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THE ROLE OF ECOLOGICAL STOCK-FLOW-CONSISTENT INPUT-OUTPUT MODELS IN THE ENVIRONMENTAL MACROECONOMIC MODELLING LANDSCAPE

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ABSTRACT

This paper reviews the development of Ecological Stock-Flow-Consistent Input-Output models as an emerging alternative to mainstream climate-economy modelling frameworks. In light of the limitations of neoclassical approaches, which rely on restrictive behavioral and equilibrium assumptions, Ecological Stock-Flow-Consistent Input-Output models offer a coherent framework to analyze climate policies by jointly representing financial dynamics, the real economy, and ecological pressures within a stock-flow-consistent dynamic setting. After introducing the Stock-Flow-Consistent and input-output traditions separately, the paper explains how these approaches can be integrated and discusses the implications of disaggregating the production sector into interdependent industries. The existing Ecological Stock-Flow-Consistent Input-Output literature is then surveyed, with particular attention to the treatment of financial linkages, inter-industry relations, environmental extensions, and the calibration strategy. An important finding is that, while the models become more complex in both the production, financial and ecological interactions, most of the models remain theoretical or calibrated, with weak empirical foundation. The paper therefore evaluates the potential of Ecological Stock-Flow-Consistent Input-Output models as tools for climate policy analysis and argues for a shift of focus towards fully empirical implementations. Finally, it identifies key methodological and data-related challenges that must be addressed for Ecological Stock-Flow-Consistent Input-Output models to become robust and reliable components of the climate policy toolkit.

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The role of Ecological Stock-Flow-Consistent Input-Output models in the environmental macroeconomic modelling landscape

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Abstract

This paper reviews the development of Ecological Stock-Flow-Consistent Input-Output models as an emerging alternative to mainstream climate-economy modelling frameworks. In light of the limitations of neoclassical approaches, which rely on restrictive behavioral and equilibrium assumptions, Ecological Stock-Flow-Consistent Input-Output models offer a coherent framework to analyze climate policies by jointly representing financial dynamics, the real economy, and ecological pressures within a stock-flow-consistent dynamic setting. After introducing the Stock-Flow-Consistent and input-output traditions separately, the paper explains how these approaches can be integrated and discusses the implications of disaggregating the production sector into interdependent industries. The existing Ecological Stock-Flow-Consistent Input-Output literature is then surveyed, with particular attention to the treatment of financial linkages, inter-industry relations, environmental extensions, and the calibration strategy. An important finding is that, while the models become more complex in both the production, financial and ecological interactions, most of the models remain theoretical or calibrated, with weak empirical foundation. The paper therefore evaluates the potential of Ecological Stock-Flow-Consistent Input-Output models as tools for climate policy analysis and argues for a shift of focus towards fully empirical implementations. Finally, it identifies key methodological and data-related challenges that must be addressed for Ecological Stock-Flow-Consistent Input-Output models to become robust and reliable components of the climate policy toolkit.

Key words: Empirical Stock-Flow-Consistent models, Environmentally Extended Input-Output modelling, Ecological macroeconomics.

JEL-codes: E12, E17, F41, L16.

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1. Introduction

In recent years, there has been a growing demand for large-scale macroeconomic models capable of analyzing green transition policies. However, while climate change has long been on the policy agenda, dedicated climate-economy macroeconomic models remain limited in availability. For example, a recent global survey of finance ministries found that 56% of ministries do not use any specialized macroeconomic models for climate policy analysis (CFMCA, 2025a). The same report underscores the need for modeling tools that link the financial, real, and environmental sectors, with a particular emphasis on the financial sector's critical role in achieving a successful green transition.

Similar calls for integrated modeling approaches come from the ecological economics literature. Hardt and O'Neill (2017), for instance, emphasize the need for macroeconomic models that incorporate environmental dynamics alongside a realistic representation of the financial system. One promising approach that meets this requirement is ecological Stock-Flow-Consistent (SFC) models rooted in the post-Keynesian tradition. SFC models, as defined in the Godley-Lavoie framework (see Godley and Lavoie, 2007), rigorously link monetary flows with their corresponding financial assets and liabilities within a coherent national accounting framework. Expanded by an ecological sector, these models pose a promising tool for climate financial analysis (Dafermos et al., 2017).

The use of Ecological Stock-Flow-Consistent (E-SFC) models within the Ecological Economics literature is a relatively recent development (Berg et al., 2015; Naqvi, 2015; Campiglio et al., 2015; Jackson and Victor, 2015; Dafermos et al., 2017). For the purposes of this paper, these contributions can broadly be divided into two categories: those that represent the production sector in an aggregated manner (e.g., Campiglio et al., 2015; Jackson and Victor, 2015; Dafermos et al., 2017), and those that introduce industry-level disaggregation through Environmentally Extended Input-Output (EEIO) structures (e.g., Berg et al., 2015; Naqvi, 2015).

In the broader SFC tradition, production is often modeled in an aggregated form, which facilitates the analysis of macroeconomic and financial dynamics. However, this level of aggregation abstracts from intermediate consumption and structural heterogeneity across industries - features that are particularly important for ecological analysis. Models that combine the SFC framework with EEIO tables - commonly referred to as Ecological Stock-Flow-Consistent Input-Output (E-SFC-IO) models incorporate explicit inter-industry linkages and thereby allow for a more detailed representation of production networks.

EEIO models themselves have long been employed in the Ecological Economics literature to assess the environmental impacts of changes in final demand by tracing inter-industry linkages across the economy. At the same time, standard EEIO frameworks typically abstract from financial dynamics and macroeconomic feedback. The integration of SFC and EEIO approaches therefore enables a joint analysis of real, financial, and environmental interactions and represents a promising direction within ecological macroeconomics (Hardt & O'Neill, 2017).

More than a decade has passed since the first attempts to integrate input-output frameworks into Stock-Flow Consistent models (Berg et al., 2015; Naqvi, 2015; Valdecantos, 2015). This paper therefore provides an overview of recent advances in ecological SFC modeling, focusing on contributions that combine the SFC and EEIO approaches.

In Section 2, we introduce the SFC modelling approach, and in Section 3, input-output modeling before combining the two approaches in Section 4 when building a simple SFC-IO toy model. In Section 5, we review the publicly available studies that adopt the SFC-IO approach, with particular attention to how the production system in these models is linked to both financial and environmental variables, as well as the calibration strategy. In Section 6, we consider how Ecological SFC-IO models fit into the broader landscape of environmental macroeconomic modeling and assess their potential for becoming a tool for providing climate policy analysis. In Section 7, we reflect on possible future directions for the development of empirical E-SFC-IO models. Finally, in Section 8, we conclude.

2. Stock-Flow-consistent modeling

Stock-Flow-Consistent models have gained increased attention in the last couple of decades. Two events have been especially important for this rise in popularity: I) The publication of Monetary Economics by Wynne Godley and Marc Lavoie (2007) outlining the modelling methods of SFC-modeling, and II) the recognition that the SFC-framework were able to foresee the 2008 great financial crisis (Godley; 1999).

The Stock-Flow-Consistent methodology is grounded in the national accounting framework that traces monetary flows, as originally proposed by Copeland (1947, 1949). SFC models integrate the financial sector with the real economy by tracking both stocks and flows through social accounting and flow-of-funds matrices. The emphasis on the financial sector is a key feature that distinguishes the SFC approach from other mainstream macroeconomic modelling frameworks (Nikiforos & Zezza, 2018).

In this section, we provide an introduction to Stock-Flow-Consistent modelling. First, we outline the core principles used in SFC models. Second, we discuss the behavioral assumptions embedded in these models. Third, we classify different types of SFC models. Finally, we examine the growing interest in ecological SFC models.

2.1. The Stock flow consistent principals

The SFC modelling framework incorporates four main accounting principles, as identified by Nikiforos and Zezza (2018): (1) flow consistency, (2) stock consistency, (3) stock-flow consistency, and (4) quadruple entry. To represent these principles, the Stock-Flow-Consistent approach uses two key matrices: (i) the balance sheet matrix and (ii) the transaction flow matrix (TFM).

To help illustrate these accounting principles, we consider the simplest example - a modified version of the SIM model from Godley & Lavoie (2007), Chapter 3. Table 1 below presents the transaction flow matrix of the modified SIM model.[1] In this simplified version, only three sectors are included: the household sector, the production sector, and the government sector. The rows represent different monetary flows. Rows 1 to 6 cover flows related to the real economy, while row 7 (below the stippled line) includes financial flows. In this basic setup, only one financial asset is present: money.

Flow consistency is ensured as every transaction - whether within or between sectors - comes from somewhere and goes to somewhere. Flow consistency can be further divided into horizontal and vertical consistency. Horizontal consistency means that income for one sector must, by accounting identity, be an expense for another sector. It is this horizontal consistency that ensures each row in the transaction flow matrix sums to zero. Take, for example, private consumption (C). While this expenditure is received by the production sector (indicated by a +), it is an expense for the household sector (indicated by a –). By accounting identity, the transaction should sum to zero. Vertical consistency, on the other hand, ensures that each flow within a sector has at least two corresponding entries. For example, if households increase their expenditure on final consumption goods (everything else held fixed), this will - by accounting identity - reduce the stock of money they hold by the same amount, ΔH. Vertical consistency is what ensures that each column in the transaction flow matrix sums to zero.

[1] The main difference from the model presented in this chapter, and the SIM model in Godley and Lavoie (2007) is the introduction of gross operating surplus and mixed income in the production sector. This will be useful later in Section 4.

Table 1: Transaction-Flow-Matrix for the SIM model

Table 1: Accounting (transactions) matrix for Model *SIM*

		1. Households	2. Production	3. Government	Σ
1.	Consumption	$-C$	$+C$		0
2.	Govt. expenditures		$+G$	$-G$	0
3.	[Output]		$[Y]$		
4.	Factor income (wages)	$+WB$	$-WB$		0
5.	Gross operating surplus	$+B2$	$-B2$		0
6.	Taxes	$-T$		$+T$	0
7.	Change in the stock of money	$+\Delta H$		$-\Delta H$	0
	Σ	0	0	0	0

Stock consistency indicates that a financial liability for one sector is, by accounting identity, a financial asset for another sector. In our simple case, the only financial asset is the stock of money deposits, which is an asset for the household sector and a liability for the government sector. Stock consistency ensures that any change in households' money assets is mirrored by an equivalent change in the government's money liabilities. As a result, the sum of the last row in Table 1 also equals zero.

Stock-flow consistency introduces the second of the two core matrices used to represent the SFC approach: the balance sheet matrix, shown in Table 2. Stock-Flow-Consistency implies that the flows recorded in the transaction flow matrix are linked to changes in net financial stocks. As a result, transactions involving financial assets and liabilities - represented in our simple model solely by money ΔH - affect the balance sheet of each sector. The stock of household money holdings (+H) in a given period is defined as the previous period's stock (H_{t-1}) plus the current period's transactions (ΔH_t).[2] In the balance sheet matrix, a positive sign indicates that households hold money as a net asset, while a negative sign indicates that the government holds money as a net liability. By accounting identity, the net financial assets held by households must equal the net financial liabilities of the government, ensuring the balance sheet sums to zero.

Table 2: Balance sheet matrix for the SIM model

Table 2: Balance sheet of Model *SIM*

	1. Households	2. Production	3. Government	Σ
Money stock	$+H$	0	$-H$	0

[2] In more complex models, also re-evaluations and capital gains should be accounted for. Still the Stock-flow-consistency principle should be fulfilled.

Lastly, the first three principles imply the fourth: the quadruple-entry principle, which states that every transaction is related to four entries in the modelling framework. In our simple case, this is best illustrated by the transaction of income taxes. An increase in income taxes will lower the income of the household sector and increase the income of the government sector. This also affects financial stocks: it lowers the asset stock of money held by households, while simultaneously reducing the liability stock of money in the government sector.

2.2. Behavior in SFC models

The set of equations used to ensure these four accounting principles just presented are often referred to as accounting identities - they can be seen as providing the skeleton of the model. However, the accounting principles in themselves do not say anything about the chain of causality or behavior introduced in the model. This is often decided by two aspects: i) The closure of the model, indicating the chain of causality which are made through the accounting identities. As noted by Taylor and Lysy (1979) the conclusions of a macroeconomic model crucially depend on its closure. II) Behavioral equations, some exogenous variables not defined through the national accounting structure, are modeled using behavioral equations, not because it is necessary to fulfill the accounting principles, but instead to add specific behavioral dynamics within the model.[3]

In SFC models, the typical closure of the model implies a chain of causality running from demand to supply, this highlights the importance of modeling final demand components and the demand for financial assets as behavioral equations. This demand-led focus is consistent with post-Keynesian theory. SFC models with this type of closure is often referred to as PK-SFC models (unless stated otherwise, SFC models hereafter refer to PK-SFC models). In contrast, neoclassical macroeconomic models (which can also be stock-flow-consistent) are typically closed with the chain of causality running from supply to demand. In these models, equilibrium between supply and demand is ultimately ensured by price and wage adjustments, even though in New Keynesian variants nominal rigidities and other frictions can prevent instantaneous market clearing in the short run.

Given the demand-led structure of SFC models, behavioural equations focus on modelling these demand components. Nikiforos and Zezza (2018) identify five types of behavioural equations commonly used in these models, covering demand on both the real and financial sides of the economy. These behavioral equations are grounded in post-Keynesian theory. The first type determines the expenditures of agents in the economy. This mainly includes the components of GDP - consumption, investment, exports, and imports - while government

[3] In some cases, it can be necessary to add behavioral equations if the system of equations is under identified where the number of endogenous variables exceeds the number of equations (Nikiforos & Zezza, 2018).

spending is typically treated as exogenous. The second type concerns how agents finance their expenditures or net borrowing positions. This includes, for example, the government's use of securities to adjust for fiscal imbalances, as well as the private sector's demand for new loans where households may borrow to finance consumption or invest in housing, while firms may seek external finance to invest when retained earnings are insufficient. The third type of equations determines the allocation of wealth, or how agents distribute additional savings among financial assets. This typically focuses on the household sector's portfolio allocation, which often builds on the contribution of Tobin (1969). In this set-up household demand for financial assets is usually modeled using three components. First, households have an exogenous demand for each financial asset, unaffected by economic or financial variables. Second, households allocate between financial assets based on the expected rate of return. Third, demand for financial assets is influenced by the ratio of disposable income to net wealth, where a higher ratio may lead to a preference for more liquid assets. The fourth type of behavioral equation focuses on productivity, wages, and inflation. These variables are central to the post-Keynesian view of the economy and modeling these by using post-Keynesian behavioral equations is one of the reasons why SFC models produce different results compared to neoclassical macroeconomic models. The final set of behavioral equations focus on the banking sector, including both the central bank and commercial banks. For the central bank, this involves monetary policy rules - specifically, how it responds to inflation and changes in output growth. For commercial banks, it concerns the setting of interest rates on loans and deposits, as well as credit rationing.

2.3. Types of SFC models

Up until this point, we have discussed the accounting framework and the behavioral assumptions that characterize Stock-Flow-Consistent models. While these features are common to all SFC models, the models themselves can be further classified based on how they relate to observed data. In this section, we distinguish between three broad types of SFC models: i) Theoretical/Calibrated models, ii) Empirical models, and iii) Fully empirical models.

We start by defining empirical SFC models as those that aim to represent the structure of a specific country or region. As a result, the skeleton of the model (the accounting identities) is built using national accounting relationships based on the ESA 2010 (Eurostat 2013). An Empirical SFC-model ensures that all real flows and stocks for a specific economy are accounted for within the model. This leads to two requirements which an empirical model must satisfy:

- *National accounts integration* - All real and financial flows (observed in the TFM) must be consistently modelled based on an economy's national accounts.

- *Balance sheet and flow-of-funds consistency* - The model must track all financial transactions and capital gains and relate them to net financial stocks of the economy (observed in the Balance Sheet matrix).

These two criteria ensure that the accounting principles presented in Section 2.1 are satisfied through the adoption of national accounting, allowing an empirical model to accurately reflect the accounting structure of a specific economy or region. However, this also means that the model's reliability depends on the quality and consistency of the national accounts, which can vary significantly across countries and regions - posing challenges for empirical modeling in areas with less developed statistical systems.

Following Caverzasi & Godin (2015), we also define "fully empirical" SFC models as those that go beyond accounting consistency by also incorporating time-series data, empirically estimating behavioral parameters, and validating against observed historical data. We define fully empirical models to include the following:

- *Empirical estimation of behavioral parameters* - Rather than assuming behavioral relationships based on a theoretical background, all behavioral relationships should be estimated or calculated using historical data for the economy or area modelled.
- *Exogenous variables based on observed data* - All exogenous variables should be actual timeseries to capture developments in the economic landscape over time.
- *Validation against historical data* - The model must be able to replicate past economic developments, ensuring that it captures observed dynamics of the economy over time.

While empirical SFC-models are bound to the structure of a specific economy or area, fully empirical models further ensure that the behavioral dynamics of that economy are also represented over time. Again, this puts an even higher requirement on having well-developed national accounting data for several years - which is not the case for all countries. For an overview of current developments within Empirical and Fully Empirical SFC models, see Caverzasi & Godin (2015); Zezza & Zezza (2019); Pierros (2024).

Lastly, theoretical/calibrated SFC models are defined as models where the accounting principles are not fully in line with the national accounting structure of the economy in question, whereas they will not fulfill the two requirements for an empirical SFC model listed above. The main advantage of theoretical/calibrated models is that there are no limits to the processes you include in the model as you will never be constraint by missing data. Instead, researchers can construct relationships based on theoretical assumptions and explore those within the model. However, this comes at the cost of lower realism, and an inability to draw strong conclusions for policy making and scenario analysis for specific countries or areas as in more empirically grounded SFC-models.

To conclude the introduction of the SFC modeling approach, we will comment on the recent integration of SFC models into the Ecological Economics literature. It is within this area of research that the development of

E-SFC-IO models has taken place. Section 2.4 thus provides a natural transition towards the introduction of Input-Output analysis in Section 3.

2.4. Ecological Stock-Flow-Consistent models

Ecological Economics emerged in the 1970s and 1980s in response to growing concerns about the environmental consequences of economic growth and the perceived limitations of mainstream environmental economics (see Røpke, 2004). Rather than treating environmental problems primarily as market failures, Ecological Economists emphasize that economic activity is embedded within biophysical systems and constrained by material and energy flows (Boulding, 1966; Daly, 1968; Georgescu-Roegen, 1971). A central methodological tool within this field is the use of Environmentally Extended Input-Output models, which connect monetary production structures to physical measures of resource use and emissions (Miller & Blair, 2009). The idea of using the EEIO framework to establish a connection between economic activity and ecological variables dates back to early modeling contributions such as Isard et al. (1968) and Daly (1968). Today, this framework is widely used to analyze the dynamic and spatial interdependence between human economies and natural ecosystems (e.g., Duchin & Lange, 1994), as well as to assess the life-cycle economic and environmental costs of materials (Lloyd & Lave, 2003; Hendrickson, Lave & Matthews, 2010).

While ecological economics has a longer history, its integration with Post-Keynesian macroeconomic theory - often referred to as Post-Keynesian Ecological Macroeconomics - is a more recent development (e.g., Rezai et al., 2013; Fontana & Sawyer, 2013; Rezai & Stagl, 2016). This convergence is rooted in a shared critique of orthodox growth and climate-economy models, such as DICE (Nordhaus, 2008), and a shared emphasis on demand-led dynamics, limited substitutability of inputs, and the importance of financial and structural constraints (Kronenberg, 2010).

The combination of the two approaches has proven valuable for both the Ecological Economics and Post-Keynesian frameworks, providing the missing link between economic and ecological outcomes for the Post-Keynesian tradition (Fontana and Sawyer 2013). While at the same time improving the macroeconomic framework within the Ecological Economics literature, which has been considered weak regarding macroeconomic interactions with the environment (Spash and Ryan 2012).

The merging of the two approaches has led to the development of ecological macroeconomic models built on Post-Keynesian theory. Hardt and O'Neill (2017) provide an excellent overview of macroeconomic models used within the Ecological Economics literature - many of them based on a Post-Keynesian economic framework. These models can be allocated into two broad categories: small-scale models, which elucidate key mechanisms and long-run tendencies through abstraction and analytical reasoning; large-scale models, which incorporate multiple sectors, institutions, and environmental processes into complex frameworks.

An example of a small-scale model is Fontana and Sawyer (2016), who propose a theoretical modelling framework that integrates the interconnections between the real economy, biophysical processes, and social variables, aiming to establish the building blocks of Post-Keynesian ecological macroeconomics. Similarly, Taylor et al. (2016) presents a model that combines Post-Keynesian growth theory with greenhouse gas concentration dynamics, showing that under appropriate climate policies, the economy can converge to a steady state in which GHG concentrations stabilize or decline.

More recent, Valdecantos (2025) develops a long-run demand-led model with balance-of-payments constrained growth to explore the double challenge faced by South American countries under decarbonization: the need for high growth to reduce poverty, alongside declining global demand for their carbon-intensive exports - the main driver of growth. The study shows that only through green structural change - such as lowering the carbon intensity of exports, expanding sustainable industries, or increasing carbon absorption capacities - can decarbonization along with high living standards become a realistic possibility.

Large-scale models that combine Post-Keynesian and Ecological Economics approaches typically adopt a Stock-Flow-Consistent framework.

The first group of contributions extends the SFC framework by incorporating ecological interactions while maintaining an aggregate representation of the production structure (Campiglio et al., 2015; Jackson and Victor, 2015; Dafermos et al., 2017). A prominent example is Dafermos et al. (2017), who develop the DEFINE model - an ecological Stock-Flow Consistent model calibrated at the global level. The model links physical and monetary variables by combining the SFC framework with the flow-fund approach proposed by Georgescu-Roegen (1971). It produces long-horizon simulations (up to 100 years) to analyze the interaction between financial fragility, macroeconomic dynamics, and environmental sustainability. Like most SFC models, it is demand-driven, while also incorporating supply-side constraints through natural resource depletion and climate damage functions. Their results highlight that rising private debt and financial instability can undermine both the low-carbon transition and long-run ecological stability if not addressed through coordinated policy interventions.

A common feature of this strand of models is that the production sector is represented in an aggregate manner, typically focusing on final output (GDP). While this level of aggregation facilitates the analysis of macroeconomic-ecological feedbacks, it abstracts from intermediate consumption and structural differences across industries.

A second strand of literature integrates the SFC framework with environmentally extended input-output models, commonly referred to as Ecological Stock-Flow-Consistent Input-Output (E-SFC-IO) models (e.g., Berg et al., 2015; Naqvi, 2015; see also Section 5, Table 2). Within this framework, input-output tables serve as the key linkage between economic activity and environmental outcomes, capturing inter-industry production networks, structural heterogeneity across industries, and the role of intermediate consumption.

The main objective of this paper is to provide a systematic overview of the existing literature employing the E-SFC-IO modeling framework, presented in Section 5. Before doing so, we first introduce input-output and environmentally extended input-output modeling and discuss how these approaches are combined with SFC models.

3. Input-Output analysis:

Input-output analysis has proven to be a valuable methodology within the Ecological Economics literature, particularly for tracking monetary or physical flows across industries (Hardt and O'Neill, 2017). Like the Stock-Flow-Consistent framework, input-output models are demand-driven. They are typically used to analyze how changes in final demand affect total output and related economic variables, meanwhile capturing the interdependencies among industries through intermediate consumption. Within the Ecological Economics literature, environmentally extended input-output models have been frequently used, integrating environmental indicators - such as emissions, energy use, and natural resource extraction - by linking these variables to the monetary or physical output of industries. This allows researchers to examine the environmental consequences of shifts in final demand.

Input-output analysis was originally developed by Wassily Leontief (1936, 1986) and has recently gained renewed attention for its usefulness in analyzing various aspects of the green transition, particularly in linking environmental outcomes to production and technological processes. Before delving into the mechanics of an IO-model, we begin by presenting an input-output table, which provides the empirical foundation for constructing these models.

Table 1: Full Input-Output table for a single economy

IO TABLE – SIMPLE EXAMPLE	**INDUSTRY 1 INDUSTRY 2 INDUSTRY 3**	**CONS INV GOV EX**	**<u>TOTAL OUTPUT</u>**
R1. FLOW INDUSTRY 1 **R2. FLOW INDUSTRY 2** **R3. FLOW INDUSTRY 3**	Intermediate consumption	Final demand for domestic products	Total output of production
IMPORT FLOW INDUSTRY 1 **IMPORT FLOW INDUSTRY 2** **IMPORT FLOW INDUSTRY 3**	Specified imports used in production	Final demand for specified imports	Total specified imports
UNSPECIFIED IMPORTS	Unspecified imports used in production	Final demand for unspecified imports	Total unspecified imports
IMPORT DUTIES	Import duties associated with production	Import duties associated with final demand	Total import duties
PRODUCTION TAXES **COMPENSATION OF EMPLOYEES** **GROSS OPERATING SURPLUS AND MIXED INCOME**	Value added in intermediate production	Value added in final demand	Total value added
<u>TOTAL OUTLAYS</u>	Total outlays in production	Total aggregate demand C+I+G+EX=F	

The input-output table presented in Table 1 provides an overview of all outputs associated with domestic production (row sums), as well as the total outlays (column sums for industries) required to meet a given level of final demand (column sums for final demand components). In the following sections, we demonstrate how production responds to changes in the components of final demand within the input-output framework, specifically through the use of technical coefficients and the Leontief inverse.

3.1. Calculating Technical Coefficients and the Leontief Inverse

A key feature of input-output models is their ability to capture the interconnections between domestic industries and how these linkages influence the response to changes in the components of final demand. To define a simple input-output model, we begin by specifying the equations that determine the output of domestic industries as a function of intermediate input demand from other industries and the components of final demand.

$$x_1 = z_{11} + z_{12} + z_{13} + C_1 + I_1 + G_1 + EX_1 \qquad \text{Eq. 1a}$$

$$x_2 = z_{21} + z_{22} + z_{23} + C_2 + I_2 + G_2 + EX_2 \qquad \text{Eq. 1b}$$

$$x_3 = z_{31} + z_{32} + z_{33} + C_3 + I_3 + G_3 + EX_3 \qquad \text{Eq. 1c}$$

Instead of using single equations, we can write this system of equations using matrix algebra:[4]

$$\boldsymbol{x} = \boldsymbol{Zi} + \boldsymbol{f} \qquad \text{Eq. 2}$$

And in matrix format:

$$\boldsymbol{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}, \boldsymbol{Z} = \begin{pmatrix} z_{11} & z_{12} & z_{13} \\ z_{21} & z_{22} & z_{23} \\ z_{31} & z_{32} & z_{33} \end{pmatrix}, \boldsymbol{i} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \text{and } \boldsymbol{f} = \begin{pmatrix} C_1 + I_1 + G_1 + EX_1 \\ C_2 + I_2 + G_2 + EX_2 \\ C_3 + I_3 + G_3 + EX_3 \end{pmatrix}$$

Now consider an increase in final demand for industry 1 - for example, a rise in public spending (G_1) of 10 units. Using Equation 1a, this would initially lead to an increase in industry 1's output by exactly 10 units, without accounting for the fact that intermediate consumption is itself a function of output ($\boldsymbol{Z} = f(\boldsymbol{x})$). However, if we assume a Leontief production function - which implies fixed input proportions, constant returns to scale, and no substitution between inputs - we can endogenize the intermediate interactions between

[4] For matrix and vector notation, we use bold letters: matrices are denoted with uppercase letters, while vectors are written in lowercase.

industries. This is done by calculating the ratio of inputs required by each industry as their output increases, commonly referred to as technical coefficients (a_{ij}).

$$a_{ij} = \frac{z_{ij}}{x_j} \qquad \text{Eq. 3}$$

This ratio indicates the number of input units required by industry j from industry i to produce one additional unit of output in industry j. These input requirements can be arranged into the technical coefficient matrix $\boldsymbol{A}$.

$$\boldsymbol{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

This allows us to rewrite Equation 2 as follows:

$$\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{f} \qquad \text{Eq. 4}$$

We can now relate changes in final demand to the effect on industries output - including the feedback effects on output through intermediate consumption, by isolating $\boldsymbol{x}$ in the above equation:[5]

$$(\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}} * \boldsymbol{f} = \boldsymbol{x} \qquad \text{Eq. 5}$$

Here $(\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}}$ is known as the Leontief inverse ($\boldsymbol{L}$), which links changes in final demand to changes in the output of domestic industries. However, output may not always be the primary variable of interest following a shock to final demand. Instead, variables such as employment (measured in monetary or physical terms), value added, or environmental indicators (introduced in the next section) may be of greater relevance.

Since most input-output models assume no feedback from these variables back into production, they can be linked to industry output using simple linear coefficients. For example, consider compensation of employees in monetary terms, which is part of value added as shown in Table 1. Let $\boldsymbol{e'} = (e_1 \quad e_2 \quad e_3)$ be a row vector representing compensation of employees per unit of output in each of the three industries. We can calculate employment coefficients, dividing the initial level of employe compensation with the initial level of industries output.

$$\boldsymbol{e'_c} = \begin{pmatrix} \frac{e_1}{x_1} & \frac{e_2}{x_2} & \frac{e_3}{x_3} \end{pmatrix} = (e_{c1} \quad e_{c2} \quad e_{c3}) \qquad \text{Eq. 6}$$

We can then relate compensation of employees to changes in final demand through the following equation:[6]

$$\boldsymbol{\epsilon} = \widehat{\boldsymbol{e'_c}}\, \boldsymbol{Lf} \qquad \text{Eq. 7}$$

In the framework just presented, final demand is treated as fully exogenous, with no feedback effects from the production sector back into the components of final demand. Models with this assumption are commonly referred to as open input-output models. While open models are widely used, some approaches introduce

[5] $\boldsymbol{I}$ represents the identity matrix, a matrix which consists of ones down the diagonal, with all other elements being zero.
[6] Where $\widehat{\boldsymbol{e'_c}}$ represents $\boldsymbol{e'_c}$ as a diagonal matrix.

feedback effects through what are known as closed input-output models. The most common closure involves household final consumption. In this case, the assumption is that a shock to final demand, leading to changes in output and, consequently, in employment or compensation of employees - affects household income, which in turn influences household consumption. To incorporate this feedback mechanism, the model is closed by integrating household consumption and compensation of employees into the matrix of intermediate flows ($\boldsymbol{Z}$) as follows:

$$\boldsymbol{Z_c} = \begin{pmatrix} z_{11} & z_{12} & z_{13} & c_1 \\ z_{21} & z_{22} & z_{23} & c_2 \\ z_{31} & z_{32} & z_{33} & c_3 \\ e_1 & e_2 & e_3 & 0 \end{pmatrix}$$

As shown above in the new matrix $\boldsymbol{Z_c}$, we integrate these elements by adding both a row and a column to the matrix. Household consumption is introduced as a column, representing the consumption of goods and services by households from the different industries. Compensation of employees is added as a row, capturing the payments made by each industry to households for labor services. Finally, a zero is placed in the bottom-right corner of the matrix - this element represents households' purchases of their own labor services, which are assumed to be zero in this example.

We also need to modify the output and final demand vector:

$$\boldsymbol{x_c} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_c \end{pmatrix}, \boldsymbol{f_c} = \begin{pmatrix} I_1 + G_1 + EX_1 \\ I_2 + G_2 + EX_2 \\ I_3 + G_3 + EX_3 \\ 0 \end{pmatrix}$$

In the output vector, $x_1, x_2,$ and x_3 should be interpreted the same as before, while x_c now represents the total "sales" of labor services to the different industries. In the updated final demand vector, household consumption is removed, and a new row is added to represent the final demand associated with labor payments. This could, for instance, include the portion of government spending allocated to wages; however, in this example, we assume it to be zero.

We can now calculate the new technical coefficient matrix $\boldsymbol{A_c}$ following the same procedure as in Equation 3.

$$\boldsymbol{A_c} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{1c} \\ a_{21} & a_{22} & a_{23} & a_{2c} \\ a_{31} & a_{32} & a_{33} & a_{3c} \\ a_{e_1} & a_{e_2} & a_{e_3} & 0 \end{pmatrix}$$

In matrix $\boldsymbol{A_c}$, household's input coefficients are found in the same manner as any other element in an input-output coefficients table: The value of sector j purchases of labor (for a given period), e_j, divided by the value of total output of sector j gives us the coefficients a_{e_j}.

$$a_{e_j} = \frac{e_j}{x_j} \qquad \text{Eq. 8}$$

For the consumption coefficients a_{ic} the consumption within each industry is divided by the total income of households (measured by the sum of employee's compensation) x_c.

$$a_{ic} = \frac{c_i}{x_c} \qquad \text{Eq. 9}$$

Besides from the assumption of fixed employment coefficients in firms' production function, it also imposes the assumption that household consumption for each industry is linearly related to the level of income - whereas the consumption basket will not change as a response to income changes.

We can solve the model, using the same strategy as for the open model case:

$$\boldsymbol{x_c} = \boldsymbol{A_c x_c} + \boldsymbol{f_c} \qquad \text{Eq. 10}$$

Then isolating $\boldsymbol{x_c}$

$$(\boldsymbol{I} - \boldsymbol{A_c})^{-\mathbf{1}} * \boldsymbol{f_c} = \boldsymbol{x_c} \qquad \text{Eq. 11}$$

Although the input-output framework allows for the introduction of feedback effects from the production sector to final demand, these mechanisms are typically simplistic and rely on restrictive assumptions. In contrast, SFC models offer a more detailed representation of final demand components through behavioral equations. In SFC models, final demand can depend on variables from the production sector, but often also incorporates factors from the financial system or measures of inequality - elements that are generally not included in input-output models.

However, compared to the SFC framework, the input-output framework offers a more consistent approach to introducing heterogeneity within the production sector, allowing different industries to have distinct supply chains. It also explicitly accounts for intermediate consumption, which is excluded in SFC models with an aggregate production sector. Including heterogeneity in the production sector, as well as intermediate consumption enables a more realistic link between production and environmental variables, particularly in environmentally extended input-output models, which we introduce in the following section.

3.2. Environmentally extended input-output analysis

Environmentally extended input-output (EEIO) analysis builds on the input-output framework presented in the previous section by incorporating satellite accounts that capture the environmental impacts associated with output across different industries. This approach has laid the groundwork for much of the development in the Ecological Economics literature (Miller and Blair, 2009). Within this literature, EEIO models are primarily used to analyze the embodied environmental impacts of consumption activities (life-cycle assessment analysis) and to calculate the environmental footprint of traded goods between nations (Kitzes, 2013).

To set up a simple EEIO model, we can follow the same procedure used for modeling compensation of employees, by assuming that environmental outcomes are a linear function of total output in each industry. For example, if we wish to link changes in final demand to pollution, we can define a vector of pollution coefficients for each industry:

$$\boldsymbol{p'} = (p_{c_1} \quad p_{c_2} \quad p_{c_3})$$

Where p_{c_j} is the ratio of pollution in industry j divided by the output of industry j:

$$p_{c_1} = \frac{p_j}{x_j} \qquad \text{Eq. 12}$$

We can then perform the same equation manipulations as for employment, and we end up with an equation relating final demand changes to changes in pollution.

$$\boldsymbol{x_p} = \widehat{\boldsymbol{p}'}\,\boldsymbol{Lf} \qquad \text{Eq. 13}$$

While EEIO models used on their own provide valuable insights into the environmental impacts of changes in final demand, these models have also been extended into Environmental Computable General Equilibrium (CGE) models. These models address some of the simplifying assumptions of IO models, in particular the reliance on fixed prices, fixed input shares, and the absence of supply constraints (Banerjee et al. 2016). However, CGE models also come with notable limitations, especially in their behavioral foundations, which typically rely on an optimizing representative agents (Metcalf & Stock 2020). A proper introduction to CGE models and their limitations are presented in Section 6. Some of these limitations have motivated the development of alternative approaches, including the integration of EEIO models into Stock-Flow Consistent (SFC) frameworks - the focus of the next section.

4. Combining IO with SFC

Following the introduction of SFC modeling in Section 2 and IO modeling in Section 3, this section provides an introduction on how to combine these two frameworks. As mentioned, the combination of SFC and IO models has recently seen a rise in attention, with several authors identifying it as one of the most promising frameworks for capturing the interactions between the economy and the ecological and financial sectors (Hardt and O'Neill, 2017; Bimpizas-Pinis et al., 2023).

The combination of these two approaches can be viewed from two angles: SFC modelers incorporating the IO framework, and IO modelers adopting the SFC framework. We have already outlined some of the strengths and limitations of each approach which showcase the incentives for each framework to adopt the other. However, in current literature, the focus has been on integrating IO-models into Stock-Flow-Consistent models. As a result, the IO-structures are in most cases simple, with only a few industries interacting.[7] In this section, we will provide a simple example on how to introduce the IO-framework into a simple SFC-model.

4.1. A simple SFC-IO model

Three main advantages arise for an SFC modeler when disaggregating the production sector using IO tables. First, the ability to capture heterogeneity within the production structure where producing a unit of output in one industry can have very different economic, financial, or environmental effects than producing a unit of output in another industry. Second, the explicit representation of intermediate consumption, which allows the model to account for total gross output in the economy, rather than focusing solely on GDP as in most SFC models with an aggregate production sector. This distinction is particularly important in ecological SFC models, where both final and intermediate production drive environmental impacts. Finally, the possibility of introducing bottom-up dynamics which enable industry-specific shocks or policy interventions at the disaggregated level to propagate through inter-industry linkages and give rise to aggregate macroeconomic effects.

In what follows, we will extend the SIM model presented in Section 2 by introducing a disaggregated production sector consisting of three industries. In Table 2, we present the updated Transaction-Flow-Matrix, where the production column is now split into three. In addition, two changes have been made to the rows. First, row three has been renamed "Final Demand". Since we are working with a closed economy, the sum of final demand - comprising household and government consumption - corresponds to GDP. Second, row four has been added to reflect intermediate consumption flows between the two industries. As we are dealing with a closed economy, the total intermediate inputs used by domestic industries equals the total intermediate inputs sold by domestic industries, and the row therefore sums to zero.

[7] Future research could include models integrating the two approaches with a larger focus on the topics analyzed by IO-modelers for example Life-cycle assessment analysis. This would require IO-structures with higher dimensions, which could adopt the stock-flow-consistency approach and behavioral equations from the SFC-literature to better model final demand components.

Table 2: Accounting (transactions) matrix for Model *SIM* with three production industries

		1. Households	2. Industry 1	3. Industry 2	4. Industry 3	5. Government	Σ
1.	Consumption	$-C$	$+C_1$	$+C_2$	$+C_3$		0
2.	Govt. expenditures		$+G_1$	$+G_2$	$+G_3$	$-G$	0
3.	Final demand		F_1	F_2	F_3		Y
4.	Intermediate consumption		$\pm Z_1$	$\pm Z_2$	$\pm Z_3$		0
5.	Factor income (wages)	$+WB$	$-WB_1$	$-WB_2$	$-WB_3$		0
6.	Gross operating surplus	$+B2$	$-B2_1$	$-B2_2$	$-B2_3$		0
7.	Taxes	$-T$				$+T$	0
8.	Change in the stock of money	$+\Delta H$				$-\Delta H$	0
	Σ	0	0	0	0	0	0

We present here the key equations used to introduce the disaggregated production sector, while the full set of model equations is provided in Appendix B. We begin with the output equation for each of the three industries, represented by i:

$$X_i = Z_{i1} + Z_{i2} + Z_{i3} + C_i + G_i \qquad \text{Eq. 14}$$

Here output in industry i is the sum of all sales of intermediate inputs $(Z_{i1} + Z_{i2} + Z_{i3})$ and sales of final demand $(C_i + G_i)$. This equation is similar to the single equation systems presented for the IO-models in Section 3. As intermediate consumption itself is a function of total output, we model the four flows of intermediate consumption using technical coefficients:

$$Z_{ij} = a_{ij} * X_j \qquad \text{Eq. 15}$$

Where a_{ij} is the technical coefficient showing how much input industry j demand from industry i as industry j changes its output X_j.

Assume now an exogenous demand shock to G_1 of 10 units. Initially, this increases output in industry 1 by 10 units, following Equation 14. This rise in output raises industry 1's demand for inputs, increasing Z_{11}, Z_{21}, and Z_{31}. These changes, in turn, affect the output equations, leading to additional increases in output for both industry 1, 2, and 3 - which again raise input requirements for all three industries. In this way, a feedback loop is introduced into the model which, after multiple iterations, converges to a final solution - provided that the production system is well-defined. When considering the production system in isolation, this converged solution corresponds to the static solution obtained by applying the Leontief inverse to the new final demand vector (Equation 5).

As SFC models are dynamic models, they do not directly use Leontief inverse coefficients to solve the production system in a static manner. This has both advantages and disadvantages. One advantage of solving the production system as in the equations above is that it allows one to incorporate other substitution effects or feedback effects in period t. For example, in some of the models presented in Section 5, relative prices are used to introduce substitution effects between final consumption productions, and domestically and foreign-produced goods. A disadvantage of this approach lies in solving the model: first, it requires multiple iterations to achieve convergence toward the final solution of the production system;[8] and second, the number of equations needed increases exponentially with the number of industries included. We comment on this issue in Section 4.2.2 where we discuss the role of aggregation in the production system.

Moving on with the model equations, we can link the total output in each industry to employment; we use productivity to measure how many workers are required to produce one unit of output within each industry. Productivity is just the inverse of the labor coefficients used in the IO-literature (see Equation 6)

$$N_1 = \frac{X_1}{prod_1} \qquad \text{Eq. 16}$$

$$N_2 = \frac{X_2}{prod_2} \qquad \text{Eq. 17}$$

$$N_3 = \frac{X_3}{prod_3} \qquad \text{Eq. 18}$$

Similarly, we could extend the model to include environmental variables, for example linking CO2-emissions to the level of production in each industry - in the following scenarios, effects on employment can be seen as the effect on any variable that could be linearly linked with output (for example emissions or energy usage).

4.1.1. Model simulations – the effects of disaggregating the production system

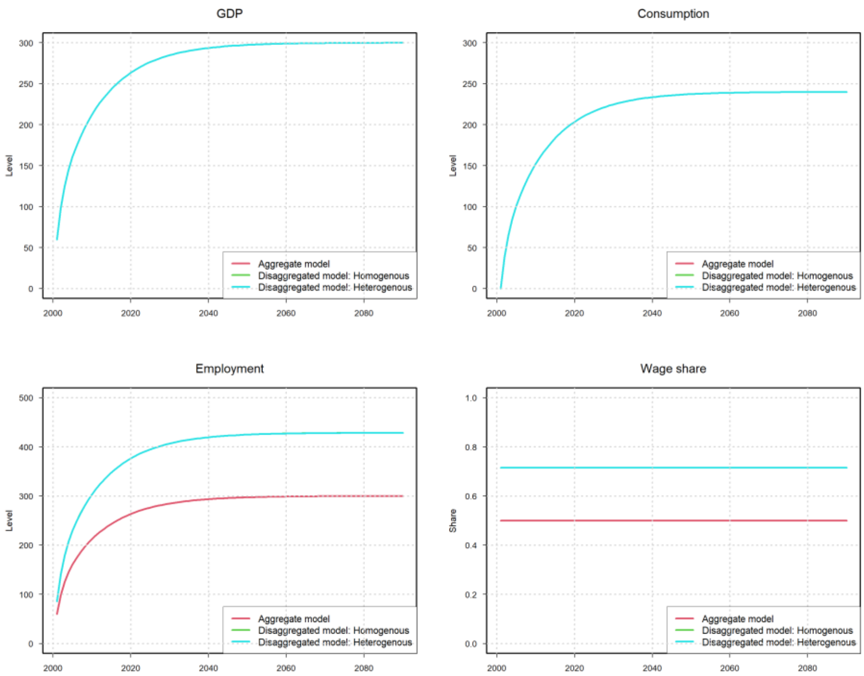
We now present model simulations using three different versions of the SIM model to illustrate the implications of having different representations of the production sector. *Model 1* includes an aggregate production sector, following the setup presented in Section 2.1. *Model 2* features a disaggregated production sector with homogeneous industries, where interactions are governed by the matrix of technical coefficients $\boldsymbol{A_{SIM}^{Homo}}$. *Model 3* also includes a disaggregated production sector, but with heterogeneous industries represented by $\boldsymbol{A_{SIM}^{Hetero}}$, which is calibrated to result in the same level of total output given the final demand in the model as in *Model 2*.

$$\boldsymbol{A_{SIM}^{Homo}} = \begin{pmatrix} 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 \end{pmatrix}, \ \boldsymbol{A_{SIM}^{Hetero}} = \begin{pmatrix} 0.0104 & 0.0218 & 0.0495 \\ 0.0977 & 0.1361 & 0.1776 \\ 0.0216 & 0.1142 & 0.2245 \end{pmatrix}$$

[8] As a result, the model cannot be solved analytically.

In Figure 1 below, we see that disaggregating the production system into industries does not affect GDP or final demand components, since intermediate consumption does not enter these variables. However, producing intermediate goods requires labor. As a result, employment is higher in the two models that include a disaggregated production sector. In our simple model, this leads to a redistribution of income, as more workers leads to a larger wage-bill (and lower profits) for the industries, which changes the functional income distribution in the economy. It is important to highlight that in this basic setup, the level of employment and the functional income distribution have no feedback effects on final demand - so final demand and GDP remain unchanged.[9] We will introduce such a feedback mechanism later.

Figure 1: Disaggregation of the production system into 3 homogenous industries

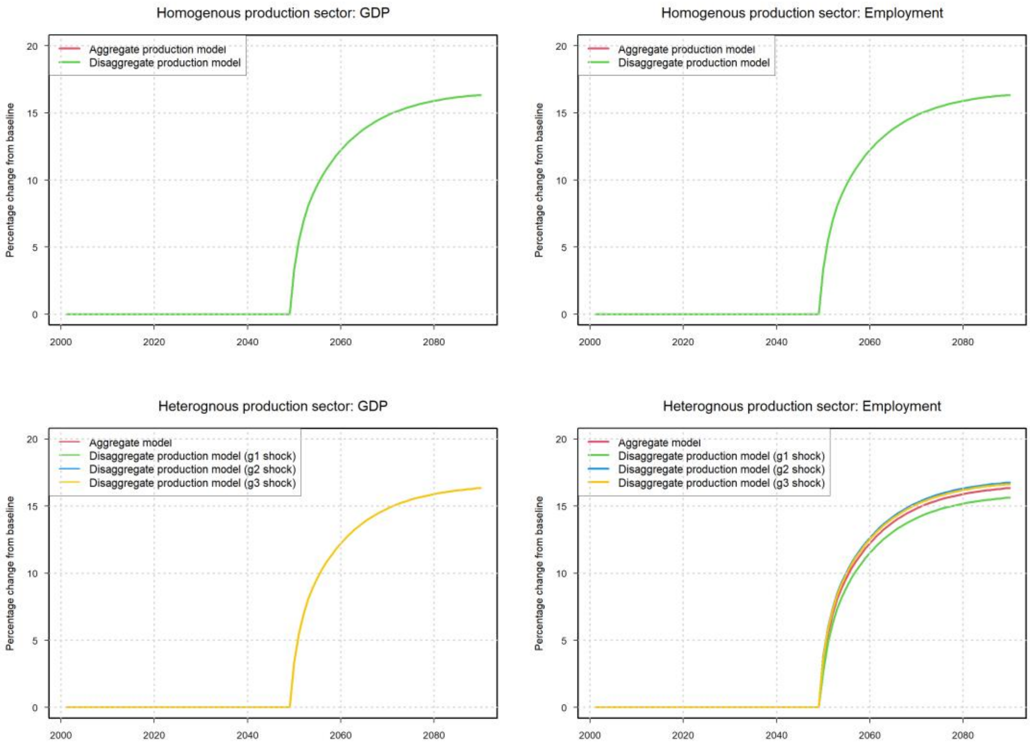


In Figure 2, we introduce a shock to government spending of 10 units to obtain the fiscal multiplier of government spending in each of the three models. In the disaggregated model with homogeneous industries, the increase is implemented in industry 1, whereas in the heterogeneous model, we show the multiplier for each of the three industries separately. As expected, the multiplier for GDP is identical across all three models, as no feedback effects are introduced from industry output to final demand. For employment, which is directly linked to output, the multiplier in the aggregated model and the disaggregated model with homogeneous industries is similar - despite the level differences shown in Figure 1. In the disaggregated model with

[9] As all profits obtained in the production sector is transferred to households, the change from profits to wages in the economy has no effect on final demand.

heterogeneous industries, however, the employment multiplier differs from the other two models and depends on which industry receives the additional government spending.

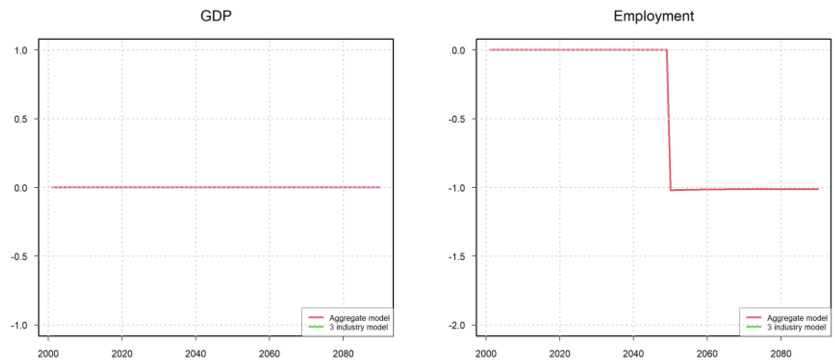
Figure 2: Fiscal multipliers



Furthermore, we can show that changes in the composition of final demand can affect total output and employment in the model with heterogeneous industries. In Figure 4, we show the effect on GDP and employment as we reallocate 10 units of government spending from industry 3 to industry 1. While total final demand remains unchanged, this shift leads to a 1% reduction in overall employment as a result of lower intermediate consumption.[10]

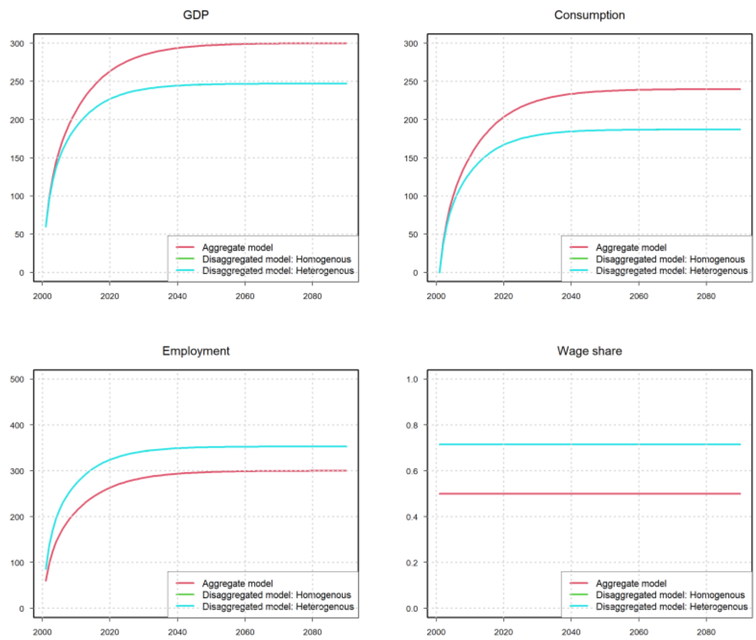
[10] We set the productivity in each industry to 1, whereas all three industries have the same labor requirement to produce one unit of output.

Figure 3: Change in final demand Heterogenous industry model



Until now, the effect on final demand and GDP did not differ between the three models. However, if we allow functional income distribution to feed back into final demand - for example, by introducing different tax rates on wage income (higher) and profits (lower) - final demand and GDP are affected. When intermediate consumption is introduced, the resulting increase in the wage share implies that a larger portion of household income is subject to the higher tax rate. This reduces disposable income, thereby lowering consumption and, ultimately, GDP. We show this in Figure 4 below:

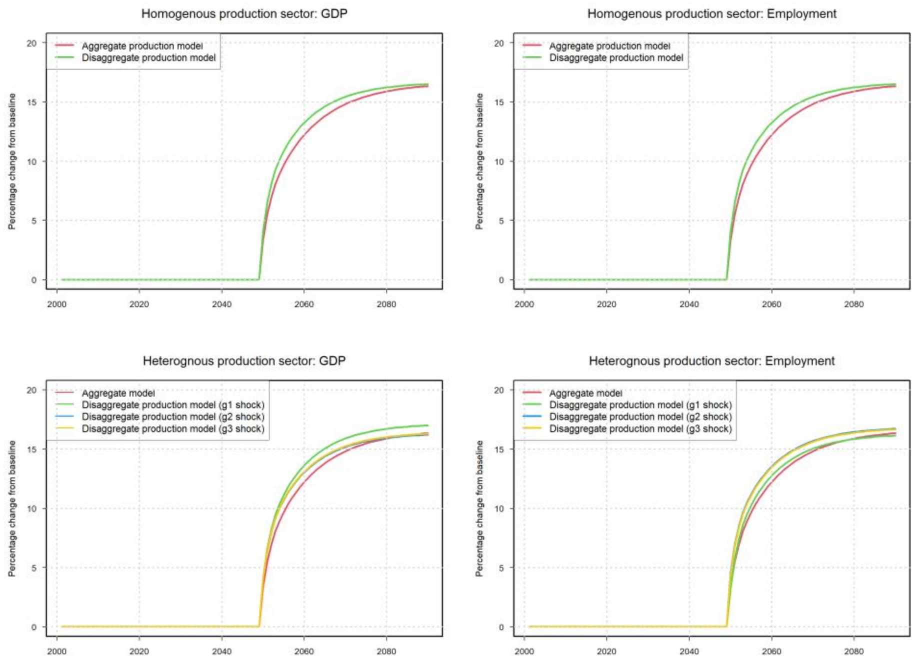
Figure 4: Adding feedback effects from income distribution to final demand



Note: *The green line representing the disaggregated model with heterogenous industries lies beneath the blue line representing the disaggregated model with homogenous industries.*

The introduction of this feedback mechanism also means that the fiscal multiplier on GDP is different within each of the three models as shown in Figure 5.

Figure 5: Adding feedback effects from income distribution to final demand - Fiscal multipliers



It is important to note that including this feedback effect within time period t is only possible when the production system is solved dynamically - using Equation 14 and 15. If, instead, the feedback is introduced with a lag (as in the above), the production system could instead be solved in a static manner - using Leontief coefficients to link final demand to output directly in the model code. In this case, the feedback effect will affect final demand in the following period, which then feeds into the production system. In a larger model, this might improve the time of simulation.

The results presented in this section highlight that disaggregation of the production sector allows for important dynamics associated with intermediate consumption and heterogeneity within shocks across industries. To dive deeper into the role of disaggregating the production sector, the next section discusses the implications of different levels of aggregation in the production system and how these affect model complexity and computational requirements. It also considers how an overly aggregated representation of the production system may lead to aggregation bias.

4.2. The role of aggregation

The level of aggregation in the production system plays a crucial role in the design of SFC-IO models, and several trade-offs arise when deciding how disaggregated the system should be. Some of these issues in the context of IO-models are discussed by Miller and Blair (2009). In general, the appropriate level of aggregation should depend on the research question. However, important considerations include the potential for aggregation bias, as well as the complexity and computational requirements associated with disaggregated models. We now turn to a discussion of these two aspects.

4.2.1. Aggregation bias

Aggregation bias has been investigated since the early years of the input-output literature (see, e.g., Ara (1959); Balderston and Whitin (1954); Hatanaka (1952); McManus (1956)). It can occur when industries with different production structures - reflected in dissimilar columns in the technical coefficient matrix - are aggregated into a single industry. As the current literature on SFC-IO models typically uses fairly aggregated IO tables compared to standard IO analysis, aggregation bias is likely to be present. To quantify this bias, we use a formula closely related to the one presented in Miller and Blair (2009):

$$\boldsymbol{\tau} = \boldsymbol{\Delta x}^{*} - \boldsymbol{S\Delta x} \qquad \text{Eq. 19}$$

Here, $\boldsymbol{\tau}$ represents the level of aggregation bias, where $\boldsymbol{\Delta x}^{*}$ denotes the change in the output vector resulting from a shock to final demand in the aggregated production system (indicated by the star). In contrast, $\boldsymbol{S\Delta x}$ consists of an aggregation matrix $\boldsymbol{S}$ multiplied by the change in output following a shock to final demand in the disaggregated production system.

Aggregation bias: a simple theoretical model

We provide a simple example from Miller and Blair (2009), which considers three different production systems: one disaggregated system that serves as the baseline, and two aggregated production systems derived from it. We begin with the disaggregated production system, which includes four industries, as shown below:

$$\boldsymbol{Z_4} = \begin{pmatrix} 26.5 & 75 & 46 & 53 \\ 34 & 5 & 68 & 68 \\ 41.5 & 38 & 52 & 83 \\ 33.5 & 6 & 53 & 67 \end{pmatrix}, \boldsymbol{f_4} = \begin{pmatrix} 659.5 \\ 1835 \\ 2515.5 \\ 1560.5 \end{pmatrix}$$

From this, we can calculate the output vector:

$$\boldsymbol{Z_4 i_4} + \boldsymbol{f_4} = \boldsymbol{x_4} = \begin{pmatrix} 860 \\ 2010 \\ 2730 \\ 1720 \end{pmatrix} \qquad \text{Eq. 20}$$

We now define the two aggregated production systems. In the first, we aggregate industries 3 and 4; in the second, we aggregate industries 1 and 4. To do this, we define two aggregation matrices: $\boldsymbol{S_{34}}$ used to aggregate industries 3 and 4, and $\boldsymbol{S_{14}}$, used to aggregate industries 1 and 4.

$$\boldsymbol{S_{34}} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix}, \boldsymbol{S_{14}} = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

We start by aggregating the intermediate flows:

$$\boldsymbol{S'_{34}Z_4S_{34}} = \boldsymbol{Z_{34}} = \begin{pmatrix} 26.5 & 75 & 99 \\ 34 & 5 & 136 \\ 75 & 44 & 255 \end{pmatrix} \quad \text{Eq. 21}$$

$$\boldsymbol{S'_{14}Z_4S_{14}} = \boldsymbol{Z_{14}} = \begin{pmatrix} 5 & 68 & 102 \\ 38 & 52 & 124.5 \\ 81 & 99 & 180 \end{pmatrix} \quad \text{Eq. 22}$$

And then the final demand vector:

$$\boldsymbol{S'_{34}f_4} = \boldsymbol{f_{34}} = \begin{pmatrix} 659.5 \\ 1835 \\ 4076 \end{pmatrix} \quad \text{Eq. 23}$$

$$\boldsymbol{S'_{14}f_4} = \boldsymbol{f_{14}} = \begin{pmatrix} 1835 \\ 2515.5 \\ 2220 \end{pmatrix} \quad \text{Eq. 24}$$

We can then calculate total output:

$$\boldsymbol{Z_{34}i_3} + \boldsymbol{f_{34}} = \boldsymbol{x_{34}} = \begin{pmatrix} 860 \\ 2010 \\ 4450 \end{pmatrix} \quad \text{Eq. 25}$$

$$\boldsymbol{Z_{14}i_3} + \boldsymbol{f_{14}} = \boldsymbol{x_{14}} = \begin{pmatrix} 2010 \\ 2730 \\ 2580 \end{pmatrix} \quad \text{Eq. 26}$$

We then calculate the technical coefficients for each of the three set-ups, which provides us with the three matrices:[11]

$$\boldsymbol{A_4} = \begin{pmatrix} 0.031 & 0.037 & 0.017 & 0.031 \\ 0.040 & 0.003 & 0.025 & 0.040 \\ 0.048 & 0.019 & 0.019 & 0.048 \\ 0.039 & 0.003 & 0.019 & 0.039 \end{pmatrix}$$

[11] We have removed decimals for presentability, the exact matrices can be derived from the replication code using the document "IO aggregation bias".

$$\boldsymbol{A_{34}} = \begin{pmatrix} 0.031 & 0.037 & 0.022 \\ 0.040 & 0.003 & 0.040 \\ 0.047 & 0.022 & 0.057 \end{pmatrix}$$

$$\boldsymbol{A_{14}} = \begin{pmatrix} 0.002 & 0.025 & 0.040 \\ 0.019 & 0.019 & 0.048 \\ 0.040 & 0.036 & 0.070 \end{pmatrix}$$

Whereas final demand can be linked to total output through the Leontief inverse:

$$\boldsymbol{x_4} = (\boldsymbol{I_4} - \boldsymbol{A_4})^{-1} * \boldsymbol{f_4} \qquad \text{Eq. 27}$$

$$\boldsymbol{x_{34}} = (\boldsymbol{I_3} - \boldsymbol{A_{34}})^{-1} * \boldsymbol{f_3} \qquad \text{Eq. 28}$$

$$\boldsymbol{x_{14}} = (\boldsymbol{I_3} - \boldsymbol{A_{14}})^{-1} * \boldsymbol{f_3} \qquad \text{Eq. 29}$$

We now introduce a shock to final demand. In the disaggregated model, we apply an increase of 10 units in each industry. In the aggregated models, we increase final demand by 10 units in industry 1 and 2, while increasing final demand by 20 units in industry 3, as this represents the aggregated industry in both cases. The new final demand vectors are shown below:

$$\boldsymbol{f_4^{new}} = \begin{pmatrix} 669.5 \\ 1845 \\ 2525.5 \\ 1570.5 \end{pmatrix}, \qquad \boldsymbol{f_{34}^{new}} = \begin{pmatrix} 669.5 \\ 1845 \\ 4096 \end{pmatrix}, \qquad \boldsymbol{f_{14}} = \begin{pmatrix} 1845 \\ 2525.5 \\ 2240 \end{pmatrix}$$

We can now calculate the new total output vectors:

$$(\boldsymbol{I_4} - \boldsymbol{A_4})^{-1} * \boldsymbol{f_4^{new}} = \boldsymbol{x_4^{new}} = \begin{pmatrix} 871.30 \\ 2021.20 \\ 2741.51 \\ 1731.13 \end{pmatrix} \qquad \text{Eq. 30}$$

$$(\boldsymbol{I_3} - \boldsymbol{A_{34}})^{-1} * \boldsymbol{f_3^{new}} = \boldsymbol{x_{34}^{new}} = \begin{pmatrix} 871.26 \\ 2021.16 \\ 4472.52 \end{pmatrix} \qquad \text{Eq. 31}$$

$$(\boldsymbol{I_3} - \boldsymbol{A_{14}})^{-1} * \boldsymbol{f_3^{new}} = \boldsymbol{x_{14}^{new}} = \begin{pmatrix} 2021.20 \\ 2741.51 \\ 2602.43 \end{pmatrix} \qquad \text{Eq. 32}$$

And then calculate the aggregation bias, using Equation 18:

$$\boldsymbol{\tau_{34}} = (\boldsymbol{x_{34}^{new}} - \boldsymbol{x_{34}}) - \boldsymbol{S'_{34}}(\boldsymbol{x_4^{new}} - \boldsymbol{x_4}) = \begin{pmatrix} 0.04 \\ 0.04 \\ 0.13 \end{pmatrix} \qquad \text{Eq. 33}$$

$$\boldsymbol{\tau_{14}} = (\boldsymbol{x_{14}^{new}} - \boldsymbol{x_{14}}) - \boldsymbol{S'_{14}}(\boldsymbol{x_4^{new}} - \boldsymbol{x_4}) = \begin{pmatrix} 0.00 \\ 0.00 \\ 0.00 \end{pmatrix} \qquad \text{Eq. 34}$$

As mentioned earlier, aggregation bias arises when two industries with different production structures are combined. In the case of aggregating industries 1 and 4, we can see from the technical coefficient matrix ($\boldsymbol{A_4}$) of the disaggregated system that they share identical production structures. Consequently, the results of shocking final demand show no evidence of aggregation bias. In general, the greater the asymmetries in the production structures of aggregated industries, the larger the resulting aggregation bias.

Aggregation bias: Using Danish IO data

To provide a more realistic example, we use the 117-industry input-output table provided by Statistics Denmark, along with an aggregated version of this table presented in Thomsen et al. (2025). In that study, the 117-industry IO table is aggregated to 9 industries and used to model the production system in an ecological SFC-IO model for Denmark. We calculate the resulting aggregation bias as follows:

$$\boldsymbol{\tau_9} = (\boldsymbol{x_9^{new}} - \boldsymbol{x_9}) - \boldsymbol{S_9'}(\boldsymbol{x_{117}^{new}} - \boldsymbol{x_{117}}) \qquad \text{Eq. 35}$$

Where $\boldsymbol{x_9}$ and $\boldsymbol{x_{117}}$ are the vectors of output in the 9-industry and 117-industry models. $\boldsymbol{x_{117}}$ is derived directly from the data, while $\boldsymbol{x_9}$ is constructed by aggregating the 117-industry IO table into only 9 industries using an aggregation matrix $\boldsymbol{S_9}$. Following the same notation as in Equations (33) and (34), $\boldsymbol{x_9^{new}}$ and $\boldsymbol{x_{117}^{new}}$ are the output vectors in the 9-industry and 117-industry models, after a shock to final demand.

We perform three types of shocks to final demand: (i) a 1 percent increase in final demand across all 117 industries; (ii) an increase of 2 billion DKK in final demand across all industries; (iii) a redistribution of final demand, increasing demand by 2 billion DKK in 58 randomly chosen industries and decreasing demand by 2 billion DKK in 58 other industries (with demand in one industry left unchanged), such that total final demand remains constant.

Below, we show the vector of aggregation bias for the three shocks:[12]

$$\boldsymbol{\tau_9^{S1}} = \left(\boldsymbol{x_9^{new,S1}} - \boldsymbol{x_9^{S1}}\right) - \boldsymbol{S_9'}\left(\boldsymbol{x_{117}^{new,S1}} - \boldsymbol{x_{117}^{S1}}\right) = \begin{pmatrix} 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \end{pmatrix} \qquad \text{Eq. 36}$$

[12] Differences in equation 36-38 er in billion DKK.

$$\boldsymbol{\tau}_{9}^{S2} = \left(\boldsymbol{x}_{9}^{new,S2} - \boldsymbol{x}_{9}^{S2}\right) - \boldsymbol{S}'_{9}\left(\boldsymbol{x}_{117}^{new,S2} - \boldsymbol{x}_{117}^{S2}\right) = \begin{pmatrix} 0.20 \\ 0.37 \\ 0.19 \\ -0.01 \\ -0.24 \\ 1.99 \\ 0.90 \\ -0.63 \\ 19.6 \end{pmatrix} \qquad \text{Eq. 37}$$

$$\boldsymbol{\tau}_{9}^{S3} = \left(\boldsymbol{x}_{9}^{new,S3} - \boldsymbol{x}_{9}^{S3}\right) - \boldsymbol{S}'_{9}\left(\boldsymbol{x}_{117}^{new,S3} - \boldsymbol{x}_{117}^{S3}\right) = \begin{pmatrix} -0.14 \\ 0.23 \\ -0.09 \\ -0.12 \\ -0.56 \\ 4.38 \\ 0.48 \\ 0.57 \\ 0.78 \end{pmatrix} \qquad \text{Eq. 38}$$

The results of equation 36-38 provides another key insight into the role of aggregation bias - commonly unexplored. Even though the aggregation from 117 industries to 9 industries using Danish IO data clearly involves grouping industries with different production systems, we find no aggregation bias in Shock 1, where final demand is increased by 1% in all 117 industries. The reason is that the structure of the final demand vector remains unchanged, as demand increases proportionally across all industries. In contrast, we find aggregation bias in both Shock 2, where final demand increases by a uniform amount in each industry, and Shock 3, where final demand is redistributed across industries. In both cases, the structure of the final demand vector is altered, which gives rise to aggregation bias.

While the previous examples illustrate aggregation bias by examining output, the issue has also been studied in the context of environmentally extended IO models. Lenzen (2011) shows that aggregating sectors with differing economic and environmental characteristics can result in a significant loss of information, leading to biased estimates of input-output multipliers. This highlights the importance of keeping a disaggregated production system to reduce aggregation bias. However, doing so may increase model complexity and computational demands - we discuss this in the following section.

4.2.2. Complexity and computational power

Since the production structures of most industries differ substantially, avoiding aggregation bias by grouping only industries with very similar characteristics often results in a large number of industries in the production sector. While allowing for heterogeneity across many industries makes the model more realistic and reduces aggregation bias, it also increases complexity and computational demands by expanding the number of equations.

As shown earlier, IO models are typically solved using matrix algebra, providing static solutions to the production system. In contrast, the SFC framework is inherently dynamic, with the production system often represented through single equations that form feedback loops and converge iteratively to a final solution. Among the studies reviewed in Section 5, only Almeida et al. (2022) solve the model using matrix algebra.

The majority of models include all interactions between industries using individual equations. As the size of the production system increases, the number of equations grows rapidly. For example, the SIM model presented in Section 4.1 consists of 28 equations when including two industries, 38 equations with three industries, and 52 equations when expanded to four industries. While many of these equations are structurally similar, for example the accounting identities applied across industries, they still increase the complexity of the model and place additional demands on computational resources.

However, if the researcher does not wish to model substitution effects or feedback effects on final demand within time period t, and instead introduce these dynamics with a one-period lag, the production system can be solved using matrix algebra and integrated into the SFC framework. This approach allows for the inclusion of larger IO models without expanding the number of equations and reduces computational requirements, as the production system no longer needs to converge dynamically. For simpler models, such as the SIM model discussed here, this also makes it possible to solve the system analytically - an option that is not feasible when the production sector is modeled using single equations.

5. Presentation and Categorization of the existing literature:

In this section, we review some of the key contributions of Stock-Flow-Consistent Input-Output modelling presented in the ecological macroeconomic modelling literature. As this modelling framework is still at an early stage of development, only 14 publicly available studies adopting the Stock-Flow-Consistent Input-Output approach have been identified at the time of writing. However, several additional studies appear to be under development, and new contributions may emerge as the literature continues to evolve. Table 2 lists the 14 identified studies and provides a general classification across five categories. In this section, we examine each of these studies in more detail, focusing on how the production structure is modelled and linked to the financial and ecological sectors, as well as the calibration strategy employed. First, we start by presenting some of the earlier works which have laid the ground for the current rise in popularity of SFC-IO modelling.

Table 2: Overview of SFC-IO papers

Papers (by year)	Production system	Linkage to Financial system	Linkage to Ecological or energy sector	Calibration method and target	Research area
Berg et al (2015)	Two industries Theoretical	Low complexity Theoretical	One-directional link	Theoretical/calibrated (Germany)	Economic non-growth, energy shocks, and anthropogenic heat emissions.
Naqvi (2015)	Two industries Theoretical	Low complexity Theoretical	Two-way link using damage functions and firm costs	Theoretical/calibrated (EU)	Evaluating green transition strategies.
Valdecantos (2015)	Four industries Theoretical	Low complexity Theoretical	No Ecological sector	Theoretical/calibrated (Latin American economies)	Modelling economic structures of Latin-American countries
Monasterolo & Raberto (2018)	Three industries Theoretical	Medium complexity Theoretical	One-directional link	Theoretical/calibrated (middle-to-high-income economy)	financial stability and investment dynamics in the green transition
D'Alessandro et al. (2020)	Ten industries IO data	Low complexity Calibrated	Two-way link using firm costs	Theoretical/calibrated (France)	Comparing green growth, social equity policies, and degrowth strategies
Dunz et al. (2021)	Three industries Theoretical	Medium complexity Theoretical	Two-way link using firm costs	Theoretical/calibrated (EU)	Comparing carbon taxation with green supporting factors
Jackson & Jackson (2021)	Three industries theoretical	Medium complexity Theoretical	One-directional link	Theoretical/calibrated (middle-to-high-income economy)	Effects of declining Energy Return on Investment (EROI)
Valdecantos (2021)	31 industries IO data	Medium complexity Fully data driven	One-directional link	Empirical (Argentina)	Trilemma of low growth, external unsustainability, and environmental unsustainability in Argentinian
Almeida et al. (2022)	Six industries IO data	Low complexity Theoretical	One-directional link	Theoretical/calibrated (Saving propensities)	Introducing second-order-effects in LCA analysis
Sers (2022)	Three industries Theoretical	Low complexity Theoretical	Two-way link using damage functions	Theoretical/calibrated (investment-to-GDP ratio)	Strategies to meet the 1.5°C target
Di Domenico et al. (2023)	Eight industries Theoretical	High complexity Theoretical	One-directional link	Theoretical/calibrated (relative cost of inputs)	transition to a circular economy and the risk of rebound effects
Fevereiro et al. (2024)	Four industries IO data	Medium complexity Theoretical	One-directional link	Theoretical/calibrated (EU)	Effects of circular economic policies on economic, social, and environmental variables
Thomsen et al. (2025)	Nine industries IO data	Medium complexity Fully data driven	Two-way link using firm costs	Fully Empirical (Denmark)	Agriculture green transition
Jackson & Jackson (2025)	Four industries theoretical	Medium complexity Theoretical	One-directional link	Theoretical/calibrated (an advanced economy)	Energy technology transitions

5.1. The early developments of SFC-IO models:

The introduction of industry heterogeneity within the production sector of Stock-Flow-Consistent models was first proposed by Berg et al. (2015). Coming from the ecological macroeconomic literature, Berg et al. (2015) combines Stock-Flow-Consistent modeling with Environmentally Extended Input-Output modeling, which up until then, had only been used separately within the Ecological Economics literature.

Their model consists of three sectors: households, non-financial corporations, and a combined government/banking sector. The integration of an input-output setup allows for the disaggregation of the non-financial corporate sector into two industries: an energy industry and a production industry. The energy industry supplies energy as an input to the production sector, which in turn produces goods for final consumption and intermediate use. A simple financial sector enables firms to take loans to finance inventories, while households hold money deposits. The model is applied to analyze whether a non-growing economy can be sustained with positive interest rates, provided that household consumption out of wealth and income dynamics remain stable. Additionally, the model is used to examine the macroeconomic effects of energy price shocks, highlighting how price increases in the energy sector can lead to recessions due to cost-push inflation and multiplier effects through the input-output linkages. The study also briefly explores the impact of anthropogenic heat emissions, linking economic activity to environmental consequences.

Simultaneously with Berg et al. (2015), a project under the WWWForEurope initiative led to a multi-industry Stock-Flow-Consistent model, presented by Naqvi (2015). The model includes a household, production, government, and financial sector, with the production sector divided into an energy industry and a production industry. Firms use capital, labor, and energy as inputs, with the energy sector supplying both renewable and fossil-based energy, where firms choose between the two energy types.

The model introduces feedback effects between the economy and the environment: production using fossil-based energy leads to higher GHG emissions and matter usage, GHG emissions leading to increasing capital depreciation, and higher matter usage leading to increased resource extraction costs. Social aspects are also incorporated, with households divided into workers and capitalists, and unemployment explicitly modeled, allowing for an analysis of functional income distribution.

The model is applied to policy experiments evaluating different green transition strategies. Results show that shifting to renewables or improving energy and capital efficiency can achieve a "triple-win" of economic growth, equity, and environmental sustainability.

Another early contribution to the SFC-IO literature is Valdecantos (2015), the model includes eight institutional agents: households, four productive industries (food-producing agriculture, non-food agriculture, mining, and services), commercial banks, the government, the central bank, and the rest of the world. Compared to the other early attempts, this model includes a more detailed productive framework; each industry combines intermediate inputs, labor, and capital to generate output, consumed by both domestic and foreign agents - except in the service industry, which serves only domestic demand. Desired production is based on last period’s output, adjusted for the gap between sales and prior output, while in services it simply follows last year’s level. Actual production is constrained by the scarcest input.

Investment in capital depends on profitability, capacity utilization, and debt. Firms finance investment through retained earnings and, if those are insufficient, by seeking loans, which are subject to exogenous credit rationing by banks. If loans are restricted, firms instead adjust deposits. Households allocate savings between bank deposits and central bank-issued cash, and the government closes its budget using domestically issued bonds. The nominal exchange rate adjusts to clear the international bond market unless the central bank intervenes via foreign reserve operations.

The model examines three external shocks applied to four stylized productive structures (agro-industrial, oil, mining, and maquila). Results show that price shocks affect each structure differently, while an increase in international interest rates leads to capital outflows, currency depreciation, rising inflation, and declining real wages and consumption across all productive structures.

5.2. Modelling the production sector

The early attempts to incorporate input-output tables into Stock-Flow-Consistent models marked an important step towards addressing a key limitation of SFC frameworks: the aggregate treatment of the production sector. These developments enabled more detailed representations of inter-industry linkages and production processes within a SFC modelling framework. In the following, we review more recent contributions that build on these early attempts. In this section, we focus on the production sector - whereas the following section will target the link to financial and ecological sectors.

For the production sector, we distinguish between studies that integrate actual input-output data and those that adopt a more theoretical or stylized approach. In presenting these models, we focus on the structure of the production sector - specifically, the types of industries included, and the inputs used in each industry's production.

We begin with models in which inter-industry interactions are not based on actual input-output data but instead are more theoretically based (Berg et al., 2015; Naqvi, 2015; Valdecantos, 2015; Monasterolo & Raberto, 2018; Dunz et al., 2021; Jackson & Jackson, 2021; Jackson & Jackson, 2025; Sers, 2022; Di Domenico et al., 2023). While the theoretical approach decreases the realism of the production sector for these models, it provides a larger flexibility to model more complex relations - for which data might not be available. Additionally, some of these models adopt an Agent Based (AB) approach in which industry behavior is defined by a representative agent (Monasterolo & Raberto 2018; Dunz et al. (2021)) or heterogenous firms (Di Domenico et al. 2023).

Jackson & Jackson (2021) develop an SFC-IO model called TranSim to study the effect of declining Energy Return on Investment (EROI). They divide the production sector into three industries: an energy sector producing both renewable and non-renewable energy, a capital sector supplying fixed and non-fixed capital, and another production sector producing a single composite good. To produce output, firms combine labor, capital, and intermediate goods. A distinguishing feature of this model is that energy firms can purchase both green capital (which does not emit CO2) and fossil fuel capital (which does emit CO2), with the share of green capital exogenously increasing over time to simulate a green energy transition. In Jackson and Jackson (2025) an extended version of Transim (Transim 2) is presented. Compared to the previous model, Transim 2 includes a disaggregation of the energy sector into a fossil fuel sector and a green sector. Furthermore, this model also adds financial relationships between the firm, bank, and household sectors.

Sers (2022) develops a Stock-Flow-Consistent Input-Output Integrated-Assessment-Model (SFC-IO-IAM) to analyze how global temperature increases can be limited to below 1.5°C without relying on unproven negative emissions technologies. They divide the production sector into a fossil-fuel industry, renewable energy industry, and a manufacturing industry. Renewable energy production requires labor and capital but no intermediate inputs, whereas fossil-fuel energy production requires both labor, capital, and self-produced inputs. The manufacturing sector requires energy (from either fossil-fuel or renewable sources), self-produced inputs, capital, and labor.[13]

A key feature of the model is the endogenous determination of energy substitution in production, implemented through endogenous technical coefficients. As the manufacturing industry increases its share of electricity-driven capital, its demand for fossil-fuel energy declines. At the same time, as production capacity in the renewable energy industry expands, this further reduces demand for fossil fuels while increasing demand for renewable energy. The renewable industry invests in capital until it can fully meet the manufacturing industry's energy needs, while the fossil-fuel industry only invests to meet the demand for its output.

Monasterolo and Raberto (2018), develop the EIRIN model, an SFC-IO-AB model used to analyze financial stability and investment dynamics related to the green transition. They divide the production sector into a consumption good industry, a green capital goods industry, and a brown capital goods industry - each represented by a representative agent. The green and brown capital good industries use only labor in their production, while the consumption goods industry use labor and capital. Capital is accumulated by investing in either green or brown capital products, with the decision being based on expected additional future cash flow due to investments, net their present costs (net present value). Dunz et al. (2021) follow a similar production set-up as Monasterolo and Raberto (2018) dividing the production sector into a consumption goods industry, a green capital goods industry, and a brown capital goods industry as they compare carbon taxation with green supporting factors (GSF) to assess their ability to scale up green investments while preventing

[13] Labor inputs are modeled as a residual to make costs equal to output in the IO-table (in the form of wage-bill) which is quite untraditional.

macroeconomic risks and financial instabilities. In contrast to Monasterolo and Raberto (2018) all production industries use labor and capital in their production function. While the two capital industries only accumulate their own type of capital, the consumption good sector chooses between green and brown capital determined by the relative price and productivity of the two types of capital.

Di Domenico et al. (2023) develop an SFC-IO-AB model to study how a market-driven circular economy transition can unintentionally increase energy and material use, despite aiming to reduce resource consumption. The production sector is disaggregated into one energy firm, firms extracting raw materials through mining, firms producing materials via recycling, firms producing consumption goods, and four capital goods sectors - each producing a specific type of capital used only by one of the other production sectors. Each industry consists of a fixed number of firms, whose size varies endogenously based on demand. Firms use Leontief production functions, where Consumption Good firms use labor, capital, energy, and materials as inputs. Materials are provided either from mining or recycling firms, depending on relative prices (as they are perfect substitutes). The energy firm produces energy using capital, labor, and a non-renewable energy source. Each capital goods sector uses labor and energy to produce capital and engages in R&D to lower production costs for its client industry by improving the capital-to-output ratio, capital-to-labor ratio, or energy efficiency of the capital goods. Technological change is embodied in new capital goods, which endogenously affect the technical coefficients over time.

While the studies just presented introduce theoretically driven IO-dynamics, we now reach the studies following a more data-driven approach. These studies model intermediate connections across industries based on actual input-output tables (D'Alessandro et al. 2020; Valdecantos 2021; Almeida et al. 2022; Fevereiro et al. 2024; Thomsen et al. 2025). While the use of real input-output tables adds realism, the data-driven approach increases the difficulty of adding complex intermediate relationships between industries, such as endogenous technical coefficients.

D'Alessandro et al. (2020) assess whether current green growth policies may increase inequality and unemployment, and whether complementary social policies are needed to avoid adverse distributional effects. The production sector consists of 10 industries, with technological change endogenized via R&D investment that improves both labor and energy productivity. Production relies on capital, labor, and intermediate inputs (including energy), and follows demand-driven dynamics. Technical coefficients for intermediate inputs are calibrated using 2014 French data from the World Input-Output Database. Desired capital accumulation depends on profit rates, capacity utilization, and depreciation. If firms' retained earnings can finance a minimum share of investment, the remaining share is financed through bank loans. Industries demand labor differentiated by three skill levels, with employment driven by output and productivity. Labor supply is endogenous and responds to unemployment.

Fevereiro et al. (2024) develop a model under the JUST2CE project to evaluate the effects of circular economy (CE) policies and practices on economic, social, and environmental outcomes. They present a two-region SFC-IO model, where one region represents the EU and the other the rest of the world. The production sector in each region consists of four industries: Manufacturing, Agriculture, Services, and Waste Management. The first three industries generate both output and waste, while the Waste Management industry processes waste into reusable inputs, which can be reintegrated into production as the circular economy expands. Production in all industries requires labor, intermediate inputs, and fixed capital. Intermediate consumption is modeled using EXIOBASE3 input-output data. Investment in fixed capital is based on an industry-specific capital-to-output ratio and capital depreciation. Labor supply adjusts in line with industry-specific labor demand, which is determined by output levels.

Almeida et al. (2022) develop an SFC-IO model to show how Life Cycle Assessment (LCA) analysis can be extended beyond first-order effects - where consumption spending is kept fixed - without leading to an infinite expansion of the system. These second-order effects arise from the redistribution of income across different household groups that occurs due to changes in final consumption expenditures across industries. The production sector is divided into six industries -Agriculture, Mining, Nonmetal Products, Metal Products, Energy, and Services - each producing using intermediate inputs and labor. Labor is classified by three skill levels, each with distinct consumption patterns and an industry-specific share of value-added. Intermediate consumption is modelled using Input-Output data from France.

Thomsen et al. (2025a) develop an empirical Ecological Stock-Flow Consistent Input-Output (E-SFC-IO) model for the Danish economy.[14] The production sector is divided into nine industries, each using intermediate inputs (based on Danish input-output tables from 1995-2020), labor, and fixed capital to meet final demand. Labor is supplied on demand and investments are determined based on profits, interest rates on loans and the capacity utilization within industries. However, supply site factors feed back into final demand through industry specific prices and profit rates.[15]

Valdecantos (2021) analyze the trilemma of low economic growth, external unsustainability, and environmental unsustainability in the Argentinian economy, using an Empirical Ecological Stock-Flow Consistent Input-Output (E-SFC-IO) model for Argentina. The production sector is divided into 31 industries, each using labor, intermediate inputs, and capital in production. Intermediate consumption occurs across all industries based on Argentinian input-output data for the year 2017, the production sector thereby includes 916 intermediate relationships - the most disaggregated production sector in this review. Industries produce to meet

[14] Further extensions of this model are introduced in Thomsen et al. (2025b) and Thomsen (2026).
[15] Relative prices are used to determine substitution effects across product types, and whether these are imported or produced domestically.

final demand, labor is fully demand driven and fixed capital formation is determined by profits, capacity utilization and the interest rate on loans.

5.3. Linkage to the financial sector

A key feature of the Stock-Flow-Consistent approach is the explicit and internally consistent integration of the financial sector. Disaggregating the production structure within this framework opens up the possibility of analyzing financial dynamics and stability at the industry level. In this section, we therefore examine how the financial sector is modelled in the E-SFC-IO literature and how financial variables are linked to the production structure across different studies.

Existing contributions differ substantially in how they integrate the financial sector with the production sectors, both in terms of model complexity and the extent to which empirical data are used. A large share of the literature relies on theoretical or stylized frameworks, featuring what we define as low- or medium-complexity integrations of the financial sector, as classified in Table 2 (Berg et al., 2015; Naqvi, 2015; D'Alessandro et al., 2020; Sers, 2022; Almeida et al., 2022; Jackson and Jackson, 2021, 2025; Fevereiro et al., 2024).

Berg et al. (2015) introduce a simple linkage between the production and financial sector through two financial assets. The two industries in the production sector do not retain profits and therefore finance their inventory holdings through bank loans. Households place their savings in money deposits, with banks-modelled within the government sector-acting as the counterpart to these deposits.

Naqvi (2015) incorporates four financial assets: advances, deposits, treasury bills, and loans. Since industries in the production sector do not retain profits, they finance both expected nominal inventories and nominal investment through loans from the financial sector. The financial sector also provides deposits to households. When household deposits do not fully cover industries' loan demand, the financial sector borrows the residual from the central bank in the form of advances. In addition, the central bank purchases any treasury bills issued by the government.

D'Alessandro et al. (2020) include four financial assets: deposits, loans, equities, and public bonds. Low-skilled households place all their net lending in deposits and receive no interest payments. Medium-skilled households hold deposits and government bonds, the latter paying interest. High-skilled households and capitalists hold deposits, government bonds, and equities, with equity holders receiving dividends. Households' demand for financial assets depends on relative rates of return, following Tobin's portfolio theory (Tobin, 1969). Firms finance investment through retained earnings and loans. A fixed proportion of new investment must be financed by retained earnings, consistent with a target debt-to-equity ratio. The government issues new bonds to cover its budget deficit, using last year's bond prices as a reference. If changes in bond prices lead to an excess or shortfall of funds, the government issues or withdraws short-term bills to close the gap.

In both Jackson and Jackson (2021) and Jackson and Jackson (2025), households also follow Tobin's portfolio theory as they allocate their savings between bank deposits and firm-issued equities based on relative rates of return. Interaction between the production and financial sectors is introduced, incorporating three financial assets: deposits, loans, and equities. When new investments are undertaken, firms finance them using a combination of retained earnings, loans from commercial banks, or equities issued to households-depending on the relative cost of each financing option. The model ensures market clearing by equating the demand and supply of equities and by matching household deposits with firms' loan requirements.

Similar to Jackson and Jackson (2021), Fevereiro et al. (2024) model industry-specific investment as being financed through retained earnings, loans, and equity issuance. However, their specification of household portfolio allocation differs. Households allocate savings across domestic and foreign government bills, as well as equities issued by domestic and foreign firms, again according to Tobin's portfolio theory and relative rates of return. Demand for cash is proxied by the previous year's consumption expenditure, while household borrowing depends on durable goods purchases and the gap between consumption and disposable income. Demand for bank deposits is determined as the residual.

Sers (2022) includes four financial assets: money, deposits, loans, and advances. As industries in the production sector do not retain earnings - wages are set so that total wage payments equal total industry outlays - firms finance investment entirely through loans from the banking sector. Households allocate excess savings between deposits and cash, with the share held in deposits depending on the interest rate and the level of disposable income (higher income increases cash demand). If household deposit supply and industry loan demand do not match, commercial banks borrow the residual from the central bank (included under the government sector) in the form of advances. The central bank also supplies cash to households if demanded.

Almeida et al. (2022) include only two financial assets: deposits and loans. Households adjust their bank deposits based on the difference between wage income and consumption, while industries take out loans to cover the gap between total outlays and total sales. By model construction, changes in deposits and loans are always equal.

Within the banking sector, if household deposit supply exceeds firms' loan demand, banks purchase government bills; if loan demand exceeds deposit supply, banks borrow the difference from the central bank in the form of advances. The government sector supplies cash and advances on demand and adjusts the outstanding stock of government bills in line with the fiscal balance.

The studies presented so far introduce relatively simple financial interactions and are therefore classified as low or medium complexity in Table 2. However, several studies incorporate a higher level of complexity in the interaction between the production and financial sector. For example introducing financial stability measures such as capital adequacy ratios (CAR) (Monasterolo & Raberto, 2018; Dunz et al., 2021) and non-performing loan (NPL) ratios (Monasterolo & Raberto, 2018; Dunz et al., 2021; Di Domenico et al., 2023).

Monasterolo and Raberto (2018) include four financial assets. Firms in the production sector finance investments in green and brown capital through loans from the commercial bank. However, the bank is subject to a Basel II-style capital adequacy requirement, with credit supply constrained by the ratio of equity to a regulatory parameter. If credit demand exceeds this limit, firms face credit rationing. Loan repayments and interest payments influence the bank's equity and profit distribution, while the central bank passively ensures liquidity in the system.

Dunz et al. (2021) stand out by endogenously determining interest rates through a two-step process within the banking sector. First, a base lending rate is set based on the exogenously defined central bank policy rate and the bank's capital adequacy ratio (CAR), defined as the ratio of bank equity to risk-weighted loans. If the CAR falls below its target level, the base lending rate is increased to maintain financial stability. Second, this base rate is adjusted to generate sector-specific lending rates, taking into account each sector's non-performing loan (NPL) ratio, expected future profits, and a Green Supporting Factor (GSF) that incentivizes green investments. Additionally, banks incorporate a forward-looking climate sentiment mechanism, adjusting lending rates based on anticipated impacts of climate policies on future industry profitability.

Di Domenico et al. (2023) include four financial assets: deposits, loans, bonds, and advances. Production firms finance investment using retained earnings or loans from commercial banks. If firms are unable to repay their debt, they go bankrupt - resulting in non-performing-loans. Households accumulate deposits in commercial banks, while entrepreneurs also demand government bonds. If household deposits do not fully cover firms' loan demand, commercial banks either request advances from the central bank or deposit excess reserves with it. To cover fiscal imbalances, the government issues bonds; if household demand for bonds is insufficient, the central bank acts as a lender of last resort by purchasing the remaining bonds.

Finally, two studies differ from the others by using actual financial balance sheets from national accounts to model the connection between the production and financial sectors (Valdecantos, 2021; Thomsen et al., 2025a). Although their approach is fully data-driven, the complexity of the interactions between the production and financial sectors is not as detailed as in the studies just discussed - primarily due to data constraints.

Valdecantos (2021) models the financial balance sheets of institutional agents in the Argentinian economy, incorporating seven financial assets: money, foreign assets, credit, bills and bonds, foreign liabilities, green bonds, and equity. Production is linked to the financial balance sheets through industry profits. As profits are generated in each industry these are distributed to households as part of their disposable income and contribute to savings in the private non-financial sector (both consisting of firms and households), besides profits made in the financial industry which are allocated to the financial sector's savings. Households allocate their savings across financial assets according to a set of behavioral equations including demand for loans, foreign assets, foreign liabilities and the supply of green bonds, lastly money demand is modeled to ensure the overall budget constraint of the private non-financial sector. The main choice made by the financial sector is the demand for green bonds, while loans are given on demand, and government bonds act as the budget constraint.

Thomsen et al. (2025a) also model the financial balance sheet of the institutional sector level, allowing the gap between savings and investment to be financed through eight financial assets: gold, deposits, securities, loans, equities, pension and insurance entitlements, financial derivatives, and trade credits. Since here, production is assumed to occurs in multiple institutional sectors the model links industry specific profits and investment at the industry level to institutional sectors using industry-specific allocation shares. This approach allows changes in the producing industries to influence net lending in all four domestic institutional sectors which then affect the demand for financial assets at the institutional level through either estimated behavioral equations or accounting identities ensuring horizontal or vertical consistency.

5.4. Linkage to the Ecological sector

Disaggregating the production sector enhances the representation of ecological linkages, as it enables specific industries to interact differently with the ecological subsystem. This is the main reason why the SFC-IO framework has become popular within the field of ecological economics. Most studies in this area explicitly include an ecological sector or account for environmental variables. Some of these studies include a one-directional connections between the production sector and ecological or energy variables (Berg et al. (2015); Jackson and Jackson (2021); Jackson and Jackson (2025); Almeida et al. (2022); Monasterolo and Raberto (2018); Fevereiro et al. (2024); Valdecantos (2021); Di Domenico et al. (2023)). While some studies model feedback effects from ecological variables to the economy, where environmental taxation or material scarcity affect firms' costs (Naqvi (2015); Dunz et al. (2021); D'Alessandro et al. (2020); Thomsen et al. (2025a)) or through damage functions affecting capital depreciation and productivity (Naqvi (2015); Sers (2022)). Most of the modelling approaches use theoretical relationships to connect production to ecological variables, while only a few studies are data-driven (Thomsen et al. 2025a; Valdecantos 2021).

Starting with the studies introducing a one-directional linkage, the production structure in Berg et al. (2015) includes an energy industry that supplies energy to both the manufacturing sector and itself. Energy usage from the economic model is linked to a climate module that tracks anthropogenic heat emissions based on thermodynamic principles. As energy is consumed, it is converted into waste heat, adding to an anthropogenic heat flux that raises equilibrium temperature. However, the model includes no feedback from temperature changes back to the economy.

Jackson and Jackson (2021) and Jackson and Jackson (2025) relate the production of energy to CO2 emissions, where energy firms can produce using either green capital - which does not emit CO2 - or fossil fuel capital - which does. CO2 emissions do not have any feedback effects on economic outcomes.

Almeida et al. (2022) in an extension of their model simply link industries activity to CO2 emissions using industry specific emissions intensities.

In Monasterolo and Raberto (2018), the three-industry production sector includes both a green and a brown capital industry. Using green capital is more resource-efficient, resulting in lower levels of resource depletion and CO2 emissions compared to brown capital. However, there are no feedback effects from resource depletion or emissions back to the economy.

Di Domenico et al. (2023) model an economy with mining firms and energy firms that extract virgin materials and produce energy, respectively. A recycling sector is also introduced, supplying recycled materials as substitutes for virgin inputs. Mining firms deplete natural resource stocks directly, while energy firms draw from an oil stock. Energy use by industries results in pollution. Consumption good firms will start buying material produced by the recycling sector as it becomes relatively cheaper than virgin material produced by the mining sector. As the recycling sector replaces the mining sector, this will affect the material and energy intensity, as well as the level of total output in the economy. The model does not incorporate feedback effects from ecological variables (e.g., resource depletion or pollution accumulation) to economic dynamics.[16]

Fevereiro et al. (2024) incorporates ecological variables by modelling waste as a by-product of industrial production, alongside the introduction of a recycling-reuse-repair industry. The model includes industry-specific energy intensity coefficients, accounting for both renewable and non-renewable energy sources. CO2 emissions are linearly linked to non-renewable energy use within each industry and accumulate in a CO2 stock. Atmospheric temperature is derived from the concentration of CO2. Industrial production also leads to material usage, and both energy and material consumption contribute to the depletion of natural resource stocks. However, these ecological variables do not feed back into the economic dynamics of the model.

Valdecantos (2021) links the ecological sector through a GHG emissions module, where emissions are determined by a linear relationship with production, using actual emission data for Argentina. Emissions from both energy use and other production processes are included, with energy-related emissions being determined based on the technical coefficients of energy-producing industries. This endogenization allows the model to

[16] In one scenario they do introduce environmental taxation on the mining sector, however, the tax is not applied to energy or emissions levels but rather set to make the price of mining output 10% more expensive than output from the recycling sector.

simulate the emissions impact of different production and energy sector transitions. No feedback effects are introduced from emissions to the economy.

For the studies introducing a two-way-linkage between economic and ecological variables, the simplest linkage goes through the introduction of carbon taxation.

In D'Alessandro et al. (2020), industries and households use four energy sources: gas, oil, coal, and electricity. Electricity is produced using a mix of fossil fuels, renewable sources, and nuclear power. Consumption of these energy types is used to calculate CO2E emissions. These emissions then affect production costs through the implementation of a carbon tax.

Dunz et al. (2021) also introduce green and brown capital industries. While brown capital has the highest productivity at the start of the simulation, the model assumes that green capital experiences higher productivity growth over time. The model does not include any environmental variables; however, it introduces a carbon tax that is levied on nominal output in industries based on the share of production using brown capital.

Thomsen et al. (2025a) introduce an ecological block that links industry production and household consumption to six types of emissions, then aggregated into CO2-equivalents. These emissions arise from both energy usage - categorized into 21 energy types - and non-energy related emissions. Industry-specific energy coefficients are calculated for each energy type linking output to energy usage, and emission coefficients are calculated for each industry and energy combination. Environmental outcomes feed back into the economy through CO2e taxation at the industry level by applying industry-specific tax rates to total CO2-equivalent emissions - directly affecting industries costs and thereby prices. All relationships are based on data from the Danish energy and emission accounts.

Other examples introduce feedback effects from ecological variables to the economy through damage functions and resource extraction costs.

An example of introducing such bidirectional feedback effects is provided by Naqvi (2015). The model includes an energy sector that supplies both fossil-based and renewable energy, with firms choosing their energy mix based on relative prices. Production that relies on fossil fuels results in higher greenhouse gas (GHG) emissions and increased material use. These outcomes feed back into the economy, as GHG emissions raise the depreciation rate of capital, while higher material use increases resource extraction costs.

Sers (2022) couples their economic module with a carbon cycle model from Glotter et al. (2013). The climate module tracks carbon levels in the atmosphere, upper ocean, and lower ocean, which in turn affect global mean surface temperature and deep ocean temperature. Economic activity influences these variables through emissions, which are calculated proportionally to the physical output of the fossil fuel industry and directly linked to the atmospheric carbon stock. Climate effects feed back into the economy via damage functions where higher temperatures reduce capital productivity across industries and increase the depreciation rate of the capital stock.

5.5. Calibration Strategy

In Section 2.3, we covered different types of SFC-models based on how the models relate to observed data. In this section, we will classify the SFC-IO models presented so far into the categories presented in Section 2.3; whether the models are theoretical/calibrated SFC-IO models or empirical SFC-IO models (including fully empirical SFC-IO models).

Theoretical/calibrated models:

From the models presented in the previous section, most of them are theoretical/calibrated models, meaning they do not fully apply the national accounting structure of a specific region (Berg et al. (2015); Naqvi (2015); Monasterolo & Raberto (2018); D'Alessandro et al. (2020); Dunz et al. (2021); Sers (2022); Almeida et al. (2022); Di Domenico et al. (2023); Fevereiro et al. (2024)). While not relying on a national accounting structure, these models calibrate parameters based on both empirical findings and theoretical assumptions.

Some studies calibrate model parameters to match key macroeconomic variables for a specific country or region. For example, Berg et al. (2015) calibrate their model to match certain variables for the German economy, Valdecantos (2015) to the structure of Latin American economies, while Naqvi (2015), Dunz et al. (2021), and Fevereiro et al. (2024) focus on the European economy, and D'Alessandro et al. (2020) on the French economy. Although these models are tailored to a particular country or region, they do not fully capture the underlying economic structure, as they do not account for the complete set of real and financial flows within the respective economies.

Other studies calibrate their models to represent a particular type of economy or to impose key economic conditions aligned with their research questions. Monasterolo & Raberto (2018) and Jackson & Jackson (2021) calibrate their models to resemble a middle- to high-income economy, while Jackson & Jackson (2025) aims to represent an advanced economy. Sers (2022) calibrates the model to achieve a specific renewable-investment-to-GDP ratio. Di Domenico et al. (2023) calibrate key parameters to ensure that recycled inputs remain more costly to produce than raw materials, thereby influencing firms' production choices. Almeida et al. (2022) assign different saving propensities to various household groups to introduce income-distribution dynamics.

Empirical (country specific) models:

From the Ecological Stock-Flow-Consistent Input-Output models in the previous section, only two can be classified as empirical models: Valdecantos (2021) for Argentina and Thomsen et al. (2025a) for Denmark.

Unlike the theoretical/calibrated models presented earlier, these models integrate the full national accounting structures to ensure stock-flow consistency, therefore fulfilling our definition of an empirical model.

The calibration strategy followed by Valdecantos (2021) includes the development of a Social Accounting Matrix (SAM) for the Argentinian economy for the year 2017, complemented by an input-output table with 31 industries. The SAM is adapted to fit within a Stock-Flow Consistent framework by treating the financial industry as an institutional sector and incorporating interest payments into the income accounts. Real flows captured in the SAM are linked to net financial stocks in the balance-sheet matrix through an approximated flow-of-funds matrix, also constructed using accounting data for Argentina in 2017. In addition, environmental accounts (in the form of industry-level GHG emissions) are compiled for the same year.

The modelling framework integrates these matrices in a consistent manner through accounting identities, thereby capturing the structural features of the Argentinian economy in 2017 and meeting the definition of an empirical SFC model. However, because of limited data availability for Argentina, the data is only included for year 2017, making it impossible to empirically estimate behavioral parameters or incorporate exogenous variables as time series, as would be required for a fully empirical model. Instead, the model uses the economic structure observed in 2017 to calculate key parameters, while certain exogenous variables are projected forward using assumed growth rates to represent economic trends over time.

Thomsen et al. (2025a) use sectoral national accounts to construct a Transaction-Flow-Matrix (TFM), covering all real and financial flows within the Danish economy. Changes in the TFM are consistent with changes in the balance sheets of institutional sectors, ensuring that financial net stocks evolve correctly over time.

Furthermore, production is divided into nine industries, represented by national input-output tables. These input-output tables are linked to sectoral national accounts using Industry-by-Sector matrices, ensuring consistency between the input-output tables and sectoral national accounts using gross operating surplus and mixed income (B2) on the real side and investments on the capital side. Production in the nine industries is also connected to energy and environmental variables using Denmark's national energy and emissions accounts.

Due to the detailed data availability for Denmark, this model is constructed using time-series data from 1995 to 2020. This allows for the inclusion of economic behavioral equations, which are estimated econometrically using historical data, while exogenous variables follow the real developments observed in the Danish economy. As a result, the model can be evaluated based on its ability to replicate observed data. If behavioral equations are excluded, leaving only accounting identities, the model will replicate the sectoral national accounts, input-output tables, and energy and emissions accounts one-to-one for the entire period (1995-2020). Considering this, the model can be classified as a fully empirical model.

6. The role of SFC-IO models in policy analysis

In a recent report by the Coalition of Finance Ministers for Climate Action, an overview of modelling tools used to support climate policy analysis in finance ministries is presented (CFMCA, 2025b). Within this overview, Computable General Equilibrium (CGE) models, Dynamic Stochastic General Equilibrium (DSGE) models, and Integrated Assessment Models (IAMs) emerge as the most commonly employed frameworks for assessing climate policies. In contrast, only one empirical ecological Stock-Flow Consistent model is mentioned - a model for the UK currently under development at SOAS University.

In the following, we provide an introduction to these dominant modelling approaches, used for climate analysis, whereafter we discuss how the E-SFC-IO models presented in Section 5 could supplement the existing policy tools by overcoming some of their main limitations. We begin by providing an overview of the modelling frameworks that currently play a central role in informing climate policy recommendations.

6.1. Macroeconomic models used as climate policy tools:

In what follows, we provide a concise introduction to the modelling frameworks commonly used for climate policy recommendations. We focus on their core assumptions, key limitations, and typical applications. Table 3 summarizes these frameworks, including the E-SFC-IO models, whose role and positioning within the current modelling landscape are discussed in the subsequent section.

Table 3: Modelling frameworks used for climate policy recommendations

Model	Examples of popular models for policy analysis[17]	Behavioral assumptions	Data and calibration / estimation	Key limitations	Typical policy applications
(E)-DSGE	E-QUEST (Varga et al., 2022) GEEM (Annicchiarico et al., 2017)	Representative rational agents maximize intertemporal utility or profits. Monopolistic competition with nominal and real rigidities.	Estimated using Bayesian methods; some parameters calibrated based on theory.	Strong reliance on rational expectations; limited role for effective demand in the long run; highly stylized financial sector; climate damage functions remain ad hoc and weakly empirically grounded.	Primarily used for evaluating optimal carbon taxation and welfare effects of climate policy.
(E)-CGE	GreenREFORM (DREAM, 2025) MANAGE-WB (Mitik-Beyene et al., 2025)	Representative optimizing agents in static or recursive-dynamic market clearing systems.	Calibrated using national accounting data, in the form of a SAM, and IO tables. Some parameters are calibrated based on theory.	Reliance of rational optimizing agents; Economy can only be in equilibrium; financial sector typically treated in a reduced or exogenous manner; limited empirical identification of key behavioral parameters; High sensitivity to elasticity assumptions.	Used for analyzing carbon pricing, industrial policies, structural change, and trade effects.
IAM	DICE (Barrage and Nordhaus, 2024)	Social planner maximizes intertemporal welfare under neoclassical growth framework.	Mainly calibrated, with only limited empirical grounding.	Strong reliance on rational expectations; Highly aggregated; weak empirical basis; limited treatment of uncertainty and structural change.	Used for estimating social cost of carbon and long-term mitigation pathways.
(E)-SFC-IO (calibrated models)	EUROGREEN model (D'Alessandro et al. (2020))	Behavioral equations based on Post-Keynesian theoretical assumptions	Transaction-flow-Matrix and balance sheet matrix, models with limited empirical grounding.	Missing link to micro-level behavior; important parameters are not empirically grounded but instead rely on theoretical assumptions.	Used for analyzing distributional or financial impacts of the green transition.
(E)-SFC-IO (Empirical models)	Still at early stage	Stock-flow consistent accounting with empirically estimated or data-driven behavioral relations, typically informed by Post-Keynesian theory.	Constructed Transaction-flow-matrix, and Balance sheet matrix using national accounts; production sector based on IO tables; Environmental accounts based on national energy and emissions accounts.	Missing link to micro-level behavior; Ability to model policy-regime shifts; Large Data constraints, especially for developing countries.	Used for analyzing distributional and financial impacts of the green transition, mainly based on specific policy cases.

[17] The model examples listed do not necessarily exhibit all of the general characteristics described for each modeling framework.

DSGE models:

Dynamic Stochastic General Equilibrium models emerged from the real business cycle tradition (see eg. Kydland and Prescott (1982), and Long and Plosser (1983)) and were designed with an aim to address the Lucas Critique (Lucas, 1976) by ensuring that agents' expectations respond to policy changes. Expectations are derived from explicit microfoundations: representative households maximize intertemporal utility, and firms maximize profits under monopolistic competition with nominal and real rigidity in prices and wages (Christiano et al., (2005), Smets & Wouters, 2007). DSGE frameworks typically also include a monetary authority that follows a Taylor-type interest rate rule, and in some cases a fiscal rule in which government spending or tax rates adjust to stabilize public debt. Because output is fundamentally supply-determined in the long run, and because demand shocks primarily influence economic activity through short-run nominal rigidities, purely demand-driven shocks tend to have only transitory effects, fading as the economy returns to its steady-state equilibrium.

Modern DSGE models aim to be empirically well founded and are estimated using formal econometric methods, primarily through either limited-information approaches - such as matching model-implied second moments or minimizing the distance between model and data impulse response functions - or full-information Bayesian estimation that exploits the entire model structure (Christiano et al., 2018). However, as DSGE models become larger and more complex, the number of parameters often exceeds what can be reliably identified from the data. As a result, some parameters are fixed based on theory or prior assumptions, rather than being freely determined by the data (Blanchard, 2018).

Environmental DSGE (E-DSGE) models extend the standard framework by incorporating climate dynamics and environmental policy instruments into agents' optimization problems. These models typically introduce greenhouse-gas emissions as a by-product of production or consumption, link them to a climate-damage function, and evaluate how environmental policies - in most cases carbon taxes - affect macroeconomic outcomes (Heutel, 2012; Golosov et al., 2014). Early E-DSGE models relied on a single-sector structure, but more recent contributions introduce a multisectoral framework to account for heterogeneous carbon intensities and industry-specific responses to climate policy (Varga et al., 2022; García-Villegas & Martorell, 2024).

While DSGE and E-DSGE models are one of the most popular policy tools, they have been criticized both internally and externally. Internal critiques focus for example on; (i) their reliance on fully rational, intertemporally optimizing agents; (ii) the fact that, while DSGE models are usually presented as empirically estimated, some important parameters (such as the discount rate) are frequently calibrated and therefore lack solid empirical foundations; and (iii) the absence or oversimplified representation of the financial sector (Blanchard, 2018; Stiglitz, 2018; Christiano et al., 2018). While Heterodox economists agree with these limitations, they further extend this criticism also mentioning the marginal role assigned to demand in the long run, the restrictive commitment to general-equilibrium dynamics, and an unrealistic representation of the financial sector (Dafermos et al., 2024). Extra emphasis is put on the later as the financial framework in DSGE models are usually modelled based on the financial-accelerator mechanism that rules out endogenous money creation (Bernanke et al., 1999). This means that policies such as green public investment are mostly ineffective due to crowding out of private investments.

Further criticism is placed on the damage functions used in DSGE models, as the use of smooth, differentiable climate-damage functions limits their ability to capture tipping points, deep uncertainty, and irreversible climate impacts (Rezai & Stagl, 2016; Pindyck, 2013; Dafermos et al., 2024). Based on these limitations, E-DSGE models are primarily used for analyzing optimal carbon taxation strategies which maximize welfare under the restrictive assumptions mentioned above and provide only narrow guidance on alternative climate policies and climate-related financial risks.

CGE models:

Computable General Equilibrium models were developed as an extension of input-output models, mainly to allow researchers to relax assumptions of fixed prices, fixed input coefficients, the absence of supply constraints, and exogenous final demand (Banerjee et al., 2016). Early multisector general equilibrium work by Johansen (1960) and later developments by Dervis, de Melo and Robinson (1982) established the modern CGE tradition. As in DSGE models, the CGE framework relies on neoclassical microfoundations: households maximize utility, firms maximize profits, and markets clear through relative price adjustments. In this sense, their behavioral assumptions resemble those of DSGE models. However, CGE models are generally static or recursive-dynamic and do not incorporate forward-looking expectations, intertemporal optimization, or stochastic shocks. Instead, representative agents solve within-period optimization problems using constant-elasticity functional forms (e.g., CES, Cobb-Douglas). As the model is solved, supply and demand reach equilibrium through price adjustments in a set of interlinked markets; disequilibrium in one market, by accounting identity, implies disequilibrium elsewhere.[18] As solving CGE models require the economy to reach equilibrium, all markets must simultaneously clear (Babatunde et al., 2017).

The empirical foundation of CGE models, relies on the Social Accounting Matrix (SAM), which records the monetary flows between industries and institutional sectors and is usually constructed using national accounting data and supply-use or input-output tables (Pyatt & Round, 1977; Pyatt, 1988; Pyatt, 1991). Parameters are mainly calibrated based on the SAM of an economy/region for a specific year, but also relies on parameters estimated in the literature, for example based on micro econometric methods.

[18] As CGE models relies on being in equilibrium, there are no rigidities in wages and prices like in DSGE models (Varga et al., 2022).

Environmental CGE (E-CGE) models apply the CGE framework to the analysis of energy use, emissions, and environmental policy. The GTAP-E model (first presented in Burniaux and Truong, 2002) has become the workhorse of E-CGE modeling and extends the standard GTAP framework by allowing industries to substitute between different energy types as relative prices change, as well as between capital, labor, and energy in the production functions. Emissions are then typically linked to the usage of different energy types through fixed emissions coefficients. In contrast to the DSGE framework, CGE models do not rely on damage functions. Instead, emissions affect the cost structure of industries directly - typically through carbon pricing or emissions trading schemes - which then influences equilibrium prices. While technological change is often kept exogenous, some endogenize it using marginal abatement cost curves in which emission coefficients are endogenized. For a review of E-CGE models, see Babatunde et al. (2017).

While CGE models do not rely on intertemporal optimization like DSGE models, the assumption of rational, optimizing representative agents remains a clear limitation to their behavioral set-up (Metcalf & Stock, 2020). CGE models are also criticized for being unable to capture short-run or transition dynamics of shocks, as they generally provide only long-run equilibrium solutions. Furthermore, model outcomes heavily depend on the values chosen for supply and demand elasticities, which are often calibrated rather than econometrically estimated - as performing econometric estimation of all elasticities can be challenging due to data constraints (Beckman et al., 2011).

Lastly, although the data structure of CGE models is built on national accounting principles, they - like DSGE models - typically omit or highly simplify the financial sector (Pollitt & Mercure, 2018). As a result, financial flows (such as interest payments or dividends) and sectoral balance sheets are usually absent from the SAM (Valdecantos, 2021), the latter implying that changes in net lending have no explicit financial counterpart, and thereby no impact on financial payments. The absence of an explicit financial sector, like in DSGE models, implies that CGE models cannot capture endogenous money creation through bank lending; instead, investment is often tied to an exogenous savings rule or representative-agent intertemporal optimization. As a result, E-CGE models heavily favor carbon taxation policies while alternative climate policies like green public investments are deemed non-optimal.

Where E-CGE models has gained increasing attention, is for their highly disaggregated representation of the production sector, which enables a more realistic analysis of environmental analysis based on structural change, industrial policies, and international trade interactions than is typically possible in the other neo-classical frameworks (Varga et al., 2022).

IAM models:

Integrated Assessment Models are employed across several disciplines, which can lead to ambiguity regarding their primary purpose and policy implications. Broadly, IAMs can be divided into two categories: process-based IAMs and cost-benefit IAMs (Weyant, 2017; CFMCA, 2025b). Process-based IAMs provide detailed representations of biophysical systems in specific industries (e.g. energy or agriculture) and analyze how emissions are generated within these systems. Cost-benefit IAMs, by contrast, offer a more aggregated representation of climate mitigation costs embedded within a macroeconomic framework. As the latter aligns more closely with the macroeconomic focus of this paper, it is these models that are described in this section (and to which we refer as IAMs in the remainder of the text). Nevertheless, even these aggregated IAMs are often calibrated using inputs from sector-specific process-based IAMs, implying a persistent structural link between the two approaches.

Unlike the CGE and DSGE frameworks, IAMs do not originate from a single coherent macroeconomic tradition. Instead, they aim to integrate insights from multiple scientific domains into a unified framework. In this discussion, we focus on IAMs rooted in neoclassical growth theory (see Solow, 1996), as this is the most common approach, with the most popular example being the DICE model (see Barrage and Nordhaus, 2024 for the latest version), which is built upon a Ramsey growth framework. In this setting, a representative social planner maximizes the discounted sum of intertemporal utility by choosing optimal paths of consumption and investment, subject to an aggregate resource constraint (Nordhaus, 2013; Weyant, 2017). Production is typically described by a constant-returns-to-scale production function combining capital and labor, while economic growth is driven by capital accumulation and exogenous technological progress.

This economic core is augmented by a climate module in which economic activity generates emissions that accumulate in the atmosphere through the global carbon cycle, thereby affecting temperature and other physical climate variables such as sea level. These environmental changes feed back into the economy via damage functions that reduce effective output or productivity. Climate policy is therefore framed as an intertemporal optimization problem involving a trade-off between present consumption and future climate damage, rendering mitigation an optimal control problem (Pindyck, 2013; Nordhaus, 2013).

Because the behavioral foundations of IAMs closely resemble those of DSGE models - particularly their reliance on intertemporal optimization and rational, forward-looking agents - IAMs face similar critiques regarding the realism of these assumptions. However, IAMs primarily focus on long-run welfare and optimal mitigation pathways and typically rely on coarse time steps and deterministic perfect foresight, which limits their ability to capture short-run macroeconomic dynamics, including business-cycle fluctuations and monetary transmission mechanisms, which DSGE models are specifically designed to analyze (Cai et al., 2012; McKibbin et al., 2020; Wilson et al., 2021).

IAMs are further criticized for their highly aggregated structure, which limits their ability to capture structural change, heterogeneity across industries, and the underlying causal mechanisms driving economic adjustment. This reduces their suitability for analyzing distributional impacts and sectoral reallocation during the climate transition (CFMCA, 2025b).

Finally, the limited empirical grounding of key parameters in IAMs has been widely questioned, particularly with respect to discount rates and damage functions, as well as the weak theoretical justification for the chosen functional forms of these damage functions (Pindyck, 2013; 2017; Weyant, 2017). This concern is especially significant given that the damage functions have been shown to be a primary driver of the results obtained by IAMs.

The combination of strong aggregation and weak empirical foundations has led some authors to question the usefulness of IAMs for providing concrete policy recommendations (Pindyck, 2017; Gambhir et al., 2019). Despite these criticisms, IAMs remain widely used to estimate optimal climate policies, largely because their simple structure makes them attractive and accessible to policymakers. Historically, IAMs have primarily been employed to evaluate the costs of climate inaction and to compute the social cost of carbon, defined as the welfare loss associated with an additional ton of emissions (Weyant, 2017).

6.2. Finding the place for SFC-IO models for policy recommendation

While the three modelling frameworks presented in the previous section (CGE, DSGE, and IAMs) have been - and continue to be - the most widely used tools for providing climate policy recommendations, a demand for alternative modelling approaches has emerged. Reports published by the Coalition of Finance Ministers for Climate Action highlight a growing interest for alternative modelling frameworks capable of analyzing the complex interactions between the environment, the economy, and the financial sector (CFMCA, 2025a; CFMCA, 2025b). Hepburn et al. (2025) further identify several challenges faced by existing models in analyzing the green transition, some of which call for fundamentally new approaches to both the modelling structures and their underlying core assumptions.

While the E-SFC-IO models presented in Section 5 address several of the criticisms made at current policy tools - such as their reliance on neoclassical behavioral assumptions, the absence or unrealistic treatment of the financial sector, and the neglect of demand-led policy mechanisms - it remains essential to clarify the role of E-SFC-IO models as policy tools. Blanchard (2018) discuss different classes of macroeconomic models (primarily focusing on DSGE models) and emphasizes the importance of distinguishing between *theoretical* and *policy models*.

He mentions that *Theoretical models* should prioritize conceptual clarity and aim to capture the essential features of firm and household behavior, rather than attempting to replicate real-world dynamics. They therefore serve primarily as platforms for theoretical exploration and debate. *Policy models*, on the other hand, should prioritize empirical fit and practical relevance, even if this comes at the cost of weaker theoretical coherence, including the relaxation of assumptions such as fully rational, forward-looking agents. This distinction highlights the risk of forcing theoretically-driven models to conform to empirical data and subsequently employing them for policy analysis, as their underlying theoretical foundations may not be applicable across different economic contexts or institutional settings.[19]

Using the distinction of Blanchard (2018) specifically in relation to E-SFC-IO models it reflects many of the same conceptual features as the classification performed in Section 2.3 in which we differentiated between theoretical/calibrated E-SFC-IO models and empirical E-SFC-IO models.

Most theoretical or calibrated E-SFC-IO models (classified in Section 5.2.5) should primarily serve as tools for theoretical exploration rather than empirical policy evaluation. It is important not to overstate their capacity to provide concrete policy recommendations for specific economies. When such models are employed for policy analysis, they are subject to critiques similar to those directed at the mainstream frameworks discussed in the previous section, in which key parameters are often calibrated or derived from theoretical assumptions and lack empirical foundation, thereby limiting their realism and weakening their suitability for providing policy guidance tailored to specific economies or institutional contexts.

On the other hand, empirical and fully empirical SFC models more closely meet the criteria of *policy models*, as their structure and parameters are grounded in national accounts data for specific economies or regions. Fully empirical models and their ability to fit the observed data of an economy or region over time exceed the capabilities of the other frameworks currently used as policy tools. This empirical grounding provides a clearer basis for their potential use as *policy models*.

While the number of fully empirical SFC models has grown over the past decade, fully empirical E-SFC-IO models remain limited, with Thomsen et al. (2025b) representing the only publicly available example to date. One key constraint has been the lack of suitable data, particularly industry level data, which must be directly linkable to national accounts. However, as such data are becoming increasingly available, several ongoing projects now aim to develop fully empirical E-SFC-IO models.

[19] This distinction reflects a broader methodological debate about internal versus external consistency in macroeconomic models: *internal consistency* refers to the logical coherence of a model's assumptions and behavioral equations within a unified theoretical framework, whereas *external consistency* concerns the model's alignment with real-world data and observed behavior. Microfounded models often prioritize internal consistency but struggle with external consistency (Wren-Lewis, 2011).

While empirical E-SFC-IO models represent a promising complement to existing approaches to climate policy analysis by addressing several of the gaps identified in currently used policy tools, and having a strong empirical foundation, their development remains at an early stage. Ongoing projects and future work should aim to further improve some of the strengths associated with E-SFC-IO models to enable them as reliability policy tools. The following section outlines some areas in which E-SFC-IO models could place further attention to become even more relevant to accompany the existing policy tools.

7. Future steps for empirical E-SFC-IO models

Since the introduction of the first SFC-IO frameworks in 2015 (Berg et al., 2015; Naqvi, 2015; Valdecantos, 2015), most efforts have focused on advancing theoretical or calibrated E-SFC-IO models by increasing the complexity of the production, financial, or ecological modules (see Section 5). However, as highlighted in the previous section, a stronger empirical foundation is required if these models are to function as credible instruments for policy analysis.

While further strengthening of the theoretical structure remains important, an increasing attention towards building empirical E-SFC-IO models has emerged. To guide the discussion on how these models can evolve into reliable policy tools, it is useful to focus on the areas in which E-SFC-IO models could offer particular advantages over the existing modelling tools. In what follows, we highlight three such areas, and what further development remains necessary.

7.1. Modelling behavior

As suggested in Section 2.2, most SFC models introduce behavior using post-Keynesian theory. Many empirical SFC models try to relate these theoretical relationships to national accounting data for specific economies using econometric approaches. However, because a main goal for empirical SFC models is to be data driven, which makes them valuable as policy tools, the theoretical foundation might be weaker and should not be forced to follow post-Keynesian relations. While the aggregate econometrically estimated behavioral equations used in SFC models does not rely on the highly criticized behavioral assumptions of neoclassical models. The behavioral framework does face critics related to missing micro-foundations, and the missing acknowledgment of the Lucas Critique.

The lack of micro foundations

Behavioral relations in empirical SFC models are specified directly at the aggregate level and estimated using macroeconomic time-series data. This set-up means that SFC models are not exposed to the fallacy-of-composition critique - namely, the questionable assumption that behavioral relations at the individual level carries over to the aggregate. This critique does apply to the representative-agent framework commonly used in neoclassical models. Nevertheless, the lack of explicit micro-foundations has raised concerns about the extent to which aggregate SFC models can explicitly represent mechanisms that operate at the micro level - such as heterogeneous agent behavior, interaction effects, and non-linear adjustment processes - which are abstracted from by construction in the aggregate set-up (Godley and Lavoie, 2007).

A prominent response to this critique has been the integration of agent-based models (ABMs) with stock-flow-consistent frameworks. ABMs model the economy as a system of interacting, heterogeneous agents, in contrast to the representative-agent structure typically employed in neoclassical macroeconomic models, which has been widely criticized (Kirman, 1992; Skott, 2012). By studying economic dynamics as arising from interactions among many heterogeneous agents, ABMs allow micro-level behavior to affect aggregate outcomes through a bottom-up mechanism. When combined with SFC accounting, these models embed agent-level interactions within a consistent macroeconomic framework, thereby addressing the absence of micro-foundations in traditional aggregate SFC models.

Some of the E-SFC-IO frameworks discussed in Section 5 adopt this combined ABM-SFC approach (Monasterolo and Raberto, 2018; Dunz et al., 2021; Di Domenico et al. 2023). In these models, agents are often defined at the industry level and interact through intermediate input-output linkages, although they typically still rely on representative agents within each industry. While the integration of ABMs into a theoretical SFC framework is already a popular approach, incorporating agent-based structures into empirically estimated SFC and E-SFC-IO models remains an important avenue for future research. In particular, empirical validation in agent-based models typically relies on calibration to stylized facts and simulation-based validation strategies - such as moment matching and distributional comparisons of artificial and real-world data - often complemented by micro-level behavioral evidence, rather than formal likelihood-based estimation against aggregate macroeconomic time-series data (Windrum et al., 2007; Fagiolo et al., 2019). As a result, reconciling the complexity of agent-based interactions with empirical consistency at the level of national accounting data remains a challenge.

The Lucas critic

The Lucas critique remains a central point of discussion in policy evaluation and has played a key role in the development of macroeconomic models such as DSGE models. Skott (2012) derives three elements from the Lucas critique: (i) economic behavior is goal-oriented, has an intertemporal dimension, and is influenced by expectations; (ii) reduced-form equations linking current decisions to observable variables reflect these expectations (and underlying goals); and (iii) in light of this, models should rely on explicit microeconomic optimization, since structural elements such as preferences and production technologies are assumed to remain invariant across policy regimes.

Skott (2012) suggests that while the first two points are valid, the idea that economies should be analyzed exclusively through models of forward-looking behavior in which rational agents form expectations under intertemporal optimization is questionable and at odds with observed economic behavior. Nevertheless, this approach has remained dominant in mainstream macroeconomics and underpins climate macro models in the DSGE and IAM traditions, and to some degree CGE models, which abstract from intertemporal optimization yet still rely on representative optimizing agents and equilibrium adjustment mechanisms.

Heterodox economists should nevertheless take the first two points seriously. In particular, the second point raises a relevant critique for SFC models: statistical relationships estimated on historical data are inherently shaped by the expectations formation and institutional arrangements prevailing under a given policy regime. If the policy regime changes, expectations adjust accordingly, implying that behavioral parameters may no longer be invariant. This concern is especially salient when such models are used to analyze large structural transformations - such as those required for the green transition - where it is unlikely that parameters inferred from reduced-form relationships estimated on past data will remain stable.

One way to address this critique is to model agents' expectations explicitly. In SFC models, the approach typically differs from the micro-founded representative-agent framework adopted in neoclassical models. Most SFC models rely on backward-looking expectations. In their simplest form, these are so called naïve expectations, where expectations in period t are set equal to the observed outcome in period t - 1. More sophisticated variants include adaptive expectations, in which agents update their expectations based on past forecast errors.

Alternative specifications are also used. These include forward-looking expectation rules in which agents adjust their expectations relative to some fundamental value, as well as hybrid formulations that combine backward- and forward-looking elements. Such mechanisms aim to progressively reduce expectation errors over time. Meijers et al. (2023) demonstrate that the choice of expectation formation plays a crucial role for both the dynamic behavior and the stability properties of SFC models.

For empirical E-SFC-IO models, a similar approach can be adopted in principle. Forward-looking expectation rules can be introduced; however, doing so requires the modeler to specify a fundamental or steady-state reference value. In practice, this is often implemented using target variables derived from the data, such as a desired capital stock implied by a capital-output ratio. For backward-looking expectations, adaptive rules can be employed, with the adjustment parameter being implicitly calculated using historical data. This raises the question of whether such implementations impose overly restrictive assumptions on the functional form of expectation formation in empirical SFC-models. Rather than relying on ad hoc specifications, empirical models should aim to represent expectations in a way that more closely reflects the observed behavior of agents in the economy under study. One alternative approach is to incorporate observed measures of expectations directly from the data, such as consumer confidence or business sentiment indices. These indicators offer potential proxies for agents' expectations, reducing reliance on imposed functional forms. However, endogenizing such measures within an empirical stock-flow-consistent framework remains an important avenue for future research.

While not modelling expectations explicitly, some empirical SFC models allow behavioral parameters themselves to depend on economic or policy variables. One approach is to introduce regime shifts in behavioral equations, for instance by allowing parameters or functional forms to change once certain thresholds are crossed. Another approach is to endogenize key behavioral parameters directly as functions of economic or policy variables. Developing such regime-dependent specifications could be particularly relevant for empirical E-SFC-IO models, as they would enhance the models' ability to capture path-dependent dynamics.

Accounting for path dependence is especially important for macroeconomic models applied to the green transition. Hepburn et al. (2025) emphasize that such models should be capable of representing path-dependent dynamics and transitions between distinct economic regimes and argue that many existing climate-economic models lack these features (see also Pindyck, 2013; Rezai and Stagl, 2016; Dietz et al., 2021). Developing endogenous and regime-sensitive behavioral specifications therefore constitutes a key avenue for future research on empirical E-SFC-IO models.

7.2. Financial sector

One of the highlighted strengths of E-SFC-IO models is their ability to consistently relate the real and financial side of the economy with environmental aspects (Hardt and O'Neill (2017)). However, as shown in Section 5, only a few papers include complex interactions between the production sector and the financial sector, with all of these being theoretical/calibrated models. As the main selling point of empirical E-SFC-IO, as a policy tool, will be to introduce a realistic and in-depth integration between environment, the real economy, and the financial side, more work is needed on the interaction between the production and financial sector. We focus on two key topics, the aggregate time frequency of SFC models, and the lack of financial data at the industry level.

Time Frequency

Financial variables - such as stock prices - exhibit substantially higher volatility than aggregate macroeconomic variables. Empirical SFC models, however, typically operate at an annual or quarterly frequency. When financial variables, whose fluctuations may occur and be corrected within very short time horizons, are aggregated to lower frequencies, much of this information is lost. This issue is particularly pronounced in climate-related models, where environmental variables are often only available at low (typically annual) frequencies. Below, we highlight three proposals aimed at addressing some of these issues.

As most empirical Stock-Flow-Consistent modelers convert high-frequency financial data to lower frequencies to match the time frequency of macroeconomic and environmental variables, one option is to adopt a similar strategy but, instead of simply omitting information at the higher frequency level, to retain elements of the high-frequency information within low-frequency variables - for example, by constructing measures of volatility or minimum and maximum values. These variables can then be used as exogenous inputs to model agents' behavior or to introduce shocks to the financial sector. A remaining question is how such variables could be endogenized within the model when only low-frequency data are available.

An alternative approach is to align macroeconomic variables with the higher frequency of financial data through interpolation. This, however, raises concerns about data quality and model credibility, as constructing higher-frequency macroeconomic series (e.g. monthly GDP) from lower-frequency observations requires strong assumptions about their intra-period evolution.

Lastly, the solution might be to develop models that accommodate mixed frequencies. Nonetheless, significant methodological challenges remain regarding the consistent integration of variables observed at different time scales. One possible action which might make this easier, is to move away from discrete-time modelling and adopt a continuous-time framework (see, e.g., Ryoo, 2010; Yilmaz et al., 2025). Future research should aim to develop modelling strategies that allow high-frequency financial volatility to be meaningfully incorporated into SFC and E-SFC-IO models.

Industry variables

A promising avenue for empirical E-SFC-IO models is to provide insights into industry-level financial stability. However, a detailed disaggregation of the production side complicates integration with the financial dimension, as accounts beyond production and income distribution would also need to be available at the same level of industry detail and be fully consistent with the national accounting framework. As a result, constructing a fully integrated SFC-IO model in which each industry is endowed with its own financial and capital accounts is not feasible using the currently available national accounts data.

By contrast, many of the theoretical and calibrated models discussed in Section 5 explicitly model balance sheets for individual industries, as these frameworks are not constrained by data availability. This highlights a key challenge for empirical SFC-IO models, which must adhere closely to the structure and consistency of the national accounts. While complementary data sources can occasionally provide partial insights, reconciling these with the sectoral accounts reported in the national accounts remains difficult. One example is Thomsen et al. (2025b), who use industry-by-sector shares to allocate profits and investment from the industry to the sectoral level, then modelling balance sheets only at the sectoral level.

7.3. Demand led policies

When designing macroeconomic models, the modeler must choose how causality is structured, with model closure being a key decision. In the models presented in Section 6, the causality runs from supply to demand. Given a level of supply, workers and capitalists earn income through production, which in turn generates demand. These models are therefore supply-driven: increases in supply directly raise demand, while increases in demand alone have only limited short-run economic effects.

By contrast, the SFC models presented in Section 5 are demand-driven. In these models, final demand - such as consumption, investment, or government spending - determines firms' production and thus the level of supply. While some SFC models are fully demand-driven, others incorporate supply constraints. Even in these cases, substitution effects in firms' production functions are typically assumed to be weak or absent in the short run, in contrast to their prominent role in the mainstream frameworks.

Given the central role of demand in the SFC framework, we highlight several aspects that future research on E-SFC-IO models should consider.

Disaggregated production sector

As shown in Section 4, introducing a disaggregated production structure has important implications for the transmission of final demand shocks. Two main benefits arise from explicitly modelling input-output linkages. First, the model accounts for intermediate production, which amplifies the demand multiplier whereas increases in final demand raise not only output in the targeted industries but also intermediate output, which in turn requires additional labor or other inputs for its production, further increasing economic activity. Second, when industries with substantially different production technologies are aggregated this will result in aggregation bias, whereas shocks that alter the composition of final demand across industries can generate biased results in model simulations (see Section 4.2.1).

Aggregation further affects the assessment of environmental outcomes. When industries with heterogeneous emission intensities are aggregated, changes in the composition of demand and production cannot be properly captured, resulting in biased estimates of emission responses to demand-side shocks.

Allowing for supply effects

Just as many of the neoclassical frameworks discussed in Section 6 can be criticized for insufficiently capturing demand-side effects, E-SFC-IO models are often criticized for their limited role for supply-driven dynamics. Although the introduction of an input-output structure into SFC models allows for a more detailed representation of the production process, it does not in itself imply a stronger role for supply-side effects. Nevertheless, it may facilitate their introduction.

One approach has been to impose supply constraints, whereby an industry's capacity to meet demand is limited by its access to required inputs, such as capital, intermediate goods, or labour, and - particularly in environmental models - natural resources. In such cases, this may imply adjustments in other variables, such as prices or wages. However, one important feature of SFC models is that equilibrium does not need to be imposed. As a result, these models do not require full market clearing to reconcile demand and supply in goods markets, as is common in many neoclassical frameworks.

Supply constraints may also arise in the labor market. Most existing E-SFC-IO models implicitly assume that labor demand equals labor supply. However, as unemployment falls, upward pressure on wages increases firms' production costs and can reduce labor demand. In contrast, neoclassical models typically allow labor supply to be endogenous, with workers choosing not to participate when wages are insufficient, potentially giving rise to binding supply constraints on production. Developing a more detailed and endogenous representation of the labor market therefore constitutes an important avenue for future research in E-SFC-IO modelling.

8. Conclusion

To address the growing challenges posed by climate change, policymakers must rely on a broad set of modelling tools. Until now, most of these tools have been fixed on a set-up which mainly rely on neoclassical foundations. However, there is increasing recognition that to solve climate issues, it is not sufficient to solely rely on one type of one modelling framework which all adopt the same assumptions about economic behavior and ecosystem functioning. A new generation of models is therefore needed to provide an alternative to the often narrow and equilibrium-focused perspective that dominates climate policy debates.

In this paper, we have argued that Empirical Ecological Stock-Flow-Consistent Input-Output models constitute a promising alternative to existing climate policy tools. By integrating financial, economic, and ecological interactions within a fully stock-flow-consistent and dynamic accounting framework, these models allow for a coherent representation of real-financial linkages, production structures, and environmental pressures, without relying on the neoclassical assumptions of representative, utility-maximizing agents.

The development of E-SFC-IO models are still relatively recent, with much of the existing literature being dominated by theoretical or calibrated models, which face similar limitations as other climate-economy frameworks due to their weak empirical grounding. This paper therefore calls for a shift towards the development of fully empirical E-SFC-IO models, in which both accounting structures and behavioral relationships are firmly anchored in observed data. We have outlined key directions for future research with the aim of strengthening the empirical foundations, improving sectoral and financial detail, and enhancing the policy relevance of this modelling approach. Advancing along these lines is essential if E-SFC-IO models are to become a robust and integral part of the climate policy toolbox available to policymakers.

References

Almeida, D. T., Weidema, B. P., & Godin, A. (2022). Beyond normative system boundaries in life cycle assessment: The environmental effect of income redistribution. Cleaner Environmental Systems, 4, 100072.

Annicchiarico, B., Battles, S., Di Dio, F., Molina, P., & Zoppoli, P. (2017). GHG mitigation schemes and energy policies: A model-based assessment for the Italian economy. Economic Modelling, 61, 495-509.

Ara, K. (1959) ‘The aggregation problem in input–output analysis’, *Econometrica*, 27(2), pp. 257–262.

Balderston, J.B. and Whitin, T.M. (1954) ‘Aggregation in the input–output model’, in *Economic Activity Analysis*. New York: Wiley, pp. 79–128.

Banerjee, O., Cicowiez, M., Horridge, M., & Vargas, R. (2016). A conceptual framework for integrated economic–environmental modeling. *The Journal of Environment & Development*, *25*(3), 276-305.

Barrage, L., & Nordhaus, W. (2024). Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. Proceedings of the National Academy of Sciences, 121(13), e2312030121.

Babatunde, K. A., Begum, R. A., & Said, F. F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. Renewable and Sustainable Energy Reviews, 78, 61-71.

Beckman, J., Hertel, T., & Tyner, W. (2011). Validating energy-oriented CGE models. Energy Economics, 33(5), 799-806.

Berg, M., Hartley, B., & Richters, O. (2015). A stock-flow consistent input–output model with applications to energy price shocks, interest rates, and heat emissions. New journal of physics, 17(1), 015011.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, *1*, 1341-1393.

Bimpizas-Pinis, M., Fevereiro, J.B.R.T., Genovese, A., Kaltenbrunner, A., Kesidou, E., Purvis, B., Vallès Codina, O. and Veronese Passarella, M. (2023). Using input-output stock-flow consistent models to simulate and assess ‘circular economy’ strategies. In R. Passaro (Ed.), Circular Economy for Social Transformation: multiple paths to achieve circularity, JUST2CE E-book.

Blanchard, O. (2018). On the future of macroeconomic models. Oxford Review of Economic Policy, 34(1-2), 43-54.

Burniaux, J. M., & Truong, T. P. (2002). GTAP-E: an energy-environmental version of the GTAP model. GTAP technical papers, 18.

Cai, Y., K.L. Judd and T.S. Lontzek (2012). Continuous-Time Methods for Integrated Assessment Models. NBER working paper No. 18365.

Campiglio, E., Godin, A., & Kinsella, S. (2015, June). The economic implications of the transition to a low-carbon energy system: a stock-flow consistent model. In *Presentation at the 11th Biennial Conference of the European Society for Ecological Economics, Leeds* (Vol. 30, pp. 06-03).

Carnevali, E., Deleidi, M., Pariboni, R., & Veronese Passarella, M. (2024). Economy-finance-environment-society Interconnections in a Stock-flow Consistent Dynamic Model. *Review of Political Economy*, *36*(2), 844-878.

Caverzasi, E., & Godin, A. (2015). Post-Keynesian stock-flow-consistent modelling: a survey. *Cambridge Journal of Economics*, *39*(1), 157-187.

Coalition of Finance Ministers for Climate Action (CFMCA). (2025b). Economic analysis and modeling tools to assist ministries of finance in driving green and resilient transitions. https://openknowledge.worldbank.org/handle/10986/40372

Coalition of Finance Ministers for Climate Action (CFMCA). (2025a). A Global Survey of Ministries of Finance: The pressing policy questions Ministries of Finance face in driving green and resilient transitions and their use of analytical tools to address them. Report for the HP4 initiative 'Economic Analysis for Green and Resilient Transitions'. Helsinki Principle 4 Core Series. https://www.greenandresilienteconomics.org

Copeland, M. A. (1947). Tracing money flows through the United States economy. The American Economic Review, 37(2), 31-49. https://www.jstor.org/stable/1821110

Copeland, M. A. (1949). Social accounting for moneyflows. The Accounting Review, 24(3), 254-264. https://www.jstor.org/stable/240684

Christiano, L. J., Eichenbaum, M. S., & Trabandt, M. (2018). On DSGE models. Journal of Economic Perspectives, 32(3), 113-140

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. Journal of political Economy, 113(1), 1-45.

Dafermos, Y., McConnell, A., Nikolaidi, M., Storm, S. T., & Yanovski, B. (2024). Macroeconomic modeling in the Anthropocene: why the E-DSGE framework is not fit for purpose and what to do about it. Institute for New Economic Thinking Working Paper Series, (229).

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2017). A stock-flow-fund ecological macroeconomic model. *Ecological Economics*, *131*, 191-207.

Danish Research Institute for Economic Analysis and Modelling (DREAM). (2025). The GreenREFORM model. DREAM.

D'Alessandro, S., Cieplinski, A., Distefano, T., & Dittmer, K. (2020). Feasible alternatives to green growth. Nature Sustainability, 3(4), 329-335.

Dervis, K., J. de Melo and S. Robinson, (1982), General equilibrium models for development policy (Cambridge University Press, Cambridge, England).

Di Domenico, L., Raberto, M., & Safarzynska, K. (2023). Resource scarcity, circular economy and the energy rebound: A macro-evolutionary input-output model. Energy Economics, 128, 107155.

Dietz, S., Rising, J., Stoerk, T., & Wagner, G. (2021). Economic impacts of tipping points in the climate system. Proceedings of the National Academy of Sciences, 118(34), e2103081118.

Dunz, N., Naqvi, A., & Monasterolo, I. (2021). Climate sentiments, transition risk, and financial stability in a stock-flow consistent model. Journal of Financial Stability, 54, 100872.

European Commission (Eurostat). (2013). *European system of accounts – ESA 2010* (Catalogue No. KS-02-13-269-EN-C; ISBN 978-92-79-31242-7, DOI:10.2785/16644). Publications Office of the European Union. Retrieved from https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-02-13-269

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A., & Roventini, A. (2019). Validation of agent-based models in economics and finance. In Computer simulation validation: fundamental concepts, methodological frameworks, and philosophical perspectives (pp. 763-787). Cham: Springer International Publishing.

Fevereiro, J.B.R.T, A. Genovese, O. Vall` es Codina, and M. Veronese Passarella (2024) "A Just Transition to the Circular Economy: Scenario Analysis,"Technical report.

Fontana, G., & Sawyer, M. (2013). Post-Keynesian and Kaleckian thoughts on ecological macroeconomics. *European Journal of Economics and Economic Policies*, *10*(2), 256-267.

Fontana, G., & Sawyer, M. (2016). Towards post-Keynesian ecological macroeconomics. *Ecological Economics*, *121*, 186-195.

Gambhir, A., Butnar, I., Li, P. H., Smith, P., & Strachan, N. (2019). A review of criticisms of integrated assessment models and proposed approaches to address these, through the lens of BECCS. Energies, 12(9), 1747.

Garcia-Villegas, S., & Martorell, E. (2024). Climate transition risk and the role of bank capital requirements. *Economic Modelling*, *135*, 106724.

Georgescu-Roegen, N. (1971). *The entropy law and the economic process*. Harvard university press.

Glotter, M., Pierrehumbert, R., Elliott, J., & Moyer, E. (2013). A simple carbon cycle representation for economic and policy analyses. 13.

Godley, W., & Lavoie, M. (2007). Monetary Economics: An Integrated Approach to Credit, Money, Income, Production and Wealth. Palgrave Macmillan. https://doi.org/10.1057/9780230626546

Godley, W. (1999). Seven unsustainable processes. *Special report*.

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. Econometrica, 82(1), 41-88.

Hatanaka, M. (1952) 'Note on consolidation within a Leontief system', *Econometrica*, 20(2), pp. 301–303.

Hepburn, C., Ives, M. C., Loni, S., Mealy, P., Barbrook-Johnson, P., Farmer, J. D., ... & Stiglitz, J. (2025). Economic models and frameworks to guide climate policy. Oxford Review of Economic Policy, graf020.

Heutel, G. (2012). How should environmental policy respond to business cycles? Optimal policy under persistent productivity shocks. Review of Economic Dynamics, 15(2), 244-264.

Hardt, L., & O'Neill, D. W. (2017). Ecological macroeconomic models: assessing current developments. *Ecological economics*, *134*, 198-211.

Jackson, A., & Jackson, T. (2021). Modelling energy transition risk: The impact of declining energy return on investment (EROI). Ecological economics, 185, 107023.

Jackson, A., & Jackson, T. (2025). Macroeconomic, sectoral and financial dynamics in energy transitions: A stock-flow consistent, input-output approach. Ecological Economics, 230, 108507.

Jackson, T., & Victor, P. A. (2015). Does credit create a 'growth imperative'? A quasi-stationary economy with interest-bearing debt. Ecological Economics, 120, 32-48.

Jacques, P., Delannoy, L., Andrieu, B., Yilmaz, D., Jeanmart, H., & Godin, A. (2023). Assessing the economic consequences of an energy transition through a biophysical stock-flow consistent model. Ecological Economics, 209, 107832.

Johansen, L. (1960) A Multi-sectoral Study of Economic Growth, North-Holland, Amsterdam.

Kirman, A. P. (1992). Whom or what does the representative individual represent?. Journal of economic perspectives, 6(2), 117-136.

Kitzes, J. (2013). An introduction to environmentally-extended input-output analysis. Resources, 2(4), 489-503.

Kronenberg, T., 2010. Finding common ground between ecological economics and post-Keynesian economics. Ecol. Econ. 69, 1488–1494.

Kydland, F. E., & Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, 1345-1370.

Leontief, W. W. (1936). Quantitative input and output relations in the economic systems of the United States. *The review of economic statistics*, 105-125.

Leontief, W. (1986). *Input-output economics*. Oxford University Press.

Lenzen, M. (2011). Aggregation versus disaggregation in input–output analysis of the environment. Economic Systems Research, 23(1), 73-89.

Long Jr, J. B., & Plosser, C. I. (1983). Real business cycles. *Journal of political Economy*, *91*(1), 39-69.

Lucas Jr, R. E. (1976, January). Econometric policy evaluation: A critique. In *Carnegie-Rochester conference series on public policy* (Vol. 1, pp. 19-46). North-Holland.

McManus, M. (1956) 'General consistent aggregation in Leontief models', *Bulletin of Economic Research*, 8(1), pp. 28–48

McKibbin, W. J., Morris, A. C., Wilcoxen, P. J., & Panton, A. J. (2020). *Climate change and monetary policy: Issues for policy design and modelling*. *Oxford Review of Economic Policy*.

Metcalf, Gilbert E. and James H. Stock. 2020. "Measuring the Macroeconomic Impact of Carbon Taxes." AEA Papers and Proceedings, 110 : 101–06. DOI: 10.1257/pandp.20201081

Miller, R. E., & Blair, P. D. (2009). *Input-output analysis: foundations and extensions*. Cambridge university press.

Mitik-Beyene, L., Christiansen, M., Galindev, R., Reidt, N., Lam, M. M., & Camarra, A. (2025). MANAGE-WB: A recursive-dynamic CGE model. World Bank.

Meijers, H., Muysken, J., & Piccillo, G. (2023). Expectations and the stability of stock-flow consistent models.

Monasterolo, I., Raberto, M., 2018. The EIRIN flow-of-funds behavioural model of green fiscal policies and green sovereign bonds. Ecological Economics 144, 228–243. doi:10.1016/j.ecolecon.2017. 07.029.

Naqvi, A. (2015). Modeling Growth, Distribution, and the Environment ina Stock-Flow Consistent Framework.

Nikiforos, M., & Zezza, G. (2018). Stock-flow consistent macroeconomic models: A survey. Analytical Political Economy, 63-102. https://doi.org/10.1002/9781119483328.ch4

Nordhaus, W. (2008). *A question of balance: Weighing the options on global warming policies*. Yale University Press.

Nordhaus, W. (2013). Integrated economic and climate modeling. In Handbook of computable general equilibrium modeling (Vol. 1, pp. 1069-1131). Elsevier.

Pierros, C. (2024). Empirical stock–flow consistent models: evolution, current state and prospects. *European Journal of Economics and Economic Policies*, *1*(aop), 1-16.

Pollitt, H., & Mercure, J. F. (2018). The role of money and the financial sector in energy-economy models used for assessing climate and energy policy. *Climate Policy*, *18*(2), 184-197.

Pindyck, R. S. (2013). Climate change policy: what do the models tell us?. *Journal of Economic Literature*, *51*(3), 860-872.

Pindyck, R. S. (2017). The use and misuse of models for climate policy. Review of Environmental Economics and Policy.

Pyatt, G. (1991). SAMs, the SNA and national accounting capabilities. Review of Income and Wealth, 37(2), 177-198.

Pyatt, G. (1988). A SAM approach to modeling. Journal of policy modeling, 10(3), 327-352.

Pyatt, G., & Round, J. I. (1977). Social accounting matrices for development planning 1. Review of Income and Wealth, 23(4), 339-364.

Rezai, A., Taylor, L., & Mechler, R. (2013). Ecological macroeconomics: An application to climate change. *Ecological Economics*, *85*, 69-76.

Rezai, A., & Stagl, S. (2016). Ecological macroeconomics: Introduction and review. *Ecological Economics*, *121*, 181-185.

Ryoo, S. (2010). Long waves and short cycles in a model of endogenous financial fragility. Journal of economic behavior & organization, 74(3), 163-186.

Røpke, I. (2004). The early history of modern ecological economics. *Ecological economics*, *50*(3-4), 293-314.

Sers, M. R. (2022). Ecological macroeconomic assessment of meeting a carbon budget without negative emissions. Global Sustainability, 5, e6.

Skott, P. (2012). *Pluralism, the Lucas critique, and the integration of macro and micro* (No. 2012-04). Working Paper.

Smets, F., & Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. American economic review, 97(3), 586-606.

Solow, R. M. (1996). Growth theory. In *A guide to modern economics* (pp. 229-247). Routledge.

Spash, C. L., & Ryan, A. (2012). Economic schools of thought on the environment: investigating unity and division. *Cambridge Journal of Economics*, *36*(5), 1091-1121.

Stiglitz, J. E. (2018). Where modern macroeconomics went wrong. Oxford Review of Economic Policy, 34(1-2), 70-106.

Taylor, L., & Lysy, F. J. (1979). Vanishing income redistributions: Keynesian clues about model surprises in the short run. *Journal of Development Economics*, *6*(1), 11-29.

Taylor, L., Rezai, A., Foley, D.K., 2016. An integrated approach to climate change, income distribution, employment, and economic growth. Ecol. Econ. 121:196–205. http://dx.doi.org/10.1016/j.ecolecon.2015.05.015.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of money, credit and banking*, *1*(1), 15-29.

Thomsen, S. F., Byrialsen, M. R., & Raza, H. (2025a). A Benchmark Ecological Stock-Flow-Consistent Input-Output model for Denmark. FMM working paper series. https://www.imk-boeckler.de/de/faust-detail.htm?sync_id=HBS-009060

Thomsen, S. F., Raza, H., & Byrialsen, M. R. (2025b). An assessment of carbon taxation policies: The case of Denmark. *Ecological Economics*, *238*, 108741.

Thomsen, S. F., Raza, H., & Byrialsen, M. R. (2026). Agricultural Carbon Taxation, Food Prices, and Financial Instability: An Empirical Framework with Endogenous Balance Sheets. *Under review in Economic modelling*.

Valdecantos, S. (2015), Topics on Open Economy Macroeconomics: A stock-flow-consistent approach. PhD thesis.

Valdecantos, S. (2021), Grasping Argentina's Green Transition: Insights from a Stock-Flow Consistent Input-Output Model, Macroeconomic Methodology, Theory and Economic Policy (MaMTEP) Working Paper Series No. 4, 2021. Available at: https://www.boeckler.de/pdf/v_2021_10_30_valdecantos.pdf

Valdecantos, S. (2025). The green transition dilemma: The impossible (?) quest for prosperity of South American economies. Ecological Economics, 230, 108508.

Varga, J., & Roeger, W. (2022). E-QUEST: A multisector dynamic general equilibrium model with energy and a model-based assessment to reach the EU climate targets. *Economic Modelling*, *114*, 105911.

Weyant, J. (2017). Some contributions of integrated assessment models of global climate change. Review of Environmental Economics and Policy.

Wilson, C., Guivarch, C., Kriegler, E., Van Ruijven, B., Van Vuuren, D. P., Krey, V., ... & Thompson, E. L. (2021). Evaluating process-based integrated assessment models of climate change mitigation. *Climatic Change*, *166*(1), 3.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. Journal of Artificial Societies and Social Simulation, 10(2), 8.

Wren-Lewis, S. (2011). Internal consistency, price rigidity and the microfoundations of macroeconomics. *Journal of economic methodology*, *18*(2), 129-146.

Yilmaz, S. D., Ben-Nasr, S., Mantes, A., Ben-Khalifa, N., & Daghari, I. (2025). Climate change, loss of agricultural output and the macroeconomy: The case of Tunisia. Ecological Economics, 231, 108512.

Zezza, G., & Zezza, F. (2019). On the design of empirical stock–flow consistent models. *European Journal of Economics and Economic Policies*, *16*(1), 134-158.

Appendix:

Appendix A: Aggregate production model

$$Y_t = C_t + G_t \quad \text{Equation A1}$$

$$N_t = Y_t/PROD_t \quad \text{Equation A2}$$

$$WB_t = N_t * W_t \quad \text{Equation A3}$$

$$B2_t = Y_t - WB_t \quad \text{Equation A4}$$

$$T_t = \theta * (WB_t + B2_t) \quad \text{Equation A5}$$

$$YD_t = WB_t + B2_2 - T_t \quad \text{Equation A6}$$

$$C_t = \alpha_1 * YD_t + \alpha_2 * H_{h,t-1} \quad \text{Equation A7}$$

$$H_{h,t} = H_{h,t-1} + YD_t - C_t \quad \text{Equation A8}$$

$$H_{s,t} = H_{s,t-1} + G_t - T_t \quad \text{Equation A9}$$

Appendix B: Dis-Aggregate production model

$$Y_t = C_t + G_t \quad \text{Equation B1}$$

$$S_{1,t} = Z_{11,t} + Z_{12,t} + C_{1,t} + G_{1,t} \quad \text{Equation B2}$$

$$S_{2,t} = Z_{21,t} + Z_{22,t} + C_{2,t} + G_{2,t} \quad \text{Equation B3}$$

$$Z_{11,t} = a_{11} * S_1 \quad \text{Equation B4}$$

$$Z_{12,t} = a_{12} * S_2 \quad \text{Equation B5}$$

$$Z_{21,t} = a_{21} * S_1 \quad \text{Equation B6}$$

$$Z_{22,t} = a_{22} * S_2$$ Equation B7

$$N_{1,t} = S_{1,t}/PROD_{1,t}$$ Equation B8

$$N_{2,t} = S_{2,t}/PROD_{2,t}$$ Equation B9

$$WB_{1,t} = N_{1,t} * w_1$$ Equation B10

$$WB_{2,t} = N_{2,t} * w_2$$ Equation B11

$$B2_1 = S_{1,t} - (Z_{11,t} + Z_{21,t} + WB_{1,t})$$ Equation B12

$$B2_2 = S_{2,t} - (Z_{12,t} + Z_{22,t} + WB_{2,t})$$ Equation B13

$$T_t = \theta_1 * WB_t + \theta_2 * B2_t$$ Equation B14

$$YD_t = WB_t + B2_t - T_t$$ Equation B15

$$C_t = \alpha_1 * YD_t + \alpha_2 * H_{h,t-1}$$ Equation B16

$$C_{1,t} = C_t * S_{c_1}$$ Equation B17

$$C_{2,t} = C_t * S_{c_2}$$ Equation B18

$$H_{h,t} = H_{h,t-1} + YD_t - C_t$$ Equation B19

$$H_{s,t} = H_{s,t-1} + G_t - T_t$$ Equation B20

$$G = G_{1,t} + G_{2,t}$$ Equation B21

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