ENhancing our understanding of Trade Impacts on Climate, industries, and the Environment

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D1.4 – Modelling Research Needs

WP1 – Framing – theoretical underpinnings, public perceptions, and policy needs

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Preface

In today's interconnected global economy, understanding the trade-climate nexus is more critical than ever. Trade policies significantly influence environmental outcomes, while climate change affects trade flows. However, the complex relationship between these areas remains insufficiently explored, often due to data limitations, gaps in economic modelling and the evolving nature of global supply chains. The ENTICE project aims to bridge these knowledge gaps by advancing our understanding of the trade-climate-industry (TCI) nexus. It examines how trade policies impact environmental sustainability and how climate policies shape global trade dynamics. By developing fact-based insights and innovative modelling tools, ENTICE supports informed decision-making at this crucial intersection of trade, climate, and sustainability.

E3M – E3-MODELLING AE	EL	
CMCC – FONDAZIONE CENTRO EURO-MEDITERRANEOSUI CAMBIAMENTI CLIMATICI	IT	
WI – WUPPERTAL INSTITUT FUR KLIMA, UMWELT, ENERGIE GGMBH	DE	
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Executive summary

Large-scale macroeconomic and integrated assessment models have been widely used in analysing policy scenarios at the intersection of trade, climate, and industry (TCI). They have been utilised to assess policy impacts, distributional effects, and transition pathways within an increasingly interconnected global economy. As climate ambitions intensify and global trade patterns evolve, the capacity of these models to adequately represent the TCI interconnections is a core issue within the modelling community. This deliverable provides a systematic assessment of the current modelling landscape with respect to this nexus, and demarcates research capabilities, limitations, and modelling challenges.

This analysis focuses primarily on the Computable General Equilibrium (CGE) models and Integrated Assessment Models (IAMs), which form the backbone of quantitative analysis for trade, climate, and industry (and their interface)—as well as the bedrock of one of the key lines of evidence in IPCC assessments. By means of a series of (systematic) literature reviews and exchanges with the modelling community, it examines not only the depth of model coverage but also theoretical and structural assumptions shaping models' response to shocks. Two core modelling dimensions, which are both central in the ENTICE project, are given particular attention: the representation of international trade and the treatment of technological progress. In addition, the review considers complementary dimensions that are relevant to the project's activities, including international transport, material flows, sectoral granularity, and land-use impacts.

The analysis first reveals that, despite their widespread use, most economy-wide models continue to rely on highly stylised representations of international trade, most notably the Armington assumption of product differentiation by origin. Despite its clear advantages in terms of tractability, this approach constrains the ability of models to capture firm-level heterogeneity and relevant re-allocation effects. Over the past few years, there has been a bundle of literature exploring "beyond-Armington" trade frameworks, especially the firm heterogeneity model proposed by Melitz (2003), which combines the intensive and extensive margin effects of trade liberalisation capturing the self-selection of firms into export markets based on their respective productivity levels (Akgul et al. 2014). However, these advances have largely remained confined to experimental small-scale models or conditional implementations (e.g., limited to a short number of sectors) and have only partially been operationalised in established large-scale models.

Second, we find emerging modelling enhancements also in the treatment of technological change. While endogenous technological change is widely recognised as essential for analysing long-term policy scenarios, exogenous representations remain dominant in many CGE models and various IAMs. Endogenous mechanisms, such as learning-by-doing and learning-by-researching (R&D-driven innovation), are also found to be operationalised in IAMs and macroeconomic models—albeit often in reduced, sector-specific forms. Direct linkages between trade dynamics and technological change remain relatively stylised, despite the strong empirical evidence of these bidirectional interactions. In particular, learning-by-exporting effects, where firms improve productivity and innovation performance through exposure to foreign markets, are rarely captured in large-scale modelling frameworks (Freixanet & Federo, 2023).

Third, beyond trade theory and technological progress, our analysis identifies certain additional structural limitations across the modelling landscape. In particular, international transport is typically represented in a highly aggregated mode in most models—often in the form of a "global sector", thereby constraining the level of analysis of international transport emissions and related policies. Moreover, material flows (including distinctions between primary, secondary, and recycling activities) are poorly captured in most economy-wide models due to high sectoral aggregation and data constraints. Land-use impacts and relevant environmental indicators (e.g., concerning biodiversity loss) appear more commonly considered in sectoral or partial equilibrium models.

Methodologically, this deliverable combines three complementary approaches: (i) the structured exploration of well-known model inventories and platforms, (ii) systematic literature reviews of recent advances in trade theory and endogenous technological change, and (iii) a targeted survey across EU-funded research projects that have implemented or experimented with relevant modelling developments and innovations. This approach has allowed us to capture both the state-of-the-art in applied climate-trade policy models and the emerging/planned advances in methodological research.

Overall, our findings highlight a clear gap between conceptual advances in economic and trade theory and their practical implementation in large-scale models. While promising methodological pathways exist, their wider adoption is constrained by data requirements, calibration challenges, and computational complexity. Within ENTICE, this deliverable aims to provide a structured evidence basis for identifying priority areas for model development. It directly informs the project's work on extending and improving the modelling of trade and its environmental impacts (WP3), by clarifying which modelling features are already mature, which are emerging but underutilised, and which remain largely unexplored. It also seeks to support decisions on how to enhance international trade treatment, endogenise technological progress, and improve the representation of materials, transport, and land-use impacts in a consistent way. More broadly, this report contributes to a clearer understanding of the strengths and limitations of existing modelling frameworks, thereby also supporting scenario design, cross-model comparison, and interpretation of results in ENTICE and beyond.

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1 Introduction

1.1 Objectives of the deliverable

Large-scale economic models like Computable General Equilibrium (CGE) and Integrated Assessment Models (IAMs) play a central role in informing climate, trade, and industrial policy. They provide the quantitative backbone for assessing policy trade-offs, distributional impacts, and long-term transition pathways in an interconnected global economy. As climate policies intensify and trade patterns evolve, the modelling capacity to represent these dynamics in a consistent way is of critical importance.

The ability of models to capture the trade-climate-industry (TCI) nexus depends not only on coverage and scale but also on theoretical and structural assumptions embedded in their design. Two dimensions, which also constitute among the ENTICE project's core objectives, are particularly impactful. First, the representation of international trade affects how economic shocks and/or policies propagate across regions and sectors, how competitiveness and leakage effects are assessed, and how global value chains are represented. Second, the treatment of technological change determines whether models can capture dynamic adjustment processes, learning effects, and feedback between investment and productivity.

Traditionally, large-scale macroeconomic models (especially CGE) have relied on tractable but rather stylised representations of trade, most notably on the Armington assumption of product differentiation. While this approach has enabled a wide range of applications, it abstracts from firm-level heterogeneity and endogenous productivity responses that are central to state-of-the-art trade and industrial policy analysis. In parallel, technological change has often been treated as exogenous in large-scale models, thereby limiting their technical capacity to analyse innovation-driven transitions or spillovers across sectors and regions. Over the past years, there has been a growing interest for substantial methodological advances in both dimensions. Regarding trade theory, there have been some attempts to move beyond the Armington framework, although pacing has been limited to small-scale experiments. Similarly, CGE models and IAMs have increasingly experimented with endogenous technological change mechanisms, including learning-by-doing and R&D-driven innovation. These developments offer the potential for a more realistic representation of the trade-technology interface, but they also introduce data and calibration requirements.

Beyond trade theory and technical change, there are other dimensions offering space for modelling improvements. For instance, international transport, which is not treated as detailed as domestic transport in models, is in most cases represented in the form of a "global service" sector allocated to each country based on an indicator in the reference year. Moreover, material flows are most often poorly represented due to high aggregation, without distinguishing between primary, secondary, or recycling activities. Another modelling challenge is the quantification of land use impacts in such models: despite cases of quantification of land use alongside other environmental effects (water stress, biodiversity loss, etc.) especially in sectoral models focusing on agriculture, expansion to economy-wide models remains a challenge.

In this context, the objective of this deliverable is to systematically record and assess the current modelling capacity of large-scale IAM and CGE models of the TCI intersection to identify gaps that must be bridged as well as modelling approaches that are theoretically desirable to implement in the ENTICE model ensemble, taking into account the project's timeframe and data constraints. By mapping existing model features, reviewing recent methodological advancements, and identifying limitations, this deliverable aims to (i) provide a structured overview of the state-of-the-art, and (ii) identify priority areas where further model development could be pursued and support policy assessment within the ENTICE project and beyond.

1.2 Positioning within the project

This deliverable is embedded within Work Package 1 *"Framing – theoretical underpinnings, public perceptions, and policy needs"* of the ENTICE project and serves as a bridge between conceptual framing and model development activities. It directly supports Task 1.1 *"Groundwork"*, which aims to identify theoretical, empirical, and modelling gaps in the analysis of the TCI nexus, and provides critical inputs to all downstream work packages, particularly Work Package 3 *"Extend and improve the modelling of trade and its environmental impacts"* that focuses on advancing the modelling capabilities.

The assessment presented in this deliverable is closely linked to other work packages in various ways. First, it complements the conceptual and policy-oriented insights developed in Work Package 1, by translating high-level research needs to concrete modelling requirements.

Second, it informs Work Package 3 by identifying which modelling features are already available, which have been implemented only in limited settings, and which remain largely unexplored in applied large-scale models. In this sense, the deliverable provides an "evidence basis" for informing model enhancements across the ENTICE modelling teams. The outcomes of this analysis are structured to align with the main modelling innovation axes of Work Package 3, including advances in trade theory, endogenous technological change, sectoral detail, material flows, international transport, and quantification of land use impacts. By organising the assessment along these dimensions, the deliverable directly supports decisions on which theoretical approaches are most promising, where simplifications may be unavoidable, and how different modelling approaches (CGEs, IAMs, etc.) can be extended appropriately.

Third, beyond informing model development, the findings of this deliverable may also contribute to the scenario design of Work Package 4 *"Explore the effects of trade and climate and environment"* and the development and interpretation of policy scenarios across the project. Understanding the strengths and limitations of existing modelling frameworks is essential for designing scenarios and interpreting the differences in results across models. Therefore, this assessment could support the project's multi-model strategy, by clarifying which mechanisms can be meaningfully compared across models.

This deliverable is also linked to other WP1 deliverables, by contributing to the broader literature review under Subtask 1.1.1 *"Literature Review"* and should be read in conjunction with Deliverable D1.3 *"State of the art of TCI economic theory, political science, economic modelling"*, which provides the overall synthesis of the literature on trade and climate interactions. While D1.3 offers a cross-disciplinary perspective, this report focuses specifically on the modelling dimension, assessing the capability of large-scale models to capture trade-climate dynamics. The work builds also on Deliverable D1.2 *"TCI framework and synthesis of cocreation results"*, which established the TCI framework and identified initial research capacity needs, by providing a more detailed assessment of modelling capabilities and limitations that might be relevant to the policy landscape.

The rest of this deliverable is organised as follows: Section 2 includes the methodological framework of the analysis, while offering an overview of the strategy and the explored sources. Section 3 presents the modelling landscape and specific features of the reviewed models. Finally, Section 4 summarises key takeaways and modelling challenges.

2 Methodological framework

2.1 Layout of the review strategy

The scope of the methodological framework is to systematically survey the modelling capacity of macroeconomic models, with a particular focus on CGE models and IAMs, with respect to their ability to explore the climate (policy) – trade (policy) nexus, in line with the objectives of Task 1.1.1 of the ENTICE project. The assessment of this modelling capacity focuses not only on the two primary enhancement targets of ENTICE (i.e., trade theory and technological change) but also on additional dimensions such as the representation of international transport and material flows, and the capacity to assess land-based effects and broader environmental impacts.

To comprehensively address these dimensions and following the methodological framework described in Section 6 of Deliverable 1.3[1], this work has been organised along three complementary analytical axes:

- A structured assessment of existing modelling inventories and platforms,
- A systematic review of recent methodological advancements, focusing on modern trade theories and endogenous technological change mechanisms,
- A targeted exchange with ongoing and recently completed EU funded projects that interact strongly with climate-economy modelling in ways (potentially) relevant to trade and trade policy.

The combination of these methodological axes allows us to capture both the current modelling landscape and any emerging developments of relevance, beyond what a typical review of well-documented models could offer. The work is further broken down per dimension of interest to align with the scope of WP3, while also accounting for what is required by the description of Task 1.1 (see Figure 1):

- Representation of critical sectors (related to Task 3.2)
- Underlying trade theory (related to Task 3.3)
- Technological change (related to Task 3.4)
- Material flows (related to Task 3.5)
- Quantification of land-use impacts (related to Task 3.6)

In addition, our assessment attempts to capture the representation of international transport in the models reviewed, which is not straightforward in macroeconomic modelling, due to data restrictions—with most models following the Input-Output Table granularity of data input that fails to capture flows for consuming international transport services in a manner similar to the domestic transport sector.

Three types of sources are selected to explore said modelling capacity: the Scopus database, existing model inventories, and recent model development efforts in relevant research projects. The results of the assessment are subsequently summarised and presented in the form of key takeaways, challenges, and

[1] In Deliverable D1.3, there is also a fourth axis concerning the exploration of the capabilities of ENTICE models. Since this activity has been addressed both in D3.1 and the enclosed survey, it was decided not to explicitly re-produce the whole set of outcomes but to complement the current report with the most relevant features.

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limitations.

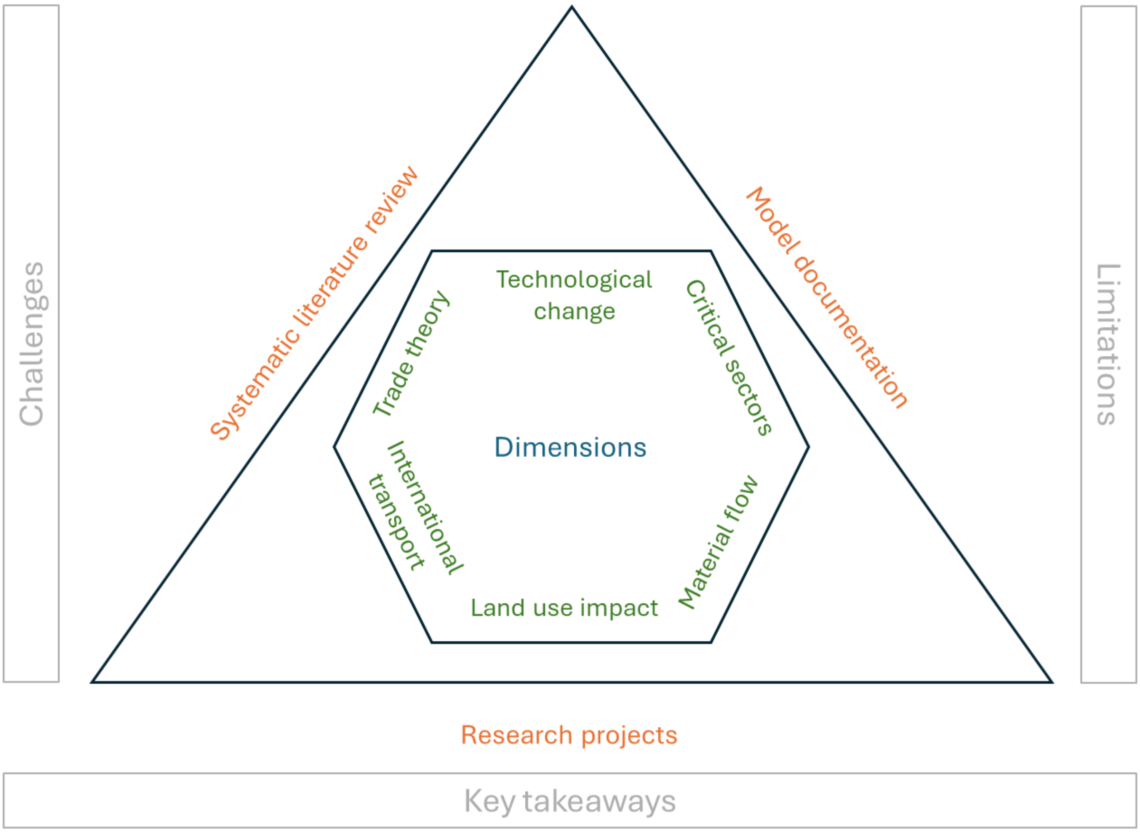

Figure 1. Layout of the literature review.

2.2 Model inventory exploration

Model inventories and online platforms constitute key "concentration" points for "stocktaking" the current modelling landscape. They provide summarised information on model structure, scope, and applications, and are commonly explored by research modelling teams. This inventory review aimed to: (i) identify widely used macroeconomic models (as a starting point), (ii) document their stated modelling features across a number of dimensions, and (iii) establish a "baseline" on existing gaps and limitations. To this end, three (CGE, IAM, and broader energy-climate-economic) model inventories, very well established in the scientific community, were explored:

- the Integrated Assessment Modeling Consortium (IAMC) wiki and model documentation section[2]
- the IAM PARIS Platform detailed model documentation section[3], and
- the Global Trade Analysis Project (GTAP) inventory[4]

[2] https://www.iamconsortium.org/resources/models-documentation/
[3] https://iamparis.eu/detailed_model_doc
[4] https://www.gtap.agecon.purdue.edu/models/default.asp

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These inventories were screened manually, and the model documentations (technical notes, references, etc.) were collected and/or traced, where available. If documentation was absent/unfindable, the model was excluded from the review process. This pre-screening process resulted in a total of **97** models, the review of the documentation of which was assigned across project partners for further exploration.

A well-structured template was designed to capture the following:

- *Model type:* this identifies the principal modelling framework and the purpose[5] of the model, by classifying whether the model is, for example, a CGE model, an IAM, a macro-econometric (i.e., input-output econometric/post-Keynesian) model, a partial equilibrium model, or a hybrid modelling framework.
- *Geographic coverage:* this refers to the spatial resolution of the model, by indicating whether the model represents a single country or region, multiple regions[6], or the entire world.
- *Sectoral coverage:* this describes the level of detail of economic activities represented in the model—models covering the whole economy (e.g., several CGE models) are classified as "economy-wide"; otherwise, more detailed sectoral coverage is mentioned (e.g. industrial sectors, energy, transportation, AFOLU, etc.).
- *Trade theory:* this captures the theoretical assumptions governing international trade in the model (Armington specification, Melitz heterogeneity, etc.).
- *Technological change mechanism:* this refers to how technological progress is represented in the model and what drives it, including whether technological change is exogenous or endogenous, whether it occurs through learning-by-doing or R&D investments, and how it affects productivity, energy efficiency, or other production parameters.
- *Representation of international transportation:* this refers to whether international transportation is represented explicitly, by proxy (e.g., via energy demand), or as a "global sector" (as in GTAP models).
- *Representation of material flows:* this refers to the model's capacity to analyse supply chain dependencies and material flow dynamics (raw materials, intermediate inputs, waste, and recycling).

The aim of this model inventory exploration was to provide a broad overview of modelling capacities, not to evaluate the model quality or performance.

2.3 Systematic literature review

The two core objectives of WP3 activities, in terms of model developments, are to (a) "go beyond Armington"

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[5] Task 1.1.1 of the ENTICE Description of Action states that the scope of the literature review is constrained to integrated assessment and macroeconomic models. However, the considered inventories include also sectoral specific models, such as energy system optimisation models and agriculture-focused models. Since these may also feature aspects such as endogenous technological change mechanisms or trade theories and their modelling approaches and novelties could equally be of interest to ENTICE, it was decided to broaden our analysis by considering all documented models.
[6] Many multi-regional models allow for aggregating at country level (e.g., GTAP model). In this review, by "multi-regional" we mean both cases: disaggregation is at regional and/or country level. When a model is classified as "global multi-regional", it means that the entire world is covered and the disaggregation may reach region and/or country level.

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regarding the underlying trade theory and (b) endogenise technological change. To better inform these activities regarding the state-of-the-art, two systematic literature reviews were conducted to capture explicitly these two dimensions. In particular, the systematic literature review aimed to identify and synthesise recent methodological advancements in two areas:

- new or extended trade theories implemented in macroeconomic models

- mechanisms that endogenise technological change in macroeconomic models

Importantly, moving beyond Armington also "opens the door" to the representation of firm-level dynamics that are central to studying the TCI nexus (e.g., competitiveness and innovation responses to trade dynamics). However, explicit modelling of these dimensions remains limited in the reviewed literature.

The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA[7]) framework. A review protocol was defined specifying research questions, exclusion criteria, and screening and selection processes. This comprehensive review was carried out on the Scopus database.

For the case of new trade theories, the following research string was applied:

> *(TITLE-ABS-KEY ("computable general equilibrium") OR TITLE-ABS-KEY ("CGE model") OR TITLE-ABS-KEY ("macroeconomic model") AND TITLE-ABS-KEY ("Krugman") OR TITLE-ABS-KEY ("Melitz") OR TITLE-ABS-KEY ("firm heterogeneity") OR TITLE-ABS-KEY ("product differentiation"))*

This query resulted in 50 papers, which were evaluated against the relevance of their scope and content, eventually leading to 26 papers. The exclusion process was based on the examination of title and abstract and, in many cases, the introduction. Papers were further narrowed down to identify the most important contributions, eventually reaching the end pool of 10 papers, based on one critical criterion—i.e., the extent to which papers add to the state-of-the art regarding the incorporation of beyond-Armington trade mechanisms in CGE models. Figure 2 shows the PRISMA flow diagram.

[7] https://www.prisma-statement.org/

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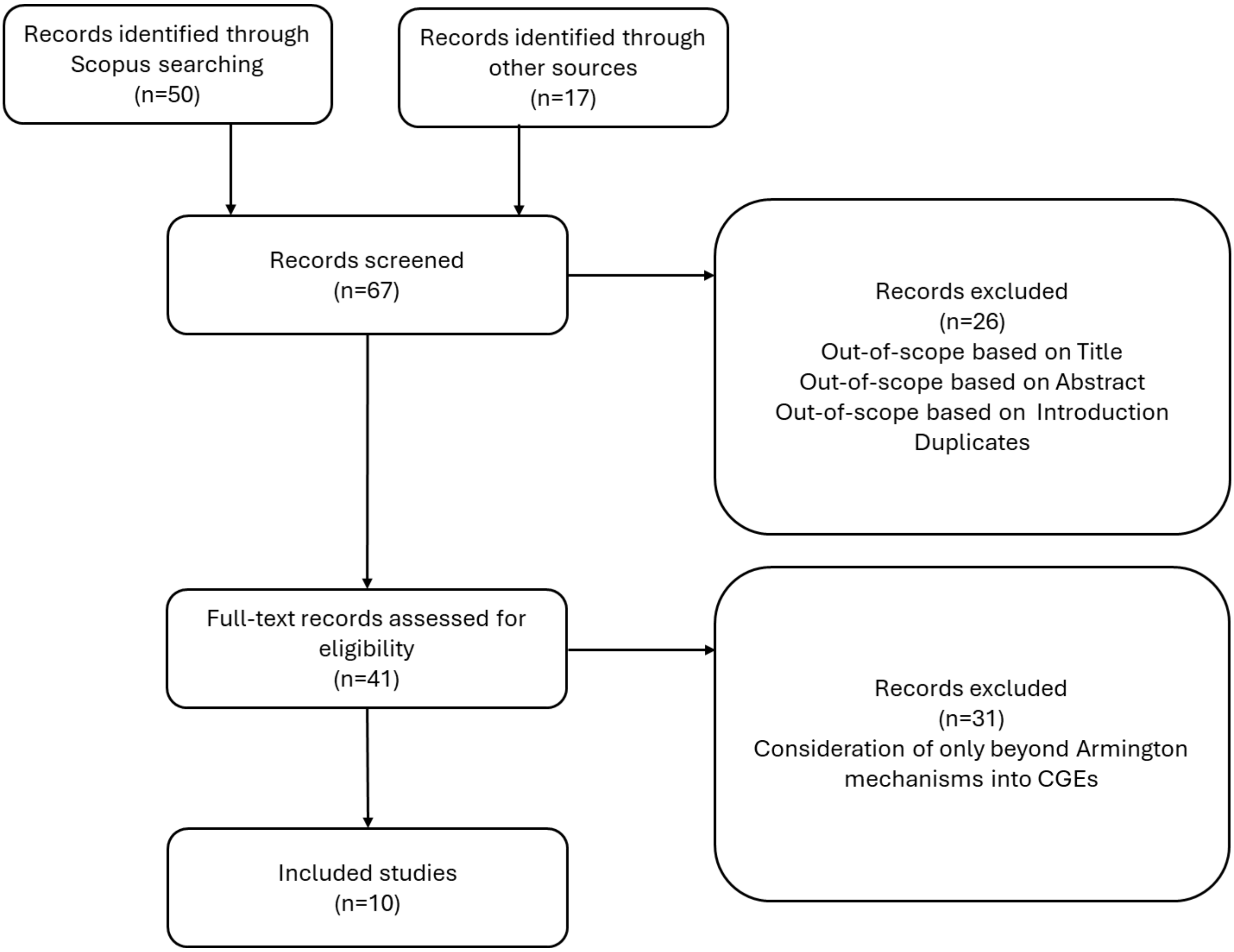

Figure 2. PRISMA flow diagram for trade theory.

For each selected publication, the following information was extracted and coded in our analysis:

- model type
- international trade mechanism
- integration details
- critical computational aspects

For the case of technological change mechanism, the following research string was applied:

(TITLE-ABS-KEY ("computable general equilibrium") OR TITLE-ABS-KEY ("CGE") OR TITLE-ABS-KEY ("macroeconomic model") AND TITLE-ABS-KEY ("technical change") OR TITLE-ABS-KEY ("technological progress") OR TITLE-ABS-KEY ("technical progress") OR TITLE-ABS-KEY ("endogenous innovation") OR TITLE-ABS-KEY ("knowledge transfer") OR TITLE-ABS-KEY ("knowledge flow") OR TITLE-ABS-KEY ("learning by doing") OR TITLE-ABS-KEY ("learning by researching") OR TITLE-ABS-KEY ("endogenous productivity")

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OR TITLE-ABS-KEY ("endogenous growth") OR TITLE-ABS-KEY ("technological spillover") OR TITLE-ABS-KEY ("knowledge spillover") OR TITLE-ABS-KEY ("learning by exporting") OR TITLE-ABS-KEY ("firm heterogeneity"))

The above search resulted in 265 papers. These were then evaluated against the relevance of their scope and content, eventually leading to 85 papers. As in the case of trade theories, the exclusion process was based on the examination of title and abstract of the papers and, in many cases, their introduction. The papers were further narrowed down to identify the most relevant ones, reaching the final pool of 28 papers; this latter exclusion was based on the following criteria: “papers focusing only on human capital-based productivity improvements”, “models not entailing trade features”, “purely bottom-up studies without economy-wide features”, “papers before 2015 with less than 10 citations”. Figure 3 shows the PRISMA flow chart for the case of the technological change.

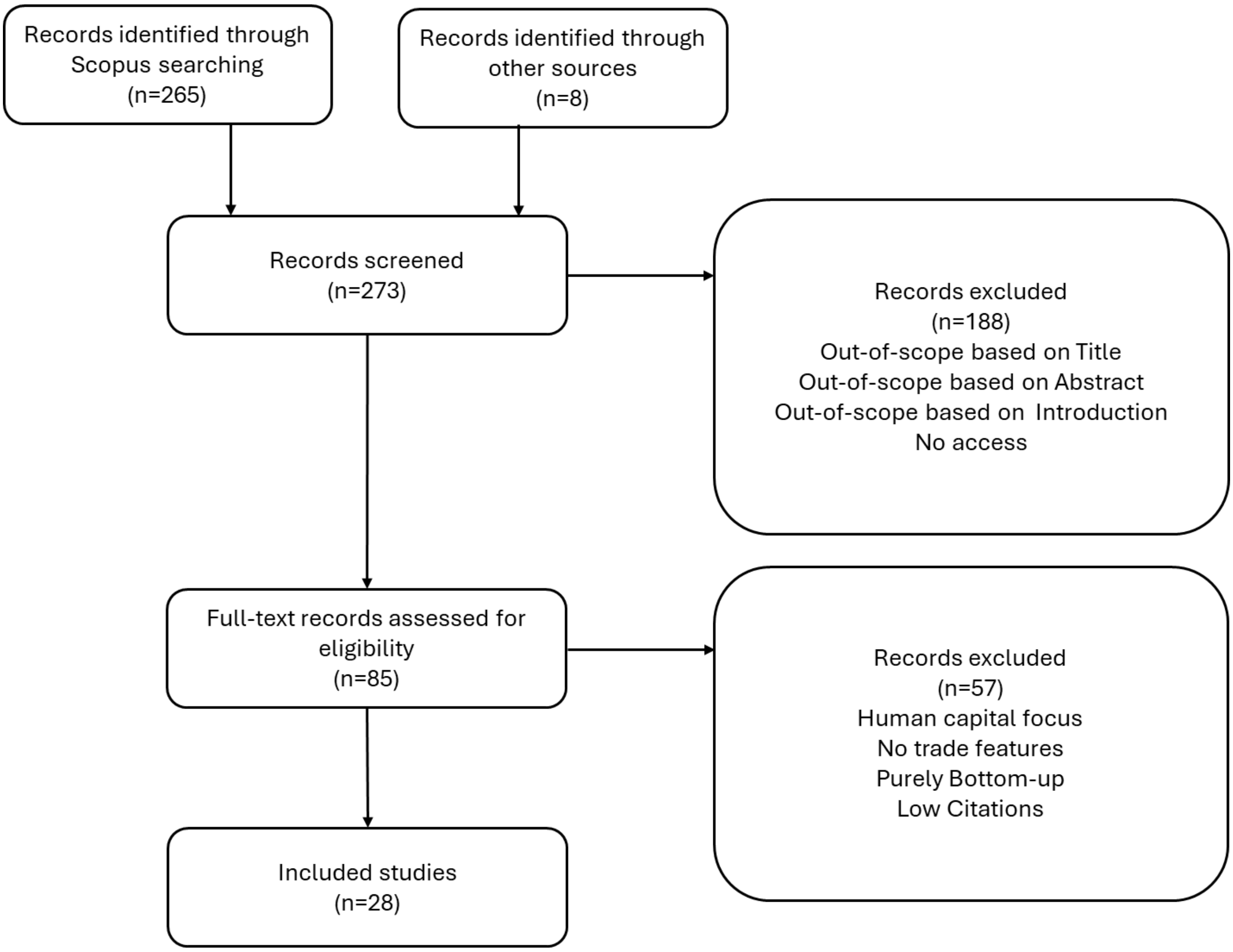

Figure 3. PRISMA flow diagram for technological change.

For each selected publication, the following information was extracted:

- model type
- underlying endogenous technological change (ETC) mechanism

- brief description of the ETC rationale
- linkage of trade to technological change (if available)

In both cases, the results were synthesised to highlight patterns, trends, and methodological weaknesses and challenges. Particular attention was paid to whether the proposed theoretical advancements had been operationalised in large-scale models or remained at a conceptual stage.

2.4 Relevant EU-funded projects

EU-funded research projects often serve as "incubators" for methodological innovation, integrating new model features—often in applied policy contexts. Such advancements are not always immediately reflected in academic publications or model inventories. Therefore, to consider potential advancements in such projects and complement our inventory and literature review, the following projects were selected:

- ACCLIMATE[8]

- AMIGDALA[9]

- DIAMOND[10]

- IAM COMPACT[11]

- PRISMA[12]

- TRANSIENCE[13]

- UPTAKE[14]

To capture the features of interest, a dedicated questionnaire was designed and circulated, either directly to the consortia's modelling teams (in cases an ENTICE partner is strongly involved in a project, such as DIAMOND, IAM COMPACT, and TRANSIENCE via ICCS, or UPTAKE, PRISMA, and ACCLIMATE via E3M) or to the project coordination (as in the case of AMIGDALA). Initially, respondents were informed on the objectives of the project and the survey and, subsequently, asked to respond to a number of questions regarding the models involved in their project. The questionnaire included questions such as the following:

- Model type and structure:
    - Which category best describes your model?
    - Describe briefly the conceptual framework and key modelling philosophy
    - Which is the geographic scope?
    - Which is the sectoral coverage?

[8] https://acclimate-project.eu/
[9] https://amigdalaproject.eu/
[10] https://climate-diamond.eu/
[11] https://www.iam-compact.eu/
[12] https://www.net0prisma.eu/
[13] https://www.transience.eu/
[14] https://www.cdr-uptake.eu/

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  - Does the model cover individually specific sectors that are closely related to energy transition and/or their trade is going to be intensified in the next years? E.g. metals (e.g. steel, aluminium, copper), plastics, cement, fertilisers, critical minerals (e.g. lithium, nickel, cobalt, REEs), green tech manufacturing, green industrial processes. If yes, please indicate them.
  - Does the model follow a framework such as GTAP sectors, WIOD sectors, EXIOBASE, etc.? If yes, please indicate.
- International trade theory
  - Describe briefly the underlying international trade mechanism
  - If sectors within the model are addressed differently (e.g., some sectors are covered by Melitz, while others by Armington), please specify which sectors are covered by each mechanism.
- Technological change
  - Describe briefly the underlying technological change mechanism.
  - If there is an endogenous technological change mechanism, is it connected to international trade? If yes, please specify how.
- Material flows
  - Does the model represent material flows (e.g. minerals)?
  - If no, is the model linked to a physical stock model (e.g. soft-linkage)?
- International transport
  - Does the model represent international transport for maritime, aviation, or other?
  - If yes, please specify the modelling approach.
  - How are international transport-related emissions treated?
- Land use
  - Does the model represent land-use impacts and relevant environmental indicators? If yes, which indicators does your model quantify?
  - If not, is the model linked to a land use / biodiversity model (e.g., through soft linkage)?
- Recent advancements
  - Are there any major modelling advancements achieved within the project? If yes, how are these advancements related to the abovementioned features?

After the completion of the survey, informative outcomes were extracted for the following models: CLEWs-EU v2 (DIAMOND), GCAM-Europe (DIAMOND), EnergyPLAN 16.3 (IAM COMPACT), NEMESIS World v1.0 (DIAMOND), Policy Lab's Global Trade Model (AMIGDALA), CLEWs (IAM COMPACT), OMNIA_V1.0 (DIAMOND), Imaclim-R World v2.0 (PRISMA), NEMESIS EU v5.1 (DIAMOND), PROMETHEUS V2 (UPTAKE), Aalto-EU-TIMES 1.0 (IAM COMPACT), Kenya CLEWs Model - Version 2 (IAM COMPACT), ENGAGE (DIAMOND), IMAGE 3.4

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(PRISMA), GEMINI-E3 EU (DIAMOND), GCAM 8.2 (ACCLIMATE), REMIND-MFA (TRANSIENCE)[15]. The modelling dimensions of the models were then integrated into the table-structure format of Section 3.

The above list was further expanded to include the models involved in the ENTICE project or managed by the consortium's modelling teams (GEM-E3, ICES, NEMESIS, GEMINI-E3, ENVISAGE, FIDELIO, ZEW model). Modelling capabilities were also explored and reported in D3.1; however, results were also integrated in Tables 1-8 below, to allow comparability among a broader ensemble of models.

[15] Many of these are used in multiple research projects (e.g., OMNIA is used in DIAMOND and TRANSIENCE alike). In the parentheses, only the project indicated by the survey participants is displayed.

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3 Landscape of existing models

3.1 Models from existing inventories and the survey

To establish a comprehensive overview of the current landscape of macroeconomic and climate-economy models, this section draws on the systematic exploration of the three model inventories described in Section 2. These inventories provide a broad and representative coverage of modelling frameworks used in climate, energy, trade, and macroeconomic policy analysis at global, regional, and national scales. As discussed above, the results were further complemented with the features captured from the survey, as well as with the ENTICE models.

The objective of this exercise is to map some key structural characteristics that define modelling capacity, with a specific focus on aspects that are central to trade-climate policy interactions. For each identified model, a harmonised set of descriptors was collected to enable cross-model comparison along common dimensions (model type, geographical coverage, sectoral coverage, international trade representation, and technological change mechanisms—distinguishing between exogenous representations and various forms of endogenous technological change). Table 1 provides a comparative snapshot of the state-of-the-art[16] across a large number of modelling frameworks currently in use. Regarding technological change, it makes sense only for dynamic models. However, we use the same term also for the static cases, for the sake of text sharpness, where "technology" comes from assumptions outside the model.

Table 1 highlights some patterns identified across the model landscape. CGE models predominantly rely on Armington type representations, reflecting a continued preference for tractable trade structures. In contrast, many IAMs and energy system models treat international trade either implicitly or through stylised, cost-based mechanisms. Although energy system models rarely feature international trade in the strict sense (as it is related to imports and exports of electricity and fossil fuels), they were included in the stocktake nonetheless, due to relevant insights into technological change and environmental impacts.

With respect to technological change, exogenous representations remain prevalent across most model families, especially in recursive dynamic CGE models, while endogenous mechanisms, such as learning-by-doing or R&D-driven innovation, are more frequently observed in IAMs and macro-econometric models, albeit often in stylised or sector-specific forms.

Table 1. Inventory and survey key dimensions.

Note: CGE stands for Computable General Equilibrium, IAM for Integrated Assessment Model, LBD for Learning by doing, and AFOLU for Agriculture Forestry and Land Use.

Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
CGE models					
AIM/CGE 2.0 (Fujimori et	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous

[16] Although the primary focus of this stocktake is on large-scale macroeconomic frameworks, the analysis was deliberately extended to include selected sectoral and energy system models that appear in the inventories under consideration. While these models typically feature simplified representations of trade, their insights are highly relevant, especially concerning technological change.

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
al., 2012)					
ENGAGE[17]	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
ENVISAGE (van der Mensbrugghe, 2024)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Endogenous (R&D)
ENV-Linkages (Château et al., 2014)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
EPPA (2015)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
EXIOMOD 2.0 (Bulavskaya et al., 2016)	CGE	Global multi-regional	Economy-wide	Armington	Exogenous
GEM-E3 (2017)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Endogenous (LBD, Learning by Researching)
GEMINI-E3 (Bernard & Vielle, 2008)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
GLOBE (2021)	CGE	Global multi-regional (flexible w.r.t. the defined region)	Economy-wide	Armington	Exogenous
GRACE (2022)	CGE	Global multi-regional	Economy-wide	Armington	Exogenous
G-RDEM (2019)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
GTAP models (AEZ, E, Power, GMig 2, POV)	CGE	Global multi-regional	Economy-wide	Armington	Exogenous
GTEM (Pant et al., 2002)	Intertemporal CGE	Global multi-regional	Economy-wide	Armington	Exogenous
ICES (2019)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
IMACLIM (Bertrand & Bourguignon, 2001)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
MAGNET (2020)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
MANAGE (van der Mensbrugghe, 2020)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
MIRAGE (2002)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
REMES (2009)	CGE (either static, recursive dynamic or a	National (Norway)	Economy-wide	Armington	Exogenous

[17] https://www.sciencedirect.com/science/article/pii/S0305750X19304243?via%3Dihub

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
	forward-looking dynamic model)				
IMF-ENV (Chateau et al., 2025)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
WTO Global Trade model (Aguiar et al., 2019)	Recursive dynamic CGE	Global multi-regional	Economy-wide	Flexible to switch from Armington to Krugman or Melitz	Exogenous
ZEW model	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Endogenous (energy-type specific directed)
GEMINI-E3 EU[18]	Recursive dynamic CGE	Global multi-regional	Economy-wide	Armington	Exogenous
IAMs					
BET-GLUE (Tsutsui et al., 2020)	IAM	Global multi-regional	Economy-wide	Armington	Exogenous
C³IAM (Wei et al., 2018)	IAM	Global with detailed China	Industry, energy, transport	Not explicit	Exogenous
DICE (2013)	IAM	Global	Economy-wide	Not applicable	Exogenous
DNE21+ (2015)	IAM	Global multi-regional	Industry, energy, buildings, transport	Not explicit	Exogenous
ETCU-RICE (Castelnuovo et al., 2005)	IAM	Global multi-regional	Economy-wide	Not explicit	Endogenous (R&D + LBD)
FUND (2014)	IAM	Global multi-regional	Economy-wide	Each region is open to international trade, but with fixed/exogenous assumptions	Exogenous
GAINS (2021)	IAM	Flexible to be used as Global, regional, national, sub-national	Economy-wide	Not explicit	Exogenous
GCAM v8.2 (2025)	IAM	Global multi-regional	AFOLU, industry, transport, energy, buildings, water	Armington-style	Exogenous
GCAM-Europe (Sampedro et al., 2025)	IAM	Global multi-regional	AFOLU, industry, transportation, energy, buildings, water	Armington-style	Exogenous
GLUCOSE (Beltramo et al., 2021)	IAM	Global	Industry, AFOLU, energy	Not applicable	Exogenous
IMAGE 3.0 (2014)	IAM	Global multi-regional	AFOLU, industry, transportation, energy, buildings, water	Not explicit	Exogenous
IMED (2018)	IAM	Global multi-regional	Economy-wide	Armington	Exogenous

[18] https://climate-diamond.eu/

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
MEDEAS-World (2019)	IAM	Global	Economy-wide	Not applicable	Exogenous
MERGE-ETL (Marcucci & Turton, 2012)	IAM	Global multi-regional	Economy-wide	Armington	Endogenous (LBD and Learning by Researching for key technologies)
MESSAGEix-GLOBIOM (2020)	IAM	Global multi-regional	Buildings, industry, energy, transport, AFOLU, water	Cost-based driven	Exogenous
MIMOSA (van der Wijst et al., 2021)	IAM	Global multi-regional	Economy-wide	Not explicit	Endogenous (LBD)
PLAIA (Stegmann et al., 2022)	IAM	Global multi-regional	Industry, water, AFOLU	Not explicit	Exogenous
RICE50+ (Gazzotti, 2022)	IAM	Global multi-regional	Economy-wide	Not explicit	Exogenous
WITCH (2019)	IAM	Global multi-regional	Economy-wide	Trade is represented through endogenous markets for fossil fuels and carbon permits	Endogenous (LBD, directed R&D investments, and knowledge spillovers across regions and technologies)
MUSE (Giarola et al., 2022)	Agent-based IAM	Global multi-regional	Industry, buildings, transport, AFOLU	Not explicit	Exogenous
REMIND (2020)	Intertemporal optimisation IAM	Global multi-regional	Economy-wide	Heckscher–Ohlin	Exogenous
Kenya CLEWs v2[19]	IAM	National	AFOLU, transportation, energy, water	Simplified exogenous manner: fixed imports and exports	Exogenous
IMAGE 3.4[20]	IAM	Global multi-regional	AFOLU, industry, transportation, energy, buildings, water	For most sectors, trade is modelled based on costs (both commodity costs and transport costs between regions). These costs (both domestic costs and the costs of imports) are put in a multinomial logit equation to get final trade shares. Where historic data is available, they correct for historic trade by adding premium factors to the trade costs. Trade of biomass is an exception, due of scarcity issues (here trade results from an optimisation script).	Exogenous and endogenous (LBD); more experience/capacity, lower costs; Spillovers are considered between regions, and also between sectors (like carbon capture costs in industry/electricity/hydrogen); it is connected in a sense that exports can result in additional learning in an exporting region because of increased experience gained. This will partly flow back to importing regions via spillovers.

[19] https://zenodo.org/records/13643022

[20] https://www.net0prisma.eu/

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
DSK (Reissl et al., 2025)	Agent-based IAM	National	Economy-wide	Not explicit	Endogenous (Schumpeterian treatment)
GCAM v8.2[21]	IAM	Global multi-regional	Economy-wide	The default model represents an Armington global pool trade (or regional pools for pipeline gas), with differentiation between imports vs. domestic resources. Development versions of the model further include Armington bilateral trade with competition between different exporters (in addition to differentiation of imports vs. domestic resources). All trade structures are implemented via logit sharing. The model by default represents trade in both fossil fuels, and agricultural products as a global pool trade, and pipeline gas as regional pools.	Exogenous; the model tracks vintages of technologies, and cost and performance assumptions are exogenous, with some prescribed dynamics (informed by literature); there also are specific project applications where learning-by-doing or learning-by-R&D is simulated via scenario assumptions, partly using the gcamwrapper functionality).
Macro-econometric models					
E3ME (2022)	Macro-econometric	Global multi-regional	Economy-wide	Imports are estimated econometrically from domestic demand and relative prices following a two-tier Armington model; consideration of the stock of knowledge in the definition of imports.	Two approaches: 1. For key energy-using technologies, the Future Technology Transformations (FTT) approach, 2. Top-down index-based approach applied at sectoral level broadly consistent with mainstream theories of endogenous growth.
E3MG (Pollitt et al., 2012)	Macro-econometric	Global multi-regional	Economy-wide	Econometrically estimated import/export equations	Endogenous (LBD)
NEMESIS (2019)	Macro-econometric	Regional (EU+UK)	Economy-wide	Specific import and export functions	Endogenous (R&D, ICT, and other intangible investments driven)
Land-use oriented models					

21 https://acclimate-project.eu/

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
BLUES (Rochedo et al., 2018)	Land use and energy system optimisation	National (Brazil)	Energy, AFOLU, industry, transport, buildings	Not explicit	Exogenous
FASOM-GHG (Beach et al., 2012)	Inter-temporal dynamic mathematical programming model	National (US)	AFOLU	Not explicit	Exogenous
MAgPIE (Dietrich et al., 2019)	Recursive dynamic PE for land use sectors	Global multi-regional	AFOLU, water, transport	Based on historical trade patterns	Endogenous (R&D)
GLOBIOM (2023)	PE for land use sectors	Global multi-regional	AFOLU, water	Computes bilateral trade flows through trading costs' minimisation	Exogenous
CAPRI (2022)	PE (agriculture-focused)	Global multi-regional (EU detailed)	AFOLU	Armington	Exogenous
Dynamic I/O models					
CONTO (Shirov, A. A., & Yantovsky, A. A., 2014)	Dynamic I/O model	National	Economy-wide	Not explicit	Exogenous
DYNERIO (Rinaldi et al., 2023)	Dynamic I/O model	Multi-regional	Economy-wide	Not explicit	Exogenous
Energy system models					
China MAPLE (Yang & Teng, 2018)	Energy system optimization	National (China)	Industry, energy, buildings, transport	Not explicit	Exogenous
China TIMES (Jia et al., 2011)	Energy system optimization	National (China)	Industry, energy, buildings, transport	Not explicit	Exogenous
CLEWS (OSEMOSYS)(Ramos et al., 2021)	Energy system optimisation	National (flexible to extensions)	Water, AFOLU, energy (flexible to cover transport, buildings, industry)	Not explicit	Exogenous
CLEWs-EU v2[22]	Energy system optimisation	Regional (EU)	AFOLU, industry, transport, energy, buildings, water	Only electricity trade (calculated endogenously based on the marginal cost differentials across EU member states)	Exogenous
EMPIRE (Backe et al., 2022)	Energy system stochastic optimisation	Regional (Europe)	Energy	Not explicit	Exogenous
EnergyPLAN (2024)	Energy system simulation	National	Industry, energy, transport	Not explicit	Exogenous
EPMM (Mezősi et al., 2020)	Energy system optimisation	Regional (Europe)	Energy	Not explicit	Exogenous
Euro-Calliope (Lombardi et al., 2019)	Energy system optimisation	Regional (Europe)	Energy, buildings, transportation	Not explicit	Exogenous

[22] https://zenodo.org/records/17722074

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
EU-TIMES (2017)	Energy system optimisation	Regional (Europe)	Industry, energy, buildings, transport	Not explicit	Exogenous
EXPANSE (Sasse & Trutnevyte, 2019)	Energy system optimisation	National (Switzerland)	Energy	Not explicit	Exogenous
HEB (Chatterjee et al.,2025)	Energy system simulation	National	Buildings	Not applicable	Exogenous
EGMM (Selei et al., 2017)	Partial equilibrium	Regional (Europe)	Natural gas	Not explicit	Exogenous
IFs (Hughes, 2016)	Partial equilibrium energy-economy model	Global multi-regional	Economy-wide	Imports/exports, only for energy commodities, depend upon levels of production and demand, as well as past propensities to import and export energy.	Exogenous
LEAP (2005)	Scenario-based energy-environment simulation tool	National	Industry, energy, buildings, transport	Not applicable	Exogenous
MENA-EDS (Fragkos et al., 2013)	Recursive dynamic partial equilibrium energy system model	National	Buildings, industry, energy, transport	Captured exogenously, for energy commodities only	Exogenous
NATEM (2024)	Energy system optimisation	Regional (North America)	Economy-wide	Not explicit	Exogenous
OPEN-PROM	Energy system optimisation	Global multi-regional	Transport, energy, industry, buildings	Global pool for oil, gas, and coal	Endogenous (LBD)
OSEMOSYS (Howells et al., 2011)	Energy system optimisation	National	Transport, energy, buildings, industry	Not applicable	Exogenous
STEM (Kannan, 2018)	Energy system optimisation	National (Switzerland)	Buildings, industry, energy, transport	Not applicable	Exogenous
TIAM-Grantham (Pye et al., 2020)	Energy-economy optimisation	Global multi-regional	Buildings, industry, energy, transport	Not explicit	Exogenous
US-REGEN (2025)	Energy-economy optimisation	National (USA)	Buildings, industry, energy, transport	Not explicit	Exogenous
POLES (Criqui et al., 2015)	PE energy system	Global multi-regional	Buildings, industry, energy, transport	Not explicit	Endogenous (LBD + R&D) two factor learning curves
EnergyPLAN 16.3[23]	Energy system optimisation	Regional and national	Industry, transport, energy	Not applicable	Exogenous
PROMETHEUS (2018)	Energy system optimisation	Global multi-regional	Buildings, industry, energy, transport	Armington-like	Endogenous and stochastic (LBD)

[23] https://energyplan.eu/wp-content/uploads/2024/10/documentation.pdf

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
PROMETHEUS V2[24]	Energy system PE	Global multi-regional	Industry, transportation, energy, buildings	Global pool of oil, gas, and coal trade	Endogenous (LBD and R&D); two-factor learning curve specification for clean energy technologies in both energy supply (power generation/hydrogen production) and in energy demand sectors (electric vehicles, H2 vehicles, heat pumps, etc).
Aalto-EU-TIMES 1.0[25]	Energy system optimisation	National (EU countries plus UK, Norway, Iceland, Switzerland)	AFOLU, industry, transportation, energy, buildings	Trade outside EU is simply represented using exogenous assumptions regarding the maximum amounts and prices. Trade between the EU countries follows the economic rationale of minimizing the total system discounted cost over the time horizon.	Exogenous
reV (Maclaurin et al., 2021)	Geospatial techno-economic model	National	Energy	Not applicable	Exogenous
Other models					
WTMBT (Hammer Strømman & Duchin, 2006)	Linear programming world trade model	Global multi-regional	Economy-wide	Transportation-determined trade flows	Exogenous
REMIND-MFA[26]	Dynamic material flow analysis model	Global multi-regional	Industry	It is based on a logit discrete-choice model, with the choices of imports from different regions, or domestic production. The model reacts to temporally changing supply curves (i.e., price structures) in different regions by adjusting trade shares, but it never fully chooses only one option, which corresponds to patterns seen in practice due to	Exogenous

[24] https://www.cdr-uptake.eu/
[25] https://www.iam-compact.eu/
[26] https://www.transience.eu/

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Model	Type	Geographical coverage	Sectoral coverage	International trade mechanism	Technological change
				heterogeneity of the traded products. Cost penalties for trade are implemented and calibrated to historic data.	
FIDELIO[27]	Neo-Keynesian general equilibrium	Global multi-regional	Economy-wide	Armington-like	Exogenous
CLIMACRED (Battiston et al., 2017)	Climate risk model	Global	Economy-wide	Not applicable	Exogenous
CLIMADA (2017)	Impact-based risk assessment model	Global	Buildings	Not applicable	Exogenous
FeliX (Ye et al., 2024)	System dynamics model	Global	Economy-wide	Not applicable	Endogenous (LBD for energy)
En-ROADS (2021)	System dynamics model	Global multi-regional	Energy, transport, industry, buildings, AFOLU	Not explicit	Exogenous & endogenous (R&D)
EUCalc (2020)	Simulation model of energy, land, materials, product and food	Regional (Europe)	Industry, energy, transport, water, AFOLU, buildings	Not explicit	Exogenous
FORECAST (Fleiter et al., 2018)	Forecasting-based simulation model	Global multi-regional	Industry, buildings, energy, transport	Not explicit	Endogenous (diffusion process driven)
IPAC (Jiang et al., 2019)	Multi-model framework: IPAC-SGM(CGE) + IPAC-AIM-technology (bottom-up) + IPAC-global	National (China)	Economy-wide	Not explicit	Exogenous
WILIAM (2023)	System dynamics model	Global multi-regional	Economy-wide	Armington	Exogenous

3.2 Beyond-Armington trade modelling perspectives

The theoretical mechanism underlying international trade in large-scale macroeconomic models plays a crucial role in the interpretation of results; moreover, it is a central aspect of the ENTICE project—especially WP3, with the aim of Task 3.3 being to go beyond Armington specification and examine possibilities of involving heterogeneity in trade (e.g., heterogenous productivity, imperfect competition) and modern trade theories[28]. To capture the state-of-the-art, in this section, the results of our trade theory-focused systematic literature review are captured to explore beyond-Armington capabilities and inform WP3 modelling teams. It should be noted that a preliminary assessment of the bibliography had already been conducted in the

[27] https://joint-research-centre.ec.europa.eu/projects-and-activities/trade-and-industrial-policy-analysis/industrial-policy/fidelio-model_en

[28] It is important to clarify that approaches discussed in this review remain within the typical market-based general equilibrium modelling. As such, they do not explicitly represent physical or material constraints on trade.

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context of D3.1; in this section, that preliminary analysis is enriched, and a more extensive/detailed analysis of the key takeaways is provided.

Since the early years of large-scale economic model development, representation of international trade has been dominated by the Armington assumption of differentiated commodities by country of origin, within a constant returns-to-scale perfect competition framework (Armington, 1969). The Armington trade structure first appeared in CGE modelling through the ORANI model (Dixon et al., 1977), and its tractability advantages explain its wide adoption by such macroeconomic models. Its simplicity, however, also constitutes its main limitation: it does not allow representing and quantifying firm-level or productivity effects.

This is also why, alongside improving computational capacities, there have been ever-growing discussions among the economic modelling community on shifting from the traditional Armington assumption to more modern theories that are more consistent with micro-level observations. In this direction, the Krugman[29] (1980) and Melitz (2003) models have constituted modern trade schemes reflecting firm-level differentiation. However, their integration into large-scale quantitative models representing a large number of commodities still entails considerable computational and empirical data challenges. Despite computational barriers, the Krugman and Melitz models have remained at the centre of debate, especially among those attempting to go beyond the Armington assumption in computational economics, and particularly in CGE modelling.

The Krugman trade theory assumes that product varieties are distinguished by firms, where each firm produces a unique variety under increasing returns-to-scale. It is a monopolistic competition model with symmetric firms. Producers are monopolistically competitive and consumer preferences are characterised by love-of-variety between varieties produced by different firms (Dixon et al., 2018). Intra-industry trade effects emerge naturally due to (i) the desire of consumers to buy as many different varieties as possible, and (ii) the love-of-variety benefits. However, the Krugman approach has also been criticised over its assumption that all firms are identical in terms of productivity (Bekkers & Francois, 2018). One more caveat of the Krugman model is that once a variety is offered to one market, it is offered to all markets. Therefore, only when trade costs “approach infinity” will some consumers around the globe not consume that commodity (Balistreri et al., 2025).

The Melitz trade scheme, in turn, preserves Krugman’s features but, additionally, assumes heterogeneous productivity at firm level. While both assume imperfect competition, the Krugman model assumes homogeneous firm productivity, and the Melitz model assumes heterogeneous firm productivity. This inclusion of firms’ differentiation under the Melitz scheme adds more realism in trade representation, as it allows endogenous changes in productivity in response to trade or other policies. Also, firm heterogeneity provides an additional mechanism for welfare effects from trade, with re-allocation of within-sector market shares between less and more productive firms (Dixon et al. (2019), Balistreri et al. (2025)). The Melitz approach is also especially important for the analysis of free trade agreements, where the impacts depend also largely on changes in non-tariff measures (NTMs), which affect largely the trade costs. In particular, the differentiation between fixed and variable costs in bilateral trade that is embodied in Melitz-driven CGE models allows for more realistic assessments of NTMs (Fugazza & Maur, 2008). On the other hand, the endogenisation of free entry and exit in a multi-sector, multi-region Melitz model that includes intermediate

[29] Also called Ethier-Krugman theory due to the work of Ethier (1982).

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inputs may give rise to computational difficulties related to multiple and/or corner equilibria.

To summarise the core features of the transition in computational economics and CGE modelling, from Armington to Krugman, and, subsequently, to Melitz:

- In Armington, firms in a country behave competitively; in Krugman and Melitz, they are monopolistically competitive.
- In Armington and Krugman, producers in a country have the same productivity (homogenous firm productivity), while Melitz allows for productivity variation across a country's producers (heterogenous firm productivity).
- In Armington and Krugman, producers in a country sell on all trade links; in Melitz, only high productivity firms "survive"—they may sell in some markets, but not in all.

Beyond Armington, Krugman, and Melitz, there are also other trade mechanisms that have gained traction recently, such as the Eaton-Kortum (Eaton & Kortum, 2002) and Bilateral Representative Firm (BRF) models (Balistreri et al., 2025):

- The Eaton-Kortum international trade mechanism is based on countries' differences in comparative advantage, while it additionally assumes a continuum of varieties based on stochastic specification for productivity. An important feature of this model is that, contrary to Armington, the landed bilateral import price does not vary by source country.
- The BRF model, introduced quite recently in the CGE modelling domain, proposes a trade structure that includes monopolistic competition among bilateral representative firms[30], capturing the import-variety gains while retaining the Melitz model's bilateral selection with relatively low computational effort.

Following the methodology presented in Section 2, Table 2 presents the final list of papers considered and reviewed, along with three main features: the underlying trade mechanism, a brief description of important incorporation details, and provision of important computational aspects.

Table 2. Cases of modern trade theory integrated in large-scale models (beyond Armington).

Study	Model name	Model type	Trade mechanism	Important incorporation details	Important computational aspects
Akgul et al. (2016)	GTAP-HET	CGE	Melitz	- GEMPACK-based. - They define average firms and average productivity for each exporter; the average exporter productivity is not destination-specific. - They consider fixed and variable cost components (as different bundles) at sector and trade link level, allowing the ratio of fixed to variable costs to change; fixed cost bundles use only added value. - The price of the representative firm to all markets does not differ by market, based on bilateral representative firm productivities;	- Since data on firm numbers and sales are limited, they aggregate firm-level variables into industry-level variables in the model; this aggregation eliminates the need for firm-level information to be included in the dataset. - Firm heterogeneity requires additional information that is not readily available in the standard GTAP Data Base, such as information on key firm-heterogeneity parameters, fixed set-up costs, and fixed trading costs.

[30] This is an alternative to Melitz trade structure characterised by monopolistic competition between bilateral representative firms. The core feature is that it allows for bilateral entry and exit of varieties (firms).

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Study	Model name	Model type	Trade mechanism	Important incorporation details	Important computational aspects
				this simplification precludes bilateral selection. - They eliminate the two-tier import/ domestic substitution specification.	
Zhai, F. (2008)	N/A	CGE	Melitz	- Their model does not allow endogenous entry/exit of firms. - They assume no fixed production costs, but fixed domestic trading costs for heterogenous sectors. - Trade relating to sectors with homogenous goods is Armington-based. - They assume "large group" monopolistic competition. - They consider competitive selection of heterogeneous firms.	- Their model does not allow endogenous entry/exit of firms, in order to avoid corner solutions. - Required information that is not available in the GTAP Data Base (e.g., degree of returns to scale, shape of productivity distribution) is extracted from literature.
Dixon et al. (2016)	MelitzGE	GE[31]	Melitz	- GEMPACK-based. - Two-country, two-commodity model. - There are no intermediate inputs. - Industries are identical. - There is only one primary sector. - They also propose a way to model Melitz, Krugman, and Armington in one encompassing model.	- To lower dimensionality, there is only one primary sector, and there are no intermediate inputs. Hence, they do not calibrate the model in a complete CGE structure.
Jafari & Britz (2018)	GTAP (GAMS)	CGE	Melitz	- They apply Melitz for 22 (manufacturing) of the 57 GTAP sectors (based on a previous version of the GTAP Data Base); remaining sectors remain in perfect competition mode. - They assume fixed costs only for primary inputs.	- They use a bilateral regional index to lower the dimensionality. - A procedure improving numerical stability is introduced, allowing removing love-of-variety effects and price markups.
Bekkers & Francois (2018)	GTAP	CGE	Melitz	- GEMPACK-based. - They make a conversion from Armington to Melitz, by introducing three shift variables for demand, supply, and trade cost. - They use a set of endogenous supply and demand shifters, such that an otherwise conventional Armington model mimics the Melitz model responses. - Incorporation of Melitz with Pareto productivity distribution. - Medium-size model with 11 sectors.	- To cope with convexity and corner solution issues, the following two approaches have been adopted: (a) imperfect mobility of production factors, and (b) nested import demand with a smaller substitution elasticity between imports and domestic goods than between imports from different sources; the framework comes along with a relatively easy calibration of parameters and baseline, requiring only tariff elasticities, shape parameters of the firm size distribution, and import shares without needing specific information about the size of fixed trade costs or markups.
Dixon et al. (2019)	GTAP-A2M	CGE	Melitz	- They convert the Armington-based GTAP into a Melitz type model.	- Through appropriate closure swaps, they turn on/off the introduction of Melitz assumptions for chosen

[31] Not CGE in the strict sense.

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Study	Model name	Model type	Trade mechanism	Important incorporation details	Important computational aspects
				- They also present the Armington to Melitz (A2M) conversion method; the proposed method leaves unchanged the theory and data of the standard GTAP model.	industries; there are no specific data requirements beyond assigning values for the Pareto shape parameter and revising the Armington substitution elasticities. - There are no dimensional limitations.
Balistreri & Rutherford (2013)	N/A	GE	Melitz	- GAMS-based. - They incorporate a decomposition algorithm to "interface" an auxiliary GE model with a PE Melitz model; the latter is used to get the average sector productivity parameters on the basis of output volumes and prices, which are obtained from the GE model. - They consider 9 sectors (only 2 of which are Melitz).	- Dimensionality and non-convexity issues are addressed by developing a decomposition algorithm that "interfaces" a PE Melitz model and a GE Armington model.
Aguiar et al. (2019)	WTO Global Trade model	Recursive dynamic CGE	Melitz, Krugman	- GEMPACK-based. - Flexible structure combining perfect competition with Armington preferences and monopolistic competition for either Krugman or Melitz.	- The switch among the different trade structures is implemented through appropriate changes in the parameters file.
Bekkers et al. (2023)	GTAP	CGE	Eaton-Kortum	- GEMPACK-based. - The underlying trade mechanism and the associated gravity equations of GTAP are modified from the Armington to the Eaton-Kortum structure.	- Due to complexities related to the import prices of the Eaton-Kortum model, the code is structured such that the price index is first determined based on costs, while tariffs, transportation margins, and export taxes are subtracted for the calculation of bilateral prices.
Balistreri et al. (2025)	GTAP (GAMS)	CGE	Bilateral Representative Firms (BRF)	- GAMS-based. - Monopolistic-competition bilateral entry. - BRF may be considered as an opposite to the average-firms approach. - Entry happens on a bilateral basis. - They consider BRF structure for 28 of the 57 sectors of the GTAP Data Base v10 (i.e., manufacturing and business services); only these sectors are modelled as imperfectly competitive, with the rest being of Armington type, along with the GTAP elasticities.	- To ensure convexity, the price of composite input is bilateral. - Calibration: one additional parameter is necessary to calibrate the responses to factors (i.e., elasticity of supply).

The key challenges, limitations, and takeaways concerning trade theory are presented in Section 4.

From a feasibility viewpoint, while bibliography provides rich theoretical foundations, the adoption of beyond-Armington trade structures in CGE modelling is not straightforward. In Table 3, a qualitative assessment of feasibility is presented, based on a summation of the results of Table 2. Overall, the reviewed literature suggests that integration feasibility varies across beyond-Armington approaches. Methods that

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"preserve" the core structure of standard modelling, such as Armington-to-Melitz conversion techniques and partial implementations, where firm heterogeneity is applied to only selected sectors, minimise data and calibration requirements. In the Armington-to-Melitz conversion case, requirements could be characterised as low to moderate, since the extension relies largely on the GTAP Data Base with limited additional parameters, while the core model is almost unchanged. A similar situation holds for partial treatment of the Melitz model, where additional assumptions on fixed costs are required. In both cases, policy value is moderate, since scalability remains low, while firm selection and productivity effects are considered. In contrast, complete Melitz schemes entail substantial integration challenges due to additional data requirements, which are not typically available in standard databases.

Table 3. Feasibility assessment.

Approach	Data requirements	Computational complexity	Policy value
Armington to Melitz conversion	Low to moderate	Low	Moderate
Partial Melitz implementations (sector-specific firm heterogeneity)	Moderate	Moderate	Moderate to high
Full Melitz implementation	High	High	High
Eaton-Kortum	Moderate	Moderate to high	High
Bilateral representative firm	Low to moderate	Moderate	High

3.3 Endogenisation of technological change

In the context of linking WP1 with WP3 and informing ENTICE modelling teams on current modelling capacity and potential modelling developments, this section is a more detailed version of Section 3.3 of Deliverable D3.1. Here, the results of our technology change endogenisation-focused systematic literature review are captured, as described in Section 2.

Early models typically relied on exogenous technological change (TC)—e.g., represented through the 'autonomous energy efficiency improvement' (AEEI) parameter (Duan et al., 2017). With the rise of endogenous growth theory, modelling has moved toward the endogenisation of technological change. In this direction, technological progress is increasingly calculated endogenously in the models as a result of R&D investment, economies of scale and learning-by-doing processes, rather than an exogenously determined trend.

The modern endogenous growth literature draws heavily on the work of Romer (1990) and places knowledge, as a distinct form of capital accumulated through R&D activities, at the centre of the growth process. A branch of technological change endogenisation uses learning/experience curves to represent the technical progress through cost reductions of technologies, depending on cumulative production (or capacity) levels, while another established approach emphasises the concept of knowledge spillovers, by representing the diffusion of production experience across sectors and/or countries (Gersbach & Schmutzler, 2003).

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Developments in growth theory have “driven” the incorporation of TC in macroeconomic models, especially in CGE models, in which technology is typically represented through nested sectoral production functions. Introducing endogenous technological change (ETC) into such models entails the specification of a mechanism that links economic variables (e.g., output/production, R&D expenditure, trade flows, etc.) to production functions’ parameters that represent some type of efficiency and makes sense to be improved (e.g., Total Factor Productivity).

Below, a number of endogenous and semi-endogenous technological change mechanisms are presented, along with some general mathematical formulations, which are based on the pioneering survey of Wing (2006).

The recent work of Witajewski-Baltvilks (2025) identifies two dominant trends in endogenising technical change in large-scale economic and Integrated Assessment models:

- **Learning-by-doing (or learning-by-using) mechanisms** that relate efficiency parameters or production costs to cumulative sectoral production/output; the core assumption here is that potential productivity improvements are a by-product of production. In particular, the family of learning-by-doing mechanisms is mostly represented through the so-called *learning-by-doing* (LBD) *curves*. Learning is interpreted as a by-product of production in the sense that producers become more efficient, the more a technology is used (i.e., the more quantity output it produces).

  Learning-by-doing aims to mimic the role of experience in productivity dynamics and has been extensively employed in bottom-up models that have engineering-oriented representation of production technologies (Baccianti & Löschel, 2014). In modelling terms, the learning process is often expressed as a function of the capital stock or the accumulated production. For instance, in a model with a learning-by-doing mechanism, technological progress is expressed in terms of decreasing specific costs of a technology (C) as a function of cumulative capacity (K). The cumulative capacity is then used as a measure of knowledge accumulation occurring during the utilisation of a technology. A commonly used LBD function is as follows:

  $$C = aK^{-b}$$

  where a stands for a baseline level of costs and b is the learning rate (Löschel, 2002).

- **Learning-by-researching (or R&D investment based) mechanisms** entailing the incorporation of knowledge stock that is built up through R&D investments; in this approach, knowledge is treated in a form similar to physical capital. This family of ETC mechanisms in macroeconomic and CGE models treats technical knowledge as a “capital-like” stock that accumulates through “deliberate” activities such as R&D investments (public and private). Potential invested resources in R&D activities result in productivity improvements. In a macroeconomic setting, these insights are typically implemented via a knowledge accumulation equation, where the knowledge stock grows with R&D expenditure but depreciates over time, simulating knowledge depreciation. In CGE models, a typical approach is that the R&D expenditure of a sector accumulates into an R&D stock that enters as a total factor productivity (TFP) growth in the production function (Wang et al., 2009). In particular, knowledge stock in learning-by-researching accumulates similarly to physical capital. This specification is particularly convenient in large-scale models with nested production structures (Baccianti & Löschel, 2014).

  A common implementation of R&D-driven technological change in a CGE framework can be found in Hwang et al. (2021), where production nest could be shaped as in Figure 4. In particular, let the production function be formulated as follows:

$$Y_t = \gamma^Y \left(\theta M_t^{\rho} + (1-\theta) RVA_t^{\rho}\right)^{\frac{1}{\rho}}$$

where M_t and RVA_t denote the aggregated intermediate input and value-added composite, respectively, and γ, θ, and ρ stand for the scale, share, and substitution parameters, respectively, and

$$RVA_t = \gamma^{RVA} \left(\theta^{RVA} VA_t^{\rho^{RVA}} + (1-\theta^{RVA}) RP_t^{\rho^{RVA}}\right)^{\frac{1}{\rho^{RVA}}}$$

$$VA_t = A_t \left(\theta^{VA} K_t^{\rho^{VA}} + (1-\theta^{VA}) L_t^{\rho^{VA}}\right)^{\frac{1}{\rho^{VA}}}$$

where VA_t, K_t, L_t, and RP_t denote value added, physical capital, labour, and R&D capital stock, respectively; A_t stands for the total factor productivity, affected by private and public R&D investment:

$$A_t = A_t(\text{aggregate private and public R\&D stock})$$

and is determined endogenously.

The predominance of learning-by-doing-based and R&D-based mechanisms in large-scale economic models is not only due to their conceptual simplicity, but also to their strong empirical foundations. Learning-by-doing mechanisms can be empirically estimated using observed relationships between cumulative production and unit technology costs, with a substantial body of econometric evidence available for key energy technologies such as photovoltaics and wind power (Haas et al, 2023). This empirical grounding allows learning rates to be directly calibrated or validated against historical data, enhancing the credibility of model projections. Similarly, R&D-based approaches are supported by a well-established literature linking R&D expenditures to productivity growth, which can be readily incorporated into macroeconomic and CGE frameworks through knowledge accumulation equations. Beyond learning-by-doing and learning-by-researching, there is also the option of learning-by-exporting (Silva et al., 2012), which represents the possibility of enhancing firms' productivity through exports. However, this approach has been rather poorly or indirectly integrated in macroeconomic modelling.

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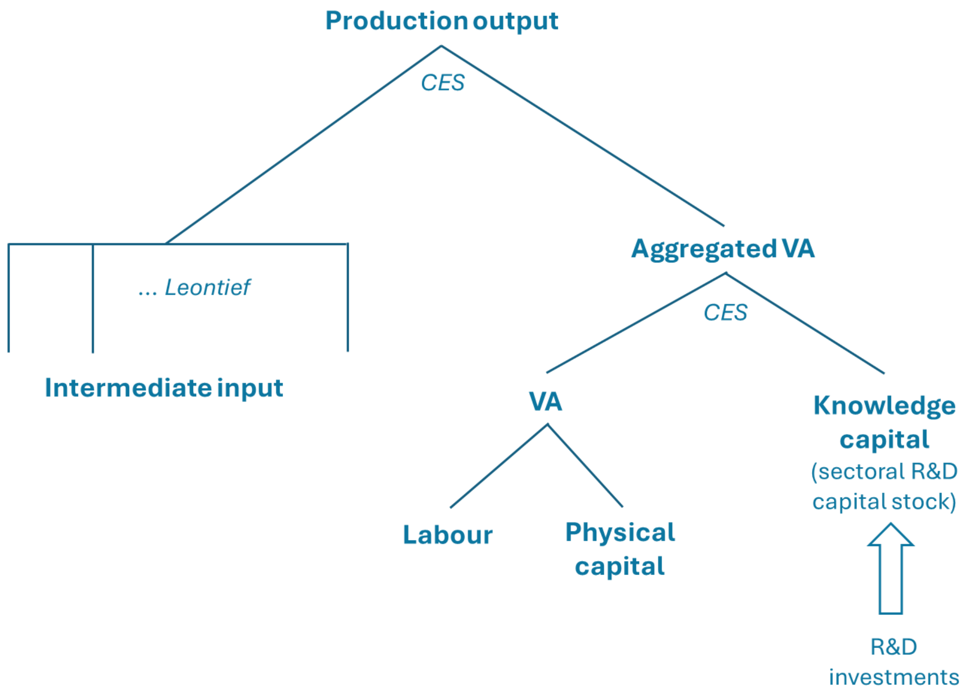

Figure 4. CGE production block with R&D-driven technological change (Hwang et al., 2021).

A more sophisticated variant used in models is the two-factor learning curve, which combines learning-by-doing with learning-by-searching. For instance, Klaassen et al. (2005) specify cost as a log-linear function of both cumulative capacity and cumulative R&D investment. In these models, R&D expenditure is aggregated into a stock of "R&D capital," making it comparable to cumulative capacity as a driver of unit cost reductions. Witajewski-Baltvilks (2025) notes that such two-factor learning curves address the absence of intentional innovation in pure learning-by-doing models. However, the log-linear relationships have not yet been linked to a micro-founded modelling basis of innovation markets.

Beyond learning-by-doing, learning-by-researching, or learning-by-exporting mechanisms, Wing (2006) identifies two additional modes to introduce technological change endogenously (or semi-endogenously): the price-induced input augmentation and the consideration of backstop technologies. Both approaches are less popular relative to the learning-by-doing and R&D-based ones, while, especially, backstop technologies fit better to bottom–up engineering models rather than system-wide macroeconomic models (Löschel, 2002). In particular:

- **Price-induced input augmentation** mechanisms link factor-augmenting parameters directly to relative input prices; although conceptually appealing, they are rather rarely adopted due to difficulties in empirically specifying and calibrating the relationship between prices and technological augmentation.
- **Backstop technology mechanisms** are considered as a semi-endogenous approach; the "adoption" of a technology is considered endogenous due to a price-induced response, with the technology/production parameters themselves remaining exogenous.

Compared to LBD- and R&D-based approaches, both methods are less commonly used. In particular, backstop technologies are more consistent with bottom–up engineering models (Löschel, 2002), as they are closely linked to the notion of a "technology snapshot".

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Two additional modes are also present in the literature: directed technological change (DTC), and spillover mechanisms:

- **Spillover mechanisms:** With productivity improvements *de facto* closely connected to various forms of spillovers and technology diffusion, the knowledge created in one sector or region may benefit other sectors or regions through the channels of trade, FDI, knowledge diffusion, etc. (Löschel, 2002). Roughly speaking, technological spillovers occur when innovation in one place also benefits others; for instance, when a region develops a new technology, trading partners may learn from it and become more productive even without innovating themselves. In modelling terms, these interactions may be captured by letting technological change drivers to depend not only on "local" variables (i.e., local production or R&D expenditures) but also on how these variables develop in other regions or sectors. For instance, in knowledge stock-based CGE models, this feature can be implemented by letting a sectoral TFP depend on both domestic and foreign knowledge stocks, which can be weighed by trade shares—see Fragkos et al. (2017), Parrado & De Cian (2014), Kim & Verdolini (2023). Of course, the absorptive capacity of a region might restrict the positive spillover effects (i.e., unless a region has the required skills, it cannot fully absorb the spillovers from other regions).

  Considering the ENTICE project's modelling needs, an example of representing trade-driven spillovers in a CGE framework can be found in the work of (Parrado & De Cian, 2014). In particular, an extended version of the ICES model is presented considering an endogenous relationship between machinery and equipment (M&E) imports, and energy-biased technological change, as well as capital-biased technological change. Let

  $$Y_{j,r} = f\left(A_{K,j,r}, K_{j,r}, A_{L,j,r}, L_{j,r}, A_{E,j,r}, E_{j,r}, A_{M,j,r}, M_{j,r}\right)$$

  be the generic production function for sector j in region r, where $A_{i,j,r}$ describes the improvement in a technological change related to the use of capital, labour, energy, and other intermediate inputs ($i = K, L, E, M$).

  Parrado & De Cian (2014) implement an endogenous version of technological change for the ICES recursive dynamic CGE model, by exploiting an empirical relationship between energy and capital productivity, and M&E imports. In this version of ICES, only $A_{K,j,r}$ and $A_{E,j,r}$ are endogenised. The percentage change of productivity is given by:

  $$a_{i,j,r} = \gamma_{i,j,r} m\&e_r$$

  where the spillover coefficient $\gamma_{i,j,r}$ represents the calibrated sector-specific elasticity of the capital and energy productivity with respect to the rate of change in M&E imports. This coefficient is defined as follows:

  $$\gamma_{i,j,r} = \gamma_{0i} MS_r CR_{r,r'} CS_{j,r}$$

  where MS_r is the share of region r M&E output over world M&E output, $CR_{r,r'}$ represents region r M&E imports from r' over total imports from r', $CS_{j,r}$ represents sector j M&E imports over total region r M&E imports, and γ_{0i} is a calibration coefficient for energy and capital.

- **Directed technological change mechanisms:** In directed technological change (DTC), innovation can be targeted toward specific factors and corresponds to endogenous responses against applied policies and/or changes to relative prices (Van den Bijgaart, 2017). Macroeconomic models may operationalise this rationale, e.g., by allowing factor-augmenting productivity parameters to depend on policy-driven R&D allocation (Otto et al., 2008).

As also presented in Table 4, technological change mechanisms may operate jointly. For instance, in the ENTICE model (Popp, 2006), backstop technologies co-exist with R&D-based induced technological change. In particular, if production output is modelled as follows:

$$Q_t = A_t K_t^{\gamma} L_t^{1-\gamma-\beta} E_t^{\beta} - p_{B,t} B_t$$

then, technological advances can lower the price of using a backstop technology through

$$p_{B,t} = \frac{p_{B,0}}{H_{B,t}{}^{\eta}}$$

where $H_{B,t}$ defines the stock of knowledge pertaining to the backstop. Moreover, knowledge stocks are created by the accumulation of research and development ($R_{i,t}$):

$$H_{i,t} = h(R_{i,t}) + (1-\delta)H_{i,t-1}$$

Table 4. Cases of endogenous technological change in peer-reviewed articles.

Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
Becker et al. (2025)	N/A	CGE	R&D + DTC	- R&D, as a service, is endogenously directed to sectors in response to policies - Knowledge is assumed to be a factor of production - Knowledge services constitute the total amount of knowledge demanded by producers that can be produced through R&D investment	Not directly[32]
Witajewski-Baltvilks (2025)	MANAGE	CGE	R&D + DTC	- Producers choose the optimal level of R&D intensity - Producers choose the direction of TC (Romer-type DTC) - Decisions on R&D take place in each sector separately - Endogenisation of share parameters in the CES nests	Not directly

[32] "Not directly" in the sense that potential technology improvement parameters are not directly related to a trade variable, e.g. sectoral imports.

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Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
				- Endogenisation of the speed of TC	
Jiang et al. (2023)	CEEPA	CGE	R&D	- Knowledge capital is a production function input - R&D investment is a proxy of knowledge capital	Not directly
Shi et al. (2023)	N/A	CGE	LBD	- LBD for the RES sectors - The LBD module applies an LBD mechanism via the accumulation of electricity output - TFP in the rest sectors is exogenous	Not directly
Yeo et al. (2023)	N/A	CGE	R&D + spillovers	- Knowledge is a factor of production - Formation of knowledge capital in the investment account of the SAM - R&D investment goods are produced with a distinctive production function - Newly generated knowledge from R&D is accumulated into pre-existing knowledge stocks - The knowledge capital of a particular sector can be utilised by other sectors (spillover effects from knowledge capital accumulation) - Skill accumulation of labour is also endogenous	Not directly
Fierro et al. (2022)	N/A	Agent-based (ABM) macroeconomic	DTC + R&D	- Endogenous skill-based TC - R&D efforts impact the share of high- and low-skilled labour - R&D activity is stochastic	Not directly
Liang et al. (2022)	3E-CGE	CGE	LBD	- Technological improvement through a logistic curve for energy technologies	Not directly
Hassler et al. (2022)	N/A	Macroeconomic	DTC + R&D	- Energy-saving DTC - R&D-affected productivity	Not directly

Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
von Brasch et al. (2021)	KVARTS	Macro-econometric model	R&D + spillovers	- TFP by sector depends on R&D knowledge stock - R&D knowledge stock is modelled as a function of both domestic and international knowledge stock - A dynamic econometric model is used to express the relationship of TFP by sector with R&D knowledge stock	Not directly
Jung (2021)	N/A	CGE	DTC	- Endogenous aggregate productivity (for country/region) is determined by skill-technology assignment in equilibrium	Heterogenous labour is endogenously sorted into different technologies, based on comparative advantage.
Marcucci & Zhang (2019)	CITE	CGE	R&D	- R&D investments drive all factor productivities - R&D investments are also derived endogenously	Not directly
Das (2019)	N/A	CGE	Spillovers	- The productivity of primary inputs is affected by technology embodied in traded intermediates	Through imported intermediates
Schütze (2017)	GEM-E3-M50	CGE	LBD	- LBD mechanism of adaptive expectations - Upper bounds to prevent implausible LBD market share effects	Not directly
Hong & Lee (2016)	N/A	CGE	R&D	- Two kinds of knowledge are introduced: government knowledge stock and sectors' knowledge stock - Knowledge stock is accumulated via R&D investment - Accumulation of R&D follows the PIM method	Not directly
Kristkova et al. (2016)	MAGNET	CGE	R&D	- Land productivity TC is modelled as a function of growth of cumulated domestic R&D stocks	Not directly

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Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
				- Instead of linking R&D to TFP consistent with a Cobb-Douglas production function, a factor-augmenting TC is modelled that consists of an exogenous and an endogenous part, following the approach of Parrado and de Cian (2014), in line with a CES production function - Public R&D investments are linked to land-augmenting TC - Private R&D investments are linked to the labour-saving effect on TC	
Yang et al. (2016)	N/A	CGE	R&D	-TC is endogenized through the accumulation of knowledge capital that is derived from investments in R&D - Terleckyj's method is used to estimate knowledge capital (see Wing, 2006)	Not directly
Böhringer et al. (2016)	(Rutherford and Tarr, 2010) model	CGE	Spillovers	- There are endogenous productivity effects from additional varieties of goods in imperfectly competitive sectors - FDI is incorporated in business services with endogenous productivity effects from additional varieties of business services - Reflects the theory of Markuses (1989), Francois (1990), and Markuses et al. (2005), in which greater availability of services results in TFP gains to the manufacturing sectors	There are endogenous technology spillovers from the Dixit-Stiglitz variety effect
Henriet et al. (2014)	N/A	Hybrid macroeconomic model with	DTC + R&D	- The rate of technical progress on fossil energy can be stimulated by a price effect and by size	Not directly

Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
		detailed energy module		effect of the research effort directed at saving fossil energy - TC is not fully endogenised: the total amount of resources devoted to research is exogenous - DTC because an increase in energy price induces R&D aimed at saving energy, at the expense of R&D aimed at increasing labour productivity - Main assumption: research effort of the economy is a proportion of output; given the total amount of resources devoted to R&D, the direction of tech progress is endogenised, building on Smulders & de Nooij (2003) and Acemoglu et al (2012)	
Gerlagh & Kuik (2014)	GTAP-E	CGE	PII augmentation	- In general, GTAP-E has exogenous TC - TC is endogenised as follows: the rate of induced TC is a fraction of the relative price-induced change in demand for energy	Not directly
Parrado & De Cian (2014)	ICES	Recursive dynamic CGE	Spillovers	- Productivity of capital and energy are linked endogenously with machinery & equipment (M&E) imports - Capital and energy-biased TC as a function of the rate of change of M&E imports	Through imports in Machinery & Equipment (M&E)
Tarr (2013)	N/A	CGE	Spillovers	- Endogenous productivity effects from services - To capture the productivity effects of trade, the Dixit-Stiglitz-Ethier mechanism is employed (gains from Dixit-Stiglitz externality)	Through the Dixit-Stiglitz-Ethier mechanism

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Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
				- Additional service varieties increase TFP in the sector using the service; as barriers against multinational service providers fall, the total number of varieties increases, and so does TFP	
Robinson et al. (2002)	N/A	CGE	Spillovers	- They introduce a parameter in the production function as an exponent to the productivity shift parameter. This parameter increases with the trade intensity of the sector - The change in the trade intensity of each sector is endogenous; therefore, the productivity increase is endogenous.	Import embodied technology transfer
Bye et al. (2011)	N/A	CGE	R&D + spillovers	- Productivity growth within R&D sector caused by dynamic spillovers from the accumulated R&D knowledge stock - Absorbed productivity improvements depend on sectors' extent to the foreign trade and the input share or R&D-based capital	Through the absorption mechanism
Balistreri et al. (2009)	Jensen et al (2007) model	CGE	Spillovers	- Endogenous productivity effect via the Dixit-Stiglitz-Ethier framework for services, implying endogenous productivity gains from the net introduction of new varieties of service providers - The increased availability of services results in an endogenous increase in productivity.	Through the Dixit-Stiglitz-Ethier mechanism
Müller-Fürstenber & Stephan (2007)	N/A	CGE (IAM)	LBD + R&D	- Two types of endogenous TC: LBD in non-fossil energy supply technologies, R&D-driven	Not directly

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Study	Model name	Model type	ETC mechanism	Brief description of ETC rationale	Trade impact on TC
				energy-saving technical progress in production	
Köhler (2006)	E3MG	Dynamic macro-econometric model	LBD	- TC is endogenous though its effects on general energy use and sectoral demand, and on energy technologies through the cost-reducing effects of LBD and economies of scale	Not directly
van der Zwaan et al. (2002)	DEMETER	Neoclassical (optimal growth)	LBD	- TC is a function of cumulative capacity	No
Fragkos et al. (2017)	GEM-E3	Recursive dynamic CGE	R&D & spillovers	- Endogenous learning for clean energy technologies - Incorporation of spillover effects from innovation in low and zero carbon technologies	Not directly

The key challenges, limitations, and takeaways concerning technological change are presented in Section 4.

3.4 International transport

In most models (especially those based on the GTAP Data Base), domestic and international transport are treated differently. While domestic transport modes (air, land, water) in the GTAP Data Base constitute distinct services sectors and are represented as separate economic activities, this is not true for international transport. In domestic transport, there are explicit sectors in each region, using region-specific factors (labour, capital, fuels), and the output is supplied to domestic users (firms, households, government). In contrast, international transport is not a regional sector to be consumed by domestic agents directly—it appears only as trade margins.

In Standard GTAP model v7, given the lack of bilateral supplies of shipping services, each mode of transport is supplied at a uniform price across the globe (Corong et al., 2017). This global transport price is a composite based on the price of national margin services exports. To compute the composite Free on Board – Cost, Insurance, and Freight (FOB-CIF) price, it is necessary to aggregate these modal-specific prices over all relevant nodes of transport for any particular commodity.

The simplified treatment of international transport as a globally pooled trade is not "accidental". It reflects deliberate modelling choices driven by several constraints. Most CGE models are calibrated to Social Accounting Matrices (SAMs) derived from national input–output tables; national accounts record domestic transport sectors. Moreover, shipping revenues are often registered in flag-of-convenience countries, while there is lack of bilateral transport cost of data. Additionally, CGE trade blocks are grounded in Armington differentiation (see also Section 3.2), constant elasticities of substitution, and representative agents, which treat international transport service as a pure cost wedge. Therefore, a global transport margin is the only

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way to keep accounting consistency across countries. Given these constraints, in ENTICE, we will attempt to treat international transport primarily as (i) better bilateral cost wedges and emission factors, and (ii) scenario/sensitivity levers, rather than considering a fully endogenised global shipping sector.

Most large-scale CGE models are based on the GTAP Data Base and, therefore, international transport representation is aligned to the structure of the database. Apart from CGEs (GTAP standard v7 and its extensions, ENVISAGE, GTEM, GEM-E3, IMF-ENV, WTO Global Trade model, AIM/CGE 2.0, GEMINI-E3), models in this class also include some IAMs such as C^3IAM. A typical implementation considers global demand for international transport that is allocated to each country based on the share of the reference year (e.g. in GEMINI-E3).

There are models considering a partial representation of international transport, as extracted in this literature review and presented in Table 5; however, this is done mostly from an energy end-user point of view (mainly as demand agents).

Table 5. International transport consideration in different studies/models

Model	Model type	International transport representation
BET-GLUE (Tsutsui et al., 2020)	IAM	Via energy demand for transport
DNE21+ (2015)	IAM	Road, rail, aviation, maritime: via energy use and emissions
EGMM (Selei et al., 2017)	Partial equilibrium	Shipping of LNG
GLOBIOM (2023)	PE for land use sectors	Representation of international transport costs for road and maritime transport, using distance between country pairs and weight-value ratio of agricultural products
MEDEAS-World (2019)	IAM	Via demands for fuels
MERGE-ETL (Marcucci & Turton, 2012)	IAM	Transport costs for energy carriers
MUSE (Giarola et al., 2022)	Agent-based IAM	Freight and passengers
POLES (Criqui et al., 2015)	PE energy system	Bunker fuels for maritime and aviation
TIAM-Grantham (Pye et al., 2020)	Energy-economy optimisation model	Via energy demand
EnergyPLAN 16.3[33]	Energy system simulation	Maritime, aviation (via energy flows)
PROMETHEUS V2[34]	Energy system PE	Maritime, aviation (via energy flows)
Aalto-EU-TIMES 1.0[35]	Energy system optimisation	Maritime, aviation (via energy flows)
GCAM v8.2[36]	IAM, PE	Maritime, aviation; international transport is broken into regional components, which by default are part of the region's emissions (though emission targets can be set for total emissions excluding these)

[33] https://energyplan.eu/wp-content/uploads/2024/10/documentation.pdf
[34] https://www.cdr-uptake.eu/
[35] https://www.iam-compact.eu/
[36] https://acclimate-project.eu/

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Since international transport is a core issue in trade modelling, there are cases of soft-linked CGE models with sector-specific models to evaluate economic shocks lying at the interface of transport and trade. Ferrari et al. (2023) link the MAGNET CGE model with a detailed transport database, define a set of shocks by transportation mode, region and commodity, and quantify the impacts of the increase in freight transport costs on the global economy and on selected regions. In Zhang et al. (2024), a shipping cost model is linked to GTAP model to analyse the impact of Northern Sea Route on the trade and the economies of China and the EU; different fuel cost scenarios, consisting of fuel prices are then considered: they measure the changes in shipping costs between China and the EU, brought about by NSR navigation, which are used as a basis to quantify changes in transport technology. A shipping cost model integrated with GTAP is also used by Wang & Countryman (2025) to investigate economic and equity effects of increased transport costs from potential carbon taxes on the shipping industry under the 2023 IMO net-zero emission strategy. In the same context, Pereda et al. (2025) extend the GTAP model, by incorporating transport mode substitution and exogenously determining maritime transport costs using machine learning techniques and rich-level dataset on ships, to estimate emissions by origin-destination and sector pairs. A general equilibrium model for shipping is developed in (Pereda & Lucchesi, 2022) to support the evaluation of global impacts. The model takes into account a sector of international transportation that can be disaggregated into sea transport and other types of carriage, emissions parameters, and detailed maritime transport equations that allow the simulation of any mitigation policy. A GTAP model is also combined with an intermodal logistics models and voyage statistics in (Tran et al., 2025) to analyse GHG pricing scenarios in international shipping. Finally, Halim et al. (2018) link the International Transport Forum's International Freight Model (IFM) with a CGE framework to examine possible decarbonisation pathways for shipping.

Similarly to maritime, in aviation, several CGE model-based studies assess various economic impacts in the literature (Robson et al., 2018), often relying on the GTAP Data Base, which potentially limits the analysis of detailed transport policies. Norman-López (2024) goes beyond the typical GTAP structure and splits the air transport sector into two sectors (passenger and freight) to assess their response in carbon taxation. Few studies in the literature have worked on improving the splitting of the GTAP data base into passenger and freight modes (Karkatsoulis et al., 2017), but with limited focus on the baseline construction for the transport sectors. Other approaches include linking GTAP-based models to detailed energy system models that include a disaggregated representation of transport (Schäfer & Jacoby, 2005). Interlinkage of CGEs with sector-specific models is also present here. For instance, Wei & Kallbekken (2024) linked the AIM aviation model with the GRACE CGE model, where the setup was based on linking information such as fuel consumption and substitution.

To summarise our key takeaways of this review, international transport emerges as a systematically under-represented dimension in economy-wide modelling. While its policy relevance is very important, most CGE frameworks rely on stylised trade-margin representations, whereas transport-detailed approaches in sectoral models remain weakly connected to trade and economic modelling in general. This results in a structural gap between economic realism and economic modelling, limiting the ability of existing tools to analyse policies that simultaneously affect trade costs and transport systems.

3.5 Enhanced sectoral granularity

With many models relying on the GTAP Data Base, sectoral model granularity generally attains the level of

76 sectors (in the latest GTAP-Power version). Of course, there are disaggregation utilities such as SplitCom[37] designed to allow for more detailed sectoral splits. However, macroeconomic models should also be able to allow a potential split within a model's structure in such cases.

An interesting question is if there already exist models representing individually some sectors of the economy that are critical for ENTICE research (in the sense that they are related to energy-intensive products, clean technology manufacturing, critical materials supply chain, etc.). Since trade for such sectors is expected to intensify in the coming years, it is crucial for modellers to be able to quantify various relevant policy scenarios, allowing the required granularity in input data and results.

In this section, we explore the level of models' granularity in terms of sectoral coverage for critical sectors. In particular, the objective of this section is to answer to the following question:

Does current modelling capacity allow for individual representation of critical sectors such as steel, aluminium, copper, plastics, cement, fertilisers, critical minerals (e.g., lithium, nickel, cobalt, REEs), green tech manufacturing, green industrial processes, and others of relevance?

The results of this exercise can be found in Table 6, which records sectors beyond the typical 76-sectoral granularity of the GTAP Data Base.

Table 6. Representation of critical sectors in large-scale models.

Model	Model type	Critical sectors represented individually
DYNERIO (Rinaldi et al., 2023)	Dynamic I/O model	Copper, lithium, REEs, wind turbines, batteries, PV panels
E3ME (2022)	Macro-econometric	Construction minerals, industrial minerals, ferrous ores, non-ferrous ores
E3MG (Pollitt et al., 2012)	Macro-econometric	Basic metals
EXIOMOD 2.0 (Bulavskaya et al., 2016)	CGE	Copper, aluminium, precious metals, lead, zinc, tin
GLUCOSE (Beltramo et al., 2021)	IAM	Aluminium, ammonia, cement, fertilisers, steel
ICES (2019)	recursive dynamic CGE	Circular economy for iron, steel, cement, copper
IPAC (Jiang et al., 2019)	Multi-model framework: IPAC-SGM(CGE) + IPAC-AIM-technology (bottom-up) + IPAC-global	Steel, cement, ammonia
MAGNET (2020)	CGE	Cement, fertilisers
MAgPIE (Dietrich et al., 2019)	Recursive dynamic PE for land use sectors	fertilisers
MERGE-ETL (Marcucci & Turton, 2012)	IAM	Steel, cement, hydrogen, biofuels, synthetic fuels, solar, wind, hydro, nuclear cycles (LWR/FBR), CCS technologies
MESSAGEix-GLOBIOM (2020)	IAM	Energy-intensive materials

[37] https://www.gtap.agecon.purdue.edu/resources/splitcom.asp

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Model	Model type	Critical sectors represented individually
MUSE (Giarola et al., 2022)	Agent-based IAM	Iron, steel, pulp, paper, aluminium, cement
NATEM	Energy system optimisation	steel, aluminium, cement
PLAIA (Stegmann et al., 2022)	IAM	plastics
POLES (Criqui et al., 2015)	PE Energy system	steel, cement, petrochemicals, refineries, fertilisers, biofuels, emerging low-carbon technologies
REMIND (2020)	Inter-temporal optimisation IAM	Cement, steel
TIAM-Grantham (Pye et al., 2020)	Energy-economy optimisation model	Cement
WILIAM (2023)	System dynamics model	Copper, aluminium, iron, nickel, metals needed for green technologies
WITCH (2019)	IAM	Bioenergy, renewables, hydrogen, CCS
GCAM-Europe (Sampedro et al., 2025)	IAM	Iron, steel, cement, fertilisers, aluminium, biomass
PROMETHEUS V2[38]	Energy system PE	Metals, plastics, cement
ENGAGE[39]	Recursive dynamic CGE	bauxite, alumina, primary aluminium, secondary aluminium, aluminium scrap, iron ore, blast furnace, blast furnace with CCS, direct reduced iron (DRI) with gas or coal, DRI with hydrogen, basic oxygen furnace, DRI-based electric arc furnace (EAF), high and low scrap-based EAF, high- and low-quality steel scrap, cement, and clinker; by using the GTAP-CE database it could, in addition, represent copper, plastics and fertilisers.
IMAGE 3.4[40]	IAM	Steel, cement, biomass, hydrogen
GEMINI-E3 EU[41]	Recursive dynamic CGE	It considers some critical industries aggregated as energy-intensive ones
GCAM v8.2[42]	IAM, PE	The default model version models the supply side for cement and steel and both demand and supply for fertilisers as separate sectors, but there is also a version under developments that models demands for 13 additional materials (steel, aluminium, copper, silicon, graphite, lithium, cobalt, nickel, manganese, platinum, neodymium, tellurium, and vanadium, across technologies in multiple end-use sectors, including electricity (generation and T&D), transportation, H2 production, buildings, and an aggregate "other" sector)

In the context of WP2 activities of ENTICE, the representation of energy transition supply chains in the GTAP Data Base is going to be improved via sector disaggregation and addition. This will be done with the development of an algorithm that allows extending MRIO databases and is based on previous and ongoing work of POLIMI and ENEXTGEN on the Multi-Regional Analysis of Regions through Input-Output (MARIO) framework (Tahavori et al., 2023).

[38] https://www.cdr-uptake.eu/
[39] https://www.sciencedirect.com/science/article/pii/S0305750X19304243?via%3Dihub
[40] https://www.net0prisma.eu/
[41] https://climate-diamond.eu/
[42] https://acclimate-project.eu/

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3.6 Material flows

One of the core targets of WP3, and especially Task 3.5, is to bridge the gap between economic modelling and real-world resource and material dynamics to enhance applicability. Typically, in most CGE models—especially the GTAP based ones—materials are not tracked as physical flows (e.g., tons of steel), but instead as monetary flows embedded in sectoral input-output structures. For example, in the 11th version of the GTAP-Power Data Base, material flows are typically represented implicitly as intermediate inputs, measured in value terms, and aggregated at the sectoral level of 76 activities. For instance, steel used in construction is treated as a monetary input from the "iron and steel" sector to the "construction" sector, with no explicit accounting for physical stocks or recycling loops. This approach implies:

- no explicit material flow consistency,
- no distinction between primary, secondary, and recycling economic activities, and
- difficulty in analysing policies relating to circular economy, critical materials, and resource efficiency.

In the GTAP Data Base, materials (e.g., metals, minerals, energy carriers) appear as sectoral commodities that are traded internationally like other goods, and the flows are purely monetary (i.e., not physical). There is no explicit material flow tracking (e.g., tonnes of copper embedded in electronic equipment). Moreover, mineral resources are usually modelled as a sector producing a resource commodity (e.g., mining), using sector-specific factors (e.g., "natural resources"). Standard CGE models do not track mineral stocks or depletion paths and treat scarcity economically.

As of v.11, the GTAP Data Base does not distinguish between primary, secondary, and recycling material markets. However, there are ongoing efforts to distinguish between primary, secondary, and recycling activities, e.g., through the circular economy version of the Data Base (GTAP CE[43]).

As Chepeliev (2025) discusses, there exist studies representing circular economy splits within the global CGE and IO modelling framework:

- - MRIO assessments based on EXIOBASE (Tisserant et al., 2017; Wiebe at al., 2019)
- - CGE-based assessments focusing on selected sectors (e.g., Winning et al. (2017) for iron and steel)
- - GTAP-based assessments with more detailed splits (e.g., Dellink, 2020)

In the context of D1.4, an important research question revolved around the level of representation of material flows in the models. Of course, most CGE models rely on the GTAP Data Base, so representation is dictated by the sectoral granularity of the base, as described above. Expectedly, most models do not have an explicit representation of material flows; however, there are individual cases where critical materials might be present, as listed in Table 7.

Table 7. Material flow representation.

Model	Model type	Material flow capabilities
AIM/CGE 2.0 (Fujimori et al., 2012)	Recursive dynamic CGE	Augmented representation of energy carriers; lower detail in critical minerals (GTAP based)
China TIMES (Jia et al., 2011)	Energy system optimisation	Limited to some primary energy resources

[43] https://www.gtap.agecon.purdue.edu/databases/Utilities/v11.aspx

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Model	Model type	Material flow capabilities
DNE21+ (2015)	IAM	Material and mineral flows are partially represented via energy demand
DYNERIO (Rinaldi et al., 2023)	Dynamic I/O model	Primary material extraction, material use in production, scrap generation, recycling and secondary material flows
E3ME (2022)	Macro-econometric	The model includes a material module that describes in physical terms a limited number of materials, similarly to energy consumption
EGMM (Selei et al., 2017)	Partial equilibrium	Natural gas flows
EPPA (2015)	Recursive dynamic CGE	Flows for coal, oil, gas, uranium
EUCalc (2020)	Simulation model of energy, land, materials, product and food	Partially: it covers material demand and flows related to construction materials, biomass, and selected critical raw materials
FIDELIO[44]	Neo-Keynesian general equilibrium	An optional disaggregated version is available, distinguishing over 20 individual material categories such as anthracite, crude petroleum, iron ores, copper, and other critical or non-ferrous ores.
MAGNET (2020)	CGE	Waste collection, composting, recycling; endogenous natural resource stocks, circularity module
MEDEAS-World (2019)	IAM	Module for materials for electricity generation and transition to RES
MERGE-ETL (Marcucci & Turton, 2012)	IAM	Energy and fuel cycles (coal, oil, gas, uranium, biomass); nuclear material flows detailed (uranium, plutonium, reprocessed fuels)
MESSAGEix-GLOBIOM (2020)	IAM	Flows in key industrial materials (steel, aluminium, cement, ammonia, methanol, high-value chemicals, pulp, paper)
PLAIA (Stegmann et al., 2022)	IAM	Plastics
ENGAGE[45]	Recursive dynamic CGE	Detailed in steel mining, production, and downstream activities
ENVISAGE (van der Mensbrugghe, 2024)	Recursive dynamic CGE	Coupled with GTAP CE: mining of iron, aluminium, and copper ores; primary, secondary, and recycling for plastics, iron & steel, aluminium, and copper
EnergyPLAN 16.3[46]	Energy system simulation	Soft-linked to MARIO for modelling supply chains and material demands
REMIND-MFA[47]	Dynamic material flow analysis model	Steel, plastics, cement
ZEW model	Recursive dynamic CGE	Production and use of fossil fuels (coal, natural gas, crude oil, refined oil), and electricity

3.7 Land-use impact and relevant environmental indicators

Trade-induced land use changes, particularly, within the agriculture sector, can yield substantial environmental repercussions. In Task 3.6 of ENTICE, one of the core issues is to define appropriate indicators for quantifying land-use and trade-related impacts. In this context, this section provides an overview of

[44] https://joint-research-centre.ec.europa.eu/projects-and-activities/trade-and-industrial-policy-analysis/industrial-policy/fidelio-model_en
[45] https://doi.org/10.1016/j.worlddev.2019.104775
[46] https://energyplan.eu/wp-content/uploads/2024/10/documentation.pdf
[47] https://www.transience.eu/

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existing capabilities towards quantifying the land-use impacts and broader environmental implications through macro-level models. In Table 8, a list of models and relevant indicators are presented for models with enhanced land-use representation.

Table 8. Quantification of land-use impact in macro-models.

Model	Model type	Indicators for quantifying land use effects
AIM/CGE 2.0 (Fujimori et al., 012)	Recursive dynamic CGE	Air pollutants related to biomass consumption
CAPRI (2022)	PE (agriculture-focused)	(1) GHG emissions from enteric fermentation (CH_4), manure management (CH_4, N_2O), manure and mineral fertiliser application to soils (N_2O, CO_2), animal grazing (N_2O), crop residues (N_2O), cultivation of histosols (N_2O, CO_2), indirect emissions from the volatilisation of ammonia (N_2O), indirect emissions from leaching and runoff (N_2O), land use change emissions from carbon stock changes in above- and below-ground biomass (CO_2), soils carbon stock changes (CO_2,N_2O), the burning of biomass (CH_4,N_2O); (2) Ammonia emissions from manure management, manure and mineral fertiliser application; (3) Nitrate leaching and runoff; (4) Soil erosion; (5) Moreover, CAPRI provides the complete nutrient cycle for nitrogen and carbon, while for phosphate and potassium only the separate nutrient balances for crops and feed are considered.
En-ROADS (2021)	System dynamics simulation	Land use CO_2 emissions
ENVISAGE (van der Mensbrugghe, 2024)	Recursive dynamic CGE	Agricultural yields changes, water use for irrigation by crop, emissions from agriculture activities among other (CO_2, CH_4, N_2O, F-gases)
EUCalc (2020)	Simulation model of energy, land, materials, product and food	GHG emissions, air pollution, fertiliser demand, water availability, food waste, biodiversity (impact of land use allocation, species habitat)
EXIOMOD 2.0 (Bulavskaya et al., 2016)	CGE	GHG and non-GHG emissions, agricultural land use, water consumption
FASOM-GHG (Beach et al., 2012)	Inter-temporal dynamic mathematical programming model	Biomass change, land use changes; GHG emission/absorption of CO_2, CH_4, and N_2O surface, subsurface, and groundwater pollution for nitrogen, phosphorous, and soil erosion
FeliX (Ye et al., 2024)	System dynamics model	Water availability change, land use change, fertilisers' impact, MSA (biodiversity), CO_2, CH_4, N_2O from agriculture
FUND (2014)	IAM	Change in agricultural production, change in water resources, loss of ecosystems
GAINS (2021)	IAM	Acidification and eutrophication of ecosystem areas
GCAM v8.2 (2025)	IAM	Land use change, water use, greenhouse gases and short-lived species impact
GLOBIOM (2023)	PE for land use sectors	N_2O from application of synthetic fertilisers and manure to soils, N_2O from manure dropped on pastures, CH_4 from rice cultivation, N_2O and CH_4 from manure management, and CH_4 from enteric fermentation, and CO_2 emissions/removals from above- and below-ground biomass changes for other natural vegetation following conversion; land use change; biodiversity indicators (Biodiversity Intactness Index BII, fraction of global species at risk of extinction)
GTAP-AEZ	CGE	Intra- and inter-regional land and land-based GHG emissions; three types of GHG emissions, with (i) sector outputs (e.g., methane emissions from agricultural residue burning), (ii) intermediate input usage (e.g., nitrous oxide emissions from fertiliser use in crops), and (iii) primary factors (e.g., emissions from livestock capital, or alternatively sequestration associated with forest land cover); land-use change within and across sectors, and across regions

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Model	Model type	Indicators for quantifying land use effects
IMAGE 3.0 (2014)	IAM	Forest cover; land cover and use; GHG emissions and air pollutants; biomass and carbon stocks and flows; potential and actual crop yields and grazing intensities; renewable water availability, irrigation and water stress; nutrient balances and their fate in soils and surface waters; terrestrial biodiversity (wilderness area, land use and land-use intensity, MSA, SRI); aquatic biodiversity (algal blooms in lakes, aquatic MSA), flood risks (statistics on river discharges, statistics on inundation depths, statistics on inundation extent, expected value of affected GDP, expected number of affected people), land degradation (erosion risk, change in soil properties); water availability
MAGNET (2020)	CGE	Land use change, change in agricultural crop yields, change on agricultural production, food waste. To account for land use emissions a separate module is used to calculate change in emissions associated with transition of land across different categories—cropland, grassland, other land, forest (land use change emissions); and for land not moving across the categories but staying in its original use (land use unchanged emissions). This module imputes quantity of physical water in model by agricultural sector. It also introduces means of implementing change (reducing or increasing) in the share of crop output that is irrigated and its impact on land productivity.
MAgPIE (Dietrich et al., 2019)	Recursive dynamic PE of the land sector	Land based emissions: CO_2, N_2O, CH_4; forest cover; land-use intensity;
MESSAGEix-GLOBIOM (2020)	IAM	GLOBIOM-style; Emissions from land (GLOBIOM): crop emissions, livestock emissions, land use change emissions
MUSE (Giarola et al., 2022)	PE energy system model	CO_2 land use, CH_4 land use, N_2O land use
WILIAM (2023)	System dynamics simulation model	Agriculture emissions: N_2O emissions from synthetic fertilisers application, CH_4 emissions from rice crops; N_2O and CH_4 emissions from livestock, LULUCF emissions (from land use and land use changes, including cropland and grassland management practices); Biodiversity: Biodiversity Habitat Index (BHI), Net Primary Production (NPP), Human Appropriated Net Primary Production (HANPP), Proportion of NPP appropriated by humans
WITCH (2019)	IAM	GLOBIOM-style
IMF-ENV (J Chateau et al., 2025)	Recursive dynamic CGE	CO_2 from LULUCF, CH_4 from rice cultivation, N_2O from crops (nitrogenous fertilisers), livestock (manure management), chemicals (non-combustion industrial processes), and services (landfills)

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4 Concluding remarks

This section synthesises the main insights emerging from the literature review, combining key findings and associated modelling challenges. The aim here is to “filter” the reviewed material into a form that will inform and support the rest work packages of ENTICE, highlighting opportunities and limitations in advancing the modelling of trade-climate-industry nexus.

Trade theory

Across the literature reviewed, a consistent finding is that most Computable General Equilibrium (CGE) models and related macroeconomic frameworks rely on highly stylised representations of international trade, typically based on the Armington assumption. This specification treats domestic and imported goods as imperfect substitutes differentiated by origin. While analytically convenient and tractable, this approach does not allow models to capture firm-level heterogeneity, productivity effects, extensive-margin trade responses, and re-allocation effects of trade policy. A core weakness of the Armington model is also that it cannot capture selection effects, since the trade diversion comes only through the Armington elasticities. Moreover, changes in trade flows are conditioned by pre-existing shares in the base year of the model. Therefore, Armington-based macroeconomic models can only capture adjustments coming from changes in export volumes. This is not aligned with empirical studies highlighting the contribution of new varieties in export markets (Akgul et al., 2016).

Modern trade theories offer richer alternatives. The Krugman model introduces demand-side variety effects under monopolistic competition, whereas the Melitz framework adds supply-side heterogeneity enabling productivity changes driven by firm composition. However, the Krugman model has inherent shortcomings, as once a commodity is produced, it goes to every region; once a variety is offered to one market, it is offered to all markets. Therefore, only when trade costs “approach infinity” will some consumers around the globe not consume that commodity (Balistreri et al., 2025). By contrast, there is Melitz approach, which is especially important for the analysis of free trade agreements, where the impacts depend largely on changes in non-tariff measures (NTMs), affecting the trade costs. In particular, the differentiation between fixed and variable costs in bilateral trade that is embodied in Melitz-driven models allows for more realistic assessments of NTMs (Fugazza & Maur, 2008). A core feature of the Melitz scheme is that trade may induce changes in productivity, even though the production technology of a country is the same. Aggregate productivity changes are brought by the composition of the firms within a sector, as opposed to the allocative efficiency effects in traditional models with homogeneous firms and the Armington assumption. An alternative approach to represent global trade is found in Douchin (2005), and Douchin & Levine (2001), where global trade is represented through a physically constrained input-output allocation model. While such approaches are not part of the mainstream CGE/IAM families reviewed here, an alternative paradigm is highlighted where, rather than prices alone, material availability and technical coefficients govern trade patterns.

Despite these theoretical advantages, the implementation of modern trade theory in large-scale models remains challenging. While the Melitz specification for international trade is theoretically appealing, its existing implementations in CGE models seem to struggle with numerical stability, implying challenges to combine Melitz model in large-scale models with high sectoral and regional detail. Additionally, the endogenisation of free entry and exit in a multi-sector, multi-region Melitz model that includes intermediate inputs, may give rise to computational difficulties related to multiple and/or corner equilibria (Löschel, 2002). Faced with the inherent computational challenges, modellers have invented various solutions to overcome

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associated barriers and adopt—at least partially, not globally across their models—a Melitz-based mechanism. For instance, Bekkers & Francois (2018) use a set of endogenous supply and demand shifters, such that an Armington model “mimics” a Melitz one. Their computational approach has similarities with the decomposition algorithm of Balistreri & Rutherford (2013), where the Armington demand system is iteratively re-calibrated; in the latter case, the model involves nine sectors in total, with only two being of Melitz type. Finally, a complete implementation covering all sectors of the GTAP Data Base (65 sectors in version 11) seems to be numerically challenging. Firm heterogeneity requires additional information that is not readily available in the standard database, such as on key firm heterogeneity parameters, fixed set-up costs, and fixed trading costs.

Technological change

Advances in endogenous growth theory have increasingly influenced macroeconomic modelling, leading to a growing interest in endogenising technological change. Mechanisms such as learning-by-doing, R&D-driven knowledge accumulation, learning-by-exporting, and spillover-driven diffusion are progressively incorporated into CGE and other models. These mechanisms allow technological progress to emerge endogenously from production, investment, or trade interactions, rather than being imposed exogenously.

The majority of modern large-scale models adopt endogenous technological change mechanisms that are grounded on learning-by-doing or knowledge stock accumulation through R&D, reflecting the foundations of Arrow’s (1962) learning model and Romer’s (1990) capital formulation, respectively. Learning-by-doing mechanisms remain attractive due to their intuitive interpretation: production becomes more efficient as it increases. R&D-based knowledge mechanisms are also quite popular since they model more explicitly the innovation efforts (private and public). However, it should be mentioned that, in most cases, such endogenous technological change mechanisms are integrated for clean energy technologies and not for all sectors of CGEs. Endogenous technological change mechanisms are also more visible in energy focused models, which provide better technological detail, but tend to abstract from economy-wide feedback. Energy system and sectoral models provide richer engineering detail, which allows them to explicitly model mechanisms like learning, thus, making endogenous technological change more feasible compared to “aggregate” models like many CGEs.

The review also highlights the growing importance of spillover mechanisms (across sectors and/or regions). Spillovers are often transmitted through trade, FDI, or the introduction of new varieties. Approaches such as Parrado & De Cian (2014), Tarr (2013), and Robinson et al. (2002) demonstrate that international trade can serve as a key driver for embodied technology transfer, making the intersection of trade and technology a central element of endogenous technological change modelling.

Directed technological change enabled models allow the innovation to be endogenously targeted toward specific factors (e.g., labour of different skill levels, energy vs. capital). These frameworks capture feedback loops between policy (e.g., carbon pricing, trade liberalisation), factor prices, and the direction of innovation—something that neither simple learning-by-doing mechanisms nor pure R&D accumulation models can represent.

Price-induced input augmentation and backstop technology approaches are rarely used as primary endogenous mechanisms in macroeconomic modelling and are classified as semi-endogenous technological change mechanisms. They remain conceptually important but are more often employed in bottom-up models, rather than in general equilibrium frameworks.

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Integrating endogenous technological change introduces several conceptual and practical challenges. Conceptually, CGE models, by construction, rely on a well-structured behaviour of agents (e.g., nested CES structure for producers). Innovation processes, which might be characterised by increasing returns to scale, non-linear dynamics, heterogeneity in agents, etc. are difficult to be “aligned” with the structure and granularity level of established large-scale macroeconomic models. For instance, increasing returns to knowledge might conflict with the constant return assumptions of standard CGE production functions. Also, empirically, in R&D-based mechanisms, knowledge stocks depend heavily on assumptions on initial stocks and depreciation rates. Additionally, sector-specific R&D expenditures are poorly documented for various countries. Furthermore, in learning-based mechanisms, when historical data are sparse, the determination of learning rates entails uncertainties that should be taken into account by modellers.

Another caveat of learning-by-doing is as follows: pre-determined learning curves might constrain the capacity of models to capture innovation responses to trade and climate policies and resulting non-linear effects. While assuming that technology evolves via learning-by-doing may fit historical correlations between installed capacity and the cost of energy technologies, such learning is treated as a black box. As a result, learning-by-doing models do not address the costs of acquiring new knowledge. This is important because new energy R&D may crowd out other forms of R&D.

From a computational perspective, endogenous technological change dynamic mechanisms might increase models’ “non-linearity” in various ways, which might lead to non-convexities and the presence of multiple equilibria (Löschel, 2002). There are also barriers relevant to data, since availability on aggregate innovation expenditures has a limited coverage over sectors and countries, and, usually, the focus is on the energy sectors.

Finally, there are also policy interpretation challenges. Endogenisation of technological change introduces new layers of feedback between policy (exogenous) variables and model outputs. For instance, modellers should take into account potential double counting of technological improvements when learning-by-doing and R&D-driven effects are considered simultaneously in the mechanism. In particular, if both mechanisms are implemented, then learning parameters should be extracted from similar estimations (not from learning-by-doing alone). Moreover, the trade-technology interactions might be modelled in a quite simplified way, e.g., ignoring domestic or other inter-regional/sectoral spillovers.

Beyond trade theory and technological change, the literature highlights structural limitations in several complementary modelling dimensions as follows:

International transport

There is asymmetry between domestic and international transport representation. Most computable general equilibrium models represent explicitly – as separate economic activities - the domestic transport sectors, while international transport is treated indirectly as a trade margin. In GTAP-based models, international transport services are often supplied at a uniform global price and allocated across regions, using fixed reference-year shares.

Several integrated assessment models and energy system models consider international transport through energy demand, fuel use, or emissions accounting (e.g., maritime and aviation bunker fuels). However, these representations remain largely decoupled from trade flows. In particular, while both approaches often capture transport emissions and fuel use in more detail, these insights are not systematically integrated with macroeconomic trade and welfare analysis.

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A more explicit modelling of international transport exists mainly through model linkages. Advances in international transport modelling are primarily achieved via soft linkages between CGE and sector-specific transport or shipping models. These hybrid approaches enable often richer policy analysis, but remain case-specific and not yet mainstream.

Finally, there are inherent barriers complicating the representation of international transport in economy-wide models. One core issue is the data availability for bilateral and modal transport costs: progress in modelling international transport critically depends on better data on bilateral freight flows, transport modes, fuel use, and associated emissions. Another complication relates to transport technology transitions: current macroeconomic models often struggle to represent technology shifts in a way that feeds back into trade costs. This holds also for international transport (e.g. regarding the possibility to consider alternative fuels).

Material flows

The representation of material flows constitutes another major limitation. While computable general equilibrium models, such as the GTAP-based ones, provide a consistent economy-wide framework for analysing price-mediated resource scarcity and trade effects, the treatment of material flows and mineral resources remains largely implicit and monetary. This limits their suitability for analysing physical resource constraints, mineral criticality, and circular economy policies without substantial model extensions or hybridisation with material flow accounting approaches. Some additional limitations of existing approaches may be summarised as follows (Chepeliev, 2025): (i) some approaches rely on cost structures and output values, which do not always correspond to the actual observations, (ii) they focus on selected commodities or specific aggregate regional representations, (iii) they are not consistently updated over time, and (iv) they are not publicly available.

Undoubtedly, the modelling of material flow policies requires an explicit representation of the primary and secondary production activities. As Chepeliev (2025) analyses, it is required to represent country-specific production volumes of primary and secondary activities, and, also, distinguish between corresponding supply and cost structures. However, such representation is not available in the standard version of the GTAP Data Base. Finally, there are additional barriers that complicate a more explicit representation, which could be summarised as follows: (i) inconsistencies between trade, output, and underlying GTAP data, (ii) unavailability of certain supply/use structures, and (iii) lack of explicit representation of the country-specific sources of scrap/waste by sectors and agents.

Capacity assessment

In terms of capacity assessment, macroeconomic feedback remains a source of concern. Some integrated assessment models (e.g., partial equilibrium models) do not capture economy-wide interactions such as cross-sectoral re-allocations throughout the whole economy. As a result, transition dynamics associated with trade and climate policies may be inadequately represented. In terms of granularity, several models exhibit limited sectoral and regional resolution. Lower sectoral detail may obscure critical heterogeneity in trade exposure and, also, make impossible the assessment of policies targeting specific industries. A rather rough regional aggregation may also “hide” important asymmetries between developed and developing economies, and reduce the credibility of results concerning, e.g., industrial competitiveness or carbon leakage. Finally, in Table 9, potential benefits along with the core difficulties are presented for each modelling improvement dimension.

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Table 9. Potential benefits vs. main difficulties for each ENTICE improvement dimension.

Improvement dimension	Potential benefits	Main difficulties
Melitz trade mechanism	Captures selection effects, firm heterogeneity, trade-driven productivity effects, and re-allocation effects of trade policy	Firm heterogeneity data requirements, numerical stability issues
Endogenous technological change	Captures innovation dynamics, spillovers, and trade-technology feedback	Parameter uncertainty, R&D data sparsity, calibration issues
International transport representation	Improved assessment of transport-related policies	Lack of bilateral transport data
Material flows	Enables improved assessment of policies related to resource and critical materials	Data requirements in distinguished economic activities (primary, secondary, recycling)
More detailed sectoral granularity	Better representation of industrial transitions	Higher dimensionality in models

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5 Abbreviations

Acronyms	Full-form
ACCLIMATE	Accelerating Climate Action: Navigating towards a Low-Emissions, Climate-Resilient Future
AFOLU	Agriculture FOrestry Land Use
AIM-CGE	Asian-Pacific Integrated Model- Computable General Equilibrium
AMIGDALA	Alliance for Modelling Industries towards the Green Deal's objectives And circuLArity
BET-GLUE	Bioenergy Economic Trade- Global Land Use Model
BLUES	Brazilian Land Use and Energy System
C3IAM	China's Climate Change Integrated Assessment Model
CAPRI	Common Agricultural Policy Regionalised Impact
CGE	Computable General Equilibrium
China MAPLE	China-Multi-pollutant Abatement Planning and Long-term benefit Evaluation
China TIMES	China The Integrated MARKAL-EFOM1 System
CIF	Cost, Insurance and Freight
CLEWs	Climate, Land, Energy, Water systems
CLIMACRED	CLIMAte CREDit risk model
CLIMADA	CLIMate ADAptation model
DICE	Dynamic Integrated model of Climate and the Economy
DNE21+	Dynamic New Earth 21+
DSK	Dystopian Schumpeter meeting Keynes
DTC	Directed Technological Change
DYNERIO	Dynamic Extraction and Recycling Input-Output
E3ME	Energy-Environment-Economy Macro-Econometric model
E3MG	Energy-Environment-Economy Model at the Global level
EGMM	European Gas Market Model
EMPIRE	European Model for Power system Investments with Renewable Energy
En-ROADS	Energy ROADS
ENVISAGE	ENVironmental Impact and Sustainability Applied General Equilibrium model
ENV-Linkages	ENVironment-Linkages
EPMM	European Power Market Model
EPPA	Economic Projection and Policy Analysis

Acronyms	Full-form
ETC	Endogenous Technological Change
ETCU-RICE	Endogenous Technical Change with Uncertainty RICE model
EU-Calc	EUropean-Calculator
EU-TIMES	European Union – TIMES
EXIOBASE	EXtended Input-Output dataBASE
EXIOMOD	EXtended Input-Output MODel
EXPANSE	EXploration of PAtterns in Near-optimal energy ScEnarios
FASOM-GHG	Forest and Agricultural Sector Optimization Model with Greenhouse Gases
FeliX	Full of Economic-Environment Linkages and Integration
FOB	Free On Board
FORECAST	FORecasting Energy Consumption Analysis and Simulation Tool
FUND	Framework for Uncertainty, Negotiation and Distribution
GAINS	Greenhouse gas - Air pollution INteractions and Synergies
GAMS	General Algebraic Modeling System
GCAM	Global Change Analysis Model
GEM-E3	General Equilibrium Model – Economy, Energy, Environment
GEMINI-E3	General Equilibrium Model of International-National Interactions between Economy, Energy and the Environment
GEMPACK	General Equilibrium Modelling PACKage
GLOBIOM	GLObal BIOsphere Management model
GLUCOSE	Global Least-cost User-friendly CLEWs Open-Source Exploratory model
GRACE	Global Responses to Anthropogenic Changes in the Environment
GTAP	Global Trade Analysis Project
GTEM	Global Trade and Environment Model
HEB	High Efficiency Buildings
IAMs	Integrated Assessment Models
IAM COMPACT	expanding Integrated Assessment Modelling: COMprehensive and COMprehensible science for sustainable, co-created climate ACTion
ICES	Inter-temporal Computable Equilibrium System
IFs	International Futures model
IMACLIM	IMpact Assessment of CLIMate policies
IMAGE	Integrated Model to Assess the Global Environment
IMED	Integrated Multi-regional Economic Dynamics

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Acronyms	Full-form
IPAC	Integrated Policy Assessment Model for China
LBD	Learning By Doing
LEAP	Long-range Energy Alternatives Planning system
MAGNET	Modular Applied GeNeral Equilibrium Tool
MagPIE	Model of Agricultural Production and its Impact on the Environment
MANAGE	Mitigation, Adaptation and New Technologies Applied General Equilibrium
MEDEAS-World	Modelling the Energy Development under Environmental And Socioeconomic constraints-World
MENA-EDS	Middle East and North Africa Energy Demand and Supply
MERGE-ETL	Model for Evaluating Regional and Global Effects- Energy, Technology, and Learning
MESSAGEix-GLOBIOM	Model for Energy Supply Strategy Alternatives and their General Environmental Impact- GLObal BIOsphere Management model
MIMOSA	Mathematical Integrated Model for Optimal and Stylised Assessment
MIRAGE	Modelling International Relationships in Applied General Equilibrium
MRIO	Multi-Regional Input-Output
MUSE	ModUlar energy system Simulation Environment
NATEM	North American TIMES Energy Model
NEMESIS	New Econometric Model of Evaluation by Sectoral Interdependency and Supply
NTM	Non-Tariff Measures
OSeMOSYS	Open Source energy MOdelling SYStem
PLAIA	PLAstics Integrated Assessment model
POLES	Prospective Outlook on Long-term Energy Systems
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R&D	Research and Development
REMES	Regional Equilibrium Model for Energy Systems
REMIND	REgional Model of INvestment and Development
RICE50+	Regional Integrated model of Climate and the Economy 50+
SISGEMA	Sistema Integrado de Gestão Ambiental
STEM	Swiss TIMES Energy systems Model

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Acronyms	Full-form
TC	Technological Change
TFP	Total Factor Productivity
TIAM-Grantham	TIMES Integrated Assessment Model-Grantham
TIMES	The Integrated MARKAL-EFOM System
TRANSIENCE	TRANSItioning towards an Efficient, carbon-Neutral Circular European industry
US-REGEN	U.S. Regional Economy, Greenhouse Gas, and Energy
WILIAM	Within Limits Integrated Assessment Model
WIOD	World Input–Output Database
WITCH	World Induced Technical Change Hybrid
WTMBT	World Trade Model with Bilateral Trade
IMF-ENV	International Monetary Fund-ENVironment
WTO	World Trade Organisation

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