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SimPaths: An open-source microsimulation model for life course analysis*

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Abstract

The paper introduces SimPaths, an open-source framework for individual and household life course events. The framework is designed to project life histories through time, building up a detailed picture of career paths, family (inter)relations, health, and financial circumstances. The modular nature of the SimPaths framework is designed to facilitate analysis of alternative assumptions concerning the tax and benefit system, sensitivity to parameter estimates and alternative approaches for projecting labour/leisure and consumption/savings decisions. SimPaths builds upon standardised assumptions and data sources, which facilitates adaptation to alternative countries – models based on the framework currently exist for the UK, Greece, Hungary, Italy, and Poland, and are under development for Germany, Spain and Sweden. Projections for a workhorse model parameterised to the UK context are reported, which closely reflect observed data throughout a validation window between the Financial crisis (2011) and the Covid-19 pandemic (2019).

Keywords: Dynamic microsimulation, static-dynamic microsimulation linkage, population ageing, open source. **JEL codes:** C51, C61, C63, H31

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1 Introduction

The demographic transition currently unfolding across the world has profound implications for diverse aspects of societies, including the functioning and financing of the welfare state. As baby boomers (those born in the two decades after WWII) move out of work and into retirement and are replaced by smaller cohorts of working-aged individuals, the shares of national populations in employment are projected to decline, which will reduce public tax receipts at the same time as needs in terms of health care and social assistance are projected to rise.

The old-age dependency ratio (the population aged 65 and over, relative to the population aged 20 to 64) of OECD countries doubled from 14% in 1950 to 30% in 2020 and is projected to double again to 59% by 2075.[1] Although increases in age dependency ratios are anticipated in *all* OECD countries, there is substantial cross-country variation. Korea is an outlier in this series, projected to rise from the lowest dependency ratio in 1950 (6%) to the highest in 2075 (79%). EU countries also feature prominently in the transition, accounting for eight of the ten countries with the highest projected age dependency ratios in the OECD by 2075.

The current rises in age dependency ratios are driven by unprecedented declines in fertility and rises in life expectancy, as well as the ageing of the baby boom generation. The OECD average total fertility rate fell by more than half from 3.3 children per woman in 1960 to 1.6 children in 2020.[2] During this same period, the total fertility rate in EU countries fell from 2.6 to 1.5, and from 6.0 to 0.8 in Korea. Furthermore, average life expectancy at birth in OECD countries increased from 68.1 years in 1960 to 80.5 years in 2020, from 69.7 to 79.9 years in EU countries, and in Korea from 58.7 years in 1970 to 80.5 years in 2020.[3]

These remarkable shifts in fertility and life expectancy have a pervasive bearing on social and private organisation. From partner relations to education decisions, labour market participation to housing demand, changing gender roles, caring needs, and healthcare provisions; few aspects of modern life are left unaffected. With longer lives, inequalities in income, wealth and health also have more time to compound. In short, OECD countries are passing through a period of social revolution.[4]

Many current trends are now well established, displaying predictable patterns over time. The influence that these trends have on margins of concern are also often predictable. For example, an older population implies a greater prevalence of age pensions in payment and more demand

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[1] OECD (2023), Old-age dependency ratio (indicator). doi: 10.1787/e0255c98-en (accessed on 29 March 2023).

[2] OECD (2023), Fertility rates (indicator). doi: 10.1787/8272fb01-en (accessed on 29 March 2023). Total fertility describes the number of children that would be born to each woman if she were to live to the end of her child-bearing years and give birth to children in alignment with the prevailing age-specific fertility rates.

[3] OECD (2023), Life expectancy at birth (indicator). doi: 10.1787/27e0fc9d-en (accessed on 29 March 2023).

[4] To a different degree, this is true also for most non-OECD countries.

for health care, both of which impose a burden on the public purse. Yet, to move beyond basic postulations, numerical analyses are required. This is particularly true when attempting to take into consideration multiple inter-related temporal trends.

Most numerical approaches used to anticipate the scale and scope of population ageing provide limited detail for exploring distributional effects at a given point in time, longitudinal effects over individual life courses, and implications for financing of the welfare state. The European Commission and OECD, for example, both adopt a cohort methodology to project the scale and effects of population ageing.[5] These methods are based on assumptions concerning cohort-average effects for employment, fertility, health, and mortality. Such cohort averages, however, are ill-suited for exploring fiscal flows associated with the welfare state, which crucially depend upon distributional differences within (as well as between) cohorts.

Interest in within-cohort variation and heterogeneity in life course trajectories has motivated the development of dynamic microsimulation models, especially during the last three decades. In dynamic microsimulation models, the characteristics of each micro unit (individual people in our case) are projected through time from a starting point usually derived from cross-sectional survey (micro-)data. Temporal projections are based on biological, institutional, or behavioural rules. Examples of biological rules are ageing and death. Examples of institutional rules are tax and benefits systems. Examples of behavioural rules are any choices that the units can make, for instance related to education, household composition, fertility, labour supply, lifestyle and health behaviour, savings, and investments.

The output from a dynamic microsimulation can usefully be conceptualised as a database that reports evolving information for the population of interest.[6] In a dynamic microsimulation, individuals can be linked, so that partner and household characteristics complement individual state variables. New individuals can enter the simulation at later periods, for instance as the result of immigration or fertility. The rules for updating the simulated population include parameters with values that are either exogenously assumed (e.g. tax-benefit parameters) or estimated from available survey data.

Use of dynamic microsimulation methods has grown substantially during the last four decades, benefitting from the increasing availability of high-quality microdata, analytical advances, and increases in computing power.[7] Despite the emergence of generic software packages

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[5] See Carone (2005), Scherer (2002), Burniaux *et al*. (2003), and European Commission (2020).

[6] As Guy Orcutt, the father of dynamic microsimulation, put it, "I thought, 'If you could represent a real population with a real sample, why couldn't we represent a theoretical population with a synthetic sample? Why couldn't we have a real sample representation of the real population at the start, and then move forward in time according to behavioral relationships applied to micro entities?'" (interview with Duo Qin, 1988, reported in Cheng, 2020).

[7] See O'Donoghue and Dekkers (2018) for a review, and O'Donoghue (2021) for an applied companion study.

(GENESIS, JAS-mine, LIAM2, MODGEN, openM++)[8], bespoke analytical frameworks continue to be (re-)implemented in the literature. Each independent research group has typically developed its own model code, which is often maintained as a proprietary asset. This imposes considerable developmental overhead on prospective entrants to the literature and limits external validation of reported results.

One way to mitigate developmental costs and facilitate external validation is to publish all research materials as open source. This approach is being actively promoted by the European Commission in its "open access" requirements for funded research, which extend to peer-reviewed publications and research metadata.

This paper describes a novel open-source framework for dynamic microsimulation modelling, which we refer to as SimPaths. All source code is freely available for download under a European Free/Open Source Software (F/OSS) EUPL-1.2 license, alongside evolving, increasingly detailed documentation.[9] The framework incorporates many state-of-the-art features which are rarely combined in dynamic models.

First, SimPaths generates data for a diverse range of life course domains – education, work, family life and health – explicitly modelling the dynamic feedback effects between them.

Second, SimPaths is linked to an underlying tax-benefit model, which provides a realistic description of the impact of taxes and benefits at both the individual and population level. The detailed tax-benefit description that reflects prevailing public policy is important for any evaluation of the funding and distributional implications of population ageing for the welfare state.

Third, SimPaths features rich behavioural models over the principal economic margins of decision making (time-use and savings), where projected choices depend not only on individual characteristics, but also on the influence of fiscal incentives on future expectations.

Fourth, from an architectural perspective, SimPaths is built following a highly modular approach. This facilitates switching between alternative methods for projecting behaviour to allow for sensitivity and robustness analysis. The model is written in Java, using the JAS-mine suite of simulation libraries (Richiardi and Richardson, 2017).

Fifth, SimPaths is built with an eye to facilitate adaptation to different countries. This is achieved by decoupling the dynamic structure from the tax-benefit model, so that alternative tax-benefit systems can be easily interchanged within the model. Furthermore, care has been

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[8] GENESIS: Gillman (2017). JAS-mine: Richiardi and Richardson (2017). LIAM2: de Menten *et al.* (2014). MODGEN: https://www.statcan.gc.ca/en/microsimulation/modgen/modgen. openM++: https://openmpp.org.

[9] See https://github.com/centreformicrosimulation/SimPaths. License information is available from https://commission.europa.eu/about/departments-and-executive-agencies/digital-services/open-source-strategy-history/european-union-public-licence_en.

taken to describe model dynamics that can be estimated on a single standardised data source for European Union countries (Statistics on Income and Living Conditions, EU-SILC).

The remainder of the paper is structured as follows. Section 2 places SimPaths in the context of contemporary microsimulation models. Section 3 presents the architecture behind SimPaths. Section 4 discusses model estimation and validation. Section 5 describes existing applications of the framework, and planned extensions. Section 6 discusses the funding strategy and governance structure. Section 7 concludes.

2 Background

Dynamic microsimulation models require significant resources to develop and maintain, and are consequently most commonly developed within policy institutions (e.g. government departments), or form part of the modelling infrastructure of research institutions (e.g. Statistics Canada, Urban Institute, CeMPA, GenIMPACT, NATSEM).[10] This is a marked departure from the common academic practice framed upon 'one model – one paper'.[11] It also presents challenges to assessment of prevailing best-practices in research, as models are often proprietary, and developers typically have few incentives to publish accompanying documentation.

This section reviews a selection of microsimulation models that satisfy three conditions: there is evidence that the model is in current active use; the model is publicly documented; and the model focuses on life-course dynamics of people. These filters identify seven examples for discussion. The condition on "active use" is a particularly important, as it excludes the majority of examples discussed in previous surveys (O'Donoghue and Dekkers, 2014, 2018; Li et al., 2014; Li and O'Donoghue, 2013; Harding, 2023; O'Donoghue, 2001; Klevmarken, 1997).[12]

DYNASIM (Favreault et al., 2015) projects a representative sample of the US population forward in time, simulating demographic events such as births, deaths, marriages, divorces, and health status, and economic events such as labour force participation, earnings, hours of work, and retirement. The model is developed at the Urban Institute and has evolved from the original work of Orcutt (1976). The model simulates home and financial assets, living

[10] Statistics Canada: https://www.statcan.gc.ca/en/microsimulation/index;; Urban Institute: https://www.urban.org/research/data-methods/data-analysis/quantitative-data-analysis/microsimulation; CeMPA: www.microsimulation.ac.uk; GenIMPACT: https://www.mq.edu.au/research/research-centres-groups-and-facilities/centres/genimpact-centre-for-economic-impacts-of-genomic-medicine. For NATSEM (now defunct), see Schofield et al. (2023). All websites accessed Dec 19,2024.

[11] With exceptions: models are sometimes used for different applications, and small tweaks to a model often lead to related publications.

[12] The interest in life-course events is interpreted as excluding the numerous models that focus exclusively on health - for a review, see Schofield et al. (2018).

arrangements, and includes a detailed calculation of tax and benefit entitlements. In recent years the scope of the model has expanded considerably to cover health-related outcomes, including disability, chronic conditions, and projections of health insurance coverage, premium costs, and out-of-pocket medical spending.

MOSART (Andreassen et al., 2020) is a life course model based on administrative data for the entire Norwegian population, which projects birth, death, migration, marriage, divorce, educational activities, labour force participation, retirement, income and wealth based on estimated transition probabilities. The model first emerged in 1990 and is used by Statistics Norway and the Norwegian government for projections and policy analyses related to the pension system.

IrpetDin (Maitino et al., 2020) and T-DYMM (Conti et al., 2024) are two models calibrated to Italian data. IrpetDin is estimated on two different samples: the whole of Italy, and the Tuscany region. It simulates death, ageing, marriage, fertility, divorce, leaving parental home, migration, secondary school enrolment and graduation, university enrolment and graduation, labour force participation, employment status, income, health status, pensions, social assistance for old people and retirees, disability and long-term care. Education is a particular focus of IrpetDin, and (endogenous) projections of labour supply are matched with (exogenous) projections of labour demand derived from an auxiliary macroeconomic model.

T-DYMM, developed at the Italian treasury, is comprised of a demographic module (fertility, mortality, immigration and emigration, education, exit from parental home, marriages, divorces), a labour market module (employment), a pension module (public and private pensions), a wealth module (home ownership and income from other assets), and a tax-benefit module. Employment distinguishes between self-employment and dependent employment, contract type (open-ended vs. fixed term), part-time vs. full time, and public vs. private sector. All transitions are modelled as reduced-form probabilities.

A more limited focus on the labour market characterises SLAMM, a microsimulation model for Slovakia (Štefánik and Miklošovič, 2020). The microsimulation model projects labour supply, and is coupled with an external input-output model that projects sectoral employment levels, with wages endogenously adjusting to ensure market closure.

The LifeSim model by Skarda et al. (2020) projects developmental, economic, social and health outcomes from birth to death for each child in the Millennium Birth Cohort (MCS) in England. The model controls for a large number of individual characteristics and behaviour, including human capital development in childhood (social skills, cognitive skills, teenage smoking), and has a focus on mental and physical health, and well-being. All transitions are governed by reduced form probabilities, while life course income profiles are adjusted for individual shifters, such as disability. Taxes and benefits are modelled using stylised functions.

microWELT (Spielauer et al., 2020) reproduces demographic projections for Austria, Spain, Finland, and the UK, by simulating fertility, mortality, education, partnership formation and dissolution, and migration. These projections are then used to re-weight cross-sectional microdata generated by the EUROMOD tax-benefit model (Sutherland and Figari, 2013).

DYNASIM, MOSART, IrpetDin, and T-DYMM are all proprietary models. SLAMM code is available upon request, while LifeSim and microWELT are open-source, although with contributors limited to the original developers.

Many characteristics are common to the models discussed above. Most start with a representative population cross-section, which is evolved forward in time (LifeSim is cohort-based). Most simulate events at discrete (annual) intervals (microWelt is cast in continuous time). Most include demographic events related to family composition, health events, and economic events (SLAMM is limited to education and economic activity). Most give at least some consideration to tax and benefit policies (SLAMM is again an exception).

Differences between models mostly relate to the respective analytical focus, technical implementation, and econometric specification. In this regard, DYNASIM stands out for its comprehensiveness in both economic and health-related outcomes, while IrpetDin and SLAMM are noticeable for their interaction with macroeconomic projections.

Relative to the models discussed above, the main innovations of SimPaths are: (i) focus on facilitating new research in the field by maintaining open-source coding and associated documentation (in common with LifeSim and microWELT); (ii) externalisation of the tax-benefit component to a third-party dedicated tax-benefit model (see Section 3.9 below); and (ii) use of a structural model of individual decision-making, rather than simple transition probabilities.

The workhorse version of SimPaths employs a structural model of labour supply where households choose hours worked by each adult of each benefit unit in each period as though associated decisions are made to optimise the trade-off between leisure and disposable income. An advanced version extends this behavioural model to take into account intertemporal considerations along the income-leisure and consumption-savings margins (Section 3.8.2). The advantage of using structural approach to project behaviour, relative to the more commonly applied reduced-form statistical approach, is that the structural approach is theoretically designed to be invariant to the policy context. Use of utility theory in the case of SimPaths, allows simulated behaviour to respond in a coherent fashion to changes in incentives, including those described by tax and benefits policy (see, e.g. Blundell et al., 2016, 2021).

In contrast to some of the models discussed above, SimPaths does not benefit from dedicated institutional funding. Rather, development is driven by modelling needs of specific research projects (and associated funding). Between 2014 and 2018, SimPaths (originally LABSim) was developed at the Institute for New Economic Thinking (INET), University of Oxford. The model now benefits from a growing community of researchers based at diverse institutions, with core development conducted at the Centre for Microsimulation and Policy Analysis

(CeMPA), University of Essex, and the Social & Public Health Sciences Unit, University of Glasgow. See Section 7 for more details.

3 Model description

SimPaths models are currently estimated for the United Kingdom, Greece, Hungary, Italy and Poland, and are under development for Germany, Spain and Sweden. Two master versions are currently maintained: one for the UK, and one for EU countries. The UK version is the most comprehensive variant where developments are usually introduced and tested. For this reason, in this paper we focus on validation of the UK model parameterisation (Section 4).

SimPaths implements an hierarchical architecture where individuals are organised in benefit units (for fiscal purposes), and benefit units are organised in households.[13] The model projects data at yearly intervals, reflecting the yearly frequency of the survey data used to estimate model parameters.[14] The model is composed of eleven modules: (i) Ageing, (ii) Education, (iii) Health, (iv) Family composition, (v) Social care, (vi) Investment income, (vii) Labour income, (viii) Disposable income, (ix) Consumption, (x) Health (2), and (xi) Statistical display. Variables from different modules characterise (multi-dimensional) well-being. Each module is composed of one or more processes; for example, the ageing module contains ageing, mortality, child maturation, and population alignment processes. Empirical specification of dynamic processes makes extensive use of cross-module characteristics (state variables).[15]

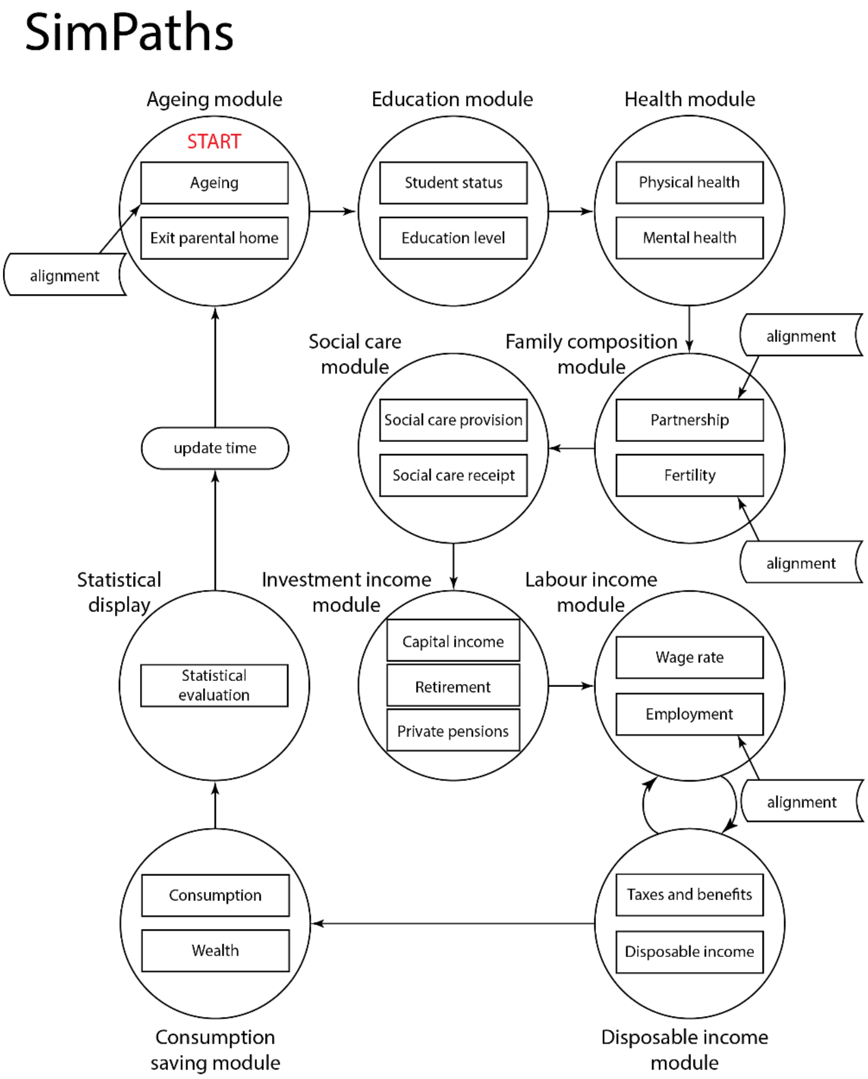
The model described in this paper is the public release 2023.12.18 of SimPaths. Simulated modules and processes are organised as displayed in Figure 1 and Table 1.

[13] A benefit unit is comprised of a single adult or adult couple and their dependent children. There can be households comprised of a single benefit unit, and benefit units comprised of a single individual. A household can be comprised of multiple benefit units only in case of *adult children* continuing to live at their parental home.

[14] The JAS-mine architecture also allows to introduce simulated processes cast in continuous time, where events are scheduled at precise moments in time. However, the nature of the available data sources for estimating and calibrating model parameters has thus far favoured a discrete time modelling approach, where state variables are updated at a yearly frequency. Both discrete time and continuous time processes can co-exist in JAS-mine.

[15] For example, lagged employment-related characteristics are not defined for students, but a valuable source of information for other simulated individuals.

Figure 1: Structure and order of processes modelled in SimPaths



In each simulated year, agents are first subject to the ageing process, followed by population alignment. The alignment process adjusts the simulated population to match official population projections distinguished by gender, age (single-year brackets[16]), and geographic region at

[16] Up to age 99, and bundled together for centenarians.

NUTS1 level[17], which ensures that simulated output remains representative of the country's population.

The education module determines transitions into and out of student status. Students are assumed not to work and therefore do not enter the labour supply module. Individuals who leave education have their level of education re-evaluated[18] and can become employed.

The health module projects an individual's health status, comprising both self-rated general health and mental health metrics (based on a clinically validated measure of psychological distress using a Likert scale and a caseness indicator), and determines whether an individual is long-term sick or disabled (in which case, he/she is not at risk of work and may require social care).

The family composition module is the principal source of interactions between simulated agents in the model. The module projects the formation and dissolution of cohabiting relationships and fertility. Where a relationship forms, then spouses are selected via a matching process that is designed to reflect correlations between partners' characteristics observed in survey data. The proportion of the population in a cohabiting relationship is, by default, aligned to the population aggregate in the years for which observational data is available, to account for changes in household structure introduced by the population alignment.

Females in couples can give birth to a (single) child in each simulated year, as determined by a process that depends on a range of characteristics including age and presence of children of different ages in the household. In case of divergence from the officially projected number of newborns, fertility rates are adapted by an alignment process to match population projections for new-born children distinguished by gender, region, and year.

The social care module projects provision and receipt of social care activities for people in need of help due to poor health or advanced age. The module is designed to distinguish between formal and informal social care, and the social relationships associated with informal care. The social care module accounts for the time cost incurred by care providers with respect to informal care, and the financial cost incurred by care receivers with respect to formal care.

The investment income module projects income from investment returns and (private) pensions. The approach taken to project these measures of income depends upon the model variant considered for analysis. Where consumption/savings decisions are simulated using a structural behavioural framework, then asset income is projected based on accrued asset values and exogenously projected rates of return. Alternatively, computational burden of model

[17] Ongoing work is aimed at disaggregating outcomes at NUTS3 level.

[18] Students are assumed to have a "Low" level of education until they leave school for the first time, when it is re-evaluated. Individuals who return to full time education can only improve their level of education.

projections can be economised by proxying non-labour income without explicitly projecting asset holdings.

The labour income module projects potential (hourly) wage rates for each simulated adult in each year and their associated labour activity. Given potential wage rates, hours of paid employment by all adult members of a benefit unit are generated. Labour (gross) income is then determined by multiplying hours worked by the wage rate.

The disposable income module uses information concerning disability, relationship status and fertility, social care, investment income and labour income to evaluate taxes and benefits and disposable income for each projected benefit unit in each year. The model includes alternative methods for projecting employment status, some of which involve interactions between the labour income and disposable income modules to identify preferred combinations of labour supply and disposable income. An alignment routine is used to match projected rates of employment against population aggregates, to correct for biases in the labour supply model.[19]

Given disposable income and household demographics, the consumption module projects measures of benefit unit expenditure. Where the model projects wealth, then a simple accounting identity is used to track the evolution of benefit unit assets through time. A regression-based homeownership process predicts if the primary residence is owned by either of the responsible adults in a benefit unit, in which case the benefit unit is considered to own its home.

A secondary mental health process adjusts estimates obtained by the primary process to account for the effect of exposure to labour market transitions, such as moving in and out of employment and/or poverty.

At the end of each simulated year, SimPaths generates a series of year specific summary statistics. All of these statistics are saved for post-simulation analysis, with a subset of results also reported graphically as the simulation proceeds.

[19] These might be related, for instance, by the lack of consideration of demand-side constraints in the estimation/simulation process. Employment is ultimately an equilibrium concept based on interaction between labour supply (by households) and labour demand (by firms). SimPaths however does not have a productive sector, and following a common approach in the economic literature equates labour supply with employment.

Table 1: List of modules and estimated processes

Module	Process
Ageing	Age increases.
	Probability of leaving the parental home for those who have left education. (Students stay in the parental home).
Education	Probability of remaining in education for those who have always been in education without interruptions.
	Probability of returning to education for those who had left school.
	Level of education for those leaving education.
Health	Self-rated health status for those in continuous education.
	Self-rated health status for those not in continuous education (out of education or returned having left education in the past).
	Probability of becoming long-term sick or disabled for those not in continuous education.
	(Mental Health (1)) Level of psychological distress on GHQ-12 Likert scale and binary case-based indicator of psychological distress.
	(Mental Health (2)) Effect of exposure to employment-state transitions, household income change, and poverty for individuals aged 25 – 64 on psychological distress (GHQ-12).
Family composition	Probability of entering a partnership for those in continuous education.
	Probability of entering a partnership for those not in continuous education.
	Probability of partnership break-up.
	Probability of giving birth to a child.
Social care	Probability of needing care for individuals over an age threshold.
	Probability of receiving care for individuals under an age threshold with a disability or long-standing illness or over the age threshold, distinguished by formal, partner, son, daughter, and other providers.
	Hours of care for those in receipt of care, and financial cost for those receiving formal care.
	Probability of providing informal social care.
	Hours of informal social care, among those providing care.
Investment income	Probability of retiring for single individuals.
	Probability of retiring for partnered individuals.
	Probability of receiving capital income for those in continuous education.
	Probability of receiving capital income for those not in continuous education.
	Amount of capital income for those in continuous education.
	Amount of capital income for those not in continuous education.

	Amount of pension income for those who are retired and were not retired in the previous year.
Labour income	Heckman corrected wage equation; females not employed last period.
	Heckman corrected wage equation; males not employed last period.
	Heckman corrected wage equation; females employed last period.
	Heckman corrected wage equation; males employed last period.
	Hours worked, single males.
	Hours worked, single females.
	Hours worked, single male adult children.
	Hours worked, single female adult children.
	Hours worked, males with dependent partner.
	Hours worked, females with dependent partner.
	Hours worked, couples.
Disposable income	Benefit recipiency indicator.
	Amount of disposable income.
Consumption & saving	Consumption.
	Home ownership.
	Savings and assets.
Statistical display	Evaluate summary statistics for simulated population.

3.1 Demographics

3.1.1 Ageing

The first simulated process in each period increments the age of each simulated person by one year. Any dependent child that reaches an exogenously assumed "age of independence" (18 years-of-age in the parameterisation for the UK) is extracted from their parental benefit unit and allocated to a new benefit unit. Individuals are then subject to a risk of death, based on age, gender and year specific probabilities that are commonly reported as components of official population projections. Death is simulated at the individual level but omitting single parent benefit units (to avoid the creation of orphans).

Alignment

Population alignment is performed to adjust the number of simulated individuals to national population projections by age, gender, region, and year. Alignment proceeds from the youngest to the oldest age described by national population projections. Each age is considered in two discrete steps. First, within each age-gender-region-year subgroup, the simulated number of individuals is compared against the associated population projection. Regions with too few simulated individuals (relative to the respective target) are partitioned from those with too many. Net "domestic migration" is then projected by moving individuals from regions with too many simulated people to those with too few, until all options for (net) domestic migration are exhausted. All migratory flows are simulated at the benefit unit level, with reference to the youngest benefit unit member.

Following domestic migration, remaining disparities between simulated and target population sizes are adjusted to reflect international immigration (if the simulated population is too small), or emigration and death (if the simulated population is too large). Like domestic migration, international migration is simulated net of opposing flows[20] and at the benefit unit level with reference to the youngest benefit unit member. Death is simulated in preference to international emigration for population alignment for all ages above an exogenously imposed threshold (65 for the UK).

Except for the distinction between age, gender, region, and year, all transitions simulated for population alignment are randomly distributed. This means that the model does not reflect, for example, the higher incidence of international emigration among prior international immigrants. Furthermore, the model projects international immigration by cloning existing benefit units (e.g. Duleep and Dowhan, 2008) without taking into consideration any systematic disparities between the domestic and migrant populations, including with regard to their respective financial circumstances.

3.1.2 Leaving parental home

Individuals who have recently attained the assumed age of independence and were moved to separate benefit units (see 3.1.1) are evaluated to determine if they leave their parental home. Any individual still in education is assumed to remain a member of their parental household.[21] For mature children not in education, the probability of leaving their parental home is based on a probit model conditional on gender, age, level of education, lagged employment status, lagged household income quintile, region, and year (to reflect observed time trends). Mature children who are projected to remain in their parental homes may leave in any subsequent year.

3.2 Education

3.2.1 Student status

Individuals leave continuous full-time education during an exogenously assumed age band (16 to 29 for the UK). The probability of leaving continuous full-time education within this age

[20] That is, only immigration or emigration is projected for each population subgroup, not both.

[21] In the simulation, this is represented by a household comprised of the parental benefit unit, and one, or more, benefit units representing adult children.

band is described by a probit model conditional on gender, age, mother's education level, father's education level, region, and year.[22]

Individuals who are not in education may re-enter education within another exogenously assumed age band (16 to 45 for the UK). In this case, the probability of re-entering education is described by a probit model conditional on gender, age, lagged level of education, lagged employment status, lagged number of children in the household, lagged number of children aged 0-2 in the household, mother's and father's education levels, region, and year.

Students are considered not to work. Those who return to education can leave again in any subsequent year.

3.2.2 Educational level

Individuals who cease to be students are assigned a level of education based on an ordered probit model that conditions on gender, age, mother's and father's education level, region, and year. The education level of individuals who exit student status after re-entering education may remain unchanged or increase but cannot decrease.

3.3 Health

3.3.1 Physical health

Physical health status is projected on a discrete 5-point scale, designed to reflect self-reported survey responses (between "poor" and "excellent" health). Physical health dynamics are based on an ordered probit, distinguishing those still in continuous education. For continuing full-time students, the ordered probit conditions on gender, age, lagged benefit unit income quintile, lagged physical health status, region, and year. The same variables are considered for individuals who have left continuous education, with the addition of education level, lagged employment status, and lagged benefit unit composition.

3.3.2 Long-term sick and disabled

Any individual aged 16 and above who is not in continuous education can become long-term sick or disabled. The probability of being long-term sick or disabled is described by a probit equation defined with respect to lagged disability status, prevailing and lagged physical health status, gender, age, education, income quintile, and lagged family demographics.

[22] Conditioning on parental education introduces a correlation between socio-economic position across generations and facilitates investigation of intergenerational inequality.

3.3.3 Psychological distress 1 (baseline level and caseness)

In each simulation cycle, a baseline level of psychological distress for individuals aged 16 and over is determined using the 12-item General Health Questionnaire (GHQ-12). Two indicators of psychological distress are computed: a Likert score, between 0 and 36, estimated using a linear regression model; and a dichotomous indicator of the presence of potentially clinically significant common mental disorders[23] is obtained using a logistic regression model. Both specifications are conditional on the lagged number of dependent children, lagged health status, lagged mental health, gender, age, level of education, household composition, region, and year.

3.3.4 Psychological distress 2 (impact of economic transitions and exposure to the Covid-19 pandemic)

The baseline measures of the level and caseness of psychological distress described above are modified by the effects of economic transitions and non-economic exposure to the Covid-19 pandemic. Fixed effects regressions are used to estimate the direct impact of transitions from employment to non-employment, non-employment to employment, non-employment to long-term non-employment, non-poverty to poverty, poverty to non-poverty, and poverty to long-term poverty, as well as changes in growth rate of household income, a decrease in household income, and non-economic effect of the exposure to Covid-19 pandemic in years 2020 and 2021. The effects of economic transitions are estimated on pre-pandemic data to ensure validity in other periods. The non-economic effects of the pandemic are estimated using a multilevel mixed-effects generalized linear model. Further details of the estimation procedure are provided in Kopasker et al. (2024).

3.4 Family composition

3.4.1 Partnerships and cohabitation

Individuals aged 18 and over who do not have a partner may decide to enter a partnership based on the outcome of a probit model. For students, the probit conditions on gender, age, lagged household income quintile, lagged number of (all) dependent children, lagged number of children aged 0-2, lagged self-rated health status, region, and year. For non-students, the probit conditions on the same set of variables as for students, expanded to include level of education and lagged employment status.

Individuals who enter a partnership are matched using either a parametric or non-parametric process, focussing exclusively on opposite-sex relationships. In the (default) parametric matching process, the model searches through the pools of males and females identified as cohabiting in each simulated period to minimise the distance between individual expectations,

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[23] Individuals scoring four points or more on a 0-12 scale are classified as positive cases.

in terms of partner's ideal earnings potential and age, and individual characteristics of each individual in the matching pool. The matching procedure prioritises matching individuals within regions, but if the sufficient quantity and / or quality of matches cannot be achieved, matching is performed nationally. In contrast, the non-parametric process uses an iterative proportional fitting procedure to replicate the distribution of matches observed in survey data between different types of individuals, where a type is defined as a combination of gender, region, education level, and age.

Partnership dissolution is modelled at the benefit unit level with the probability described by a probit model conditional on female partner's age, level of education, lagged personal gross non-benefit income, lagged number of (all) children, lagged number of children aged 0-2, lagged self-rated health status, lagged level of education of the spouse, lagged self-rated health status of the spouse, lagged difference between own and spouse's gross, non-benefit income, lagged duration of partnership in years, lagged difference between own and spouse's age, lagged household composition, lagged own and spouse's employment status, region, and year.

Alignment

The matching processes for new relationships outlined above fails to identify matches for all individuals flagged as entering a partnership by the related probit equations. This tends to bias the simulated population, resulting in an under-representation of partner couples. An alignment process is consequently used to match the rate of incidence of partner couples to survey targets (shares of adults in cohabiting benefit units described by annual population cross-sections reported by the Family Resources Survey, observed between 1994 and 2021). The alignment process works by adjusting the intercept of the probit relationships governing relationship formation, increasing the intercepts where the incidence of couples is too low.

3.4.2 Fertility

Females aged 18 to 44 can give birth to a child whenever they are identified in a partnership. The probability of giving birth is described by a probit model conditional on a woman's age, benefit unit income quintile, lagged number of children, lagged number of children aged 0-2, lagged health status of the woman, lagged partnership status for those in continuous education. For those not in continuous education, the probability of giving birth is described by a probit model conditional on a woman's age, the fertility rate of the UK population, benefit unit income quintile, lagged number of children, lagged number of children aged 0-2, lagged health status of the woman, lagged partnership status, lagged labour market activity status, level of education, and region. The inclusion of the overall fertility rate allows the model to capture fertility projections for future years, whereas the overall change in projected fertility is distributed across individuals according to their observable characteristics.

Alignment

The number of projected births is aligned to the number of newborns supplied by the official projections used for population alignment. The alignment procedure randomly samples fertile women and adjusts the outcome of the fertility process until the target number of newborns has been met.

3.5 Social care

3.5.1 Receipt of social care

The model distinguishes between individuals aged above and below an age threshold when projecting receipt of social care. This reflects the relatively high prevalence of social care received by older people, for whom more detailed information is often reported by publicly available data sources.

Receipt of social care among older people

For individuals aged above an exogenously defined threshold (65 years in the UK), the model begins by considering whether an individual is in need of care. This is simulated as a probit equation that varies by gender, education, relationship status, whether care was needed in the preceding year, self-reported health, and age. The probability of receiving care is projected using a similar set of explanatory variables. Where an individual is identified as receiving care, a multinomial logit equation is used to determine if the individual receives: i) only informal care; ii) formal and informal care; or iii) only formal care. This multinomial logit varies by education, relationship status, and age band in addition to a lag dependent variable.

For individuals projected to receive informal care, a multi-level model is used to distinguish between alternative care providers. The first level considers whether a partner provides informal care, for individuals with partners. For individuals who receive social care from their partner, the second level uses a multinomial logit to consider whether they also receive care from a daughter, a son, or someone else (other). For individuals in receipt of informal care who do not have a partner caring for them, another multinomial logit is used to select from six potential alternatives that allow for up to two carers from “daughter”, “son”, and “other”. Log-linear equations are then used to project the number of hours of care received from each identified carer. Finally, hours of formal care are converted into a cost, based on the year-specific mean hourly wages for all social care workers.

Receipt of social care among younger people

Receipt of social care among individuals under the exogenously assumed age threshold is simulated using a more stylised approach to that described for older people, reflecting the less detailed data available for parameterisation. In this case, the model focusses exclusively on informal social care for individuals simulated to be long-term sick or disabled. At the time an individual is projected to enter a disabled state, a probit equation is used to identify whether the individual receives informal social care. This identification is assumed to persist for as long as the person remains disabled.

If an individual under age 65 is identified as receiving social care, then the time of care received is described by a log-linear equation.

3.5.2 Provision of social care

The model is adapted to project provision of social care by informal sector providers; the characteristics of formal sector providers of social care are beyond the current scope of the model. The approach adopted for simulating receipt of social care described above identifies the incidence and hours of informal social care that individuals are projected to receive. In the case of people over the assumed age threshold, it also identifies the relationship between those in receipt of informal social care and their informal care providers, and the persistence of those care relationships. These details consequently provide much of the information necessary to simulate provision of informal social care, in addition to the receipt of care.

Nevertheless, the data sources for starting populations considered for SimPaths – with the notable exception of partners – generally omit social links that are implied to exist between informal social care providers and those receiving care. Specifically, links between adult children and their parents, and the wider social networks that often supply informal social care services are generally not recorded. The method that is used to project informal provision of social care is designed to accommodate limitations of the simulated data in a way that broadly reflects projection of social care receipt discussed above.

Specifically, the model distinguishes between four population subgroups with respect to provision of informal social care: (i) no provision; (ii) provision only to a partner; (iii) provision to a partner and someone else; and (iv) provision but only to non-partners. For people who are identified as supplying informal care to their partner via the process described in Section 3.5.1, a probit equation is used to distinguish between alternatives (ii: provision only to partner) and (iii: provision to a partner and someone else). Similarly, for the remainder of the population, another probit equation is used to distinguish between alternatives (i) and (iv). A log linear equation is then used to project number of hours of care provided, given the classification of who care is provided to.

3.6 Retirement

Simulation of retirement varies slightly depending on the accommodation of forward-looking expectations (see Section 3.8.2). In both cases, retirement is possible for any adult above an assumed age threshold (50 in the parametrisation for the UK). When forward-looking expectations are implicit, entry to retirement is based on a probit model that controls for gender, age, education, lagged employment status, lagged (benefit unit) income quintile, lagged disability status, indicator to distinguish individuals in excess of state pension age (accounting for changes in the state pension age), region, and year. For couples, characteristics of the spouse (employment status, reaching retirement age) also affect the probability of retirement. When forward-looking expectations are explicit, then entry to retirement is considered to be a control variable. Retired individuals may receive pension income, as described in Section 3.7.

3.7 Investment income

Investment income in SimPaths is comprised of capital income and private (non-public, personal, or occupational) pensions. The methods used to project these sources of income vary depending on whether wealth is included in the set of characteristics projected by the model. Wealth is omitted from the simulation by default but is tracked when discretionary consumption and employment decisions are simulated to reflect forward-looking behavioural incentives (described in Section 3.8.2).

3.7.1 Capital income

Wealth implicit

When wealth is not projected by the model, then the incidence of capital income among the simulated population aged 16 and over is based on probabilities described by a logit regression equation that varies by age, lagged health, lagged gross employment and capital income, region and year. For individuals not in continuous education, the list of explanatory variables for the logit equation also includes education status, lagged employment status, and lagged household composition.

For individuals simulated to be in receipt of capital income, the amount of capital income is described by linear regression models that condition on gender, age, lagged health status, lagged gross employment income, lagged capital income, region, and year for individual in continuous education. Individuals not in continuous education are also distinguished by their level of education, lagged employment status, and lagged household composition.

Wealth explicit

When wealth is explicitly projected by the model, then capital income is the product of net asset holdings and an assumed rate of return. The rate of return varies by year, and by the value of benefit unit net wealth, $w_{i,t}$, as described by:

$$r_{i,t} = \begin{cases} r_{a,t} & \text{if } w_{i,t} \geq 0 \\ r_{dl,t} + (r_{du,t} - r_{dl,t})\varphi_{i,t} & \text{otherwise} \end{cases} \quad (1)$$

where i denotes the benefit unit and t time. $1 \geq \varphi_{i,t} \geq 0$ denotes the (bounded) ratio of benefit unit debt to full-time potential earnings. Assuming $r_{du,t} \geq r_{dl,t}$ reflects a 'soft constraint' where interest rates increase with indebtedness.

3.7.2 Private pensions

Private pensions are projected for adults identified as having retired in the model. The projection of retirement is described in Section 3.6.

Wealth implicit

When wealth is implicit in the model, then private pension income is projected using a linear regression model that conditions on age, level of education, lagged household composition, lagged health status, lagged private pension income, region, and year for individuals who continue in retirement. For individuals entering retirement, the probability of receiving private pension income is first determined using a logit model that conditions on having reached the state pension age, level of education, lagged employment status, lagged household composition, lagged health status, lagged hourly wage potential, region, and year. The amount of pension income is projected using a linear regression model conditional on the same observed characteristics.

Wealth explicit

When the simulation projects wealth explicitly, then an assumed fraction of benefit unit wealth at the time of retirement is converted into a life annuity, or joint-life annuity for adult couples. Annuity rates in the model are actuarily fair, given (cohort specific) mortality rates and an assumed internal rate of return.

3.8 Labour income

3.8.1 Wage rates

Hourly wage rates are simulated for each adult in the model based on Heckman-corrected regressions stratified by gender and lagged employment status (distinguishing between employed and not-employed individuals) that include as explanatory variables, part-time employment identifiers, age, education, student status, parental education, relationship status, presence of children, self-rated health, and region. For individuals observed in employment in the previous year, lagged (log) hourly wage rates are also included as an explanatory variable.

3.8.2 Employment decisions

Two alternative methods for projecting employment decisions can be considered by the model. These alternatives are both designed to reflect the influence of financial incentives on behaviour and are distinguished by whether they reflect forward-looking expectations.

Expectations implicit

The default specification of SimPaths projects labour supply using a non-forward-looking random utility model. This approach is common in the associated literature (see review by Li and O'Donoghue, 2013), and has the advantage that it limits computational burden.

The method projects labour supply as though employment decisions are made to maximise within-period benefit unit utility over a discrete set of labour/income alternatives (by default, 5 alternatives for individuals, and 25 for couples). Given any labour alternative, labour income is computed by combining hours of work with the respective hourly wage rate, projected as discussed in Section 3.8.1. The utility of the benefit unit is calculated using a quadratic utility function and takes as arguments benefit unit disposable income (see Section 3.9) and the number of hours worked by adult members.

Alignment

The estimated utility of single men, single women, and couples is adjusted to align the aggregate employment rate to the employment rate observed in the data in the validation period. The final adjustment value is used in the subsequent periods, for which no data is available. This procedure accounts for the existence of unemployment in the real economy and the fact that labour supply decisions simulated using the random utility model assume no constraints on labour demand in the economy.

Expectations explicit

The model can be directed to project labour and discretionary consumption to reflect forward-looking expectations for behavioural incentives. As for the implicit expectations case, the unit of analysis is the benefit unit. Incentives are translated into behaviour via an assumed intertemporal utility function. By default, the model adopts a nested constant elasticity of substitution (CES) utility function as described by equation (2), although the model is designed to facilitate experimentation with alternative specifications.

$$U_{i,t} = \frac{1}{1-\gamma}\left\{u\left(\hat{c}_{i,t}, l_{i,t}\right)^{1-\gamma} + E_{i,t}\left[\sum_{j=t+1}^{\infty} \delta^{j-t}\left(\varphi_{i,j} u\left(\hat{c}_{i,j}, l_{i,j}\right)^{1-\gamma} + \left(1-\varphi_{i,j}\right) Z\left(w_{i,j}\right)^{1-\gamma}\right)\right]\right\} \tag{2}$$

$$u\left(\hat{c}_{i,t}, l_{i,t}\right) = \left[\hat{c}_{i,t}{}^{1-1/\varepsilon} + \alpha^{1/\varepsilon} l_{i,t}{}^{1-1/\varepsilon}\right]^{\frac{1}{1-1/\varepsilon}} \tag{3}$$

$$Z\left(w_{i,j}\right) = \zeta_0 + \zeta_1 w_{i,j}^{+} \tag{4}$$

where subscripts i denotes benefit unit and t time. $u\left(\hat{c}_{i,t}, l_{i,t}\right)$ represents within period utility derived from equivalised discretionary consumption ($\hat{c}$) and time spent in leisure (l). $Z(w)$ represents the warm-glow model of bequests, derived from non-negative net wealth at death (w^{+}). E is the expectations operator and φ the probability of survival of the benefit unit reference person, which varies by gender, age and year. $\gamma > 0$ is the coefficient of relative risk aversion, $\varepsilon > 0$ the elasticity of substitution between equivalised consumption and leisure, α the utility price of leisure, and δ the constant exponential discount factor.

Each adult is considered to have three alternative labour supply options, corresponding to full-time, part-time and non-employment. Labour supply and discretionary consumption are projected as though they maximise the assumed utility function, subject to a hard constraint on net wealth and assumed agent expectations. Expectations are “substantively rational” in the sense that uncertainty is characterised by the random draws that underly dynamic projection of modelled characteristics. As no analytical solution to this problem exists, numerical solution methods are employed as is now standard in the dynamic programming literature (see e.g. van de Ven, 2017).

The model proceeds in two discrete steps. The first step involves solution of the lifetime decision problem for any potential combination of agent specific characteristics, with solutions stored in a look-up table. The second step uses the look-up table as the basis for projecting labour supply and discretionary consumption. Technical details of the numerical solution method are provided in Appendix C.

3.9 Disposable income

Disposable income is simulated by matching each simulated benefit unit in each projected period with a *donor* benefit unit reported by a tax-benefit reference database, following the procedure described by van de Ven *et al*. (2022). The database stores details of taxes and benefits alongside associated demographic and private income characteristics for a sample of benefit units. This database could be populated from a wide range of sources. The approach was originally formulated to draw upon output data derived from the UK version of EUROMOD (UKMOD), a static tax-benefit microsimulation model (see Richiardi *et al*., 2021), and then extended to accommodate projections from any EUROMOD country.

The matching procedure for benefit units applies coarsened exact matching over a number of discrete-valued characteristics, followed by nearest-neighbour matching on a set of continuous variables. The nearest neighbour matching is performed with respect to Mahalanobis distance measures evaluated over multiple continuous valued characteristics.

The default set of discrete value characteristics considered for matching includes age of the benefit unit reference person, relationship status, numbers of children by age, hours of work by each adult member, disability status, and informal social care provision. Similarly, the default set of continuous value matching characteristics includes original (pre-tax and benefit) income, second income (to allow for income splitting withing couples), and formal childcare costs.

Having matched a simulated benefit unit to a donor, disposable income is imputed via one of two methods. For benefit units with original income above a “poverty threshold”, disposable income is imputed by multiplying original income of the simulated benefit unit by the ratio of disposable to original income of the donor unit. For benefit units below the considered poverty threshold, disposable income is set equal to the (growth adjusted) disposable income of the donor.

Finally, adjustments to account for public subsidies for the costs of (formal) social care are evaluated separately from the database approach described above, based on internally programmed functions. This is done because public subsidies for social care are not always included in database sources (e.g. tax-benefit models) considered for analysis.

3.10 Consumption and savings

3.10.1 Non-discretionary expenditure

The model can project two forms of non-discretionary benefit unit expenditure: formal social care costs and formal childcare costs. As described in Section 3.5, social care costs are projected based on projections of hours of formal social care received and assumed hourly wage rates for social care workers.

Childcare costs are projected using a double-hurdle model, characterised by a probit function describing the incidence of formal childcare costs and a linear least-squares regression equation describing the value of childcare costs when these are incurred. Both equations include the same set of explanatory variables describing the number and age of dependent children in a benefit unit, the relationship status and employment status of adults in the benefit unit, whether any adult in the benefit unit is higher educated, region, and year.

3.10.2 Discretionary consumption

As discussed in Section 3.8.2, the model can be directed to project employment and discretionary consumption jointly to reflect forward-looking expectations for behavioural incentives. The projection of discretionary consumption varies depending on whether forward-looking expectations are chosen to be explicit or implicit within a simulation.

Expectations implicit

Yearly equivalised disposable income is calculated by adjusting disposable income (see Section 3.9) to account for benefit unit demographic composition via the modified OECD scale. Equivalised consumption is set equal to equivalised disposable income for retired individuals, and to disposable income adjusted by a fixed discount factor to account for an implicit savings rate otherwise. The assumed savings rate, in turn, influences simulated capital income (see Section 3.7.1).

Expectations explicit

As discussed in Section 3.8.2, the model evaluates solutions to the lifetime decision problem in the form of a look-up table when directed to reflect forward-looking expectations for behavioural incentives. In the case of discretionary consumption, the look-up table stores the ratio of consumption to "cash on hand", where cash on hand is the sum of net wealth, disposable income, and available lines of credit. This ratio has the advantage that it is bounded between zero and one, which facilitates the computational routines and consideration of selected policy counterfactuals.

3.10.3 Assets accumulation

Net wealth is the key transition mechanism that balances intertemporal behavioural incentives when forward-looking expectations are treated explicitly by the model. In this case, dynamic evolution of wealth in most periods is described by the accounting identity:

$$w_{i,t} = w_{i,t-1} + y_{i,t} - c_{i,t} - \bar{c}_{i,t} \tag{5}$$

where $w_{i,t}$ denotes the net wealth of benefit unit i in period t, $y_{i,t}$ disposable income, $c_{i,t}$ discretionary consumption, and $\bar{c}_{i,t}$ non-discretionary expenditure. The only departures from equation (5) are at the time of retirement if $w_{i,t} > 0$, when a fixed fraction of net wealth is converted into a fixed life annuity (see Section 3.7.2), or if there is a change in relationship status. In context of relationship formation, the wealth of each new partner is aggregated to obtain the wealth of the new benefit unit. In context of relationship dissolution due to separation, each spouse is assumed to take half the wealth of their preceding benefit unit. Relationship dissolution due to spouse death has no effect on benefit unit with, reflecting the implicit assumption that all wealth of the deceased passes to their surviving spouse.

Home ownership

Although net wealth is not disaggregated in the model, the incidence of home ownership is reflected, as this is used as an input to for projection of psychological distress (Section3.3.3 – 3.3.4). Home ownership is evaluated at the benefit unit level, by considering if at least one of the adult occupants is classified as a homeowner. At the individual level, home ownership is determined using a probit regression model conditional on gender, age, lagged employment status, education level, lagged self-rated health, lagged benefit unit income quintile, lagged gross personal non-employment non-benefit income, region, lagged household composition, lagged spouse's employment status, and a time trend.

3.11 Assessing simulated uncertainty

Uncertainty regarding a model's projections arise for a variety of reasons (Bilcke *et al*., 2011; Creedy *et al*., 2007):

(i) Input data; due to sampling or measurement errors in initial survey populations.

(ii) Model structure[24]; referring to the validity of the modelling approach adopted.

(iii) Model specification; concerning the choice of the covariates and the functional forms used, and in particular the crucial assumption that any regularity observed in the data will persist into the future.

(iv) Model parameters; concerning the statistics imprecision of parameter estimates and/or exogenously derived parameters.

(v) Montecarlo variation; concerning sensitivity of simulated aggregates of interest to the set of random draws used to project diversity among simulated agents.

Studies based on microsimulation methods frequently ignore these sources of uncertainty, which is a recognised source of critique (e.g. Goedemé et al., 2013). This omission can generally be attributed to the observation that "the calculation of confidence intervals around model results that account for all sources of error remains a major challenge" (Mitton et al., 2000).

The first source of uncertainty listed above (i) should decline with the increasing availability of high-quality survey data, and in any case is generally beyond the scope of expertise of data analysts. Sources (ii) and (iii) that focus on model specification can be explored using established statistical techniques based on in-sample and out-of-sample measures of fit.

SimPaths accounts for parameter uncertainty (iv) by including routines that facilitate bootstrapping parameter estimates, based on estimated point values and covariance matrices. This involves repeated simulations, each based on a different random draw for model parameters. Similarly, Montecarlo variation (v) can be explored by conducting repeated simulations each based on fresh set of random draws or by arbitrarily scaling-up the simulated population size. These methods can be used to generate a distribution of model outcomes, around central projections.

4 Data, estimation and validation

4.1 Data and estimates

SimPaths uses three types of data as input:

1. The *initial population* to be evolved over time.
2. *Donor populations* used to impute the effects of tax and benefit policy.
3. Estimated *parameters* governing transition probabilities assumed by the model.

The model has been designed to draw the initial population from data reported by the UK Household Longitudinal Study (UKHLS). The UKHLS, (sometimes referred to as

[24] Sometimes referred to as "methodological uncertainty".

Understanding Society), is the successor to the British Household Panel Survey, and is the principal general-purpose panel survey administered in the UK. Multiple initial populations are derived from the UKHLS, corresponding to different years of data reported by the survey (from 2011 to 2017), and used for model validation (see below).

The donor populations for tax and benefit imputations are derived from UKMOD and are based on data reported by the Family Resources Survey (FRS). These data include a wide range of benefit unit characteristics in addition to tax and benefit payments. SimPaths imputes tax and benefit payments from these data by matching simulated individuals to individuals described by donor populations.

Parameters for the UK have been estimated on UKHLS data, Waves 1 to 8, and FRS (labour supply and social care, various years). Estimates are reported in Appendix A. The estimates are currently being updated to include waves 9 and 10 (up to 2019). This also involves minor changes in the specification of some of the processes.

Table 2 offers a high-level description of the specifications used in each process.

Table 2: Relationship between state variables in SimPaths

	Dependent variable																				
Control variable	student status	education level	health status	mental health	disability status	partnership status	fertility	childcare cost	home owner	retirement status	pension income (£)	capital income (£)	low wage offer	potential wage (£)	hours worked	need social care	receive social care	type of care received	amount of care received	provide social care	amount of care provided
gender	c	c	c	c	c	c	c		c	c	c	c	c	c	c	c	c	c	c	c	c
age	c	c	c	c	c	c	c		c	c	c	c		c	c	c	c	c	c	c	c
education	l	l	c	c	c	c,l	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c
maternal education	c	c		l										c							
paternal education	c	c												c							
partnership status			l	c,l	l	l	c,l	c	l	c	l	l			c	c	c	c	c	c	c
number of children	l		l	l	l	l	l	c	l		l	l			c						
age of children	l					l	l	c													
health status			l	l	c,l	c,l	c		l		l	l	c	c		c	c		c	c	c
mental health				l																	
disability status			l	l	l					l				c				c			
need social care																l					
receive social care																	l				
type of care received																		l	c		
amount of care received																					
provide social care																				l	c
amount of care provided																					
activity status	l		l	c,l		l	l	c	l	l	l	l	l	c							
hours worked														c	c,l						
disposable income (£)			l	c,l	l	l			l	l					c						
employment income (£)												l									
benefit income (£)				c																	
capital income (£)						l			l			l,l2									
pension income (£)						l			l		l, l2	l,l2									
potential wage (£)						l			l		l			l							
home owner				c					l												
region	c	c	c	c	c	c	c	c	c	c	c	c	c	c		c	c	c	c	c	c
year	c	c	c	c	c	c	c		c	c	c	c	c								

Note: Each column reports the controls used to update a specific individual characteristics.
'c' denotes covariate reported in same period as projected characteristic.
'l' denotes covariate lagged one period relative to projected characteristic.

'l2' denotes covariate lagged two periods relative to projected characteristic

The EU version of SimPaths, on the other hand, is estimated on longitudinal EU-SILC data, which is also used to build the initial population.

4.2 Validation

In this paper we report validation statistics for the workhorse version of SimPaths, parameterised to the UK. As described in Section 4 above, this version of the model uses static labour supply optimisation and includes alignment to population projections, cohabitation rates, and aggregate employment rates. The validation was undertaken by comparing simulated and observed data, starting with observations reported for 2011, and then at annual intervals to 2019. This sample window avoids complications associated with the 2008 Financial crisis on the one hand, and the Covid-19 pandemic on the other. This validation window overlaps the sample frame used to estimate model parameters (2009-2017).

Validation is always motivated by the need to increase confidence in the model (National Research Council, 2012). This, in turns, depends on the research questions that the model is designed to address, which should ultimately determine what validation tests the model has to pass. SimPaths is currently being used for a number of different research projects (see Section 5), with more applications being evaluated: a discussion of all the different research questions involved is therefore outside the scope of the present paper. Consequently, we opt here for a generic evaluation of how "realistic" the full set of model outcomes are, under a baseline parameterisation. Given the large number of state variables in the model, such a broad validation strategy spans multiple dimensions, covering both cross-sectional (evolution of summary statistics of variables over time) and longitudinal measures (transitions between states), referring both to individual variables and to their joint distribution (e.g. correlations).[25]

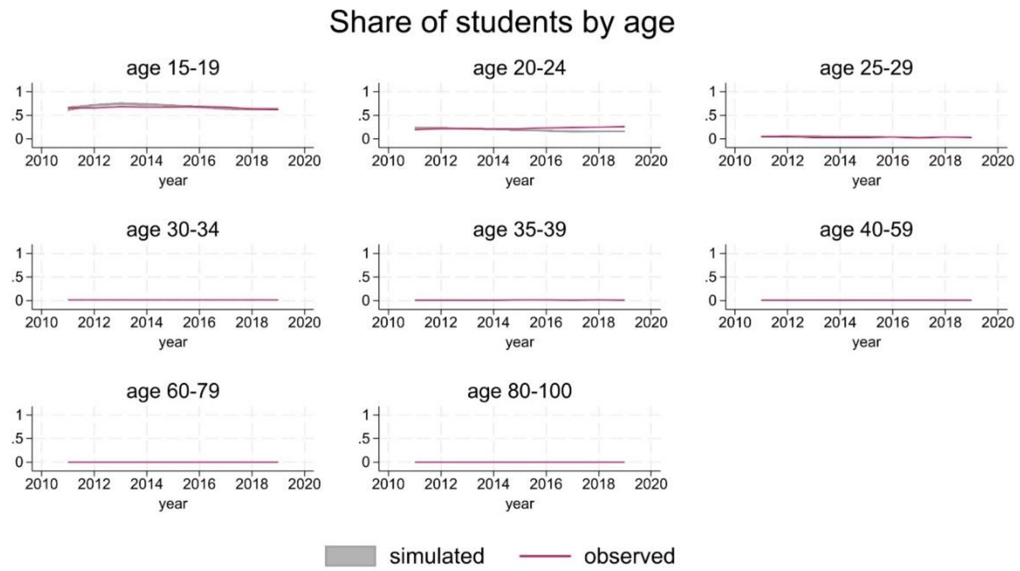
[25] Details of the process undertaken to arrive at the validation reported here are too numerous to recount succinctly, and so the current section focusses on the outcome of the process rather than the process itself, and the lessons learnt. A quick aside may, however, provide the reader with some appreciation for the issues involved. Empirical estimations of the equations that govern evolution of relationship status in the model were evaluated using pooled data from the UKHLS. From this basis, it was found that SimPaths tended to understate proportions of population projected to be in a relationship during the validation window. After further analysis, it was found that the discrepancy between the model and survey data was attributable to the interaction between the matching method used to identify partners from within the pool of simulated individuals identified as entering a relationship, and the probit relationships governing the incidence of relationship transitions. This type of mismatch reflects an issue that underlies any effort to identify parameters outside of a given model's structure. Ideally, all model parameters should be evaluated together and endogenous to the model of interest. This is the case, for example, in related two-stage econometric methods including Simulated Minimum Distance (Lee & Ingram, 1991), Method of Simulated Moments (Stern, 1997), Indirect Estimation (Gourieroux, et al, 1993), and Efficient Method of Moments (Gallant and Tauchen, 1996). In practice that is often not possible, which generates a source of model mis-identification. In the current context, an alignment method was implemented to account for the model mismatch. The alignment method adjusts the intercept of the estimated probit equations governing the incidence of entering a relationship until the model reflects summary statistics for the proportions of the population observed

For the sake of brevity, we discuss here only a selection of cross-sectional measures, presented in graphical form for ease of visualisation, leaving validation of longitudinal measures to a future exercise. For each simulated series, 95% confidence bands are displayed, computed based on the uncertainty assessment strategy outlined in Section 3.11. The simulated confidence bands are shown against the weighted means of the corresponding variables computed on the UKHLS data.

4.2.1 Education

SimPaths reproduces the distribution of students by age accurately (Figure 2).

Figure 2: Student status

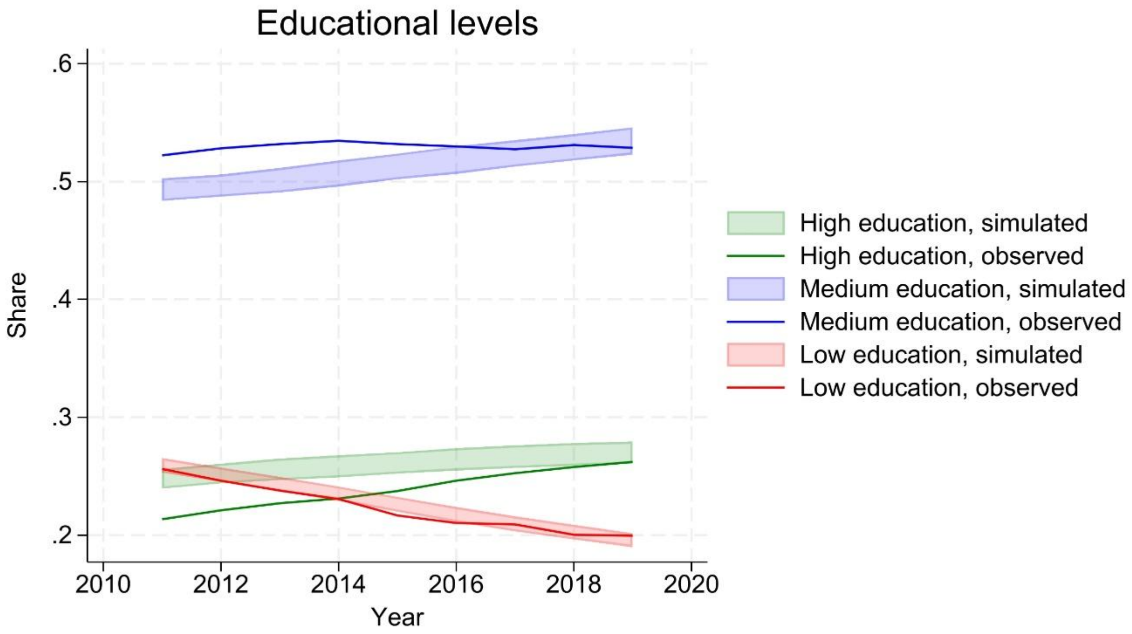


Simulated educational attainments show convergence between the simulated and observed share of the population with high education, starting from a higher simulated level (Figure 3). This implies a slower increase than observed in the data. This is partly attributable to a conservative choice about continuation of estimated trends in the projections. More in details, specifications assume a linear time trend. This is motivated by the relatively short length of the estimation panel, which would not support a more flexible modelling of the time trend. However, extrapolating a linear trend is problematic, as it will eventually lead to implausible levels of the variable of interest. In projections, SimPaths stops the estimated linear trends after a given calendar year. The default option – adopted in this and other processes - is to stop any

in survey data to be in a relationship. For years beyond the validation period, the intercept is kept constant at the last calibrated level.

estimated time trend at the end of the estimation sample (2017). Data shows that the trend towards increasing educational levels is continuing beyond 2017.

Figure 3 : Educational attainment



4.2.2 Health

The version of SimPaths described here distinguishes between a general health score (Likert scale 1-5), and a psychological distress score (Likert scale 0-36). Projected distribution of general health by age and gender is in line with observations (Figures 4 and 5).

Figure 4: General health score, men

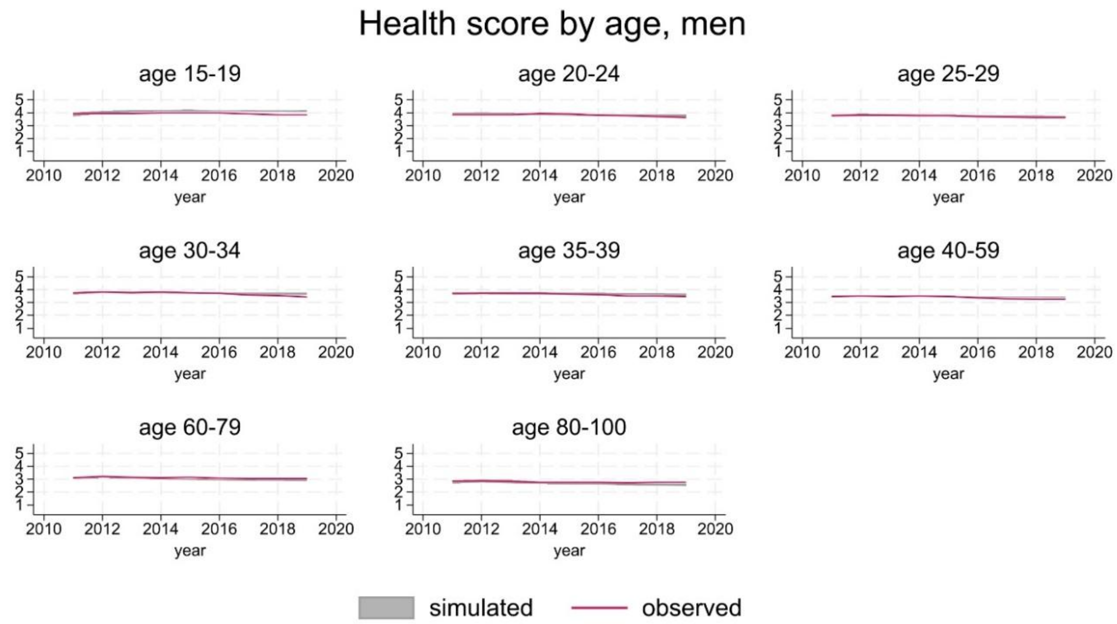
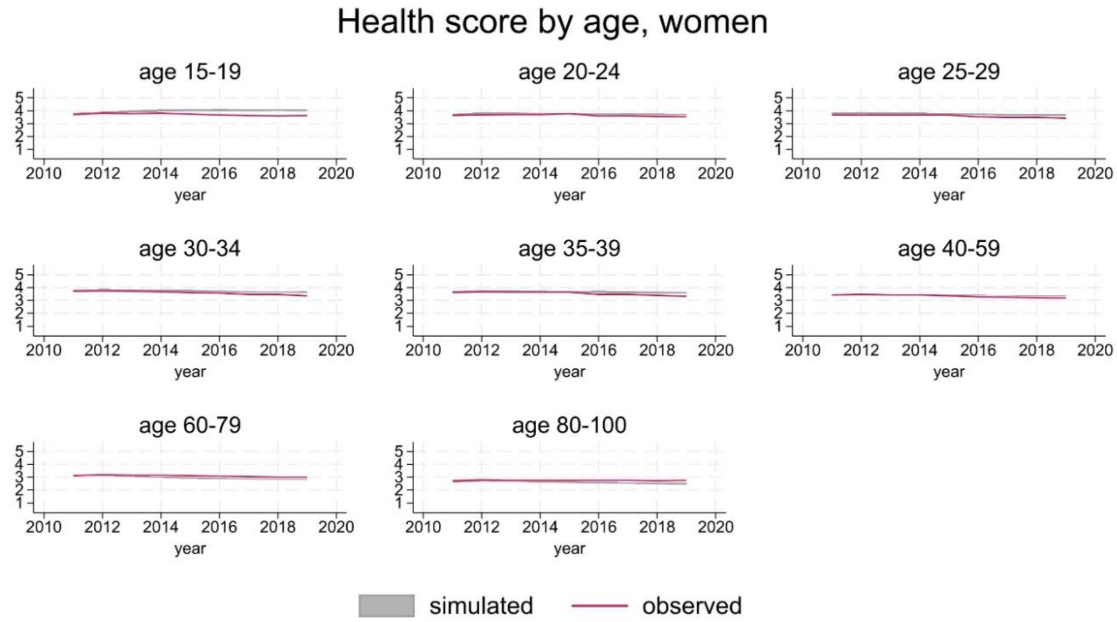
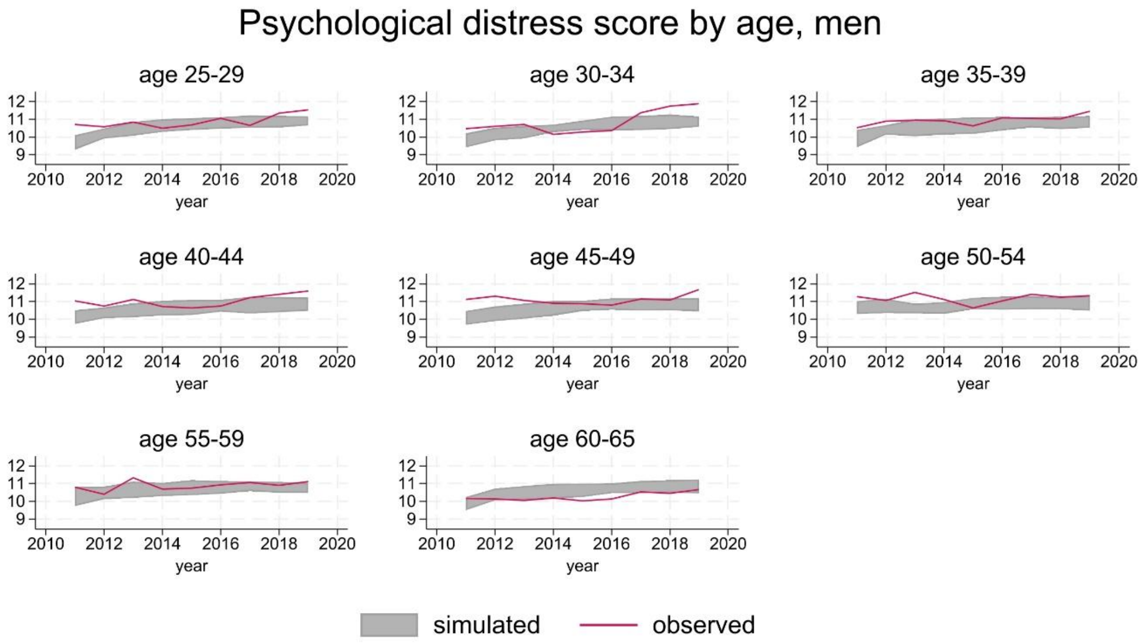


Figure 5: General health score, women

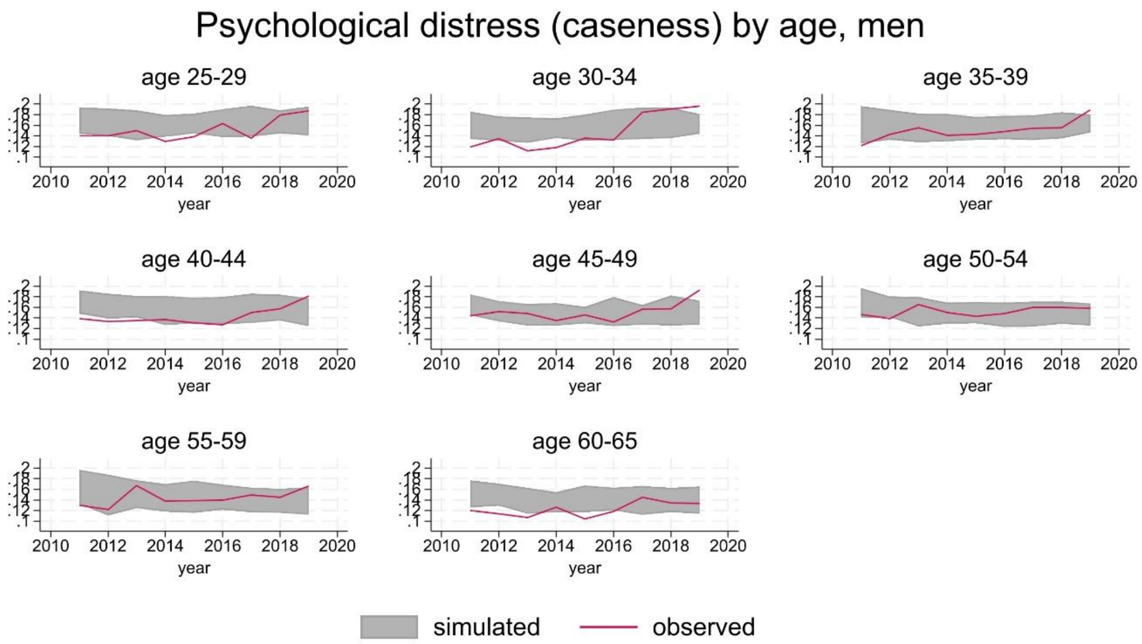


For ease of interpretation, we report caseness of psychological distress (see Section 3.3.3), in addition to the score. Distributions by age and gender are substantially in line with the observations, considering the volatility implied by the level of prevalence of psychological distress in the population (Figures 6 and 7).

Figure 6: Psychological distress, men

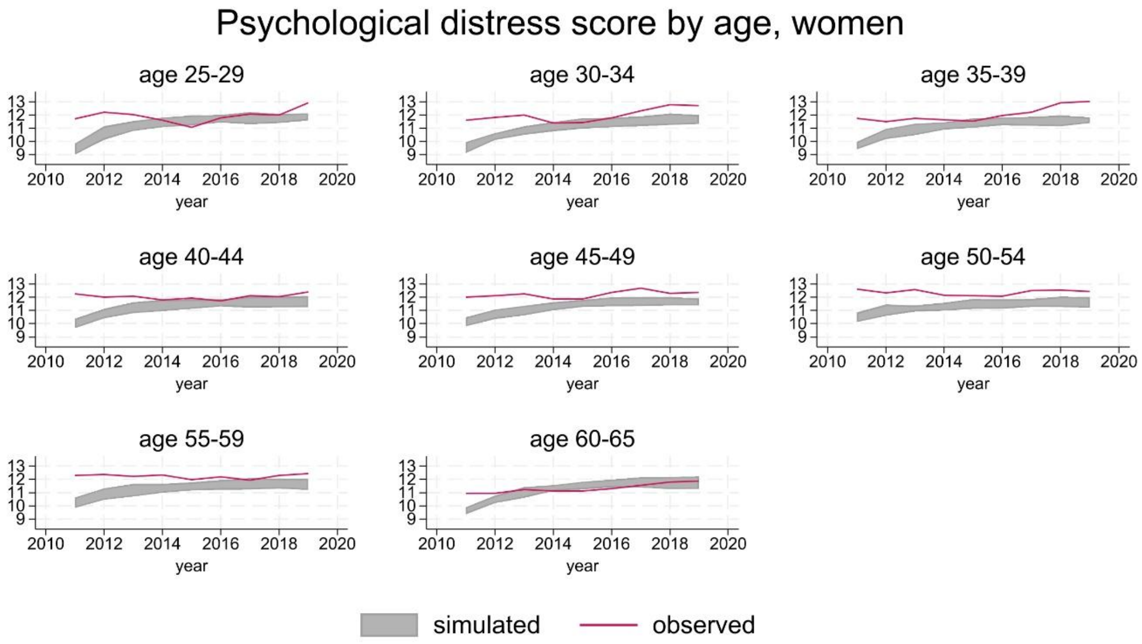


(a) Score

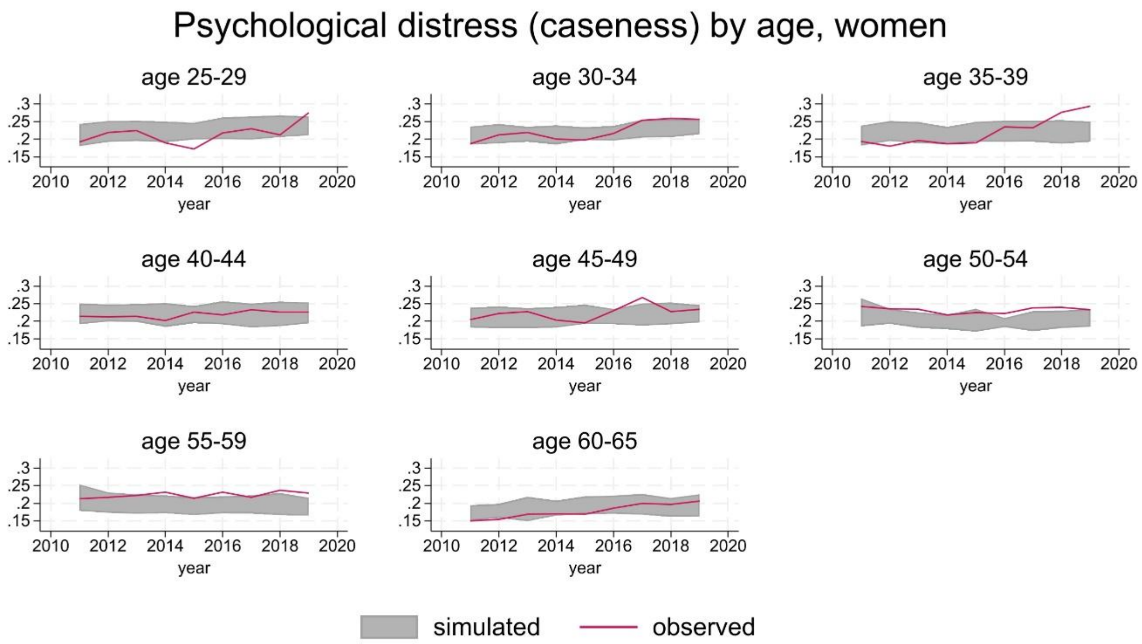


(b) Caseness

Figure 7: Psychological distress, women



(a) Score

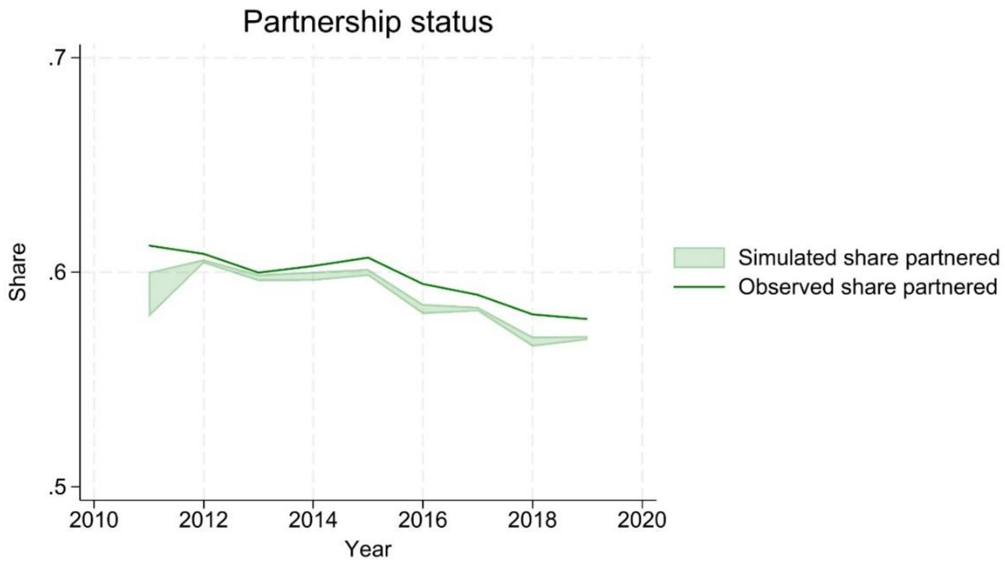


(b) Caseness

4.2.3 Household structure

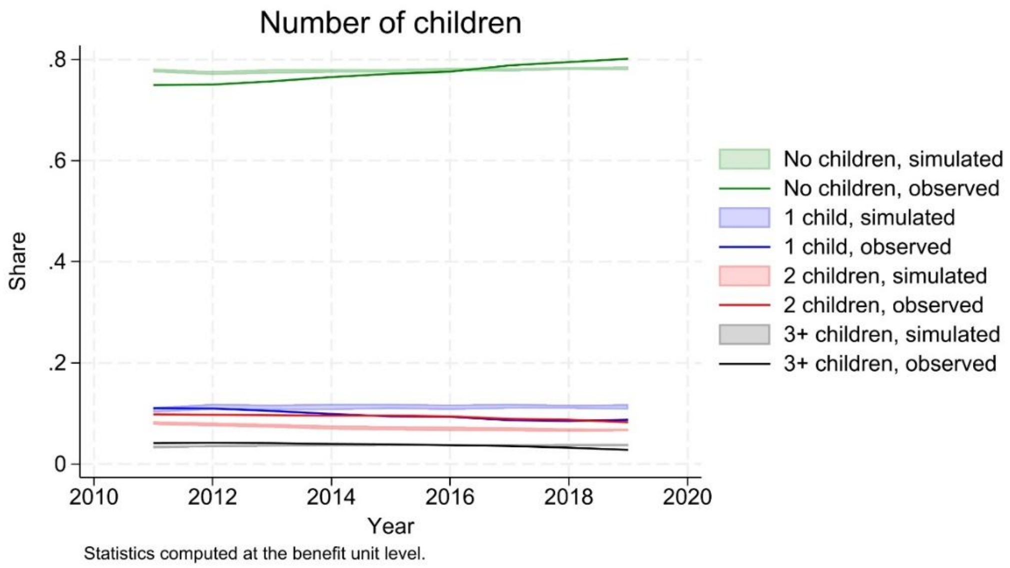
Projections correctly reproduce a declining share of partnered households (Figure), although the simulated series is slightly below the observed one.

Figure 8: Partnership status



The simulations also reproduce, with some approximation, the distribution of benefit units by number of children (Figure 9).

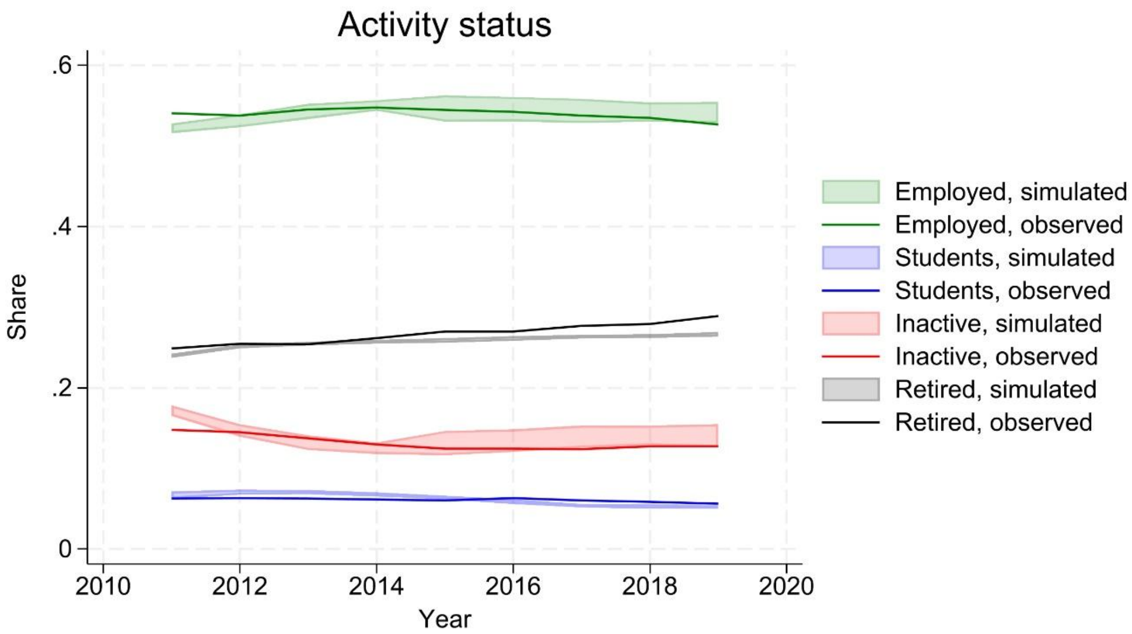
Figure 9: Number of children



4.2.4 Activity status, employment and wages

As discussed above, we calibrate the labour supply model to align to observed employment rates, in the validation period. This is done by modifying the estimated parameters, rather than the simulated outcomes, resulting in a non-perfect hitting of the target. The other possible activity statuses on the other hand (in education, inactivity, retirement) are not aligned. Figure shows that the simulated activity statuses broadly follow observed data, with a slight under-projection of pensioners.

Figure 10: Activity status



While projections are broadly aligned to aggregate employment figures, the distribution of employment by individual characteristics is freely determined by the model.

Figures 11 and 12 show that group-specific employment rates are substantially in line with the data, replicating the gender and age gradient and showing little trend over time. The main discrepancies are limited to younger men (20-24 age group), where simulations over-predict employment rates, and older women (50-59 age group), where simulations under-predict employment rates.

Figure 11: Employment rates, men

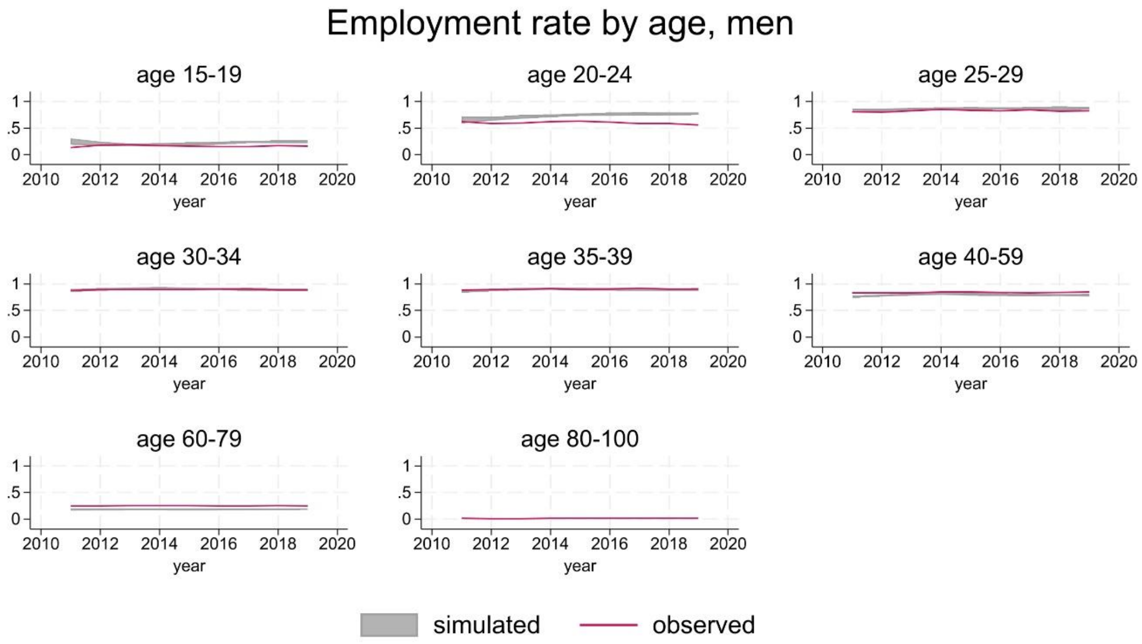
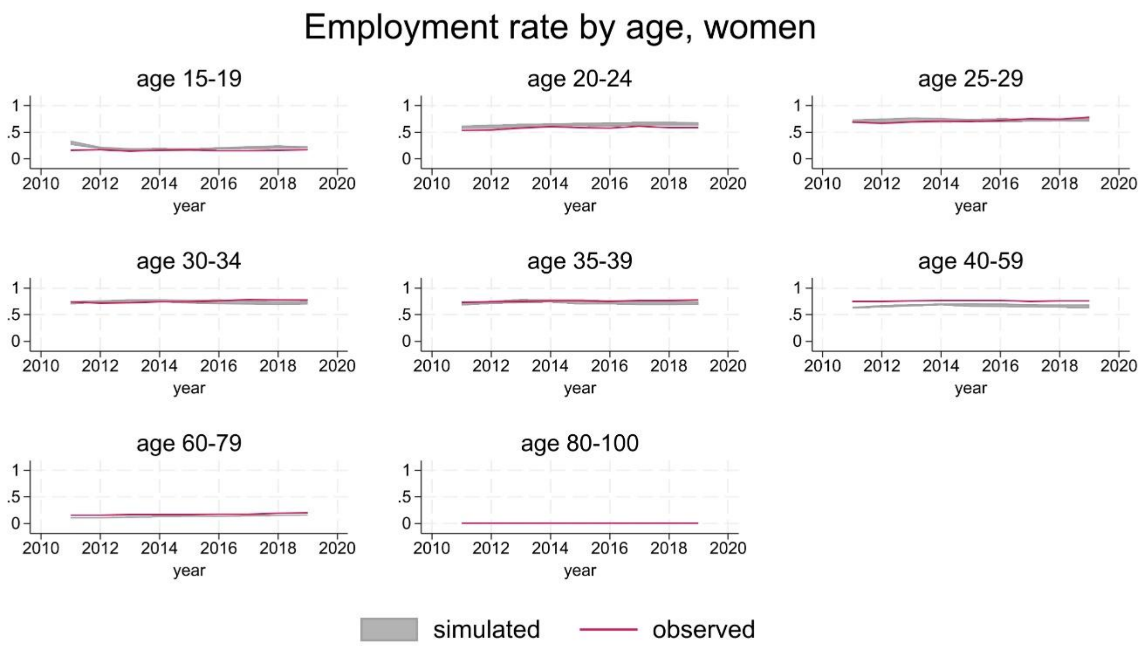


Figure 12: Employment rates, women



The growth in real wages is captured by the model to a good extent (Figure 13), while simulated and observed distributions are also largely overlapping (Figure 14).

Figure 13: Real wages, trend

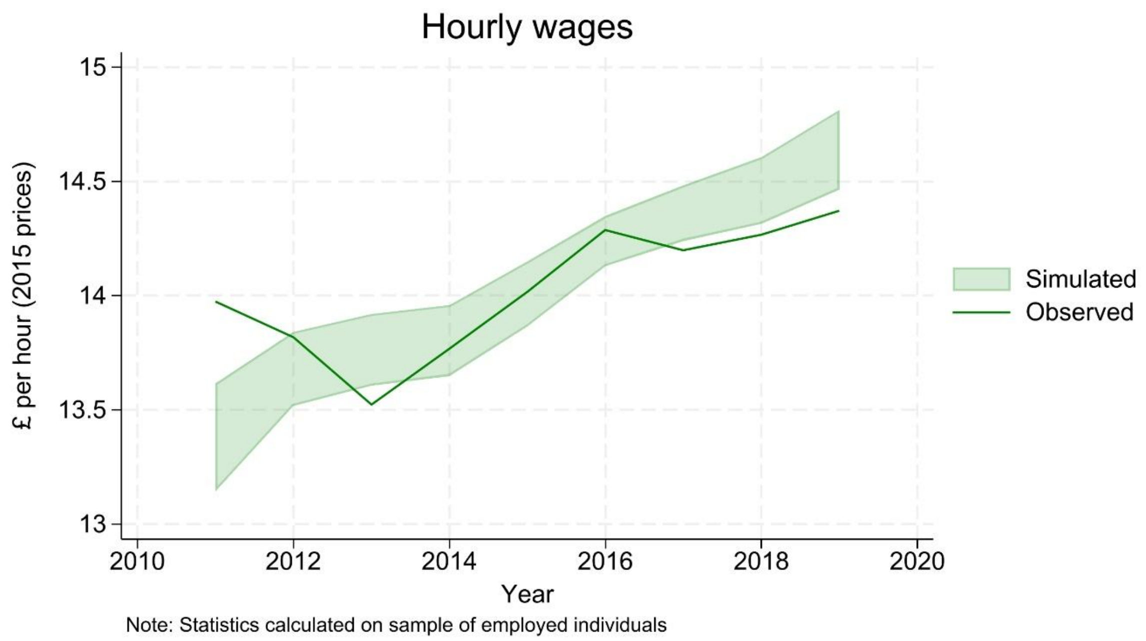
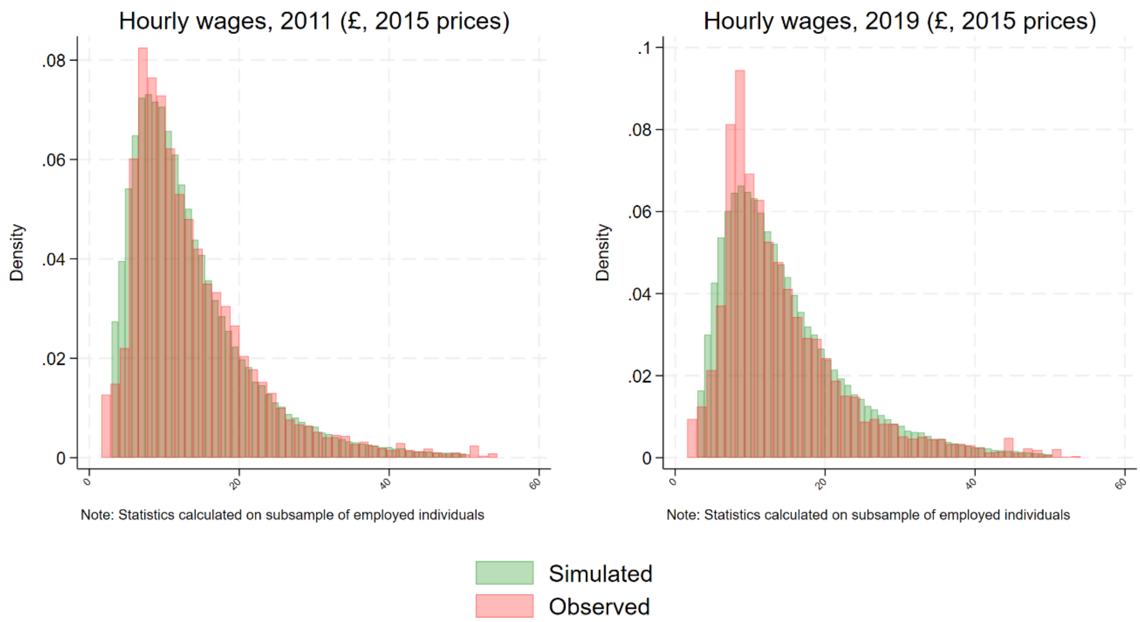
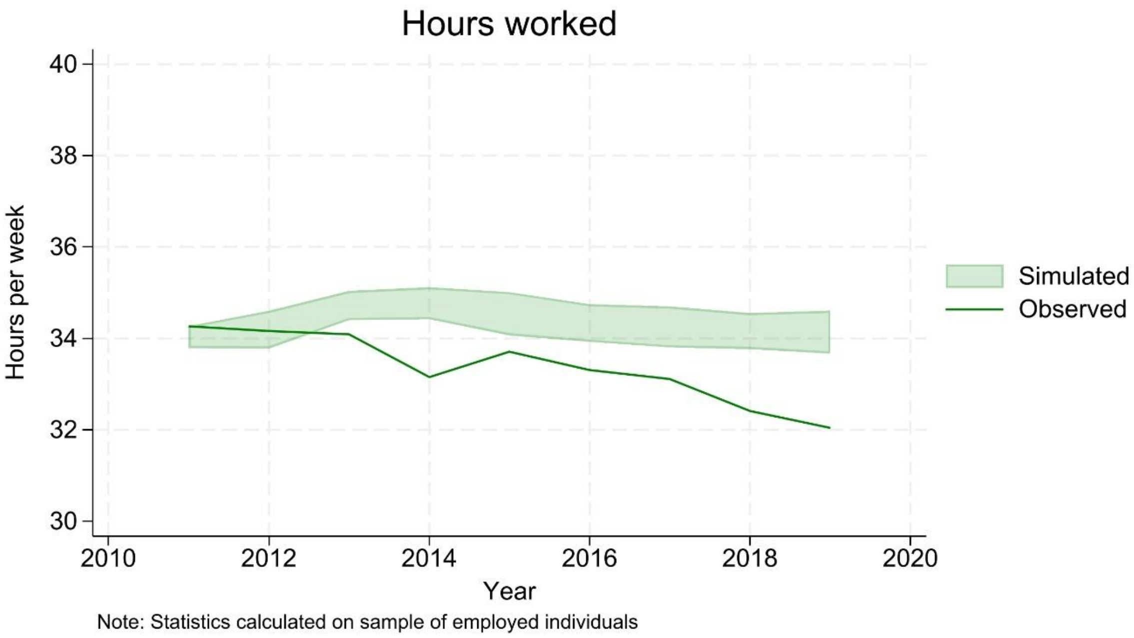


Figure 14: Real wages, distribution



Finally, the model struggles a bit in replicating the observed downward trend in hours worked (Figure 15). This is potentially due to the fact that the underlying random utility model of labour supply is estimated on one cross section of data only (2017). Sensitivity analysis shows that estimating the model on previous years results in broadly constant coefficients, which is consistent with the assumed structural nature of the model. However, the data seems to suggest that preferences might have indeed changed slightly over time.

Figure 15: Hours worked



4.2.5 Gross income

The model is able to replicate well both the trend and the distribution of individual gross income (Figures 16 and 17).

Figure 16: Gross income, trend

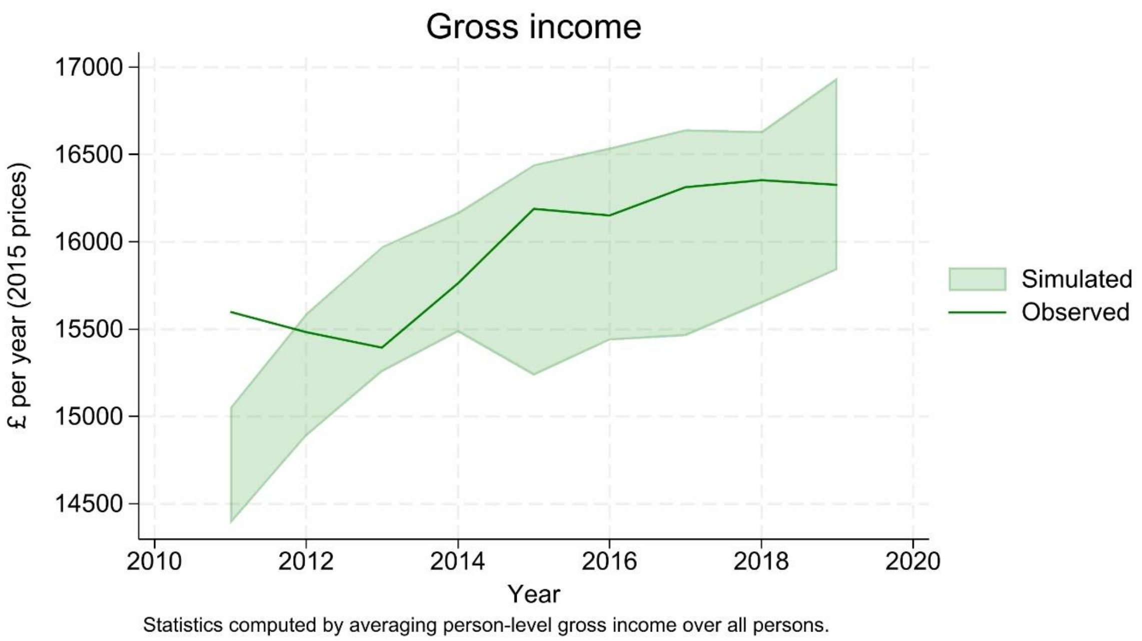
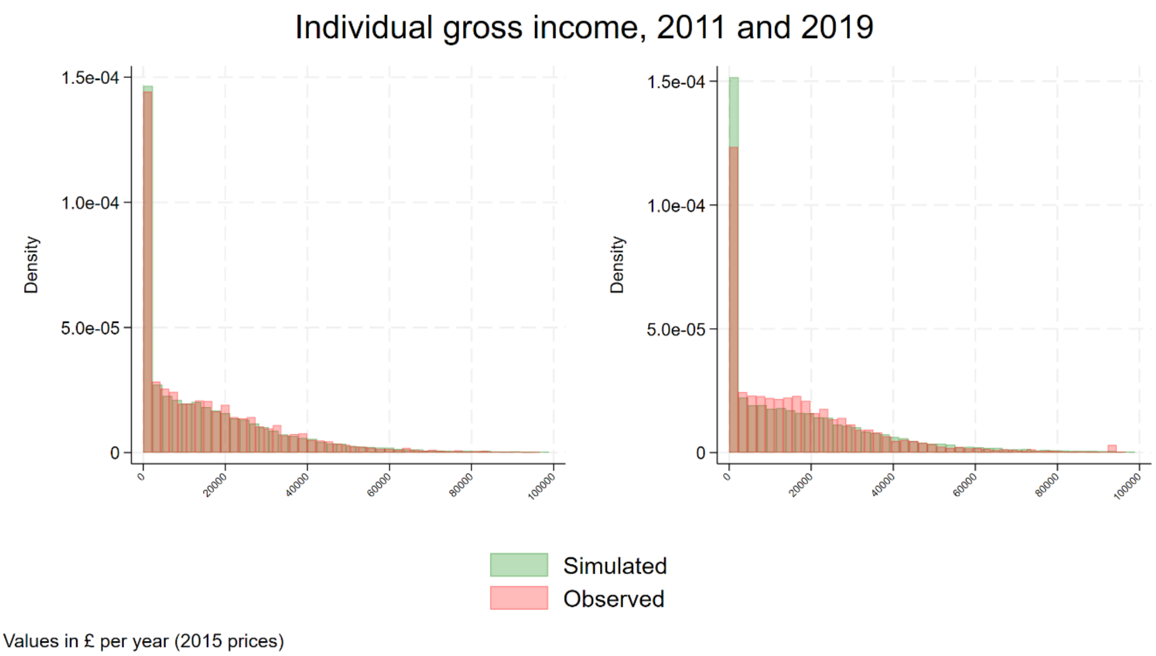


Figure 17: Gross income, distribution



Projected contributions of different income sources (labour, pension, capital and miscellaneous) by age groups along the income distribution also mimic the observed ones, both in levels (Figure 18) and in shares (Figure 19).

Figure 18: Income sources, value

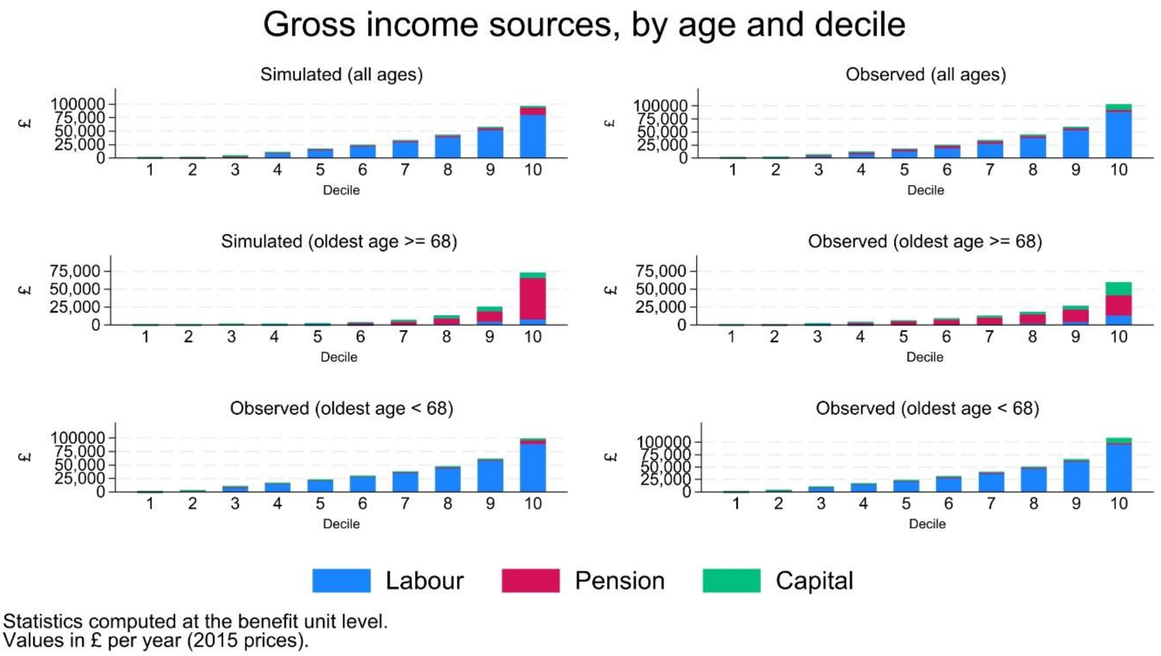
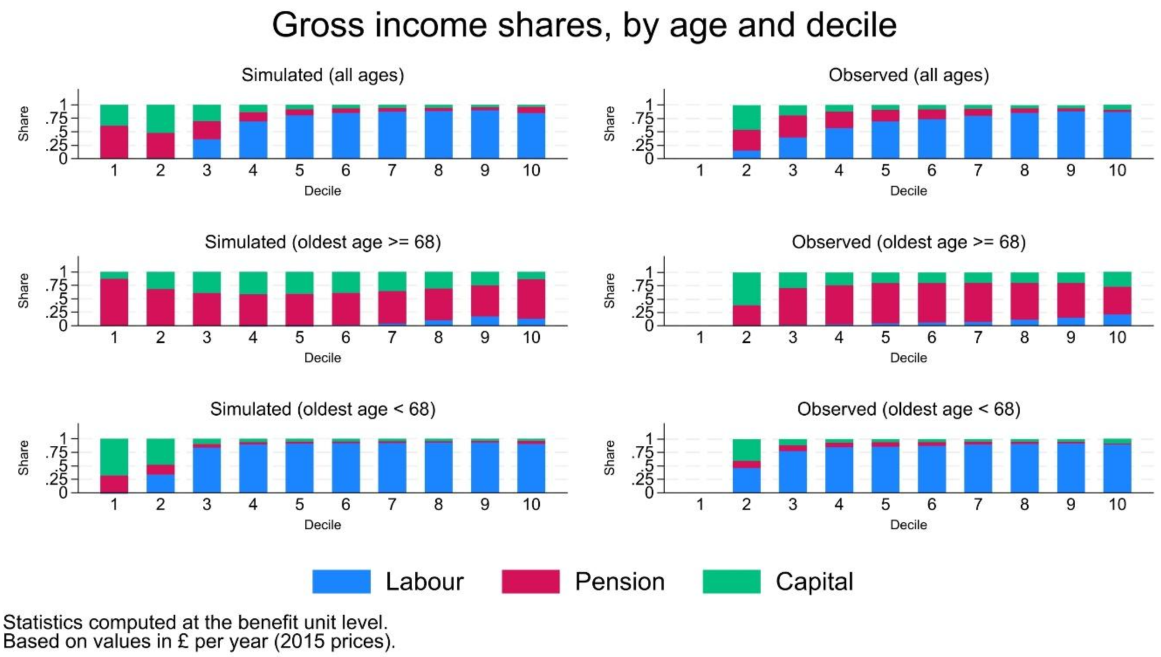


Figure 19: Income sources, share

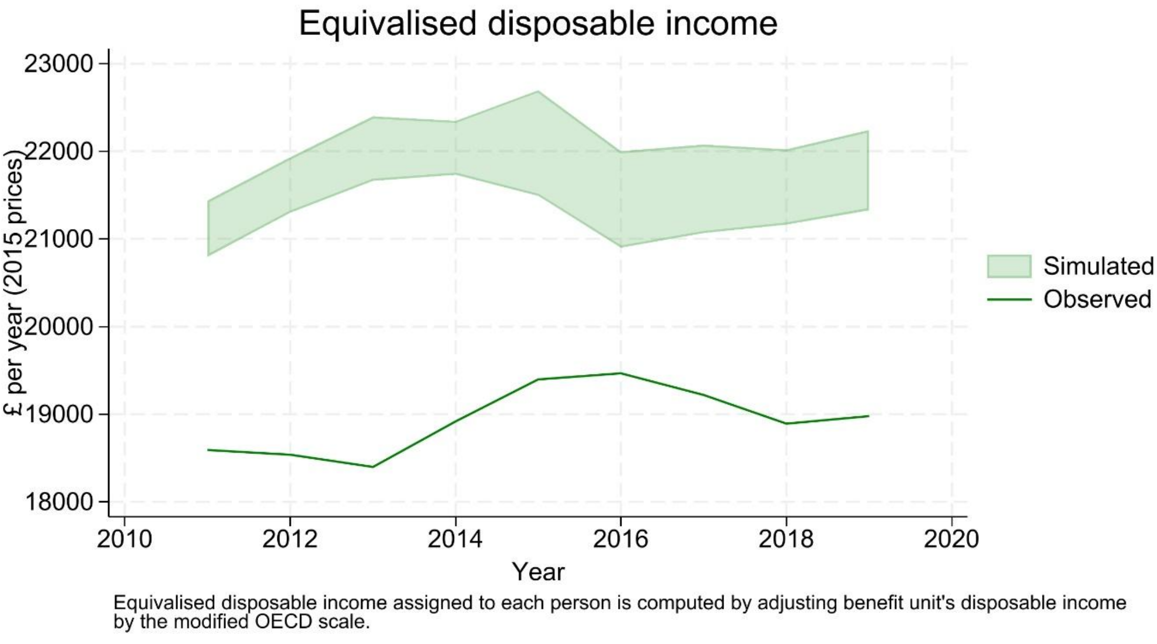


Labour income, computed by multiplying simulated hours worked by simulated wages, is obviously the main source of income for individuals below retirement age, while pension income is the main source for individuals above, on average. Both are projected with a fair level of accuracy (results not shown, but available on request). Capital income, on the other hand, is under-estimated in the simulations (average simulated values of around £1,200 - in 2015 prices - against observed values of around £1,700). However, the limited relevance of this source of income for the vast majority of the population – reflected in its small average value – limits the consequences of inadequate model specification.

4.2.6 Net income

Gross income is transformed into net income by means of the procedure described in Section 3.9. Results displayed in Figure 20 point to a slight over-estimation of disposable income (around 10%), possibly due to the fact that not all the characteristics relevant to the tax-benefit system can be simulated and controlled for in the matching procedure.[26]

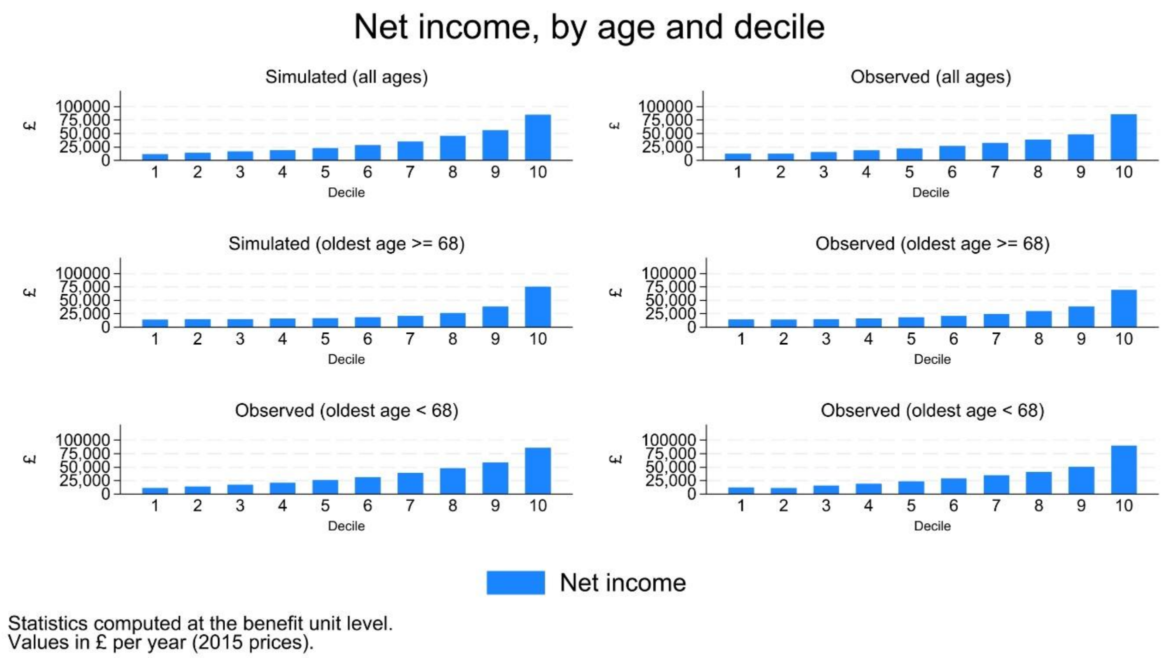
Figure 20: Equivalised disposable income



[26] Figures for disposable income, where disposable income is not adjusted for the benefit unit composition, follow a similar pattern.

The distribution of simulated disposable income however looks remarkably similar the observed one, both for the working age population, and for the population above retirement age (Figure 21).

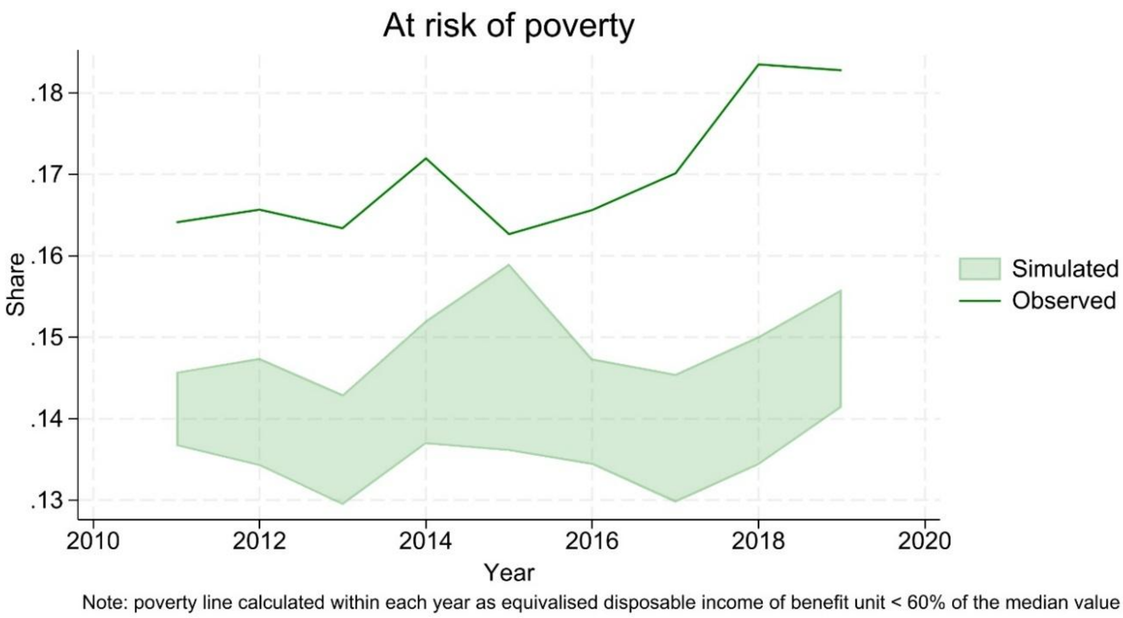
Figure 21: Disposable income, distribution



4.2.7 Poverty and inequality

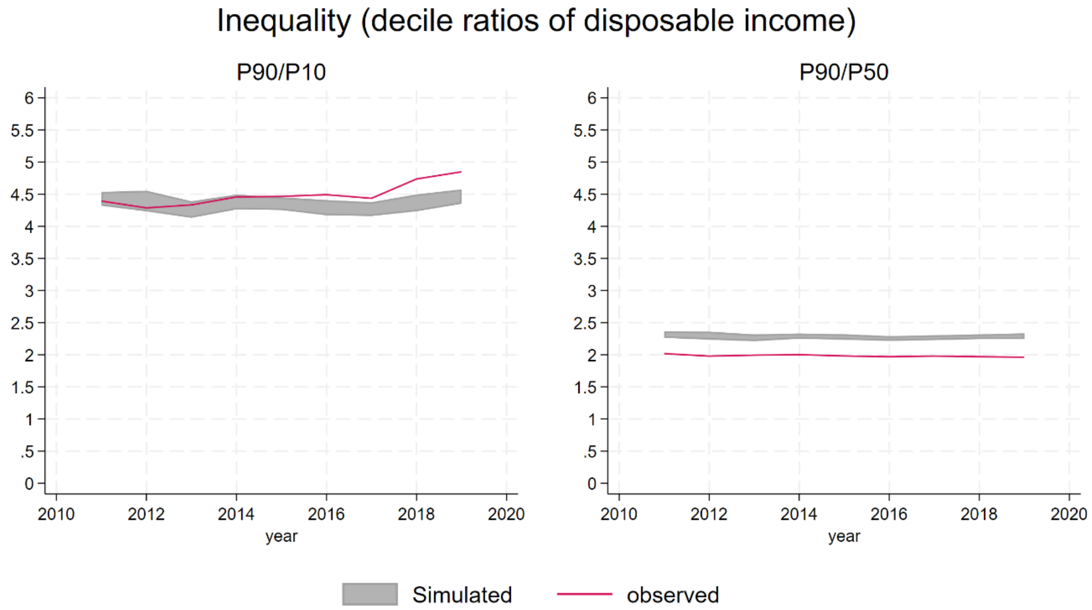
Biases in the simulation of disposable income translate into an under-estimation of poverty rates (Figure 22), although the error is small (around 2.5 percentage points), and the trends broadly comparable.

Figure 22: Poverty



Income inequality however, as measured by percentile ratios, is very much aligned with observed measures (Figure 23).

Figure 23: Inequality



4.2.8 Correlations

Maintaining the cross-sectional perspective of the previous sections, we conclude with an assessment of pairwise correlations between the main outcome variables.

Figure 24: Correlations

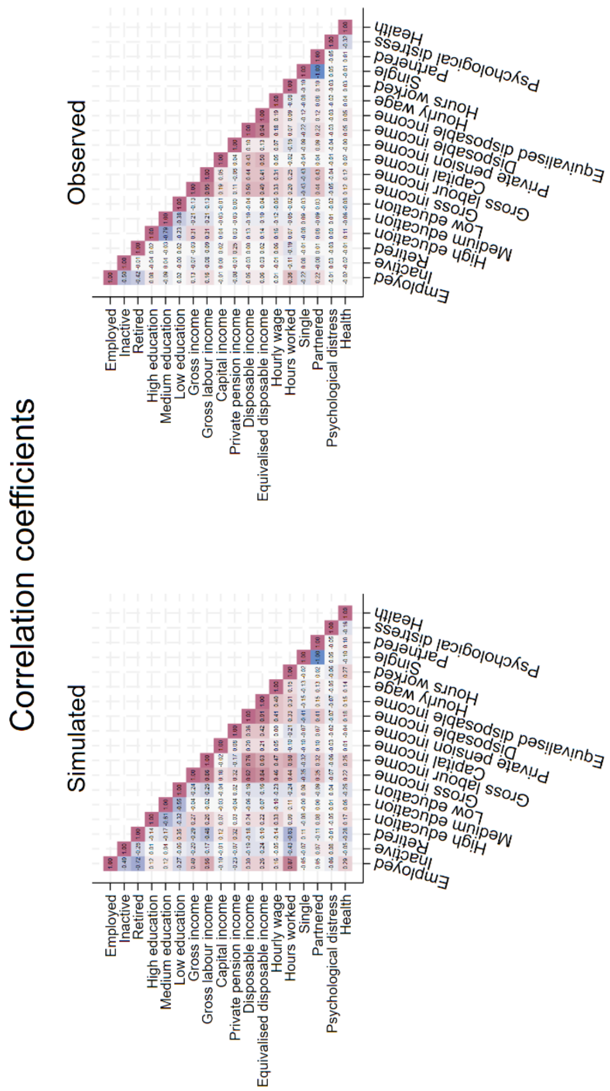


Figure 24 compares simulated and observed correlation coefficients. The main features of the data are reproduced by the model, from the most trivial (positive correlation between various income measures) to less straightforward ones (positive correlation between being partnered and labour income). Health is more positively correlated with income in the simulations than in the data, possibly because we force disabled people to drop off the labour market. The negative correlation between general health and psychological distress is faithfully reproduced, as well as the very tenuous negative correlation between psychological distress and income on the one hand, and psychological distress and being partnered on the other.

5 Applications and extensions

Early applications of the SimPaths framework focussed on the short-to-medium term impact of social policies on mental health outcomes. Kopasker et al. (2024) consider the UK policy response to COVID-19, comparing baseline simulations with the policies that the UK government enacted in 2020-2021 to sustain incomes during the pandemic with counterfactual simulations where pre-crisis policies remained in place. Their period of analysis is 2017 to 2025. Results show that the policy response prevented a further 3.4 percentage points (pp) increase in the prevalence of common mental disorders (CMDs) with respect to pre-covid levels, on top of the more than 10pp increase observed in 2020-2021 with covid-19 legislation in place. This amounts to approximately 1.2 million additional cases of CMDs prevented by the covid-19 policy response. Beyond 2021, as employment levels rapidly recovered, psychological distress returned to the pre-pandemic trend.

Thomson et al. (2024) consider the effects of hypothetical basic income schemes over the period 2022-2026. They show that the policy has potential to improve short-term population mental health by reducing poverty, particularly among women, but impacts are highly dependent on whether individuals choose to remain in employment following its introduction. Sensitivity analysis concerning employment alternatives is conducted by replacing the labour supply module of SimPaths with alternative assumptions on the behavioural responses to the policy change.

Ongoing work investigates the employment effects and associated impact on psychological distress of the job search requirements of Universal Credit (UC), a major social protection scheme in the UK. The analysis distinguishes two channels by which conditionality affects employment outcomes. On the one hand, being on UC forces individuals to search more. On the other, the same search requirements impact mental health, reducing search effectiveness. Two more effects are identified. Individuals who are successful in their job search get a boost to their mental health associated with both entering employment and exiting UC. However, some individuals might be deterred by the search requirements from taking-up UC, resulting in reduced coverage and effectiveness of the policy. All of these effects are reinforced over time, hence requiring a dynamic analysis.

A separate analysis explores the impact of maintenance payments on mothers, fathers, and children. Both the provision and the receipt of maintenance payments impact labour supply decisions and income dynamics. These in turn affect the life course trajectories of children.

Other applications focus less on the impact of policies, and more on life course dynamics. Van de Ven et al. (2024) study the individual and societal implications of increased care needs associated with population ageing over the next five decades in the UK. The analysis projects a sharp rise in the incidence of need for social care, from just under 4.0 million in 2020 to 7.6 million by 2070, with 70% of this increase driven by people aged 80 and over. The coincident costs of social care are projected to rise from £35 billion in 2020 (1.6% of GDP) to 152 billion by 2070 (2.8% of GDP), with a large fraction of this cost being sustained by depleted savings.

Informal social care provided by partners is projected to account for over half of all social care throughout the simulated time period, with the formal sector being the next largest provider accounting for approximately 15% of provisions. Van de Ven et al. (2024) also compare simulations where individuals make decisions based on future expectations (the 'expectations explicit' approach described in Section 3) with simulations without forward looking behaviour. They show that the anticipation of the need to provide informal care leads to reduced employment and earnings. Yet the model projections suggest that precautionary savings set aside against the risk of requiring formal social care more than off-set the above factors, so that the net impact of care on savings to age 55 is positive when averaged over the population cohorts born between 1990 and 1999.

Richiardi et al. (2024) use SimPaths to explore the feedback loops between health, family and labour market outcomes, and the associated implications for income and health inequalities over alternative time horizons. They devise a computational procedure to isolate direct and indirect (mediated) effects in a microsimulation framework, consisting in artificially shocking one domain (e.g. by forcing a partnership dissolution on the simulated individuals) and comparing simulations where the impact of the shock is allowed to affects other domains (e.g. because labour market outcomes depend on, amongst other things, partnership status) with simulations where the evolution of the other domains remains unaffected and follow baseline simulations – the shock is only allowed to influence the future evolution of the shocked variable itself. Results indicate that partnership status has significant effects on other life domains, and highlight attenuation mechanisms that facilitate bouncing back to a partnered status following a union dissolution. On the other hand, health is found to have fewer connections to other life domains, with limited feedback that attenuate or exacerbate the effects of an adverse shock.

A number of ongoing funded projects provide further applications, together with the need for extending and updating the model. Major areas of development are the inclusion of measures of well-being, interaction with macro models, adoption of a spatially disaggregated synthetic population as a starting point of the simulations, and improved modelling of wealth dynamics (and associated impacts on health). The latter will distinguish between housing, pensions, other assets and unsecured debt. Private transfers between households (e.g. parents helping with the home purchase of their children) will also be included, with implications for intergenerational fairness and the intergenerational transmission of inequality. Self-rated health and psychological distress are being replaced by the physical score component (PSC) and mental score component (MCS) respectively of the SF-12 health assessment. More health outcomes are also being added, including loneliness, nutrition, and tobacco consumption. Measures of neighbourhood safety and housing quality are being introduced as pathways between socio-economic position and health outcomes. A separate workstream looks at improving modelling of external migration, which is currently treated as a residual (see Section 3.1.1). Estimates are being updated to include more recent waves of the input data, account for migrant status and ethnicity, and improve the modelling of health outcomes (including mortality). Finally, as already mentioned simplified models are being estimated for Germany, Greece, Hungary, Italy, Poland, Spain and Sweden.

6 Funding and governance

While the open source nature of SimPaths imposes no limitation on potential users, the framework is primarily used by academic researchers. It has no institutional backing nor benefits from institutional funding. Rather, it is developed mostly through research grants. A first version of the model, then called LABSim, was developed with funding from the National Institute for the Analysis of Public Policies (INAPP), an Italian government institution (2016-2017; 2019-2022)[27], building on a simpler model developed for Eurofound, the EU Agency for the improvement of living and working conditions (2015)[28]. The modelling framework received further funding from the UK Health Foundation (2021-2022)[29], the UK National Institute for Health Research (NIHR, 2021-2028)[30], the Joint Programming Initiative More Years, Better Lives (JPI MYBL, 2021-2025)[31], the European Research Council (ERC, 2021-2025)[32], the European Commission Horizon Europe programme (HE, 2023-2027)[33], the European Spatial Planning Observation Network (ESPON, 2023-2025)[34], and the

[27] Project “Investigating Economic Insecurity: A Microsimulation approach”.

[28] Project “Anticipating the future trend of female labour market participation and its impact on economic growth”.

[29] Project “Understanding the impacts of income and welfare policy responses to COVID-19 on inequalities in mental health: A microsimulation model”.

[30] Projects “Evaluation of the health impacts of Universal Credit: A mixed methods study”, and “The HealthMod Cluster: Enhancing Policy Modelling Capabilities to Tackle the Economic Determinants of Health and Health Inequality”.

[31] Project “Caring Over the Lifecycle: the Roles of Families and Welfare States Today and Into the Future (WELLCARE)”.

[32] Project “Health Equity of Economic Determinants (HEED): A Pan-European Microsimulation model for Health impacts of Income and Social Security Policies”.

[33] Project “Sustainable Welfare: Rethinking the roles of Family, Market and State (SUSTAINWELL)”.

[34] Project ““Overlapping crises: (Re)shaping the future of regional labour markets (OVERLAP)”.

Collaboration of Humanities and Social Sciences in Europe – NORFACE network (CHANSE, 2025-2028)[35]. The two main institutions involved in the modelling work around the SimPaths framework for the above projects are the Centre for Microsimulation and Policy Analysis (CeMPA) at the University of Essex, and the MRC/CSO Social and Public Health Sciences Unit at the University of Glasgow.

As with all open-source projects, governance presents challenges and opportunities. In terms of the six open-source governance models identified by Neary et al. (2020)[36], SimPaths initially followed a Founder-leader configuration, and is now migrating towards a Self-appointing council or board structure.[37] Active developers meet with a weekly frequency to coordinate project developments, and maintain single versions of the master code for the UK and the EU models respectively. "SimPaths community meetings" are held with a monthly frequency, to support adopters and users around the globe (these are mainly PhD students and policy analysts). Procedural rules are being drafted to guide contributions and ensure, as far as possible, a shared and unitary management of the project. Ultimately, the project rests on trust between developers, and on the incentives provided by the benefits of an enlarged team of developers in the context of a highly competitive funding environment.

7 Conclusion

In this paper we have introduced SimPaths, a novel dynamic microsimulation model of individual life course trajectories covering demographic, family, health and work-related events, and discussed parameterisation to the United Kingdom. The innovative features of the model lie in the flexible integration with an external tax-benefit model, and in the structural behavioural modelling at the core of individual decision making over important margins of interest. Extensive validation over the period 2011-2019 shows that the model is able to replicate well the joint evolution of individual characteristics.

SimPaths is fully open source with increasingly detailed documentation, which sets it apart from most comparable models in the existing literature. The objective of the developmental team in this regard is to facilitate, and thereby encourage researcher entry into a field that we believe presents extensive opportunities to further understanding of a wide range of practically important phenomena. From theoretical descriptions of individual decision making,

[35] Project "WELLSIM – A life course microsimulation perspective on multi-dimensional well-being in five European countries".

[36] "Do-ocracy", Founder-leader, Self-appointing council or board, Electoral, Corporate-backed, and Foundation-backed.

[37] For a discussion of the issues involved in the governance of open-source software projects, see the special issue of the *Journal of Management and Governance* on "Roundtable on the Governance of Open Source Software" (Volume 11, Issue 2, May 2007), and Feller et al. (2005).

sustainability of personal and public finances, and the nature of burdens and opportunities to which people are and will be subject during the prospective half century, there is much of interest to explore.

The open-source nature and governance structure of SimPaths is a radical departure from the major past and current dynamic microsimulation endeavours, which typically developed as proprietary, institutional models. While some of them passed the test of time, few have produced a consistent stream of academic outputs over the years.[38] History will tell whether SimPaths will remain an ephemeral convergence of interests by a relatively small group of researchers, or will evolve into a broader research infrastructure freely available to the scientific and policy communities.

[38] An exception, albeit in the static microsimulation camp, is EUROMOD – see Sutherland (2018).

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Appendix A Estimates

The estimates for the utility functions used in the labour supply model are separately described in Richiardi and He (2021).

The estimates for the psychological distress models are separately described in Kopasker et al. (2024).

Estimation sample is UKHLS waves “a”-“h”, unless differently specified.

Table A.1: Process E1a: Probability of being in education.
Sample: Individuals aged 16-29 in continuous education.

Probit In education	(1) Coef.	(2) s.e.
Gender = 1, Male	-0.02	0.03
Age	-1.23***	0.07
Age Squared	0.03***	0.00
Mother's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.10**	0.04
Mother's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.12**	0.06
Father's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.30***	0.04
Father's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.30***	0.05
Region = 1, North East	-0.02	0.09
Region = 2, North West	-0.26***	0.07
Region = 3, Yorkshire and the Humber	-0.13*	0.07
Region = 4, East Midlands	-0.22***	0.07
Region = 5, West Midlands	-0.13*	0.07
Region = 6, East of England	-0.09	0.07
Region = 8, South East	-0.21***	0.06
Region = 9, South West	-0.24***	0.07
Region = 10, Wales	-0.20**	0.09
Region = 11, Scotland	-0.28***	0.08
Region = 12, Northern Ireland	-0.07	0.08
Year	-0.12***	0.01
Constant	16.65***	0.74
Observations	11,841	
R2	0.134	
Chi2	1160	
Log-likelihood	-5413	

*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Process E1b: Probability of being in education.
Sample: Individuals aged 16-35 not in continuous education.

Probit In education	(1) Coef.	(2) s.e.
Gender = 1, Male	-0.12***	0.04
Age	-0.36***	0.02
Age Squared	0.00***	0.00
Lagged Educational Attainment: 3 Category = 2 Other Higher/A-level/GCSE,	0.08*	0.05
Lagged Educational Attainment: 3 Category = 3 Other/No Qualification,	-0.38***	0.10
Lagged Employment Status: 3 Category = Student,	1.78***	0.05
Lagged Employment Status: 3 Category = Not employed,	0.26***	0.04
Lagged Number of Children in Household,	0.08***	0.02
Lagged Number of Children aged 0-2 in Household,	-0.23***	0.06
Mother's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.20***	0.05
Mother's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.24***	0.06
Father's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.15***	0.05
Father's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.27***	0.06
Region = 1, North East	0.05	0.09
Region = 2, North West	-0.15**	0.07
Region = 3, Yorkshire and the Humber	-0.18**	0.08
Region = 4, East Midlands	-0.30***	0.08
Region = 5, West Midlands	-0.15**	0.07
Region = 6, East of England	-0.24***	0.07
Region = 8, South East	-0.20***	0.06
Region = 9, South West	-0.41***	0.08
Region = 10, Wales	-0.06	0.09
Region = 11, Scotland	0.08	0.07
Region = 12, Northern Ireland	-0.17*	0.10
Year	-0.01	0.01
Constant	4.60***	0.32
Observations	51,525	
R2	0.393	
Chi2	3151	
Log-likelihood	-5278	

*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Process E2: Educational attainment.
Sample: Respondents from Process 1a who have left education.

Ordered probit Educational attainment: High, Medium, Low	(1) Coef.	(2) s.e.
Gender = 1, Male	-0.03	0.03
Age	1.43***	0.10
Age Squared	-0.03***	0.00
Mother's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.13***	0.04
Mother's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.26***	0.06
Father's Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.04	0.04
Father's Educational Attainment: 3 Category = 3, Other/No Qualification	-0.15***	0.06
Region = 1, North East	0.04	0.10
Region = 2, North West	0.12*	0.07
Region = 3, Yorkshire and the Humber	0.02	0.07
Region = 4, East Midlands	0.08	0.07
Region = 5, West Midlands	-0.02	0.08
Region = 6, East of England	0.20***	0.07
Region = 8, South East	0.17***	0.06
Region = 9, South West	0.20***	0.07
Region = 10, Wales	-0.09	0.09
Region = 11, Scotland	0.09	0.09
Region = 12, Northern Ireland	0.04	0.09
Year	0.02**	0.01
/cut1	15.70***	1.05
/cut2	19.72***	1.10
Observations	11,431	
R2	0.304	
Chi2	1076	
Log-likelihood	-4,663	

*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Process H1a: Self-rated Health Status.
Sample: Individuals aged 16-29 in continuous education.

Ordered probit Self-rated health status, categories 1 to 5	(1) Coef.	(2) s.e.
Gender = 1, Male	0.15***	0.04
Age	0.27**	0.11
Age Squared	-0.01**	0.00
Lagged Annual Household Income Quintile = 2,	-0.04	0.05
Lagged Annual Household Income Quintile = 3,	-0.06	0.07
Lagged Annual Household Income Quintile = 4,	0.13	0.11
Lagged Annual Household Income Quintile = 5,	-0.01	0.16
Lagged Self-rated Health = 1,	-2.62***	0.32
Lagged Self-rated Health = 2,	-2.17***	0.10
Lagged Self-rated Health = 3,	-1.58***	0.06
Lagged Self-rated Health = 4,	-0.83***	0.05
Region = 1, North East	-0.00	0.10
Region = 2, North West	0.11	0.08
Region = 3, Yorkshire and the Humber	0.02	0.08
Region = 4, East Midlands	-0.01	0.08
Region = 5, West Midlands	0.18**	0.08
Region = 6, East of England	-0.06	0.08
Region = 8, South East	0.06	0.07
Region = 9, South West	0.05	0.08
Region = 10, Wales	0.14	0.10
Region = 11, Scotland	0.07	0.09
Region = 12, Northern Ireland	0.22**	0.10
Year	-0.01	0.01
/cut1	-1.02	1.12
/cut2	0.12	1.11
/cut3	1.33	1.11
/cut4	2.71**	1.11
Observations	4,549	
R2	0.135	
Chi2	996.2	
Log-likelihood	-4747	

*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Process H1b: Self-rated Health Status.
Sample: Individuals aged 16 or older not in continuous education.

Ordered probit Self-rated health status, categories 1 to 5	(1) Coef.	(2) s.e.
Gender = 1, Male	-0.00	0.01
Age	-0.01***	0.00
Age Squared	0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.10***	0.01
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.18***	0.01
Lagged Employment Status: 3 Category = Student,	0.10***	0.03
Lagged Employment Status: 3 Category = Not employed,	-0.11***	0.01
Lagged Annual Household Income Quintile = 2,	0.11***	0.02
Lagged Annual Household Income Quintile = 3,	0.16***	0.02
Lagged Annual Household Income Quintile = 4,	0.21***	0.02
Lagged Annual Household Income Quintile = 5,	0.32***	0.02
Lagged Self-rated Health = 1,	-3.80***	0.03
Lagged Self-rated Health = 2,	-2.61***	0.02
Lagged Self-rated Health = 3,	-1.70***	0.01
Lagged Self-rated Health = 4,	-0.87***	0.01
Lagged Household Type: 4 Category = Couple with children,	0.04***	0.01
Lagged Household Type: 4 Category = Single without children,	-0.02*	0.01
Lagged Household Type: 4 Category = Single with children,	0.04*	0.02
Region = 1, North East	-0.01	0.02
Region = 2, North West	-0.01	0.02
Region = 3, Yorkshire and the Humber	0.02	0.02
Region = 4, East Midlands	0.03	0.02
Region = 5, West Midlands	0.01	0.02
Region = 6, East of England	0.00	0.02
Region = 8, South East	0.01	0.02
Region = 9, South West	0.02	0.02
Region = 10, Wales	0.03	0.02
Region = 11, Scotland	0.01	0.02
Region = 12, Northern Ireland	0.02	0.02
Year	-0.01***	0.00
/cut1	-4.40***	0.05
/cut2	-3.13***	0.05
/cut3	-1.86***	0.05
/cut4	-0.44***	0.05
Observations	118,011	
R2	0.237	
Chi2	34000	
Log-likelihood	-132736	

** p<0.01, ** p<0.05, * p<0.1

Table A.6: Process H2b: Probability of becoming long-term sick or disabled.
Sample: Individuals aged 16 or older not in continuous education.

Probit Long-term sickness or disability	(1) Coef.	(2) s.e.
Self-rated Health	-0.48***	0.02
Gender = 1, Male	0.03	0.03
Age	0.11***	0.01
Age Squared	-0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	0.12***	0.04
Educational Attainment: 3 Category = 3, Other/No Qualification	0.22***	0.05
Lagged Annual Household Income Quintile = 2,	-0.50***	0.04
Lagged Annual Household Income Quintile = 3,	-0.58***	0.04
Lagged Annual Household Income Quintile = 4,	-0.69***	0.05
Lagged Annual Household Income Quintile = 5,	-0.86***	0.05
Lagged Self-rated Health,	-0.10***	0.02
Lagged Long-term Sick or Disabled,	1.87***	0.04
Lagged Household Type: 4 Category = Couple with children,	-0.18***	0.04
Lagged Household Type: 4 Category = Single without children,	0.16***	0.04
Lagged Household Type: 4 Category = Single with children,	-0.14**	0.06
Region = 1, North East	0.16**	0.08
Region = 2, North West	0.13*	0.07
Region = 3, Yorkshire and the Humber	0.13*	0.07
Region = 4, East Midlands	-0.03	0.08
Region = 5, West Midlands	-0.07	0.07
Region = 6, East of England	0.04	0.07
Region = 8, South East	0.05	0.07
Region = 9, South West	0.11	0.07
Region = 10, Wales	0.11	0.08
Region = 11, Scotland	0.15**	0.07
Region = 12, Northern Ireland	0.18**	0.08
Year	-0.02**	0.01
Constant	-2.55***	0.23
Observations	118,011	
R2	0.635	
Chi2	7485	
Log-likelihood	-6269	

*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Process P1a: Probability of leaving the parental home.
Sample: All non-student respondents living with a parent.

Probit Leaving parental home	(1) Coef.	(2) s.e.
Gender = 1, Male	0.16***	0.02
Age	-0.08***	0.00
Age Squared	0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.07***	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.24***	0.04
Lagged Employment Status: 4 Category = Student,	-0.27***	0.05
Lagged Employment Status: 4 Category = Sick / disabled,	-0.05	0.07
Lagged Employment Status: 4 Category = Not employed,	-0.17***	0.04
Lagged Annual Household Income Quintile = 2,	-0.12***	0.04
Lagged Annual Household Income Quintile = 3,	-0.17***	0.04
Lagged Annual Household Income Quintile = 4,	-0.28***	0.04
Lagged Annual Household Income Quintile = 5,	-0.49***	0.05
Region = 1, North East	0.11*	0.06
Region = 2, North West	-0.04	0.05
Region = 3, Yorkshire and the Humber	0.01	0.05
Region = 4, East Midlands	0.03	0.05
Region = 5, West Midlands	-0.03	0.05
Region = 6, East of England	0.01	0.05
Region = 8, South East	0.08*	0.05
Region = 9, South West	0.01	0.05
Region = 10, Wales	-0.01	0.07
Region = 11, Scotland	-0.15***	0.06
Region = 12, Northern Ireland	-0.04	0.08
Year	-0.01	0.01
Constant	0.72***	0.12
Observations	117,942	
R2	0.182	
Chi2	3090	
Log-likelihood	-14292	

*** p<0.01, ** p<0.05, * p<0.1

Table A8: Process U1a: Probability of entering a partnership.
Sample: All single respondents aged 16 and older, in continuous education.

Probit Entering partnership	(1) Coef.	(2) s.e.
Gender = 1, Male	0.04	0.15
Age	0.71*	0.40
Age Squared	-0.01	0.01
Lagged Annual Household Income Quintile = 2,	-0.41*	0.21
Lagged Annual Household Income Quintile = 3,	-0.19	0.27
Lagged Annual Household Income Quintile = 4,	-0.43	0.37
Lagged Annual Household Income Quintile = 5,	0.00	0.00
Lagged Number of Children in Household,	0.16	0.24
Lagged Number of Children aged 0-2 in Household,	0.15	0.38
Lagged Self-rated Health,	0.00	0.09
Region = 1, omitted	-	-
Region = 2, North West	0.53	0.41
Region = 3, Yorkshire and the Humber	0.30	0.44
Region = 4, East Midlands	0.30	0.41
Region = 5, West Midlands	-0.19	0.50
Region = 6, East of England	-0.18	0.49
Region = 8, South East	0.08	0.47
Region = 9, South West	-0.60	0.54
Region = 10, omitted	-	-
Region = 11, Scotland	0.17	0.43
Region = 12, omitted	-	-
Year	-0.20***	0.05
Constant	-8.29**	4.12
Observations	1,759	
R2	0.181	
Chi2	85.50	
Log-likelihood	-210.6	

*** p<0.01, ** p<0.05, * p<0.1

Table A.9: Process U1b: Probability of entering a partnership.
Sample: All single respondents aged 16 and older, not in continuous education.

Probit Entering a partnership	(1) Coef.	(2) s.e.
Gender = 1, Male	-0.06**	0.03
Age	-0.01*	0.01
Age Squared	-0.00**	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.04	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.07	0.05
Lagged Employment Status: 5 Category = Student,	-0.37***	0.08
Lagged Employment Status: 5 Category = Not employed,	-0.15***	0.04
Lagged Annual Household Income Quintile = 2,	-0.22***	0.05
Lagged Annual Household Income Quintile = 3,	-0.36***	0.05
Lagged Annual Household Income Quintile = 4,	-0.40***	0.05
Lagged Annual Household Income Quintile = 5,	-0.57***	0.05
Lagged Number of Children in Household,	-0.23***	0.02
Lagged Number of Children aged 0-2 in Household,	-0.20***	0.05
Lagged Self-rated Health,	-0.00	0.01
Region = 1, North East	-0.09	0.08
Region = 2, North West	0.00	0.06
Region = 3, Yorkshire and the Humber	0.05	0.07
Region = 4, East Midlands	0.01	0.06
Region = 5, West Midlands	0.03	0.06
Region = 6, East of England	-0.02	0.07
Region = 8, South East	-0.04	0.06
Region = 9, South West	0.04	0.06
Region = 10, Wales	0.10	0.08
Region = 11, Scotland	-0.04	0.07
Region = 12, Northern Ireland	-0.41***	0.11
Year	-0.01	0.01
Constant	-0.48**	0.19
Observations	93,826	
R2	0.136	
Chi2	1385	
Log-likelihood	-8151	

*** p<0.01, ** p<0.05, * p<0.1

Table A.10: Process U2: Probability of partnership break-up.
Sample: Female member of a couple aged 16 or older, not in continuous education.

Probit Partnership dissolution	(1) Coef.	(2) s.e.
Age	-0.02	0.02
Age Squared	0.00	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	0.04	0.09
Educational Attainment: 3 Category = 3, Other/No Qualification	0.14	0.14
Lagged Personal Non-benefit Gross Income,	-0.07	0.07
Lagged Personal Non-benefit Gross Income Squared,	0.01	0.01
Lagged Number of Children in Household,	0.01	0.05
Lagged Number of Children aged 0-2 in Household,	-0.02	0.09
Lagged Self-rated Health,	-0.05	0.04
Spouse's Educational Level: 3 Category = 2, Other Higher/A-level/GCSE	0.26***	0.10
Spouse's Educational Level: 3 Category = 3, Other/No Qualification	0.24*	0.14
Lagged Spouse's Self-rated Health,	-0.06	0.04
Lagged Differential Personal Non-Benefit Gross Income,	-0.02	0.02
Lagged Number of Years in Partnership,	-0.02***	0.00
Lagged Difference in Age between partners in a couple,	0.02***	0.01
Household Type: 4 Category = Couple with children,	-0.05	0.12
Lagged Couple Employment Status = Employed, spouse not,	0.23	0.17
Lagged Couple Employment Status = Not employed, spouse employed,	-0.29*	0.15
Lagged Couple Employment Status = Both not employed,	0.24	0.23
Region = 1, North East	0.03	0.20
Region = 2, North West	0.03	0.16
Region = 3, Yorkshire and the Humber	-0.11	0.18
Region = 4, East Midlands	0.10	0.17
Region = 5, West Midlands	-0.16	0.19
Region = 6, East of England	-0.05	0.17
Region = 8, South East	0.04	0.16
Region = 9, South West	0.11	0.16
Region = 10, Wales	0.00	0.22
Region = 11, Scotland	-0.09	0.20
Region = 12, Northern Ireland	-0.05	0.36
Year	0.00	0.02
Constant	-1.42**	0.58
Observations	50,347	
R2	0.131	
Chi2	160	
Log-likelihood	-724	

*** p<0.01, ** p<0.05, * p<0.1

Table A.11: Process F1a: Probability of giving birth to a child.
Sample: Women aged 18-29 in continuous education.

Probit Giving birth	(1) Coef.	(2) s.e.
Age	-0.13	0.53
Age Squared	0.00	0.01
UK Fertility Rate	0.17*	0.09
Lagged Household Income Quintile (Ref = 1st Quintile)		
2nd Quintile	-0.63**	0.26
3rd Quintile	0.24	0.25
4th Quintile	0.00	
5th Quintile	-0.64*	0.38
Lagged Number of Children in the Household	0.03	0.23
Lagged Number of Children Aged 0-2 in the Household	0.32	0.68
Lagged Self-rated Health Status	0.06	0.12
Lagged Partnership Status (Ref = Married)		
Single	-0.19	0.52
Previously Partnered	1.69*	1.01
Constant	-11.91	9.92
Observations	1,477	
R2	0.0955	
Chi2	36	
Log-likelihood	-73	

*** p<0.01, ** p<0.05, * p<0.1

Table A.12: Process F1b: Probability of giving birth to a child.
Sample: Women aged 18-44 not in continuous education.

Probit Giving birth	(1) Coef.	(2) s.e.
Age	0.17***	0.02
Age Squared	-0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	0.05	0.04
Educational Attainment: 3 Category = 3, Other/No Qualification	0.10	0.07
UK Fertility Rate	0.21***	0.01
Lagged Employment Status: 3 Category = Student,	-0.23***	0.09
Lagged Employment Status: 3 Category = Not employed,	0.16***	0.04
Lagged Annual Household Income Quintile = 2,	-0.07	0.06
Lagged Annual Household Income Quintile = 3,	-0.08	0.06
Lagged Annual Household Income Quintile = 4,	-0.14**	0.06
Lagged Annual Household Income Quintile = 5,	-0.03	0.06
Lagged Number of Children in Household,	-0.12***	0.02
Lagged Number of Children aged 0-2 in Household,	0.17***	0.04
Lagged Self-rated Health,	0.06***	0.02
Lagged Marital Status = Single never married,	-0.62***	0.05
Lagged Marital Status = Previously partnered,	-0.24***	0.08
Region = 1, North East	-0.19**	0.09
Region = 2, North West	-0.20***	0.06
Region = 3, Yorkshire and the Humber	-0.27***	0.07
Region = 4, East Midlands	-0.14**	0.07
Region = 5, West Midlands	-0.07	0.07
Region = 6, East of England	-0.20***	0.07
Region = 8, South East	-0.12**	0.06
Region = 9, South West	-0.21***	0.07
Region = 10, Wales	-0.07	0.08
Region = 11, Scotland	-0.23***	0.07
Region = 12, Northern Ireland	-0.13	0.09
Constant	-16.44***	0.97
Observations	25,646	
R2	0.113	
Chi2	906	
Log-likelihood	-4801	

*** p<0.01, ** p<0.05, * p<0.1

Table A.13: Process HO1: Probability of being a homeowner.
Sample: Individuals aged 16 and above.

Probit Home ownership	(1) Coef.	(2) s.e.
Gender	-0.09***	0.03
Age	0.07***	0.01
Age Squared	-0.00***	0.00
Employment Status: 5 Category = 2, Student	-0.43***	0.13
Employment Status: 5 Category = 3, Not Employed	-0.06*	0.03
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.07**	0.04
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.40***	0.05
Lagged Self-rated Health	0.09***	0.01
Lagged Adjusted Annual Household Income Quintile = 2	0.47***	0.05
Lagged Adjusted Annual Household Income Quintile = 3	0.89***	0.05
Lagged Adjusted Annual Household Income Quintile = 4	1.30***	0.05
Lagged Adjusted Annual Household Income Quintile = 5	1.67***	0.06
Lagged Inverse Hyperbolic Sine Gross Non-employment or Benefit Personal Income	0.05***	0.00
Region = 1, North East	0.34***	0.08
Region = 2, North West	0.60***	0.06
Region = 3, Yorkshire and the Humber	0.40***	0.07
Region = 4, East Midlands	0.45***	0.07
Region = 5, West Midlands	0.43***	0.07
Region = 6, East of England	0.26***	0.06
Region = 8, South East	0.26***	0.06
Region = 9, South West	0.37***	0.06
Region = 10, Wales	0.58***	0.08
Region = 11, Scotland	0.31***	0.07
Region = 12, Northern Ireland	0.57***	0.09
Lagged Household Type: 4 Category = 2, Couples with Children	0.40***	0.03
Lagged Household Type: 4 Category = 3, Single with No Children	0.26	0.32
Lagged Household Type: 4 Category = 4, Single with Children	0.28	0.26
Lagged Spouse's Labour Force Status: 3 Category = 2, Student	-0.36***	0.11
Lagged Spouse's Labour Force Status: 3 Category = 3, Not Employed	-0.08**	0.03
Year	-0.00	0.00
Constant	-3.61***	0.16
Observations	75,437	
R2	0.256	
Chi2	3376	
Log-likelihood	-29043	

*** p<0.01, ** p<0.05, * p<0.1

Table A.14: Process R1a: Probability of retiring.
Sample: Non-partnered individuals aged 50+ who are not yet retired.

Probit Retiring	(1) Coef.	(2) s.e.
Gender = 1, Male	0.21***	0.04
Age	0.43***	0.04
Age Squared	-0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.08	0.06
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.12*	0.06
Reached State Pension Age = 1, Yes	0.78***	0.07
Lagged Employment Status: Not employed,	0.99***	0.07
Lagged Adjusted Annual Household Income Quintile = 2,	0.43***	0.07
Lagged Adjusted Annual Household Income Quintile = 3,	0.30***	0.09
Lagged Adjusted Annual Household Income Quintile = 4,	0.39***	0.09
Lagged Adjusted Annual Household Income Quintile = 5,	0.50***	0.09
Lagged Long-term Sick or Disabled,	-0.03	0.06
Region = 1, North East	0.01	0.11
Region = 2, North West	0.04	0.09
Region = 3, Yorkshire and the Humber	-0.09	0.10
Region = 4, East Midlands	-0.13	0.10
Region = 5, West Midlands	-0.08	0.10
Region = 6, East of England	-0.15	0.09
Region = 8, South East	-0.15*	0.08
Region = 9, South West	0.00	0.09
Region = 10, Wales	0.01	0.11
Region = 11, Scotland	-0.07	0.09
Region = 12, Northern Ireland	-0.02	0.11
Year	-0.01	0.01
Constant	-17.60***	1.35
Observations	29,065	
R2	0.491	
Chi2	1559	
Log-likelihood	-2246	

*** p<0.01, ** p<0.05, * p<0.1

Table A16: Process R1b: Probability of retiring.
Sample: Partnered individuals aged 50+ who are not yet retired.

Probit Retiring	(1) Coef.	(2) s.e.
Gender = 1, Male	0.01	0.03
Age	0.52***	0.04
Age Squared	-0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.12***	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.23***	0.04
Reached State Pension Age = 1, Yes	0.43***	0.05
Lagged Employment Status: Not employed,	0.76***	0.05
Lagged Adjusted Annual Household Income Quintile = 2,	0.15**	0.07
Lagged Adjusted Annual Household Income Quintile = 3,	0.22***	0.07
Lagged Adjusted Annual Household Income Quintile = 4,	0.27***	0.07
Lagged Adjusted Annual Household Income Quintile = 5,	0.43***	0.07
Lagged Long-term Sick or Disabled = 1,	-0.06	0.06
Spouse of Pension Age = 1, Yes	0.07*	0.04
Spouse's Labour Force Status: 3 Category = Student,	0.04	0.34
Spouse's Labour Force Status: 3 Category = Not employed,	0.33***	0.03
Spouse's Disability Status = 1,	-0.10	0.07
Region = 1, North East	0.32***	0.08
Region = 2, North West	0.18***	0.06
Region = 3, Yorkshire and the Humber	0.28***	0.07
Region = 4, East Midlands	0.22***	0.07
Region = 5, West Midlands	0.13**	0.07
Region = 6, East of England	0.10	0.06
Region = 8, South East	0.03	0.06
Region = 9, South West	0.07	0.06
Region = 10, Wales	0.19**	0.08
Region = 11, Scotland	0.15**	0.07
Region = 12, Northern Ireland	0.11	0.09
Reached State Pension Age = 1#Lagged Employment Status: Not employed	0.62***	0.07
Year	0.00	0.01
Constant	-20.34***	1.15
Observations	27,198	
R2	0.286	
Chi2	3328	
Log-likelihood	-5561	

*** p<0.01, ** p<0.05, * p<0.1

Table A17: Process I3a selection: Probability of receiving capital income.
Sample: Individuals aged 16 - 29 who are in continuous education.

Logit Receiving capital income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Age	1.27	0.41
Age Squared	-0.03	0.01
Lagged Self-rated Health,	0.16	0.08
Lagged Inverse Hyperbolic Sine Gross Employment Personal Income,	-0.07	0.02
Lagged Inverse Hyperbolic Sine Gross Capital Income,	0.20	0.03
Region = 1, North East	-0.08	0.32
Region = 2, North West	-0.18	0.30
Region = 3, Yorkshire and the Humber	0.17	0.28
Region = 4, East Midlands	0.56	0.29
Region = 5, West Midlands	0.14	0.31
Region = 6, East of England	0.48	0.30
Region = 8, South East	0.17	0.24
Region = 9, South West	0.62	0.29
Region = 10, Wales	0.92	0.36
Region = 11, Scotland	0.20	0.33
Region = 12, Northern Ireland	0.24	0.38
Year	-0.04	0.03
Constant	-14.46	4.10
Observations	950	
R2	0.0859	
Chi2	71.52	
Log-likelihood	-653.8	

*** p<0.01, ** p<0.05, * p<0.1

Table A18: Process I3b selection: Probability of receiving capital income.
Sample: Individuals aged 16+ who are not in continuous education.

Logit Receiving capital income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Age	0.00	0.00
Age Squared	0.00	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.35	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.70	0.04
Lagged Employment Status: 3 Category = Student,	-0.34	0.15
Lagged Employment Status: 3 Category = Not employed,	0.43	0.09
Lagged Household Type: 4 Category = Couples with children,	-0.39	0.03
Lagged Household Type: 4 Category = Singles without children,	-0.01	0.03
Lagged Household Type: 4 Category = Singles with children,	-0.35	0.15
Lagged Self-rated Health,	0.12	0.01
Lagged Inverse Hyperbolic Sine Gross Employment Personal Income L =1,	0.05	0.01
Lagged Inverse Hyperbolic Sine Gross Capital Income L = 1,	0.36	0.01
Inverse Hyperbolic Sine Gross Employment Personal Income L = 2,	0.07	0.01
Lagged Inverse Hyperbolic Sine Gross Capital Income L = 2,	0.21	0.01
Region = 1, North East	-0.01	0.08
Region = 2, North West	0.14	0.06
Region = 3, Yorkshire and the Humber	0.18	0.06
Region = 4, East Midlands	0.36	0.06
Region = 5, West Midlands	0.29	0.06
Region = 6, East of England	0.31	0.06
Region = 8, South East	0.40	0.06
Region = 9, South West	0.37	0.06
Region = 10, Wales	0.15	0.08
Region = 11, Scotland	0.05	0.07
Region = 12, Northern Ireland	0.07	0.08
Year	0.02	0.01
Constant	-3.16	0.19
Observations	43,310	
R2	0.298	
Chi2	6594	
Log-likelihood	-24199	

*** p<0.01, ** p<0.05, * p<0.1

Table A19: Process I3a: Amount of capital income.
Sample: Individuals aged 16 - 29 who are in continuous education and receive capital income.

Linear regression Amount of capital income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Age	2.01	0.48
Age Squared	-0.04	0.01
Lagged Self-rated Health,	-0.05	0.08
Lagged Inverse Hyperbolic Sine Gross Employment Personal Income,	0.00	0.03
Lagged Inverse Hyperbolic Sine Gross Capital Income,	0.30	0.04
Region = 1, North East	-0.58	0.38
Region = 2, North West	0.18	0.34
Region = 3, Yorkshire and the Humber	-0.06	0.26
Region = 4, East Midlands	0.09	0.30
Region = 5, West Midlands	0.01	0.32
Region = 6, East of England	0.11	0.32
Region = 8, South East	0.04	0.25
Region = 9, South West	0.27	0.31
Region = 10, Wales	0.97	0.26
Region = 11, Scotland	0.15	0.30
Region = 12, Northern Ireland	0.03	0.38
Year	-0.10	0.04
Constant	-17.71	4.79
Observations	656	
R-squared	0.25	
R2	0.250	
RMSE	2.007	

*** p<0.01, ** p<0.05, * p<0.1

Table A20: Process I3b: Amount of capital income.
Sample: Individuals aged 16+ who are not in continuous education and receive capital income.

Linear regression Amount of capital income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Age	0.05	0.00
Age Squared	0.00	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	0.04	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.10	0.04
Lagged Employment Status: 3 Category = Student,	0.24	0.15
Lagged Employment Status: 3 Category = Not employed,	0.07	0.09
Lagged Household Type: 4 Category = Couples with children,	0.04	0.03
Lagged Household Type: 4 Category = Singles without children,	-0.15	0.03
Lagged Household Type: 4 Category = Singles with children,	0.60	0.15
Lagged Self-rated Health,	0.04	0.01
Lagged Inverse Hyperbolic Sine Gross Employment Personal Income L = 1,	-0.01	0.01
Lagged Inverse Hyperbolic Sine Gross Capital Income L = 1,	0.33	0.01
Lagged Inverse Hyperbolic Sine Gross Employment Personal Income L = 2,	0.02	0.01
Lagged Inverse Hyperbolic Sine Gross Capital Income L = 2,	0.17	0.01
Region = 1, North East	-0.26	0.08
Region = 2, North West	-0.16	0.06
Region = 3, Yorkshire and the Humber	-0.23	0.06
Region = 4, East Midlands	-0.33	0.06
Region = 5, West Midlands	-0.15	0.06
Region = 6, East of England	-0.28	0.06
Region = 8, South East	-0.22	0.06
Region = 9, South West	-0.28	0.06
Region = 10, Wales	-0.18	0.08
Region = 11, Scotland	-0.13	0.07
Region = 12, Northern Ireland	-0.08	0.08
Year	-0.03	0.01
Constant	1.75	0.19
Observations	21,567	
R-squared	0.37	
R2	0.374	
RMSE	1.775	

*** p<0.01, ** p<0.05, * p<0.1

Table A21: Process I4b: Amount of pension income.
Sample: Retired individuals who were retired in the previous year.

Linear regression Amount of pension income	(1) Coef.	(2) s.e.
Age	-0.20***	0.02
Age Squared	0.00***	0.00
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.18***	0.03
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.29***	0.03
Lagged Household Type: 4 Category = Couples with children,	0.01	0.20
Lagged Household Type: 4 Category = Singles without children,	0.01	0.02
Lagged Household Type: 4 Category = Singles with children,	-0.02	0.19
Lagged Self-rated Health,	0.03***	0.01
Lagged Inverse Hyperbolic Sine Gross Private Pension Income L = 1,	0.66***	0.01
Lagged Inverse Hyperbolic Sine Gross Private Pension Income L = 2,	0.26***	0.01
Region = 1, North East	0.02	0.05
Region = 2, North West	0.03	0.04
Region = 3, Yorkshire and the Humber	-0.00	0.05
Region = 4, East Midlands	0.04	0.05
Region = 5, West Midlands	0.03	0.05
Region = 6, East of England	0.04	0.04
Region = 8, South East	0.05	0.04
Region = 9, South West	-0.02	0.04
Region = 10, Wales	0.02	0.05
Region = 11, Scotland	-0.01	0.05
Region = 12, Northern Ireland	-0.05	0.05
Growth Rate	-0.42	1.01
Year	-0.01	0.01
Constant	9.04***	1.13
Observations	26,750	
R-squared	0.82	
R2	0.820	
RMSE	1.423	

*** p<0.01, ** p<0.05, * p<0.1

Table A22: Process I5a_selection: Probability of receiving private pension income. Sample: Retired individuals who were not retired in the previous year.

Logit Receiving private pension income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Above State Pension Age	0.28	0.19
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-0.32*	0.17
Educational Attainment: 3 Category = 3, Other/No Qualification	-0.69***	0.20
Lagged Employment Status: 3 Category = Employed,	0.66***	0.17
Lagged Employment Status: 3 Category = Not Employed,	0.00	0.00
Lagged Household Type: 4 Category = Couples with children,	-0.23	0.32
Lagged Household Type: 4 Category = Singles without children,	-0.05	0.16
Lagged Household Type: 4 Category = Singles with children,	-0.55	1.17
Lagged Self-rated Health,	0.08	0.06
Lagged Hourly Wage Potential,	-0.00	0.00
Region = 1, North East	0.55	0.38
Region = 2, North West	0.44	0.33
Region = 3, Yorkshire and the Humber	0.55	0.34
Region = 4, East Midlands	0.29	0.35
Region = 5, West Midlands	0.47	0.34
Region = 6, East of England	0.40	0.32
Region = 8, South East	0.10	0.30
Region = 9, South West	0.25	0.33
Region = 10, Wales	0.33	0.39
Region = 11, Scotland	0.08	0.35
Region = 12, Northern Ireland	0.14	0.37
Growth rate	-1.51	5.03
Year	-0.04	0.04
Constant	1.70	4.79
Observations	1,202	
R2	0.0488	
Chi2	60.37	
Log-likelihood	-809.3	

*** p<0.01, ** p<0.05, * p<0.1

Table A23: Process I5b_amount: Amount of private pension income.
Sample: Retired individuals who were not retired in the previous year and receive private pension income.

Linear regression Amount of private pension income	(1) Coef.	(2) s.e.
Gender = 1, omitted	-	-
Above State Pension Age	-398.11***	102.91
Educational Attainment: 3 Category = 2, Other Higher/A-level/GCSE	-331.87***	100.65
Educational Attainment: 3 Category = 3, Other/No Qualification	-676.12***	118.93
Lagged Employment Status: 3 Category = Employed,	126.78	110.02
Lagged Employment Status: 3 Category = Not Employed,	0.00	0.00
Lagged Household Type: 4 Category = Couples with children,	-129.88	142.53
Lagged Household Type: 4 Category = Singles without children,	-184.97*	102.33
Lagged Household Type: 4 Category = Singles with children,	-252.97	177.48
Lagged Self-rated Health,	92.07**	36.11
Lagged Hourly Wage Potential,	15.46***	3.84
Region = 1, North East	-358.45	286.18
Region = 2, North West	-426.01	287.05
Region = 3, Yorkshire and the Humber	-140.91	314.69
Region = 4, East Midlands	136.49	382.75
Region = 5, West Midlands	-337.23	303.80
Region = 6, East of England	-118.07	294.96
Region = 8, South East	-194.72	300.50
Region = 9, South West	-284.52	320.28
Region = 10, Wales	-199.00	301.17
Region = 11, Scotland	-174.80	318.36
Region = 12, Northern Ireland	64.55	316.53
Growth rate	5,333.02*	2,733.35
Year	-3.02	23.74
Constant	-4,182.81	2,735.74
Observations	713	
R-squared	0.28	
R2	0.281	
RMSE	1006	

*** p<0.01, ** p<0.05, * p<0.1

Table A24: Process S1a: Probability of receiving informal care, working age population. Sample: Pooled data reported by FRS at annual intervals between 2015/16 and 2019/20, and 2021/22, individuals between age 16 and 64 with a long-term illness or disability.

Probit Receiving informal care	(1) Coef.	(2) s.e.
Education Level (Ref = High)		
Medium	0.0018**	0.0009
Low	-0.0231***	0.0013
Gender (Ref = Women)		
Men	0.0937***	0.0008
under age 25	0.3368***	0.0013
Region (Ref = London)		
North East	0.2579***	0.0022
North West	0.2259***	0.0017
Yorkshire and the Humber	0.1577***	0.0019
East Midlands	0.2917***	0.0020
West Midlands	0.1143***	0.0019
East of England	0.1945***	0.0020
South East	0.1999***	0.0019
South West	0.2308***	0.0019
Wales	-0.0191***	0.0021
Scotland	0.1728***	0.0018
Northern Ireland	0.2750***	0.0024
Constant	-0.7291***	0.0015
Observations	7,248	
Pseudo R2	0.0098	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. Long term illness or disability identified as code 9 of variable empstati.

Table A25: Process S1b: Hours of informal care per week received, working age population. Sample: Pooled data reported by FRS at annual intervals between 2015/16 and 2019/20, and 2021/22, individuals between age 16 and 64 with a long-term illness or disability and in receipt of some informal social care.

Linear regression Hours per week	(1) Coef.	(2) s.e.
Education Level (Ref = High)		
Medium	0.064***	0.0014
Low	0.077***	0.0020
Gender (Ref = Women)		
Men	-0.039***	0.0013
Age (Ref = under age 25)		
25 to 39	-0.308***	0.0022
40+	-0.568***	0.0018
Region (Ref = London)		
North East	-0.008**	0.0032
North West	0.046***	0.0027
Yorkshire and the Humber	0.066***	0.0030
East Midlands	-0.202***	0.0031
West Midlands	0.022***	0.0030
East of England	-0.148***	0.0032
South East	-0.154***	0.0030
South West	-0.251***	0.0031
Wales	-0.033***	0.0033
Scotland	-0.001	0.0029
Northern Ireland	-0.086***	0.0035
Constant	4.213***	0.0028
Observatioms	2,265	
RMSE	1.1671	
R-squared	0.0359	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. Long term illness or disability identified as code 9 of variable empstati.

Table A26: Process S2a: Probability of needing care, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and over without missing variables.

Probit Needing social care	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.040	0.0293
Education Level (Ref = High)		
Medium	0.074*	0.0402
Low	0.180***	0.0420
partner	0.216***	0.0324
need care (lag)	2.429***	0.0342
Self-rated health (Ref = Excellent)		
Very good	0.082	0.0818
Good	0.395***	0.0786
Fair	0.836***	0.0796
Poor	1.404***	0.0903
Age group (Ref = 65-66)		
67-68	-0.322***	0.0580
69-70	-0.241***	0.0554
71-72	-0.177***	0.0538
73-74	-0.084	0.0563
75-76	-0.036	0.0593
77-78	0.032	0.0621
79-80	0.082	0.0662
81-82	0.061	0.0681
83-84	0.194***	0.0683
85+	0.532***	0.0647
Region (Ref = London)		
North East	0.076	0.0945
North West	0.064	0.0759
Yorkshire and the Humber	0.086	0.0795
East Midlands	0.190**	0.0806
West Midlands	0.183**	0.0788
East of England	0.152**	0.0759
South East	0.149**	0.0731
South West	0.123	0.0751
Wales	0.198**	0.0782
Scotland	0.150*	0.0762
Northern Ireland	0.354***	0.0773
Constant	-2.441***	0.1091
Observations	20464	
Proportion positive	0.2906	
Pseudo R2	0.5683	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. "Need care" defined as requiring assistance with any one of the activities of daily living reported by the UKHLS (including instrumental activities).

Table A27: Process S2b: Probability of receiving care, elderly population. Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and over without missing variables.

Probit Receiving care	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.100***	0.0284
Education Level (Ref = High)		
Medium	0.026	0.0387
Low	0.082**	0.0407
partner	0.201***	0.0312
receive care (lag)	2.296***	0.0323
Self-rated health (Ref = Excellent)		
Very good	0.124	0.1012
Good	0.498***	0.0988
Fair	0.916***	0.0995
Poor	1.423***	0.1071
Age group (Ref = 65-66)		
67-68	-0.250***	0.0564
69-70	-0.121**	0.0539
71-72	-0.128**	0.0528
73-74	-0.070	0.0549
75-76	-0.030	0.0591
77-78	0.059	0.0610
79-80	0.141**	0.0628
81-82	0.205***	0.0660
83-84	0.289***	0.0657
85+	0.542***	0.0631
Region (Ref = London)		
North East	0.041	0.0920
North West	0.022	0.0737
Yorkshire and the Humber	0.030	0.0769
East Midlands	0.037	0.0789
West Midlands	0.123	0.0753
East of England	0.074	0.0733
South East	-0.001	0.0725
South West	0.048	0.0729
Wales	0.177**	0.0769
Scotland	0.134*	0.0742
Northern Ireland	0.268***	0.0764
Constant	-2.376***	0.1227
Observations	21,723	
Proportion positive	0.2116	
Pseudo R2	0.5372	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. "Receive care" defined as reported receipt of help with at least one of the activities of daily living reported by the UKHLS in the week preceding the survey.

Table A28: Process S2c: Type of social care received, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and over receiving social care without missing variables.

Multinomial logit Type of social care received	(1) Coef.	(2) s.e.	(3) Coef.	(4) s.e.
Ref = Only informal care (67.1%)	*Formal and informal care (20.6%)*		*Only formal care (12.3%)*	
Education Level (Ref = High)				
Medium	-0.292*	0.1570	-0.387*	0.1950
Low	-0.416***	0.1533	-1.145***	0.1938
partner	-0.576***	0.1050	-1.687***	0.1460
care market (lag, ref = none)				
informal only	-1.244***	0.1160	-2.543***	0.2109
formal and informal	2.987***	0.1364	0.777***	0.2076
only formal	1.607***	0.2781	4.191***	0.2431
aged 85 and over	0.258**	0.1295	-0.006	0.1761
Region (Ref = London)				
North East	-0.020	0.3503	-1.156**	0.5184
North West	0.021	0.2964	-0.197	0.3457
Yorkshire and the Humber	0.456	0.2991	-0.118	0.3707
East Midlands	0.081	0.3118	0.345	0.3586
West Midlands	0.124	0.3065	0.044	0.3583
East of England	0.769***	0.2929	0.359	0.3368
South East	0.493*	0.2940	0.094	0.3353
South West	0.445	0.2892	0.143	0.3363
Wales	0.093	0.2918	-0.272	0.3481
Scotland	0.321	0.2875	-0.310	0.3440
Northern Ireland	0.534**	0.2881	0.017	0.3273
Constant	-1.128***	0.2862	-0.267	0.3131
Observations	5,726			
Pseudo R2	0.4481			

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. "lag" defined as preceding year.

Table A29: Process S2d: Probability of receiving care from the partner, elderly population. Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and over receiving social care, with a partner, and without missing variables.

Probit Receiving care	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	0.254***	0.0864
care from partner (lag)	1.446***	0.0971
formal care received	-0.301***	0.1025
aged 85 and over	-0.548***	0.1142
Region (Ref = London)		
North East	0.190	0.3080
North West	-0.047	0.2286
Yorkshire and the Humber	-0.154	0.2354
East Midlands	-0.106	0.2416
West Midlands	-0.303	0.2281
East of England	-0.043	0.2497
South East	0.235	0.2435
South West	0.121	0.2535
Wales	-0.251	0.2330
Scotland	0.108	0.2485
Northern Ireland	-0.329	0.2318
Constant	0.825***	0.2017
Observations	3,176	
Proportion positive	0.9186	
Pseudo R2	0.2505	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. "lag" defined as preceding year.

Table A30: Process S2e: Probability of receiving supplementary care from persons in addition to the partner, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and over receiving social care from their partner and without missing variables.

Multinomial logit Receiving care	(1) Coef.	(2) s.e.	(3) Coef.	(4) s.e.	(5) Coef.	(6) s.e.
Ref = None (83.1%)	*Daughter (10.5%)*		*Son (4.1%)*		*Other (2.4%)*	
Population share	0.1048		0.0406		0.0238	
Supplementary carer (lag, ref = none)						
Daughter	5.253***	0.2482	2.305***	0.5646	1.332	1.0583
Son	2.345***	0.6135	5.988***	0.3731	2.999***	0.7267
Other	2.479***	0.6058	3.424***	0.6542	6.108***	0.4798
Care from partner (lag)	1.087	0.7086	1.419*	0.8477	16.038***	0.5285
Constant	-4.752***	0.7263	-5.889***	0.8788	-20.810***	0.6080
Observations	1,998					
Pseudo R2	0.5285					

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported. "lag" defined as preceding year.

Table A31: Process S2f: Probability of receiving care from persons other than the partner, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care but not from a partner and without missing variables.

Multinomial logit Receiving care	(1) Coef.	(2) s.e.	(3) Coef.	(4) s.e.
Ref = Daughter only (36.1%)	*Daughter and son (8.2%)*		*Daughter and other (9.3%)*	
Carer(s) (lag, ref: none)				
Daughter only	-2.279***	0.3566	-1.701***	0.3164
Daughter and son	3.415***	0.3473	-2.708**	1.0562
Daughter and other	-0.955	0.6524	3.162***	0.3449
Son only	2.537***	0.5140	-0.147	0.6953
Son and other	2.944**	1.4254	1.149	1.4277
Other only	-0.285	1.0008	0.757	0.6439
Constant	-1.533***	0.1756	-1.586***	0.1931
	Son only (16.4%)		*Son and other (5.2%)*	
Carer(s) (lag, ref: none)				
Daughter only	-4.261***	0.5518	-2.628***	0.6440
Daughter and son	-0.152	0.4764	0.488	0.8075
Daughter and other	-3.164***	1.0421	-1.710	1.0677
Son only	4.475***	0.4313	2.982***	0.5800
Son and other	4.226***	1.0790	7.554***	1.0474
Other only	0.400	0.5718	1.446**	0.7086
Constant	-0.784***	0.1372	-2.216***	0.2696
	Other only (24.9%)			
Carer(s) (lag, ref: none)				
Daughter only	-4.145***	0.4039		
Daughter and son	-1.396*	0.7752		
Daughter and other	-1.607**	0.6581		
Son only	-0.606	0.7058		
Son and other	1.213	1.3403		
Other only	3.771***	0.4380		
Constant	-0.264**	0.1181		
Observations	2,232			
Pseudo R2	0.5311			

*** p<0.01, ** p<0.05, * p<0.1
Note: Regression considers six possible alternatives: none daughter only (reference), daughter and son, daughter and other, son only, son and other, and other only. Robust standard errors reported. "lag" refers to preceding year.

Table A32: Process S2g: Hours of informal care per week provided by partner, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care.

Loglinear regression Hours per week	(1) Coef.	(2) s.e.
Gender (ref = Women)		
Men	0.144*	0.070
Education Level (ref = High)		
Medium	0.056	0.109
Low	0.288***	0.109
Supplementary carer (ref = none)		
Daughter	0.355***	0.127
Son	0.280*	0.153
Other	0.522***	0.161
Formal market	0.264***	0.096
Self-rated health poor	0.659***	0.085
Region (Ref = London)		
North East	0.314	0.254
North West	0.024	0.193
Yorkshire and the Humber	0.131	0.200
East Midlands	-0.053	0.198
West Midlands	-0.267	0.194
East of England	-0.014	0.187
South East	-0.128	0.197
South West	-0.177	0.189
Wales	-0.012	0.187
Scotland	-0.090	0.191
Northern Ireland	-0.026	0.199
Constant	1.641***	0.189
Observations	1,626	
RMSE	1.2093	
R-squared	0.1179	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A33: Process S2h: Hours of informal care per week provided by daughter, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care.

Loglinear regression Hours per week	(1) Coef.	(2) s.e.
Gender (ref = Women)		
Men	-0.053	0.088
Education Level (ref = High)		
Medium	-0.236	0.193
Low	-0.198	0.186
Supplementary carer (ref = none)		
Partner	-0.282***	0.095
Son	-0.002	0.094
Other	-0.124	0.089
Formal market	0.176*	0.091
Self-rated health poor	0.305***	0.091
Region (Ref = London)		
North East	-0.389*	0.233
North West	0.012	0.225
Yorkshire and the Humber	-0.075	0.243
East Midlands	-0.204	0.219
West Midlands	0.013	0.199
East of England	-0.361*	0.201
South East	-0.329	0.202
South West	-0.084	0.209
Wales	0.061	0.206
Scotland	-0.057	0.202
Northern Ireland	0.023	0.203
Constant	1.982***	0.234
Observations	894	
RMSE	0.9889	
R-squared	0.0570	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A34: Process S2i: Hours of informal care per week provided by son, elderly population. Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care.

Loglinear regression Hours per week	(1) Coef.	(2) s.e.
Gender (ref = Women)		
Men	-0.039	0.109
Education Level (ref = High)		
Medium	-0.293	0.244
Low	-0.080	0.228
Supplementary carer (ref = none)		
Partner	-0.255**	0.124
Daughter	-0.070	0.097
Other	-0.145	0.098
Formal market	-0.045	0.110
Self-rated health poor	0.340***	0.116
Region (Ref = London)		
North East	0.245	0.453
North West	0.031	0.207
Yorkshire and the Humber	-0.017	0.220
East Midlands	-0.056	0.257
West Midlands	-0.146	0.205
East of England	-0.255	0.210
South East	-0.291	0.192
South West	-0.230	0.226
Wales	-0.207	0.211
Scotland	0.177	0.254
Northern Ireland	0.191	0.203
Constant	1.892***	0.283
Observations	547	
RMSE	0.9513	
R-squared	0.0760	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported.

Table A35: Process S2j: Hours of informal care per week provided by others, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care.

Loglinear regression Hours per week	(1) Coef.	(2) s.e.
Gender (ref = Women)		
Men	0.076	0.086
Education Level (ref = High)		
Medium	0.072	0.147
Low	0.239	0.147
Supplementary carer (ref = none)		
Partner	-0.186**	0.093
Daughter	0.006	0.086
Son	-0.088	0.098
Formal market	0.113	0.094
Self-rated health poor	0.285***	0.089
Region (Ref = London)		
North East	-0.604*	0.310
North West	-0.717**	0.281
Yorkshire and the Humber	-0.536*	0.279
East Midlands	-0.418	0.300
West Midlands	-0.572*	0.293
East of England	-0.859***	0.295
South East	-0.642**	0.281
South West	-0.536*	0.313
Wales	-0.401	0.277
Scotland	-0.276	0.285
Northern Ireland	-0.432	0.296
Constant	1.760***	0.261
Observations	585	
RMSE	0.8472	
R-squared	0.0934	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A36: Process S2k: Hours of formal care per week, elderly population.
Sample: Pooled data reported by waves "g", "i", and "k" of UKHLS, individuals aged 65 and receiving social care from a partner and without missing variables.

Loglinear regression Hours per week	(1) Coef.	(2) s.e.
Gender (ref = Women)		
Men	0.234***	0.078
Education Level (ref = High)		
Medium	-0.015	0.108
Low	0.183*	0.109
Informal carer	0.196***	0.071
Self-rated health poor	0.306***	0.087
Region (Ref = London)		
North East	0.016	0.272
North West	-0.010	0.199
Yorkshire and the Humber	-0.141	0.211
East Midlands	0.168	0.224
West Midlands	0.048	0.210
East of England	-0.062	0.199
South East	-0.159	0.190
South West	-0.044	0.194
Wales	-0.240	0.187
Scotland	-0.009	0.190
Northern Ireland	0.094	0.189
Constant	1.293***	0.179
Observations	1,026	
RMSE	0.9433	
R-squared	0.0681	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A37: Process S3a: Probability of providing informal care to non-partners in addition to the partner.
Sample: Pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS, individuals aged 18 and over with partners to whom they provide informal care and without missing variables.

Probit Providing informal care to non-partners	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.100**	0.0463
Education Level (Ref = High)		
Medium	0.006	0.0641
Low	-0.118*	0.0715
care for partner (lag, Ref = no care)		
care only for partner	-0.135**	0.0566
care for partner and non-partner	1.236***	0.0688
care only for non-partner	1.253***	0.0897
Self-rated health (Ref = Excellent)		
Very good	0.001	0.1030
Good	-0.005	0.0991
Fair	-0.033	0.1009
Poor	-0.007	0.1146
Age group (Ref = 18-19)		
20-24	0.472	0.4815
25-29	0.344	0.2273
30-34	0.592***	0.1996
35-39	0.781***	0.1789
40-44	0.641***	0.1701
45-49	0.775***	0.1502
50-54	0.741***	0.1434
55-59	0.590***	0.1422
60-64	0.436***	0.1384
65-69	0.275**	0.1370
70-74	0.181	0.1346
75-59	0.164	0.1402
80-84	-0.031	0.1475
85+		
Constant	-1.373***	0.1868
Observations	6,355	
Proportion positive	0.2057	
Pseudo R2	0.2115	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity (available upon request).

Table A38: Process S3b: Probability of providing informal care to non-partners only.
Sample: Pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS, individuals aged 18 and over who do not provide informal care to a partner and without missing variables.

Probit Providing informal care to non-partners	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.139***	0.0112
Education Level (Ref = High)		
Medium	0.099***	0.0128
Low	0.007	0.0181
Care for partner (lag, Ref = no care)		
care only for partner	0.259***	0.0561
care for partner and non-partner	1.514***	0.0744
care only for non-partner	1.806***	0.0119
Self-rated health (Ref = Excellent)		
Very good	0.043**	0.0193
Good	0.063***	0.0195
Fair	0.082***	0.0223
Poor	-0.007	0.0293
Partner	-0.107***	0.0123
Age group (Ref = 18-19)		
20-24	0.106**	0.0476
25-29	0.173***	0.0482
30-34	0.216***	0.0475
35-39	0.320***	0.0459
40-44	0.342***	0.0447
45-49	0.434***	0.0437
50-54	0.534***	0.0433
55-59	0.526***	0.0431
60-64	0.483***	0.0437
65-69	0.395***	0.0439
70-74	0.255***	0.0448
75-59	0.106**	0.0482
80-84	0.005	0.0537
85+	-0.188***	0.0639
Constant	-1.902***	0.0473
Observations	167,458	
Proportion positive	0.1355	
Pseudo R2	0.3021	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity (available upon request).

Table A39: Process S3c: Probability of providing informal care, single individuals.
Sample: Pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS, individuals aged 18 and over who do not have a partner and without missing variables.

Probit Providing informal care	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.093***	0.0193
Education Level (Ref = High)		
Medium	0.109***	0.0233
Low	0.025	0.0308
Care for partner (lag, Ref = no care)		
care only for partner	0.400***	0.1061
care for partner and non-partner	1.198***	0.1898
care only for non-partner	1.778***	0.0202
Self-rated health (Ref = Excellent)		
Very good	-0.008	0.0333
Good	0.038	0.0333
Fair	0.076	0.0369
Poor	-0.012	0.0442
Age group (Ref = 18-19)		
20-24	0.110**	0.0483
25-29	0.191***	0.0537
30-34	0.261***	0.0581
35-39	0.351***	0.0578
40-44	0.423***	0.0556
45-49	0.472***	0.0517
50-54	0.499***	0.0503
55-59	0.446***	0.0491
60-64	0.453***	0.0510
65-69	0.361***	0.0515
70-74	0.291***	0.0522
75-59	0.156***	0.0563
80-84	0.025	0.0609
85+	-0.160**	0.0689
Constant	-1.922***	0.0581
Observations	61,235	
Proportion positive	0.1353	
Pseudo R2	0.2956	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A.40: Process S3d: Probability of providing informal care, partnered individuals. Sample: Pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS, individuals aged 18 and over who have a partner and without missing variables.

Multinomial logit Providing informal care	(1) Coef.	(2) s.e.	(3) Coef.	(4) s.e.	(5) Coef.	(6) s.e.
Ref = Not providing social care (80.8%)	*Only care for partner (4.9%)*		*Care for partner and other (1.3%)*		*Only care for other (13.0%)*	
Gender (Ref = Women)						
Men	-0.028	0.046	-0.194**	0.075	-0.336***	0.026
Education Level (Ref = High)						
Medium	0.366***	0.057	0.410***	0.096	0.157***	0.029
Low	0.632***	0.069	0.415***	0.118	-0.059	0.042
Care for partner (lag, Ref = no care)						
care only for partner	4.707***	0.055	4.601***	0.110	0.317**	0.133
care for partner and non-partner	4.549***	0.120	6.771***	0.134	2.742***	0.129
care only for non-partner	0.404***	0.099	2.561***	0.113	3.198***	0.026
Self-rated health (Ref = Excellent)						
Very good	0.045	0.094	0.094	0.157	0.155***	0.045
Good	0.191**	0.092	0.218	0.152	0.157***	0.045
Fair	0.522***	0.099	0.611***	0.159	0.140***	0.052
Poor	0.606***	0.122	0.722***	0.190	-0.026	0.075
Age group (Ref = under 35)						
35-44	0.069	0.123	0.292	0.213	0.296***	0.055
45-54	0.251**	0.116	0.572***	0.192	0.626***	0.052
55-64	0.651***	0.112	0.554***	0.192	0.701***	0.052
65+	1.203***	0.108	0.472**	0.191	0.199***	0.053
Constant	-5.068***	0.162	-6.623***	0.257	-3.274***	0.076
Observations	112,579					
Pseudo R2	0.3560					

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors reported. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity.

Table A41: Process S3e: Hours of informal care provided.
Sample: Pooled data reported by waves "f" to "l" of UKHLS, individuals aged 18 and over supplying some social care and without missing variables. See table A.17 for further details.

Linear regression Hours per week	(1) Coef.	(2) s.e.
Gender (Ref = Women)		
Men	-0.260***	0.0179
Education Level (Ref = High)		
Medium	0.250***	0.0208
Low	0.523***	0.0285
Self-rated health (Ref = Excellent)		
Very good	0.011	0.0328
Good	0.172***	0.0331
Fair	0.329***	0.0367
Poor	0.553***	0.0477
Social care provided (Ref = care only for partner)		
care for partner and non-partner	-0.205***	0.0502
care only for non-partner	-1.272***	0.0278
Partner	-0.234***	0.0219
Age group (Ref = 18-19)		
20-24	0.165*	0.0913
25-29	0.279***	0.0936
30-34	0.526***	0.0926
35-39	0.597***	0.0888
40-44	0.564***	0.0864
45-49	0.309***	0.0837
50-54	0.223***	0.0818
55-59	0.196**	0.0811
60-64	0.152**	0.0812
65-69	0.065	0.0820
70-74	0.068	0.0833
75-59	0.071	0.0874
80-84	0.068	0.0946
85+	-0.072	0.1086
Constant	2.704***	0.0933
Observations	31,490	
RSME	1.2789	
R2	0.1783	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors reported.

Table A42: Heckman-corrected wage equation.
Sample: women who were not in employment in the previous year.

Log of hourly wage	(1) Wage equation coef.	(2) Wage equation s.e.	(3) Selection equation coef.	(4) Selection equation s.e.
Age	0.02	0.02	0.10***	0.01
Age squared	-0.00	0.00	-0.00***	0.00
Educational Level: 3 Category = Medium	0.01	0.08	-0.36***	0.08
Educational Level: 3 Category = Low	0.06	0.25	-1.15***	0.14
Medium education#Age	-0.01***	0.00	0.00	0.00
Low education#Age	-0.01***	0.00	0.01***	0.00
In Education: Binary	0.01	0.11	-0.63***	0.05
Mother's Educational Level: 3 Category = Medium	-0.04*	0.03	-0.01	0.04
Mother's Educational Level: 3 Category = Low	-0.06	0.05	-0.22***	0.04
Father's Educational Level: 3 Category = Medium	-0.08***	0.02	0.03	0.03
Father's Educational Level: 3 Category = Low	-0.05*	0.03	0.05	0.04
Partnered	0.13***	0.03	-0.12***	0.03
Has children	-0.01	0.11	-0.54***	0.03
Long-term Sick or Disabled	-0.09	0.38	-1.55***	0.11
Self-rated Health = 2	-0.05	0.09	0.29***	0.06
Self-rated Health = 3	-0.05	0.12	0.53***	0.06
Self-rated Health = 4	-0.01	0.14	0.66***	0.06
Self-rated Health = 5	0.05	0.15	0.67***	0.06
Government Office Region = North East	-0.08	0.06	-0.18***	0.06
Government Office Region = North West	-0.04	0.03	-0.06	0.04
Government Office Region = Yorkshire and the Humber	-0.11***	0.04	-0.10**	0.05
Government Office Region = East Midlands	-0.03	0.04	-0.03	0.05
Government Office Region = West Midlands	-0.05	0.04	-0.07	0.05
Government Office Region = East of England	0.04	0.03	-0.04	0.05
Government Office Region = London	0.07*	0.04	-0.11***	0.04
Government Office Region = South West	-0.01	0.04	0.06	0.05
Government Office Region = Wales	-0.03	0.05	-0.06	0.06
Government Office Region = Scotland	0.00	0.04	0.05	0.05
Government Office Region = Northern Ireland	-0.07	0.05	-0.08	0.06
Works part-time	0.08***	0.02		
Growth	2.09***	0.47		
Lagged Employment Status = Not Employed			-0.14***	0.04
lambda	-0.15	0.25		
Constant	0.01	0.75	-1.89***	0.16
Observations	22,171		22,171	

*** p<0.01, ** p<0.05, * p<0.1

Table A43: Heckman-corrected wage equation.
Sample: men who were not in employment in the previous year.

Log of hourly wage	(1) Wage equation coef.	(2) Wage equation s.e.	(3) Selection equation coef.	(4) Selection equation s.e.
Age	0.06***	0.02	0.05***	0.01
Age squared	-0.00*	0.00	-0.00***	0.00
Educational Level: 3 Category = Medium	-0.20	0.16	-0.55***	0.10
Educational Level: 3 Category = Low	-0.56	0.43	-1.43***	0.16
Medium education#Age	-0.00	0.00	0.01***	0.00
Low education#Age	-0.00	0.01	0.02***	0.00
In Education: Binary	-0.30	0.26	-0.72***	0.06
Mother's Educational Level: 3 Category = Medium	-0.03	0.04	0.04	0.05
Mother's Educational Level: 3 Category = Low	-0.15***	0.04	-0.04	0.05
Father's Educational Level: 3 Category = Medium	0.01	0.03	0.00	0.04
Father's Educational Level: 3 Category = Low	0.04	0.04	-0.01	0.05
Partnered	0.22**	0.09	0.27***	0.04
Has children	-0.04	0.03	0.01	0.04
Long-term Sick or Disabled	-0.65	0.66	-1.69***	0.12
Self-rated Health = 2	0.17	0.15	0.32***	0.08
Self-rated Health = 3	0.32	0.21	0.56***	0.08
Self-rated Health = 4	0.40*	0.24	0.66***	0.08
Self-rated Health = 5	0.41*	0.25	0.69***	0.08
Government Office Region = North East	-0.16*	0.09	-0.23***	0.07
Government Office Region = North West	-0.18**	0.08	-0.24***	0.06
Government Office Region = Yorkshire and the Humber	-0.20**	0.09	-0.27***	0.06
Government Office Region = East Midlands	-0.16**	0.08	-0.20***	0.06
Government Office Region = West Midlands	-0.14**	0.07	-0.16***	0.06
Government Office Region = East of England	-0.02	0.06	-0.10*	0.06
Government Office Region = London	-0.05	0.07	-0.20***	0.05
Government Office Region = South West	-0.17***	0.05	-0.09	0.06
Government Office Region = Wales	-0.21**	0.10	-0.25***	0.07
Government Office Region = Scotland	-0.16*	0.09	-0.22***	0.07
Government Office Region = Northern Ireland	-0.16**	0.08	-0.17**	0.08
Works part-time	0.09***	0.02		
Growth	1.37**	0.57		
Lagged Employment Status = Not Employed			0.11**	0.05
lambda	0.53	0.43		
Constant	-0.72	0.95	-1.13***	0.19
Observations	12,989		12,989	

*** p<0.01, ** p<0.05, * p<0.1

Table A44: Heckman-corrected wage equation
Sample: women who were in employment in the previous year.

Log of hourly wage	(1) Wage equation coef.	(2) Wage equation s.e.	(3) Selection equation coef.	(4) Selection equation s.e.
Lagged log hourly wage	0.68***	0.00		
Age	0.02**	0.01	0.17***	0.01
Age squared	-0.00**	0.00	-0.00***	0.00
Educational Level: 3 Category = Medium	-0.07***	0.02	-0.10	0.07
Educational Level: 3 Category = Low	-0.11*	0.06	-0.87***	0.17
Medium education#Age	-0.00***	0.00	0.00	0.00
Low education#Age	-0.00*	0.00	0.01***	0.00
In Education: Binary	-0.04	0.04	-0.50***	0.07
Mother's Educational Level: 3 Category = Medium	-0.02**	0.01	0.09***	0.03
Mother's Educational Level: 3 Category = Low	-0.04***	0.01	0.09**	0.04
Father's Educational Level: 3 Category = Medium	-0.02***	0.01	0.02	0.03
Father's Educational Level: 3 Category = Low	-0.02***	0.01	-0.04	0.03
Partnered	0.01***	0.00	-0.01	0.02
Has children	-0.02**	0.01	-0.23***	0.02
Long-term Sick or Disabled	-0.06	0.15	-1.78***	0.11
Self-rated Health = 2	0.01	0.02	0.37***	0.06
Self-rated Health = 3	0.03	0.03	0.45***	0.06
Self-rated Health = 4	0.05*	0.03	0.50***	0.06
Self-rated Health = 5	0.06**	0.03	0.48***	0.06
Government Office Region = North East	-0.03***	0.01	0.13**	0.05
Government Office Region = North West	-0.03***	0.01	-0.02	0.03
Government Office Region = Yorkshire and the Humber	-0.03***	0.01	0.01	0.04
Government Office Region = East Midlands	-0.04***	0.01	0.04	0.04
Government Office Region = West Midlands	-0.02**	0.01	0.04	0.04
Government Office Region = East of England	-0.00	0.01	0.10***	0.04
Government Office Region = London	0.02***	0.01	-0.08**	0.03
Government Office Region = South West	-0.02**	0.01	0.01	0.04
Government Office Region = Wales	-0.03***	0.01	0.05	0.05
Government Office Region = Scotland	-0.01	0.01	0.06	0.04
Government Office Region = Northern Ireland	-0.03***	0.01	0.09*	0.05
Works part-time	0.02***	0.00		
Growth	0.36***	0.10		
lambda	0.02	0.14		
Constant	0.13	0.21	-2.29***	0.15
Observations	40,572		40,572	

*** p<0.01, ** p<0.05, * p<0.1

Table A45: Heckman-corrected wage equation.
Sample: men who were in employment in the previous year.

Log of hourly wage	(1) Wage equation coef.	(2) Wage equation s.e.	(3) Selection equation coef.	(4) Selection equation s.e.
Lagged log hourly wage	0.69***	0.00		
Age	0.02***	0.01	0.11***	0.01
Age squared	-0.00**	0.00	-0.00***	0.00
Educational Level: 3 Category = Medium	-0.08***	0.03	-0.35***	0.08
Educational Level: 3 Category = Low	-0.23***	0.07	-1.13***	0.15
Medium education#Age	-0.00	0.00	0.01***	0.00
Low education#Age	0.00	0.00	0.02***	0.00
In Education: Binary	-0.09	0.08	-0.78***	0.08
Mother's Educational Level: 3 Category = Medium	-0.00	0.01	-0.03	0.04
Mother's Educational Level: 3 Category = Low	-0.03***	0.01	-0.05	0.04
Father's Educational Level: 3 Category = Medium	-0.02***	0.01	0.03	0.03
Father's Educational Level: 3 Category = Low	-0.03***	0.01	-0.02	0.04
Partnered	0.06***	0.01	0.21***	0.03
Has children	-0.00	0.01	-0.09***	0.03
Long-term Sick or Disabled	0.03	0.19	-1.80***	0.13
Self-rated Health = 2	-0.02	0.02	-0.03	0.08
Self-rated Health = 3	0.01	0.02	0.07	0.08
Self-rated Health = 4	0.03*	0.02	0.11	0.08
Self-rated Health = 5	0.04**	0.02	0.10	0.08
Government Office Region = North East	-0.05***	0.01	-0.00	0.06
Government Office Region = North East	-0.05***	0.01	-0.01	0.04
Government Office Region = Yorkshire and the Humber	-0.05***	0.01	-0.14***	0.04
Government Office Region = East Midlands	-0.05***	0.01	-0.04	0.04
Government Office Region = West Midlands	-0.03***	0.01	-0.05	0.04
Government Office Region = East of England	-0.02*	0.01	-0.03	0.04
Government Office Region = London	-0.02	0.01	-0.15***	0.04
Government Office Region = South West	-0.05***	0.01	-0.02	0.04
Government Office Region = Wales	-0.07***	0.01	-0.08	0.05
Government Office Region = Scotland	-0.04***	0.01	0.04	0.05
Government Office Region = Northern Ireland	-0.07***	0.01	0.04	0.06
Works part-time	0.12***	0.01		
Growth	0.33***	0.12		
lambda	0.06	0.18		
Constant	0.12	0.19	-0.52***	0.17
Observations	33,567		33,567	

*** p<0.01, ** p<0.05, * p<0.1

Appendix B Dynamic microsimulations; a formal sketch

Mathematically, dynamic microsimulation models are Markov chains, where at each time t an agent $i \in \{1, \dots, N\}$ is fully described by some state variables $\boldsymbol{x}_{i,t} \in \mathbb{R}^K$. The evolution of her (vector of) state variables is specified by the difference equation:

$$\boldsymbol{x}_{i,t+1} = \boldsymbol{f_i}(\boldsymbol{x}_{i,t}, \boldsymbol{x}_{-i,t}, \boldsymbol{\theta}, \boldsymbol{P}_t, \boldsymbol{\xi}_{i,t}) \tag{1}$$

where $\boldsymbol{\theta}$ is a vector of behavioural parameters, $\boldsymbol{P}_t$ are time-varying environmental parameters (including current and announced or expected future policies), and $\boldsymbol{\xi}_{i,t}$ are stochastic disturbances. Individual outcomes can also depend on the state variables of other agents $\boldsymbol{x}_{-i,t}$, for instance their partners or children.

Structural modelling, in this context, refers to the parameters $\boldsymbol{\theta}$ governing behaviour – for instance those describing utility functions – being policy-invariant. Expectations about the future are accommodated in the notation as they can be expressed as a function of the state variables $\boldsymbol{x}$ and the policy parameters $\boldsymbol{P}$. Realism in the policy description requires $\boldsymbol{P}$ to be a fairly detailed mapping from real-world policy environment. Finally, the notation can easily be generalised from partial equilibrium approaches – where there are only specific types of agents in the economy (say, individuals but not firms) – to general equilibrium approaches – where there are more agent types *i,j,h*,… each defined by their own state variables $\boldsymbol{x}_{i,t}, \boldsymbol{x}_{j,t}, \boldsymbol{x}_{h,t} \dots$ possibly depending on the state variables of all other agents of any type.

In this context, interaction between different life domains is simply defined as lagged variables pertaining to one domain having a causal impact on the evolution of other domains. Consider for instance health (h) and employment (e) and suppose their law of motion is specified as follows: [39]

$$h_{i,t+1} = h(h_{i,t}, e_{i,t}, \dots, \boldsymbol{\theta}_h, \boldsymbol{P}_t, \boldsymbol{\xi}_{i,t}) \tag{2}$$
$$e_{i,t+1} = e(e_{i,t}, h_{i,t}, \dots, \boldsymbol{\theta}_e, \boldsymbol{P}_t, \boldsymbol{\xi}_{i,t}) \tag{3}$$

Health status at time t affects both health and employment outcomes at time t+1, and similarly for employment status at time t. The structure is similar to micro-level Dynamic Factor Models (Altonji et al., 2022; Barigozzi and Pellegrino, 2023), with the added flexibility associated to the algorithmic nature of the simulation approach.

[39] The example easily generalises to more domains.

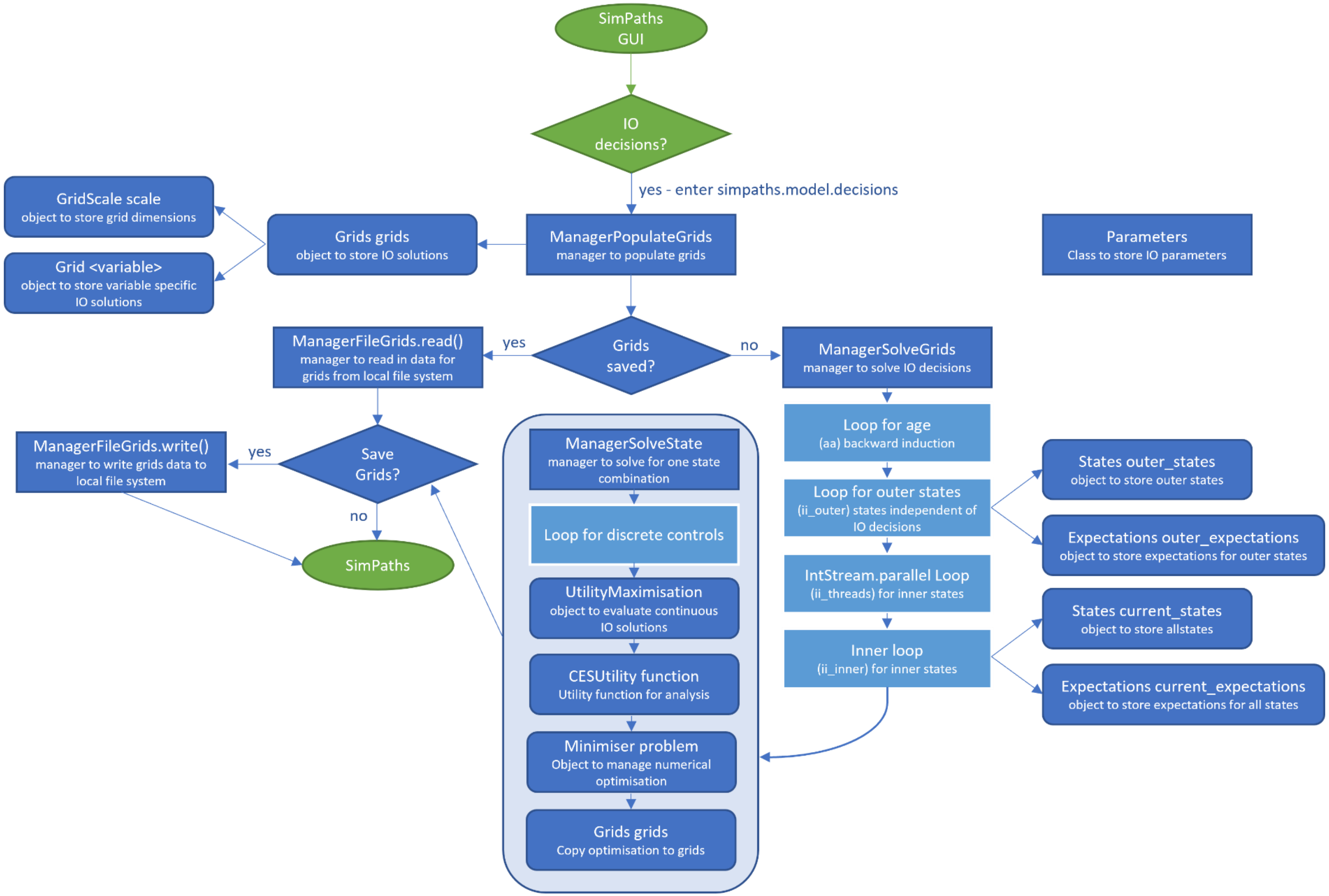
Appendix C Dynamic programming methods in SimPaths

Projections based on the DP approach proceed in two discrete stages. In the first stage, the model evaluates a look-up table that describes utility maximising decisions for all feasible simulated combinations of individual specific circumstances (the model state-space). In the second stage, starting from data for a reference population cross-section, the model projects panel data at discrete intervals over the simulated time-horizon. These panel data are generated using statistical descriptions for the intertemporal evolution of individual specific characteristics and the behavioural descriptions evaluated in the first stage. Importantly, the utility maximising decisions evaluated in the first stage are based on the same statistical descriptions for intertemporal evolution as are used in the second stage of the projection. It is this feature that makes the projected decisions 'rational'.

The key to the DP approach is that it seeks to obtain a complete solution to the lifetime decision problem at each point in time – that is for all feasible combinations of characteristics at a point in time – before it proceeds to consideration of earlier time periods. This systematic consideration of the entire state-space is important because it does not impose any conditions on statistical out-turns associated with earlier time periods.

Solution of the lifetime decision problem – the 'first stage' of the simulation noted above – is evaluated by a dedicated Java package in SimPaths: simpaths.model.decisions. This appendix provides technical detail of that program package.

Figure C.1: Flow chart of Java package to evaluate solutions to dynamic programming problem



Green elements are parts of SimPaths not involved in solution of lifetime decision problem. Manager methods in dark blue rectangles with square corners – these provide logic to organise the computations. Objects are denoted by dark blue rectangles with rounded corners. Light blue rectangles denote computational loops.

Figure C.1 displays a schematic of the *decisions* package, which proceeds as follows:

1. The user chooses to implement intertemporal optimising (IO) decisions via the SimPaths GUI (Graphical User Interface).
    a. SimPaths routes work to the simpaths.model.decisions package
2. ManagerPopulateGrids
    a. This class is responsible for creating and populating the look-up table used to simulate IO decisions – this table is referred to as "the grids".
3. ManagerFileGrids
    a. Reads and writes data for the grids to and from the file system
4. ManagerSolveGrids
    a. This class is responsible for managing evaluation of the IO solutions and storing these in the grids.
    b. The solution proceeds via a series of concentric loops.
    c. In the inner-most loop,
        i. the state combination is defined by object: States current_states
        ii. expectations are defined by object: Expectations expectations
5. ManagerSolveState
    a. This class manages numerical optimisation of all control variables for a given combination of state characteristics, as supplied by ManagerSolveGrids.
        i. Search over discrete control variables (labour options) is conducted via an outer set of loops in the ManagerSolveState class.
        ii. Search over continuous control variables (consumption) is passed to a dedicated UtilityMaximisation object.
6. UtilityMaximisation
    a. This class defines:
        i. the function to optimise
            1. Defined as the CESUtility object by default
        ii. upper bounds for the control variables
        iii. lower bounds for the control variables
        iv. a set of control variables to start the numerical search
    b. The optimisation problem is then passed to a generic Minimiser object for evaluation.
7. Minimiser
    a. Is instantiated with the factors defined by the UtilityMaximisation class
    b. Runs numerical optimisation routines via a call to the minimise() method
8. Minimiser.minimise()
    a. Passes the optimisation problem to:
        i. the brent() method if optimising over a single continuous control
            1. e.g. consumption only
        ii. the powell() method if optimising over 2 or more continuous controls
            1. e.g. consumption and portfolio allocation
9. CESUtility

a. Is accessed by Minimiser via the IEvaluation interface, to facilitate testing of alternative utility specifications.
b. The CESUtility object is instantiated with Expectations and Grid objects supplied by the UtilityMaximisation class
    i. The Expectations object describes expectations reflecting all but the decisions described by the continuous controls over which the Minimiser object conducts its search.
    ii. The Grid object records valueFunction solutions obtained via preceding age-specific loops evaluated by the ManagerSolveGrids class.
c. Calls to the CESUtility.evaluate(double[] args) method returns a (real number) variable describing (minus) the expected lifetime utility associated with the set of continuous control variables listed in the "args" array.
    i. This result is generated by combining within-period utility, with expected utility, via an intertemporal CES function.
        1. The within-period measure of utility is a simple CES function of consumption and leisure time associated with the prevailing combination of control variables (consumption and employment)
        2. Expected utility is evaluated by:
            a. identifying the set of expected states in the immediately succeeding period associated with the prevailing set of control variables (based on the Expectations object)
            b. identifying the value function outcome associated with each set of expected states, via a call to the Grid.interpolation(States) method for the valueFunction attribute.
            c. aggregating up the measures of the value function, by weighting each by its associated probability
d. Calls to the Grid.interpolateAll(States states, boolean solution_call) method return a (real number) variable, by interpolating over the respective Grid object.
    i. The interpolation begins by identifying a grid slice for all continuous states associated with the combination of discrete states described by the "states" object supplied to the method.
        1. The (Boolean) "solutionCall" variable is used to determine whether the birth year state is considered to be a discrete or continuous state for the interpolation routine.
    ii. Interpolation over the set of continuous states described by the "states" object supplied to the interpolateAll method is evaluated by the interpolateContinuous method.
        1. The interpolateContinuous method implements a linear spline interpolation

Evaluation of solutions to the dynamic programming problem are organised by a series of "manager" classes, which are described at further length below.

C.1 ManagerPopulateGrids

ManagerPopulateGrids is the highest-level manager class in the decisions package, providing the entry and exit point of the package. ManagerPopulateGrids instantiates the "grids" object that stores solutions to the lifetime decision problem. The manager then organises for the "grids" object to be populated, either by delegating solution of the lifetime decision problem to the ManagerSolveGrids Class, or delegating reading from the file system to the ManagerFileGrids class. Finally, ManagerPopulateGrids organises for the populated grids object to be saved to the file system, via another reference to ManagerFileGrids.

C.2 ManagerSolveGrids

ManagerSolveGrids is called by ManagerPopulateGrids if new solutions to the IO problem are required. ManagerSolveGrids organises solutions to the IO problem using four concentric loops.

The first loop (aa) proceeds backward from the last potential age in life, to the first age at which an individual is considered to enter the model as a responsible adult of a benefit unit. This backward iterating loop allows the solution to proceed via backward induction.

All state characteristics other than age are divided into two groups, considered in either an "inner" or "outer" loop. Outer loop characteristics are treated in the first loop following age (ii_outer). These characteristics are predominantly comprised of discrete variables that are exogenous to IO decisions (control variables). Consideration of these variables in a separate loop is useful because it allows their state combinations and associated expectations to be evaluated once and re-used for all of the state combinations considered within the inner set of loops.

The "inner" states are divided into chunks that are iterated over by a parallel loop (IntStream.parallel) to make use of multi-core processing. Inner states are grouped into chunks helps to economise the computational overhead associated with creation and destruction of worker threads.

Combinations of states are recorded by ManagerSolveGrids in objects of the States class. State combinations identified in the outer grid are stored in the object outerStates, and these are used to initialise state combinations identified in the inner loops: States currentStates. A similar approach is used to manage state expectations, via objects of the Expectations class.

C.3 ManagerSolveState

A solution needs to be obtained for utility maximising decisions at each grid ordinate visited via the loop structure of ManagerSolveGrids. This solution is obtained for an assumed utility function, and expectations consistent with the intertemporal dynamics used to project states (individual characteristics) through time.

The code starts from a prevailing set of individual specific characteristics, as supplied by the ManagerSolveGrids class. Each potential discrete decision (control variable, e.g. labour alternative) is considered in turn. For each discrete decision, numerical methods are used to optimise expected lifetime utility with respect to the set of continuous decision variables (e.g. consumption). A preferred set of decision variables is then identified as that with the highest overall measure of expected lifetime utility.

Expected lifetime utility is evaluated in two components. The first and most straight-forward is (current) within-period utility, which is evaluated as a CES function of current period consumption and leisure (the corollary of employment). The second component is expected utility for all periods following the current period. Expected lifetime utility at age A+1, from age A, is evaluated as a weighted sum of a discrete set of alternative possibilities calculated previously by the solution routine. This is made possible by the following features of the solution method:

- Starting with the maximum potential age, and iteratively solving backwards through time.
- Assumption of a von Neumann Morgenstern utility function.
- Use of the Gaussian quadrature to approximate summation over continuous normal distributions via a discrete set of weights and abscissae.
- Use of linear interpolation for approximating off-grid solutions (Keys, 1981).

The numerical optimisation method is based on value function calls rather than first order conditions as the value function is not guaranteed to be smooth or concave, and the computational overhead associated with evaluating first order conditions can outweigh advantages of zero-search algorithms.[40] Brent's method is used to search over a single (continuous) dimension, and Powell's method to search over multiple dimensions (see Press *et al.*, 2007).

C.3.1 Dimensionality of the grids object

Key features assumed for each of the states considered for analysis are listed here.

- *Scale* describes the scale used to describe the respective state in the decision grids.
- *Loop* indicates the loop structure (inner/outer) used to represent the characteristic when solving the IO problem
- *Endogenous* indicates whether or not evolution of the respective state is permitted to depend upon IO decisions (control variables)
- *Uncertain* indicates whether or not the respective state is considered to evolve stochastically when solving the IO problem
- *Dynamics* summarises the intertemporal dynamics assumed to solve the IO problem.

The order of the list reflects the assumed grid structure, as set out in the Grids class.

[40] This observation was obtained using a model structure that included alternative solutions procedures; see van de Ven (2011).

- Net wealth
  - Scale: Continuous, adjusted logarithmic
  - Loop: inner
  - Endogenous: yes
  - Uncertain: no
  - Dynamics: Follows an accounting identity, where wealth in next period is equal to wealth in current period plus disposable income less consumption.
- Wage potential
  - Scale: Continuous, adjusted logarithmic
  - Loop: inner
  - Endogenous: yes
  - Uncertain: yes
  - Dynamics: Based on estimated latent wage equation.
- Private pension
  - Scale: Continuous, adjusted logarithmic
  - Loop: inner
  - Endogenous: yes
  - Uncertain: no
  - Dynamics: Assumed fraction of net wealth converted to a fixed life annuity upon retirement.
- Health status
  - Scale: Continuous indicator variable
  - Loop: outer
  - Endogenous: no
  - Uncertain: yes
  - Dynamics: Based on a linear regression equation
- Birth cohorts (year of birth)
  - Scale: Discrete for IO solutions, continuous for projections
  - Loop: outer
  - Endogenous: no
  - Uncertain: no
  - Dynamics: none
- Retirement status
  - Scale: Discrete, distinguishing between those in and out of retirement
  - Loop: outer
  - Endogenous: yes
  - Uncertain: no
  - Dynamics: Entry to retirement is non-reversible, and occurs in the first period of non-employment beyond a "minimum age of retirement"
- Disability status
  - Scale: Discrete, distinguishing those affected by disability
  - Loop: outer

- Endogenous: no
- Uncertain: yes
- Dynamics: Based on an estimated probit regression

- Region
  - Scale: Discrete
  - Loop: outer
  - Endogenous: no
  - Uncertain: no (ignored)
  - Dynamics: none (ignored)
- Student status
  - Scale: Discrete
  - Loop: outer
  - Endogenous: no
  - Uncertain: yes
  - Dynamics: Based on an estimated probit regression
- Education attainment
  - Scale: Discrete
  - Loop: outer
  - Endogenous: no
  - Uncertain: yes
  - Dynamics: Education assigned at transition from student status and otherwise remains invariant.
- Number and age of dependent children
  - Scale: Discrete number of 'birth ages', with discrete number of children permitted per birth age
  - Loop: outer
  - Endogenous: no
  - Uncertain: yes
  - Dynamics: Scaled to reflect fertility probabilities described by estimated probit regressions
- Cohabitation status
  - Scale: Discrete, distinguishing single/couple
  - Loop: outer
  - Endogenous: no
  - Uncertain: yes
  - Dynamics: Based on estimated probit regressions
- Gender
  - Scale: Discrete, distinguishing male/female
  - Loop: outer
  - Endogenous: no
  - Uncertain: no
  - Dynamics: none

- Age
  - Discrete: Annual increments
  - Loop: first (before both outer loop, which is before inner loop)
  - Endogenous: no
  - Uncertain: no
  - Dynamics: age next period equals age this period + 1

C.4 ManagerFileGrids

There are a wide range of methods available for reading and writing data to disk available in Java. Some of the available approaches are legacy methods that have been superseded by newer ones. Nevertheless, there is no single method that is most efficient to apply in all contexts, which complicates design. In the current context, we seek the quickest method for reading and writing large double formatted arrays. For our use case, two methods currently stand out:

- BufferedOutputStream with byte arrays
- FileChannel with direct byte buffer

Of these two methods, FileChannel was selected for the ManagerFileGrids class.