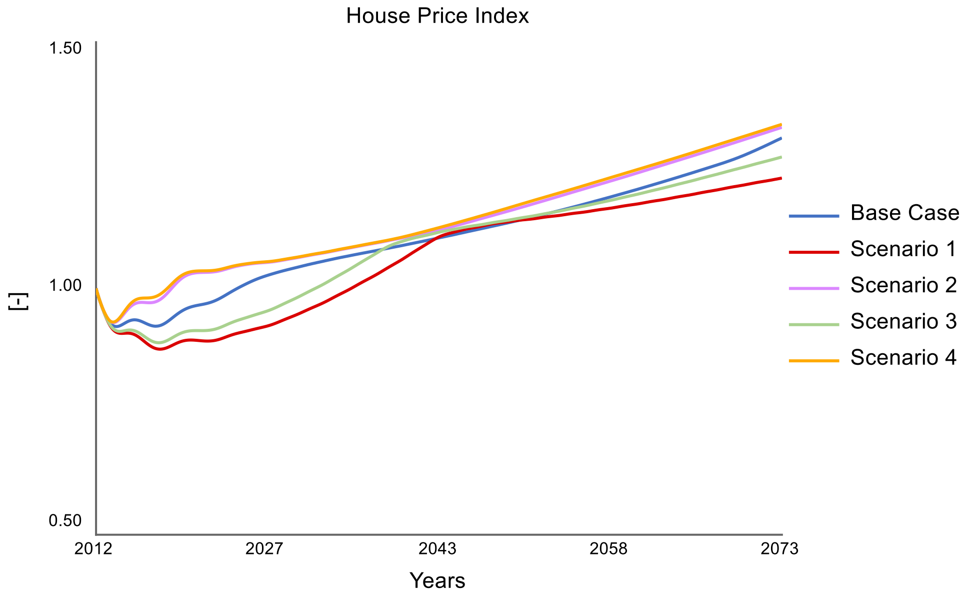

Figure I.5: Development of House Price Index in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

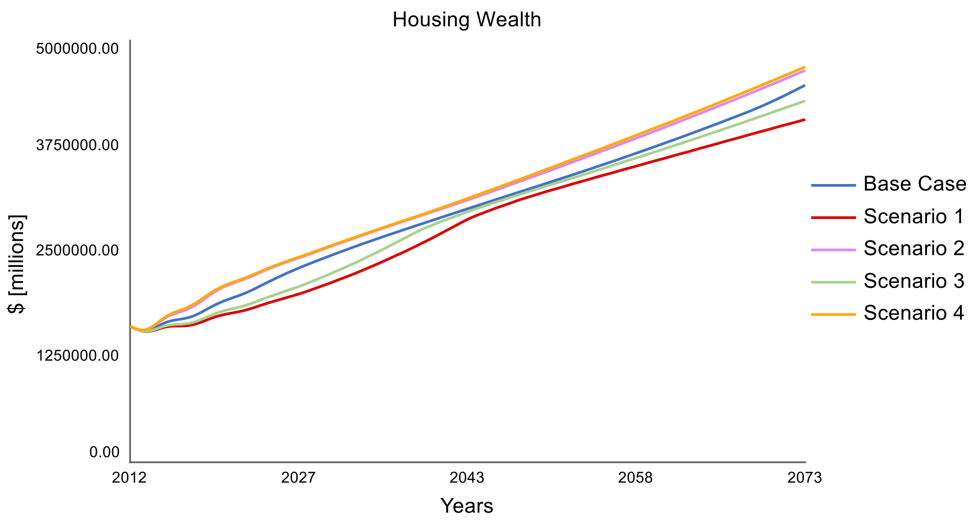

Figure I.6: Development of Housing Wealth in Base Case Scenario (Blue), Scenario 1 (Red), Scenario 2 (Pink), Scenario 3 (Green), and Scenario 4 (Orange)

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