

# Exploring effects of climate policies and mitigation strategies for vulnerable households in Austria – Methodological issues related to model linkage

## TransFair-AT Working Paper #1

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## 1 Introduction

The aim of the TransFair-AT project was to analyse policy scenarios to achieve a complete decarbonisation of housing and mobility in Austria by 2040. This was achieved by linking a top-down macroeconomic model with bottom-up modelling of household vehicle choice, transport demand and building stock. The purpose of this model linkage was to assess the emission impacts as well as the macroeconomic and distributional effects of the policy packages on different types of households. The final objective of the project was to develop compensation measures to ensure that the disposable income of disadvantaged household groups was not reduced.

The aim of this working paper is to give a summary of the methodological issues related to linking the top-down macro-economic model DYNK the bottom-up mobility model MARS/SERAPIS and the bottom-up building stock model Invert/EE-Lab. The remainder of the paper is organised as follows. Section 2 summarises the results of a literature review about the state of art in linking top-down and bottom-up models. Section 3 gives a brief overview about the individual sector models utilised in TransFair-AT. Section 4 describes the process and results of model linkage in TransFair-AT. Section 5 summarises the findings and draws conclusions.

## 2 State of the art linking top-down and bottom-up models

A literature review was carried out to assess the status quo of linking top-down and bottom-up models. A Scopus query<sup>1</sup> resulted in 172 potentially relevant references. Using a hierarchical screening of titles, abstracts and full texts, 16 sources were identified as relevant. Some additional references originate from a snowball search.

### 2.1 Motivation for linking top-down and bottom-up models

Bottom-up models on the one hand provide a detailed description of their underlying system, e.g. in the case of a model of the energy system primary energy sources via multiple processes of conversion, transport, and distribution to final energy use (Böhringer and Rutherford 2008 p. 595). But, on the other hand such models neglect potentially important interactions of their sector with the rest of the economy (Rocco et al. 2018 p. 1; Böhringer and Rutherford 2008 p. 595). In contrast, top-down macroeconomic models are able to capture market interactions and inefficiencies in a comprehensive manner but typically lack technological details that might be relevant for the policy issue under consideration (Böhringer and Rutherford 2008, p. 595). Linking the two types of models in an iterative manner allows to take the heterogeneity of agents into account, while still considering the general equilibrium effects of proposed policy reforms (Colombo 2010). These circumstances motivated the idea of linking the two types of model. Luc Savard was probably the first to iteratively link a top-down Computable General Equilibrium (CGE) model with a bottom-up microsimulation model (Savard 2003).

### 2.2 Different linking approaches

The integration of top-down and bottom-up models can follow a soft-linking or a hard-linking approach (Andersen and Termansen 2013 p. 4). In the soft-linking approach the top-down model and the bottom-up model are linked through an iterative process, which is repeated until a convergence criterion for central parameters, like price or quantity parameters, is satisfied. Hard-linking, by contrast, means that properties of the bottom-up and top-down models are integrated into a single model, which is then solved in a simultaneous optimization. A disadvantage of this approach is that this typically implies simplified descriptions of either bottom-up or top-

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<sup>1</sup> Advanced query: TITLE-ABS-KEY ( linking ) AND TITLE-ABS-KEY ( "top-down" ) AND TITLE-ABS-KEY ( "bottom-up" ) AND TITLE-ABS-KEY ( model )

down aspects in the integrated model. Hard-linking can be further subdivided into two categories (Andersen and Termansen 2013 p. 4):

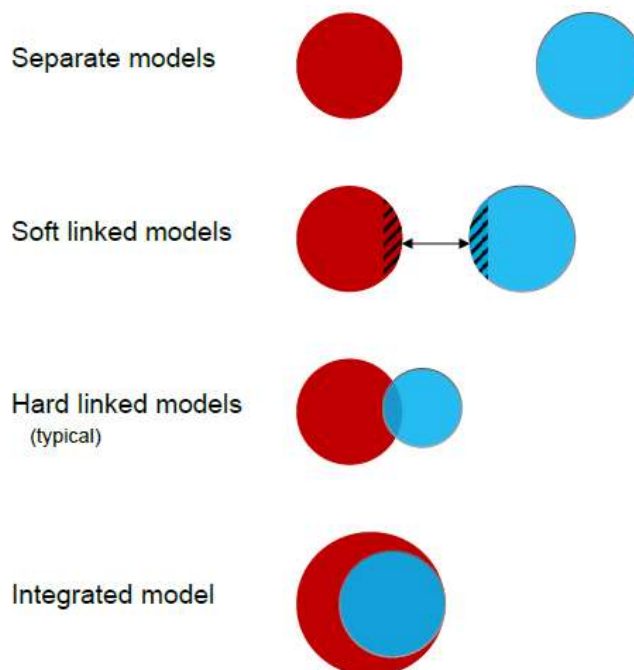
- combining one model type with a “reduced form” representation of the other, and
- combining bottom-up and top-down characteristics directly through the specification of market equilibrium models as mixed complementarity problems.

A slightly different classification is given by (Helgesen 2013):

- **Soft-linked:** *Processing and transfer of information is controlled by the user. The user evaluates results from the models and decides if and how the inputs of each model should be modified to bring the two sets of results more in line with each other, i.e. how to make the models converge* (Helgesen 2013 p. 11).
- **Hard-linked:** *All information processing and transfer is formalized and usually handled by computer programs. In areas where the models overlap an algorithm may be used to negotiate results. Usually one model is given control over certain results, and the other model is set up to reproduce the same results* (Helgesen 2013 p. 11f).
- **Integrated:** *The models are directly influencing each other, and are not run independently in stand-alone mode* (Helgesen 2013 p. 12).

In the case of soft-linking the models should exchange feedback information through iterations, providing adjustments in the model inputs to reach consistency (Helgesen 2013 p. 12). Nevertheless, there exist also studies using one-directional soft-linking approaches (Andersen et al. 2019 p. 279). As such an approach does not secure convergence between the top-down and bottom-up model results, it is likely to suffer from a certain degree of inconsistency. Graph 1 illustrates the different types of model linkage.

Graph 1: Different types of linking



Source: (Helgesen 2013 p. 13)

Any of the abovementioned approaches has specific advantages and potential drawbacks. Soft-linking has advantages concerning practicality, transparency and learning while hard-linking has advantages concerning productivity, uniqueness and control (Helgesen 2013 p. 12). A potential drawback of soft-linking is that it can produce noise in form of differences between the results (Helgesen 2013 p. 12). The differences in model setup and calculation methods can cause problems for the convergence in the soft-linking approach. Inconsistencies in the behavioural assumptions in the used models are mentioned as a major drawback of soft-linking top-down and bottom-up models (Crespo del Granado et al. 2018 p. 232). In the “reduced form” hard-linking approach there exists the risk that one model is simplified too much. The integrated mixed complimentary approach may also suffer from complexity and dimensionality issues and as a consequence impose limitations on its practical application (Böhringer and Rutherford 2009). On the basis of this information Anderson and Termansen conclude that coupling bottom-up and top-down models by soft-linking is the best option to exploit the strength of each of the two modelling approaches (Andersen and Termansen 2013 p. 4). Winkler et al., testing different approaches, conclude that neither hard-linking nor soft-linking is better, but rather that both have advantages and limitations (Winkler et al. 2017 p. 563). Soft-linking can sometimes be a necessary step in order to test linking approaches (“proof of concept”) in the development of hard-linked or integrated models (Helgesen 2013 p. 27). Helgesen and Tomasgard argue that a significant advantage of linking models rather than integrating them is that the models can be kept separated and intact (Helgesen and Tomasgard 2018 p. 1228). Integrating two models requires combined knowledge and modelling skills from both areas, while linking allows to retain models separate and also retain the consistency of their database (Helgesen and Tomasgard 2018 p. 1229). This makes linking models a natural first step to combine different areas of expertise.

### 2.3 Examples operational model linking

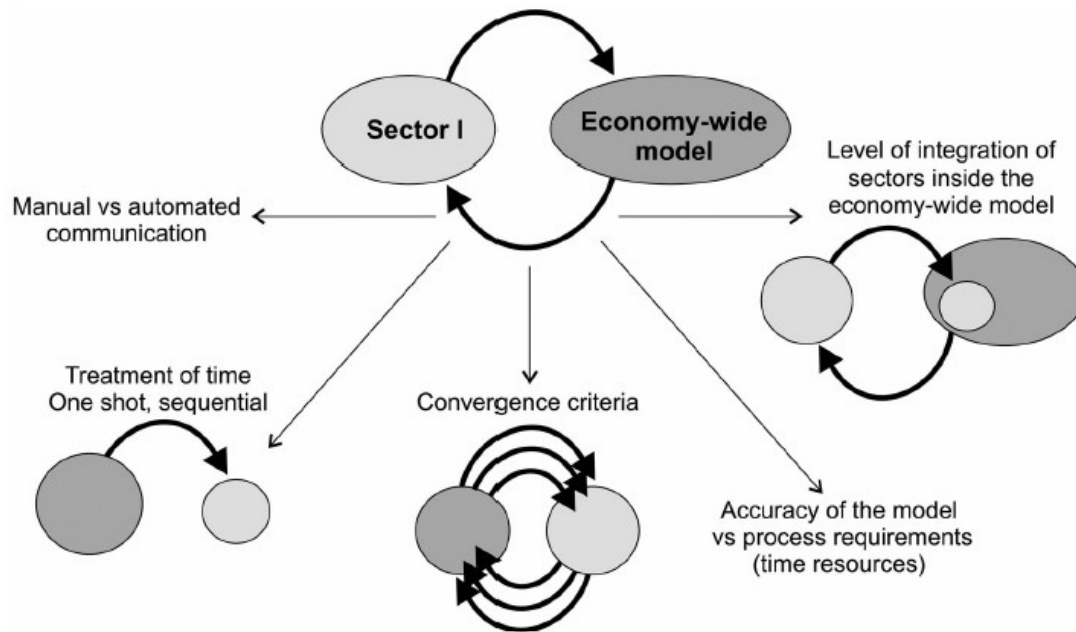
In (Schönhart et al. 2013) a set of bottom-up models representing the Austrian agricultural sector is linked with a CGE model of Austria in order to analyse the impacts of climate change on the sectoral and macroeconomic level. The bottom-up models are upward-linked to the CGE model. The work is therefore an example for a one-direction soft-linking approach. An example of a one-directional soft link between an energy sector bottom-up model and a top-down Input-Output model is presented in (Rocco et al. 2018). The linked models have been used to assess the effects of the evolution of the Egyptian electricity mix.

In (Winkler et al. 2017) research teams in five different countries<sup>2</sup> use different linked bottom-up and top-down models to assess socio-economic effects of a transition to a low-carbon society. While using different models, the following common challenges could be identified by the research teams: communication between the models, treatment of time, convergence criteria, trade-offs between model accuracy and requirements for stakeholder processes and level of integration of sectors within the economy-wide model (Winkler et al. 2017 p. 559). Graph 2 illustrates these challenges.

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<sup>2</sup> Brazil, Chile, Colombo, Peru and South Africa.

Graph 2: Challenges in linking sectoral and economy-wide models



Source: (Winkler et al. 2017 p. 563)

(Krook-Riekkola et al. 2017) provides an example for applying an iterative soft-linking strategy within a national climate and energy policy context. The study raises two concerns. First, the analysed studies do not formally account for macroeconomic impacts of changes in demand for investments related to sectoral energy service demand. Although it accounts implicitly for capital adjustment in the electricity generation sector of the CGE model. The second concern addresses the overall consistency across models. As the study relies on existing top-down and bottom-up models, this is a source of inconsistency as sector definitions and energy supply/demand structures differ between models. The heterogeneity of the models hampers the linkage. It requires the use of translation modules between the top-down and bottom-up models. Due to the lack of consistency full convergence was not achieved. On this basis (Andersen et al. 2019) develop a novel soft linking method for bridging the gap between top-down and bottom-up models. To overcome the issue of inconsistencies the top-down and bottom-up model (together constituting the InterACT model) were built from scratch. A novel feature of this parallel structure is the explicit modelling of energy service demands in the top-down model (Andersen et al. 2019 p. 279). The modelling framework was used to assess the effect of the policy of unilateral, obligatory carbon capture and storage in the Danish concrete production sector.

(Helgesen et al. 2018) present an example of hard-linking a bottom-up energy system model and a top-down CGE model. The objective is to analyse energy system and economic impacts of reducing greenhouse gas emissions from transport.

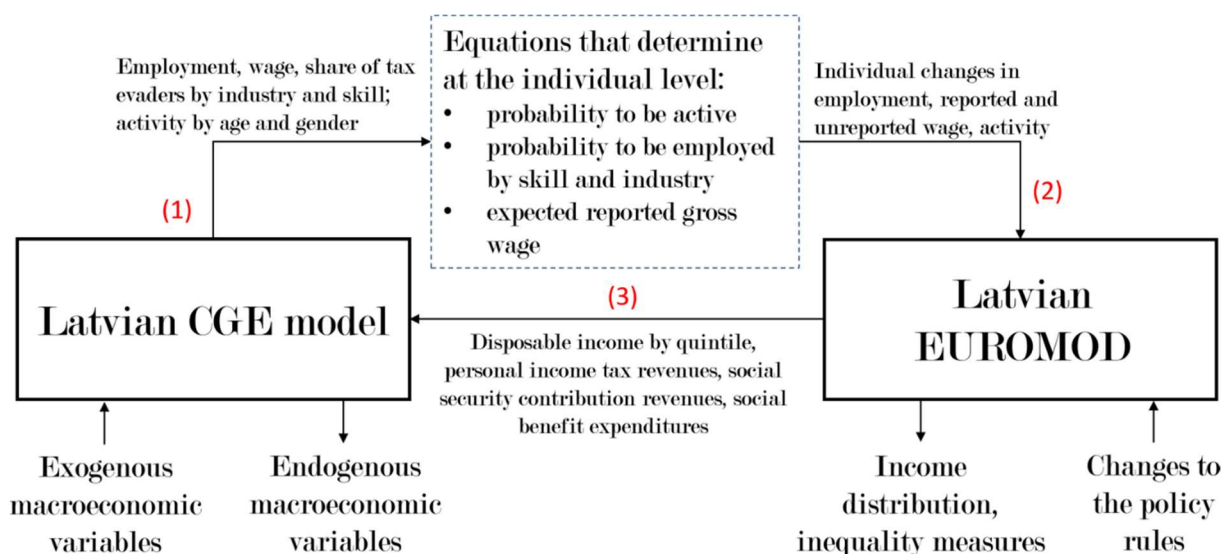
A stochastic agent based model (ABM) is linked with a top-down CGE model in (Niamir, Ivanova, and Filatova 2020). The mean value of 100 ABM simulations is used to feed the CGE model. Furthermore, it is necessary to scale up the regional behavioural patterns from the ABM to the level of NUTS2 regions, which are used by the CGE model. So far, the model linkage is one-directional from the bottom-up model to the top-down model. Developing a bi-directional model linkage, feeding the ABM with GDP projections from the CGE model, is suggested for future work.

(Yang et al. 2021) provide an example for an iterative soft-linking approach combining an energy sector bottom up model with a top-down CGE model. The purpose of the model linkage is to identify environmental co-benefits and economic impacts of low-carbon pathways in China. (Timilsina, Pang, and Xi 2021) provide another example for soft-linking a bottom-up energy sector model with a top-down CGE model in order to assess the economic impacts of emission reduction targets in China as set under the Paris Climate Agreement. (Fattahi et al. 2023) use an iterative soft-linking approach of a bottom-up energy system model and a CGE model to assess the economic impacts of climate change policies in the Netherlands.

(Su et al. 2022) provide an example for using an iterative hard-linking approach to analyse the economic impacts of a deep decarbonisation pathway in China. (Durand-Lasserve et al. 2023) use an iterative hard-linking approach to assess sectoral and economy-wide consequences of domestic energy price reforms in Saudi Arabia.

In (Beňkovskis et al. 2024) a CGE model is linked with the tax-benefit microsimulation model EUROMOD for Latvia. The model linkage uses an iterative process to achieve convergence of the changes in disposable income, employment and wages in the two models. The authors argue that linking the models has significant advantages. On the one hand, the microsimulation model can overcome the lack of income distribution and fiscal instruments in the CGE. On the other hand, CGE provides macroeconomic spill-over effects missing from the microsimulation model. Graph 3 gives an graphical overview of the iterative model linkage. The model iterations always start with a CGE model run (1). Any changes in the CGE labour market output adjust the economic status and income from labour at an individual level in EUROMOD (2), while changes in disposable income, tax payments and benefits create a new exogenous change for the CGE model (3) (Beňkovskis et al. 2024 p. 133).

Graph 3: Latvian CGE model linked with Latvian EUROMOD



Source: (Beňkovskis et al. 2024)

## 2.4 Model convergence

Experience from Sweden shows that linking a static top-down CGE model with the bottom-up energy system model TIMES converges after a few iterations (Andersen and Termansen 2013 p. 5). In this application information about changes in prices and quantities of energy services, fuel mix and investment profiles are fed from the bottom-up energy system model to the top-down CGE model. The CGE model determines a new optimum of



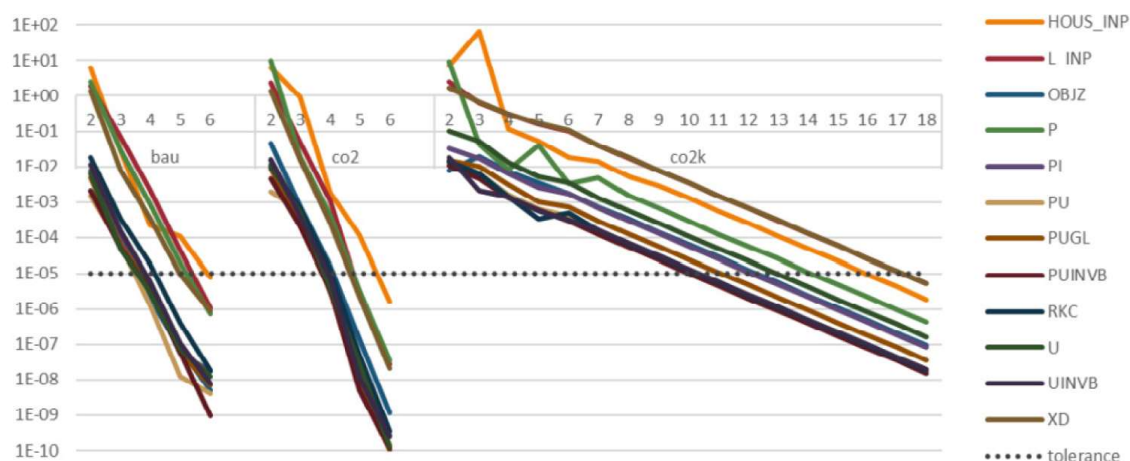
utility and profit maximization and thus estimates new prices for energy services which are fed to the bottom-up model.

In (Krook-Riekkola et al. 2017) the top-down and bottom-up model adjust quickly to one another already in the second reference iteration. After the second iteration only small changes were observed. However, full convergence was not achieved.

For the policy experiment of banning oil fuelled boilers the iterative soft-linking approach presented in (Andersen et al. 2019) converges fully within five iterations. Convergence was assessed using the variables fuel for heat service and capital input costs, cost of heat service production and welfare change.

(Helgesen et al. 2018) measure convergence using the maximum of the absolute relative difference of key variables between two successive iterations. The tolerance for convergence is set to be  $10^{-5}$ . The following variables are used in this process: commodity prices, sectoral output, household consumption, sectoral labour use, price of labour, price of capital, total energy system cost, consumer welfare, public welfare, investor welfare as well as hicksian prices of consumer welfare, public welfare and investor welfare (Helgesen et al. 2018 p. 203). Graph 4 shows the development of the key variables until convergence in three different scenarios: a business as usual scenario without CO<sub>2</sub>-restrictions (*bau*), a CO<sub>2</sub>-reduction scenario with investments not affecting capital growth (*co2*) and a CO<sub>2</sub>-reduction scenario with the assumption that investments which exceed those in the business as usual scenario will reduce capital growth (*co2k*). The *bau* and *co2* scenarios reach convergence in the 6<sup>th</sup> iteration and converge much faster than the *co2k* scenario, which needs 18 iterations. The study observed situations in which convergence could not be reached because of cycling (Helgesen et al. 2018 p. 206). Two reasons could be identified. First, at the macro level, the top-down model found different equilibria. These equilibria alternated in different iterations. Depending on starting points and how the solutions progressed convergence could be reached or not. This behaviour could be avoided when one degree of freedom was removed. Nevertheless, the possibility of non-uniqueness could not be ruled out completely. Second, on the micro level, Leontief coefficients could alternate between iterations. Generalizing the Leontief adjustment calculation, capturing situations where an energy carrier went out of the energy mix and then returned into the mix due to an undefined Leontief adjustment factor, could avoid this behaviour (Helgesen et al. 2018 p. 206).

Graph 4: Largest relative variable deviations per scenario until convergence



Source: (Helgesen et al. 2018 p. 206)

Helgesen and Tomasgard use the relative change from one iteration to the next in total energy system cost, gas input share to electricity sector and projected future demand to measure convergence. The tolerance is set to be  $10^{-6}$  (Helgesen and Tomasgard 2018 p. 1224).



Yang et al. report that their soft-linked bottom-up and top-down models converge after several iterations (Yang et al. 2021 p. 5). The convergence is measured using the variable energy consumption and the threshold is set to be a difference of 10% between two consecutive iterations.

The hard-linking approach in (Durand-Lasserve et al. 2023) converges in all tested scenarios in not more than 12 iterations. The convergence criterion includes prices as well as quantities. The threshold for the difference between two consecutive runs is  $10^{-4}$  (Durand-Lasserve et al. 2023 p. 13).

Fattahi et al. use energy demand as the variable to measure convergence (Fattahi et al. 2023 p. 10). The threshold for convergence is set at  $10^{-2}$ . Convergence is reached after three iterations (Fattahi et al. 2023 p. 11).

In (Beňkovskis et al. 2024) the model linkage does not use a fixed number of iterations but repeats the iterations until full convergence is reached. Growth rates are used to assess the consistency rather than levels. The following 13 variables are used to assess the consistency of both models: nominal disposable income by quintile, personal income tax payments, social security payments by employees, social security payments by employers, unemployment benefits, parental benefits, sickness benefits, disability pension benefits, and other social benefits (Beňkovskis et al. 2024 p. 134). Two different criteria are used to assess the degree of consistency and convergence: the root mean square deviation of the growth rates should not exceed  $2.5 \cdot 10^{-4}$  and the maximum deviation in growth rates should be below 0.1 percentage points (Beňkovskis et al. 2024 p. 134). Most of the simulations converge after around five iterations. Larger changes tended to need more iterations.

### 3 Overview TransFair-AT sector models

The brief description of the top-down-model and the bottom-up models in this section is based on the TransFair-AT project description and web page (TransFair-AT 2022d).

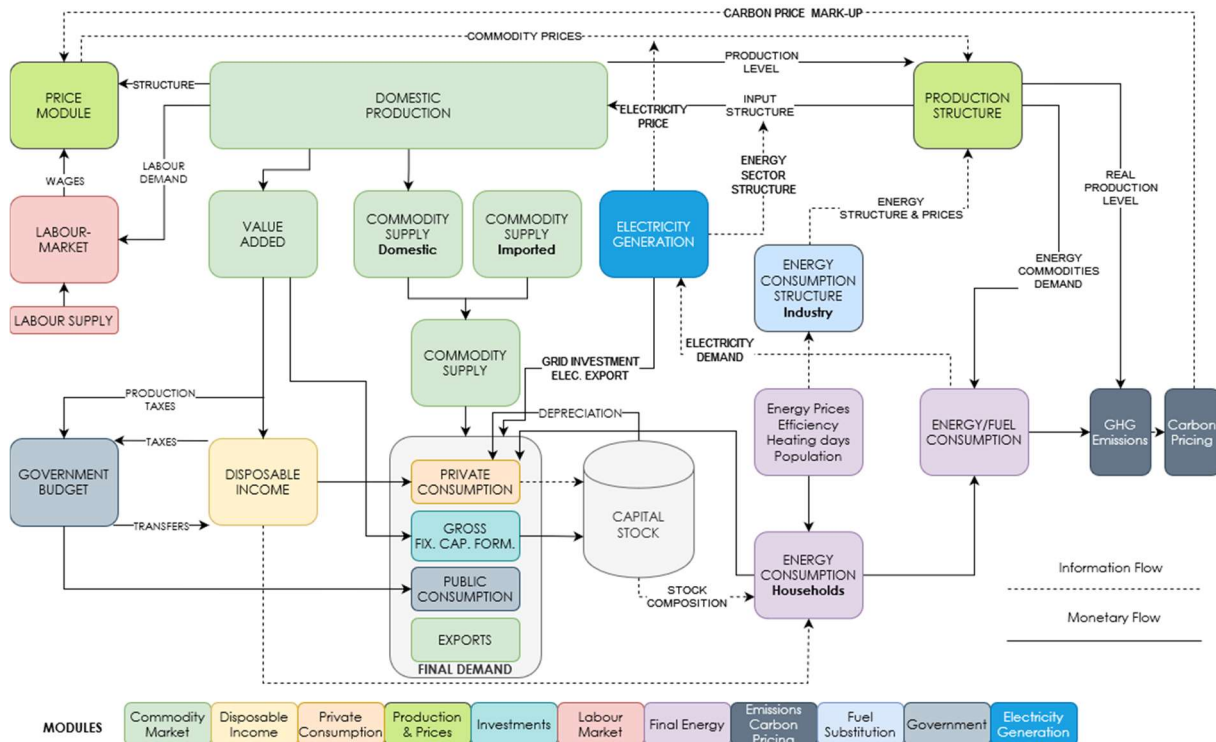
#### 3.1 Top-down model DYNK

The top-down model DYNK (Dynamic New Keynesian) is a hybrid econometric Input-Output (IO) and computable general equilibrium (CGE) model (TransFair-AT 2022a). The model represents the linkages between 74 NACE industries<sup>3</sup> and deals with the Austrian economy. Households are divided into 15 different categories (income quintiles times regional structure). These are characterised by their specific consumption patterns in 47 consumption categories (COICOP<sup>4</sup>) and their sources of disposable income. Consumption of consumer durables, consumer non-durables and energy goods is modelled individually. Parts of the model resemble a CGE model in the long run. The term "New Keynesian" indicates the existence of a long-run full-employment equilibrium, which - starting from an unemployment equilibrium - cannot be reached in the short run due to institutional inflexibilities. DYNK has been used widely for policy analysis and is linked to energy statistics and can link sectoral activities to final energy demand, process CO<sub>2</sub> emissions and energy-related CO<sub>2</sub> emissions. Graph 5 illustrates the basic structure of the model DYNK. A detailed description of the DYNK model is provided e.g. in (Kirchner et al. 2019).

<sup>3</sup> Nomenclature statistique des activités économiques dans la Communauté européenne, <https://ec.europa.eu/eurostat/web/nace/>, accessed: 3/10/2024

<sup>4</sup> Classification of individual consumption by purpose, [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Classification\\_of\\_individual\\_consumption\\_by\\_purpose\\_\(COICOP\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Classification_of_individual_consumption_by_purpose_(COICOP)), accessed: 3/10/2024

Graph 5: Basic structure of the model DYNK



### 3.2 Bottom-up mobility models MARS and SERAPIS

The mobility sector is represented through the use of two different models. The first is MARS (Metropolitan Activity Relocation Simulator). MARS represents a strategic and dynamic Land-Use and Transport Interaction (LUTI) model (TransFair-AT 2022c). The second is SERAPIS (Simulating the Emergence of Relevant Alternative Propulsion technologies in the car and motorcycle fleet Including energy Supply). SERAPIS represents a dynamic car fleet and propulsion technology model. The two models are founded on the principles of system thinking and systems dynamics and have been implemented in VENSIM®, which is a system dynamics software environment.

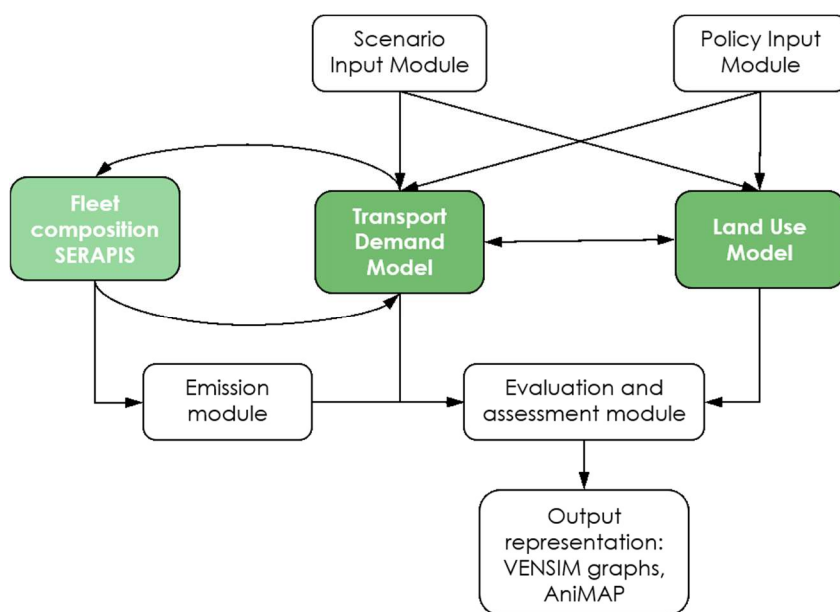
MARS consists of two sub-models for transport demand and land use model and a set of sub modules, e.g. for the representation of the composition of the car fleet and the calculation of emissions. Given its inherently dynamic nature, MARS is designed to simulate the evolution of the transport and land use system in discrete time steps, from its base year up to a predefined time horizon. Given the strategic nature of MARS, the level of spatial aggregation is relatively high. The territory of Austria is subdivided into 116 zones, representing the Austrian political districts (Statistik Austria 2021). The intra-zonal traffic is further classified into five distinct distance bands. The transportation demand model of MARS is capable of calculating the generation of trips, the distribution of trips, and the choice of modes in each discrete time step. The choice of options is dependent upon the application of a multinomial logit model, which employs a generalised cost structure comprising a weighted sum of both time and cost components of a given trip.

The SERAPIS model is designed to simulate the development of a fleet of vehicles across three propulsion technology categories (internal combustion engine, plug-in electric and battery electric), three vehicle size categories (compact, family and luxury) and for both first and second cars in a household. The selection of propulsion technologies is predicated upon a multinomial logit model. The utility of a propulsion technology is determined by a number of factors, including the initial investment costs, the operating costs, the variety of available makes

and models, the density of service stations, the range of the technology, and the time saved by users due to exemptions from traffic regulations. Accordingly, the model is responsive to policy instruments such as tax exemptions and subsidies. The output of SERAPIS is a representation of the evolution of the passenger car fleet, disaggregated by propulsion technology. The resulting fuel and energy consumption and costs are incorporated as inputs into the transport demand model of MARS. Conversely, the car operation costs per year are included as inputs into the utility function of the multinomial logit model of SERAPIS. The principal outputs of MARS and SERAPIS are the number of trips by origin-destination pair by mode, the monetary costs associated with each trip, fuel and energy consumption, and CO<sub>2</sub> and other emissions.

Graph 6 illustrates the basic structure of the mobility sector modelling framework consisting of the models MARS and SERAPIS. A more detailed description of MARS and SERAPIS is provided e.g. in (Soteropoulos et al. 2021), (Emberger and Pfaffenbichler 2020) and (Pfaffenbichler et al. 2024).

Graph 6: Basic structure of the mobility sector modelling framework



### 3.3 Bottom-up building stock model Invert/EE-Lab

Invert/EE-Lab is a bottom-up model for analysing space heating, hot water and cooling in existing buildings (TransFair-AT 2022b). It aims to quantify the impact of different frameworks on overall energy demand, fuel and technology mix, CO<sub>2</sub> emissions and costs. These include price scenarios for energy sources, cost scenarios for technologies and efficiency measures, different settings of economic and regulatory incentives, consumer behaviour, climate change and resource constraints. Invert/EE-Lab relies on a highly disaggregated description of building stock in each analysis region. These include building type, age, state of renovation, existing heating systems, occupancy patterns and regional aspects such as the availability of gas or district heating infrastructure. Both residential and tertiary buildings are usually included in the analyses. In addition, different structures of housing provision and household income classes are represented in the model. The model uses an extended technology and efficiency database with technical and economic characteristics. On the one hand, it integrates current and potential future technologies for space heating, hot water and space cooling, including on-site solar thermal and photovoltaic generation, as well as the heat distribution systems in the building. On the other hand, a wide range of options for the renovation of the building envelope and heat recovery systems are considered to reduce the energy demand of the buildings.

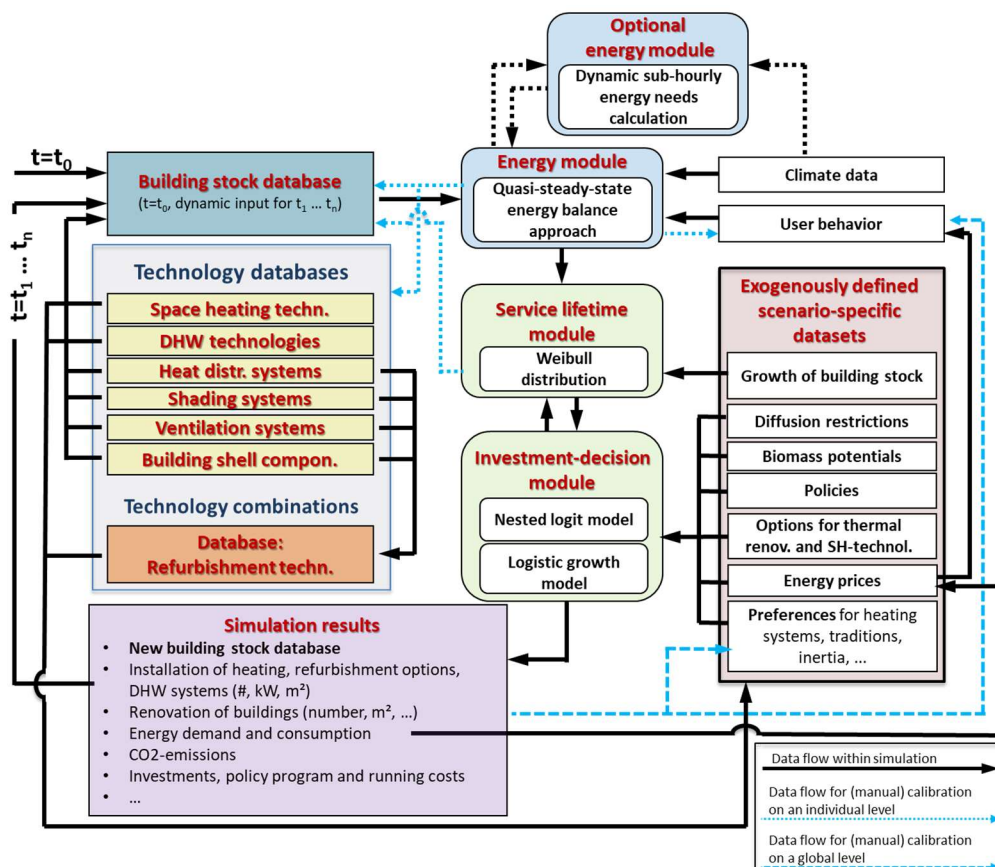
Invert simulates energy-related investment decisions in the building stock and is used in particular to study the impact of economic and regulatory incentives on the decisions of different agents (i.e. owner types) when an investment decision has to be made for a specific building segment. This takes into account the inhomogeneous structure of decision-makers in the building sector. A myopic multinomial logit approach, which optimises agents' objectives under imperfect information, is at the core of the EE-Lab version. The market shares of heating systems and energy efficiency measures are calculated by building and investor type using a nested logit approach. A detailed description of the decision algorithm can be found in (Müller 2015) and (Steinbach 2016).

The model allows different owner types to be defined as instances of predefined investor classes: owner-occupiers, private landlords, shared owners and housing associations. The different perspectives on building-related investment motivate this structure. For example, saving on energy costs is only relevant to those who own and occupy the building. Refinancing energy saving measures through additional rental income (investor-tenant dilemma) is the relevant variable for landlords.

Owner types are distinguished by their investment decision behaviour and their environmental perceptions, the former being captured by investor-specific weights of economic and non-economic attributes of alternatives (Kranzl et al. 2019 p. 229). Perception-relevant variables - environmental awareness, energy price expectations or risk aversion - influence the attribute values.

The basic structure of Invert using the EE-Lab version of the tool is shown in Graph 7.

Graph 7: Basic structure of the Invert/EE-Lab model



## 4 Linking the Transfair-AT models

### 4.1 History

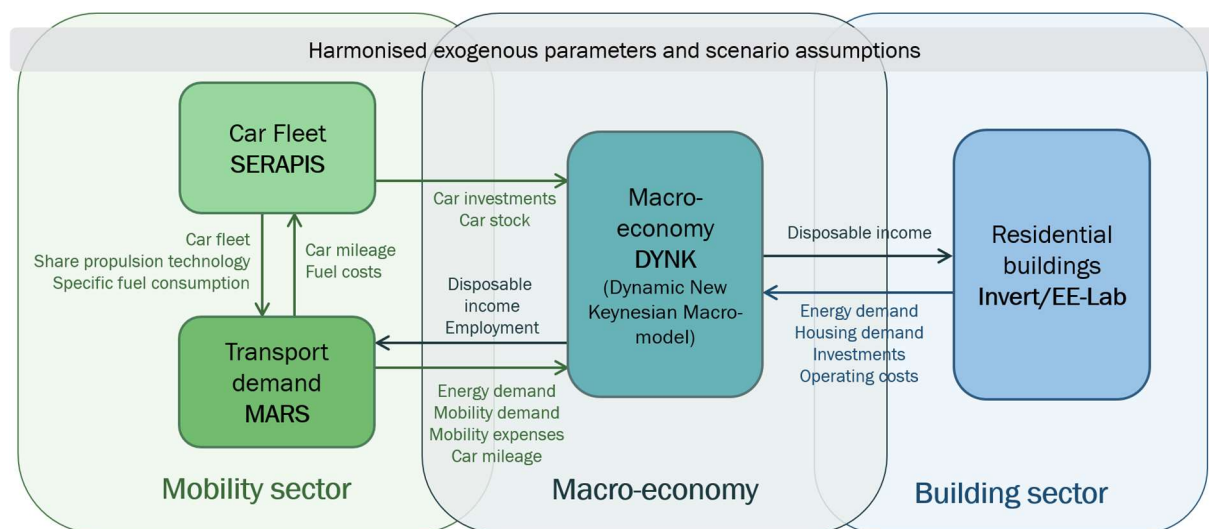
All three models, DYNK, MARS and Invert/EE-Lab, were or are used in the biannual reports on emission projections for 2030 und 2050, which analyse sectoral energy consumption and greenhouse gas emissions in Austria (Krutzler et al. 2017; Krutzler, Wasserbauer, and Schindler 2023). In these reports typically two scenarios are analysed, one focussing on already implemented or passed measures (WEM – with existing measures) and the other on additional measures currently discussed and likely to be implemented (WAM – with additional measures). Usually the models DYNK, MARS and Invert/EE-Lab were applied independently in these reports. Although, occasionally the models have been linked in a very simple unidirectional manner. That means no feedback mechanisms and iterations have been implemented in the past. In addition, variables such as operation costs were not exchanged between the models and especially the financial implications of different policy measures on different household groups have not been assessed.

### 4.2 Process of linking the models

Prior to linking the models each of the three modelling groups revised their models and updated them with the most recent data available. Selected exogenous parameters and scenario assumptions were harmonised in this process. Additionally, modifications necessary to tackle the topic of the project were implemented. E.g. the composition of household types in the models was adjusted to fit the requirements of the project, i.e. household types have been aligned. Subsequently, a coordination group with one representative of each modelling team has been set up. The members of the coordination group were Paul Pfaffenbichler (BOKU), Mark Sommer (WIFO) and Andreas Müller (e-think). Due to the major structural differences between the sector models and technical obstacles, hard-linking or integration of the models was no viable option within the resources of the project. Therefore, a soft-linking approach was selected for model linkage in the project TransFair-AT. This approach has also some significant advantages (see section 2.2). Linking rather than integrating models allows to retain models separate and also retain the consistency of their database. Coupling bottom-up and top-down models by soft-linking is seen by some references as the best option to exploit the strength of each of the two modelling approaches.

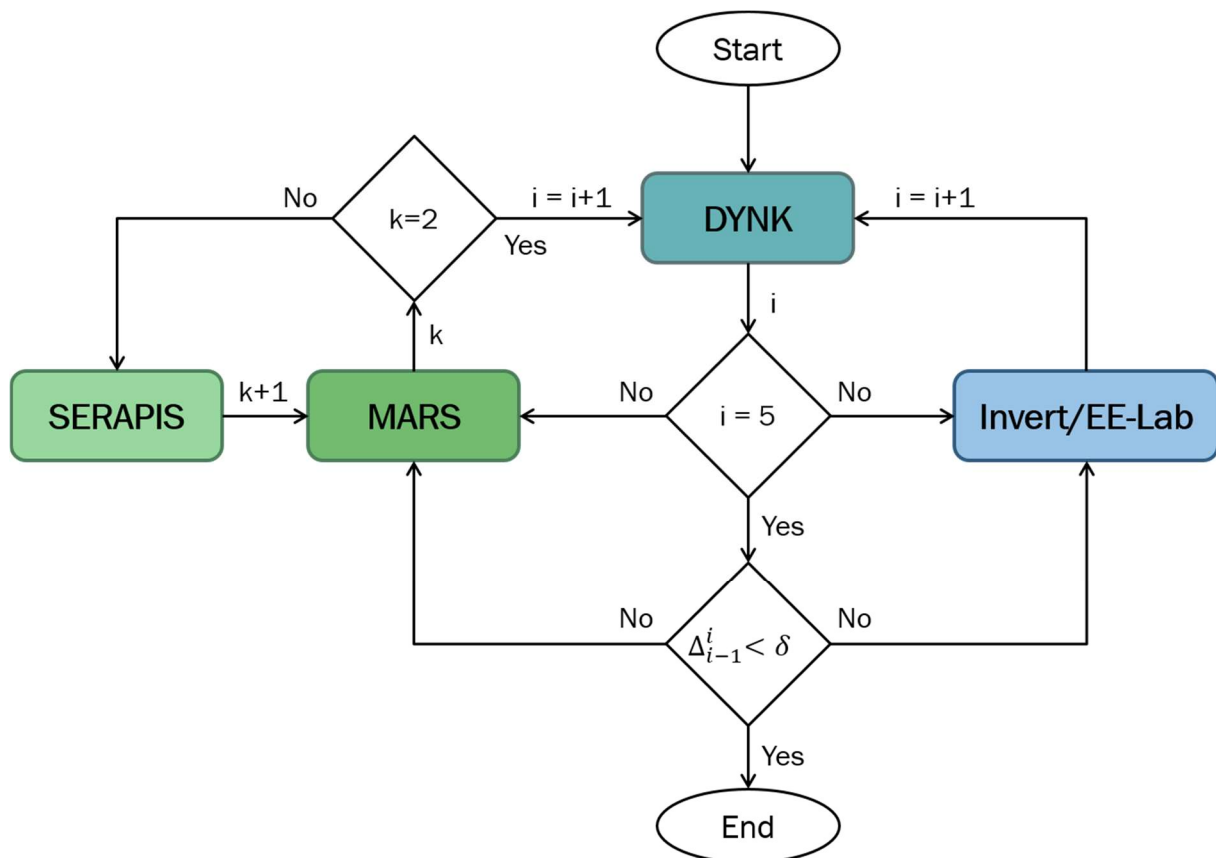
As a first step of the soft-linking approach the coordination group defined a list of relevant data, the "interface variables" for model linkage, and revised the basic structure from the project proposal (Graph 8).

Graph 8: Basic structure TransFair-AT model linkage



Graph 9 illustrates the iterative soft-linking approach. Each iteration starts with a simulation of the top-down model DYNK. The resulting interface variables are exported to the building sector bottom-up model Invert/EE-Lab and the mobility sector bottom-up model MARS. Both sector bottom-up models run their simulations in parallel, as there is no direct interaction between the sectors. While Invert/EE-Lab directly exports the interface variables back to DYNK, MARS first has to iterate with the car fleet model SERAPIS. First tests have shown that one feedback loop is sufficient to stop this process. Once the iteration MARS-SERAPIS-MARS is complete, the interface variables from the mobility sector are exported back to DYNK. A new iteration is started with a DYNK simulation using the new interface variable values from both bottom-up models. The iterations were stopped after a set of five iterations in order to analyse potential convergence. Based on the results of this analysis it was decided whether another set of five iterations had to be started. If the difference in the interface variables between the last iterations  $\Delta_{i-1}^i$  is below the target threshold value  $\delta$ , the process is stopped. If not, a new set of five iterations is started. The process was finally stopped after 20 iterations (details see section 4.3).

Graph 9: TransFair-AT model iterations



Model specific Excel spreadsheets containing the interface variable have been defined. The exchange of these interface files was organised via a git repository.



## 4.3 Results model linkage

### 4.3.1 Measurement of convergence

Two different indicators were used for to measure convergence: the maximum of the absolute relative difference between two consecutive iterations (Equation 1) and the root mean square of the relative difference between two consecutive iterations (Equation 2).

*Equation 1: Convergence indicator maximum absolute relative difference between two consecutive iterations*

$$M_{i-1}^i = \max[d_{i-1}^i(t)] = \max \left| \frac{v_i(t)}{v_{i-1}(t)} - 1 \right|$$

Where,  $M_{i-1}^i$  is the convergence indicator between two consecutive iterations  $i-1$  and  $i$ ,  $d_{i-1}^i(t)$  is the absolute relative difference between two consecutive iterations  $i-1$  and  $i$  in time step  $t$  and  $v_{i-1}(t)$  and  $v_i(t)$  are the interface variable values of two consecutive iterations  $i-1$  and  $i$  in time step  $t$ .

*Equation 2: Convergence indicator root mean square relative difference between two consecutive iterations*

$$RMS_{i-1}^i = \sqrt{\frac{\sum_t \left( \frac{v_i(t)}{v_{i-1}(t)} - 1 \right)^2}{T}}$$

Where,  $RMS_{i-1}^i$  is the root mean square between two consecutive iterations  $i-1$  and  $i$ ,  $v_{i-1}(t)$  and  $v_i(t)$  are the interface variable values of two consecutive iterations  $i-1$  and  $i$  in time step  $t$  and  $T$  is the total number of time steps.

### 4.3.2 Convergence DYNK

The four interface variables nominal consumption, nominal disposable income, consumer price index and employment in persons were used to measure the convergence for the top-down model DYNK. In line with the literature the aim was to reach a convergence tolerance of  $10^{-3}$  to  $10^{-4}$  (see section 2.4). Graph 10 summarises the convergence results for the three different scenarios REF, CLIM and COMP (Kettner et al. 2024) and the two different convergence indicators. The results for the maximum of the absolute relative difference are shown on the left side, while the results for the root mean square of the relative difference are shown on the left side.

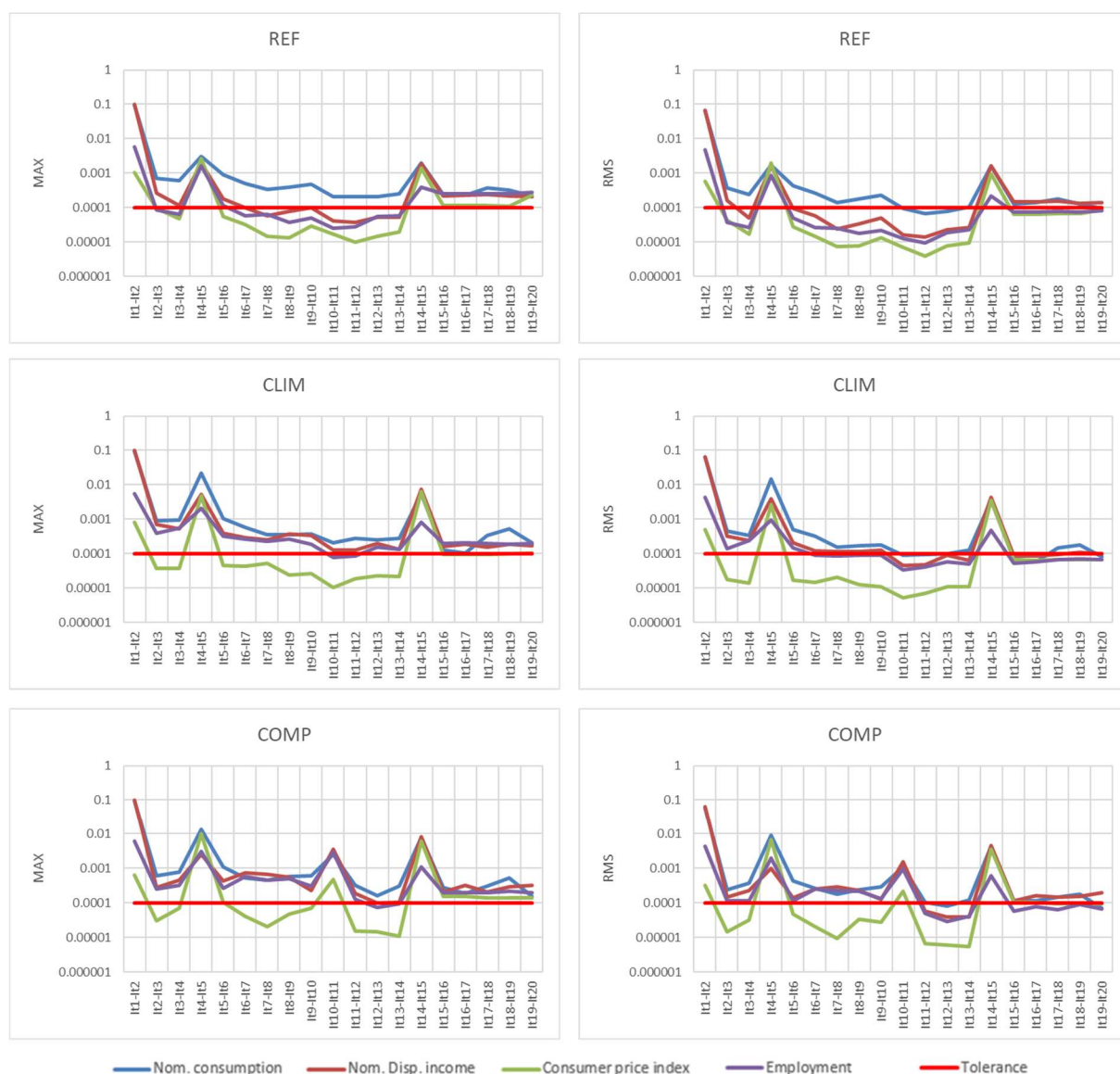
A total of 20 iterations were executed. Convergence could have been achieved faster, but in the course of the project and a closer look at the results several structural changes became necessary to the DYNK and Invert/EE-Lab models during the iterations. The final goal stayed, namely to achieve sufficient convergence between the top-down model DYNK and the bottom-up model Invert/EE-Lab. In all three scenarios the difference between iterations dropped significantly in the first three iterations after each structural change incident to about  $10^{-3}$  to  $10^{-4}$ . The following changes of the model DYNK have been made between the 4<sup>th</sup> and 5<sup>th</sup> iteration. CO<sub>2</sub> taxes and subsidies, which were exogenous parts of the households expenditures before, were integrated into the general price system of DYNK that integrates subsidies and taxes into consumer prices and consumption. This adaptation can cause changes in the actual consumer price index. Either directly or indirectly via wage negotiations which are oriented on the inflation. Furthermore, the redistribution of CO<sub>2</sub> revenues between different income quintiles was changed in order to fit to policy goals. This adaptation has an influence on total consumption and income. These changes cause the significant increase in the deviation between iteration 4 and 5. Afterwards the differences decline quickly and show a downward trend until iteration 10. The stochastics included in the bottom-up model Invert/EE-Lab cause some kind of oscillations (see section 4.3.4). Therefore, it was decided to use bundles of simulations for the model iterations rather than single simulations. Furthermore, a bug had to be fixed, which had an effect on subsidies and investments in Invert/EE-Lab which in turn affected incomes in DYNK. These



changes caused the second peak in the convergence of the scenario COMP. Between iteration 14 and 15 a CO<sub>2</sub>-tax for non-ETS sectors (mainly freight transport and space heating from service providers) was implemented in DYNK in order to simulate a consistent carbon pricing policy. This change had again an effect on employment and income. The third peak can be explained by these changes. Again the difference drops quickly, staying stable for the final five iterations.

Differences between the scenarios are not very pronounced. In all three scenarios both convergence indicators settle at values in the range of  $10^{-4}$  to  $10^{-3}$  in the final iterations. It can therefore be concluded that the model DYNK reached convergence.

Graph 10: Convergence of the DYNK interface variables



### 4.3.3 Convergence MARS/SERAPIS

The eight interface variables expenses for public transport, car mileage, parking charges, passenger kilometres car, passenger kilometres public transport, expenses road pricing, electricity demand and fuel consumption were used to measure the convergence for the bottom-up model MARS. In line with the literature the aim was to reach a convergence tolerance of  $10^{-3}$  to  $10^{-4}$  (see section 2.4). Graph 11 summarises the convergence results for the three different scenarios REF, CLIM and COMP and the two different convergence indicators. The results for the maximum of the absolute relative difference are shown on the left side, while the results for the root mean square of the relative difference are shown on the left side.

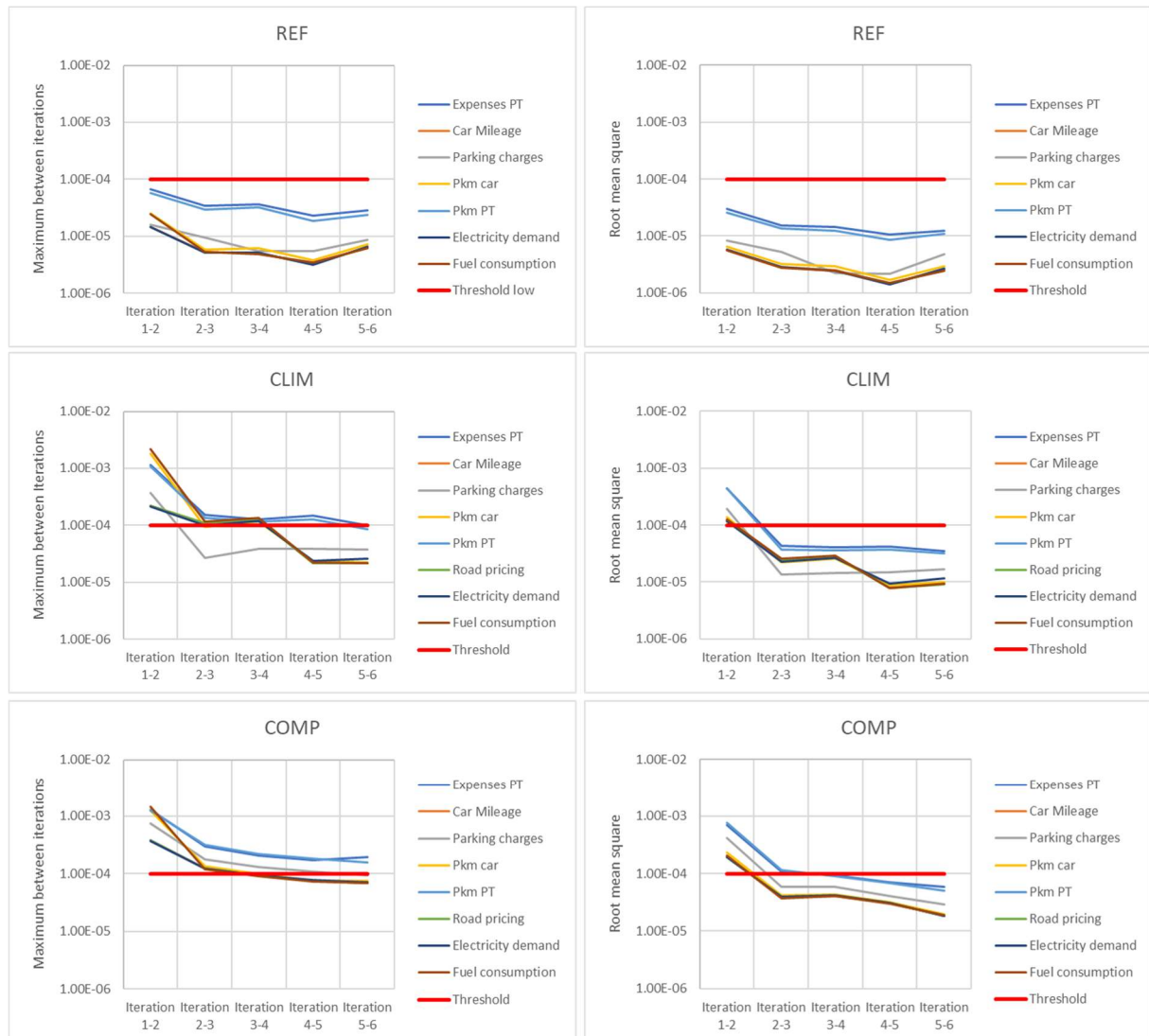
In the **REF scenario** both convergence indicators are below the tolerance for all interface variables from the first iteration onwards. A clear downward trend can be observed for all variables up to the 5<sup>th</sup> iteration. Between the 5<sup>th</sup> and 6<sup>th</sup> iteration the convergence indicators increase slightly but clearly stay below the convergence tolerance. The slightly oscillating behaviour is a spill over from the iterations with the Invert/EE-Lab model.

In the **CLIM scenario** both convergence indicators are significantly above the tolerance for the comparison of the 1<sup>st</sup> and 2<sup>nd</sup> iteration. Both indicators drop significantly for the comparison of the 2<sup>nd</sup> and 3<sup>rd</sup> iteration. Up to the 5<sup>th</sup> iteration the indicator maximum absolute relative difference stays around the tolerance for several variables. After the 6<sup>th</sup> iteration all variables settle below the tolerance. In contrast, the indicator root mean square is significantly below the tolerance from the 3<sup>rd</sup> iteration onwards.

In the **COMP scenario** both convergence indicators are significantly above the tolerance for the comparison of the 1<sup>st</sup> and 2<sup>nd</sup> iteration. Both indicators drop significantly for the comparison of the 2<sup>nd</sup> and 3<sup>rd</sup> iteration. While there is a clear downwards trend the indicator maximum absolute relative difference of the variables expenses and passenger kilometres public transport stays above the tolerance up to the 6<sup>th</sup> iteration ( $2.0 \cdot 10^4$  and  $1.6 \cdot 10^4$  respectively). In contrast the indicator root mean square is significantly below the tolerance from the 4<sup>th</sup> iteration onwards. While on indicator does not fully meet the tolerance, we nevertheless can conclude that the two models converge after five to six iterations.

The results regarding the convergence of the two models correspond well with the experience from the literature (see section 2.4). Similar to most of the examples from the literature the top-down model DYNK and the bottom-up mobility model MARS converge after some iterations. As reported in the literature larger changes, like in the CLIM and COMP scenarios, require more iterations.

Graph 11: Convergence of the MARS/SERAPIS interface variables



#### 4.3.4 Convergence Invert/EE-Lab

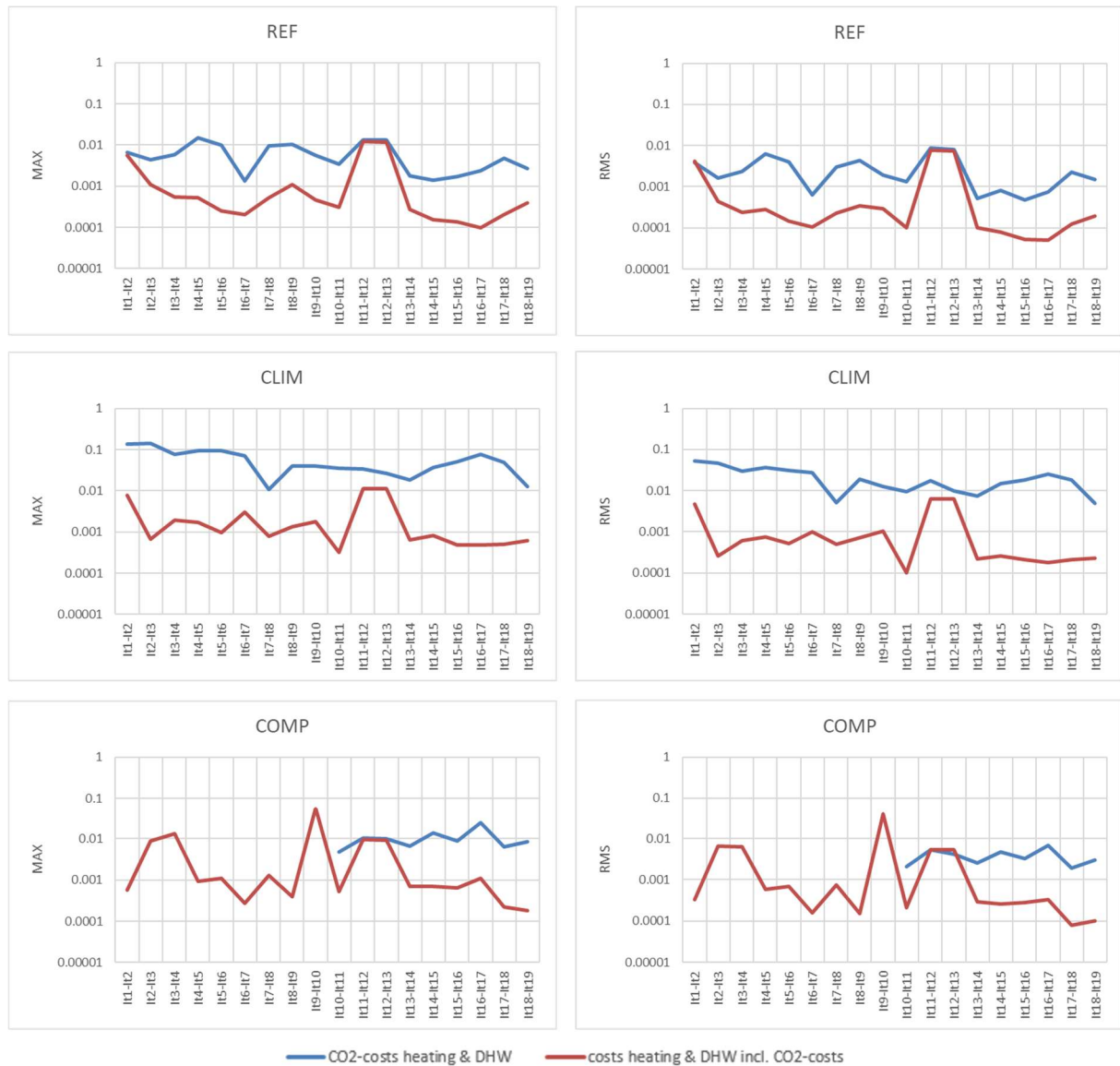
Nine different interface variables from three different areas were used to assess the convergence of the Invert/EE-Lab model. From the area of annual running costs these are the annual CO<sub>2</sub>-costs for space heating and domestic hot water (DHW) and annual running costs for space heating and domestic hot water including CO<sub>2</sub>-costs. From the field of final energy demand (FED) these are annual final energy consumption for space heating and water heating. From the field of investments these are annual investments in envelope maintenance, investments in envelope thermal refurbishment, investments in space heating, domestic hot water systems and photovoltaic, subsidies for envelope refurbishment and subsidies for space heating, domestic hot water systems and photovoltaic.

Graph 12, Graph 13 and Graph 14 summarise the convergence results for the three different scenarios REF, CLIM and COMP, the two different convergence indicators and the three interface variable areas. The results for the maximum of the absolute relative difference are shown on the left side of each graph, while the results for the root mean square of the relative difference are shown on the left side.

The Invert/EE-Lab model contains stochastic elements, i.e. it allows stochastic decisions at the building level. Different variables are randomly selected from a certain range in each model run. If the change in household income between the iterations with the DYNK model lies within a range that does not (significantly) exceed the bandwidth for the stochastic variables, then no convergence can occur when using individual model runs with Invert/EE-Lab. The random variation then dominates the movements of the deviations. The changes in the household income variables imported from DYNK are within this range. To minimize the oscillations caused by this stochastic element it was decided to run five INVERT/EE-Lab model runs and average them for each simulation run. In other words, each scenario is run five times and the average results are transferred to DYNK. This measure has been integrated at iteration 10. The effects of the structural changes of the models DYNK and Invert/E-Lab between the iterations 4 and 5, 10 and 11 and 14 and 15 (see section 4.3.2 ) could also be seen to a certain extent in Graph 12, Graph 13 and Graph 14.

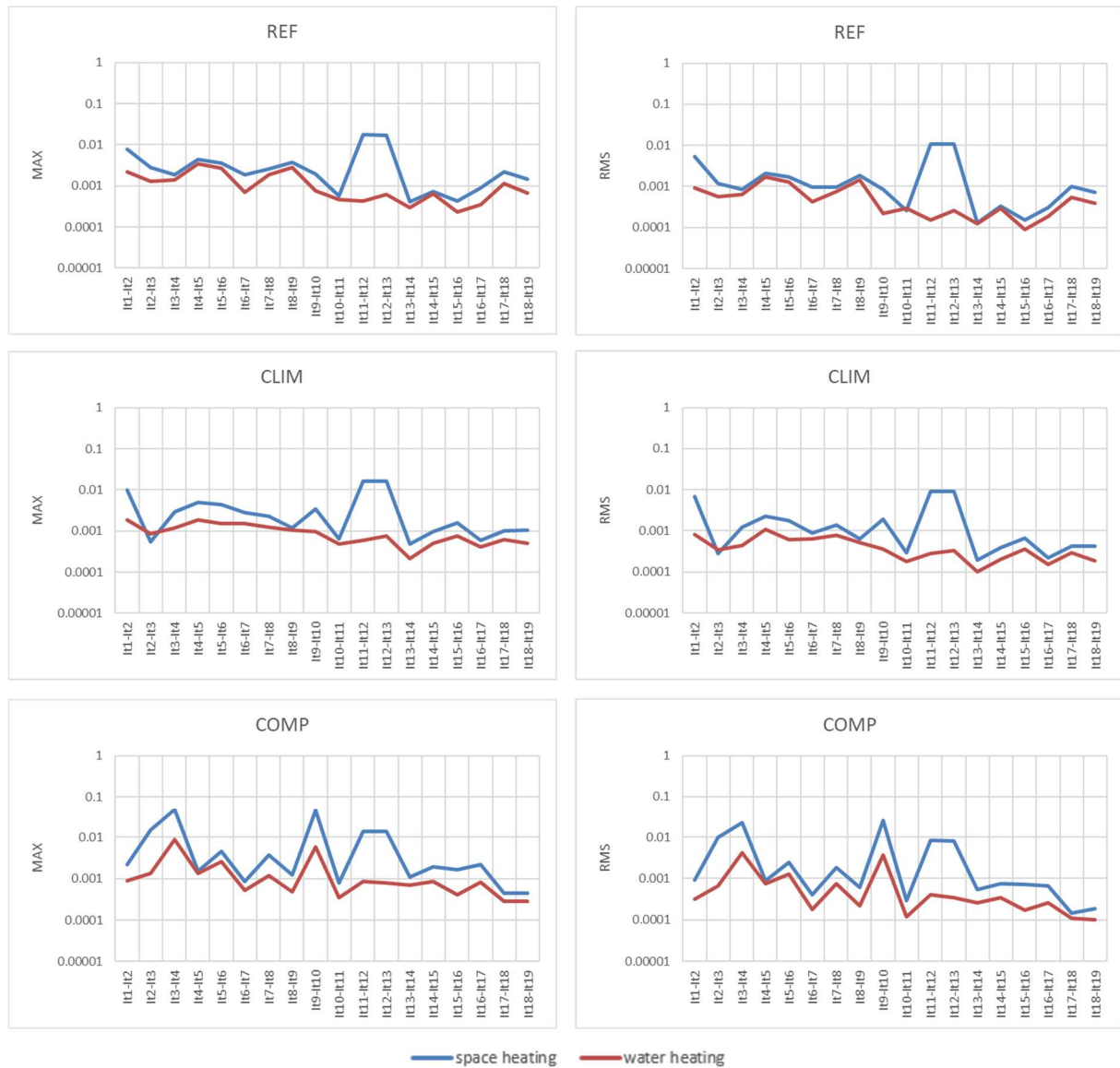
The trend in the difference between the indicators for annual costs does not show signs of clear convergence (Graph 12). This is especially true for the variable annual CO<sub>2</sub>-costs for space heating and domestic hot water, which seems to stabilise at a level of around 10<sup>-2</sup> for the later iterations. The indicators for the variable annual running costs for space heating and domestic hot water including CO<sub>2</sub>-costs are decreasing significantly in the early iterations in the scenarios REF and CLIM. But, in the scenario COMP these are even increasing in the early iterations. Nevertheless, for this variable there seems to be a certain stabilisation of the differences in the range of 10<sup>-4</sup> to 10<sup>-3</sup>.

Graph 12: Convergence of the Invert/EE-lab interface variables for annual running costs



The picture is rather the same for the interface variables in the field final energy consumption (Graph 13). Nevertheless, there seems to be a slight downward trend and differences seem to stabilise in the range of  $10^{-4}$  to  $10^3$ .

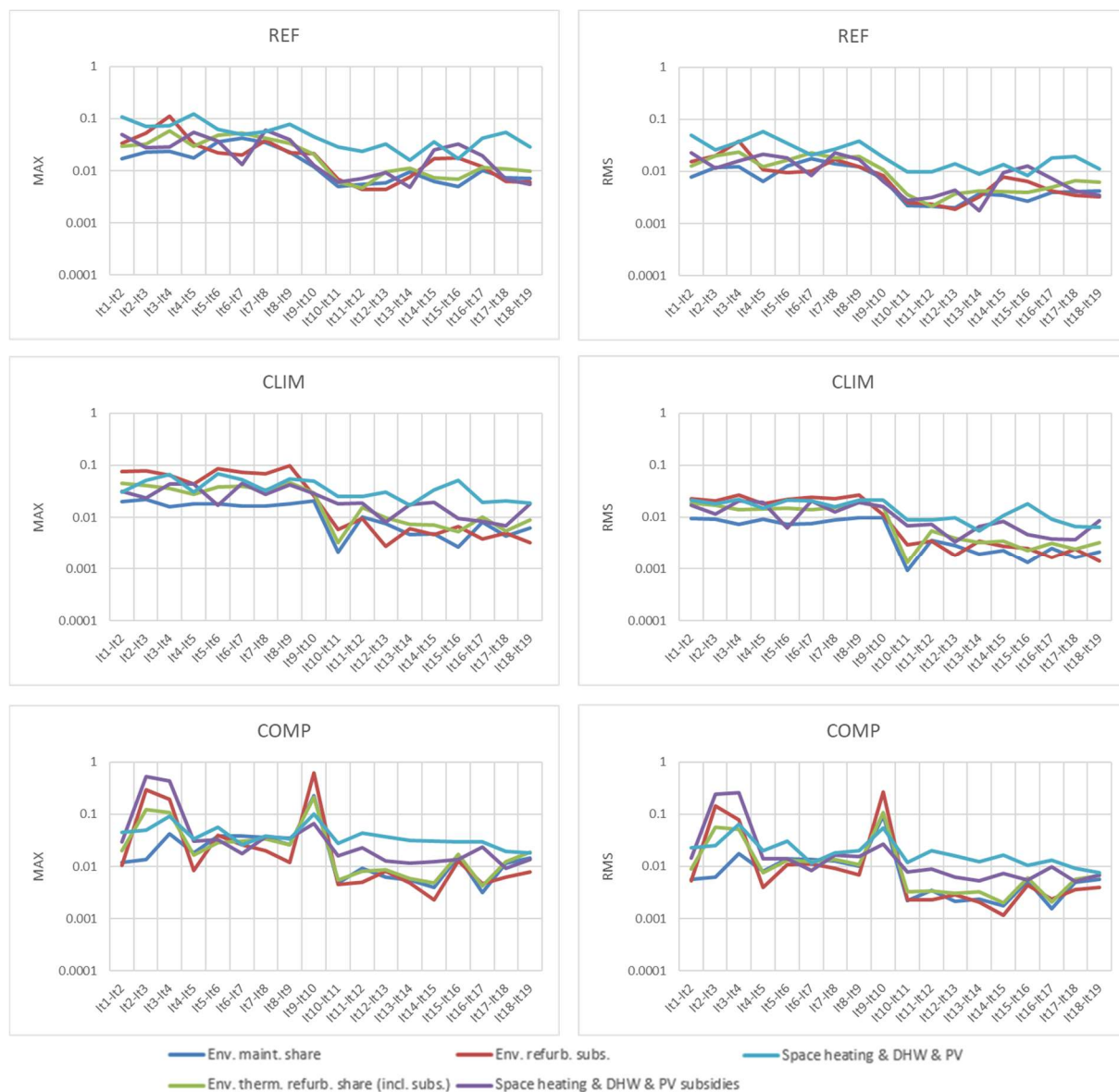
Graph 13: Convergence of the Invert/EE-lab interface variables for final energy consumption



For the interface variables from the field investments and subsidies the picture is again rather similar (Graph 14). Also in this case there seems to be a slight downward trend, but the differences seem to stabilise only in the range of  $10^{-3}$  to  $10^2$ .



Graph 14: Convergence of the Invert/EE-lab interface variables for investments and subsidies





## 5 Summary and conclusions

As the literature review has shown, linking top-down CGE models with bottom-up models covering different aspects of the energy sector is a well-established practice (section 2). First examples are documented from the early millennium onwards. Nevertheless, no application explicitly linking bottom-up models of households transport demand and supply with space heating and hot water with a top-down macroeconomic model has been found in the literature. It can therefore be concluded that the modelling approach developed and implemented in TransFair-AT represents an innovation to the state of the art.

Three different approaches to linking top-down and bottom-up models are presented in the literature: soft-linking, hard-linking and integration (section 2.2). In the soft-linking approach the user is fully responsible for processing and transferring the information between models, which provides a certain flexibility. In the hard-linking approach all information processing and transfer is fully formalized and handled by computer programs. In the integrated approach all involved models are integrated into one single model and the different parts cannot run independently anymore. Due to major structural differences between the sector models and some technical obstacles a soft-linking approach was the logical choice for TransFair-AT. While a certain part of the data exchange in TransFair-AT has been automated, substantial manual work from the user is still required. Full automation would have consumed too many resources and therefore was beyond the scope of the project.

Convergence of models is usually measured by monitoring the differences in key variables between two successive iterations (section 2.4). In TransFair-AT all interface variables which are exchanged between the models were used to monitor convergence. The difference between iterations can be computed by using a variety of indicators. The project TransFair-AT employs the indicators “maximum absolute relative difference” and “root mean square of the relative difference” (section 4.3.1). Concerning the tolerance for convergence, values in the range of  $10^{-4}$  to  $10^3$  seem to be most common in the literature (section 2.4). This value range is therefore used as a benchmark in TransFair-AT.

Model iterations always started and ended with a run of the top-down model DYNK (section 4.2). Iterations between the top-down model DYNK and the bottom-up models MARS/SERAPIS and Invert/EE-Lab were carried out in sets of five iterations. After five iterations convergence was analysed and decisions were made whether a new set of five iterations was started. Structural changes of the models DYNK and Invert/EE-Lab became necessary between iteration 4 and 5, 10 and 11 and 14 and 15. These changes led to disruptions in convergence. The whole process was finally stopped after a total of 20 iterations.

A detailed analysis of the convergence of the top-down model DYNK and the bottom-up models MARS/SERAPIS and Invert/EE-Lab is provided in section 4.3.2, 4.3.3 and 4.3.4 respectively. In the case of the DYNK model, the convergence indicators drop sharply within the first three iterations (Graph 10). Depending on the scenario, the difference continues to decrease at a slower rate (REF), stabilizes (CLIM) or increases again slightly (COMP). Each structural change leads to a disruption increasing the values of the convergence indicators significantly. Nevertheless, again they drop sharply within the next two iterations. Towards the end of the 20 iterations both convergence indicators stabilise roughly in the target range of  $10^{-4}$  to  $10^3$ . It can therefore be concluded that the model DYNK has reached a satisfying level of convergence after 20 iterations.

Also in the case of the model MARS/SERAPIS, the convergence indicators drop sharply in the first three iterations (Graph 11). For the REF scenario both convergence indicators are below the stricter target value of  $10^{-4}$  from the very beginning on. In the CLIM scenario both convergence indicators drop below  $10^{-4}$  after five iterations. A relatively similar picture emerges for the COMP scenario. Although in this scenario the convergence indicator “maximum of the absolute relative difference” of two key-variables (expenses public transport and passenger kilometres public transport) is still slightly above the stricter target value of  $10^{-4}$  after five iterations. Nevertheless, the values are significantly below the less strict target value of  $10^{-3}$ . It can therefore be concluded that the model MARS/SERAPIS reaches a satisfying level of convergence after just five iterations.

In contrast to the other two models, no clear trend towards convergence was observed in the case of the Invert/EE-Lab model. (Graph 12, Graph 13 and Graph 14). The stochastic elements of the Invert/EE-Lab model appear to be the cause of an oscillating behaviour of the differences between the iterations. To mitigate this effect, the results of bundles of five simulations were used in the later iterations with DYNK instead of the results of individual simulations. Although several interface variables seem to stabilise in the target range of  $10^{-4}$  to  $10^{-3}$ , some others only stabilise at levels of  $10^{-3}$  to  $10^{-2}$ . Even though no clear convergence could be reached, it can be concluded that the interface variables stabilise at a level which is sufficient for the purpose of TransFair-AT. Nevertheless, future research should analyse the effect of the stochastic elements in more detail.

The main conclusion from the exchange of DYNK with INVERT/EE-Lab and MARS/SERAPIS is that the changes in demand from the bottom-up models did not cause economic disturbances to change disposable income significantly. As a result, the perturbation is only marginally reflected in the next iteration. A key reason for this is the relative robustness of the DYNK demand system. Consumption of non-durable goods is structured in such a way that changes in energy consumption are accompanied by opposite changes in other non-durable goods consumption. This is simply because available surplus income is spent. In other words, if a household has a surplus of money due to lower energy expenditure, the money is spent on other non-durable goods and the overall change in disposable income remains small. Therefore, in bottom-up models, changes in energy demand have a fairly dampening effect on disposable income and hence on its use in the next round. This leads to rapid convergence.

## 6 Acknowledgements

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## 7 Disclaimer

When writing this article, the authors used DeepL to improve the linguistic formulation. The responsibility for the content lies with the authors.

## 8 Glossary

ABM.....	Agent Based Model
CGE.....	Computable General Equilibrium
CLIM .....	Decarbonization Scenario TransFair-AT
COMP .....	Compensation Scenario TransFair-AT
COICOP .....	Classification of individual consumption by purpose
DHW .....	Domestic Hot Water
ETS.....	Emission Trading System
FED .....	Final Energy Demand
GDP .....	Gross Domestic Product
LUTI .....	Land-Use and Transport Interaction
NACE .....	Nomenclature statistique des activités économiques dans la Communauté européenne
NUTS.....	Nomenclature of Territorial Units for Statistics
REF .....	Reference Scenario TransFair-AT
WAM .....	With Additional Measures
WEM.....	With Existing Measures

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