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Linking Microsimulation and Macroeconomic Models for Labor Market Analyses

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Contents

Abstract

There is a wide range of methodologies for policy evaluation and socio-economic impact assessment. A fundamental distinction can be made between micro and macro approaches. In contrast to micro models, which focus on the micro-unit, macro models are used to analyze aggregate variables. The ability of microsimulation models to capture interactions occurring at the micro-level makes them particularly suitable for modeling complex real-world phenomena. The inclusion of a behavioral component into microsimulation models provides a framework for assessing the behavioral effects of policy changes.

The labor market is a primary area of interest for both economists and policy makers. The projection of labor-related variables is particularly important for assessing economic and social development needs, as it provides insight into the potential trajectory of these variables and can be used to design effective policy responses. As a result, the analysis of labor market behavior is a primary area of application for behavioral microsimulation models. Behavioral microsimulation models allow for the study of second-round effects, including changes in hours worked and participation rates resulting from policy reforms. It is important to note, however, that most microsimulation models do not consider the demand side of the labor market.

The combination of micro and macro models offers a possible solution as it constitutes a promising way to integrate the strengths of both models. Of particular relevance is the combination of microsimulation models with general equilibrium models, especially computable general equilibrium (CGE) models. CGE models are classified as structural macroeconomic models, which are defined by their basis in economic theory. Another important category of macroeconomic models are time series models. This thesis examines the potential for linking micro and macro models. The different types of microsimulation models are presented, with special emphasis on discrete-time dynamic microsimulation models. The concept of behav-

ioral microsimulation is introduced to demonstrate the integration of a behavioral element into microsimulation models. For this reason, the concept of utility is introduced and the random utility approach is described in detail. In addition, a brief overview of macro models is given with a focus on general equilibrium models and time series models. Various approaches for linking micro and macro models, which can either be categorized as sequential approaches or integrated approaches, are presented. Furthermore, the concept of link variables is introduced, which play a central role in combining both models. The focus is on the most complex sequential approach, i. e, the bi-directional linking of behavioral microsimulation models with general equilibrium macro models.

German Abstract

Es gibt eine Vielzahl von Methoden zur Politikbewertung sowie zur Abschätzung der sozioökonomischen Folgen. Dabei kann zwischen Mikro- und Makroansätzen unterschieden werden. Im Gegensatz zu Mikromodellen, die sich auf die kleinste Einheit konzentrieren, werden Makromodelle zur Analyse aggregierter Variablen verwendet. Mikrosimulationsmodelle sind aufgrund ihrer Fähigkeit zur Erfassung von Wechselwirkungen auf der Mikroebene besonders geeignet für die Modellierung komplexer Phänomene, wie sie in der realen Welt vorkommen. Durch die Einbeziehung einer Verhaltenskomponente wird ein Rahmen für die Bewertung der Auswirkungen von politischen Maßnahmen auf das Verhalten geschaffen.

Die Projektion von arbeitsmarktbezogenen Variablen ist von besonderer Bedeutung für die Bewertung wirtschaftlicher und sozialer Entwicklungserfordernisse, da sie Einblicke in die potenzielle Entwicklung dieser Variablen bietet und die Gestaltung wirksamer politischer Maßnahmen ermöglicht. Dementsprechend stellt die Analyse des Arbeitsmarktverhaltens einen Hauptanwendungsbereich für verhaltensbasierte Mikrosimulationsmodelle dar. Verhaltensbasierte Mikrosimulationsmodelle ermöglichen es, die Folgewirkungen, einschließlich der Veränderungen in der Anzahl der geleisteten Arbeitsstunden und der Erwerbsbeteiligung, die aus politischen Reformen resultieren, zu untersuchen. Es ist jedoch zu beachten, dass die meisten Mikrosimulationsmodelle die Nachfrageseite des Arbeitsmarktes nicht berücksichtigen.

Die Kombination von Mikro- und Makromodellen bietet eine mögliche Lösung und kann die Stärken beider Modelle verbinden. Von besonderer Bedeutung ist die Möglichkeit, Mikrosimulationsmodelle mit allgemeinen Gleichgewichtsmodellen, insbesondere berechenbaren allgemeinen Gleichgewichtsmodellen (CGE-Modellen), zu verknüpfen. CGE-Modelle werden als strukturelle makroökonomische Modelle klassifiziert, die sich durch ihre wirtschaftstheoretische Fundierung auszeichnen. Eine

weitere wichtige Kategorie makroökonomischer Modelle, die mit Mikrosimulationsmodellen verknüpft werden, sind Zeitreihenmodelle. Diese Arbeit beschäftigt sich schwerpunktmäßig mit den Möglichkeiten der Verbindung von Mikro- und Makromodellen. Die verschiedenen Arten von Mikrosimulationsmodellen werden vorgestellt, wobei der Fokus auf zeitdiskreten dynamischen Mikrosimulationsmodellen liegt. Das Konzept der verhaltensbasierten Mikrosimulation wird vorgstellt und gezeigt wie Verhaltenselemente in Mikrosimulationsmodelle integriert werden können. Das Nutzenkonzept wird eingeführt und der Ansatz der Random Utility Modelle detailliert beschrieben. Es werden verschiedene Ansätze zur Verknüpfung von Mikro- und Makromodellen betrachtet. Das Konzept der Verbindungsvariablen spielt dabei eine zentrale Rolle. Der Schwerpunkt dieser Arbeit liegt auf der bi-direktionalen Verbindung von verhaltensbasierten Mikrosimulationsmodellen mit allgemeinen Gleichgewichtsmodellen, welcher als komplexester sequentieller Ansatz angesehen werden kann.

List of Figures

List of Tables

List of Notations

Unless otherwise defined, the following notations apply (in order: Latin alphabet first, then Greek alphabet):

A	Productivity
B	Brier score
B_{norm}	Normalized Brier score
B_w	Weighted Brier score
c	Consumption
C	Class indicator
d	Category weight
$\mathcal{D}$	Survey sample
$\mathcal{D}^{\mathcal{KL}}$	Kullback-Leibler divergence
$E(\cdot)$	Expected value
E_0	Expectations operator given information at time 0
$\exp(\cdot)$	Exponential function
$f(\cdot)$	Function
$F(\cdot)$	Link function
h	Hours worked
h^f	Female hours worked
h^f	Male hours worked
i	Running index for individuals in the survey sample $i = 1, ..., n$
$I(\cdot)$	Indicator function
j	Running index for states $j = 1, ..., J$
J	Number of possible outcomes
k	Running index for states $k = 1, ..., J$
K	Number of model parameters
l	Leisure

LL	Log-likelihood
$\log(\cdot)$	Logarithmic function
$\text{logit}(\cdot)$	Logit function
n	Number of individuals in the survey sample
N	Number of individuals in population $\mathcal{U}$
$\tilde{N}$	Number of individuals in population $\tilde{\mathcal{U}}$
p	Lag order
$\mathbf{P}$	Transition matrix
$P(\cdot)$	Probability function
Q	Probability distribution
r	Running index for areas $r = 1, ..., R$
R	Number of areas
s	Running index for simulation periods $s = 1, ..., \mathcal{S}$
$\mathcal{S}$	Simulation horizon
$\mathbf{S}$	Index set
t	Running index for real time periods $t = 1, ..., T$
T	T Number of real time periods
u	Running index of individuals in synthetic replica of the population $u = 1, ..., \tilde{N}$
u_i	Group-specific random effect
U	Direct utility
$\mathcal{U}$	Population with N individuals
$\tilde{\mathcal{U}}$	Synthetic replica of the population with $\tilde{N}$ individuals
V	Indirect utility
w	Wage
x_i	Vector of explanatory variables for individual i, $x_i = (1, x_{i1}, x_{i2}, ..., x_{ip})$
x_u	Vector of explanatory variables for individual u, $x_u = (1, x_{u1}, x_{u2}, ..., x_{up})$
$\mathbf{X}$	Random variable that represent individual's characteristics
y_i	Realized value of Y for individual i
y_u	Realized value of Y for individual u
Y	Random variable representing a unit characteristic for which transition probabilities are desired
z	Productivity/technology shock
Z	Taste-shifters
α	Regression coefficient for individual effects
α_c	Coefficient of consumption
α_{cc}	Coefficient of squared consumption

α_{chf}	Coefficient of interaction term between consumption and female hours worked
α_{chm}	Coefficient of interaction term between consumption and male hours worked
α_i	Group-specific constant term i
α_{hf}	Coefficient of female consumption
α_{hff}	Coefficient of squared female consumption
α_{hm}	Coefficient of male consumption
α_{hmhf}	Coefficient of interaction term between male hours worked and female hours worked
α_{hmm}	Coefficient of squared male consumption
β	Regression coefficient
γ_i	Random effect
δ	Adjustment parameter for the intercept of a regression model
Δ	Deviation
ε	Residual
η	Linear predictor
θ	Constant in MA process
λ	Wealth effect
μ	Mean
pi	Probability
ρ	Persistence parameter
σ^2	Variance function
τ	Known total
ϕ	Parameter of time-series models
φ	Coefficient of relative risk aversion
$\Phi(\cdot)$	Distribution function of the standard normal distribution
ω	Vector of structural shocks
$\hat{\cdot}$	Estimated value/parameter
$\bar{\cdot}$	Average over time
$\ddot{\cdot}$	Difference between realized value and average over time, e. g., $\ddot{y}_i^{(t)} = y_i^{(t)} - \bar{y}_i$

List of Abbreviations

ACF1	Autocorrelation of errors of lag one
AIC	Akaike information criterion
AICc	Corrected Akaike information criterion
AR(p)	Autoregressive process of order p
ARIMA(p, d, q)	Autoregressive integrated moving average process of order (p, d, q)
ARIMAX (p, d, q)	Autoregressive integrated moving average process of order (p, d, q) with explanatory variables
ARMA(p, q)	Autoregressive moving average process of order (p, q)
ARMAX(p, q)	Autoregressive moving average process or order (p, q) with explanatory variables
BIC	Bayesian information criterion
BStatG	Federal Statistics Act
CGE	Computable general equilibrium
CRRA	Constant relative risk aversion
CV	Number of folds for cross-validation
DSGE	Dynamic stochastic general equilibrium
e. g.	For example
Empl.	employment
EU	European Union
EU-SILC	European Union Statistics on Income and Living Conditions
GVAR	Global Vector autoregressive
HID	Household identification number
I(d)	Integrated process of order d
i. e.	That is
ILO	International Labour Organization
MA(q)	Moving average process of order q
MAE	Mean absolute error

MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
ME	Mean error
MikroSim	Multi-sectoral Regional Microsimulation
MPE	Mean percentage error
MZ	German Microcensus
MSE	Mean squared error
PID	Personal identification number
pp	Percentage points
RBC	Real business cycle
RMSE	Root mean squared error
RURO	Random utility random opportunity
SAE	Standardized absolute error
SAM	Social Accounting Matrix
SGB XII	Volume XII of the German Social Insurance Code
SILC	Statistics on Income and Living Conditions
TAE	Total absolute error
VAR	Vector autoregressive
%	Percent

Chapter 1

Introduction

There are a wide variety of techniques for policy evaluation and socio-economic impact assessment. A key distinction is made between micro and macro approaches. Micro models focus on the micro-unit, while macro models are employed to analyze aggregate variables. In this thesis, micro models refer to microsimulation models and macro models to macroeconomic models, including general equilibrium models and time-series models.

Microsimulation models capture interactions at the micro-level, thus enabling the modeling of complex real-world phenomena. They serve as a powerful tool for analyzing policy reforms, demographic trends, and changes in economic and social conditions. The importance of microsimulations in Germany is further evidenced by the amendment of Section 3(1) Nr. 6 Federal Statistics Act (BstatG) in 2016, which states that the Federal Statistical Office is tasked with the development and use of microsimulation models.

The labor market belongs to the euro indicators, and as such, is of central interest to economists and policymakers. The euro indicators provide economic information on the European Union (EU), the euro area, and the individual The labor market belongs to the euro indicators and thus is of central interest to economists and policymakers. Member States and are essential for the co-ordination of economic policies (Eurostat, 2024). Therefore, the projection of labor-related variables is of particular importance for the assessment of economic and social development needs. Economic and social policies include measures to promote the entry of young people into the labor market, to improve skills, and to introduce adequate minimum wages.

Non-behavioral microsimulation models are used to analyze the first-round effects of policy measures and, therefore, assume that the micro-units do not change their labor supply behavior in response to a policy change. For this reason, the analysis of labor market behavior is one of the main areas of application for behavioral microsimulation models. Behavioral microsimulation models allow to analyze second-round effects, such as changes in supplied hours worked and labor force participation due to policy reforms (Narazani et al., 2023). It should be noted, however, that most microsimulation models do not consider the demand side of the labor market. Consequently, the analysis of labor-supply behavior using microsimulation models is subject to certain limitations.

A potential solution to this short-coming is the combination of micro and macro models. In particular, microsimulation models are linked to computable general equilibrium (CGE) models and dynamic stochastic general equilibrium (DSGE) models in order to take both the supply and the demand side into account. These models are structural macroeconomic models that are based on economic theory (DeJong and Dave, 2011). Another important branch of macroeconomic models are time-series models. Time-series analysis is a statistical method used to identify and model patterns in the development of time-series data. By extrapolating the regularities identified during the observation period into the future, it is possible to forecast the time series (Neusser, 2011, p. 3). Macro models are based on a high-level aggregation and are therefore limited in their ability to map and analyze complex processes at micro-level. For this reason, a combination of micro and macro models could provide a promising approach to combine the strengths of both models.

In this thesis, we examine the potential of linking micros and macro models for labor market analysis in the context of dynamic microsimulation models. Chapter 2 introduces the basic principles of microsimulation. Initially, a technical definition of microsimulation is provided, followed by an explanation of its components. The different types of microsimulation models are then introduced, with a focus on discrete-time dynamic microsimulation models. For this type of model, different methods for estimating transition probabilities are presented, along with alignment methods. Moreover, internal and external validation methods are presented.

Chapter 3 introduces behavioral microsimulations and illustrates how a behavioral component can be incorporated into microsimulation models. The concept of utility is introduced and the random utility approach is described. Additionally, an analysis

of welfare implications of policy reforms is presented. An excursus differentiates behavioral microsimulations from agent-based simulations.

Chapter 4 is the focal point of this thesis, building upon the preceding chapters. In this chapter, both sequential approaches and the integrated approach for linking micro and macro models are presented. The concept of link variables is introduced, as it plays a central role for combining both models using sequential approaches. The focus is on linking behavioral microsimulation models with general equilibrium models, which can be considered as the most complex sequential approach.

Chapter 5 proposes an alternative approach to linking micro and macro models, namely linking micro and time-series models. Specifically, forecasts are derived from autoregressive integrated moving average (ARIMA) models and then linked to a microsimulation model. This approach requires fewer assumptions than combining behavioral microsimulation models with general equilibrium models and is therefore easier to implement.

Finally, Chapter 6 presents a synthesis of the research findings and provides insights into potential avenues for further research.

Chapter 2

Foundations of Dynamic Microsimulation Models

The following chapter introduces the basics of microsimulation models. The focus is on dynamic discrete-time microsimulations, other types of microsimulation models are only covered briefly. The chapter is structured as follows: In Section 2.1, we provide a definition of microsimulation models and give a brief overview of different types of microsimulations. In Section 2.2, we introduce modeling techniques for estimating state and transition probabilities and explain the modeling as well as the simulation process in more detail. Furthermore, we present different alignment approaches. Most microsimulation models use some kind of alignment to ensure that the simulated results meet known aggregates. Subsequently, in Section 2.3, we introduce validation methods and distinguish between internal and external validation. In Section 2.4, we present an application based on the multi-sectoral regional microsimulation (MikroSim) model, in particular the employment module. We model employment transitions using different statistical modeling techniques and evaluate the results on the basis of quality criteria. Finally, in Section 2.5, we summarize and give an outlook to further research.

2.1 Methodological Differentiation

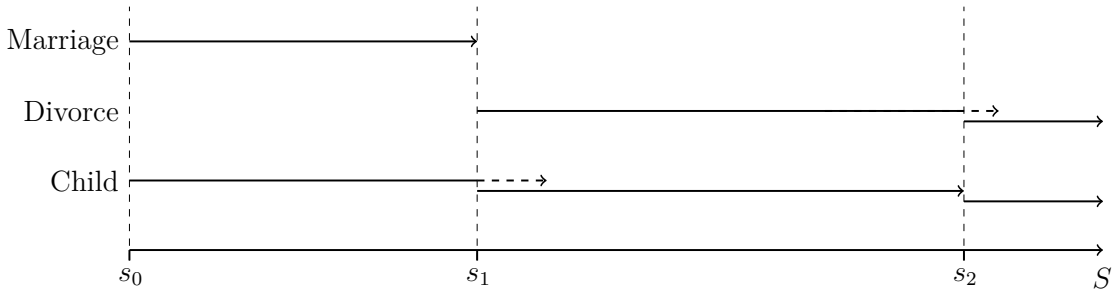
Microsimulation models are simulations of systems at the micro-unit level. They can be used to analyze complex real-world phenomena by simulating the effects of (policy) scenarios on the micro-unit (Harding et al., 2010). Thus, microsimulations offer the possibility to answer "what-if" questions (Li et al., 2014a, p. 305). Micro-units are, for example, individuals, households, or firms. In the field of economic and social research, the focus is on analyzing the impact of policy reforms at the level of individuals and households.

An important distinction in the field of microsimulation is the distinction between static and dynamic microsimulation models. Static microsimulation models are used to analyze the immediate impact of scenarios on selected target values. The EUROMOD model is one of the most popular static microsimulation models. It is an open source tax-benefit model that mainly builds on the EU Statistics on Income and Living Conditions (EU-SILC) (European Union, 2022). In static microsimulation models, the time component is considered indirectly through static aging, i. e., up-rating and re-weighting. Up-rating is the calibration of, typically monetary, variables to exogenously projected developments by inflation or deflation. Re-weighting is the adjustment of individual weights to meet known or assumed developments. Consequently, in static microsimulation models, an aging population is simulated by increasing the weights of older individuals while, at the same time, keeping the weights of younger individuals constant (Merz, 1991; Li et al., 2014b; Dekkers, 2015; Burgard et al., 2020a). Thus, individuals do not change their characteristics during the simulation process.

Dynamic microsimulation models extend static microsimulation models by including a time component. Individuals change their characteristics and progress over the simulation horizon. Therefore, dynamic microsimulation models can be used to analyze life histories of micro-units. Characteristic features of dynamic microsimulation models are stochastic transitions and direct changes of the attributes at micro-level. The probability of the occurrence of a particular even depends on the simulated time and the endogenous characteristics of the micro-unit (Merz, 1991; Bourguignon and Spadaro, 2006; Li et al., 2014a; Burgard et al., 2020a; Münnich et al., 2021). Examples of dynamic microsimulation models include DYNACAN (Rick Morrison, 1998), DynaSim (Sherfey et al., 2018) and MikroSim (Münnich et al., 2021).

Dynamic microsimulation models are either discrete-time or continuous-time models. In continuous-time microsimulation models, transitions are determined based on waiting times, i. e., the length of time that a micro-unit remains in its current state. Transitions are usually obtained using survival analysis. Once an event has occurred, the micro-unit runs through all survival functions that are feasible given its current state (Li, 2011, p. 33; Li and O'Donoghue, 2013; Burgard et al., 2020a; Münnich et al., 2021). Figure 2.1 illustrates a synthetic part of micro-unit's life-course in a continuous-time microsimulation model. At the beginning of the simulation, s_0, the individual is childless and single. The waiting time of the event of a marriage is shorter than the waiting time of the event of giving birth. Thus, the individual gets married at s_1 and the waiting time for having a child is redetermined depending on the event of a marriage. Furthermore, being married qualifies the individual for the event of a divorce. In this example, the birth of the child occurs before the divorce as the waiting time for becoming a child is shorter than the waiting time for a divorce. At time s_2 the person is married and has a child. Subsequently, the waiting times for the events of giving birth to a second child and divorce are redetermined. If the waiting time exceeds the simulation horizon $\mathcal{S}$, the person remains in the respective state.

Figure 2.1: Continuous-time microsimulation



Source: Own illustration based on Zinn (2014).

In discrete-time microsimulation models, events take place at pre-defined time intervals. The simulation horizon $\mathcal{S}$ with $\mathcal{S}$ being a finite set of periods, $\mathcal{S} := \{1, \ldots, S\}$. In each time period s, micro-units pass through several transition matrices to simulate state transitions. Transitions can occur from period to period. The exact time within the interval is disregarded (Li, 2011; Li and O'Donoghue, 2013; Burgard et al., 2020a). In the following, we focus on discrete-time dynamic microsimulations. Figure 2.2 shows an example of a discrete-time microsimulation model with annual

transitions from 2011 to 2012. The individual with household identification number (HID) 2 and personal identification number (PID) 3 changes its employment status (Empl. status) from 2011 to 2012 unemployed to employed. Moreover, the person becomes one year older.

Figure 2.2: Discrete-time microsimulation

2011

PID	**HID**	**Age**	**Sex**	**Empl. status**	**Marital status**
1	1	22	male	employed	single
2	2	35	male	employed	married
3	2	29	female	unemployed	married
4	2	4	female	not active	single
5	3				
6	3				
7	4				

2012

PID	**HID**	**Age**	**Sex**	**Empl. status**	**Marital status**
1	1	23	male	employed	single
2	2	36	male	employed	married
3	2	30	female	employed	married
4	2	5	female	not active	single
5	3	50	female	employed	divorced
6	3	19	male	unemployed	single
7	4	16	male	not active	single

Source: Own illustration based on Harding et al. (2010) and Burgard et al. (2020b, p. 287).

The choice between continuous-time and discrete-time microsimulation models depends on whether the exact timing of the event is relevant to the research question, and, from a methodological perspective, on the assumptions for estimating transition probabilities. Discrete-time microsimulations, compared to continuous-time microsimulations, require fewer assumptions regarding the modeling of transition probabilities. However, they are also less flexible in addressing complex interdependent event sequences (Burgard et al., 2020a).

In closed dynamic microsimulation models, the population development is determined by internal events. With the exception of migration across national borders, the individuals can be tracked over time. According to Li and O'Donoghue (2013, p. 22), "[a] model is often considered to be closed if, except in the case of new born and migrants, the model only uses a fixed set of individuals to create and maintain social links". In open dynamic microsimulation models also internal migrants, i. e., individuals who move across regional borders within a country, cannot be tracked

over time. A household moving from one region to another is first removed from the population of the former region. Then, a household from an external population is added to the later region. Therefore, open microsimulation models are less computational demanding (Li, 2011, pp. 34, 35; Li and O'Donoghue, 2013; Burgard et al., 2020a). See Schmaus (2023, ch. 4) for the construction process of a closed migration module for dynamic microsimulation models.

Cohort and population models differ with regard to the population of interest. Cohort models consider only a part of the population, e. g., a birth cohort over its lifetime. The base population constitutes of a subset of the population that is relevant for answering the research question. Thus, cohort models significantly reduce model complexity and computing time. Population models consider the entire population regardless of the research objective (Li, 2011, p. 26; Li and O'Donoghue, 2013).

A further distinction can be made between behavioral and non-behavioral models. Non-behavioral models are also known as arithmetical models (Bourguignon and Spadaro, 2006). Behavioral models are grounded in economic theory, while non-behavioral models are based on empirical models. Traditionally, microsimulation models abstract from behavioral adjustments (Bourguignon and Spadaro, 2006; Li and O'Donoghue, 2013; Sutherland and Figari, 2013). However, some models, such as IZAΨMOD (Peichl et al., 2010), also simulate behavioral responses to policy changes. Behavioral components are frequently incorporated for the analysis of labor supply behavior (Aaberge et al., 2000; Lay, 2010; Barrios et al., 2016; O'Donoghue, 2021, p. 16). In Chapter 3, we cover behavioral microsimulation models in more detail.

2.2 Estimation and Simulation of Transitions

In microsimulation models, three types of data are considered:

1. The real population $\mathcal{U}$
2. The synthetic replica of the real population $\tilde{\mathcal{U}}$
3. A survey sample $\mathcal{D}$.

The notation is based on Burgard et al. (2021). The real population $\mathcal{U}$ consists of $|\mathcal{U}| = N$ individuals and constitutes the population of interest. It is spatially

segmented in R areas with $r = 1, ..., R$. The number of individuals per area r is defined as $|\mathcal{U}_r| = N_r$ with $\sum_{r=1}^{R} N_r = N$.

The synthetic population of $\mathcal{U}$ is denoted $\tilde{\mathcal{U}}$ and contains $\tilde{\mathcal{U}} = \tilde{N}$ individuals indexed by $u = 1, ..., \tilde{N}$. The number of individuals per area $r = 1, ..., R$ is defined as $|\tilde{\mathcal{U}}_r| = \tilde{N}_r$ with $\sum_{r=1}^{R} \tilde{N}_r = \tilde{N}$. The synthetic base population is updated over the simulation horizon $\mathcal{S} = \{1, ..., S\}$. The simulation periods are denoted by $s \in \mathcal{S}$ (Burgard et al., 2021).

Dynamic discrete-time microsimulation models aim at projecting the base population $\tilde{\mathcal{U}}$ into the future based on transition probabilities. Transition probabilities are mainly estimated using survey data $\mathcal{D} \subset \mathcal{U}$. The sample includes n unique individuals for T time periods, where $i = 1, ..., n$ and $t = 1, ..., T$. If no suitable survey data are available, alternative data sources can be used to obtain transition probabilities. For example, life tables can be used to determine individual mortality probabilities (Münnich et al., 2021).

In discrete-time dynamic microsimulation models, state transitions are either stochastic or deterministic. Stochastic transitions have a random component, while deterministic transitions are determined based on unique, pre-defined rules and depend solely on the initial state or external factors. An example for deterministic transitions is the aging of the population over the simulation horizon $\mathcal{S}$. Since most transitions in discrete-time microsimulation models are stochastic in nature, the focus is on stochastic transition probabilities in the following.

2.2.1 Transition Probabilities

Define $\mathbf{X}$ as random variable that represent individual's characteristics, which are statistically related to a random variable Y with a finite number of J outcomes. The elements Y_j are unordered, mutually exclusive and indexed by $j = 1, ..., J$. Given $x_{ur}^{(s)}$ is the realized value of $\mathbf{X}$ for some $u \in \tilde{\mathcal{U}}_r$ in $s \in \mathcal{S}$ and $y_{ur}^{(s)}$ the realized value of Y for some $u \in \tilde{\mathcal{U}}_r$ in $s \in \mathcal{S}$, the conditional transition probability from state Y_j to state Y_k in simulation period $s + 1$ is given as (Burgard et al., 2021):

$$\pi_{ur}^{(s+1)jk}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}, s\right) := P\left(y_{ur}^{(s+1)} = Y_k | y_{ur}^{(s)} = Y_j, \mathbf{X} = x_{ur}^{(s+1)}, \mathcal{S} = s\right) \tag{2.1}$$

with $0 \leq \pi_{ur}^{(s+1)jk}\left(y_{ur}^{(s)}, \mathbf{x}_{ur}^{(s+1)}, s\right) \leq 1$.

For most variables, "the values for one year depend on, or are related to, the values in the previous year or years" (McLay et al., 2015, p. 87). For notational convenience, we assume that for the transition from Y_j to Y_k it is sufficient to take into account the last period only. Moreover, we assume that the transitions are time-invariant. In discrete-time dynamic microsimulation models, transition probabilities are generally modeled as first-order Markov processes, where the state in period $s+1$ depends solely on the previous state s (Richiardi and Poggi, 2014, p. 37; Burgard et al., 2020b, p. 291) or by including the lagged dependent variable as explanatory variable in the regression model (Richiardi and Poggi, 2014). Thus (Burgard et al., 2021),

$$\pi_{ur}^{(s+1)jk}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}, s\right) := P\left(y_{ur}^{(s+1)} = Y_k | y_{ur}^{(s)} = Y_j, \mathbf{X} = x_{ur}^{(s+1)}\right). \tag{2.2}$$

The transition probabilities can be summarized in a $J \times J$ transition matrix

$$\mathbf{P}_{ur} = \begin{pmatrix} \pi_{ur}^{(s+1)11}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) & \pi_{ur}^{(s+1)12}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) & \dots & \pi_{ur}^{(s+1)1J}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{ur}^{(s+1)J1}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) & \pi_{ur}^{(s+1)J2}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) & \dots & \pi_{ur}^{(s+1)JJ}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) \end{pmatrix} \tag{2.3}$$

with $\sum_{k=1}^{J} \pi_{ur}^{(s+1)jk}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right) = 1$ (Burgard et al., 2021). Since the current status is known, $J-1$ rows of the transition matrix $\mathbf{P}_{ur}$ (2.3) are redundant. Thus, the transition probabilities for all individuals $u \in \tilde{\mathcal{U}}_r$ can be summarized in a $\tilde{N}_r \times J$ transition matrix

$$\mathbf{P}_r = \begin{pmatrix} \pi_{1r}^{(s+1)1}\left(y_{1r}^{(s)}, x_{1r}^{(s+1)}\right) & \pi_{1r}^{(s+1)2}\left(y_{1r}^{(s)}, x_{1r}^{(s+1)}\right) & \dots & \pi_{1r}^{(s+1)J}\left(y_{1r}^{(s)}, x_{1r}^{(s+1)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{\tilde{N}_r r}^{(s+1)1}\left(y_{\tilde{N}_r r}^{(s)}, x_{\tilde{N}_r r}^{(s+1)}\right) & \pi_{\tilde{N}_r r}^{(s+1)2}\left(y_{\tilde{N}_r r}^{(s)}, x_{\tilde{N}_r r}^{(s+1)}\right) & \dots & \pi_{\tilde{N}_r r}^{(s+1)J}\left(y_{\tilde{N}_r r}^{(s)}, x_{\tilde{N}_r r}^{(s+1)}\right) \end{pmatrix}, \tag{2.4}$$

where the column sums $\sum_{r=1}^{R}\sum_{u=1}^{\tilde{N}_r} \pi_{ur}^{(s+1)k}\left(y_{ur}^{(s)}, x_{ur}^{(s+1)}\right)$ equal the expected number of individuals in state k in simulation period $s+1$. The transitions probabilities $\pi_{ur}^{(s+1)jk}$ are estimated based on the sample elements $i \in \mathcal{D}$.

In the course of dynamic microsimulation models, it might be necessary to extend the base population. In particular when new thematic areas are to be integrated into a microsimulation model, variables often have to be added to the base population. This can be done either once at the beginning of the simulation process or in

each simulation run. The principles for estimating transition probabilities described above can be also applied to the estimation of state probabilities. The fundamental difference is that instead of estimating the probability of a transition from state Y_j in simulation period s to state Y_k in simulation period $s+1$, the probability of state Y_j in period s is estimated. The conditional probability for state Y_j for $u \in \tilde{\mathcal{U}}_r$ in simulation period s is given as:

$$\pi_{ur}^{(s)j}\left(x_{ur}^{(s)}\right) := P\left(y_{ur}^{(s)} = Y_j | \mathbf{X} = x_{ur}^{(s)}\right) \tag{2.5}$$

with $0 \leq \pi_{ur}^{(s)j}(x_{ur}^{(s)}) \leq 1$.

2.2.2 Estimation Stage

There are various approaches for estimating transition probabilities. The choice of the modeling strategy is crucial for the quality of the prediction. In the following, we present several modeling strategies for estimating state and transition probabilities. The description of the regression models is based on the micro-units i included in the survey sample $\mathcal{D}$. The regions are not indexed in the following, as the survey data generally does not have the geographical differentiation of base populations (for small-scale models). For notational convenience, the modeling strategies for estimating probabilities of occurrence based on cross-sectional data are described. The elements of the ith row of the $n \times p$ matrix $\mathbf{X}$ are specified as $x_i^{(t)} = \left(1, x_{i1}^{(t)}, x_{i2}^{(t)}, \cdots, x_{ip}^{(t)}\right)$. In most contexts, the first column of $\mathbf{X}$ contains 1 only, so that β_1 is a constant (Greene, 2012, p. 55).

Generalized linear models

Generalized linear models are a general class of models that includes linear models, logit models and probit models, among others (Fahrmeir et al., 2009, p. 56). Linear regression models provide the basis for more elaborate specifications for estimating transition probabilities. It is assumed that for each individual i in the survey sample $\mathcal{D}$, the observations $\left(y_i^{(t)}, x_{i1}^{(t)}, x_{i2}^{(t)}, \cdots, x_{ip}^{(t)}\right)$ are generated by the following process (Greene, 2012, p. 53):

$$y_i^{(t)} = x_{i1}^{(t)}\beta_1 + x_{i2}^{(t)}\beta_2 + \cdots + x_{ip}^{(t)}\beta_p + \varepsilon_i^{(t)}, \quad i = 1, \cdots n \tag{2.6}$$

with $y_i^{(t)}$ being the dependent variable, $\mathbf{x}_i^{(t)}$ the independent variables, and $\varepsilon_i^{(t)}$ identically and independently distributed error terms. The expected value $E\left(y_i^{(t)}\right)$ is

given as (Fahrmeir et al., 2009, p. 55):

$$E\left(y_i^{(t)}\right) = x_{i1}^{(t)}\beta_1 + x_{i2}^{(t)}\beta_2 + \cdots + x_{ip}^{(t)}\beta_p = \eta_i^{(t)} \tag{2.7}$$

with $\eta_i^{(t)}$ denoting the linear predictor. The parameters are estimated using the method of least squares, see von Auer (2007, pp. 49ff), Greene (2012, pp. 66ff), and Wooldridge (2020, pp. 20ff). Linear regression models are particularly suitable for estimating a continuous dependent variable that is approximately normally distributed (Fahrmeir et al., 2009, p. 30). However, in microsimulation models, most variables are binary or categorical, e. g., fertility, marriage, and death (Li, 2011, p. 92; Richiardi and Poggi, 2014). For this reason, (multinomial) logit models are mainly used for estimating transition probabilities in discrete-time dynamic microsimulation models.

In the case of binary dependent variables $y_i^{(t)} \in \{0, 1\}$, probabilities of occurrence can be estimated using logit models. The dependent variable follows a Bernoulli distribution with the following probability distribution (Greene, 2012, p. 727):

$$\begin{aligned} P\left(y_i^{(t)} = 1|x_i^{(t)}\right) &= F\left(\eta_i^{(t)}\right) = \pi_i^{(t)} \\ P\left(y_i^{(t)} = 0|x_i^{(t)}\right) &= 1 - F\left(\eta_i^{(t)}\right) = 1 - \pi_i^{(t)}. \end{aligned} \tag{2.8}$$

The co-domain of the link function F is in the interval $[0, 1]$ to ensure that $0 \leq P\left(y_i^{(t)} = 1|x_i^{(t)}\right) \leq 1$ (Fahrmeir et al., 2009, p. 31). In the logit model, the link function F takes the form of the logistic response function (Fahrmeir et al., 2009, p. 56):

$$E\left(y_i^{(t)}\right) = P\left(y_i^{(t)} = 1|x_i^{(t)}\right) = \pi_i^{(t)} = \frac{\exp\left(\eta_i^{(t)}\right)}{1 + \exp\left(\eta_i^{(t)}\right)} \tag{2.9}$$

with the linear predictor $\eta_i^{(t)} = x_{i1}^{(t)}\beta_1 + \cdots + x_{ip}^{(t)}\beta_p$. A logit link function is obtained by taking the logarithm of the odds ratio (called log-odds) of the probability $\pi_i^{(t)}$ and the counter-probability $1 - \pi_i^{(t)}$ (Fahrmeir et al., 2009, pp. 31f):

$$F\left(\pi_i^{(t)}\right) = \text{logit}\left(\pi_i^{(t)}\right) = \log\left(\frac{P\left(y_i^{(t)} = 1|x_i^{(t)}\right)}{1 - P\left(y_i^{(t)} = 1|x_i^{(t)}\right)}\right) = \log\left(\frac{\pi_i^{(t)}}{1 - \pi_i^{(t)}}\right) = x'^{(t)}_i\beta. \tag{2.10}$$

The log-odds can be converted back into probabilities by using the inverse link function $F^{-1}(\cdot)$:

$$\pi_i^{(t)} = F^{-1}\left(F\left(\pi_i^{(t)}\right)\right) = \frac{\exp\left(x'^{(t)}_i\beta\right)}{1+\exp\left(x'^{(t)}_i\beta\right)}. \tag{2.11}$$

If the link function $F(\cdot)$ is a probit link function, one obtains (Greene, 2012, p. 728):

$$F\left(\pi_i^{(t)}\right) = \text{probit}\left(\pi_i^{(t)}\right) = \Phi\left(\pi_i^{(t)}\right). \tag{2.12}$$

The log-odds can be converted back into probabilities by using the inverse link function $F^{-1}(\cdot)$:

$$\pi_i^{(t)} = F^{-1}\left(F\left(\pi_i^{(t)}\right)\right) = \Phi\left(x'^{(t)}_i\right). \tag{2.13}$$

Both logit and probit models can be used in microsimulations. In the following, however, we focus on (multinomial) logit models as they are mainly used for estimating probabilities in dynamic discrete-time microsimulation models.

The multinomial logit model is a generalization of the logit model for more than two categories. For the multinomial logit model with J categories indexed by $k = 1, ..., J$, one obtains a set of $J-1$ independent logit models, which are compared to the reference outcome (Hosmer and Lemeshow, 2010, p. 261; Burgard et al., 2021). Let $Y_i^{(t)k}$ be a random variable that indicates the choice made, i. e., $Y_i^{(t)k}$ takes the value 1, if $y_i^{(t)} = Y_k$, and 0 else. Moreover, we define category j as reference category.

The probability of occurrence of Y_k for individual i for $k \neq j$ is obtained as (Greene, 2012, p. 803):

$$P\left(y_i^{(t)} = Y_k | x_i^{(t)}\right) = \pi_i^{(t)k} = \frac{\exp\left(x'^{(t)}_i\beta_k\right)}{1+\sum_{l\in\{1,...,J\}\setminus j}\exp\left(x'^{(t)}_i\beta_l\right)}, \tag{2.14}$$

where β_k is the vector of regression coefficients associated with $x_i^{(t)}$.

For the reference category $k = j$, the probability occurrence of Y_j for individual i,

is obtained as:

$$\pi_i^{(t)j} = \frac{1}{1 + \sum_{l \in \{1,...,J\} \setminus j}^{J} \exp\left(x'^{(t)}_i \beta_l\right)}. \tag{2.15}$$

The log-likelihood function for a single individual $i \in \mathcal{D}$ is given by (Hosmer and Lemeshow, 2000, p. 263; Burgard et al., 2021):

$$LL_i^{(t)}(\beta_1, ..., \beta_J) = \sum_{l \in \{1,...,J\} \setminus j}^{J} y_i^{(t)} x'^{(t)}_i \beta_l - \log\left(1 + \sum_{l \in \{1,...,J\} \setminus j}^{J} \exp\left(x'^{(t)}_i \beta_l\right)\right). \tag{2.16}$$

Given that the sample observations are independent, the model parameter estimates are obtained by minimizing the sum of the negative log-likelihoods (Burgard et al., 2021):

$$(\hat{\beta}_1, ..., \hat{\beta}_J) = \underset{\beta_1,...,\beta_J}{\operatorname{argmin}} \left\{ - \left(\sum_{i \in \mathcal{D}} LL_i^{(t)}(\beta_1, ..., \beta_J) \right) \right\}. \tag{2.17}$$

As an alternative to the multinomial logit model, the multinomial probit model, which does not require the independence assumption, can be used. For more details, see Greene (2012, pp. 810f).

As previously stated, there are two approaches for modeling state-dependent transition probabilities: First, modeled as first-order Markov processes (Richiardi and Poggi, 2014, p. 37; Burgard et al., 2020b, p. 291) and second, by including the lagged dependent variable as an explanatory variable in the regression model (Richiardi and Poggi, 2014). In first-order Markov processes, the state in period $t+1$ depends solely on the previous state t. In the binary case, the variable of interest, $y_i^{(t)}$, can only take two states $\{Y_1, Y_2\}$, which are defined as $\{0, 1\}$. The transition probabilities for individual i are:

$$\begin{aligned} P\left(y_i^{(t)} = 1 | x_i^{(t)}, y_i^{(t-1)} = 0\right) &= \frac{\exp\left(x'^{(t)}_i \beta_{01}\right)}{1 + \exp\left(x'^{(t)}_i \beta_{01}\right)} \\ P\left(y_i^{(t)} = 1 | \mathbf{x}_i^{(t)}, y_i^{(t-1)} = 1\right) &= \frac{\exp\left(x'^{(t)}_i \beta_{11}\right)}{1 + \exp\left(x'^{(t)}_i \beta_{11}\right)}, \end{aligned} \tag{2.18}$$

where β_{01} (β_{11}) is the parameter vector for a transition from state 0 at time $t-1$ to state 1 at time t (from state 1 at time $t-1$ to state 1 at time t). The advantage

of Markovian transitions is the ability to include different explanatory variables in the split processes (Richiardi and Poggi, 2014, p. 37).

The probit model for modeling Markovian transition probabilities is given as (Richiardi and Poggi, 2014, p. 37):

$$\begin{aligned} P(y_i^{(t)} = 1 | x_i^{(t)}, y_i^{(t-1)} = 0) &= \Phi(x_i'^{(t)} \beta_{01}) \\ P(y_i^{(t)} = 1 | x_i^{(t)}, y_i^{(t-1)} = 1) &= \Phi(x_i'^{(t)} \beta_{11}). \end{aligned} \tag{2.19}$$

For more then two choices, i. e., in the multinomial logit model, Markovian transition probabilities for $k \neq j$ are obtained by:

$$P\left(y_i^{(t)} = Y_k | x_i^{(t)}, y_i^{(t-1)} = Y_m\right) = \frac{\exp\left(x_i'^{(t)} \beta_{mk}\right)}{1 + \sum_{l \in \{1,\ldots,J\} \setminus j}^{J} \exp\left(x_i'^{(t)} \beta_{ml}\right)} \tag{2.20}$$

and for the reference category $k = j$ by:

$$P\left(y_i^{(t)} = Y_j | x_i^{(t)}, y_i^{(t-1)} = Y_m\right) = \frac{1}{1 + \sum_{l \in \{1,\ldots,J\} \setminus j}^{J} \exp\left(x_i'^{(t)} \beta_{ml}\right)} \tag{2.21}$$

with $m = 1, ..., J$.

Alternatively, transition probabilities can be modeled by including the lagged dependent variable as explanatory variable, which is also referred to as dynamic logit model. In the binary case, where the variable of interest $y_i^{(t)}$ can only assume two states $\{Y_1, Y_2\}$, the transition probability is obtained as follows (Greene, 2012, p. 769):

$$P\left(y_i^{(t)} = 1 | x_i^{(t)}, y_i^{(t-1)}\right) = \frac{\exp\left(x_i'^{(t)} \beta + y_i^{(t-1)} \gamma\right)}{1 + \exp\left(x_i'^{(t)} \beta + y_i^{(t-1)} \gamma\right)}, \tag{2.22}$$

where γ is defined as regression coefficient for the lagged dependent variable.

The probit model for dynamic probit models is given as (Richiardi and Poggi, 2014):

$$P(y_i^{(t)} = 1 | x_i^{(t)}, y_i^{(t-1)}) = \Phi(x_i'^{(t)} \beta + y_i^{(t-1)} \gamma). \tag{2.23}$$

The multinomial model for estimating transition probabilities for $k \neq j$ is given as (Burgard et al., 2021):

$$P\left(y_i^{(t)} = Y_k | x_i^{(t)}, y_i^{(t-1)}\right) = \frac{\exp\left(x'^{(t)}_i \beta_k + y_i^{(t-1)} \gamma_k\right)}{1 + \sum_{l \in \{1,\ldots,J\} \setminus j} \exp\left(x'^{(t)}_i \beta_l + y_i^{(t-1)} \gamma_l\right)} \tag{2.24}$$

and for reference category $k = j$ as:

$$P\left(y_i^{(t)} = Y_k | x_i^{(t)}, y_i^{(t-1)}\right) = \frac{1}{1 + \sum_{l \in \{1,\ldots,J\} \setminus j} \exp\left(x'^{(t)}_i \beta_l + y_i^{(t-1)} \gamma_l\right)}. \tag{2.25}$$

Conditional inference trees

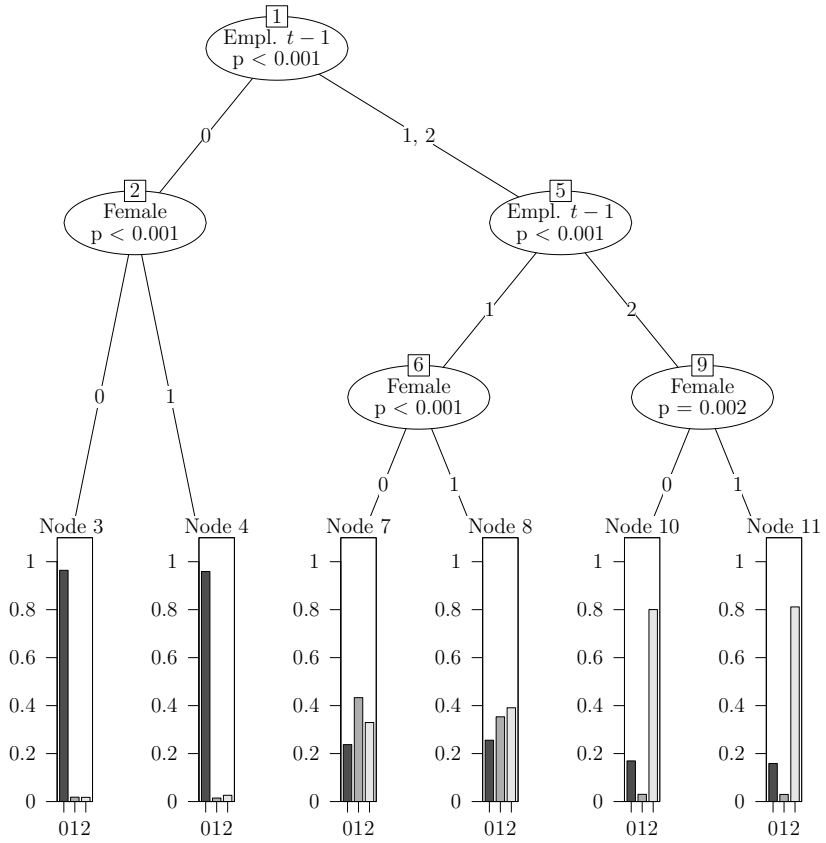
Various model-based methods exist for estimating probabilities of occurrence and transition probabilities. Alternatively to the model based approaches, some dynamic discrete-time microsimulation models, such as the SMILE microsimulation model (Rasmussen and M. F. Hansen, 2013; M. F. Hansen et al., 2019), use conditional inference trees to obtain transition probabilities. On the basis that there are no impossible state changes in the survey data, the conditional inference tree algorithm has the advantage of detecting implausible state changes and not assigning positive transition probabilities to these events (Schmaus, 2023, pp. 35f).

The conditional inference tree algorithm is well-suited for estimating discrete states using multiple individual characteristics as explanatory variables (M. F. Hansen et al., 2019). Compared to logit or multinomial models, conditional inference trees are found to provide better covariate interactions. However, this finding cannot be generalized. Generalized linear models may outperform conditional inference trees depending on the covariate selection method and type of response variable (Fernández-Delgado et al., 2014; M. F. Hansen et al., 2019).

The recursive binary partitioning algorithm is conducted step-wise. In the first step, the algorithm tests the global null hypothesis of the independence of all explanatory variables. If the null hypothesis cannot be rejected, the algorithm terminates. Otherwise, the covariates with the strongest influence on Y are selected. In the second step, the variables selected in the first step are split and the procedure is repeated. For comprehensive information on conditional inference trees, please refer to Hothorn et al. (2006) and Hothorn and Zeileis (2015).

Figure 2.3 shows a conditional inference tree that predicts the employment status using the lagged employment status (Empl. $t-1$) and sex (Female) as explanatory variables. The employment variable (Empl.; Empl $t-1$) can take three values: 0 if the individual is employed, 1 if the individual is unemployed, and 2 if the individual is inactive. The sex variable (Female) takes the value 1 if the individual is female and 0 if the individual is male. The data used is from the German Microcensus (MZ) Scientific Usefile 2014 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations). The tree's splitting criteria and corresponding p-values are located at the branches. If additional explanatory variables are considered, the resulting tree diagram becomes more complex and, therefore, unsuitable for illustrative purposes.

Figure 2.3: Conditional inference tree for modeling the employment status differentiated by lagged employment status, and sex



Source: RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations.

In many real-world applications, the data set is imbalanced, i. e., "there is a significant, or in some cases extreme, disproportion among the number of examples of each class of the problem" (Fernández et al., 2018, p. 19). A number of techniques have been developed to address the issue of imbalanced data sets. These can be grouped into: data sampling, algorithmic modification, cost-sensitive learning, and ensemble-based methods. A description can be found in Fernández et al. (2018).

Panel data models

Survey data are often available as panel data sets. Panel data have the advantage of allowing for unobserved heterogeneity. The three most commonly used regression-based approaches for panel data are pooled regression, fixed effects model, and random effects models (mixed models) (Greene, 2012, p. 383). The basic panel data model is given as (Greene, 2012, p. 385):

$$y_i^{(t)} = x'^{(t)}_i \beta + z_i' \alpha + \varepsilon_i^{(t)} \tag{2.26}$$

with $p-1$ regressors in $x_i^{(t)}$, i. e., not containing a constant term. The heterogeneity is represented by $z_i'\alpha$. The vector z_i includes a constant term and individual observed and unobserved characteristics that are constant over time t. If z_i consists of observed individual characteristics only, then the panel data model (2.26) can be considered as an ordinary linear regression model. However, in most applications z_i contains unobserved characteristics (Greene, 2012, pp. 385ff).

The pooled regression model is given as (Greene, 2012, p. 389):

$$y_{it} = \alpha + x'^{(t)}_i \beta + \varepsilon_i^{(t)}. \tag{2.27}$$

In the pooled regression model, z_i is a constant term. Therefore, ordinary least squares yield consistent and efficient estimates of α and β (Greene, 2012, pp. 386, 757).

The fixed effects approach assumes that z_i consists of unobserved characteristics that are correlated with the regressors $x_i^{(t)}$. For notational convenience, α_i is defined as $\alpha_i = z_i'\alpha$. The fixed effects model is given as (Greene, 2012, p. 386):

$$\begin{aligned} y_i^{(t)} &= \beta_1 x_{i1}^{(t)} + \beta_2 x_{i2}^{(t)} + \cdots + \beta_p x_{ip}^{(t)} + \alpha_i + \varepsilon_i^{(t)}, \qquad t = 1, \cdots, T \\ y_i^{(t)} &= x'^{(t)}_i \beta + \alpha_i + \varepsilon_i^{(t)}. \end{aligned} \tag{2.28}$$

The model is called fixed effects model due to the correlation of α_i and x_{it}. Therefore, the ordinary least squares estimator of β is biased and inconsistent (Greene, 2012, p. 386). A transformation is used to remove α_i (Wooldridge, 2020, p. 462). For each i the average over time (Wooldridge, 2020, p. 463):

$$\bar{y}_i = \beta_1 \bar{x}_{i1} + \beta_2 \bar{x}_{i2} + \cdots + \beta_p \bar{x}_{ip} + \alpha_i + \bar{\varepsilon}_i \tag{2.29}$$

is subtracted from model (2.28). This yields:

$$y_i^{(t)} - \bar{y}_i = \beta_1 \left(x_{i1}^{(t)} - \bar{x}_{i1} \right) + \beta_2 (x_{i2}^{(t)} - \bar{x}_{i2}) + \cdots + \beta_p \left(x_{ip}^{(t)} - \bar{x}_{ip} \right) + \varepsilon_i^{(t)} - \bar{\varepsilon}_i. \tag{2.30}$$

Defining $\ddot{y}_i^{(t)} = y_i^{(t)} - \bar{y}_i$ (and equivalently $\ddot{x}_{i1}^{(t)}$, $\ddot{x}_{i2}^{(t)}$, ..., $\ddot{x}_{ip}^{(t)}$, and $\ddot{\varepsilon}_i^{(t)}$), the equation (2.30) can be rewritten as (Wooldridge, 2020, p. 463):

$$\ddot{y}_i^{(t)} = \beta_1 \ddot{x}_{i1}^{(t)} + \beta_1 \ddot{x}_{i1}^{(t)} + \cdots + \beta_1 \ddot{x}_{i1}^{(t)} + \ddot{\varepsilon}_i^{(t)}. \tag{2.31}$$

The main disadvantage of the fixed effects approach is that "[a]ny time-invariant variables in $x_i^{(t)}$ will mimic the individual specific constant term [...] [and] [t]he coefficients on the time-invariant variables cannot be estimated" (Greene, 2012, p. 400). They can therefore not be taken into account as exogenous variables, which is why the method can be considered unusable for microsimulation models.

In the random effects approach, the unobserved individual effects are assumed to be uncorrelated with $x_i^{(t)}$. The model can be specified as (Greene, 2012, p. 387):

$$y_i^{(t)} = x'^{(t)}_i \beta + \alpha + u_i + \varepsilon_i^{(t)} \tag{2.32}$$

with u_i being a group-specific random element. Applying least squares yields consistent but inefficient estimates of β (Greene, 2012, p. 387). As noted above, most variables in microsimulation models are binary (or multinomial). The general formulation of binary choice models for panel data is (Greene, 2012, p. 756):

$$y_i^{(t)} = \mathbb{1} \left(x'^{(t)}_i \beta + \varepsilon_i^{(t)} > 0 \right), \qquad i = 1, \cdots, n, \qquad t = 1, \cdots T_i. \tag{2.33}$$

The random effects model can be specified as (Greene, 2012, pp. 399, 756):

$$y_i^{(t)} = \mathbb{1}\left(x_i'^{(t)}\beta + \alpha + u_i + \varepsilon_i^{(t)} > 0\right), \qquad i = 1, \cdots, n, \qquad t = 1, \cdots T_i. \tag{2.34}$$

For more details on estimating binary choice panel models, see Greene (2012, pp. 756ff).

2.2.3 Simulation Stage

After estimating the probabilities for certain states or state changes, it is determined whether a concrete state change occurs. If a state change occurs, the state must be updated and all associated changes must be taken into account. For example, if a married individual passes away, the state changes from alive to dead, and the state of the spouse changes from married to widowed.

The simulation stage represents the core of a microsimulation model and can be understood as the actual simulation. The inverse-transform method is commonly used in microsimulation models for determining state changes (van Imhoff and Post, 1998; Münnich et al., 2020, p. 119; Burgard et al., 2020b, p. 291; Frohn and Obersneider, 2020, p. 144; Münnich et al., 2021). It is a technique to generate samples from a probability distribution given its cumulative distribution function (Rubinstein and Kroese, 2016, pp. 55-57). The procedure contains the following steps (van Imhoff and Post, 1998; Burgard et al., 2020b, p. 291):

1. A uniformly distributed random number $r_u \sim Unif(0, 1)$ is drawn for each individual $u \in \tilde{\mathcal{U}}$
2. Individual u changes its state from j to k if $r_u \in [\sum_{l=1}^{k} \pi_u^{(s+1)j(l-1)}, \sum_{l=1}^{k} \pi_u^{(s+1)jl}]$ with $\pi_u^{(s+1)j0} := 0$.

The following example illustrates the procedure. Assume that the transition probability for a full-time employee to remain in this state is 0.7, to change to part-time employment 0.2, and to become unemployed 0.1. Thus, the cumulative probabilities are $\{0.7, 0.9, 1\}$. Further assume that the random number is 0.83. Consequently, the individual changes to a part-time job as $0.83 \in [0.7, 0.9]$ (Münnich et al., 2021).

Transition probabilities are typically estimated using longitudinal data sets from official statistics (Münnich et al., 2021). The inclusion of random effects in microsimulation has received limited attention. This may be due to the popularity of alignment methods in microsimulation models (Richiardi and Poggi, 2014). Nev-

ertheless, if the microsimulation model focuses on individual trajectories, it is recommended to account for unobserved heterogeneity. The inverse-transform method has to be adapted, if the transition probabilities are estimated using random effects or fixed effects models as the unobserved individual effects have to be assigned to the individuals in the base population. The assignment of unobserved individual effects to the base population $\tilde{\mathcal{U}}$ in the prediction process is not trivial since the survey sample $\mathcal{D}$ on which the models are computed does not correspond to the base population $\tilde{\mathcal{U}}$. Richiardi (2014) develops an algorithm for assigning random effects to the base population. This method, which became known as Rank method, can be applied to simulate state changes based on linear models with fixed effects as well as on binary logit and probit models with fixed or random effects (Richiardi, 2014).

The Rank method follows the eight-step procedure outlined below (Richiardi, 2014; Richiardi and Poggi, 2014):

1. Estimate the generalized mixed effects model based on the survey sample $\mathcal{D}$.
2. Simulate on $\tilde{\mathcal{U}}$ the predicted outcome $\hat{y}_u^{(s)} = I\left(x'^{(s)}_u \hat{\beta} + \hat{\gamma} y_u^{(s-1)} > 0\right)$ by imposing $\alpha_i = 0$ on all individuals requiring assignment. I is defined as an indicator function and it is assumed that $s = t$.
3. Calculate the difference between the observed outcome $y_i^{(t)}$ and the predicted outcome $\hat{y}_u^{(s)}$.
4. Order the differences from high to low. If two or more differences are equal, ordering takes place randomly.
5. Extract $\tilde{N}$ values from the estimated unconditional distribution of the random effects.
6. Extract $\tilde{N}$ values from the estimated unconditional distribution of the idiosyncratic disturbances.
7. Build the error terms based on the estimated unconditional distribution of the random disturbances from step 5 and the estimated unconditional distribution of the idiosyncratic disturbances from step 6, $\tilde{e}_u^{(s)} = \tilde{\alpha}_u^{(s)} + \tilde{\varepsilon}_u^{(s)}$, and rank them in descending order.
8. Assign the random effects $\tilde{\alpha}_u^{(s)}$ to the individuals that need assignment by matching the two ranks above.

Individuals retain their random effect until they leave the base population due to death or moving across country borders. When new individuals join the base population through birth or migration, the same procedure is followed for these new individuals. Note, however, that for individuals who enter the simulation process as newborns, random effects could also be drawn from the estimated unconditional distribution since they do not have a history of previous outcomes (Richiardi and Poggi, 2014).

In dynamic microsimulation models, the focus is generally not on point estimates, but on conducting comprehensive ceteris paribus analyses that take into account the complexity of the underlying population (Li and O'Donoghue, 2013). In the third step, the Rank method requires the calculation of the difference between the observed outcome, y_u^s, and the predicted outcome, $\hat{y}_u^s$ (Richiardi and Poggi, 2014). First and foremost, this requires that the observed outcome for individual i can be compared with the simulated result for individual u, i. e., that $i = u$. However, comparing y_u^s and $\hat{y}_u^s$ is restricted to the simulation periods where $s = t$. Therefore, it is not possible to assign random effects to immigrated individuals or newborns, when $s \neq t$. Moreover, it is questionable whether the assumption that individuals retain the random effects throughout their lives is realistic. For these reasons, the Rank method is not considered further in the following.

2.2.4 Alignment Methods

High-quality statistics and data are crucial. Especially in times when distorted facts and fake news spread quickly, quality statistics and data are of great importance. The European Statistics Code of Practice, adopted by the Statistical Programme Committee in 2005 and revised by the European Statistical System Committee in 2011 and 2017, reflects the need for official statistics to provide relevant, timely, and accurate statistics that align with the principles of professional independence, impartiality, and objectivity (European Union, 2018).

Unaligned models often result in deviations from known totals. A. Duncan and Weeks (1998, p. 151) emphasize that "even in functionally well-specified models, the predictive performance is poor, particularly where some states are relatively densely or sparsely represented in the data". In the context of microsimulation models, the process of calibrating the base population to match external aggregates is known as alignment (O'Donoghue, 2001, pp. 134ff; Klevmarken, 2002; Li, 2011, pp. 89ff; Li and

O'Donoghue, 2014; Münnich et al., 2021). A prerequisite for the use of alignment methods is that external, high quality, projections are available, which can serve as target values. Note that the use of appropriate alignment methods do not distort the original shape of the probability distribution (Stephensen, 2016; Burgard et al., 2021; Schmaus, 2023, ch. 3).

To enhance the credibility of the microsimulation model and the trustworthiness of its results, it is crucial that the dynamics and outcomes of dynamic microsimulations align closely with reality. This can be achieved by using alignment methods. Overall, the literature identifies four main reasons for the use of alignment methods (Li and O'Donoghue, 2014; Stephensen, 2016):

- Implementation of assumption-based scenarios
- Generation of consistent micro and macro models
- Mitigation of the consequences of insufficient estimation data
- Reduction of Monte Carlo variability.

Alignment methods can be classified as ex-post alignment and parameter alignment (Bækgaard, 2002; Li and O'Donoghue, 2014). Ex-post alignment directly adjusts the obtained transition probabilities or state changes, while parameter alignment modifies the estimated parameters $\hat{\beta}$ to match external benchmarks, i. e., mean alignment. Ex-post alignment has the advantage that the method used to obtain the transition probabilities does not matter. The alignment strategy can be to match the expected number of known transitions or states, i. e., mean alignment, or to eliminate the Monte Carlo variation relative to the known total, i. e., variance elimination. Ex-post alignment methods have an inherent problem as they require external benchmarks for each simulation period (Schmaus, 2023, ch. 3). If no benchmarks are available, either an arbitrary value is assumed, the last adjustment value is kept constant or the benchmarks are forecasted using time-series models, such as ARIMA models (Bijak et al., 2013).

Parameter alignment approaches include Logit-Scaling (Stephensen, 2016), Constrained Parameter Alignment (Klevmarken, 2002), and Constrained Maximum Likelihood (Burgard et al., 2021). These methods can be understood as minimization problems under constraints, where the constraint ensures that the known total are matched. As starting point serves the difference ($\Delta^{(s)k}$) between the sum of the

predicted individual transition probabilities $\hat{\pi}_u^{(s)k}$ and the known total $\tau_k^{(s)}$:

$$\Delta^{(s)k} := \left| \sum_{u=1}^{\tilde{N}} \hat{\pi}_u^{(s)k} - \tau_k^{(s)} \right| > \varepsilon^k. \tag{2.35}$$

Alignment methods aim at obtaining a new set of probabilities for the multinomial variable with J attributes so that the following conditions are met (Burgard et al., 2021; Schmaus, 2023, p. 74):

$$\Delta^{(s)1} \leq \varepsilon^1, \Delta^{(s)2} \leq \varepsilon^2, ..., \Delta^{(s)J} \leq \varepsilon^J. \tag{2.36}$$

The methods differ with respect to the target function. Logit-Scaling minimizes the relative entropy of the adjusted probabilities to the estimated probabilities under constraints, Constrained Parameter Alignment minimizes the Mahalanobis distance of the adjusted parameters to the model parameters under constraints and Constrained Maximum Likelihood maximizes the model likelihood of the original model under constraints (Schmaus, 2023, ch. 3). In the following, we focus on Logit-Scaling. This method is frequently applied in the field of microsimulations as it is straightforward to implement and intuitive.

It is not always possible to make a clear distinction between parameter and ex-post alignment. Under certain circumstances, Logit-Scaling can be considered both parameter and ex-post alignment. On the one hand, Logit-Scaling involves the sequential adjustment of probabilities using iterative proportional fitting until the known total is met. It aims to find a new probability distribution that includes the external benchmark, while largely retaining the original distribution of the probabilities. Accordingly, it is classified as ex-post alignment, as the initially estimated transition probabilities are adjusted. On the other hand, Logit-Scaling can also be considered as parameter alignment if (multinomial) logit models are used to estimate these transition probabilities. This is due to the fact that the adjustment made through iterative proportional fitting is analogous to an adjustment of the intercept.

Let $\hat{\pi}_{ur}^{[0](s+1)j}$ for $j = 1, \cdots, J$ be the initial transition probabilities, $\hat{q}_{ur}^{[0](s+1)j}$ the initial mean of the transition probabilities, $Q_r = \{q_{ur}^{(s+1)j} | u = 1, \cdots, \tilde{N}_r; j = 1, \cdots, J\}$ the joint discrete probability distribution of states and micro-units for $\tilde{U}_r$, and $Q_r^{[0]}$ the initial probability distribution. The objective of Logit-Scaling is to find a set of new probability distributions $\{Q_1^*, \cdots, Q_R^*\}$ that satisfy the external benchmark

data while minimally affecting the distribution of $\hat{\pi}_{ur}^{[0](s+1)j}$. Therefore, the Kullback-Leibler divergence between $Q_r^{[0]}$ and Q_r

$$\begin{aligned} D_r^{KL}(Q_r||Q_r^{[0]}) &= \sum_{u\in\tilde{U}_r}\sum_{j=1}^{J} q_{ur}^{(s+1)j}\log\left(\frac{q_{ur}^{(s+1)j}}{q_{ur}^{[0](s+1)j}}\right) \\ &= \frac{1}{\tilde{N}_r}\sum_{u\in\tilde{U}_r}\sum_{j=1}^{J}\hat{\pi}_{ur}^{(s+1)j}\log\left(\frac{\hat{\pi}_{ur}^{(s+1)j}}{\hat{\pi}_{ur}^{[0](s+1)j}}\right) \end{aligned} \tag{2.37}$$

$$\begin{aligned} &\text{subject to} \\ &\sum_i \hat{\pi}_{ur}^{(s+1)j} = \bar{X}_r^{(s+1)j}, j = 1,\cdots,J \\ &\sum_j \hat{\pi}_{ur}^{(s+1)j} = 1, u = 1,\cdots,\tilde{N}_r \\ &\pi_u^{(s+1)j} \geq 0, \quad u = 1,\cdots,\tilde{N}, \quad j = 1,\cdots,J \end{aligned}$$

is minimized (Stephensen, 2016; Burgard et al., 2021). Stephensen (2016) shows that the minimization problem can be solved by bi-proportional scaling.

Up to this point, the procedure can be classified as ex-post alignment. As stated above, Logit-Scaling can also be classified as parameter alignment if the transition probabilities are estimated using (multinomial) logistic regression models. In these cases, the iterative proportional fitting is equivalent to an intercept adjustment. In a binary logistic regression model, the modified probability is given as:

$$\hat{\pi}_{ur}^{(s)} = \frac{\exp\left(x'^{(s)}_{ur}\hat{\beta} + \delta\right)}{1 + \exp\left(x'^{(s)}_{ur}\hat{\beta} + \delta\right)}, \tag{2.38}$$

where δ is the intercept adjustment term. It is calculated as:

$$\delta = \log\left(\frac{\hat{\pi}_{ur}^{(s)}}{1-\hat{\pi}_{ur}^{(s)j}}\right) - \log\left(\frac{\hat{\pi}_{ur}^{[0](s)j}}{1-\hat{\pi}_{ur}^{[0](s)j}}\right). \tag{2.39}$$

In the multinomial case, the intercept adjustment term is calculated for each of the J states separately:

$$\delta_j = \log\left(\frac{\hat{\pi}_{ur}^{(s)j}}{\hat{\pi}_{ur}^{[0](s)j}}\right) - \frac{1}{J}\sum_{j=1}^{J}\log\left(\frac{\hat{\pi}_{ur}^{(s)j}}{\hat{\pi}_{ur}^{[0](s)j}}\right). \tag{2.40}$$

For more information, we refer to Stephensen (2016).

To achieve an extended regionalization effect, group-specific benchmark values can be used to improve the projection. For example, one might consider gender-specific trends in income across different regions. It is assumed that it is not possible to estimate regionalized models. Regionalization is achieved by alignment and the subsequent adjustment of intercepts via Logit-Scaling.

It is important to note that benchmark data is only available for a limited time period. Especially, when the microsimulation model projects the base population into the future, benchmark data is not available for all simulation periods. The alignment process itself can be used to calibrate the models for future projections using the adjusted intercepts. However, this raises the question of how to project the intercept adjustment values into the future. The following approaches, among others, can be used to obtain δ for periods in the future:

- Using the last observed δ for all simulation periods that lie in the future
- Calculating the mean of all past δ and using this value to adjust the intercept in the future
- Calculating the median of all past δ and using this value to adjust the intercept in the future
- Estimating an ARIMA model and forecast the evolution of δ into the future.

An overview of the different alignment techniques is provided in Li (2011, ch. 4), Li and O'Donoghue (2014), Burgard et al. (2021) and Schmaus (2023, ch. 3). The methods differ in terms of their applicability and functionality. For a comparison of different alignment methods, see Burgard et al. (2021) and Schmaus (2023, ch. 3).

2.3 Validation Methods

Validation constitutes an integral part of microsimulation models (Klevmarken, 2008, pp. 47ff; Edwards and Tanton, 2013; Li et al., 2014b, pp. 29f; Lütz and Stein, 2020, pp. 147-150). However, there is no consensus within the microsimulation community on the aspects of validation (Lütz and Stein, 2020, pp. 147-150; O'Donoghue, 2021, p. 225). In the following, we distinguish between internal and external validation.

2.3.1 Internal Validation

Internal validation is defined as the validation of the microsimulation model based on data used to estimate the models. It is commonly understood as "the process whereby the variables that were used in the estimation of the output are compared, so that the input dataset is compared with the output dataset for those variables" (Edwards and Tanton, 2013, p. 249). Thus, the estimation data $\mathcal{D}$ and the updated base population $\tilde{\mathcal{U}}$ are required for internally validating the microsimulation model. For this reason, internal validation is straightforward if the base population is a (sub-)sample of the estimation data set $\mathcal{D}$. In these cases, the estimation data set $\mathcal{D}$ can be directly compared to the updated base population $\tilde{\mathcal{U}}$ using different quality criteria.

In most dynamic microsimulation models, however, the estimation data set $\mathcal{D}$ does not contain the same micro-units as the base population and thus cannot be used for validation purposes. As a result, direct comparisons between the base population and the validation data set are not feasible. If the simulated time is equal to the time period in the validation data set, $t = s$, it might be possible to aggregate the micro-units of the base population and the validation data set to the same regional level and validate the microsimulation model at regional level (Edwards and Tanton, 2013, p. 250). In many cases, however, the estimation data set $\mathcal{D}$ is a survey sample and an aggregation to the common level might not result in reliable benchmarks.

In general, internal validation of microsimulation models goes beyond the comparison of input and output data. Further aspects of internal validation include the assessment of different statistical models (Bongers et al., 2016), plausibility as well as consistency checks, code debugging (Lütz and Stein, 2020, p. 148), handover plots, Receiver Operating Characteristics curves, and cross-validation (Archer et al., 2021). Plausibility and consistency checks within the modules of a microsimulation model ensure that the state transitions and variable outcomes adhere to logical rules. Implausible transitions should be identified and the corresponding model and modules corrected accordingly. For example, it is not feasible for an individual to obtain a high school diploma as the highest school-leaving qualification in year t and then receive a lower secondary school diploma in the subsequent year $t+1$. It is important to evaluate not only the modules separately but also the microsimulation model as a whole (Burgard et al., 2020a).

Code debugging is closely related to plausibility and consistency checks. The modular structure allows to integrate module-specific debugging devices into the microsimulation model. Ideally, users should obtain clear error messages stating the reason for the termination of the simulation. At a minimum, the exact line of the error should be displayed (O'Donoghue et al., 2009; Burgard et al., 2020a).

Handover plots are visual representations of the simulated output to assess whether the simulated data evolve as expected over time. Receiver Operating Characteristic curves are used to evaluate binary classification problems. These methods are mainly employed for the internal validation of health microsimulations (Archer et al., 2021). Since the focus of this thesis is not on classification problems, we refer to Hosmer and Lemeshow (2000, ch. 5.2.4) and Archer et al. (2021) for more information on assessing the model fit based on the Receiver Operating Characteristic curve and handover plots.

Cross-validation is very popular in the field of internal validation. In CV-fold cross-validation the data are split into CV folds and the validation is performed CV times. In each validation run, $CV - 1$ folds serve as training data and one fold is used for testing purpose and a performance measure, e. g., the Brier score (Brier, 1950), is calculated. Each fold takes the role of the test data once. The cross-validation estimate is the average of the performance measures over the CV folds (Hastie et al., 2009, p. 242). In the case of imbalanced data, it is common to use stratified cross-validation, where the distribution of the variable of interest is resembled in each fold (Japkowicz, 2013, p. 205). The Brier score is mainly used to evaluate probabilistic predictions. The Brier score is defined as the mean squared error (MSE) between the predicted probabilities and the true classes (Fernández et al., 2018, pp. 57f). For $i = 1, \ldots, n$ outcomes and J possible categories, the Brier score is defined as:

$$B^{(t)} = \frac{1}{n} \sum_{j=1}^{J} \sum_{i=1}^{n} (\hat{\pi}_i^{(t)j} - C_i^{(t)j})^2 \tag{2.41}$$

with $\hat{\pi}_i^{(t)j}$ denoting the forecast probabilities. The class indicator $C_i^{(t)j}$ takes a value of 1 if the event occurs, and 0 otherwise. The Brier score ranges between zero and two with lower values indicating better predictive properties of the model (Brier, 1950). Following Kruppa et al. (2014), the Brier score (2.41) can be divided by 2 to

normalize the value range so that the Brier scores lie between 0 and 1, $B_{norm} \in [0, 1]$:

$$B_{norm}^{(t)} = \frac{1}{2n} \sum_{j=1}^{J} \sum_{i=1}^{n} \left(\hat{\pi}_i^{(t)j} - C_i^{(t)j} \right)^2. \tag{2.42}$$

The lower the Brier score, the better the model under study. Note that in the case of unbalanced data, predictive performance for the rare class may be poor even though the model is well-specified (A. Duncan and Weeks, 1998; Wallace and Dahabreh, 2014). Therefore, the Brier score is of limited use for assessing predictive power in the case of unbalanced data as "calibration may be good *overall*, but poor for the rare class" (Wallace and Dahabreh, 2014, p. 38). Thus, the Brier score (2.41) is not appropriate for unbalanced categorical variables. A potential solution is to assess the models under study separately for each category. Alternatively, Wölwer (2023, ch. 3) proposes an extension of the Brier score to account for unbalanced categories, the weighted Brier score B_w:

$$B_w = \frac{1}{2n} \sum_{j=0}^{J} d_j \sum_{i=1}^{n} (\hat{p}_{ij} - C_{ij})^2, \tag{2.43}$$

where $\sum_{j=0}^{j} = 1$, $d_j > 0$. In the weighted Brier score, a vector of weights for the categories $d = (d_1, ..., d_J)^T$ is incorporated.

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) do not belong to the class of measures of fit as such, but to the information criteria. Both the AIC Akaike (1973) and the BIC (Schwarz, 1978) are popular model selection criteria (Greene, 2012, pp. 179, 180, 573). The AIC is based on the expected Kullback-Leibler divergence between the estimated model and the true model (Wood, 2017, p. 75). It is defined as (Greene, 2012, p. 573):

$$AIC = -2LL + 2K, \tag{2.44}$$

where K is the number of parameters in the model and LL is the log-likelihood for the estimated model. The model with the lowest AIC value is preferred. The BIC is an "asymptotic approximation to a transformation of the Bayesian posterior probability of a candidate model" (Neath and Cavanaugh, 2012, p. 199). It is defined as (Greene, 2012, p. 573):

$$BIC = -2LL + K \ln n, \tag{2.45}$$

where n is the number of observations. As with the AIC, lower BIC values indicate a better fit.

Although, the AIC and BIC are similar in structure, they differ in their theoretical foundations (Fahrmeir et al., 2009, p. 162). The BIC, on the one hand, aims at selecting from among the candidates the model that is most likely to be the true model given the data. The AIC, on the other hand, assumes that there is no identifiable true model and selects the model based on the expected prediction of new data. Thus, the BIC is more appropriate when the focus is on inference, whereas the AIC is more appropriate when the focus is on prediction (Kuha, 2004).

2.3.2 External Validation

External validation is the process of validating the base population against external data. It is designed to assess whether the simulation can replicate known external data (Edwards and Tanton, 2013, p. 249; Lütz and Stein, 2020, p. 149). A distinction is made between retrospective and prospective external validation. Retrospective microsimulation models are defined as microsimulation models that update the base population up to the present. In retrospective external validation, a retrospective microsimulation model is compared with real external data. When conducting dynamic microsimulations, comparing them with external data sources can be difficult due to the lack of suitable data at the appropriate spatial scale. In some cases, external validation problems can be avoided by aggregating the base population to the geographic level of the external validation data. Alternatively, the simulated microdata can be compared to an available microdata set that contains a variable correlated with the variable of interest, or to simulation data from other microsimulation models. Prospective microsimulation models update the base population into the future. Thus, a comparison with external real data is not feasible. In the literature, there are two approaches to prospective external validation: Either the model is validated retrospectively when the necessary external data become available (Hannappel and Troitzsch, 2015, p. 483; Lütz and Stein, 2020, p. 149), or similar models with a simulation horizon in the future are used for comparison (Richard Morrison, 2008; Lütz and Stein, 2020, p. 149).

In the microsimulation literature, external validation of the overall model is mainly based on the total absolute error (TAE), the standardized absolute error (SAE), and the root mean squared error (RMSE) (Ballas et al., 1999; Voas and Williamson, 2000; Tanton, 2014; Edwards and Tanton, 2013). Quality measures are often inspired by other research areas. We mainly follow the microsimulation literature on external validation, and we also draw upon quality and performance indicators for statistical processes and outputs (European Union, 2021).

A prerequisite for external validation of a microsimulation model is the existence of known benchmarks from Official Statistics. It is desirable that the benchmark values are available for the simulation horizon, $s = t$. The known number of individuals in state Y_k in region r at time t is given as:

$$\tau_r^{(t)k} = \sum_{i=1}^{N_r^{(t)}} \mathbb{1}(y_{i,r}^{(t)} = Y_k). \tag{2.46}$$

The MSE is defined as:

$$MSE^{(t)k} = \frac{\sum_{r=1}^{R} \left(\tau_r^{(t)k} - \sum_{u_r=1}^{\tilde{N}_r^{(t)}} y_{u,r}^{(t)} \right)^2}{R}. \tag{2.47}$$

The RMSE is the root of the MSE:

$$RMSE^{(t)k} = \sqrt{MSE^{(t)k}}. \tag{2.48}$$

The TAE determines the total difference between the simulated data and the actual data. The TAE for state Y_k is defined as (Ballas et al., 1999; Edwards and Tanton, 2013, p. 251):

$$TAE^{(t)k} = \sum_{r=1}^{R} \left| \tau_r^{(t)} - \sum_{u=1}^{\tilde{N}_r^{(t)}} \mathbb{1}(y_{u,r}^{(t)} = Y_k) \right|. \tag{2.49}$$

The SAE divides the TAE by the expected population size in state Y_k. Thus, the SAE for state Y_k is given as (Edwards and Tanton, 2013, p. 251; Timmins and

Edwards, 2016):

$$SAE^{(t)k} = \frac{TAE^{(t)k}}{\sum_{r=1}^{R} \tau_r^{(t)k}}. \tag{2.50}$$

The SAE is similar to the relative mean absolute revision. The relative mean absolute revision is the most important measure to assess the quality of the first estimate of short-term business statistics indicators as it allows for comparisons between different indicators (Eurostat, 2023).

2.4 Application: Modeling the Employment Status in the MikroSim Model

The employment module is crucial for analyzing economic scenarios as it allows, for example, the analysis of various work incentive scenarios. Additionally, the employment module serves as an essential link variable for establishing a coherent connection between micro and macro models. In this section, we compare different modeling strategies for employment transitions in the MikroSim microsimulation model and evaluate their performance based on various quality criteria.

2.4.1 The MikroSim Microsimulation Model

The MikroSim model (Münnich et al., 2021) is developed within the MikroSim project FOR 2559. It is funded by the German Research Foundation (DFG). In the first project phase, the methodological focus was on the creation of the base population and the development of appropriate methods for projecting the base population into the future. Building on this, the thematic focus was on the analysis of family structures, care, and the integration of migrants into the labor market (MikroSim, 2023a). The second project phase deals with statistical methods for the development of a simulation data center, efficiency and uncertainty measurement in microsimulations, the simulation of educational trajectories under consideration of latent decision processes, evaluation of regional hospital care, outpatient health care, transportation choices, and housing analysis (MikroSim, 2023b).

A distinctive feature of the MikroSim model is its high degree of regionalization. In the MikroSim model, individuals (and households) are geo-referenced at district level. This is particularly noteworthy as regional statistics are becoming increasingly important and have received much attention from the general public in recent years, especially in the context of the COVID-19 pandemic. The importance of regional statistics is also emphasized by the European Commission. Almost one third of the EU budget is allocated to cohesion policy for the period 2021-2027. It aims at supporting all regions and cities in the European Union in terms of job creation, business competitiveness, economic growth, sustainable development, and citizen's quality of life. In order to design different policies to achieve these objectives and to assess their impact, regional statistics are inevitable.

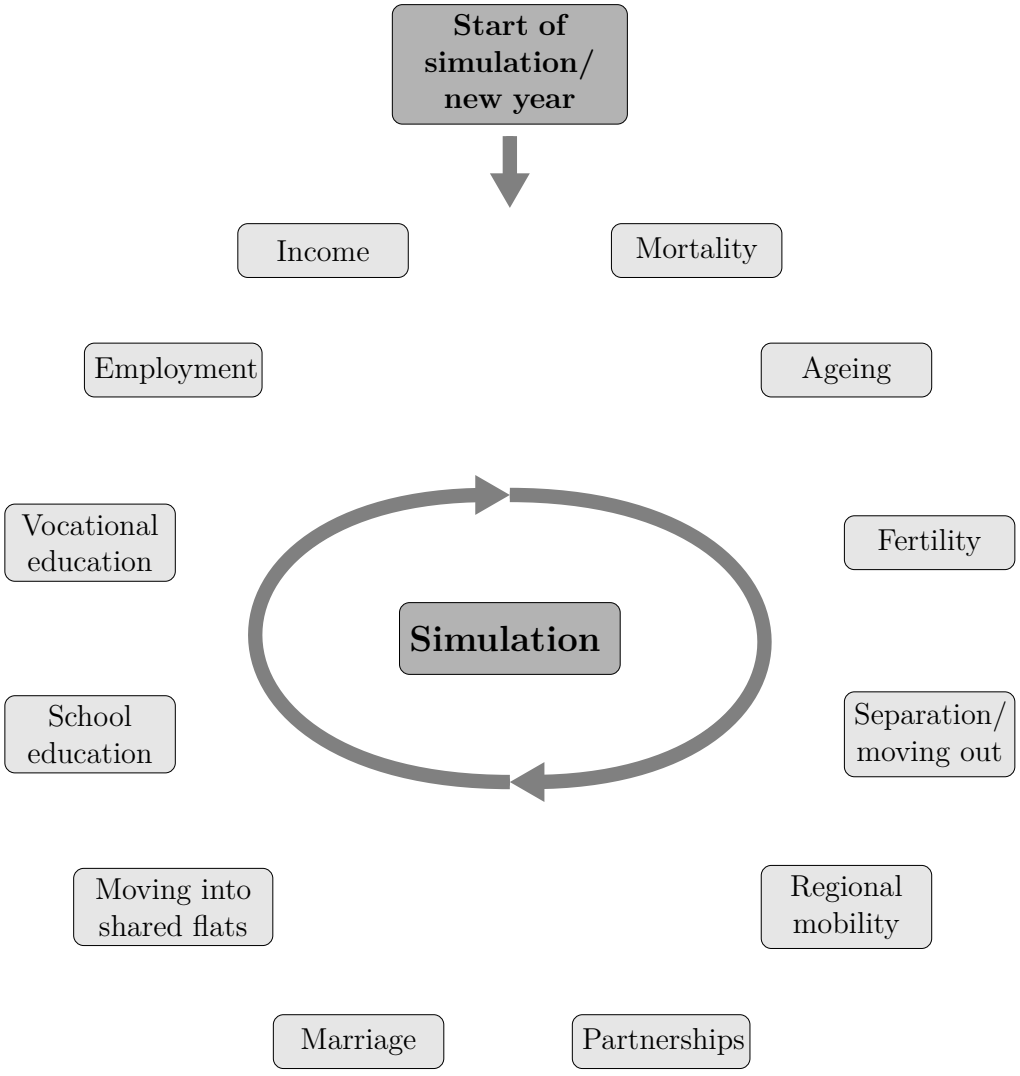
According to the differentiation in Section 2.1, the MikroSim model can be classified as a population-based regional discrete-time dynamic microsimulation model. Starting point is a synthetic base data set of Germany, which builds upon the anonymized national register of residents from the preparatory studies for the German census 2011 (Münnich et al., 2012). The base population includes all of the approximately 80 million inhabitants of Germany in 2011. Since the register contains only a limited number of (mainly demographic) variables, the base data set is extended using the German Microcensus (Münnich et al., 2021). The synthetic population is adjusted to known census totals using simulated annealing, see van Laarhoven and Aarts (1987).

The aim of the MikroSim model is to project the German population into the future by estimating individual transition probabilities using statistical modeling strategies. Multinomial logit and logit regression models are mainly used for estimating transition probabilities. The transition probabilities in the MikroSim model are modeled with annual frequency. State changes are determined based on the inverse-transform method (Münnich et al., 2021). If known totals from official statistics are available, the models are calibrated against the benchmarks. In the MikroSim model, Logit-Scaling is predominantly used as alignment method. The advantage of this method is that it is straightforward to implement for binary as well as multinomial cases and minimizes the Kullback-Leibler distance between the original and adjusted probability distribution (Stephensen, 2016; Burgard et al., 2021). For a comprehensive review of different alignment methods in dynamic microsimulations, see Schmaus (2023, ch. 3.2).

Like most discrete-time dynamic microsimulations, the MikroSim model has a modular structure with strong interconnections between the modules (Münnich et al., 2021). This allows for a high degree of flexibility, as the modules and models can be updated and exchanged on an ongoing basis. Therefore, the existing modules and the underlying models must be adapted each time the microsimulation model is updated (van Imhoff and Post, 1998; Burgard et al., 2020a).

The module sequence of the MikroSim model is depicted in Figure 2.4. A detailed description can be found in Münnich et al. (2021).

Figure 2.4: Module Sequence in the MikroSim Model



Source: Own illustration based on Münnich et al. (2021).

The simulation starts with the mortality module, which determines the probability of death based on life-tables. After simulating the event of death, individuals who have not died become one year older. In the fertility module, the probability of childbirth is estimated for all women of fertile age between 15 and 49 years. For all women who give birth, it is then determined whether it is a single or twin birth. The newborn child or, in the case of twin birth, the newborn children are assigned the same HID as the mother. The fertility module is followed by the simulation of leaving the household. In the MikroSim model, individuals leave a household for one of three reasons: separation from a partner, leaving the parental household, or moving out of a shared apartment.

Regional mobility can be modeled using an open or closed migration module. The open migration model follows a three-step procedure: First, immigrating households from outside Germany are selected from an external population and added to the base population. Second, inflows from Germany are implemented by drawing households from a copy of the base population. Third, households moving across district borders are identified and removed from the base population. In the closed migration module inflows from abroad are implemented at the beginning analogously to the open module. This is followed by the simulation of migration across district borders. Only households that were selected to move abroad are removed from the base population. All other individuals are first distributed to the federal states and then to new districts within the federal states. The main advantage of a closed migration module over an open module is that it achieves consistency in terms of moving individuals and population size. Moreover, individuals can be traced over time. For a detailed description of the migration module in the MikroSim model, see Schmaus (2023, ch. 4.5).

The partnership module simulates the formation of new partnerships. First, the probability is determined that people over the age of 18 who are not currently in a partnership will enter into a partnership. The model is estimated separately for women and men. The selected individuals are then matched using stochastic matching, taking into account covariates. As the MikroSim model uses stochastic matching, it allows for less favorable partnerships, such as those with larger age differences. The marriage module only considers individuals who are single, widowed, or divorced and in a partnership. Therefore, individuals aged 18 and above are eligible to enter into marriage. The probability of getting married is determined based on household and individual information. The MikroSim model includes a module

for moving into shared flats to account for the high number of shared flats in large cities and university towns. Single households between the ages of 18 and 35 are considered. New households are formed by randomly matching all individuals who are moving into shared flats. The average newly formed household consists of three individuals.

The school education module assigns the age of school enrollment based on the relative frequencies published by the Federal Statistical Office (Statistisches Bundesamt (Destatis), 2020). Enrollment can occur at the early age of five, the regular age of six, or the late age of seven. The module also determines the duration of schooling and the school-leaving qualification. The vocational education module assigns a vocational qualification to school leavers. The categories considered are: no vocational training, vocational training degree and university degree. The vocational education module is followed by the employment module. The employment module consists of three models: First, the employment status is assigned to individuals aged between 15 and 66 years. Second, for employed individuals it is determined whether they are employed full-time or part-time. Third, individuals older than 66 years are send into retirement. The last module in the MikroSim model is the income module. The income module is crucial for policy analyses, such as tax reforms. Currently, the income module is a standalone component in the MikroSim model and does not affect the other modules, i. e., income is not used as explanatory variable in the other models.

2.4.2 Data Description

The MikroSim base population builds upon the anonymized national register of residents from the preparatory studies for the German census 2011 (Münnich et al., 2012) and is enriched using the German Microcensus. The synthetic data generation can be described as (Münnich et al., 2021):

$$f_{(\mathbf{X}),\mathbf{Y},\mathbf{Z}}(\mathbf{x},\mathbf{y},\mathbf{z}) = f(\mathbf{x}) \cdot f(\mathbf{y}|\mathbf{x}) \cdot f(\mathbf{z}|\mathbf{x},\mathbf{y}).$$

The variable set $\mathbf{X}$ contains basic demographic variables, which are included in both the register and in the German Microcensus. The variable set $\mathbf{Y}$ contains variables from the German Microcensus related to education and employment status. This information is used to obtain the conditional distribution $f(\mathbf{y}|\mathbf{x})$. Furthermore, the variable set $\mathbf{Z}$ contains variables related to the thematic focus. The conditional dis-

tributions are usually obtained using multinomial logit models. To account for cluster effects in households, the variables for household members are generated using a household type variable (Alfons et al., 2011; Kolb, 2013; Münnich et al., 2021). The synthetic population is adjusted to known census totals using simulated annealing (van Laarhoven and Aarts, 1987; Huang and Williamson, 2011; Williamson, 2013; Tanton, 2014). For further information on the creation of the base population, see Münnich et al. (2021).

The transition probabilities for projecting the base population into the future are mainly estimated using the German Microcensus Scientific Use Files from 2012 to 2014 (Münnich et al., 2021). The German Microcensus is an Official Statistics survey that is carried out on an annual basis using a 1 percent (%) representative sample of the German population and households since 1957. For most of the questions, the answer is obligatory. Thus, the German Microcensus offers valuable insight into the population. The Microcensus covers the following topics (RDC of the Federal Statistical Office and Statistical Offices of the Federal States, 2022a):

- Population structure
- Economic and social situation of the population
- Families and households
- Employment market
- Occupational outline and training of the workforce
- Living conditions.

The Scientific Use File is a de-facto anonymized 70% sub-sample of households from the German Microcensus. Due to the anonymization, certain variables are only available in classified or coarse form. The categories are aggregated to ensure that each category contains 5,000 cases. An exception is the nationality variable, for which the categories are aggregated so that each nationality contains at least 50,000 cases (RDC of the Federal Statistical Office and Statistical Offices of the Federal States, 2022b). From 2012 it is possible to merge the Scientific Use Files to create a panel data set (RDC of the Federal Statistical Office and Statistical Offices of the Federal States, 2022c).

The employment variable in the German Microcensus `EF29` is defined according to the International Labour Organization (ILO) labor force concept (Schmidt, 2000). In accordance with the ILO definition, an individual of working age is categorized as either employed, unemployed, or outside the labor force ILO (2023, para. 15). Employed persons include "individuals of working age who, during a short reference period, were engaged in any activity to produce goods or provide services for pay or profit" (ILO, 2023, para. 27). The short reference period is defined in ILO (2023, para. 15, 19(a)) as seven days or one week. Employed persons comprise (ILO, 2023, para. 15, 27):

- Employed persons at work
- Employed persons not at work due to temporary absence from a job, or working time arrangements (such as shift work, flexible hours schedule and compensatory leave for overtime).

Unemployed persons include "all those of working age who were not in employment, carried out activities to seek employment during a specified recent period and were currently available to take up employment given a job opportunity arises" (ILO, 2023, para. 47). The sum of the employed and unemployed makes up the labor force. The part of the working age population that is neither employed nor unemployed during the short reference period is defined as being outside the labor force (ILO, 2023, para. 16). Table 2.1 gives an overview of the employment categories according to the ILO standards and the corresponding categories of the variable `EF29`.

Table 2.1: Conversion table: Employment status

ILO definition		**Variable value in MZ** (category of `EF29`)
Labor force	employed	employed (`1`)
	unemployed	unemployed (`2`)
Not in labor force	Labor force	job-seeking inactive people (`3`);
		other inactive people (`4`)

Source: Own illustration.

In the relevant sub-population for the labor module, the distribution is depicted in Table 2.2. Most of the individuals in the relevant sub-population are employed. The percentage of employed persons varies between 72% in the German Microcensus Scientific Use Files 2014 (RCD of the Federal Statistical Office and Statisti-

cal Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations) to 78% in the German Microcensus Scientific Use Files 2012 and 2013 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2012.00.00.3.1.0; 10.21242/12211.2013.00.00.3.1.0, own calculations). The percentage of unemployed persons varies between 4% in the German Microcensus Scientific Use Files 2014 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations) to 5% in the German Microcensus Scientific Use Files 2012 and 2013 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2012.00.00.3.1.0; 10.21242/12211.2013.00.00.3.1.0, own calculations) and the percentage of inactive persons varies from 17% in the German Microcensus Scientific Use File 2013 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2013.00.00.3.1.0, own calculations) to 24% in the German Microcensus Scientific Use File 2014 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations).

Table 2.2: Distribution of employment status in risk population

Microcensus wave	**Employed**	**Unemployed**	**Inactive**
German Microcensus SUF 2012	0.78	0.05	0.18
German Microcensus SUF 2013	0.78	0.05	0.17
German Microcensus SUF 2014	0.72	0.04	0.24

Source: RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2012.00.00.3.1.0 to 10.21242/12211.2014.00.00.3.1.0, own calculations.

2.4.3 Modeling Techniques for Employment Transitions

The evolution of the base population depends on the modules and the underlying models. Therefore, the choice of appropriate models for estimating transition probabilities is crucial. In most dynamic microsimulation models, the labor market status is estimated either by including the lagged labor market status as an explanatory variable or by using a Markovian transition models with the "processes [being] split up according to the initial state" (Richiardi and Poggi, 2014, p. 37). However, there are various modeling approaches available to estimate labor market transitions.

In the MikroSim model, employment transitions are estimated using a multinomial logit model with the lagged dependent variable, i. e., the employment status in the previous period $t-1$, as explanatory variable. Additionally, the model considers age, sex, school education, vocational education, marriage, citizenship, federal state, children in the household, and children under the age of 3 years are considered as explanatory variables (Münnich et al., 2021).

Burgard et al. (2020b) propose the use of Markovian transition models as the simplest method for estimating transition probabilities. The model prevents implausible transitions. Richiardi and Poggi (2014) also emphasize this modeling approach for estimating employment transitions. The transition probabilities for the labor market status in period t are estimated using three separate multinomial logit models conditional on the labor market status in the previous period.

Kiiver and Espelage (2016) model each labor market transition separately using a logit model. The dependent variable is defined as the transition from one state to another state, e. g., transition from unemployment to employment. In our case, this approach yields nine different regression models: (1) from unemployment to employed, (2) from unemployment to inactive, (3) from unemployment to unemployment, (4) from employment to unemployment, (5) from employment to inactive, (6) from employment to employment, (7) from inactive to unemployed, (8) from inactive to employed, (9) from inactive to inactive. The set of explanatory variables includes the duration of unemployment, sex, education, and age.

Tansel and Acar (2017) estimate transition probabilities in Türkiye along the formal/informal divide based on the Turkish Income and Living Conditions Survey (SILC) panel for 2006-2009 . They consider six labor market states: formal-salaried, informal-salaried, formal self-employed, informal self-employed, unemployed, and inactive. In the study, Tansel and Acar (2017) estimate four multinomial logit regression models for formal-salaried, informal-salaried, formal self-employed, and informal self-employed as initial status. The dependent variable takes the value 0, if the individual does not change his or her labor market state, and a value from 1 to 5, if it does. The set of explanatory variables contains gender, age, education level, and marital status as demographic characteristics as well as occupation, sector of economic activity, firm size, work tenure as employment characteristics of the individual.

Begg and Gray (1984) show that consistent parameter estimates of a multinomial model can be obtained by use of individual logit models. However, it has to be noted that "by dichotomizing a multinomial variable we 'throw' away information in the data, and such an estimator cannot be efficient" (Winkelmann and Boes, 2006, p. 138).

This section presents three different methodologies for estimating employment transitions within the MikroSim model. First, we consider the original MikroSim employment model, which includes the lagged labor market status as an explanatory variable. Second, a Markovian transition model is estimated. Consequently, three multinomial models are estimated, each conditioned on the respective employment status in $t-1$. Third, the conditional inference tree algorithm is considered as a non-parametric model. If not otherwise stated, the models are estimated on the basis of the German Microcensus Scientific Use File of 2014 (RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations).

For the theoretically grounded models, i. e., the multinomial model with the lagged dependent variable as explanatory variable and the Markovian transitions model, the variables are selected based on theoretical considerations in close cooperation with the thematic sub-projects. The full model is specified as follows: The employment status is used as dependent variable and the variables age, age^2, sex (0: male, 1:female), married (0: no, 1: yes), children under the age of 3 (0: no, 1: yes), care recipient (0: no, 1: yes), employment status in $t-1$ (0: employed, 1: unemployed, 2: inactive), in education (0: no, 1 yes), highest grade of education or vocational training (1: primary, 2: lower secondary, 3: upper secondary, 4: post-secondary, non-tertiary, 5: bachelor, master, phd), East Germany (0: West Germany, 1: East Germany), country of birth (0: Germany, 1: other European Union countries, 1: rest of the world) are considered as explanatory variables. Moreover, the interaction terms age $\times$ sex, age^2 $\times$ sex, sex $\times$ children under the age of 3, and sex $\times$ married are taken into account. If an explanatory variable is not statistically significant at the 10% level, it is discarded from the model specification. In a step-wise procedure, each explanatory variable is removed from the model one by one. The final models (Tables 2.3 and 2.4) are selected based on the AIC.

In the first model (Table 2.3), employment transitions are estimated by including the employment status of the previous year as explanatory variable (Münnich et al.,

2021). The dependent variable takes the value 0, if the individual is employed, 1 if the individual is unemployed, and 2, if the individual is inactive.

Table 2.3: Multinomial logit model for the employment model: LDV

	Unemployed	Inactive
Age	-0.1268***	-0.1827***
Age^2	0.0015***	0.0028***
Female	-0.9431***	-1.1049***
Married	-0.5877***	-0.4308***
Children < 3 years	0.2197***	0.2654***
Care	-1.0285***	1.1556***
Lagged dependent variable: Unemployed in $t-1$	4.2425***	3.9875***
Lagged dependent variable: Inactive in $t-1$	2.4383***	5.0408***
In Education	-1.1806***	0.6195***
Education: Lower Secondary	-0.0899***	-0.5650***
Education: Upper Secondary	-0.5698***	-1.2130***
Education: Post-Secondary, Non-Tertiary	-0.7698***	-1.3443***
Education: Bachelor, Master, PhD	-0.9503***	-1.8210***
East Germany	0.3697***	0.0882***
Country of Birth: other EU	0.2911***	0.0189***
Country of Birth: rest of the World	0.5674***	0.3259***
Age × Female	0.0413***	0.0689***
Age^2 × Female	-0.0006***	-0.0010***
Female × Children < 3 years	-0.0997***	1.5607***
Female ×Married	0.3764***	0.6883***
Intercept	-0.7951***	-0.6372***
Number of observations: 255,206		
Residual Deviance: 157,801.3		
AIC: 157,885.3		

Significance codes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

Source: RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations.

In the second model (Table 2.4), the transition probabilities for the labor market status in period t are estimated using three separate multinomial logit models conditional on the employment status in the previous period.

Table 2.4: Multinomial logit model for the employment model: Markovian Transitions

	Model		**Model**		**Model**	
	Employed in $t-1$		**Unemployed in** $t-1$		**Inactive in** $t-1$	
	Unemployed	Inactive	Unemployed	Inactive	Unemployed	Inactive
Age	-0.1736***	-0.4356***	-0.0152***	-0.0669***	0.0079*	-0.0924***
Age^2	0.0019***	0.0056***	0.0004***	0.0015***	-0.0005***	0.0019***
Female	-1.0360***	-1.6521***	0.7782***	1.4074***	-0.5799***	-0.6042***
Married	-0.7353***	-0.4014***	-0.3655***	-0.5424***	-0.1245***	-0.1169***
Children < 3 years	0.2530***	0.4256***	0.1113***	0.3133***	0.3794***	-0.0475.
Care			-1.9721***	0.3809***	-0.3800***	1.2787***
In Education	-0.1492***	2.2705***	-1.0708***	0.9056***	-1.3581***	0.7902***
Education: Lower Secondary	-0.0811***	-0.2385***	-0.1253***	-0.3007***	-0.1021***	-0.8729***
Education: Upper Secondary	-0.7911***	-0.5260***	-0.5663***	-0.9505***	-0.8955***	-1.7579***
Education: Post-Secondary, Non-Tertiary	-1.2446***	-0.6239***	-0.5727***	-1.0099***	-0.9694***	-2.0038***
Education: Bachelor, Master, PhD	-1.3427***	-0.9574***	-0.7402***	-1.4793***	-1.1789***	-2.439***
East Germany	0.5310***	0.0946*	0.0378	-0.1686***	0.5414***	0.1829***
Country of Birth: other EU	0.5414***	0.1715***	-0.2652***	-0.1308***	0.3442***	-0.0005
Country of Birth: Rest of the World	0.6908***	0.4478***	0.1758***	0.2586***	0.4488***	0.2857***
Age × Female	0.0525***	0.1101***	-0.0530***	-0.0449***	0.01716***	0.0360***
Age^2 × Female	-0.0007***	-0.0015***	0.0006***	0.0002*	0.0001	0.0005***
Female × Children < 3 years	-0.4855***	2.0558***	0.0489***	1.4109***	-0.5838***	1.1112***
Female × Married	0.2182***	0.5795***	0.2068***	0.4288***	0.0825***	0.5754***
Intercept	0.6164***	3.6236***	0.9278***	1.0525***	-0.1589***	3.0326***
Number of observations:	177,393		13,999		63,814	
Residual Deviance:	59,864.77		28,777.01		64,798.34	
AIC:	59,936.77		28,853.01		64,874.34	

Significance codes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

Source: RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations.

Additionally to the theoretically grounded models presented above, we also consider non-parametric conditional inference trees for estimating employment transitions. We implement the conditional inference tree algorithm using the `ctree`-function

from the `partykit`-package (Hothorn et al., 2006; Hothorn and Zeileis, 2015). However, due to its complexity, the plot of the conditional inference tree is not suitable for visualization purposes. An exemplary plot for modeling the employment status based on age and sex using the conditional inference tree algorithm is shown in Figure 2.3.

2.4.4 Validation

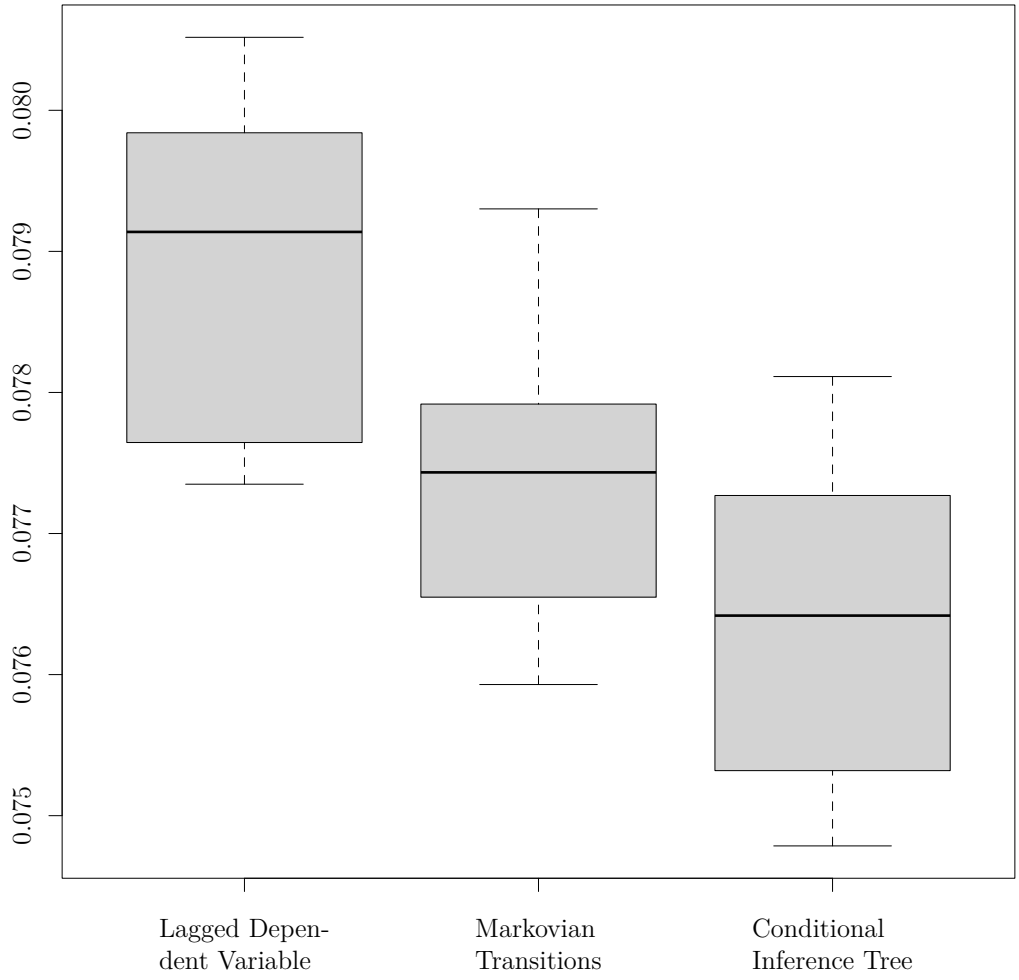
The importance of theoretically sound models for estimating transition probabilities is often emphasized in the microsimulation literature (Klevmarken, 2008, p. 49; Münnich et al., 2020, p. 126; McLay et al., 2015). When setting up a statistical model for microsimulations, it is important to ensure that the model is suitable for the analysis of the full range of desired scenarios (McLay et al., 2015). The set of candidate variables is selected based on the following considerations (Klevmarken, 2008, p. 49; Münnich et al., 2020, p. 126; McLay et al., 2015):

- Relevance of the variables for explaining the dependent variable according to sociological / economic theory
- Availability of the variables in an estimation data set $\mathcal{D}$
- Availability of the variables in the base population of the microsimulation model $\tilde{\mathcal{U}}$. If the variable does not exist in the base data set $\tilde{\mathcal{U}}$, the data set can be extended using methods described in Section 2.2.

Internal Validation

The predictive performance of each model is evaluated using stratified 10-fold cross-validation. The Brier score is used as performance criterion in the 10-fold cross-validation.

Figure 2.5: Internal validation: Brier score



Source: Own calculation.

Figure 2.5 shows that the predictive performance is the best for the conditional inference tree model, followed by the Markovian transition model. The model with the lagged employment status as an explanatory variable performs the worst among the three models compared.

In the case of unbalanced data, the weighted Brier score (Wölwer, 2023, ch. 3) and an assessment based on all categories separately is recommended for evaluating the predictive performance. Table 2.5 shows the (mean) Brier scores based on 10-fold cross-validation.

Table 2.5: Internal validation: Brier score

Brier scores	**Model**		
	Lagged dependent variable	Markovian transitions	Conditional inference tree
Brier	0.0789	0.0774	0.0764
Brier_w	0.0702	0.0687	0.0683
$\text{Brier}_{employed}$	0.0414	0.0409	0.0404
$\text{Brier}_{unemployed}$	0.5513	0.5399	0.5392
$\text{Brier}_{inactive}$	0.1121	0.1091	0.1065

Source: Own calculation based on 10-fold cross-validation.

The classical Brier score (Brier), the weighted Brier score (Brier_w), as well as the Brier score calculated separately for all categories of the employment variable ($\text{Brier}_{employed}$, $\text{Brier}_{unemployed}$, $\text{Brier}_{inactive}$) lead to the same overall conclusion. The conditional inference tree algorithm performs best, followed by the Markovian transition model and the model with lagged dependent variable as explanatory variable. The Brier score separately for each category shows that all model specifications perform best in estimating transitions into employment, i. e., employed to employed, unemployed to employed, and inactive to employed, with Brier scores ranging from 0.0404 for the conditional inference tree model to 0.0414 for the model with the lagged dependent variable as the explanatory variable. The Brier score is worst for estimating transitions to unemployment, ranging from 0.5392 for the conditional inference tree model to 0.5513 for the lagged dependent variable model. For the estimation of transitions to inactivity, the Brier score ranges from 0.1065 for the conditional inference tree model to 0.1121 for the model with the lagged dependent variable. Thus, based on the internal validation, we choose the conditional inference tree algorithm for estimating employment transitions because it outperforms both parametric regression models.

External Validation

The validation process in the MikroSim model primarily involves comparing the simulated output with external benchmarks, which is referred to as external validation. We evaluate the predictive performance through external validation by comparing the output of the MikroSim model with external data at district level. This is justifiable, as the MikroSim model is not primarily designed for modeling individual

employment trends, but for analyzing scenarios at regional level. As benchmark data, we use openly accessible data from INKAR (Bundesinstitut für Bau-, Stadt und Raumforschung, 2021) at the labor market region level. Labor market regions are mainly used as spatial unit for labor market analyses. The borders are determined based on the flow of commuting people, so that the majority of employees in a labor market region also lives there. The mobility of labor within labor market regions results in an equalization process of wages, rents as well as product and service prices (IAB, 2019; Bundesagentur für Arbeit, 2024).

The external validation is conducted using the TAE (2.49), SAE (2.50), and RMSE (2.48) as quality criteria. The quality measures are calculated based on relative values of unemployment, employment and inactive people in the risk population. The years 2011 to 2019 are considered. For this time-span external benchmarks from INKAR (Bundesinstitut für Bau-, Stadt und Raumforschung, 2021) as administrative sources is available. Table 2.6 gives an overview of the performance of the different model specifications based on the quality measures TAE, SAE, and RMSE.

Table 2.6: External validation: TAE, SAE, and RMSE

Labor status	**Model specification**	**TAE**(%)	**SAE**(pp)	**RMSE** (%)
Employed	Model with lagged dependent variable	3.29	0.04	3.68
	Markovian transitions	3.00	0.04	3.35
	Conditional inference tree	2.86	0.04	3.19
Inactive	Model with lagged dependent variable	2.01	0.11	2.21
	Markovian transitions	1.84	0.10	2.02
	Conditional inference tree	1.83	0.10	2.02
Unemployed	Model with lagged dependent variable	1.75	0.35	1.81
	Markovian transitions	1.65	0.33	1.71
	Conditional inference tree	1.45	0.29	1.52

Source: own calculation based on three simulation runs.

The analyzed models perform similarly im terms of TAE, SAE, and RMSE. The SAE can be used for direct comparisons. Based on the SAE, the models perform best in predicting employment and worst in predicting unemployment. For employment, all models have a SAE of 0.04 percentage points (pp). Thus, all models perform equally well. The difference in the model performance is most pronounced for predicting unemployment. Even for functionally well specified models, the predictive performance is quite poor, especially when some states are relatively dense

or sparsely represented in the data (A. Duncan and Weeks, 1998, p. 151). Overall, the conditional inference tree slightly outperforms the other models based on the selected quality measures. Based on the results of the internal and external validation, we use the conditional inference tree in the following to model the employment status in the MikroSim model.

2.5 Summary

Based on the methodological differentiation in Section 2.1, we were able to categorize the MikroSim model as population-based regional discrete-time dynamic microsimulation model. A central element of dynamic microsimulation models is the projection of the base population into the future. For this reason, it is crucial to capture the structure at the micro-level, taking into account the multivariate distribution. Various models can be used to estimate the transition probabilities. Since almost all microsimulation models are aligned to external benchmarks, the variable selection and the evaluation of different modeling techniques based on external and internal validation methods have received less attention in the field of microsimulations. We presented different modeling strategies for dynamic discrete-time microsimulation models. Employment transitions were first modeled by including the lagged employment status as explanatory variable, second, by Markovian transition models, and third, by using the conditional inference tree algorithm. The evaluation of these modeling strategies was conducted using the Brier score as an internal validation measure, and the quality measures SAE, TAE, and RMSE as external validation measures. We found that the conditional inference tree algorithm achieves the best results for estimating and simulating employment transitions in the MikroSim model. However, it is important to note that the development of the MikroSim model and its underlying modules and models is an ongoing task and that this finding cannot be generalized. The modeling strategy needs to be re-assessed each time a new module is added to the microsimulation model.

The decision to focus on the employment module stems from the fact that variables related to the employment module, in particular, the Frisch labor supply elasticity plays a central role as link variable to combine micro and macro models. Therefore, a sophisticated employment module is essential for linking micro and macro models. Chapter 4 provides a more comprehensive discussion of the role of the employment variable as a link variable.

For future research, the change from annual to infra-annual labor market transitions would allow for further application fields of the MikroSim model. According to Klevmarken (1997), there are three different methods for integrating a second time unit. First, several simulation runs can be conducted within a year for the modules which operate on a shorter time unit, second, a count model can be used which simulates the number of quarters or months a person is in a specific labor market status in a year, and third, a continuous time model could be used in order to simulate the date when a individual enters and leaves a certain state.

In addition, it would be useful to further consider techniques for dealing with imbalanced data. As a consequence of imbalanced data, biased estimators and thus high prediction errors may result for the minority class (Rezaei et al., 2021). The following techniques that have been developed for dealing with unbalanced data sets could be explored: data sampling, algorithmic modification, cost-sensitive learning, and ensemble-based methods.

Furthermore, it would be interesting to consider further machine learning approaches for modeling employment transitions. The implications of integrating machine learning algorithms in microsimulation models must be taken into account. This is of particular importance for the thematic sub-projects, as most of the models in the MikroSim framework have so far been developed based on theoretical considerations grounded in social sciences with regard to the scenarios to be implemented.

Chapter 3

Behavioral Microsimulation Models

Behavioral microsimulation models are microsimulation models that include a behavioral component, allowing for the analysis of behavioral responses to policy scenarios. Policy reforms, such as labor taxation policies or cash transfer programs, aim at incentivizing individual behavior, particularly labor supply decisions. For example, foreign professionals in Italy are offered tax incentives so that 90% of their income is tax-free if they move to Italy, or childcare fees are adjusted to working hours so that those who work more pay less. However, political instruments can also have unintended consequences, such as redistributing income or wealth from the rich to the poor to combat poverty may reduce the incentive to work in response to a tax increase to finance poverty reduction measures (O'Donoghue, 2021, p. 116).

In order to evaluate the potential impact of reforms, microsimulation models often integrate behavioral components to account for behavioral responses. According to O'Donoghue (2021, p. 22), about 33% of dynamic microsimulation models include a behavioral component. The distinctive feature of behavioral microsimulation models is their strong economic foundation in combination with extensive empirical data (Zucchelli et al., 2012).

Common fields of application include (O'Donoghue, 2021, p. 6):

- Transport decisions
- Consumption behavior
- Labor participation and supply.

In the field of transportation, behavioral microsimulation models are used to analyze the demand for transportation based on the choice of means of transportation. These models consider travel times, travel costs, time of day, and car ownership (McFadden, 1974; Golob, 1990; Miller, 2014). However, factors that are not directly related to transportation conditions, such as socio-economic characteristics of transport users, as well as their habits, attitudes, and values, also influence the choice of transport mode (Salomon and Ben-Akiva, 1983; Scheiner and Holz-Rau, 2007; Rieser-Schüssler and Axhausen, 2012; Bai et al., 2020). A number of interesting scenarios could be considered for the application of behavior-oriented microsimulation models in the transport sector, e. g., the analysis of the effects of the Deutschland-Ticket or free public transport as in Luxembourg on the choice of means of transport.

Consumption-based microsimulation models that incorporate a behavioral component require the inclusion of expenditure information in the base data set. They are used to analyze consumption responses to price changes resulting from indirect tax reforms. Environmental modeling is an emerging area of research in the field of microsimulation. The structure of microsimulation models that are used to analyze environmental fiscal policies is similar to that of consumption-based microsimulation models. The main difference lies in the price changes resulting from policy reforms. For example, when simulating the effects of a carbon tax, the price changes depend on the carbon dioxide equivalent. In the context of microsimulation models with an environmental focus, geo-referenced models are particularly suitable, as the interaction between individuals and the environment is strongly influenced by the location (O'Donoghue, 2021, p. 19).

However, in the field of microsimulations, the labor market is by far the most common area that contains a behavioral component. This chapter examines behavioral labor supply microsimulations and a potential extension of the MikroSim model. The chapter is structured as follows: Section 3.1 provides an overview of the state of research on microsimulation models with a behavioral labor supply component. Section 3.2 presents the methodological basics of behavioral microsimulation mod-

els, including the concept of utility and random utility models. Additionally, we discuss conceptual decisions that need to be made in the modeling process. Subsequently, Section 3.3 provides an overview of agent-based labor market models and differentiates them from behavioral models of labor supply. Section 3.4 introduces the first approach for integrating a behavioral component into the MikroSim model. Section 3.5 summarizes and gives an outlook to further research.

3.1 Literature Overview

Microsimulation models have been to analyze behavioral responses since the 1980s. The behavioral component is mainly included in microsimulation models to analyze the behavioral response to policy reforms that affect the labor supply decision. Blundell et al. (2000) use a discrete behavioral model of labor supply to analyze the effects of the introduction of the Working Families' Tax Credit in the United Kingdom. They estimate separate discrete labor supply models for single parents and married couples using the 1995 and 1996 Family Resources Survey. Based on the estimated model, Blundell et al. (2000) simulate the labor supply effects of the new policy using the tax-benefit microsimulation model TAXBEN developed by the Institute for Fiscal Studies. Hoynes (1996) and Keane and Moffitt (1998) conduct similar analysis for the United States, van Soest and Das (2001) for the Netherlands, Bonin et al. (2002) for Germany, and Aaberge et al. (1998) for Italy.

In addition to the direct behavioral response of labor supply (and demand) to policy reforms, social welfare effects are also of great interest. Behavioral microsimulation models allow for the analysis of welfare implications of various policy scenarios. In this context, Labeaga et al. (2008) analyze efficiency and welfare effects of income tax reforms in Spain, accessing social welfare using the equivalent variation. Similarly, Capéau et al. (2016) evaluate the impact of changes in educational levels on labor supply in Belgium, while Creedy et al. (2020) analyze labor responses to income tax reforms in New Zealand and evaluate welfare effects using the compensation variation. Islam and Flood (2020) introduce a tax-benefit microsimulation model for Luxembourg. They analyze the transition from joint taxation to individual taxation and assess the resulting welfare implications.

Some behavioral microsimulation models also consider the labor demand side in addition to the labor supply side. The ifo Tax and Transfer Behavioral Microsimulation Model for Germany, for instance, comprises a static tax-benefit model, a behavioral labor supply component, and a demand model that accounts for labor demand restrictions (Blömer and Peichl, 2020). Narazani et al. (2023) develop the multidimensional labor supply-demand microsimulation model EUROLAB, which covers 27 countries. EUROLAB is a behavioral microsimulation model that is based on the static tax-benefit model EUROMOD (European Union, 2022). It uses a discrete choice labor supply model to analyze labor supply behavior and allows to assess changes in labor market responses as a reaction to tax transfer reforms.

In addition to analyzing labor supply behavior, behavioral microsimulation models are also used to assess the potential effects of policy reforms on consumption patterns (Creedy, 1999; Decoster and Camp, 2001; Kaplanoglou and Newbery, 2003), polluting behavior (Hynes and O'Donoghue, 2014), transportation choices (Miller, 2014), and childcare choices (Kornstad and Thoresen, 2007).

3.2 Methodological Basics

Behavioral microsimulation models build on preferences. Preferences are defined as rankings of all available bundles based on attitudes and values related to the outcomes of these options. Individuals have preferences over a set of available bundles. The satisfaction that an individual obtains from a given bundle can be expressed using a numerical score, i. e., utility (H. R. Varian, 2010, pp. 34f; Schumann et al., 2011, pp. 78f). The underlying concept is that of a rational decision-making individual (Schumann et al., 2011, pp. 103f).

3.2.1 Utility Theory

Utility functions can be differentiated into cardinal and ordinal utility functions. Cardinal utility functions assign a real number to each bundle of goods and measure utility in utility units. If a household assigns a utility of 100 to bundle j and a utility of 200 to bundle k, it means that bundle k yields twice the utility of bundle j for this household. According to cardinal utility theory, utility differences are quantifiable.

The underlying concepts of utility functions in the household theory are the following (Schumann et al., 2011, pp. 51-57):

1. Non-saturation
2. Decreasing marginal utility
3. Decreasing marginal rate of substitution

The concept of non-saturation states that the slope of the utility curve is positive. This means that consuming more of one good while keeping the consumption of other goods constant leads to an increase in utility. Gossen's first law, which is the principle of decreasing marginal utility, states that the additional utility of a good decreases as the consumption of that good increases. In the case of two goods, the indifference curve illustrates the rate at which one good can be exchanged for the other while maintaining the same level of utility. The marginal rate of substitution decreases due to the convexity of the indifference curves.

The ordinal utility theory is also based on indifference curves but requires weaker assumptions. According to the ordinal theory, the utility difference between bundle j and bundle k cannot be quantified in the example given. It can only be stated that the household prefers bundle k to bundle j. It is important to note that Gossen's first law only applies to cardinal utility functions (Schumann et al., 2011, p. 82).

In order to assign a monetary value to utility, one can determine either the equivalent variation (Flood and Islam, 2005) or the compensating variation (Bourguignon and Spadaro, 2006; Labeaga et al., 2008). The two approaches are based on the same underlying concept. The equivalent variation is a measure of the amount of money that an individual would require prior to the implementation of a policy in order to maintain the same level of utility. In contrast, the compensating variation represents the amount of money necessary after the introduction of a policy to sustain the same level of utility (Labeaga et al., 2008; H. R. Varian, 2010, pp. 258-262).

Indifference curves describe the preferences of the households. Preferences build on the following assumptions (Schumann et al., 2011, pp. 80f):

1. Completeness: Individuals have a preference order for all alternative courses of action they face
2. Transitivity: Individuals make consistent choices
3. Non-saturation: The utility curve has a positive slope

4. Convexity: The rate of substitution diminishes
5. Reflexivity: Any bundle is at least as good as itself
6. Continuity: A prerequisite for the existence of a utility function.

Preferences can be obtained through stated preferences or revealed preferences. Stated preferences and revealed preferences are two different approaches to collect data. In the stated-preferences approach, the interviewer presents the respondents a series of hypothetical choices and the respondents are asked about their preferences over the alternatives. A choice experiment is conducted to identify choice-specific attributes (Greene, 2012, p. 822; O'Donoghue, 2021, p. 118). The stated preference approach is frequently applied in the field of policy analysis, such as public services (Schläpfer, 2017), choices of transportation (Hensher, 1994; Arencibia et al., 2015), and environmental decisions (Tu et al., 2016).

In the revealed-preferences approach, the observed behavior is depicted in the data but not the alternative choices. Policy analysis can be conducted using either ex-post or ex-ante methods. Ex-post methods involve comparing a treatment group with a control group. The treatment group is affected by the policy measure, while the control group is not. Consequently, the ex-post method can be considered an actual experiment with control and treatment groups or a natural experiment that utilizes the natural diversity in the population. Ex-ante methods are based on simulations with the natural diversity of individual characteristics and choices in the data (Aaberge and Colombino, 2014).

The use of stated-preferences data has the advantage of including information on the full choice set and allowing for individual heterogeneity. However, it should be noted that the data are only hypothetical, which introduces an inherent risk that individuals may misstate their preferences. In contrast, revealed-preferences data include actual choices but do not account for individual heterogeneity (Greene, 2012, p. 822; O'Donoghue, 2021, pp. 118f).

3.2.2 Random Utility Models

Behavioral microsimulation models of labor supply are specified as random utility models (Labeaga et al., 2008; Barrios et al., 2016; Blömer and Peichl, 2020; Islam and Flood, 2020; Narazani et al., 2023), which were introduced by McFadden (1973). Random utility, defined over the available alternatives, provides a theoretical frame-

work for studying discrete choices (Greene, 2012, pp. 724-726, 801–803). They can be implemented either as continuous-choice random utility models or as discrete-choice random utility models. Since the continuous-choice approach may exhibit problems in obtaining tractable closed form solutions of labor supply functions in the case of non-linear and non-convex budget sets, the discrete-choice approach (van Soest, 1995; Aaberge et al., 1995) is favored in the literature (Blundell and Macurdy, 1999; Haan, 2004; Creedy et al., 2006; Zucchelli et al., 2012; Capéau et al., 2016). In the discrete-choice approach, working hour choices are restricted to a pre-specified set of discrete possibilities (Bargain et al., 2014).

The random utility model is based on the idea that an individual who faces two choices k and j will choose the option that results in the greatest utility. However, the unobserved utilities are not revealed. A linear random utility model for $j \neq k$ can be represented as (Greene, 2012, p. 724):

$$\begin{aligned} V_i^{(t)k} &= U_i^{(t)k} + \varepsilon_i^{(t)k} = w'^{(t)k}_i \beta_k + z'^{(t)k}_i \gamma_k + \varepsilon_i^{(t)k} \\ V_i^{(t)j} &= U_i^{(t)j} + \varepsilon_i^{(t)j} = w'^{(t)j}_i \beta_j + z'^{(t)j}_i \gamma_j + \varepsilon_i^{(t)j}. \end{aligned} \tag{3.1}$$

The utility of choice k is denoted as V_k and the utility of choice j as V_j. The individual's observable characteristics, denoted by w, the vectors z_k, and z_j, contain choice-specific attributes of the two alternatives k and j, respectively. ε_k and ε_j are random terms. Assuming that the identical and independent errors follow an extreme value Type-I distribution, the random utility model becomes a conditional logit model (Bourguignon and Spadaro, 2006; Aaberge and Colombino, 2018; Croissant, 2020). For each alternative j, there is an additive stochastic component that follows an extreme value Type-I distribution. This distribution ensures that the probabilities are positive and continuous in the parameters. The error terms can be regarded as unobserved alternative-specific utility components or errors in the perception of the utility of the alternatives (van Soest et al., 2002).

Individuals reveal their preference ranking through the choices they actually make. Let $y_i^{(t)} = 1$ indicate the individual's choice of alternative k. Therefore, we can infer from $y_i = 1$ that $U_i^{(t)k} > U_i^{(t)j}$. The probability of choosing alternative k over alternative j is given as (Greene, 2012, p. 725):

$$P\left(y_i^{(t)} = 1 | w_i^{(t)}, z_i^{(t)k}, z_i^{(t)j}\right) = P\left(V_i^{(t)k} > V_i^{(t)j}\right). \tag{3.2}$$

The difference between the multinomial logit and the conditional logit models is linked to the distinction between the stated-preferences model and the revealed-preferences model (Hoffman and G. Duncan, 1988; Croissant, 2020). Thus, the multinomial model is a reduced-form model, while the conditional logit model is a structural model. In the multinomial logit model, the explanatory variables depend on the characteristics of the individual, whereas in the conditional logit model, the explanatory variables depend on choice-specific variables (O'Donoghue, 2001, p. 145). Therefore, the multinomial logit is also known as the "characteristics of the chooser" approach, while the conditional logit model is referred to as the "characteristics of the alternative" approach (Hoffman and G. Duncan, 1988, p. 415).

The conditional logit model focuses on the set of alternatives and is based on the stated-preferences approach. In the stated-preferences approach, individuals are asked about their preferences for the different available alternatives, resulting in a data set with information about the entire choice set. This means that, if the labor supply model is based on a conditional logit model, it is necessary to obtain information about each leisure-consumption combination. The multinomial logit model, which focuses on the individual, is based on the revealed-preferences approach, i. e., the actual choice observed in the data. Preferences are derived directly from observed behavior (Hoffman and G. Duncan, 1988; O'Donoghue, 2021, p. 118).

The random utility model can be extended to the random utility random opportunity (RURO) model (Capéau et al., 2016). Beyond the willingness to trade-off leisure for consumption, the RURO model takes into account other non-observable attributes influencing the decision on the number of working hours. Examples of factors that may influence the availability of jobs include societal relevance, task difficulty, as well as health and safety considerations. The RURO model acknowledges that job opportunities and non-market activities are not equally accessible to all individuals and depend on personal and job-related characteristics. For further information on the RURO model, see Capéau et al. (2016).

In microsimulation models, alignment methods are crucial for ensuring the credibility of the model (see Section 2.2.4). For random utility models, it is necessary to replicate actual choices based on residuals drawn from the assumed distribution, while following the theoretical framework in order to ensure consistency between the simulation and the benchmark data. For this purpose, O'Donoghue (2021, pp. 131-133) proposes to derive unobserved residuals for the simulation.

The conditional logit model assumes that the error term ε follows a standard Gumble (Type-I, extreme value) distribution with the following density function (Greene, 2012, p. 802):

$$f\left(\varepsilon_i^{(t)k}\right) = \exp\left(-\exp\left(-\varepsilon_i^{(t)k}\right)\right). \tag{3.3}$$

As noted above, it is assumed that utility is maximized for the actual choice j, with $j \neq k$. Therefore, the following relationship should hold:

$$\left(w'^{(t)}_i \beta_k + z'^{(t)k}_i \gamma_k + \varepsilon_i^{(t)k}\right) > \left(w'^{(t)}_i \beta_j + z'^{(t)j}_i \gamma_j + \varepsilon_i^{(t)j}\right) \tag{3.4}$$

The error terms can be generated using different approaches. O'Donoghue (2021, pp. 131-133) proposes a computationally fast method for obtaining the error terms $\varepsilon_i^{(t)}$ in one iteration. Let the error terms $\varepsilon_i^{(t)j}$ take the extreme value distribution of the following shape (O'Donoghue, 2021, p. 133):

$$\varepsilon_i^{(t)j} = -\log\left(-\log\left(u_i^{(t)j}\right)\right), \tag{3.5}$$

with u being a uniform random number. The error term $\varepsilon_i^{(t)}$ is obtained by randomly drawing and maximizing the expression

$$\left[\max\left(x'^{(t)}_i \beta + \varepsilon_i^{(t)j}\right), \infty\right]. \tag{3.6}$$

Given (3.5), this is equivalent to randomly drawing a uniform random number

$$u_i = \exp(-\exp(-\varepsilon_i)) \tag{3.7}$$

in the interval

$$\left[\exp\left(-\exp\left(-\left(\max\left(x'^{(t)}_i \beta + \varepsilon_i^{(t)j}\right)\right)_j\right)\right), 1\right]. \tag{3.8}$$

For more information on the derivation of unobserved residuals, we refer to O'Donoghue (2021, pp. 131-133).

3.2.3 Labor-Supply-Choice Modeling

The random utility model of labor supply represents consumption-leisure preferences using a utility function with fixed costs. We use a quadratic utility function following Keane and Moffitt (1998), as it is a popular choice in the field of behavioral microsimulation models due to its ability to model complex interactions (Bargain et al., 2014; Barrios et al., 2016; O'Donoghue, 2021, p. 129). In a discrete labor supply model, utility increases with income and the second-order derivative of income with respect to leisure is positive. Therefore, the quadratic utility function is quasi-concave.

In modeling labor supply choice, the quadratic utility function typically uses the following variables as explanatory variables (O'Donoghue, 2021, p. 129):

- Disposable income
- Quadratic disposable income
- Leisure of male partner
- Leisure of female partner
- Quadratic leisure of male partner
- Quadratic leisure of female partner
- Leisure interacted with individual-specific attributes, such as age and number of children.

Individual-specific attributes do not vary between the choice attributes and would drop-out of the probability of an individual selecting a specific choice. However, individual-specific attributes are likely to affect labor-supply choice. Therefore, these attributes are interacted with a choice-varying variable to serve as taste shifters. The fixed costs of working are modeled as dummy variable (O'Donoghue, 2021, p. 129).

The deterministic utility U of a couple i at discrete choice $j = 1, ..., J$ is given as (Bargain et al., 2014):

$$\begin{aligned} U_{ij} =& \alpha_{ci} c_{ij} + \alpha_{cc} c_{ij}^2 + \alpha_{hfi} h_{ij}^f + \alpha_{hmi} h_{ij}^m + \alpha_{hff} \left(h_{ij}^f\right)^2 + \alpha_{hmm} \left(h_{ij}^m\right)^2 \\ &+ \alpha_{chf} c_{ij} h_{ij}^f + \alpha_{chm} c_{ij} h_{ij}^m + \alpha_{hmhf} h_{ij}^f h_{ij}^m - \eta_j^f \cdot 1\left(h_{ij}^f > 0\right) \\ &- \eta_j^m \cdot 1\left(h_{ij}^m > 0\right) \end{aligned} \tag{3.9}$$

with household consumption c_{ij}, spouses' work hours h_{ij}^f and h_{ij}^m and fixed costs η. For reasons of style, the time index t is omitted in the following.

In the case of single individuals, the equation reduces to:

$$\begin{aligned} U_{ij} =& \alpha_{ci} c_{ij} + \alpha_{cc} c_{ij}^2 + \alpha_{hi} h_{ij} + \alpha_{hh} \left(h_{ij}\right)^2 + \alpha_{ch} c_{ij} h_{ij} \\ & - \eta_j \cdot 1 \left(h_{ij} > 0\right). \end{aligned} \tag{3.10}$$

The coefficients on consumption and hours worked are defined as (Bargain et al., 2014):

$$\begin{aligned} \alpha_{ci} &= \alpha_c^0 + Z_i^c \alpha_c + u_i \\ \alpha_{hfi} &= \alpha_{hf}^0 + Z_i^f \alpha_{hf} \\ \alpha_{hmi} &= \alpha_{hm}^0 + Z_i^m \alpha_{hm}. \end{aligned} \tag{3.11}$$

The coefficients are assumed to vary with taste-shifters Z_i. The coefficient on consumption α_{ci} can also include unobserved heterogeneity ε_i.

The budget set is determined by a finite number of disposable incomes and their corresponding discrete hour choices (Creedy et al., 2006). Disposable income is calculated as a function of earnings $w_i h_{ij}$, non-labor income y_i, and household/individual characteristics x_i for each labor supply choice. For couples, disposable income is calculated as (Bargain et al., 2014):

$$c_{ij} = f\left(w_i^f h_{ij}^f, w_i^m h_{ij}^m, y_i, x_i\right), \tag{3.12}$$

and for singles, it is calculated as:

$$c_{ij} = f\left(w_i h_{ij}, y_i, x_i\right). \tag{3.13}$$

3.2.4 Conceptual Issues

In order to estimate labor-supply functions, certain modeling decisions must be made. These decisions include selecting the population of interest, such as the working-age or prime working-age population, and determining whether to include self-employed individuals, civil servants, and people with disabilities. Exclusions can be made for various reasons. For self-employed individuals, working hours are often not precisely recorded. Civil servants cannot be dismissed easily and may have

different options for working hours compared to other occupational groups, and individuals with disabilities may have special working conditions. It is also crucial to determine whether to incorporate individuals who are currently unemployed, as it might be argued that job seekers do not voluntarily choose to be unemployed (O'Donoghue, 2021, p. 125).

Several modeling strategies are available. The choice is between the continuous labor supply model and the discrete-choice model. In the continuous labor supply model, the labor supply is linear, quadratic, or semi-logarithmic, while in discrete-choice models, a quadratic, transcendental logarithmic, or generalized Stone-Geary utility function is used (Bargain et al., 2012). If the labor-supply choice is modeled using the discrete-choice model, predetermined intervals for hours worked must be established. The choice of hours worked intervals directly affects the complexity of the simulation. Assuming there are m available hour choices for each person, this results in m^2 choices for couples. Once the intervals have been defined, the counterfactual hours worked are sampled from the hours in the hours band (O'Donoghue, 2021, p. 125).

The availability of counterfactual choices is essential for modeling labor-supply choices. Determining the potential labor income of unemployed individuals in the event of employment and the out-of-work income of employed individuals in the event of unemployment is often a challenge. However, in microsimulations with an income module, it is possible to change the individual's characteristics in order to simulate counterfactual choices. Microsimulation models typically capture only one income component, such as labor income or total disposable income, without distinguishing between individual labor components. It can therefore be problematic to distinguish between unemployed and inactive individuals based on the wage-and-hours framework.

3.3 Excursus: Agent-Based Models of Labor Markets

Modeling of labor-supply choices is similar to agent-based models of labor supply. In the following, we provide a brief introduction to agent-based models, with a focus on those related to labor supply, and highlight the differences between these approaches.

Agent-based models typically consist of three elements (Michel et al., 2009; Macal and North, 2010):

- Agents
- Interactions
- Environment.

Agents are autonomous and proactive decision-makers who interact with each other and the environment. The environment includes information on the agents' location and may also include details such as groundwater levels or infrastructure. Thus, the environment restricts the actions of the agents (Macal and North, 2010). For examples of agent-based models of labor markets, see Richiardi (2004), Neugart (2008), Blanchet et al. (2009), and Kant et al. (2020).

Agent-based models of labor markets are based on search theory and consider both the supply side and the demand side. The search theory focuses on the behavior of unemployed individuals who receive job offers, including wage, that they can either accept or reject in order to wait for an alternative job offer. The theory can be extended to include inactive and employed individuals. Individuals who are not currently employed decide whether or not to enter the labor market, while those who are employed decide whether to remain in their current position, seek new employment opportunities, or exit the labor market (Devine and Kiefer, 1991).

We introduce the central components of agent-based models of labor markets using the newly developed WorkSim model (Kant et al., 2020) as an example. The model includes two types of agents: individuals and private firms. The environment is complex and comprises job advertisements, a statistical institute that provides information labor market tension, and a public sector that recruits people. Additionally, WorkSim takes into account the institutional framework. The WorkSim model extends the search approach by:

- Matching workers and employers through bilateral meetings. Both individuals and firms can prefer to match to a bad match.
- Multi-job firms have the option to offer either fixed-term contracts or permanent contracts.
- Search and other costs, such as search costs of replacement and psychological costs.

Each simulation run consists of four steps. First, firms decide on the creation and destruction of jobs and assess the employees through evaluations. Second, individuals decide whether to enter or leave the labor market or to change jobs. Third, firms receive applications, select candidates and possibly hire them. If the firm decides to hire an internal candidate, the process is called internal promotion. Fourth, household dynamics, retirement, and aging are simulated.

The fundamental difference between agent-based models and dynamic microsimulation models is that agents act autonomously and interact with other agents and the environment. In agent-based models, actions and interactions between the agents are of primary interest, while in dynamic microsimulation models, interactions are only incorporated indirectly, if at all (Michel et al., 2009; Kim and Hammond, 2021, pp. 22f; Schmaus, 2023, p. 20).

3.4 Application: Labor-Supply-Choice Modeling in the MikroSim Model

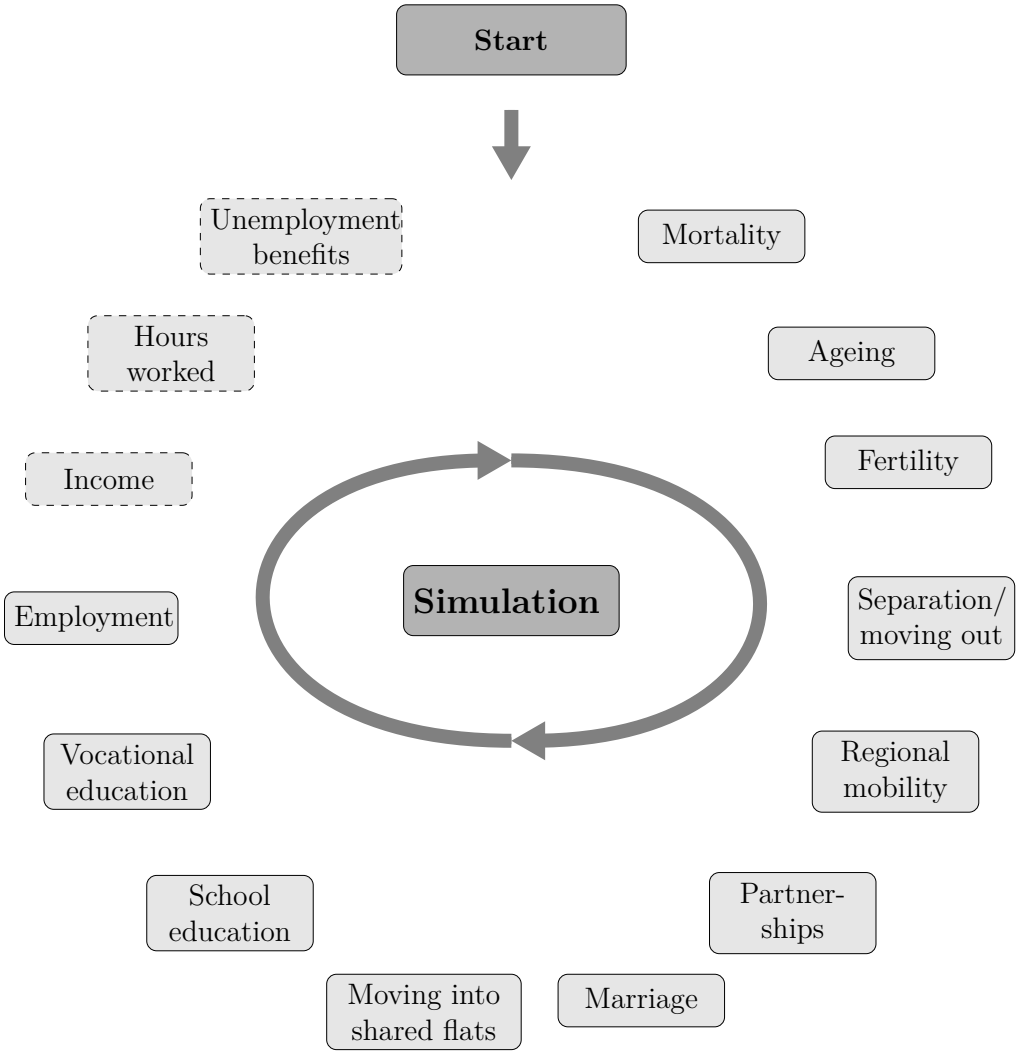
Labor market behavior, or more precisely labor supply, is one of the most important areas for behavioral analysis in the area of microsimulations (O'Donoghue, 2021, p. 16). No attempt has yet been made to implement a dynamic behavioral microsimulation model of labor supply into the MikroSim model to analyze behavioral responses of labor supply to policy reforms. In the following, we present an extension of the MikroSim model presented in Section 2.4. The extension transforms the MikroSim model from an arithmetic microsimulation model into a behavioral microsimulation model. Using this extended model, we analyze the impact of a 1% wage increase on the supplied hours of work. The extended MikroSim model enables the analysis of changes in individual behavior in response to policy reforms. The underlying assumption is that individuals aim to maximize their utility. The behavioral microsimulation model allows the ranking of individuals' attainable states of affairs using the ordinal utility approach. Additionally, we assess the impact of proposed changes in monetary units based on the utility function.

3.4.1 Extension of the MikroSim Model

The MikroSim model is a non-behavioral microsimulation model. It can be categorized as a data-driven discrete-time dynamic microsimulation model that aims to capture micro-level structures while taking into account the multivariate distribution (Münnich et al., 2021). Non-behavioral models are also known as arithmetic models (Bourguignon and Spadaro, 2006).

The extension of the MikroSim model with the addition of a behavioral labor supply module enables the investigation of further research questions, particularly those related to the behavioral responses of individuals to changes in public policy. In a behavioral model, alterations in individual behavior are driven by policy shifts. Consequently, the policy parameters must have a direct or indirect impact on the model (Li, 2011, p. 34). To incorporate behavioral labor supply, the base data set must include information on supplied hours worked and wages. Therefore, the MikroSim model is extended with the modules for hours worked and unemployment benefits. Additionally, the income module is modified to reflect labor income. The changes made to the extended MikroSim model, compared to the original MikroSim model as depicted in Figure 2.4, are shown in Figure 3.1 with dashed lines.

Figure 3.1: Module sequence in the extended MikroSim Model



Source: Own illustration based on Münnich et al. (2021).

There are two alternatives for introducing hours worked into the MikroSim model. The first option builds on full-time employment being defined as working between 35 and 40 hours. The number of hours worked for full-time workers is randomly drawn within this interval. Then, the wage rate per hour is determined based on the resulting full-time income. The number of hours worked in part-time employment can be derived from the wage rate per hour and the resulting income.

The second option is to estimate labor supply as a function of personal characteristics such as the presence of children in the household, wage, or age following O'Donoghue (2021, p. 129). The supplied hours worked for employed people

is estimated based on the German Microcensus Scientific Use File 2014 (RCD of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2014.00.00.3.1.0, own calculations) with normal working time per week in hours (in intervals) as dependent variable and age, age squared, net income from labor, occupational status (1: self-employed, 2: state employee, 3: employee, 4: worker, 5: rest), full-time/part-time work, in education (0: no, 1: yes), presence of children under 3 years in the household (0: no, 1: yes), sex (0: male, 1: female), and country of birth (0: Germany, 1: other European Union countries, 1: rest of the world) as independent variables.

The normal working time per week in hours is discretized. The following intervals are available:

$$y_i^{(t)} = \begin{cases} 1 & \text{if individual } i\text{'s normal weekly working time is between 1 and 10 hours} \\ 2 & \text{if individual } i\text{'s normal weekly working time is between 11 and 20 hours} \\ 3 & \text{if individual } i\text{'s normal weekly working time is between 21 and 30 hours} \\ 4 & \text{if individual } i\text{'s normal weekly working time is between 31 and 40 hours} \\ 5 & \text{if individual } i\text{'s normal weekly working time is between 41 and 50 hours} \\ 6 & \text{if individual } i\text{'s normal weekly working time is between 51 and 60 hours} \\ 7 & \text{if individual } i\text{'s normal weekly working time is more than 60 hours} \end{cases}$$

Within the hours group, the counterfactual hours choice can be obtained using one of three options: (1) fixed hours, (2) uniformly sampled hours from a fixed interval, or (3) hours sampled from the observed distribution (Narazani et al., 2023). To obtain counterfactual choices, we choose to sample from the ten-hours band following the observed distribution in the German Microcensus Scientific Use File 2014 (Statistisches Bundesamt (Destatis) and Gesis, 2018). Unemployed individuals are also assigned a positive number of hours worked by uniformly sampling from the interval [1, 5]. It is assumed that the individual uses this number of hours, for example, for participation in re-training or motivational activities (Narazani et al., 2023).

In the MikroSim model, unemployment benefits are deterministically added based on an individual's employment history. We differentiate between Unemployment Benefit 1 and Citizens' Basic Income. Unemployment Benefit 1 is granted to eligible individuals who meet specific conditions. Individuals must:

1. be unemployed, but able to work at least 15 hours per week in an occupation that requires the payment of social security contributions
2. register as job seekers with the responsible Employment Agency
3. actively search for employment and cooperate with the Employment Agency
4. fulfill the qualifying period.

The Unemployment Benefit 1 amounts to 60% of the net income of the previous 12 months. If the unemployed person or his or her partner has at least one child, the Unemployment Benefit 1 increases to 67% of the net income of the previous 12 months (Federal Employment Agency, 2023).

The Citizens' Basic Income is determined according to the standard rates. Since January 1, 2023, single individuals and single parents receive a monthly payment of 502 euro per month (regular payment level 1), while couples and joint households receive 451 euro per person per month (regular payment level 2). Adults under 25 years of age who are not employed and live with their parents receive 402 euro per month (regular payment level 3). Individuals aged 14 to 17 receive 420 euros per month (regular payment level 4), children aged 6 to 13 receive 348 euro per month (regular payment level 5), and children up to the age of 5 years receive 318 euro per month (regular payment level 6). An overview of the normal requirement according to paragraph 28 of volume XII of the Social Insurance Code (SGB XII) can be found in Table 3.1.

Table 3.1: Normal requirement according to paragraph 28 SGB XII in euro

Valid from	**Regular payment**					
	Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**
1 January 2011	346	328	291	287	251	215
1 January 2012	374	337	299	287	251	219
1 January 2013	382	345	306	289	255	244
1 January 2014	391	353	313	296	261	229
1 January 2015	399	360	320	302	267	234
1 January 2016	404	364	324	306	270	237
1 January 2017	409	368	327	311	291	237
1 January 2018	416	374	332	316	296	240
1 January 2019	424	382	339	322	302	245
1 January 2020	432	389	345	328	308	250
1 January 2021	446	401	357	373	309	283
1 January 2022	449	404	360	376	311	285
1 January 2023	502	451	402	420	348	318

Regular payment level 1: Single individuals / parents
Regular payment level 2: Couples, per partner / joint households
Regular payment level 3: Adults under 25 years not in employment in parental household
Regular payment level 4: Young persons aged 14-17
Regular payment level 5: Children aged 6-13
Regular payment level 6: Children aged 0-5

The income module in the extended MikroSim model largely corresponds to the income module described in Münnich et al. (2021). It simulates the net income of individuals and households. Net income is defined as the sum of all income. The model is estimated based on the German Microcensus 2011 to 2014 (RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/12211.2011.00.00.1.2.1 to 10.21242/12211.2014.00.00.1.2.1, own calculations). In the behavioral microsimulation with labor supply, income components are of particular importance. In our case, the focus is on the wage rate. Therefore, the income module is modified in order to simulate labor income. Since labor income is not directly included in the Microcensus, we approximate it by excluding all observations with income sources other than labor income. The following income sources are available in the Microcensus: Public pensions, survivors' pensions, own pension, public payments and other income. Other income includes assets/interest,

life insurance/private pension insurance, renting/leasing, and private support. By excluding these income components, the labor income can be approximated by the net income for the remaining cases. The wage rate is determined using the information on hours worked and labor income. Based on the obtained wage rate, the labor income is determined for all counterfactual choices. Alternatively, labor income can be approximated by estimating the model only for the people, who earn the majority of their living from own employment.

The base data set must cover all possible choices at time s, which requires extending it to include each person of interest eight times. The eight options are: unemployed, working less than 11 hours per week, between 11 and 20 hours per week, between 21 and 30 hours per week, between 31 and 40 hours per week, between 41 and 50 hours per week, between 51 and 60 hours per week, and more than 60 hours per week. It is assumed that the actual choice is the choice that yields the highest utility. The potential wages of individuals who are not employed are not observable, which often poses a challenge for modeling labor supply choice (O'Donoghue, 2001, p. 126). The advantage of the MikroSim model is that it allows for the simulation of potential labor income for unemployed individuals if they were employed. This makes the MikroSim model an ideal tool for conducting counterfactual simulations. By changing the status of originally unemployed individuals in the employment module from unemployed to employed, it is possible to determine an income for those who are actually unemployed.

Unemployed individuals are those who are available and actively seeking work, while inactive individuals are those who are either unavailable or not seeking work. Therefore, the appropriate treatment of unemployed individuals is ambiguous. It could be argued that being unemployed is not a voluntary choice. Therefore, some analyses exclude this group, while most include them, e. g., Narazani et al. (2023) and O'Donoghue (2021, p. 125). We choose to include unemployed individuals as well.

3.4.2 Analysis of Income Incentives on Labor Supply Choices

Behavioral responses are often analyzed using a combined dynamic and static microsimulation model (Merz, 1993). The base population is projected up to 2019 using the MikroSim model. Then, the base population is augmented with the variables hours worked and unemployment benefits. The MikroSim model needs to be adapted to incorporate counterfactual choices, allowing the preferences of indi-

viduals to be revealed through their labor choices. The resulting MikroSim base population contains each individual of the population of interest eight times. All possible labor supply choices per person are included in the base population, i. e., seven hours choices plus one out-of-work state are available:

- Not working
- In-work (1-10, 11-20, 21-30, 31-40, 41-50, 51-60, $>$ 60 hours)

Singles have a total of eight different hour choices, while couples are assumed to maximize a joint utility function, with each combination of the two hour categories of each partner being a separate category. This results in 64 categories for couples.

In the MikroSim model, the income model is designed to simulate total net income. It does not contain any information on the individual income components. Therefore, it is not possible to consider predicted wages along with other sources of family income, as done in Narazani et al. (2023), among others. Consequently, parental allowances, for example, cannot be attributed to inactive individuals on parental leave. Thus, the employment module in the adapted MikroSim model distinguishes mostly between unemployed and employed individuals.

Within the framework on a static microsimulation, the supplied hours of work in the baseline scenario is compared with the hours supplied in response to a 1% wage increase for singles and partners. To estimate the choice model, a structural model with explanatory variables that are a function of choice-specific variables is used (O'Donoghue, 2021, p. 145). For singles, the explanatory variables include leisure, leisure^2, labor income, labor income^2, and in-work fixed effects. Moreover, the model considers the interaction terms leisure $\times$ sex, leisure $\times$ age, leisure $\times$ age^2, income $\times$ leisure, leisure $\times$ education, and leisure $\times$ child category, where the variable child category has the following values (1: no children, 2: between one and two children, 3: three and more children). Table 3.2 presents the a conditional logit model for the employment model for singles in the city of Trier.

Table 3.2: Conditional logit for the employment model: Singles

	Estimate	**Std. Error**	**z value**	**Pr(>|z|)**	
Leisure	4.2490	0.0446	95.201	0.0000	***
Leisure^2	-0.1088	0.0011	-103.341	0.0000	***
Labor Income	0.0002	0.0000	11.232	0.0000	***
Labor Income^2	0.0000	0.0000	-2.650	0.0080	**
In-Work Fixed Effect	-3.5320	0.0446	-84.690	0.0000	***
Labor Income × Leisure	0.0000	0.0000	-5.353	0.0000	***
Leisure × Child Category: Between 1 and 2 children	0.0918	0.0167	5.495	0.0000	***
Leisure × Child Category: More than 2 children	0.0215	0.0914	2.350	0.0188	*
Leisure × Sex	0.1428	0.0039	36.560	0.0000	***
Leisure × Education: Lower Secondary	-0.0557	0.0119	-4.6900	0.0000	***
Leisure × Education: Upper Secondary	-0.2147	0.0113	-21.752	0.0000	***
Leisure × Education: Post-Secondary, not Tertiary	-0.3044	0.0125	-24.358	0.0000	***
Leisure × Education: Bachelor, Master, PhD	-0.3219	0.0116	-27.683	0.0000	***
Leisure × Age	-0.0224	0.0010	-21.546	0.0000	***
Leisure × Age^2	-0.0003	0.0000	22.553	0.0000	***
Number of observations: 36,789					

Significance codes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001
Source: Own calculation based on the MikroSim model.

For partners, the following explanatory variables are included: male leisure, female leisure, male in-work fixed effect, female in-work fixed effect, labor income, labor income^2 , male leisure^2 , female leisure^2, male leisure × female leisure, labor income × male leisure, labor income × female leisure, male leisure × child category, male leisure × education, male leisure × age, male leisure × age^2, female leisure × child category, female leisure × education, female leisure × age, and female leisure × age^2. Table 3.3 presents the conditional logit for the labor-supply model for partners in the city of Trier.

Table 3.3: Conditional logit for the employment model: Partner

	Estimate	**Std. Error**	**z value**	**Pr(>|z|)**	
Male Leisure	4.5190	0.0711	63.528	0.0000	***
Female Leisure	3.1720	0.0562	56.481	0.0000	***
Male In-Work Fixed Effect	-5.4050	0.0983	-54.996	0.0000	***
Female In-Work Fixed Effect	-1.2830	0.0446	-27.765	0.0000	***
Labor Income	0.0002	0.0000	10.330	0.0000	***
Male Leisure^2	-0.1340	0.0018	-74.014	0.0000	***
Female Leisure^2	-0.0790	0.0012	-64.439	0.0000	***
Labor Income^2	0.0000	0.0000	-1.333	0.18260	
Female Leisure × Male Leisure	-0.0005	0.0013	-0.409	0.6824	
Labor Income × Male Leisure	0.0000	0.0000	-4.861	0.0000	***
Labor Income × Female Leisure	0.0000	0.0000	0.607	0.5437	
Male Leisure × Child Category: Between 1 and 2 children	-0.0321	0.0310	-1.035	0.3005	
Male Leisure × Child Category: More than 2 children	-0.0358	0.1861	0.192	0.8476	
Male Leisure × Education: Lower Secondary	-0.0904	0.0193	-6.387	0.0000	***
Male Leisure × Education: Upper Secondary	-0.2331	0.0182	-16.813	0.0000	***
Male Leisure × Education: Post-Secondary, not Tertiary	-0.2728	0.0273	-13.394	0.0000	***
Male Leisure × Education: Bachelor, Master, PhD	-0.3271	0.0180	-21.318	0.0000	***
Male Leisure × Age	0.0018	0.0003	5.276	0.0000	***
Female Leisure × Child Category: Between 1 and 2 children	0.0502	0.0273	1.837	0.0662	.
Female Leisure × Child Category: More than 2 children	0.2288	0.2060	1.110	0.2669	
Female Leisure × Education: Lower Secondary	-0.1258	0.0197	-18.442	0.0000	***
Female Leisure × Education: Upper Secondary	-0.3057	0.0182	-16.813	0.0000	***
Female Leisure × Education: Post-Secondary, not Tertiary	-0.3633	0.0197	-18.442	0.0000	***
Female Leisure × Education: Bachelor, Master, PhD	-0.3971	0.0186	-21.318	0.0000	***
Female Leisure × Age	-0.0007	0.0003	2.515	0.0119	*
Number of observations: 14,362					

Significance codes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

Source: Own calculation based on the MikroSim model.

The simulation of a policy change is a relatively straightforward process when counterfactual options are available. The estimated models (Tables 3.2 and 3.3) allow to determine the new utility level for all available choices and to identify the best choice given the new policy scenario for singles and partners, respectively. Table 3.4 provides an overview of the labor-supply patterns for single individuals and partners in the city of Trier before and after the wage increase.

Table 3.4: Simulation of a 1% increase in the wage rate

	Singles		**Partner**	
	Baseline	**Reform**	**Baseline**	**Reform**
Work more hours		0.03%		0.06%
Work less hours		0.01%		0.01%
Work equal hours		99.96%		99.93%
Change in utility		+0.01%		+0.01%
Compensating variation (in euro)		-893,003.30		-800,593.30
Average hours worked	35.03	35.04	female: 28.52 male: 38.92	female: 28.53 male: 38.93
Costs of reform		1,065,124.00		879,279.90

Source: Own calculation based on the MikroSim model.

The reform affects the working age population and leads to an increase in utility. However, most affected individuals do not change their behavior in response to a 1% increase in wages. Only a few individuals supply more working hours. The average number of hours worked increases in response to the wage increase for both singles and partners. The compensating variation, i. e., the monetary value in euro an individual needs to reach their initial utility, is negative for both singles and partners. Despite the increase in utility, the costs of the reforms outweigh the benefits.

The ability to convert utility into monetary values based on the behavioral model allows for the possibility of a cost-benefit analyses. These types of analyses are used particularly for environmental cost-benefit analyses and in the field of legal decision making.

3.5 Summary

In Chapter 3, we provided the methodological basics for behavioral microsimulation models. We gave an overview of utility theory and differentiated between the stated-preferences approach and the revealed-preferences approach. Moreover, we introduced random utility models and dealt with conceptual issues.

The decision to include a behavioral component into the microsimulation model depends mainly on the scenario to be analyzed. Moreover, the availability of appropriate data also influences the modeling choice. Behavioral models are used to analyze potential behavioral responses to policy changes and can provide important insights into unintended consequences of reforms (O'Donoghue, 2021, p. 115). The main fields of application include: labor market analysis, transportation mode decisions, and consumption behavior.

In the field of microsimulation models, behavioral components are mainly introduced to analyze labor supply behavior (O'Donoghue, 2021, p. 16). Behavioral microsimulation models allow, for example, to model behavioral changes in response to tax reforms or to changes in the wage rate. In particular, the modeling of responses to wage increases is an important prerequisite for obtaining the Frisch labor supply elasticity. In the context of labor market analyses, the Frisch labor supply elasticity plays an important role as link variable for the sequential linking of micro and macro models as it allows to establish a coherent link between both models.

The analysis of behavioral responses in the field of microsimulation models is mainly conducted as a combination of dynamic and static microsimulation. We projected the base population into the future and extended the MikroSim model by modules of supplied working hours and employment benefits in order to analyze the effects of a 1% increase of wages on the supplied working hours. Using the city of Trier as an example, we found that a small increase in wages does not have a large impact on hours worked. For the majority of people, the best choice, i. e., the choice with the highest utility, after the wage increase is to supply the same number of hours as before the wage increase. It is also possible to assign a monetary value to the change in utility and to perform cost-benefit analyses. We found that the cost of a 1% wage increase outweighs the benefit based on the compensation variation. In evaluating the results of the application, it is essential to consider the experimental nature of the application. The income module in the MikroSim model is of paramount importance

for policy analysis. Further development of the model, particularly with regard to the inclusion of diverse income components, will allow to investigate further research question in relation to policy reforms, such as tax reforms.

Chapter 4

Linking Micro and General Equilibrium Models

Microsimulation is a quantitative tool that is used to model complex phenomena based on micro data, such as individuals and households. It promotes a comprehensive understanding of the population (Burgard et al., 2020a). Microsimulation models employ a partial equilibrium analysis, focusing on micro-units, while holding the rest of the economy constant (McKenzie, 1989, p. 1; Peichl, 2016). It is assumed that the coefficients of the model, on which the transition probabilities are based, are constant over time. This implies that the population is in a steady state and that the transition probabilities are independent of the scenario to be analyzed (Bourguignon and Spadaro, 2006, p. 96f). In contrast, general equilibrium models consider the economy as a whole at an aggregate level (Burfisher, 2016, p. 12; Gardenete et al., 2017, p. 7). The focus is on the performance of economies.

The combination of micro models and general equilibrium models is the most complex type of integration between micro and macro models. The objective is to combine the strengths of both models in a meaningful way. It is therefore essential that the models are coherent. The link between the models introduces an additional layer of complexity, increasing both the development costs and the transparency requirements (Spielauer, 2007).

There are different approaches to link micro and macro models. These include, on the one hand, the incorporation of the micro model into the macro model and, on the other hand, the combination of two distinct models, linked by appropriate link

variables. In this chapter, Section 4.1 provides a literature overview on linking micro and macro models. Section 4.2 gives an overview of structural models, which are frequently employed to link macroeconomic models with microsimulation models. Section 4.3 provides the methodological foundation for establishing a coherent link between micro and macro models. This section introduces the bottom-up approach, the top-down approach, as well as the combination of both, the top-down bottom-up approach. Moreover, we present the Frisch labor supply elasticity as a potential link variable. Section 4.4 links the MikroSim model with the classical Ramsey model. Section 4.5 provides a summary and outlook on further research in this area.

4.1 Literature Overview

Building on the seminal work of Adelman and Robinson (1978) for Korea and Lysy and Taylor (1980) for Brazil, many CGE models have been combined with micro models. Since the early 2000s, there has been considerable research on linking micro and macro models to analyze the distributional impacts of macroeconomic policies. The most common application involves combining CGE models with static behavioral microsimulation models to analyze the distributional effects of trade policies, see e. g., Savard (2003), Hérault (2007), Hérault (2009), and Lay (2010). According to Colombo (2010), the trend towards linking micro and macro models can be attributed to the fact that two perspectives are important for analyzing poverty and inequality in developing countries: First, a microeconomic focus to obtain a detailed and precise information of income and/or expenditure at the micro-level, as well as to model behavioral responses to policy changes. Second, a macroeconomic focus, since economic policies often have structural effects on the economy.

Robilliard et al. (2008) analyze the impact of the 1997 Indonesian financial crisis on poverty and inequality by combining a behavioral microsimulation with a CGE model. The study utilizes wage and employment as link variables between the behavioral microsimulation model and the CGE model. The microsimulation model is based on a sample of approximately 10,000 households from the savings-investment module of the 1996 Indonesian national socio-economic household survey. The survey includes variables on occupation and income sources. The CGE model is based on a Social Accounting Matrix (SAM). A SAM contains all transactions between economic agents for a specific period of time. It extends the Input-Output Table by mapping the complete flow of income in the economy. SAMs are commonly used as

data input for CGE models (Mainar-Causapé et al., 2018).

Savard (2003) draws on the microsimulation literature and analyzes the impact of trade and fiscal policies on the poverty and income distribution in the Philippines. He uses a CGE model to generate a price vector and a microsimulation model at the household level to determine the consumption and labor supply of households. These variables are then used to calibrate the CGE model. The procedure is repeated until some convergence criteria is met.

Hérault (2007) follows a similar approach. He investigates the effects of trade liberalization on poverty and income inequality in South Africa by combining a static behavioral microsimulation model with a CGE model. The microsimulation model is based on 26,000 households from the Income and Expenditure Survey and the 2000 Labour Force Survey. Hérault combines a static behavioral microsimulation model with a CGE model. The microsimulation model simulates new labor market decisions in response to changes in individual characteristics as a result of macroeconomic changes estimated in a CGE model. The CGE model is based on the 2000 South African SAM with 43 sectors and four production factors. Producers maximize profits subject to the production technology and households maximize utility given their budget constraint. The government has no objective function. Hérault (2007) proceeds as follows: In a first step, the removal of tariffs is simulated using the CGE model. The macroeconomic model returns the economy after the shock. Prices, return from capital and labor as well as employment levels estimated by the CGE model are used to link the microsimulation model and the macro model. In a second step, the changes in these variables due to the removal of tariffs are passed to the microsimulation model. The new prices are used to calculate household-specific consumer price indices. For the variables return from capital and labor, and employment levels, the transmission is more complex. This is because the CGE model returns macro data. Thus, the micro model has to be adjusted to meet the macroeconomic benchmarks from the CGE model. Unlike Savard, both models are executed only once.

Hérault (2007) combines a behavioral microsimulation model with a CGE model, while Hérault (2009) performs the same simulation with a non-behavioral microsimulation model combined with a re-weighting approach. The non-behavioral microsimulation is not based on an econometric model but on a detailed representation of the tax and transfer system. The difference between the two studies lies in the transmis-

sion of employment changes to the microsimulation model. Re-weighting generates new weights to meet the population benchmarks of selected variables, with minimal deviation from the initial weights. The new sample weights reflect changes in the macroeconomic variables. In contrast to the behavioral microsimulation, which allows the analysis of changes at the individual level, the re-weighting approach preserves the initial status of the household members.

Lay (2010) combines a behavioral microsimulation with a CGE model. He analyzes the impact of trade liberalization on poverty in Brazil and the impact of the Bolivian Gas Boom on poverty. The focus is on developing countries and a short to medium time horizon. The compatibility of the microsimulation income module with the labor market formulation plays a key role in combining both models, as wages and sectoral employment are used as link variables. In the analysis, Lay (2010) illustrates the importance of individual heterogeneity for the analysis of macroeconomic shocks.

CGE models are by far the most common macroeconomic models that are used to link microsimulation models and macroeconomic models. However, some studies also combine other macroeconomic models with microsimulation models, such as DSGE models (Barrios et al., 2016) and VAR models (Barrios et al., 2022). The choice of the macroeconomic model depends on the research question.

Barrios et al. (2016) conduct a dynamic scoring analysis of tax reforms for European countries, considering both first- and second-order effects. They combine the microsimulation model EUROMOD and the DSGE model QUEST. Dynamic scoring techniques are used to assess the impact of alternative fiscal policy reforms, taking into account the effect on the economy as a whole. EUROMOD is a static tax-benefit microsimulation model that covers the Member States of the European Union. It employs the European Statistics on Income and Living Conditions (EU-SILC) survey and national SILC surveys to simulate individual tax liabilities and social benefit entitlements consistent with the regulations prevailing in each Member State (European Union, 2022). Barrios et al. (2016) extend the EUROMOD model to include a labor supply model and link the extended EUROMOD model to the European DSGE model QUEST. The QUEST model is employed by the European Commission for the purpose of analyzing fiscal and structural reforms in EU Member States. It encompasses behavioral responses in macroeconomic variables within an open economy framework, thereby extending the scope of EUROMOD, which assesses the impact of a particular tax reform.

The combination of EUROMOD and QUEST is achieved through the introduction of tax policy shocks in QUEST. These shocks are obtained using EUROMOD as a basis for computing changes in the implicit tax rates. Furthermore, the elasticity of labor supply and non-participation rates by skill category in QUEST are calibrated using the values derived from EUROMOD extended by an estimated labor supply function. The labor market elasticities are crucial to achieve consistency (Barrios et al., 2016). The procedure is as follows: First, labor supply elasticities and the non-participation rate are obtained based on EUROMOD. Second, the QUEST model is calibrated for the country of interest, the euro area, and the rest of the world. Third, the impulse responses for employment, gross real wages, and the consumer price index derived from the QUEST model are used as inputs to the microsimulation model to obtain medium-term projections of tax revenues, contributions, benefits, and disposable income. Barrios et al. (2022) follow a similar approach as Barrios et al. (2016). They conduct a real-time dynamic scoring exercise by combining the EUROMOD model with VAR estimates of macro responses. VAR models are more suitable for short-term policy analysis compared to structural macro models and require less assumptions. Moreover, they provide a high degree of flexibility.

Recently, there has been particular interest in analyzing the distributional impacts of environmental reforms using linked micro-macro models. Böhringer et al. (2019) investigate whether environmental taxes have regressive effects by linking a CGE and a microsimulation model. The study assesses the impacts of revenues from green taxes, which are redistributed lump-sum to Spanish households on an equal per capita basis. They analyze the potential of a double or triple divided through green tax reforms: (1) improving the environment, (2) reducing the overall excess burden of the tax system, and (3) alleviating involuntary unemployment.

In addition to the sequential approach, there are also attempts to link micro and macro models by integrating the micro model into the macro model, i. e., the representative household of the macro model is replaced by the households from the microsimulation model. Gross and Poblacò (2017) develop a fully integrated micro-macro model based on an Integrated Dynamic Household Balance Sheet to assess the efficacy of borrower-based instruments. The model comprises six modules: (1) the GVAR, (2) the logit model for estimating transition probabilities for the employment status of household members, (3) the employment status simulator, (4) the household balance sheet simulator, (5) the counterfactual macroprudential policy simulations, and (6) the link to balance sheets.

4.2 Structural Models

Microsimulation models can be linked to various macroeconomic models, with the choice of macroeconomic model depending on the research question to be analyzed. Structural models are macroeconomic models that are grounded in economic theory. The term structural model refers to explicit assumptions about the market microstructure in the economy, the constraints faced by agents, and the functional form of their objectives (Kilian and Lütkepohl, 2017, p. 187).

4.2.1 Ramsey Model

The classical Ramsey model can be classified as neo-classical growth model. It represents the most basic dynamic general equilibrium model (Heer and Maussner, 2009, p. 4). The following illustration of the Ramsey model is based on Heer and Maussner (2009, ch. 1) and DeJong and Dave (2011, ch. 3.1). The economy is assumed to consists of many identical households. Economic analyses are carried out based on the concept of a representative household. The household strives to maximize utility U from leisure $l^{(t)}$ and consumption $c^{(t)}$ chosen at time t. The discounted utility is given by:

$$\max_{c^{(t)},l^{(t)}} U = \sum_{t=0}^{\infty} \beta^{(t)} u(c^{(t)}, l^{(t)}), \tag{4.1}$$

where $\beta^{(t)} \in (0, 1)$ denotes the subjective discount factor at time t and $U()$ an instantaneous utility function. The continuum of goods is defined by the unit interval $[0, 1]$. Leisure $l^{(t)}$ is defined as $l^{(t)} = 1 - h^{(t)}$. $h^{(t)}$ has two interpretations: Either it is interpreted as hours of work or as the number of employed individuals.

The household uses its production technology to produce a single good $y^{(t)}$ according to:

$$y^{(t)} = z^{(t)} f(k^{(t)}, h^{(t)}) \tag{4.2}$$

with $k^{(t)}$ and $h^{(t)}$ being physical capital and labor, respectively and $z^{(t)}$ denoting a productivity or technology shock. In each period, the household is endowed with one unit of time for labor and leisure activities:

$$1 = h^{(t)} + l^{(t)}. \tag{4.3}$$

The products produced at time t can be consumed or invested:

$$y^{(t)} = c^{(t)} + i^{(t)} \tag{4.4}$$

with $i^{(t)}$ being the quantity that is invested. Thus, physical capital at time $t+1$ evolves according to:

$$k^{(t+1)} = i^{(t)} + (1-\delta)k^{(t)}, \tag{4.5}$$

where $\delta \in (0,1)$ gives the depreciation rate.

The household's optimization problem is to maximize (4.1) subject to (4.2)-(4.5). Thus, the household faces two trade-offs. On the one hand, the household faces a trade-off between consumption and saving and, on the other hand, the household faces a trade-off between labor and leisure as higher labor productivity results in higher opportunity costs of leisure (DeJong and Dave, 2011, p. 23).

The functional forms of the utility function $U(\cdot)$ and the production function $f(\cdot)$ as well as the productivity or technology shock $z^{(t)}$ must be specified to allow for quantitative economic analyses. For the specification of the utility function the constant relative risk aversion (CRRA) form is widespread. The instantaneous utility function of the CRRA form is given by (DeJong and Dave, 2011, p. 21):

$$U(c^{(t)}, l^{(t)}) = \frac{\left(\left(c^{(t)}\right)^{\phi}\left(l^{(t)}\right)^{1-\phi}\right)^{1-\varphi}}{1-\varphi}, \tag{4.6}$$

where $\varphi > 0$ denotes the coefficient of relative risk aversion and defines the intertemporal elasticity of substitution. The importance of leisure in relation to consumption is determined by $\phi \in (0,1)$.

Alternatively, different utility functions, such as logarithmic utility can be assumed. The logarithmic utility is a special case of CRRA utility, with $\varphi = 1$:

$$U(c^{(t)}, l^{(t)}) = \phi \log c^{(t)} + (1-\phi)\log l^{(t)}. \tag{4.7}$$

The Cobb-Douglas production function is of the following form (DeJong and Dave,

2011, p. 22):

$$y^{(t)} = z^{(t)} \left(k^{(t)}\right)^{\alpha} \left(h^{(t)}\right)^{1-\alpha}, \tag{4.8}$$

where $\alpha \in (0, 1)$ indicates the importance of capital in relation to labor in the production process. It is assumed that the logarithm of $z^{(t)}$ follows a first-order autoregressive AR(1) process (DeJong and Dave, 2011, p. 22).

4.2.2 Computable General Equilibrium Models

CGE models are most frequently used to link micro and general equilibrium models. In contrast to the one-sector Ramsey model, CGE models are multi-sectoral models. They are economy-wide models that feature the entire economy and the interactions between the different sectors. For this reason, they are applied to simulate the impacts of policy changes on the economy as a whole and the various sectors (Perman et al., 2011, p. 279). CGE models illustrate the process of resource allocation in a market economy as the consequence of the interaction between supply and demand, resulting in equilibrium prices. The fundamental elements are represented by equations that depict the behavior of the following economic agents: consumers, producers, and the government. These agents demand or supply goods, services, and factors of production as a function of their respective prices. In general equilibrium models, the prices that lead to the clearing of all markets are determined and the resulting resource allocation an income distribution are established. The price mechanism is a powerful tool for addressing complex trade-off problems. The decisions of economic agents with regard to economic activities are informed by the prevailing price information in the markets. Many economic theories are built on the optimization behavior of economic agents subject to resource and technology constraints, with market prices serving as a signal. Households seek to maximize their utility subject to their budget constraints, while firms endeavor to maximize their profits subject to the constraints of their production technology. The solutions to these optimization problems result in the demand and supply curves. Markets achieve an equilibrium between demand and supply by adjusting prices (Hosoe et al., 2010, pp. 1f).

CGE models were introduced by Johansen (1960). Originally, the models were developed as single country models. They are characterized by the fact that the behavior of the agents is explicitly identified (Dixon and Jorgenson, 2013, p. 1).

The models are grounded in microeconomic theory combined with empirical data (Madden, 2020, p. 4). Four types of simulations can be distinguished (Dixon and Jorgenson, 2013, p. 3):

- Historical
- Decomposition
- Forecast
- Policy.

Historical simulations provide up-to-date data and estimate trends in exogenous but unobservable variables. Decomposition simulations focus on historical episodes and embed policy impacts into historical context. Forecast simulations provide baselines that combine historical simulations and expert forecasts. Policy simulations analyze the impact of policies in comparison to a baseline simulation.

In recent years, a significant number of CGE models have incorporated a regional component, reflecting an increasing interest in regional effects of national shocks, regional developments, and regional (natural) disasters (Dixon and Wittwer, 2004; Thissen, 2004; Rose and Liao, 2005; Giesecke et al., 2012). Regional CGE models are either regional disaggregations attached to national CGE models, multi-regional models of the national economy, or stand-alone models of single regions with regional elasticities borrowed from national CGE models (Giesecke and Madden, 2013, pp. 393, 434).

4.2.3 Dynamic Stochastic General Equilibrium Models

DSGE models are similar to CGE models. The main difference between CGE and DSGE models lies in their respective treatment of agent optimization. While CGE models operate within a deterministic environment, DSGE models operate within a stochastic environment, reflecting the influence of inherent uncertainties, commonly expressed as random shocks.

DSGE models are a system of nonlinear expectational difference equations, which describe the economy (DeJong and Dave, 2011, p. 4). They comprise (DeJong and Dave, 2011, pp. 9f):

- Structural shocks
- Exogenous state variables
- Endogenous state variables
- Control variables
- Expectation errors.

DSGE models build on a rigorous micro-foundation. The structure is invariant to policy interventions (Kilian and Lütkepohl, 2017, p. 177). Thus, DSGE models address the Lucas critique (Lucas, 1976), which, in summary, states that "given that the structure of an econometric model consists of optimal decision rules of economic agents, and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models" (Lucas, 1976, p. 41). This only holds, if the log-linearized equilibrium conditions are an accurate representation of reality and some parameters are treated as deep parameters (Galí, 2015, p. 6). If the parameters are not policy-invariant, they change in response to a policy change, leading to in potentially misleading conclusions.

DSGE models are business cycle models that abstract from secular growth. Consequently, DSGE models should only be evaluated using data at business cycle frequencies. Often, observed macroeconomic data fluctuate at higher or lower frequencies, leading to a discrepancy between model data and actual data. Therefore, in most cases, both actual and simulated data are transformed to isolate the variation in business cycle frequencies. Three common approaches for the removal of the trend are: detrending, differencing, and filtering. All approaches aim at converting the data into mean-zero covariance-stationary stochastic processes with time invariant second moments. In order to achieve covariance stationarity, the removal of the trend is required. Typically, deterministic detrending and Hodrick-Prescott filtering of the seasonally adjusted data, or differencing and Hodrick-Prescott filtering are applied. However, other forms of filtering can also be considered (DeJong and Dave, 2011, pp. 116, 119). For further information on removing trends and isolating cycles, see DeJong and Dave (2011, ch. 6).

DSGE models can be divided into two broad classes: Real business cycle (RBC) and New Keynesian models. While having different policy implications, key components of New Keynesian models can also be found in RBC models (Galí, 2015, p. 5).

Real Business Cycle Models

The development of RBC theory can be attributed to Kydland and Prescott (1982) and Prescott (1986). These papers made both methodological and conceptual contributions to the field of macroeconomics. The methodological contribution includes the assumption of rational behavior, the emphasis of quantitative macroeconomics, namely calibration, simulation, and evaluation of models, as well as a general shift towards DSGE models as a foundation for macroeconomic analysis. The conceptual contribution is threefold: First, economic fluctuations are best understood as the optimal response of a perfectly competitive, frictionless economy to stochastic exogenous variations. Second, productivity variation drives fluctuations in the business cycle. Third, it is abstracted from monetary policy (Kydland and Prescott, 1982; Prescott, 1986; Galí, 2015, ch. 1).

The RBC model is based on DeJong and Dave (2011, ch. 3.1) and follows Kydland and Prescott (1982). The Kydland-Prescott economy is characterized by a representative household that has an infinite life span and values consumption and leisure. It maximizes its present and expected future utility:

$$\max_{c^{(t)},l^{(t)}} U = E_0 \sum_{t=0}^{\infty} \beta^t U(c^{(t)}, l^{(t)}) \tag{4.9}$$

with $\beta^{(t)} \in (0, 1)$ being the discount factor at time t and E_0 the expectations operator given information at time 0. The functional form of the contemporary utility function is that of CRRA (4.6). The household obtains utility from consumption $c^{(t)}$ and leisure $l^{(t)}$.

The household is endowed with one unit of time. It values leisure and consumption. To finance its consumption, the household engages in remunerative activities. Consequently, time is distributed between leisure and labor:

$$1 = l^{(t)} + h^{(t)}. \tag{4.10}$$

The household produces a single good $y^{(t)}$ using physical capital $k^{(t)}$ and labor $h^{(t)}$:

$$y^{(t)} = z^{(t)} f\left(k^{(t)}, h^{(t)}\right) \tag{4.11}$$

with $f(\cdot)$ as a production function with constant returns to scale. $z^{(t)}$ denotes the productivity, which is the driving force of economic fluctuations. Productivity evolves according to a AR(1) process:

$$\log\left(z^{(t)}\right) = (1-\rho)\log\left(\bar{z}\right) + \rho_z \log\left(z^{(t-1)}\right) + \left(\varepsilon^{(t)}\right)^z. \tag{4.12}$$

The parameter $\rho^{(t)} \in (-1, 1)$ is the persistence parameter at time t. The error term $\left(\varepsilon^{(t)}\right)^z$ is normally distributed with mean 0 and variance σ_z^2.

The production function is assumed to be Cobb-Douglas:

$$y\left(\varepsilon^{(t)}\right)^z = z^{(t)}\left(k^{(t)}\right)^{\alpha}\left(h^{(t)}\right)^{1-\alpha} \tag{4.13}$$

with $\alpha \in (0, 1)$ indicating the capital's share of output and $k^{(t)}$ being defined as

$$k^{(t+1)} = i^{(t)} + (1-\delta)k^{(t)}. \tag{4.14}$$

The resource constraint

$$y^{(t)} = c^{(t)} + i^{(t)} \tag{4.15}$$

indicates that the labor and good market clear in equilibrium, i. e., output is either consumed or invested.

The basic RBC model can be extended to include search frictions according to Diamond (1982), Mortensen (1982) and Pissarides (1985). The firm wants to hire unemployed workers. Therefore, it advertises vacancies.

New Keynesian Models

New Keynesian models are based on RBC theory and have become the workhorse model for analyzing monetary policy, fluctuations, and welfare. However, there are some important differences to the RBC theory. In particular, the key differences between New Keynesian models and RBC model are that New Keynesian models are characterized by (Galí and Gertler, 2007; Galí, 2015, pp. 5f):

- Imperfect competition, i. e., each firm produces a differentiated good and acts as price setter
- Price and wage stickiness, i. e., only a fraction of firms/workers (possibly represented by unions) can adjust prices/wages in a given period
- Non-neutrality of monetary policy in the short run. Due to nominal rigidities, the real interest rate depends not only on the short-term nominal interest rate set by central banks but also on future expectations of the households. Thus, the real interest rate is subject to variations, which influences consumption and investment decisions, and consequently output and employment.

4.3 Methodological Basics

The idea to link micro and models has existed almost as long as the individual models have been available as stand-alone models. Various approaches have emerged to link micro and macro models. From a microsimulation perspective, the most straightforward approach is the top-down approach. In the top-down approach, the results of a macro model are used as input in the micro model. Since almost all microsimulation models are aligned (see Section 2.2), the microsimulation model can be calibrated to the results from the macro model. Alternative approaches to link micro and macro models are the bottom-up approach and the combination of the top-down and bottom-up approach, which is called the top-down bottom-up approach. In the following, we present the three different approaches for linking micro and macro models in more detail. Furthermore, we explain the purpose of link variables with particular emphasis on the Frisch elasticity of labor supply and point out methodological challenges. The objective is to establish a coherent link between micro and macro models.

4.3.1 Approaches for Linking Micro and Macro Models

In order to link micro and macro models, sequential and integrated approaches can be distinguished (Colombo, 2010; Bourguignon and Bussolo, 2013, pp. 1387-1394; Peichl, 2016; Teichmann, 2016). In the sequential approach, both the micro and macro models are initially constructed independently. Consequently, it is possible to develop highly sophisticated micro and macro models. The connection between the two models is established through the use of link variables. Link variables are

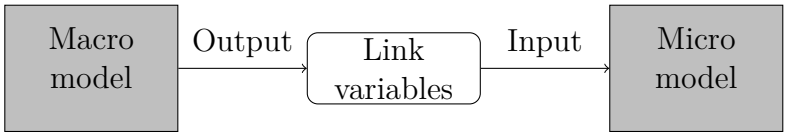
variables that are available in both models and can therefore be used to establish a link between both.

The following approaches belong to the sequential approach:

- Top-down approach
- Bottom-up approach
- Top-down/bottom-up approach.

Figure 4.1 illustrates the top-down approach. In this approach, the macro model is executed initially to simulate the macroeconomic policy or shock. Subsequently, a microsimulation is conducted, which incorporates the simulated changes to analyze the impacts of the macroeconomic policy or shock at the micro-level (Colombo, 2010; Peichl, 2016; Teichmann, 2016).

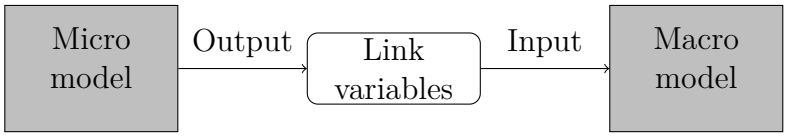
Figure 4.1: The top-down approach



Source: Own illustration based on Peichl et al. (2010) and Colombo (2010).

Figure 4.2 depicts the bottom-up approach. In contrast to the top-down approach, which integrates information from the macro into the micro model, the bottom-up approach integrates information from the micro model into the macro model. After aggregating individual changes in the link variables, they are used as input to the macro model to analyze overall changes in the economy (Bourguignon and Bussolo, 2013).

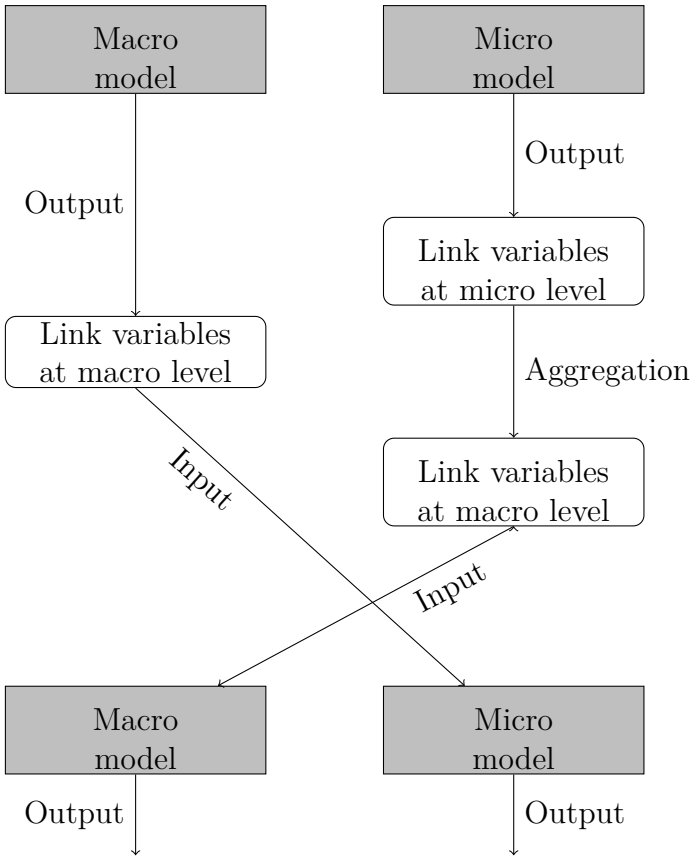
Figure 4.2: The bottom-up approach



Source: Own illustration based on Peichl et al. (2010) and Colombo (2010).

Figure 4.3 shows the top-down bottom-up approach. As the name implies, it combines the top-down and bottom-up approaches. It attempts to overcome consistency problems between the micro and macro model by using a transmission channel between the two models. Simulated changes from the macro model are integrated into the micro model and aggregated results from the micro model are used as input to the macro model. The models are run iteratively until convergence (Colombo, 2010; Peichl, 2016; Teichmann, 2016).

Figure 4.3: The top-down bottom-up approach



Source: Own illustration based on Colombo (2010).

The integrated approach is less commonly used to combine micro and macro models. In this approach, the number of representative agents in the macro model is increased up to the number of households in the micro data. The representative agent in the macro model is substituted by real households. Consequently, this approach requires the availability of a sophisticated database and high effort in the construction of

the model. In contrast to the sequential approach, the integrated approach does not contain a microsimulation model as such. This is because the micro-units are directly integrated into the macro model (Colombo, 2010; Bourguignon and Bussolo, 2013, pp. 1393f; Peichl, 2016; Teichmann, 2016).

4.3.2 The Frisch Labor Supply Elasticity as Link Variable

The concept of elasticity was first introduced in the field of economics by Alfred Marshall in 1890 (Marshall, 2013). The elasticity gives the ratio of the relative percentage change of a dependent variable a to the relative percentage change of an independent variable b (Schumann et al., 2011, p. 73; H. R. Varian, 2010, p. 275):

$$\eta_{ab} = \frac{\Delta a/a}{\Delta b/b}. \tag{4.16}$$

The labor supply elasticity is defined as the relative percentage change in supplied working hours as a response to a relative percentage increase in wage, holding constant the marginal utility of wealth (King and Rebelo, 1999, p. 975; Peterman, 2016). The concept was proposed by Frisch (1959). It is also known as Frisch elasticity or λ-constant elasticity. The term λ refers to the wealth effect (King and Rebelo, 1999, p. 975). The Frisch labor supply elasticity characterizes the labor market behavior in economic models and is the key parameter for assessing the impact of fiscal policy changes. Thus, the Frisch elasticity plays a crucial role in economic modeling.

The Frisch labor supply elasticity can be separated into the extensive and intensive elasticities. The extensive margin is defined as fluctuations in employment, while the intensive margin is defined as changes in hours worked. The (weighted) sum of the extensive and intensive labor supply elasticity gives the aggregate labor supply elasticity (Cho and Cooley, 1994). In representative agent models, the Frisch elasticity is calculated as the (weighted) sum of the intensive and extensive margin (Chetty et al., 2011; Kelly and Warren, 2015, p. 250; Peterman, 2016). Note that macro studies often do not explicitly separate the Frisch labor supply elasticity into the extensive and intensive margin (Chetty et al., 2011). If not noted otherwise, we refer to the aggregated Frisch labor supply elasticity.

The Frisch labor supply elasticity can be interpreted as the willingness to work in response to a change in wage. If the wage is increased by 1 %, the labor supply changes by more than 1 % in absolute value, indicating that the labor supply is

elastic. Conversely, if the elasticity is less than 1 in absolute value, the labor supply is inelastic. If the elasticity is exactly 1, the labor supply is unit elastic (H. R. Varian, 2010, p. 276). The impact of a change in wage rates on labor supply can be decomposed into two effects: an income effect and a substitution effect. The income effect explains the downward-sloping part of the labor supply curve, while the substitution effect accounts for the upward-sloping part. The income effect occurs when a wage increase raises the opportunity costs of leisure. This, in turn, leads to an increase in the number of hours worked. The substitution effect occurs when a wage increase reduces the opportunity costs of leisure. This, in turn, leads to a decrease in the number of hours worked. The extent to which this occurs depends on individual preferences. If the income effect outweighs the substitution effect, a wage increase may result in a decrease in labor supply (O'Donoghue, 2021, pp. 9f).

In macroeconomic models, the labor supply elasticity is typically set between 1 and 4 (Shimer, 2009). This implies that a 1 % change in the wage rate results in a 1 % to 4 % change in supplied hours worked, assuming a minimal impact on wealth. This is the case for a temporary change in wage (King and Rebelo, 1999, p. 975). Consequently, the labor supply is considered to be unit elastic or elastic in macroeconomic models. Kydland and Prescott (1982) argue that the Frisch elasticity must exceed 3 in neoclassical growth models to depict business cycle fluctuations. King and Rebelo (1999, p. 975) assume a labor supply elasticity of 4 in their basic real business cycle model. Ramey (2021, p. 227) also assumes a highly elastic labor supply behavior and sets the labor supply elasticity to 4. Cho and Cooley (1994) analyze the impact of different labor supply elasticities and calibrate the labor supply elasticity to be between 0.36 and 4. In their realistic setting, they use a labor supply elasticity of 1.29. Blanchard and Galí (2007) and Basu and House (2016, p. 324) choose a labor supply elasticity of 1 in their New Keynesian model. Smets and Wouters (2007) do not calibrate the labor supply elasticity but estimate a labor supply elasticity of 1.9 based on macroeconomic data.

The highly elastic labor supply behavior is inconsistent with microeconomic evidence. Using micro data, the Frisch labor supply elasticity varies between 0 and more than 1 for the intensive margin. For the extensive margin, it lies within a narrower interval (Chetty et al., 2013; Peterman, 2016; Whalen and Reichling, 2017). In the 1980s, the microeconomic literature on labor supply modeling focused on the continuous labor supply model. Kaiser et al. (1992) use the continuous labor supply model to estimate the Frisch labor supply elasticity for the intensive margin for West

Germany based on the 1983 wave of the Socio-Economic Panel. The elasticity is estimated to be -0.004 for married men and 1.04 for married women.

Based on the 2000 wave of the Socio-Economic Panel, Bonin et al. (2003) estimate a discrete-choice model of household labor supply for Germany. They simulate both the Frisch labor supply elasticity for the intensive margin and the Frisch labor supply elasticity for the extensive margin. Overall, they find that the labor supply effect is very moderate. The Frisch labor supply elasticity for the extensive margin is estimated at 0.019 for married men and 0.020 for married women. The Frisch labor supply elasticity for the intensive margin is estimated at 0.021 for married men and 0.027 for married women.

Steiner and Wrohlich (2004), Wrohlich (2004), and Haan and Steiner (2005) also obtain an inelastic Frisch labor supply elasticity. A discrete-choice model for married couples is estimated based on the 2002 wave of the Socio-Economic Panel. Steiner and Wrohlich (2004) find that the Frisch labor supply elasticity for the extensive margin is 0.15 for men and 0.16 for women. Wrohlich (2004) indicates that the Frisch labor supply elasticity for the extensive margin is 0.09 in East Germany and 0.13 in West Germany. Haan and Steiner (2005) state that the Frisch labor supply elasticity for the extensive margin is 0.13 for both men and women. For the intensive margin, Steiner and Wrohlich (2004) estimate a Frisch labor supply elasticity of 0.24 for men and of 0.41 for women. Wrohlich (2004) obtain a Frisch labor supply elasticity of 0.21 for women in East Germany and of 0.38 in West Germany. Haan and Steiner (2005) estimate a Frisch labor supply elasticity of 0.20 for men and 0.35 for women.

Bargain et al. (2010) also consider demand-side constraints and estimate a discrete-choice model of labor supply based on the 2003 wave of the Socio-Economic Panel. In the unconstrained model, the Frisch labor supply elasticity is estimated to be 0.150 for married women and 0.1580 for married men for the extensive margin, and 0.351 for married women and 0.207 for married men for the intensive margin. For unmarried individuals, the Frisch labor supply elasticity for the extensive margin is 0.197 for women and 0.226 for men, while for the intensive margin it is 0.267 for women and 0.300 for men.

In the constrained model, the simulated Frisch labor supply elasticities for the extensive and intensive margins are slightly lower. For married women, Bargain et al. (2010) estimate a Frisch labor supply elasticity for the extensive margin of 0.122, while for married men the value is 0.067. The Frisch labor supply elasticity for the

intensive margin is 0.316 for married women and 0.117 for married men. For single women, the elasticity is 0.069 for the extensive margin and 0.104 for the intensive margin. For single men, the elasticity for the extensive margin is 0.083 and for the intensive margin it is 0.152.

The existing literature on estimated Frisch labor supply elasticities based on microdata indicates that estimates were higher in studies conducted in the 1980s and 1990s compared to more recent studies. Bargain and Peichl (2013) analyze whether this decline in elasticity can be attributed to changes in preferences over time or to changes in methodology. The authors suggest that the decline can be explained by the time period and the estimation method, namely whether a time continuous model of labor supply or a discrete-choice model of labor supply is used. For a comprehensive overview of micro estimates of Frisch labor supply elasticities in Europe, we refer to Blundell (1995) and Bargain et al. (2012).

There are several possible explanations for the discrepancy between micro and macro estimates of the Frisch labor supply elasticity. One possible explanation is that the differences are due to to indivisible labor (G. D. Hansen, 1985; Rogerson, 1988). When labor is indivisible, changes in the wage rate can lead to significant changes in aggregate hours, even if the impact on hours worked conditional on employment is small (Chetty et al., 2013). However, Chetty et al. (2013, p. 26) argue that indivisible labor can only explain part of the difference and that "[e]ven with indivisible labor, models that require a Frisch elasticity of aggregate hours above 1 are inconsistent with micro evidence".

An alternative explanation is provided by Peterman (2016). He argues that the discrepancy between micro and macro estimates of the Frisch labor supply elasticity is due to differing definitions. The micro Frisch labor supply elasticity focuses on prime-aged married males, whereas the macro Frisch elasticity represents the entire population. Furthermore, the micro Frisch labor supply elasticity incorporates only the intensive margin, whereas the macro Frisch labor supply elasticity encompasses both the intensive and extensive margin. Peterman (2016) finds that estimating the intensive and extensive margin for prime-aged married males based on micro data yields estimates of the Frisch labor supply elasticity between 2.9 and 3.1.

In general, the elasticity is highly dependent on the definition. Other factors such as the availability of alternative sources of income, the level of non-labor income and the availability of alternatives can also affect the value of elasticity (Ljungqvist

and Sargent, 2007; Ljungqvist and Sargent, 2011). Ljungqvist and Sargent (2007) show that including unemployment benefits in the analysis of labor supply results in low employment levels compared to the benchmark data. Social benefits, such as unemployment insurance and social security programs, can be regarded as subsidies to leisure (Rogerson, 2007).

4.3.3 Methodological Challenges

The objective of linking microeconomic and macroeconomic models is to exploit the respective strengths of both models. Nevertheless, certain methodological challenges must be addressed. It has long been agreed that data from aggregate series must be consistent with individual data, since macro aggregates represent the sum of individual data (Prescott, 1986). Consequently, it seems reasonable to use the same share parameter in micro and macro studies. The Frisch labor supply elasticity determines the impact of a change in income, whether through monetary shocks or fiscal measures, on labor supply and is mainly employed as link variable in labor market analyses. However, empirical evidence indicates that micro and macro estimates of the Frisch labor supply elasticity exhibit considerable differences (see Section 4.3.2). Therefore, the identification of appropriate link variables is very important and poses a challenging task.

One of the most relevant questions is that of aggregation. Among others, Savard (2003) and Colombo (2010) argue that if the aggregated behavior of the micro-units corresponds to the representative household from the macro model, the linked micro-macro model does not provide any additional value. Consequently, the micro and the macro models are performed iteratively until a converging solution is obtained in the sequential approaches. However, it is essential to ensure consistent modeling of link variables in both models (Barrios et al., 2016).

The microsimulation models, in contrast to the macroeconomic models, are partial equilibrium models usually including only one type of agents, for example individuals or households (Peichl, 2016). The perspective of micro models differs from that of macro models and the combination of both may exhibit both empirical as well as theoretical shortcomings. In the field of labor market analysis, for instance, economic agents in macro models change their behavior in response to relative price changes, whereas in microsimulation models, labor market behavior is typically represented in a reduced form in which prices do not appear as explanatory variables (Lay,

2010; Lay, 2018). For a comprehensive overview of theoretical as well as empirical shortcomings of linked micro-macro models, we refer to Lay (2010) and Lay (2018).

4.4 Application: Linking the MikroSim Model and the Ramsey Model

Micro and macro models can be linked using different approaches, as shown in Section 4.3.1: The integrated approach and the sequential approach, including the top-down approach, the bottom-up approach and the top-down bottom-up approach can be employed. Each of these approaches requires the following decisions:

- Type of micro model
- Type of macro model
- Suitable link variables.

In the following, we present the top-down approach and the top-down bottom-up approach as the most relevant approaches for linking micro and macro models from a microsimulation perspective. In Section 4.4, we link the extended MikroSim model with a Ramsey model using the top-down bottom-up approach. A description of the extended MikroSim model can be found in Section 3.4.1. This application is an experimental statistics in the research and development stage.

The MikroSim microsimulation model is linked to a Ramsey model in order to further develop the MikroSim model with regard to policy consultation. The combination of both models allows for a general equilibrium analysis of policy reforms, taking advantage of the strengths of both the micro and the macro model. The MikroSim model serves as micro model, the Ramsey model as macro model, and employment variables as link variables.

Linking micro and macro models requires the availability of appropriate link variables. In order to establish a coherent link between the MikroSim model and the Ramsey model, we focus on the Frisch labor supply elasticity. The Frisch labor supply elasticity is estimated based on the updated base population of the microsimulation model, which can then be used to calibrate the macro model. The estimation of models using the base population $\tilde{U}$ as the estimation data set $\mathcal{D}$ to address a research question represents a novel approach in the context of region-

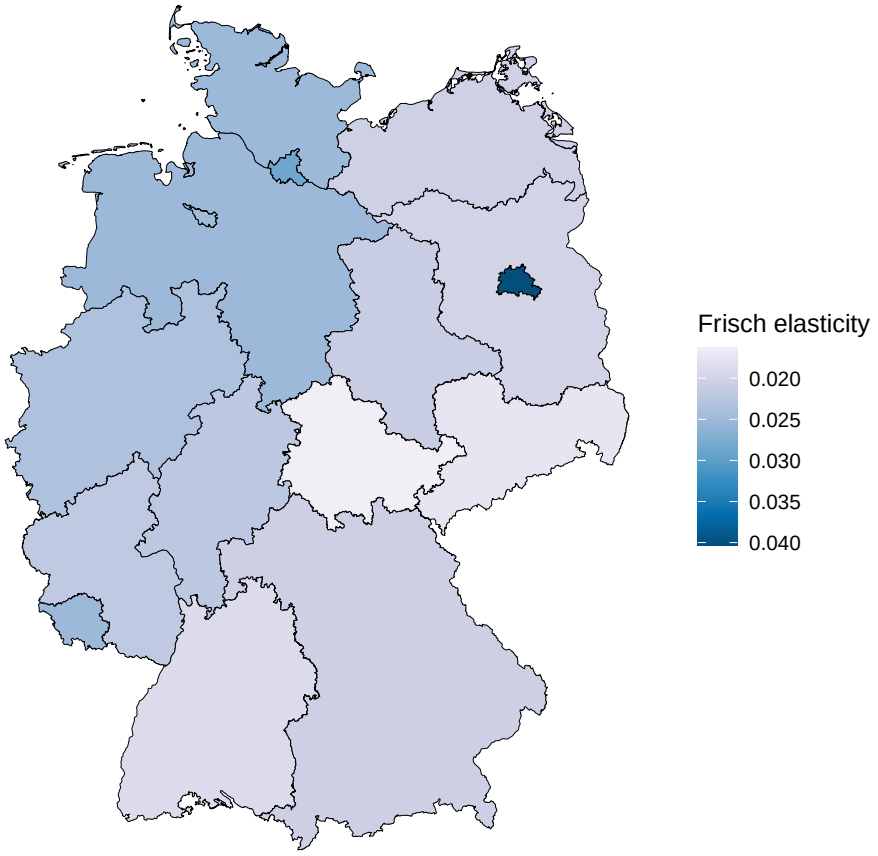
alized microsimulation models in Germany. No attempt has yet been made to use the base population at the individual level to estimate regression models for further analyses. Instead, the analysis of scenarios was based on aggregated results from regionalized microsimulations for Germany.

The foundations for estimating the Frisch labor supply elasticity are laid down in Chapter 3. In Section 3.5, we present the effect of a 1% increase in wage on supplied hours worked for the city of Trier. This approach is then applied to determine the Frisch elasticity for Germany as a whole. As the MikroSim model is a regionalized microsimulation model and due to the associated computational costs, the labor supply choice is estimated separately for each federal state. The random utility approach, which is based on the stated preferences approach, results in a base population that includes each single 8 times and each couple 64 times.

Figure 4.4 depicts the Frisch labor supply elasticity by federal state. The Frisch labor supply elasticity is estimated separately for singles and couples at the level of federal state. Note that North Rhine-Westphalia is split due to its population size and the resulting computational requirements. To obtain the overall Frisch labor supply elasticity by federal state, the weighted average of the elasticities for singles and couples is calculated. The Frisch elasticity for Germany as a whole is 0.0228. The figure shows that the differences between the federal states are not particularly large. However, there is an East-West divide, with western Germany showing a higher elasticity overall. Berlin also stands out with a very high Frisch labor supply elasticity compared to the other federal states.

It would be desirable to extend the analysis in the future to examine the influence of age and gender on the Frisch labor supply elasticity. Based on the results shown in Figure 4.4, two hypotheses can be formulated: First, it can be hypothesized that the Frisch labor supply elasticity is higher for young people than for old people. It is reasonable to assume that older workers may have stronger preferences for leisure activities or be less willing or able to find and retain new jobs. Second, the hypothesis can be put forward that the Frisch labor supply elasticity is lower for men than for women. The difference between men and women may be due to the fact that women are more likely to take parental leave and men are mainly responsible for earning wages. Therefore, one would expect a very low elasticity, especially in the external margin.

Figure 4.4: Frisch elasticity by federal state



Source: Own calculation based on the MikroSim base population (three simulation runs).

To further illustrate the differences between the federal states, Table 4.1 shows the values of the Frisch labor supply elasticity for both singles and couples by federal state. The results demonstrate that the elasticity for couples is higher than that for single individuals in all but one case. At first glance, this might seem counter-intuitive. Generally, one would expect that couples would react less strong to wage increases than singles due to synergy effects of two potential incomes and shared expenses, such as rental expenses. It should be noted, however, that the Frisch labor supply elasticity for couples is estimated at the household level, i. e., is based on the responses of two individuals (see Chapter 3). Therefore, to make a fair comparison between the Frisch labor supply elasticity for singles and couples, the elasticity for couples must be divided by 2. Since the Frisch labor supply elasticity for couples

is in most cases slightly less than twice as high as the elasticity for singles in most cases, we conclude that singles have a higher Frisch labor supply elasticity than couples. In contrast to the other federal states, Berlin is the only federal state where the Frisch labor supply elasticity for couples is lower than that for singles, even before adjustment. The analysis of the results shown in Figure 4.4 confirms that the elasticity is higher in West Germany than that in East Germany. Moreover, Berlin stands out due to its high elasticity. This is particularly evident for single individuals.

Table 4.1: Frisch elasticity in Germany by federal state: Singles/Couples

Federal state	**Frisch elasticity**	
	Singles	**Couples**
Schleswig-Holstein	0.0263	0.0479
Free and Hanseatic City of Hamburg	0.0362	0.0427
Lower Saxony	0.0271	0.0466
Free and Hanseatic City of Bremen	0.0261	0.0479
North Rhine-Westphalia	0.0257	0.0436
Hesse	0.0236	0.0433
Rhineland-Palatinate	0.0244	0.0393
Baden-Württemberg	0.0198	0.0377
Free State of Bavaria	0.0215	0.0406
Saarland	0.0263	0.0491
Berlin	0.0546	0.0514
Brandenburg	0.0255	0.0295
Mecklenburg-Western Pomerania	0.0242	0.0340
Free State of Saxony	0.0205	0.0303
Saxony-Anhalt	0.0271	0.0305
Free State of Thuringia	0.0195	0.0273

Source: Own calculation based on the MikroSim base population (three simulation runs).

The Ramsey model is then calibrated using the Frisch elasticity and employment data from the MikroSim model. A productivity shock is simulated using the Ramsey model, and the impulse response functions serve as new benchmarks for the MikroSim model. Impulse response functions show the response of model variables to an implemented shock over a defined simulation horizon $\mathcal{S}$ (DeJong and Dave, 2011, p. 303; Kilian and Lütkepohl, 2017, pp. 110-113). The MikroSim model uses district-level benchmarks. Therefore, the new benchmarks are downscaled using the ratio-synthetic estimator (Articus et al., 2019).

The obtained estimates of the Frisch labor supply elasticity based on the MikroSim model are however too small to explain economic fluctuation and thus to calibrate the macro model. As discussed in Section 4.3.2, macro models are usually calibrated with a Frisch labor supply elasticity between 1 and 4. We propose three strategies to overcome this problem and to establish a sequential link between the MikroSim model and the Ramsey model. The first strategy involves modifying the structure of the microsimulation model at the household or individual level with the aim of estimating a higher Frisch labor supply elasticity. The second strategy involves estimating the intensive Frisch labor supply elasticity based on the microsimulation model, with the extensive Frisch labor supply elasticity treated as a free parameter in the macro model that is calibrated to adjust to macroeconomic moments. The third strategy is to gradually increase the Frisch labor supply elasticity until it is large enough to calibrate the macro model, thereby shifting the focus from the absolute Frisch labor supply elasticity to the differences between singles and couples and to regional variations.

Many authors, including Savard (2003) and Colombo (2010), emphasize the importance of a bi-directional link to obtain a converging solution between the micro and the macro model. We do not introduce a bi-directional link or any measure of convergence. This may be considered a limitation of the current analysis; however, it can be mitigated by calibrating parameters, such as the Frisch labor supply elasticity in the Ramsey model with estimates on the basis of the MikroSim model. Furthermore, since the employment module can be aligned to meet known aggregates, it is straightforward to obtain consistent models without having to repeat the procedure until convergence is reached. A converging solution is obtained immediately.

As noted by Savard (2003), the value of linking micro and macro models lies in the consideration of different perspectives. Consequently, he argues that it is of

limited value to link a CGE model with a microsimulation model if the representative household is a perfect aggregate of the households in the microsimulation model. We cannot guarantee that the macro model and the MikroSim model are perfectly substitutable. Nevertheless, the employment module in the MikroSim model has been adapted to the modeling of labor supply in structural macroeconomic models, as described in Chapter 3.

4.5 Summary

In this chapter, we introduced different approaches to link micro and general equilibrium models, with a particular focus on sequential approaches, i. e., the top-down approach, the bottom-up approach, and the top-down bottom-up approach. In order to establish a link between micro and macro models, it is necessary to identify suitable link variables. We then proceeded to introduce different link variables with a focus on the Frisch labor supply elasticity to ensure consistency and to establish a coherent link between both models.

We presented the Frisch labor supply elasticity as the most important link between micro and macro models in the analysis of employment. The Frisch labor supply elasticity was estimated separately for single individuals and couples. In addition to the distinction between single and couple households, it would also be interesting to estimate the Frisch labor supply elasticity for couples at the individual level, keeping the employment status of the partner unchanged. This allows for more direct comparisons at the individual level. The analysis of differences between males and females, as well as between age groups, could provide further insights into the effects of policy changes on labor supply behavior.

In the application, we presented how to link the MikroSim model to the Ramsey model. We also linked the MikroSim model with the Ramsey model using the top-down bottom-up approach. This constitutes the most complex combination of micro and macro models. The Frisch labor supply elasticity served as a link variable to ensure consistency between the micro and macro models. In order to be able to calibrate the macro model with the estimated Frisch labor supply elasticity on the basis of the micro model, we proposed three different solution strategies to circumvent the problem of small micro estimates of the Frisch labor supply elasticity.

Chapter 5

Linking Micro and Time-series Models

While linking micro models to general equilibrium models is the most sophisticated type of integration between micro and macro models, aiming to combine the strengths of both models, it is also possible to link micro models to time-series models. In this type of linkage, the focus is on improving the micro model. Forecasts based on the time series model can be used for scenario analysis or prospective external alignment (see Section 2.2.4). The linking of micro models with time-series models is largely based on the top-down approach, however the micro model can also be linked to the forecasts of time-series models through step-wise iterative alignment. The chapter is organized as follows: Section 5.1 introduces time-series models as a foundation, Section 5.2 links the MikroSim model to forecasts from ARIMA models, and Section 5.3 provides a summary and outlines future research potential. For a detailed description of the different approaches to linking micro and macro models, we refer to Section 4.3.1.

5.1 Time-series Models

Time-series econometrics is synonymous with empirical macroeconomics (Hamilton, 1994, p. xiii). Time series are realizations of a stochastic process (Neusser, 2011, p. 10; Greene, 2012, p. 949). The analysis of time-series data serves two objectives (Mosler and Schmid, 2009, p. 203):

- Analysis of the structure of the time series
- Forecast of future values of the time series.

The concept of stationarity is very important in the field of time-series analysis. Since data are mostly available only for a limited time span. For this reason, it is crucial for a meaningful economic analysis that the regularities of the observed trajectory are also typical for all other trajectories (Neusser, 2011, p. 9). This can be formally expressed by the concept of stationarity. A stochastic process $\{Y^{(t)}\}_{t=-\infty}^{t=\infty}$ is weakly stationary if the mean and the autocovariances do not depend on the time t (Hamilton, 1994, p. 45; Neusser, 2011, p. 11). Given that j defines the time interval between the observations, the concept of weak stationarity implies that the covariance $Y^{(t)}$ and $Y^{(t-j)}$ depend on j but not on the time t (Hamilton, 1994, p. 46; Neusser, 2011, p. 12). Strict stationarity extends the concept of weak stationarity. A stochastic process $\{Y^{(t)}\}_{t=-\infty}^{t=\infty}$ is strictly stationary if the joint probability distribution ($Y^{(t)}$, $Y^{(t+j_1)}$, $Y^{(t+j_2)}$,..., $Y^{(t+j_n)}$) depends on the time intervals but not on the time t (Hamilton, 1994, pp. 45f; Neusser, 2011, pp. 11-13; Greene, 2012, p. 953).

The white noise process serves as the foundation for time-series processes. Consider the sequence $\{\varepsilon^{(t)}\}_{t=-\infty}^{t=\infty}$. This process is white noise if the elements are uncorrelated and have a mean of 0 and variance σ^2 (Hamilton, 1994, p. 47):

$$E\left(\varepsilon^{(t)}\right) = 0$$
$$E\left(\left(\varepsilon^{(t)}\right)^2\right) = \sigma^2.$$

5.1.1 Autoregressive Integrated Moving Average Models

ARIMA models are used for univariate time-series analysis. They consist of an AR(p) part with p indicating the AR order, an I(d) part with d indicating the degree of differencing, and a MA(q) part with q indicting the moving average (MA) order. The MA process builds on the white noise process $\{\varepsilon_t\}_{t=-\infty}^{t=\infty}$. The MA(1) process is defined as (Hamilton, 1994, p. 48; Neusser, 2011, p. 14; Greene, 2012, p. 950):

$$y^{(t)} = \mu + \varepsilon^{(t)} + \theta\varepsilon^{(t-1)}, \tag{5.1}$$

where μ is the mean of the process and θ is a constant. Positive values of θ imply that "an unusually large value of $[y^{(t)}]$ is likely to be followed by a larger-than-average value for $[y_{t+1}]$" (Hamilton, 1994, p. 49), while negative values of θ imply that "a large value of $[y^{(t)}]$ might be expected to be followed by a small value for $[y^{(t+1)}]$" (Hamilton, 1994, p. 49). $y^{(t)}$ is a weighted sum of the two last values of ε (Hamilton, 1994, p. 48). The MA(1) process can be generalized to an infinite-order moving average process MA(q) (Hamilton, 1994, pp. 51f):

$$y^{(t)} = \mu + \sum_{j=0}^{q} \theta_j \varepsilon^{(t-j)} \tag{5.2}$$

with $\theta_0 \equiv 1$.

The AR(1) process is given as (Hamilton, 1994, p. 53):

$$y^{(t)} = \phi y^{(t-1)} + \varepsilon^{(t)}, \tag{5.3}$$

where $\varepsilon^{(t)}$ is a white noise process. If $|\phi| < 1$, the process is covariance-stationary. The AR(1) process can be generalized to an AR(p) process (Hamilton, 1994, p. 58):

$$y^{(t)} = \sum_{j=1}^{p} \phi_j y^{(t-j)} + \varepsilon^{(t)}. \tag{5.4}$$

The AR(p) process with drift includes a constant term c: (Hamilton, 1994, p. 58):

$$y^{(t)} = c + \sum_{j=1}^{p} \phi_j y^{(t-j)} + \varepsilon^{(t)}. \tag{5.5}$$

Combining the MA process and AR process, results in the mixed autoregressive moving average (ARMA) process (Hamilton, 1994, p. 59):

$$\begin{aligned} y^{(t)} =& \phi_1 y^{(t-1)} + \phi_2 y^{(t-2)} + ... + \phi_p y^{(t-p)} + \\ & \varepsilon^{(t)} + \theta_1 \varepsilon^{(t-1)} + \theta_2 \varepsilon^{(t-2)} + ... + \theta_q \varepsilon^{(t-q)}. \end{aligned} \tag{5.6}$$

When economic variables exhibit a trend, the time series is non-stationary. Consequently, AR processes, MA processes, and ARMA processes cannot be applied. However, non-stationary data can be transformed into stationary data (Hamilton, 1994, ch. 15; Greene, 2012, ch. 21). If a non-stationary time series is integrated of order d, I(d), the non-stationary time series can be converted into a stationary

time series. The autoregressive integrated moving average (ARIMA) model can be written as (Greene, 2012, p. 983):

$$\begin{aligned}\Delta^d y^{(t)} =& \mu + \phi_1 \Delta^d y^{(t-1)} + \phi_2 \Delta^d y^{(t-2)} + ... + \phi_p \Delta^d y^{(t-p)} + \\ & \varepsilon^{(t)} - \theta_1 \varepsilon^{(t-1)} - ... - \theta_q \varepsilon^{(t-q)}\end{aligned} \tag{5.7}$$

with $\Delta y^{(t)} = y^{(t)} - y^{(t-1)}$. Thus, integration of order d transforms the ARIMA(p, d, q) into a stationary ARMA(p, q) model (Hamilton, 1994, p. 437).

The models considered above do not include covariates $x^{(t)}$. The variable of interest is regressed on its own lagged values exclusively. However, it is possible to extend the ARMA model to an ARMAX model and similarly, the ARIMA model to an ARIMAX model, which allows the inclusion of exogenous variables as explanatory variables. These models can be seen as a mix of a linear regression and ARMA (5.6) or ARIMA models (5.7). For reasons of simplicity, it is assumed that the data are stationary. The autoregressive moving average model with explanatory variable extends the ARMA model (5.6) by a covariate x:

$$\begin{aligned}y^{(t)} =& \beta x^{(t)} + \phi_1 y^{(t-1)} + \phi_2 y^{(t-2)} + ... + \phi_p y^{(t-p)} + \\ & \varepsilon^{(t)} + \theta_1 \varepsilon^{(t-1)} + \theta_2 \varepsilon^{(t-2)} + ... + \theta_q \varepsilon^{(t-q)}.\end{aligned} \tag{5.8}$$

For further information on time-series models, we refer to Hamilton (1994), Neusser (2011), and Greene (2012, ch. 20, 21).

5.1.2 Vector Autoregressive Models

In contrast to CGE and DSGE models, VAR models lack a microfoundation. Thus, an advantage of a VAR model is thus that it does not rely on "merely artificial devices intended to induce more realistic macroeconomic behavior" (Kilian and Lütkepohl, 2017, p. 187). VAR models are used for multivariate time-series analysis. The VAR model consists of a system of regressions, where the regressors are lagged variables of its own and of other model variables. The maximum lag order p is pre-specified and determines the regressions. The VAR(2) model is of the following form (Kilian

and Lütkepohl, 2017, pp. 1f):

$$\begin{aligned} y_1^{(t)} =& \beta_{11,1}\ y_1^{(t-1)} + \beta_{12,1}\ y_2^{(t-1)} + \beta_{13,1}\ y_3^{(t-1)} + \\ & \beta_{11,2}\ y_1^{(t-2)} + \beta_{12,2}\ y_2^{(t-2)} + \beta_{13,2}\ y_3^{(t-2)} + \varepsilon_1^{(t)} \\ y_2^{(t)} =& \beta_{21,1}\ y_1^{(t-1)} + \beta_{22,1}\ y_2^{(t-1)} + \beta_{23,1}\ y_3^{(t-1)} + \\ & \beta_{21,2}\ y_1^{(t-2)} + \beta_{22,2}\ y_2^{(t-2)} + \beta_{23,2}\ y_3^{(t-2)} + \varepsilon_2^{(t)} \\ y_3^{(t)} =& \beta_{31,1}\ y_1^{(t-1)} + \beta_{32,1}\ y_2^{(t-1)} + \beta_{33,1}\ y_3^{(t-1)} + \\ & \beta_{31,2}\ y_1^{(t-2)} + \beta_{32,2}\ y_2^{(t-2)} + \beta_{33,2}\ y_3^{(t-2)} + \varepsilon_3^{(t)} \end{aligned} \tag{5.9}$$

with $\varepsilon_i^{(t)}$ for $i = 1, 2, 3$ being serially uncorrelated with a diagonal covariance matrix $\sum_{\varepsilon}$.

Global VARs (GVARs) are designed with the specific purpose of handling panels of time-series data for many countries or regions. The idea is to augment a VAR model for each unit by global variables capturing the other countries. The advantage is that several countries can be modeled jointly as a global model. A review of the GVAR approach is provided in Chudik and Pesaran (2016).

VAR models can also be used for structural modeling. Structural VAR(p) models are represented as (Kilian and Lütkepohl, 2017, p. 2):

$$\mathbf{B_0} y^{(t)} = \mathbf{B_1} y^{(t-1)} + ... + \mathbf{B_p} y^{(t-p)} + \omega^{(t)}, \tag{5.10}$$

where $\mathbf{B_i}$ for $i = 1, ..., p$ is a $K \times K$ matrix of autoregressive slope coefficients, $\omega^{(t)}$ is serially uncorrelated with a diagonal covariance matrix $\sum_{\omega}$ of full rank. Each element of $\omega^{(t)}$ has its own economic interpretation. $\mathbf{B_0}$ depicts the relations of the model variables and captures the effect of the structural shocks on the model variables.

VAR(p) models are estimated using unrestricted least-squares, generalized least-squares, bias-corrected least squares, and maximum likelihood methods (Kilian and Lütkepohl, 2017, ch. 2.3).

5.2 Application: Linking the MikroSim Model and Time-series Models

The top-down approach is the simplest combination of micro and macro models. In particular, if the microsimulation model is aligned, the top-down approach can be implemented equivalently to alignment, using the macro data as a benchmark. As most of the modules in the MikroSim model are aligned, the top-down approach is straightforward to implement. We choose to link the MikroSim model with forecasted time-series data, that serve as benchmark for simulation periods that lie in the future. Thus, the top-down approach with forecasted time-series data provides a possible solution to the question of what to do with adjusted models in the absence of benchmark data (for points in time that lie in the future).

Employment variables are used as link variables. The employment module in the MikroSim model is described in Section 2.4.1. The time-series data for employed, unemployed, and inactive individuals are available from INKAR (Bundesinstitut für Bau-, Stadt und Raumforschung, 2021). The data on the unemployed are available from 1995, while the data on employment and inactivity are available from 1998. We use the ARIMA model to forecast the time-series of employment data.

ARIMA models are very popular and widely used for forecasting time-series models (see Section 5.1). We select the ARIMA model based on the corrected AIC (AICc), which is a common approach to choose ARIMA models (Hyndman et al., 2023; Hyndman and Khandakar, 2008). The AICc is a modification of the AIC (2.44). It is defined as follows (Hurvich and Tsai, 1989):

$$AICc = AIC + \frac{2(K+1)(K+2)}{n-K-2}, \tag{5.11}$$

where K is the number of parameters in the model and n the number of observations.

The procedure to forecast the time-series data for the MikroSim employment module is as follows:

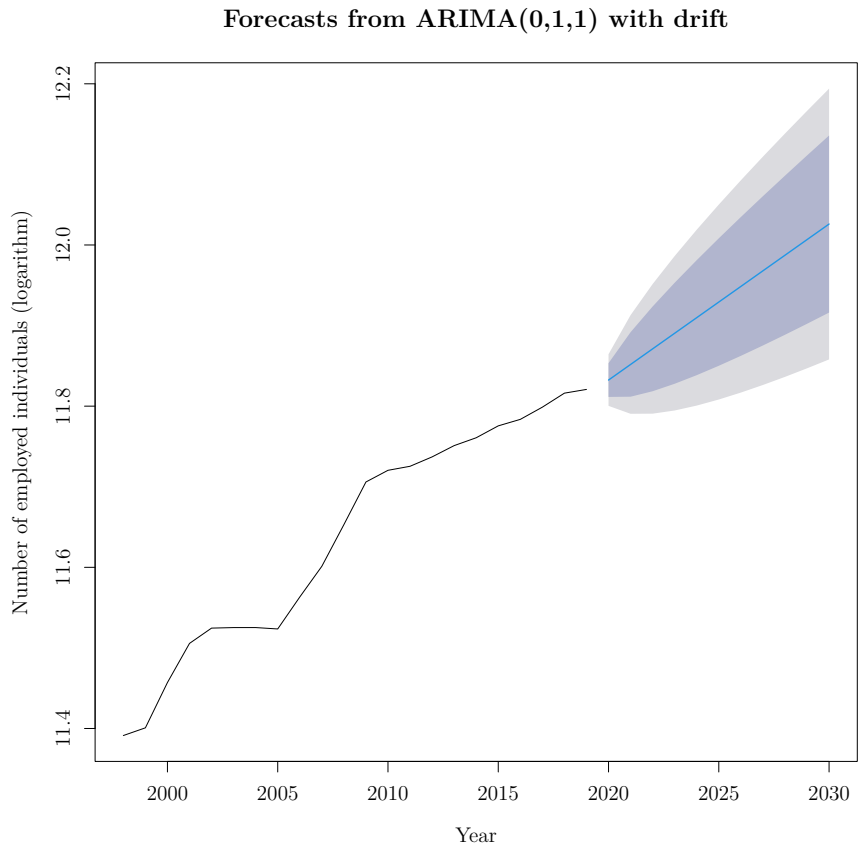
1. Data collection
2. Model selection
3. Model inference,

The data collection step includes the preparation of the estimation data. The data must be non-negative as the number of employed, unemployed, or inactive persons cannot be negative. For this reason, a logarithmic transformation is performed first. The model selection is based on the procedure described above. The entire available time period is selected as the estimation window. 2030 is chosen as the forecast horizon. The forecasted values are transformed from the logarithmic scale back into the original scale by an exponential transformation, so that they can be used as benchmark values in the MikroSim model. Subsequently, key figures, such as the unemployment rate and the employment rate, are calculated. This is necessary because the number of individuals of working age based on the forecasted time-series data will most likely not match the projected population growth of the corresponding age group in the MikroSim model.

Figure 5.1, Figure 5.2, and Figure 5.3 illustrate the forecasted time-series data based on the ARIMA models for employment, unemployment and inactivity, respectively. The gray area shows the 95% confidence interval, whereas the blue area shows the 80% confidence interval. For illustrative purposes, we present the data for the labor market region Trier, which encompasses the following districts: Trier (city), Bernkastel-Wittlich, Eifelkreis Bitburg-Prüm, Vulkaneifel, and Trier- Saarburg (Bundesagentur für Arbeit, 2024).

Figure 5.1 shows the forecasted values for employment, where the number of employed individuals is depicted on a logarithmic scale. An ARIMA(0,1,1) model with drift is chosen based on the AICc criterion. The model is a simple exponential smoothing model with growth. A positive trend is observed from 1998 to 2019. The forecasted values indicate a continuation of the positive trend for the next 11 periods.

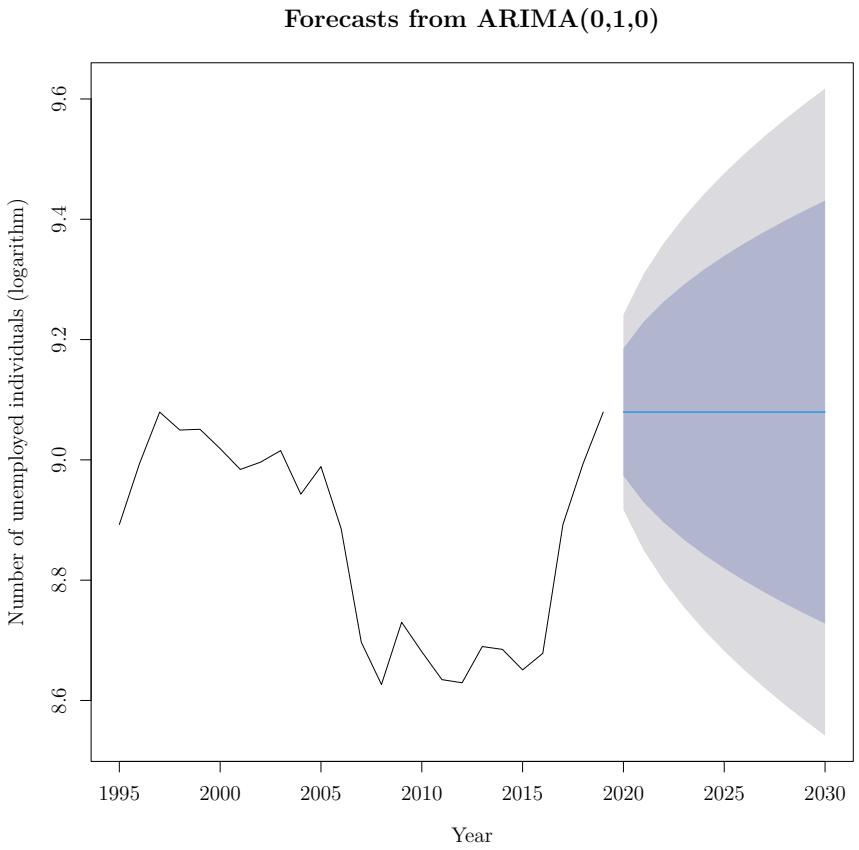
Figure 5.1: Forecast of employment in the labor market region Trier based on an auto selection algorithm for ARIMA models



Note: The gray area shows the 95% and the blue area the 80% confidence interval.
Source: Own calculation based on Bundesinstitut für Bau-, Stadt und Raumforschung (2021).

Figure 5.2 shows the forecasted values for unemployment with the number of unemployed individuals represented on a logarithmic scale. An ARIMA(0,1,0) model is estimated, i. e., a random walk model. Consequently, the forecasted series is devoid of any meaningful information, as a random walk implies that the movement of unemployment is influenced solely by random noise (Hamilton, 1994, p. 436; Neusser, 2011, p. 16). The forecast could be improved by modifying the estimation window to consider data from 2015 onward in the estimation process.

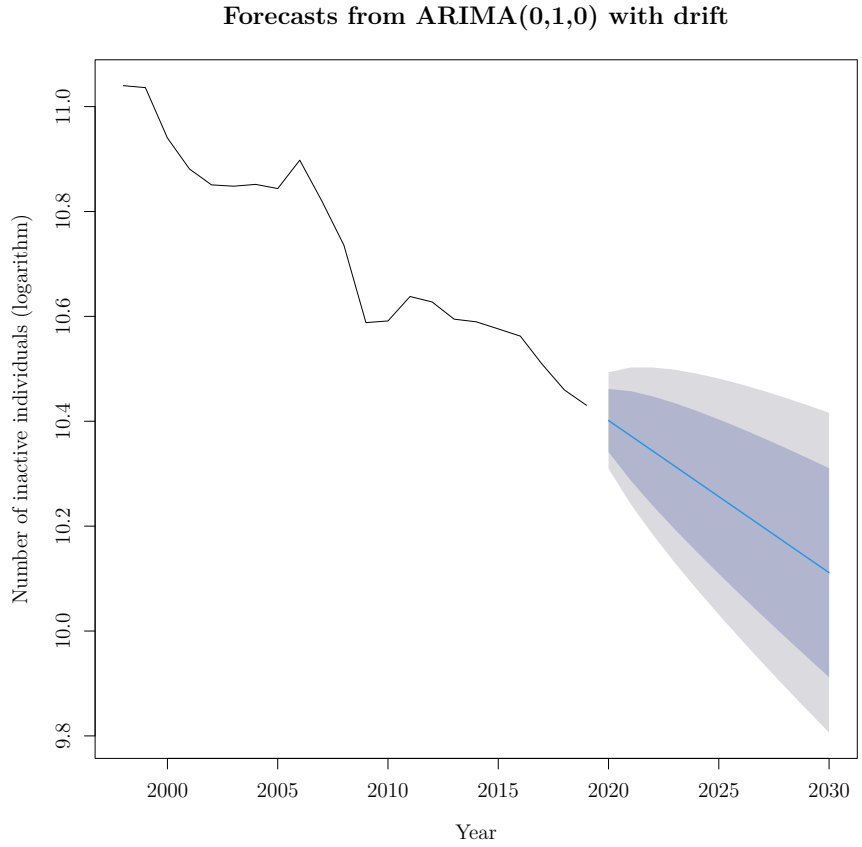
Figure 5.2: Forecast of unemployment in the labor market region Trier based on an auto selection algorithm for ARIMA models



Note: The gray area shows the 95% and the blue area the 80% confidence interval.
Source: Own calculation based on Bundesinstitut für Bau-, Stadt und Raumforschung (2021).

Figure 5.3 shows the forecasted values for individuals who are inactive. The number of inactive individuals is depicted on a logarithmic scale. An ARIMA(0,1,0) model with drift is estimated. A random walk with drift is a model that forecasts the time-series data based on the previous value plus a constant and a white noise term (Hamilton, 1994, p. 436).

Figure 5.3: Forecast of inactivity in the labor market region Trier based on an auto selection algorithm for ARIMA models



Note: The gray area shows the 95% and the blue area the 80% confidence interval.
Source: Own calculation based on Bundesinstitut für Bau-, Stadt und Raumforschung (2021).

The forecast accuracy can be assessed based on different quality measures (Hyndman et al., 2023; Hyndman and Khandakar, 2008):

- Mean error (ME)
- RMSE
- Mean absolute error (MAE)
- Mean percentage error (MPE)
- Mean absolute percentage error (MAPE)
- Mean absolute scaled error (MASE)
- Autocorrelation of errors of lag one (ACF1).

It is crucial to recognize that certain measures are contingent upon the scaling of the data. Consequently, the ME, the RMSE, and the MAE should be employed when comparing different methods on the same data set. In contrast, the percentage errors MPE and the MAPE can be used to compare prediction performance across different data sets (Hyndman and Koehler, 2006).

Table 5.1 illustrates the training set accuracy measures for the ARIMA models.

Table 5.1: Accuracy measures for forecast models

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Employment	0.0009	0.0152	0.0113	0.0084	0.0978	0.5501	0.0093
Unemployment	0.0078	0.0811	0.0615	0.0830	0.6941	0.9656	0.3404
Inactivity	0.0005	0.0447	0.0341	0.0040	0.3176	0.8691	0.2201

Source: Own calculation.

The accuracy of the forecast could possibly be improved by adding exogenous variables. However, the inclusion of additional exogenous variables is not possible in ARIMA models. The autoregressive integrated moving average with explanatory variables (ARIMAX) model is an extension of the ARIMA model that allows to incorporate exogenous variables to the model.

Exogenous variables that could be used in ARIMAX models to improve the forecast of employment data include data from official statistics, such as data on unemployment insurance claims (Ettredge et al., 2005), data from online search engines, such as web-based job search data (Ettredge et al., 2005), Google trends data for the categories *Jobs*, *Welfare...*, and *Unemployment* (Choi and H. Varian, 2012), Google trends data relating to the categories jobs, society, social services, and economic indicators (Adu et al., 2023), as well as data describing the search volumes for the search terms *unemployment benefits*, *labor market subsidy*, *unemployment office*, *unemployment claim*, *unemployment compensation*, *unemployment insurance* , *apply for unemployment*, *applying for unemployment*, *filing for unemployment*, *unemployment online*, *unemployment office locations*, *unemployment eligibility*, *ui benefits*, and *unemployment benefit* (Tuhkuri, 2016a; Tuhkuri, 2016b). These studies indicate that the incorporation of data from online search engines enhances the accuracy of short-term unemployment rate forecasts.

ARIMAX models also present novel opportunities for the MikroSim model, representing an additional method of integrating micro and macro models through the top-down-bottom-up approach. The results of the microsimulation model can be integrated into the ARIMAX model as exogenous variables, which could improve the predictive performance of ARIMA models (see above). The forecasted data based on the ARIMAX model can then serve as benchmark data for the microsimulation model. The recursive approach to forecasting, which involves the use of an increasing window for estimating the model, allows for the incorporation of the latest outcomes of the microsimulation model into the estimation process. The additional consideration of Google trends data is also an innovative and promising approach.

ARIMAX models (Section 5.1.1) are similar to VAR models (Section 5.1.2). The primary distinction between the ARIMAX and VAR models is their ability to accommodate multiple time series. VAR models are used for multivariate time-series analysis, whereas ARIMAX models are used for univariate time-series analysis with exogenous variables. As stated in Section 2.4, the base population of the MikroSim model can be extended either once at the beginning of the simulation or in each simulation run. Depending on the length and consistency of the variables in the MikroSim model, the results of the MikroSim model can also be considered as time-series data. Consequently, it is also straightforward to link the MikroSim and VAR estimates of macro variables.

5.3 Summary

In this chapter, we proposed an alternative approach to linking micro and macro models. In addition to linking micro models to general equilibrium models, combining forecasts from time-series models and micro models is another option for linking micro and macro models that is worth exploring. We introduced different time-series models and demonstrated in an application how to link the MikroSim model to time-series models. The linkage of the MikroSim model to forecasted time-series data based on the ARIMA model was conducted following the top-down approach. Furthermore, we presented a possible extension of this approach, which consists of linking the MikroSim model to ARIMAX and VAR models. This extension represents an promising alternative since it could improve the accuracy of time-series models and allows for the establishment of a bi-directional link between the micro and macro models.

Chapter 6

Summary and Outlook

The use of microsimulation models for policy evaluation and socio-economic impact assessment has increased in recent years, leading to further development of the underlying methods and to more complex microsimulation models. A major source of complexity is the incorporation of a behavioral component. Behavioral microsimulations are often linked to general equilibrium models in order to combine the strengths of both micro and macro models. The strength of microsimulation is that it allows the analysis of "what-if" scenarios at the level of the micro-unit, while the strength of general equilibrium models is that they consider the economy as a whole, at the aggregate level.

The thesis was written within the DFG research group FOR 2559 "Multi-sectoral Regional Microsimulation Model" (MikroSim). In the MikroSim project, a realistic population for Germany was created and projected into the future using statistical methods, primarily (multinomial) logit models. In order to distinguish the MikroSim model from other microsimulation models, different types of microsimulation methods were introduced and the MikroSim model was classified as a discrete-time dynamic microsimulation model. The statistical methods for creating and projecting the population into the future were presented with a focus on modeling and simulation processes. Due to the small sample size of the estimation data set and the lack of geographic information, the estimated probabilities do not correspond to known totals. Therefore, internal and external validation methods were used to assess the performance of the estimation models for projecting the base population into the future. This is particularly challenging in the field of dynamic microsimulation.

Due to its modular structure, the MikroSim model provides an ideal basis for thematic extensions. The objective of this thesis was to describe, analyze, and extend methods for linking micro and macro models. In addition to the existing literature, which mainly deals with linking static microsimulation models with CGE models, this thesis focused on linking dynamic microsimulation models with macro models in general. In addition to general equilibrium models, alternative types of macro models, such as VAR models and ARIMAX models, were considered. A prerequisite for linking micro and macro models is the identification of suitable link variables in order to establish a coherent link between both models.

The quality of link variables is of paramount importance, as they serve as the basis for linking micro and macro models and, thus, determine the quality of the linked model. One of the main fields of application is the analysis of the unintended or intended consequences of policy reforms on labor supply behavior. We also focused on employment variables as link variables and provided an overview of different methods for estimating employment transitions. These included (multinomial) logit models, Markovian transition models, random effects models, and conditional inference trees. In an application based on the MikroSim model, the conditional inference tree was shown to be particularly promising for estimating employment transitions. One of the main advantages of the conditional inference tree algorithm is its relative speed and ease of implementation. Additionally, it is capable of identifying implausible transitions, provided that the underlying data are consistent. Further investigation of machine learning algorithms for estimating employment transitions may be beneficial. This thesis demonstrated the value of exploring alternative statistical methods for estimating transition probabilities in the context of discrete-time dynamic microsimulation models. For example, conditional random forests, which are based on conditional inference trees, may provide an alternative approach.

The incorporation of a behavioral component into microsimulation models opens up new avenues for research. Behavioral microsimulation models allow the analysis of behavioral responses of micro-units to policy reforms. It was shown that behavioral microsimulation models do not reflect the theoretically possible effects of the scenarios under study, but instead produce realistic outcomes. Additionally, a cost-benefit analysis of the policy reforms was conducted. This is particularly relevant in the field of empirical legal studies.

Behavioral microsimulation could be further enhanced by integration with tax-benefit models. This integration would allow the implementation of tax policy scenarios and the subsequent analysis of the resulting behavioral responses. Thus, the combination of the microsimulation model with tax-benefit models such as EUROMOD could be a promising avenue for further research, allowing, for example, analyses of the effects of taxes on pensions and thus on the living standards of the aging population. This aspect could also be of relevance for the analysis of long-term care using a microsimulation approach.

Behavioral microsimulation models also serve as the basis for establishing a consistent link between microsimulation models and general equilibrium models. The combination of these model types represents the most complex alternative for linking micro and macro models. The sequential approach allows for the development of both a sophisticated microsimulation model and a macro model, which are then combined using link variables. A popular area of application is the analysis of labor supply behavior, where employment variables and the Frisch labor supply elasticity serve as link variables. The Frisch labor supply elasticity was estimated at the level of federal states using the MikroSim base population data. It was found to be relatively low, ranging from 0.0195 to 0.0546 for single individuals and from 0.0273 to 0.0514 for couples. This result supports the finding that micro estimates of the Frisch labor supply elasticity are generally lower than macro estimates of the Frisch labor supply elasticity.

It is also possible to link microsimulation models to other types of macro models, such as time-series models. The sequential link between microsimulation models and time-series models is more flexible as it requires fewer assumptions. In this thesis, the MikroSim model was linked to forecasts of ARIMA models. However, this link is uni-directional. Nevertheless, this approach represents a promising avenue for further exploration, with the potential to be extended to link the MikroSim model to ARIMAX models or to VAR models, thereby establishing a bi-directional link.

For future research, it would be desirable to link the MikroSim model to a regional general equilibrium model. Regional general equilibrium models are used at the subnational level to analyze the effects of different scenarios at the regional level. This would be advantageous in view of the fact that a distinctive feature of the MikroSim model is its high degree of regional disaggregation. Thus, linking the MikroSim to macro models, which are generally developed at the national level, results in a loss

of information from the viewpoint of the MikroSim model. While the results of the macro model could be disaggregated, this would introduce an additional source of uncertainty. If the main motivation for linking micro and macro models is to incorporate labor demand effects, the RURO model, which considers both labor supply and labor demand, could be a promising alternative.

Bibliography

Aaberge, Rolf and Ugo Colombino (2014). "Labour Supply Models." In: *Handbook of Microsimulation Modelling*. Bingley: Emerald Group Publishing Limited, pp. 167–221.

Aaberge, Rolf and Ugo Colombino (2018). *Structural Labour Supply Models and Microsimulation*. Discussion Paper 11562. Bonn: IZA-Institute of Labor Economics.

Aaberge, Rolf, John K. Dagsvik, and Steinar Strøm (1995). "Labor Supply Responses and Welfare Effects of Tax Reforms." In: *The Scandinavian Journal of Economics* 97.4, pp. 635–659.

Aaberge, Rolf et al. (1998). "Evaluating Alternative Tax Reforms in Italy with a Model of Joint Labour Supply of Married Couples." In: *Structural Change and Economic Dynamics* 9, pp. 415–433.

Aaberge, Rolf et al. (2000). "Joint Labour Supply of Married Couples: Efficiency and Distribution Effects of Tax and Labour Market Reforms. Challenges and Innovations." In: Mittwon, Lavinia, Holly Sutherland, and Melvyn Weeks. *Microsimulation Modelling for Policy Analysis*. Cambridge: Cambridge University Press, pp. 269–291.

Adelman, Irma and Sherman Robinson (1978). *Income Distribution in Developing Countries: A Case Study of Korea*. Oxford: Oxford University Press.

Adu, Williams Kwasi, Peter Appiahene, and Stephen Afrifa (2023). "VAR, ARIMAX and ARIMA Models for Nowcasting Unemployment Rate in Ghana Using Google Trends." In: *Journal of Electrical Systems and Information Technology* 10.12.

Akaike, Hirotsugu (1973). "Information Theory and an Extension of the Maximum Likelihood Principle." In: *2nd International Symposium on Information Theory, Tsahkadsor, Armenia, USSR, September 2-8, 1971*. Ed. by Boris N. Petrov and Figyes Csáki. Budapest: Akadémiai Kiadó, pp. 267–281.

Alfons, Andreas et al. (2011). *Synthetic Data Generation of SILC Data*. Research Project Report 6.2. Advanced Methodology for European Laeken Indicators. URL:

https://www.uni-trier.de/fileadmin/fb4/projekte/SurveyStatisticsNet/Ameli_Delivrables/AMELI-WP6-D6.2-240611.pdf (visited on 09/17/2021).

Archer, Luke, Nik Lomax, and Bryan Tysinger (2021). "A Dynamic Microsimulation Model for Ageing and Health in England. The English Future Elderly Model." In: *International Journal of Microsimulation* 14.3, pp. 2–26.

Arencibia, Ana Isabel et al. (2015). "Modelling Mode Choice for Freight Transport Using Advanced Choice Experiments." In: *Transportation Research Part A: Policy and Practice* 75, pp. 252–267.

Articus, Charlotte et al. (2019). "Measuring Well-being Using Remote Sensing and Official Statistics Data." In: *Rivista di statistica ufficiale* 2–3, pp. 9–42.

Bækgaard, Hans (2002). *Micro-macro Linkage and the Alignment of Transition Processes: Some Issues, Techniques and Examples*. Technical Paper 25. Canberra: University of Canberra. National Centre for Social and Economic Modeling.

Bai, Lu et al. (2020). "Effect of Environmental Awareness on Electric Bicycle Users' Mode Choices." In: *Transportation Research Part D: Transport and Environment* 82, 102320.

Ballas, Dimitris, Graham Clarke, and Ian Turton (1999). "Exploring Microsimulation Methodologies for the Estimation of Households Attributes." In: *Paper presented at the 4th International conference on GeoComputation*. Virgina. URL: http://www.geog.leeds.ac.uk/papers/99-11/99-11.pdf (visited on 11/02/2021).

Bargain, Olivier, Kirstian Orsini, and Andreas Peichl (2014). "Comparing Labour Supply Elasticities in Europe and the United States: New Results." In: *The Journal of Human Resources* 49.3, 723–838.

Bargain, Olivier, Kristian Orsini, and Andreas Peichl (2012). *Comparing Labor Supply Elasticities in Europe and the Us: New Results*. Discussion Paper 6735. IZA-Institute of Labor Economics.

Bargain, Olivier and Andreas Peichl (2013). *Steady-State Labor Supply Elasticities*. Discussion Paper 13-084. Mannheim: ZEW-Leibnitz-Zentrum für Europäische Wirtschaftsforschung.

Bargain, Olivier et al. (2010). ""Making Work Pay" in a Rationed Labor Market." In: *Journal of Population Economics* 23, pp. 323–351.

Barrios, Salvador et al. (2016). *Dynamic Scoring of Tax Reforms in the European Union*. JRC Working Paper on Taxation and Structural Reforms 3/2016. Seville: Joint Research Center.

Barrios, Salvador et al. (2022). *Dynamic Scoring of Tax Reforms in Real Time*. JRC Working Papers on Taxation and Structural Reforms 14/2022. Seville: European Commission.

Basu, Susanto and Christopher L. House (2016). "Allocative and Remitted Wages: New Facts and Challenges for Keynesian Models." In: Taylor, John B. and Harald Uhlig. *Hanbook of Macroeconomics*. Vol. 2. Amsterdam: Elsevier B.V.

Begg, Colin B. and Robert Gray (1984). "Calculation of Polychotomous Logistic Regression Parameters Using Individualized Regressions." In: *Biometrika* 71.1, pp. 11–18.

Bijak, Jakub et al. (2013). "Reforging the Wedding Ring: Exploring a Semi-artificial Model of Population for the United Kingdom with Gaussian Process Emulators." In: *Demographic Research* 29.27, pp. 729–766.

Blanchard, Olivier and Jordi Galí (2007). "Real Wage Rigidities and the New Keynesian Model." In: *Journal of Money, Credit and Banking* 39, pp. 35–65.

Blanchet, Didier, Muriel Barlet, and Thomas Le Barbanchon (2009). "Microsimulation et Modèles d'Agents: Une Approche Alternative pour l'Évaluation des Politiques d'Emploi." In: *Économie et Statistique* 429, pp. 51–76.

Blömer, Maximilian and Andreas Peichl (2020). *The ifo Tax and Transfer Behavioral Microsimulation Model*. ifo Working Paper 335. Munich: ifo Institute.

Blundell, Richard (1995). *The Impact of Taxation on Labour Force Participation and Labour Supply*. OECD Jobs Study Working Papers 8. Paris: OECD.

Blundell, Richard and Thomas Macurdy (1999). "Labor Supply: A Review of Alternative Approaches." In: *Handbook of Labor Economics*. Ed. by Orley C. Ashenfelter and David Card. Vol. 3. Handbook of Labor Economics Part A. North-Holland: Elsevier B.V., pp. 1559–1695.

Blundell, Richard et al. (2000). "The Labour Market Impact of the Working Families' Tax Credit." In: *Fiscal Studies* 21.1, pp. 75–103.

Böhringer, Christoph, Xaquin Garcia-Muros, and Mikel Gonzàlez-Eguino (2019). "Greener and Fairer: A Progressive Environmental Tax Reform for Spain." In: *Economics of Energy & Environmental Policy* 8.2, pp. 141–160.

Bongers, Mathilda L. et al. (2016). "Multistate Statistical Modeling: A Tool to Build a Lung Cancer Microsimulation Model That Includes Parameter Uncertainty and Patient Heterogeneity." In: *Medical Decision Making* 36.1, pp. 86–100.

Bonin, Holger, Wolfram Kempe, and Hilmar Schneider (2002). *Household Labor Supply Effects of Low-Wage Subsidies in Germany*. IZA DP 637. Munich: IZA-Institute of Labor Economics.

Bonin, Holger, Wolfram Kempe, and Hilmar Schneider (2003). "Household Labor Supply Effects of Low-Wage Subsidies in Germany." In: *Journal of Contextual Economics – Schmollers Jahrbuch* 123, pp. 199–208.

Bourguignon, François and Maurizio Bussolo (2013). "Income Distribution in Computable General Equilibrium Modeling." In: *Handbook in Computable General Equilibrium Modeling*. Ed. by Peter B. Dixon and Dale Jorgenson. Vol. 1B. Handbooks in Economics. Oxford: Elsevier B.V., pp. 1383–1438.

Bourguignon, François and Amedeo Spadaro (2006). "Microsimulation As a Tool for Evaluating Redistribution Policies." In: *The Journal of Economic Inequality* 4, pp. 77–106.

Brier, Glenn W. (1950). "Verification of Forecasts Expressed in Terms of Probability." In: *Monthly Weather Review* 1.78, pp. 1–3.

Bundesagentur für Arbeit (2024). *Sonstige regionale Gliederungen*. URL: `https://statistik.arbeitsagentur.de/DE/Navigation/Grundlagen/Klassifikationen/Regionale-Gliederungen/Weitere-Gebietsgliederungen-Nav.html` (visited on 05/08/2024).

Bundesinstitut für Bau-, Stadt und Raumforschung (2021). *INKAR - Indikatoren und Karten zur Raum- und Stadtentwicklung*. URL: `https://www.inkar.de/` (visited on 05/02/2022).

Burfisher, Mary E. (2016). *Introduction to Computable General Equilibrium Models*. 2nd ed. New York: Cambridge University Press.

Burgard, Jan Pablo, Joscha Krause, and Simon Schmaus (2021). "Estimation of Regional Transition Probabilities for Spatial Dynamic Microsimulations from Survey Data Lacking in Regional Detail." In: *Computational Statistics & Data Analysis* 154, 107048.

Burgard, Jan Pablo et al. (2020a). "A Generic Business Process Model for Conducting Microsimulation Studies." In: *Statistics in Transition new series* 21.4, pp. 191–211.

Burgard, Jan Pablo et al. (2020b). "Dynamische Mikrosimulationen zur Analyse und Planung regionaler Versorgungsstrukturen in der Pflege." In: *Mikrosimulationen: Methodische Grundlagen und ausgewählte Anwendungsfelder*. Ed. by Marc Hannappel and Johannes Kopp. Wiesbaden: Springer VS, pp. 283–313.

Capéau, Bart, André Decoster, and Gijs Dekkers (2016). "Estimating and Simulating with a Random Utility Random Opportunity Model of Job Choice Presentation and Application to Belgium." In: *International Journal of Microsimulation* 9.2, pp. 144–191.

Chetty, Raj et al. (2011). "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins." In: *American Economic Review* 101.3, pp. 471–75.

Chetty, Raj et al. (2013). "Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities." In: *NBER Macroeconomics Annual* 27, pp. 1–56.

Cho, Jang-Ok and Thomas F. Cooley (1994). "Employment and Hours Over the Business Cycle." In: *Journal of Economic Dynamics and Control* 18.2, pp. 411–432.

Choi, Hyunyoung and Hal Varian (2012). "Predicting the Present with Google Trends." In: *The Economic Record* 88, pp. 2–9.

Chudik, Alexander and M. Hashem Pesaran (2016). "Theory and Practice of GVAR Modelling." In: *Journal of Economic Surveys* 30.1, pp. 165–197.

Colombo, Giulia (2010). "Linking CGE and Microsimulation Models: A Comparison of Different Approaches." In: *International Journal of Microsimulation* 3.1, pp. 72–91.

Creedy, John (1999). *Modelling Indirect Taxes and Tax Reform*. Cheltenham: Edward Elgar.

Creedy, John, Guyonne Kalb, and Rosanna Scutella (2006). "Income Distribution in Discrete Hours Behavioural Microsimulation Models: An Illustration." In: *The Journal of Economic Inequality* 4, pp. 57–76.

Creedy, John et al. (2020). "A Microsimulation Analysis of Marginal Welfare-improving Income Tax Reforms for New Zealand." In: *International Tax and Public Finance* 27, pp. 409–434.

Croissant, Yves (2020). "mlogit: Random Utility Models in R." In: *Journal of Statistical Software* 95.11, pp. 1–41.

Decoster, André and Guy Van Camp (2001). "Redistributive Effects of the Shift from Personal Income Taxes to Indirect Taxes: Belgium 1988–93." In: *Fiscal Studies* 22.1, pp. 79–106.

DeJong, David N. and Chetan Dave (2011). *Structural Macroeconometrics*. 2nd ed. Princeton: Princeton University Press.

Dekkers, Gijs (2015). "The Simulation Properties of Microsimulation Models with Static and Dynamic Ageing – a Brief Guide into Choosing One Type of Model Over the Other." In: *International Journal of Microsimulation* 8.1, pp. 97–109.

Devine, Theresa J. and Nicholas M. Kiefer (1991). *Empirical Labor Economics: The Search Approach*. New York: Oxford University Press.

Diamond, Peter A. (1982). "Wage Determination and Efficiency in Search Equilibrium." In: *The Review of Economic Studies* 49.2, pp. 217–227.

Dixon, Peter B. and Dale W. Jorgenson (2013). "Introduction." In: *Handbook of Computable General Equilibrium Modeling*. Ed. by Peter B. Dixon and Dale W. Jorgenson. Vol. 1A. Handbooks in Economics. Oxford: Elsevier B.V., pp. 1–22.

Dixon, Peter B. and Glyn Wittwer (2004). "Forecasting the Economic Impact of an Industrial Stoppage Using a Dynamic, Computable General Equilibrium Model." In: *Australian Journal of Labour Economics* 7, pp. 39–51.

Duncan, Alan and Melvyn Weeks (1998). "Simulating Transitions Using Discrete Choice Models." In: *Papers and Proceedings of the American Statistical Association* 106, pp. 151–156.

Edwards, Kimberley L. and Robert Tanton (2013). "Validation of Spatial Microsimulation Models." In: *Spatial Microsimulation: A Reference Guide for Users*. Ed. by Robert Tanton and Kimberley L. Edwards. Understanding Population Trends and Processes. Dordrecht: Springer Science+Business Media, pp. 249–258.

Ettredge, Michael, John Gerdes, and Gilbert Karuga (2005). "Using Web-based Search Data to Predict Macroeconomic Statistics." In: *Communications of the ACM* 48.11, pp. 87–92.

European Union (2018). *European Statistics Code of Practice*. Luxembourg: Publications Office of the European Union.

European Union (2021). *European Statistical System (ESS) Handbook for Quality and Metadata Reports*. Luxembourg: Publication Office of the European Union.

European Union (2022). *What is EUROMOD?* URL: `https://euromod-web.jrc.ec.europa.eu/overview/what-is-euromod` (visited on 05/12/2022).

Eurostat (2023). *Short-term Business Statistics - Revisions*. `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Short-term_business_statistics_-_revisions`. URL: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Short-term_business_statistics_-_revisions` (visited on 12/01/2023).

Eurostat (2024). *Eurostatistics: Data for Short-term Eocnomic Analysis*. `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Short-term_business_statistics_-_revisions`. URL: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Short-term_business_statistics_-_revisions` (visited on 12/01/2023).

Fahrmeir, Ludwig, Thomas Kneib, and Stefan Lang (2009). *Regression. Modelle, Methoden und Anwendungen*. Berlin, Heidelberg: Springer-Verlag.

Federal Employment Agency (2023). *Arbeitslosengeld: Anspruch, Höhe, Dauer*. https://www.arbeitsagentur.de/arbeitslos-arbeit-finden/arbeitslosengeld/finanzielle-hilfen/arbeitslosengeld-anspruch-hoehe-dauer. URL: https://www.arbeitsagentur.de/arbeitslos-arbeit-finden/arbeitslosengeld/finanzielle-hilfen/arbeitslosengeld-anspruch-hoehe-dauer (visited on 12/14/2023).

Fernández-Delgado, Manuel et al. (2014). "Do We Need Hundreds of Classifiers to Solve Real World Classification Problems?" In: *Journal of Machine Learning Research* 15.90, pp. 3133–3181.

Fernández, Alberto et al. (2018). *Learning from Imbalanced Data Sets*. Cham: Springer.

Flood, Lennart and Nizamul Islam (2005). "A Monte Carlo Evaluation of Discrete Choice Labour Supply Models." In: *Applied Economics Letters* 12.5, pp. 263–266.

Frisch, Ragnar (1959). "A Complete Scheme for Computing All Direct and Cross Demand Elasticities in a Model with Many Sectors." In: *Econometrics* 27.2, pp. 177–196.

Frohn, Christoph and Monika Obersneider (2020). "Modellierung der Entwicklung des Pflegebedarfs in Deutschland. Eine dynamische Mikrosimulation." In: *Mikrosimulationen*. Ed. by Marc Hannappel and Johannes Kopp. Wiesbaden: Springer VS, pp. 315–353.

Galí, Jordi (2015). *Monetary Policy, Inflation, and the Business Cycle*. 2nd ed. Princeton: Princeton University Press.

Galí, Jordi and Mark Gertler (2007). "Macroeconomic Modeling for Monetary Policy Evaluation." In: *Journal of Economic Perspectives* 21.4, pp. 25–46.

Gardenete, Manuel Alejandro, Ana-Isabel Guerra, and Ferran Sancho (2017). *Applied General Equilibrium. An Introduction*. 2nd ed. Springer Texts in Business and Economics. Berlin, Heidelberg: Springer-Verlag.

Giesecke, James A. and John R. Madden (2013). "Regional Computable General Equilibrium Modeling." In: *Handbook of Computable General Equilibrium Modeling*. Ed. by Peter B. Dixon and Dale W. Jorgenson. Vol. 1A. Handbooks in Economics. Oxford: Elsevier B.V., pp. 379–476.

Giesecke, James A. et al. (2012). "Assessment of the Regional Economic Impacts of Catastrophic Events. CGEAnalysis of Resource Loss and Behavioral Effects of an RDD Attack Scenario." In: *Risk Analysis* 32.4, pp. 583–600.

Golob, Thomas F. (1990). "The Dynamics of Household Travel Time Expenditures and Car Ownership Decisions." In: *Transportation Research Part A: General* 24.6, pp. 443–463.

Greene, William H. (2012). *Econometric Analysis*. Essex: Pearson.

Gross, Marco and Francisco Javier Poblacò (2017). "Assessing the Efficacy of Borrower-Based Macroprudential Policy Using an Integrated Micro-Macro Model for European Households." In: *Economic Modelling* 61, pp. 510–528.

Haan, Peter (2004). *Discrete Choice Labor Supply: Conditional Logit Vs. Random Coefficient Models*. Discussion Paper 394. DIW Berlin, German Institute for Economic Research.

Haan, Peter and Viktor Steiner (2005). *Labor Market Effects of the German Tax Reform 2000*. Discussion Paper 472. DIW Berlin, German Institute for Economic Research.

Hamilton, James D. (1994). *Time Series Analysis*. Princeton, New Jersey: Princeton University Press.

Hannappel, Marc and Klaus G. Troitzsch (2015). "Mikrosimulationsmodelle." In: *Handbuch Modellbildung und Simulation in den Sozialwissenschaften*. Ed. by Norman Braun and Nicole J. Saam. Wiesbaden: Springer VS.

Hansen, Gary D. (1985). "Indivisible Labor and the Business Cycle." In: *Journal of Monetary Economics* 16, pp. 309–327.

Hansen, Marianne Frank, Tobias Markeprand, and Peter Stephensen (2019). *Estimating Sub-national Behaviour in the Danish Microsimulation Model SMILE. A General Approach for Estimating Transition Probabilities with Numerous High-dimensional Covariates*. Tech. rep. Danish Research Institute for Economic Analysis and Modelling. URL: `https://dreamgroup.dk/publications/2019/may/estimating-sub-national-behaviour-in-the-danish-microsimulation-model-smile/` (visited on 11/14/2023).

Harding, Ann, Marcia Keegan, and Simon Kelly (2010). "Validating a Dynamic Population Microsimulation Model. Recent Experience in Australia." In: *International Journal of Microsimulation* 3.2, pp. 46–64.

Hastie, Trevor, Robbert Tibshirani, and Jerome Friedman (2009). *The Elements of Statistical Learning. Data Mining, Inference, and Prediction*. 2nd ed. Springer Series in Statistics. New York: Springer Science+Business Media.

Heer, Burkhard and Alfred Maussner (2009). *Dynamic General Equilibrium Modeling: Computational Methods and Applications*. 2nd ed. Berlin, Heidelberg: Springer-Verlag.

Hensher, David A. (1994). "Stated Preference Analysis of Travel Choices: The State of Practice." In: *Transportation* 21, pp. 107–133.

Hérault, Nicolas (2007). "Trade Liberalisation, Poverty and Inequality in South Africa: A Computable General Equilibrium-Microsimulation Analysis." In: *The Economic Record* 82.262, pp. 317–328.

Hérault, Nicolas (2009). *Sequential Linking of Computable General Equilibrium and Microsimulation Models*. Working Paper 2/09. Melbourne: Melbourne Institute.

Hoffman, Saul and Greg Duncan (1988). "Multinomial and Conditional Logit Discrete-Choice Models in Demography." In: *Demography* 25, pp. 415–427.

Hosmer, David W. and Stanley Lemeshow (2000). *Applied Logistic Regression*. 1st ed. Toronto: John Wiley & Sons, Inc.

Hosmer, David W. and Stanley Lemeshow (2010). *Applied Logistic Regression*. 2nd ed. New York: John Wiley & Sons, Inc.

Hosoe, Nobuhiro, Kenji Gasawa, and Hideo Hashimoto (2010). *Textbook of Computable General Equilibrium Modelling. Programming and Simulations*. New York: Palgrave Macmillan.

Hothorn, Torsten, Kurt Hornik, and Achim Zeileis (2006). "Unbiased Recursive Partitioning: A Conditional Inference Framework." In: *Journal of Computational and Graphical Statistics* 15.3, pp. 651–674.

Hothorn, Torsten and Achim Zeileis (2015). "partykit: A Modular Toolkit for Recursive Partytioning in R." In: *Journal of Machine Learning Research* 16.118, pp. 3905–3909.

Hoynes, Hilary Williamson (1996). "Welfare Transfers in Two-Parent Families: Labor Supply and Welfare Participation Under AFDC-UP." In: *Econometrica* 64.2, pp. 295–332.

Huang, Zengy and Paul Williamson (2011). *A Comparison of Synthetic Reconstruction and Combinatorial Optimisation Approaches to the Creation of Small-Area Microdata*. Tech. rep. University of Liverpool. URL: `http://pcwww.liv.ac.uk/~william/microdata/workingpapers/hw_wp_2001_2.pdf` (visited on 09/17/2021).

Hurvich, Clifford M. and Chih-Ling Tsai (1989). "Regression and Time Series Model Selection in Small Samples." In: *Biometrika* 76.2, pp. 297–307.

Hyndman, Rob J. and Yeasmin Khandakar (2008). "Automatic Time Series Forecasting: The Forecast Package for R." In: *Journal of Statistical Software* 26.3, pp. 1–22.

Hyndman, Rob J. and Anne B. Koehler (2006). "Another Look at Measures of Forecast Accuracy." In: *International Journal of Forecasting* 22.4, pp. 679–688.

Hyndman, Rob J. et al. (2023). *forecast: Forecasting Functions for Time Series and Linear Models*. R package version 8.21.1. URL: https://pkg.robjhyndman.com/forecast/ (visited on 07/25/2024).

Hynes, Stephen and Cathal O'Donoghue (2014). "Environmental Models." In: *Handbook of Microsimulation Modelling*. Ed. by Cathal O'Donoghue. Bingley: Emerald Group Publishing Limited, pp. 449–477.

IAB (2019). *Arbeitsmarktregionen*. URL: https://www.iab-forum.de/glossar/arbeitsmarktregionen/ (visited on 01/22/2024).

ILO (2023). *International Labour Organization Resolutions Concerning International Classification of Status in Employment Adopted by the 15th International Conference of Labour Statisticians*. URL: https://www.ilo.org/global/statistics-and-databases/standards-and-guidelines/resolutions-adopted-by-international-conferences-of-labour-statisticians/WCMS_230304/lang--en/index.htm (visited on 07/25/2024).

Islam, Nizamul and Lennart Flood (2020). "A Tax Benefit Model for Policy Evaluation in Luxembourg: LuxTaxBen." In: *Statistics for Data Science and Policy Analysis*. Ed. by Azizur Rahman. Singapore: Springer, pp. 305–318.

Japkowicz, Nathalie (2013). "Assessment Metrics for Imbalanced Learning." In: *Imbalanced Learning: Foundations, Algorithms, and Applications*. Ed. by Haibo He and Yunqian Ma. Hoboken, New Jersey: Wiley-IEEE Press, pp. 187–206.

Johansen, Leif (1960). *A Multi-sectoral Study of Economic Growth*. Vol. 21. Contributions to economic analysis. Amsterdam: North-Holland Publishing Company.

Kaiser, Helmut, Ulrich van Essen, and Paul Bernd Spahn (1992). "Income Taxation and the Supply of Labour in West Germany/Einkommensbesteuerung und Arbeitsangebot in der Bundesrepublik Deutschland." In: *Jahrbücher für Nationalökonomie und Statistik* 209.1-2, pp. 87–105.

Kant, Jean-Daniel, Gérard Ballot, and Olivier Goudet (2020). "WorkSim: An Agent-Based Model of Labor Markets." In: *Journal of Artificial Societies and Social Simulation* 23.4, 4.

Kaplanoglou, Georgia and David Michael Newbery (2003). "Indirect Taxation in Greece: Evaluation and Possible Reform." In: *International Tax and Public Finance* 10, pp. 511–533.

Keane, Michael and Robert Moffitt (1998). "A Structural Model of Multiple Welfare Program Participation and Labor Supply." In: *International Economic Review* 39.3, pp. 553–589.

Kelly, Mark C. and Ronald S. Warren (2015). "Household Labor Supply and Dynamic Macroeconomic Analysis. How the Household Affects Markets and Economic Growth." In: *The Economics of Family*. Ed. by Esther Redmount. Vol. 2. Santa Barabara: Praeger, pp. 237–266.

Kiiver, Hannah and Frank Espelage (2016). *The Use of Regression Models in Labour Market Flow Statistics*. Tech. rep. Eurostat, European Commission. URL: https://ec.europa.eu/eurostat/documents/7894008/8033722/20170519-111211_Q2016_paper_flows_-_final.docx.pdf/c09d9c33-4d8c-43bd-a2b0-80926fd4ac1e (visited on 04/30/2024).

Kilian, Lutz and Helmut Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Ed. by Peter C. Phillips. Cambridge: Cambridge University Press.

Kim, Daniel and Ross A. Hammond (2021). "Rationale for New Modeling and Simulation Tools." In: *New Horizons in Modeling and Simulation for Social Epidemiology and Public Health*. John Wiley & Sons, Ltd, pp. 21–29.

King, Robert G. and Sergio T. Rebelo (1999). "Resuscitating Real Business Cycles." In: *Handbook of Macroeconomics*. Ed. by John B. Taylor and Michael Woodford. Vol. 1B. Handbook of Macroeconomics. North-Holland: Elsevier B.V., pp. 927–1007.

Klevmarken, Anders (1997). *Behavioral Modeling in Micro Simulation Models. A Survey*. Working Paper 1997:31. Upsala University, Department of Economics.

Klevmarken, Anders (2002). "Statistical Inference in Micro-simulation Models: Incorporating External Information." In: *Mathematics and Computers in Simulation* 59.1, pp. 255–265.

Klevmarken, Anders (2008). "Dynamic Microsimulation for Policy Analysis: Problems and Solutions." In: *Simulating an Ageing Population: A Microsimulation Approach Applied to Sweden*. Ed. by Anders Klevmarken and Björn Lindgren. Bingley: Emerald Group Publishing Limited, pp. 31–54.

Kolb, Jan-Philipp (2013). "Methoden zur Erzeugung synthetischer Simulationsgesamtheiten." PhD thesis. Trier University. URL: https://ubt.opus.hbz-nrw.de/frontdoor/index/index/docId/590 (visited on 04/30/2024).

Kornstad, Tom and Thor O. Thoresen (2007). "A Discrete Choice Model for Labor Supply and Childcare." In: *Journal of Population Economics* 20.4, pp. 781–803.

Kruppa, Jochen et al. (2014). "Probability Estimation with Machine Learning Methods for Dichotomous and Multicategory Outcome: Applications." In: *Biometrical Journal* 56.4, pp. 564–583.

Kuha, Jouni (2004). "AIC and BIC: Comparisons of Assumptions and Performance." In: *Sociological Methods & Research* 33.2, pp. 188–229.

Kydland, Finn E. and Edward C. Prescott (1982). "Time to Build and Aggregate Fluctuations." In: *Econometrica* 50.6, pp. 1345–1370.

Labeaga, José M., Xisco Oliver, and Amedeo Spadaro (2008). "Discrete Choice Models of Labour Supply, Behavioural Microsimulation and the Spanish Tax Reform." In: *The Journal of Economic Inequality* 6, pp. 247–273.

Lay, Jann (2010). "Sequential Macro-Micro Modelling with Behavioural Microsimulations." In: *International Journal of Microsimulation* 3.1, pp. 24–34.

Lay, Jann (2018). "Micro-econometric and Micro-Macro Linked Models: Sequential Macro-Micro Modelling with Behavioural Microsimulations." In: *Development Policies and Policy Processes in Africa*. Ed. by Christian Henning, Ousmane Badiane, and Eva Krampe. Advances in African Economic, Social and Political Development. Cham: Springer, pp. 117–136.

Li, Jinjing (2011). "Dynamic Microsimulation for Public Policy Analysis." PhD thesis. Maastricht University. URL: `https://cris.maastrichtuniversity.nl/en/publications/dynamic-microsimulation-for-public-policy-analysis` (visited on 04/30/2024).

Li, Jinjing and Cathal O'Donoghue (2014). "Evaluating Binary Alignment Methods in Microsimulation Models." In: *Journal of Artificial Social Societies and Social Simulation* 17.1, 15.

Li, Jinjing, Cathal O'Donoghue, and Gijs Dekkers (2014a). "Dynamic Models." In: *Handbook of Microsimulation Modelling*. Ed. by Cathal O'Donoghue. Esmeral Publishing Limited, pp. 305–343.

Li, Jinjing and Cathal O'Donoghue (2013). "A Survey of Dynamic Microsimulation Models: Uses, Model Structure and Methodology." In: *International Journal of Microsimulation* 6.2, pp. 3–55.

Li, Jinjing et al. (2014b). "Static Models." In: *Handbook of Microsimulation Modelling (Contributions to Economic Analysis, Vol. 293)*. Bingley: Emerald Group Publishing Limited, pp. 47–75.

Ljungqvist, Lars and Thomas J. Sargent (2007). *Do Taxes Explain European Employment? Indivisible Labor, Human Capital, Lotteries and Savings*. Discussion Paper DP6196. Centre for Economic Policy Research.

Ljungqvist, Lars and Thomas J. Sargent (2011). "A Labor Supply Elasticity Accord?" In: *American Economic Review: Papers & Proceedings* 101.3, pp. 487–491.

Lucas, Robert E. (1976). "Econometric Policy Evaluation: A Critique." In: *Carnegie-Rochester Conference Series on Public Policy* 1, pp. 19–46.

Lütz, Christopher and Petra Stein (2020). "Validierung in dynamischen Mikrosimulationsmodellen." In: *Mikrosimulationen: Methodische Grundlagen und ausgewählte Anwendungsfelder*. Ed. by Marc Hannappel and Johannes Kopp. Wiesbaden: Springer VS, pp. 141–176.

Lysy, Frank J. and Lance Taylor (1980). "The General Equilibrium Income Distribution Model." In: *Models for Growth and Distribution for Brazil*. Ed. by Lance Taylor et al. Oxford: Oxford University Press, pp. 128–139.

Macal, Charles M. and Michael J. North (2010). "Tutorial on Agent-based Modeling and Simulation." In: *Journal of Simulation* 4, pp. 151–162.

Madden, John R. (2020). "Evidence-based Analysis of Issues in Environment, Energy and Disaster Risks with CGE Models: An Introduction to Part I." In: *Environmental Economics and Computable General Equilibrium Analysis. Essays in Memory of Yuzuru Miyata*. Ed. by John R. Madden, Hiroyuki Shibusawa, and Yoshiro Higano. Singapore: Springer Nature, pp. 3–12.

Mainar-Causapé, Alfredo Jose, Emanuele Ferrari, and Scott McDonald (2018). *Social Accounting Matrices: Basic Aspects and Main Steps for Estimation*. JRC Technical Reports EUR 29297 EN. Luxembourg: European Union.

Marshall, Alfred (2013). "The Elasticity of Wants." In: *Principles of Economics*. London: Palgrave Macmillan UK, pp. 86–97.

McFadden, Daniel (1973). *Conditional Logit Analysis of Qualitative Choice Behavior*. Berkeley: Institute of Urban and Regional Development, University of California.

McFadden, Daniel (1974). "The Measurement of Urban Travel Demand." In: *Journal of Public Economics* 3.4, pp. 303–328.

McKenzie, Lionel W. (1989). "General Equilibrium." In: *General Equilibrium*. Ed. by John Eatwell, Murray Milgate, and Peter Newman. London: The Macmillan Press Limited, pp. 1–35.

McLay, Jessica M. et al. (2015). "Regression-style Models for Parameter Estimation in Dynamic Microsimulation: An Empirical Performance Assessment." In: *International Journal of Microsimulation* 8.2, pp. 83–127.

Merz, Joachim (1991). "Microsimulation - A Survey of Principles, Developments and Applications." In: *International Journal of Forecasting* 7.1, pp. 77–104.

Merz, Joachim (1993). *Market and Non-market Labour Supply and Recent German Tax Reform Impacts: Behavioural Response in a Combined Dynamic and Static*

Microsimulation Model. FFB-Discussion Paper. Version 6. University Lüneburg. URL: https://www.leuphana.de/institute/ffb/publikationen/diskussionspapiere/dp6.html (visited on 11/20/2022).

Michel, Fabien, Jacques Ferber, and Alexis Drogoul (2009). "Multi-Agent Systems and Simulation: A Survey from the Agent Community's Perspective." In: *Multi-Agent Systems. Simulation and Applications*. Ed. by Adelinde M. Uhrenmacher and Danny Weyns. 1st ed. Boca Raton: CRC Press, pp. 3–52.

MikroSim (2023a). *Research Group - First Phase*. URL: https://mikrosim.uni-trier.de/en/firstphase/ (visited on 12/28/2023).

MikroSim (2023b). *Research Group - Second Phase*. URL: https://mikrosim.uni-trier.de/en/secondphase/ (visited on 12/28/2023).

Miller, Eric J. (2014). "Transportation Models." In: *Handbook of Microsimulation Modelling*. Ed. by Cathal O'Donoghue. Esmeral Publishing Limited, pp. 385–420.

Morrison, Richard (2008). *Validation of Longitudinal Microsimulation Models: DYNACAN Practices and Plans*. Working Paper 8. NATSEM.

Morrison, Rick (1998). *Overview of DYNACAN. A Full Fledged Canadian Acturial Stochastic Model Designed for the Fiscal and Policy Analysis of Social Security Schemes*. Tech. rep. International Actuarial Association. URL: https://www.actuaries.org/CTTEES_SOCSEC/Documents/dynacan.pdf (visited on 09/01/2021).

Mortensen, Dale T. (1982). "The Matching Process as a Noncooperative Bargaining Game." In: *The Economics of Information and Uncertainty*. Ed. by John J. McCall. Chicago: University of Chicago Press, pp. 233–258.

Mosler, Karl and Friedrich Schmid (2009). *Beschreibende Statistik und Wirtschaftsstatistik*. Vol. 4. Berlin, Heidelberg: Springer-Verlag.

Münnich, Ralf et al. (2012). *Stichprobenoptimierung und Schätzung im Zensus 2011*. Vol. 12. Statistik und Wissenschaft. Wiesbaden: Statistisches Bundesamt.

Münnich, Ralf et al. (2020). "Zur Entwicklung eines kleinräumigen und sektorenübergreifenden Mikrosimulationsmodells für Deutschland." In: *Mikrosimulationen. Methodische Grundlagen und ausgewählte Anwendungsfelder*. Ed. by Marc Hannappel and Johannes Kopp. Wiesbaden: Springer VS, pp. 109–140.

Münnich, Ralf et al. (2021). "A Population Based Regional Dynamic Microsimulation of Germany: The MikroSim Model." In: *methods, data, analyses* 15.2, pp. 241–264.

Narazani, Edlira, Ugo Colombino, and Bianey Palma (2023). "EUROLAB: A Multidimensional Labour Supply-Demand Model for EU countries." In: *International Journal of Microsimulation* 16.3, pp. 49–76.

Neath, Andrew A. and Joseph E. Cavanaugh (2012). "The Bayesian Information Criterion: Background, Derivation, and Applications." In: *WIREs Computational Statistics* 4.2, pp. 199–203.

Neugart, Michael (2008). "Labor Market Policy Evaluation with ACE." In: *Journal of Economic Behavior & Organization* 67.2, pp. 418–430.

Neusser, Klaus (2011). *Zeitreihenanalyse in den Wirtschaftswissenschaften*. Vol. 3. Wiesbaden: Vieweg + Teubner Verlag.

O'Donoghue, Cathal (2001). "Redistribution in the Irish Tax-Benefit System." PhD thesis. London School of Economics. URL: `http://etheses.lse.ac.uk/2503/` (visited on 11/29/2021).

O'Donoghue, Cathal (2021). *Practical Microsimulation Modelling*. Oxford: Oxford University Press.

O'Donoghue, Cathal, John Lennon, and Stephen Hynes (2009). "The Life-Cycle Income Analysis Model (LIAM): A Study of a Flexible Dynamic Microsimulation Modelling Computing Framework." In: *International Journal of Microsimulation* 2.1, pp. 16–31.

Peichl, Andreas (2016). "Linking Microsimulation and CGE Models." In: *International Journal of Microsimulation* 9.1, pp. 167–174.

Peichl, Andreas, Hilmar Schneider, and Sebastian Siegloch (2010). *Documentation IZAΨMOD: The IZA Policy Simulation Model*. Discussion Paper 4865. Bonn: IZA-Institute of Labor Economics.

Perman, Roger et al. (2011). *Natural Resource and Environmental Economics*. 4th ed. Harlow, England: Pearson Education Limited.

Peterman, William B. (2016). "Reconciling Micro and Macro Estimates of the Frisch Labor Supply Elasticity." In: *Economic Inquiry* 54.1, pp. 100–120.

Pissarides, Christopher A. (1985). "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages." In: *The American Economic Review* 75.4, pp. 676–690.

Prescott, Edward C. (1986). "Theory Ahead of Business-cycle Measurement." In: *Carnegie-Rochester Conference Series on Public Policy* 25, pp. 11–44.

Ramey, Valerie A. (2021). "The Macroeconomic Consequences of Infrastructure Investment." In: *Economic Analysis and Infrastructure Investment*. Ed. by Edward

L. Glaeser and James M. Poterba. Chicago: University of Chicago Press, pp. 219–276.

Rasmussen, Niels Erik Kaaber and Marianne Frank Hansen (2013). *Conditional Inference Trees in Dynamic Microsimulation - Modelling Transition Probabilities in the SMILE Model*. Tech. rep. Copenhagen: Danish Research Institute for Economic Analysis and Modelling. URL: https://dreamgroup.dk/publications/2013/december/conditional-inference-trees-in-dynamic-microsimulation (visited on 05/01/2024).

RDC of the Federal Statistical Office and Statistical Offices of the Federal States (2022a). *Haushalte: Mikrozensus*. URL: https://www.forschungsdatenzentrum.de/de/haushalte/mikrozensus (visited on 04/28/2022).

RDC of the Federal Statistical Office and Statistical Offices of the Federal States (2022b). *Metadaten. DOI: 10.21242/12211.2012.00.00.3.1.0*. URL: https://www.forschungsdatenzentrum.de/de/10-21242-12211-2012-00-00-3-1-0# (visited on 04/28/2022).

RDC of the Federal Statistical Office and Statistical Offices of the Federal States (2022c). *Mikrozensus-Panel (EVAS 12211)*. URL: https://www.forschungsdatenzentrum.de/de/haushalte/mikrozensus-panel (visited on 04/28/2022).

Rezaei, Shahrbanoo et al. (2021). "Performance Evaluation of Mode Choice Models under Balanced and Imbalanced Data Assumptions." In: *Transportation Letters*.

Richiardi, Matteo (2004). "A Search Model of Unemployment and Firm Dynamics." In: *Advances in Complex Systems* 7.2, pp. 203–221.

Richiardi, Matteo (2014). *Forecasting with Unobserved Heterogeneity*. Working Paper 123. Torino: Laboratorio Riccardo Revelli.

Richiardi, Matteo and Ambra Poggi (2014). "Imputing Individual Effects in Dynamic Microsimulation Models. An Application to Household Formation and Labour Participation in Italy." In: *International Journal of Microsimulation* 7.2, pp. 3–39.

Rieser-Schüssler, Nadine and Kay W. Axhausen (2012). "Investigating the Influence of Environmentalism and Variety Seeking on Mode Choice." In: *Transportation Research Record,* 2322.1, pp. 31–41.

Robilliard, Anne-Sophie, François Bourguignon, and Sherman Robinson (2008). "Examining the Social Impact of the Indonesian Financial Crisis Using a Macro-Micro Model." In: Bourguignon, François, Maurizio Bussolo, and Luiz A. Pereira da Silva. *The Impact of Macroeconomic Policies on Poverty and Income Distri-*

bution. Macro-Micro Evaluation. Techniques and Tools. Washington, DC: The World Bank, pp. 93–118.

Rogerson, Richard (1988). "Indivisible Labor, Lotteries and Equilibrium." In: *Journal of Monetary Economics* 21, pp. 3–16.

Rogerson, Richard (2007). "Taxation and Market Work: Is Scandinavia an Outlier?" In: *Economic Theory* 32, pp. 59–85.

Rose, Adam and Shu-Yi Liao (2005). "Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions." In: *Journal of Regional Science* 45 (1), pp. 75–112.

Rubinstein, Reuven Y. and Dirk P. Kroese (2016). *Simulation and the Monte Carlo Method*. Wiley Series in Probability and Statistics. Hoboken, New Jersey: John Wiley & Sons, Inc.

Salomon, Ilan and Moshe E. Ben-Akiva (1983). "The Use of the Life-Style Concept in Travel Demand Models." In: *Environment and Planning A: Economy and Space* 15.5, pp. 623–638.

Savard, Luc (2003). *Poverty and Income Distribution in a CGE-Household Micro-Simulation Model: Top-Down/Bottom Up Approach*. Working Paper 03-43. Québec: CIRPÉE.

Scheiner, Joachim and Christian Holz-Rau (2007). "Travel Mode Choice: Affected by Objective or Subjective Determinants?" In: *Transportation* 34, pp. 487–511.

Schläpfer, Felix (2017). "Stated Preferences for Public Services: A Classification and Survey of Approaches." In: *Journal of Economic Surveys* 31.1, pp. 258–280.

Schmaus, Simon (2023). "Methoden regionalisierter dynamischer Mikrosimulationen." PhD thesis. Universität Trier. URL: `https://ubt.opus.hbz-nrw.de/frontdoor/index/index/year/2023/docId/2049` (visited on 04/30/2024).

Schmidt, Simone (2000). *Erwerbstätigkeit im Mikrozensus. Konzepte, Definition, Umsetzung*. ZUMA-Arbeitsbericht 2000/01. Mannheim: ZUMA.

Schumann, Jochen, Ulrich Meyer, and Wolfgang Ströbele (2011). *Grundzüge der mikroökonomischen Theorie*. 9th ed. Berlin, Heidelberg: Springer-Verlag.

Schwarz, Gideon (1978). "Estimating the Dimension of a Model." In: *The Annals of Statistics* 6.2, pp. 461–464.

Sherfey, Jason S. et al. (2018). "DynaSim: A MATLAB Toolbox for Neural Modeling and Simulation." In: *Frontiers in Neuroinformatics* 12.

Shimer, Robert (2009). "Convergence in Macroeconomics: The Labor Wedge." In: *American Economic Journal: Macroeconomics* 1.1, pp. 280–297.

Smets, Frank and Rafael Wouters (2007). "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." In: *The American Economic Review* 97.3, pp. 586–606.

Spielauer, Martin (2007). "Dynamic Microsimulation of Health Care Demand, Health Care Finance and the Economic Impac of Health Behaviours: Survey and Review." In: *International Journal of Microsimulation* 1.1, pp. 35–53.

Statistisches Bundesamt (Destatis) (2020). *Schulanfänger: Bundesländer, Schuljahr, Geschlecht, Einschulungsart, Schulart*. URL: `https://www-genesis.destatis.de/genesis/online?operation=table&code=21111-0010#astructure` (visited on 04/07/2020).

Statistisches Bundesamt (Destatis) and Gesis (2018). *Datenhandbuch zum Mikrozensus Scientific Use File 2014*. Tech. rep. Statistisches Bundesamt and Gesis. URL: `https://www.forschungsdatenzentrum.de/de/10-21242-12211-2014-00-00-3-1-0` (visited on 12/17/2023).

Steiner, Viktor and Katharina Wrohlich (2004). "Household Taxation, Income Splitting and Labor Supply Incentives – A Microsimulation Study for Germany." In: *CESifo Economic Studies* 50.3, pp. 541–568.

Stephensen, Peter (2016). "Logit Scaling: A General Method for Alignment in Microsimulation Models." In: *International Journal of Microsimulation* 9.3, pp. 89–102.

Sutherland, Holly and Francesco Figari (2013). "EUROMOD: The European Union Tax-benefit Microsimulation Model." In: *International Journal of Microsimulation* 6.1, pp. 4–26.

Tansel, Aysit and Elif Öznur Acar (2017). "Labor Mobility across the Formal/informal Divide in Turkey. Evidence from Individual-level Data." In: *Journal of Economic Studies* 44.4, pp. 617–635.

Tanton, Robert (2014). "A Review of Spatial Microsimulation Methods." In: *International Journal of Microsimulation* 7.1, pp. 4–25.

Teichmann, Isabel (2016). *CGE-Based Methods to Measure the Impact of Trade Liberalization on Poverty*. DIW Roundup 100. DIW Berlin, German Institute for Economic Research. URL: `https://www.diw.de/de/diw_01.c.540471.de/publikationen/roundup/2016_0100/cge-based_methods_to_measure_the_impact_of_trade_liberalization_on_poverty.html` (visited on 05/01/2024).

Thissen, Mark (2004). "The Indirect Economic Effects of a Terrorist Attack on Transport Infrastructure: A Proposal for a SAGE." In: *Disaster Prevention and Management* 13.4, pp. 315–322.

Timmins, Kate A. and Kimberley L. Edwards (2016). "Validation of Spatial Microsimulation Models: A Proposal to Adopt the Bland-Altman Method." In: *International Journal of Microsimulation* 9.2, pp. 106–122.

Tu, Gengyang, Jens Abildtrup, and Serge Garcia (2016). "Preferences for Urban Green Spaces and Peri-urban Forests: An Analysis of Stated Residential Choices." In: *Landscape and Urban Planning* 148, pp. 120–131.

Tuhkuri, Joonas (2016a). *ETLAnow: A Model for Forecasting with Big Data – Forecasting Unemployment with Goolge Searches in Europa*. Report 54. Helsiniki: ETLA Economic Research. URL: `https://www.etla.fi/en/publications/etlanow-a-model-for-forecasting-with-big-data-forecasting-unemployment-with-google-searches-in-europe/` (visited on 05/09/2024).

Tuhkuri, Joonas (2016b). *Forecasting Unemployment with Google Searches*. Working Paper 35. Helsinki: ETLA Economic Research.

van Imhoff, Evert and Wendy Post (1998). "Microsimulation Methods for Population Projection." In: *Population: An English Selection* 10.1, pp. 97–138.

van Laarhoven, Peter J. M. and Emile H. L. Aarts (1987). *Simulated Annealing: Theory and Application*. Dordrecht: Springer Science+Business Media.

van Soest, Arthur (1995). "Structural Models of Family Labor Supply: A Discrete Choice Approach." In: *The Journal of Human Resources* 30.1, pp. 63–88.

van Soest, Arthur and Marcel Das (2001). "Family Labor Supply and Proposed Tax Reforms in the Netherlands." In: *De Economist* 149, pp. 191–218.

van Soest, Arthur, Marcel Das, and Xiaodong Gong (2002). "A Structural Labour Supply Model with Flexible Preferences." In: *Journal of Econometrics* 107.1-2, pp. 345–374.

Varian, Hal R. (2010). *Intermediate Microeconomics: A Modern Approach*. 8th ed. New York: W. W. Norton & Company, Inc.

Voas, David and Paul Williamson (2000). "An Evaluation of the Combinatorial Optimisation Approach to the Creation of Synthetic Microdata." In: *International Journal of Population Geography* 6.5, pp. 349–366.

von Auer, Ludwig (2007). *Ökonometrie. Eine Einführung*. 4th ed. Berlin, Heidelberg: Springer-Verlag.

Wallace, Byron C. and Issa J. Dahabreh (2014). "Improving Class Probability Estimates for Imbalanced Data." In: *Knowledge and Information Systems* 42, pp. 33–52.

Whalen, Charles and Felix Reichling (2017). "Estimates of the Frisch Elasticity of Labor Supply: A Review." In: *Eastern Economic Journal* 43, pp. 37–42.

Williamson, Paul (2013). "An Evaluation of Two Synthetic Small-Area Microdata Simulation Methodologies: Synthetic Reconstruction and Combinatorial Optimisation." In: *Spatial Microsimulation: A Reference Guide for Users*. Ed. by Robert Tanton and Kimberley L. Edwards. Dordrecht: Springer Science + Business Media, pp. 249–258.

Winkelmann, Rainer and Stefan Boes (2006). *Analysis of Microdata*. Berlin, Heidelberg: Springer-Verlag.

Wölwer, Anna-Lena (2023). "Model-Based Prediction and Estimation Using Incomplete Survey Data." PhD thesis. Universität Trier. URL: `https://ubt.opus.hbz-nrw.de/frontdoor/index/index/docId/1961` (visited on 05/01/2024).

Wood, Simon (2017). *Generalized Additive Models. An Introduction with R*. 2nd ed. Texts in Statistical Science. Boca Raton: CRC Press.

Wooldridge, Jeffrey M. (2020). *Introductory Econometrics: A Modern Approach*. 7th ed. Victoria, Australia: Cengage Learning.

Wrohlich, Katharina (2004). *Child Care Costs and Mothers' Labor Supply: An Empirical Analysis for Germany*. Discussion Paper 412. DIW Berlin, German Institute for Economic Research.

Zinn, Sabine (2014). "The MicSim Package of R: An Entry-level Toolkit for Continuous-time Microsimulation." In: *International Journal of Microsimulation* 7.3, pp. 3–32.

Zucchelli, Eugenio, Andrew M. Jones, and Nigel Rice (2012). "The Evaluation of Health Policies through Dynamic Microsimulation Methods." In: *International Journal of Microsimulation* 5.1, pp. 2–20.

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