Demand and Supply of Care Over the Life Course*

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Abstract

We project the effects of changes in fertility and mortality rates on both the receipt and provision of care in the UK. We investigate the impact on the level and cost of care, as well as its share of total GDP, through the life course and across income and wealth distributions. SimPaths, an open-source dynamic microsimulation model, is employed to design different scenarios over a half-century period. This framework projects life histories over time, developing detailed representations of career paths, family and intergenerational relationships, health, and financial circumstances. Our estimates show that the value of care, as a share of GDP, almost doubles over the five

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1 Introduction

Giving and receiving care are defining features of life. They shape who we are and can profoundly affect diverse aspects that bear on life quality, including the two key margins of economic decision making: labour-leisure and consumption-saving. Care dynamics have garnered increasing attention, as the demographic transition towards older populations, which has been taking place throughout OECD countries, is structurally altering the demand and supply of care.

As of 2024, the OECD average share of the population aged 65 or above was 18.51% (OECD (2024)). In the UK, this proportion reaches almost 19%, showing a dramatic century-long increasing trend. At the turn of the 20th century, approximately 5% of the UK population was aged 65 or over, and less than 2 in every thousand were aged 85 or over. Since then, the proportion of the population aged 65 or over has increased by almost four times by 2024, and by more than ten times (2.5%) for the population aged 85 or over. Furthermore, the trend towards an older population is projected to continue into the next century, with the proportion of people aged 65 and over projected to exceed 30% in the early 2100s, and those aged 85 and over projected to account for almost 1 in 10 people.

In the present study, we aim to project the effects of alterations in the old-age dependency ratio[1] on both the receipt and provision of care in the UK. We investigate the impact on the level and cost of care, as well as its share of total GDP, through the life course and across income and wealth distributions. Changes in the old-age dependency ratio are simulated through changes in fertility or mortality rates. Given the primary role of partners in informal care, we also design scenarios where the probability of living in a couple is affected. SimPaths, an open-source dynamic microsimulation model, is employed to simulate these different counterfactuals over a half-century period. This framework uses data from the UK Household Longitudinal Study (UKHLS) and the Family Resources Survey (FRS) to project life histories over time, developing detailed representations of career paths, family and intergenerational relationships, health, and financial circumstances. **DS**: Our estimates show that the value of care, as a share of GDP, almost doubles over the five decades of our analysis, with informal care accounting for most of the projected rise.[Update]

The largest strand of the related literature has so far focussed on the implications for care arrangements. OECD (2022), for example, projects that public spending on long-term care across the 27 EU countries will increase from 1.7% of GDP in 2019 to 2.8% in 2070. Projected increases to 2070 vary widely by country, from near zero in

[1] The old-age dependency ratio is the share of people aged 65 and over (dependents) on the working-age population (typically 15-64). It measures how many older individuals rely on each worker.

Greece, Latvia and Bulgaria, up to 2.7% in the Netherlands and 3.4% in Denmark. In the UK, the Office for Budget Responsibility (OBR (2024)) reports that adult social care spending is projected to rise from 1.5% of GDP in 2028/29 to 2.4% by 2073/74. This increase is attributed to "a combination of demographic pressures and real-terms unit cost growth". According to Carlesworth et al. (2018), to keep up with current demographic trends, social care funding should increase by 3.9% a year across the UK over the next 15 years. Similarly, Rocks et al. (2021) estimate an average annual increase in funding for social care between 4.3% and 5.8% during the period 2019–2031, depending on the considered scenario.

The modelling work underlying the projections outlined above is often thinly documented. In the case of the UK, for example, much of the underlying modelling work has been conducted using models developed at the Personal Social Services Research Unit (PSSRU), whose most recent publicly available description is in Wittenberg et al. (2006).[2] However, the existing literature suggests that these models share a common analytical approach. That is, they combine existing population projections with statistical descriptions concerning the incidence of care and exogenous assumptions about how care needs will evolve into the future. Key assumptions underlying the OECD (2022) projections, for example, are that "half of the future gains in life expectancy are spent in good health and an income elasticity of health care spending is converging linearly from 1.1 in 2019 to unity in 2070". Such modelling assumptions help to provide a "statistical projection" of what care needs may be into the future and have the advantage of connecting in an ostensibly transparent fashion disparate statistical evidence to obtain inferences for tertiary subjects of interest. Yet, while the abstractions associated with such methods are generally transparent, they also risk obscuring important features concerning the influence of caring through the life course. In fact, although care has its most obvious consequences when it is actually required, its effects are likely to extend to other periods of life. People may anticipate the need to provide informal care in response to deteriorating health of loved ones. Similarly, a reason given for high savings rates among the elderly is the desire to self-insure against the needs consequent on adverse health shocks, including the need for (expensive) formal care. Furthermore, both informal care and incapacity of demanding care can have effects that persist well after the actual episodes of care have ended due, for example, to labour market scarring or depleted savings.

This is the first paper that explores the life-course effects associated with the demand and supply of care. The life-course perspective considered for this study is designed to account for *ex-ante* effects associated with anticipation of the possibility of

[2] See European Commission (2021) for a description of the models used in the OECD (2022) projections.

future care needs and responsibilities, the influence on individual circumstances while care is needed, as well as *ex-post* effects after care needs have passed. The effects of population aging on care are explored by comparing the baseline projections against projections generated under alternative sets of assumptions on the evolution of fertility and mortality rates. Comparisons of interest include the effects on demand and supply of care through the life-course, the overall cost of social care, and its share of total GDP.

2 Statistical Background

3 Modelling Care

The statistical analysis reported in Section 2 informed the methods used to generate projections for care that are the focus of the current analysis. These methods were implemented in SimPaths, an open-source dynamic microsimulation model parameterised to UK data.[3] The model assumed for this study is freely available for download from **DS**: GitHub.[Add link] A walk-through to facilitate replication of reported results is also provided in **DS**: Appendix E.[Update]

A brief overview of the SimPaths model is presented in the Section 3.1. We refer to Bronka et al. (2025), as well as its GitHub Wiki page,[4] for its detailed description. SimPaths' module to model receipt and provision of social care, which is the main focus of this study, is elaborated in Section 3.2 and, more thoroughly, in Appendix A.

3.1 Overview of SimPaths

SimPaths is a fully open-source structural dynamic microsimulation model of the life-course, coded in Java using the JAS-mine simulation libraries (Richiardi and Richardson (2017)). The UK version runs on a database built upon two main data sources: the UK Household Longitudinal Study (UKHLS) and the Family Resources Survey (FRS). Individuals in the model are organised in benefit units (for fiscal purposes), and benefit units are organised in households. The model projects data for all simulated individuals at yearly intervals, which reflects the yearly frequency of the survey data used to parameterise the model.

The current analysis is based on a variant of SimPaths that is composed of ten modules: (i) Ageing; (ii) Education; (iii) Health; (iv) Family composition; (v) Social care; (vi) Investment income; (vii) Labour income; (viii) Disposable income; (ix)

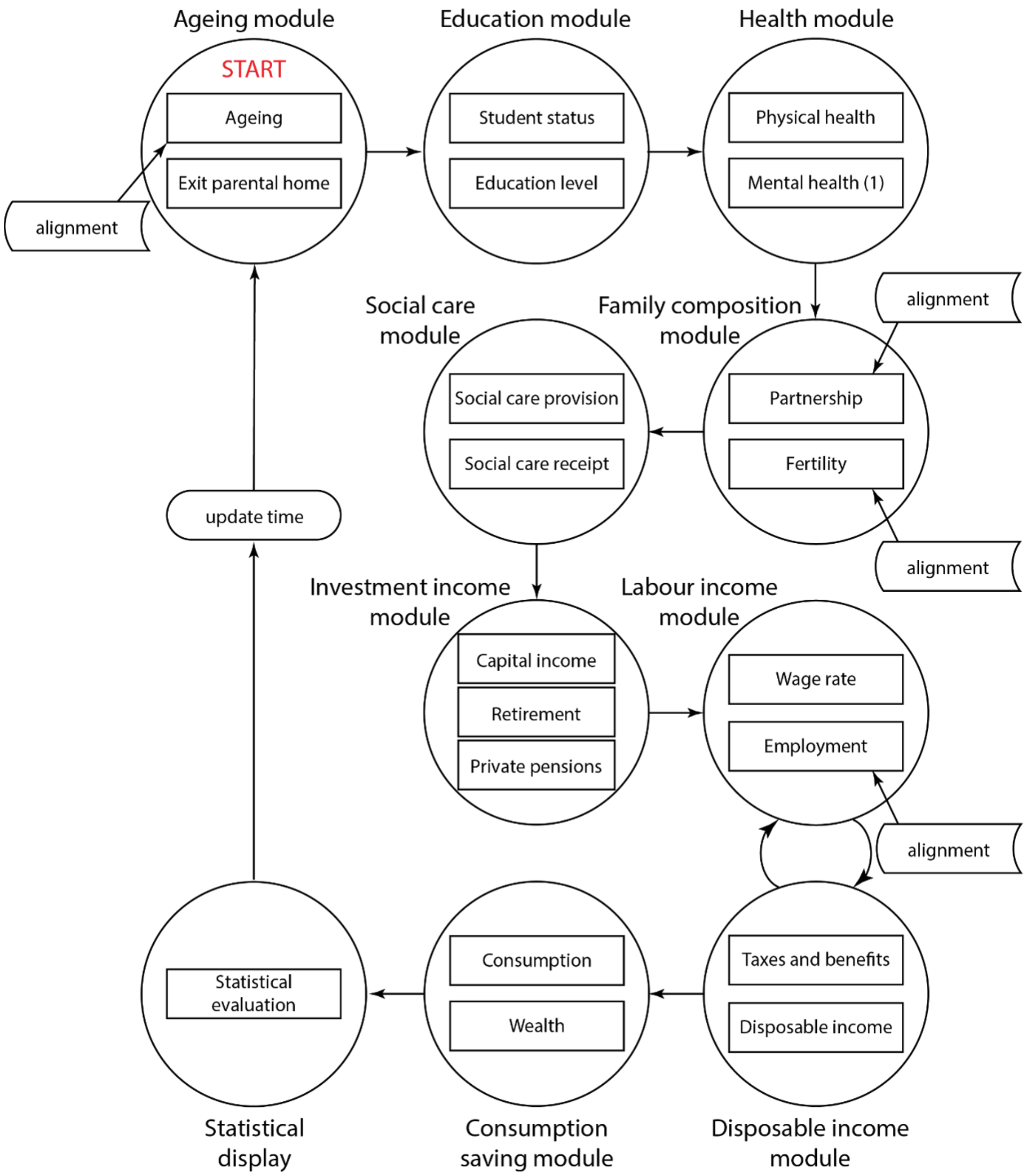
[3] SimPaths models currently exist for the UK, Greece, Hungary, Italy, and Poland.
[4] https://github.com/centreformicrosimulation/SimPaths/wiki.

Consumption, and (x) Statistical display. Each module is composed of one or more processes.[5] The empirical specifications assumed for dynamic processes include extensive cross-module interaction of simulated characteristics (state variables).

The simulated modules and processes are organised in SimPaths as displayed in Figure 1. 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.

[5] For example, the aging module contains ageing, mortality, child maturation, and population alignment processes.

Figure 1: Module configuration of the SimPaths microsimulation model



3.2 Simulating Social Care

Receipt of social care is simulated differently for individuals aged under and over 65, with a more detailed process adopted for older people, reflecting the more extensive data available for parameterisation. All empirical specifications considered for projecting receipt of social care are reported in Appendices A.1 (individuals below 65) and A.2 (individuals above 65).

The current analysis focusses exclusively on home-based social care, ignoring transitions into residential care. Residential care was not considered due to the limited data available for empirical analysis.[6] In 2022, the ONS UK Health Accounts indicate that the value of health care expenditure on providers of home healthcare services was £14.2 billion (2022 prices, 0.57% of GDP), relative to £34.1 billion (1.36% of GDP) on providers of residential long-term care facilities.[7] Similarly, the model is adapted to project provision of social care by informal sector providers (Appendix A.3); the characteristics of formal sector providers of social care are beyond the scope of this study.

Public transfers to support social care spending are not reflected by UKMOD[8] and cannot therefore be accommodated using the imputation method based on data derived from that model. SimPaths was consequently extended to reflect public subsidies for social care costs using a functional add-on to transfer payments imputed using database methods. Specifically, total transfer payments are projected by first imputing transfer payments based on UKMOD data and then projecting social care payments for relevant benefit units using a tailored function. This is facilitated by the fact that social care related public transfers are exogenous to the wider public transfers system in the UK.

3.3 Simulating forward-looking behaviour

The current study explores the influence of social care through the life-course, distinguishing among three types of effects: anticipation effects, when individuals foresee potential future periods of social care; impact effects, when social care is provided or received; and scarring effects, after periods of social care have passed.

Analysis focuses on the two main margins of economic decision making: labour/leisure and consumption/savings choices. Our interest in anticipation effects of social care motivates the adoption of a forward-looking framework to simulate decisions.

Labour supply and discretionary consumption decisions are simulated as though they are made to maximise expected lifetime utility subject to forward-looking (rational) expectations. The unit of analysis is the benefit unit, and incentives are translated into behaviour via an assumed intertemporal utility function. A nested constant elasticity of substitution (CES) utility function was adopted for analysis, as described by Equation (2).

[6] Transitions into formal care were included as a question in the forerunner to the UKHLS (British Household Panel Survey), but they were discontinued due to very low response numbers.

[7] ONS Reference tables accompanying the 2022 UK Health Accounts and 2023 provisional estimates, **DS**: Table 4a. [Source?]

[8] UKMOD is the underlying static microsimulation model for the tax-benefit system in the UK incorporated in SimPaths.

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

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

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

where subscripts i denote benefit units and t time. $u(\hat{c}_{i,t}, l_{i,t})$ 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. γ is the coefficient of relative risk aversion, ϵ 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 labour supply alternatives, 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. No analytical solution exists to the decision problem described above. Furthermore, application of the decision problem in a way that captures real-world circumstances invalidate adoption of computational short-cuts. Numerical solution methods were consequently adopted, following standard practice in the dynamic programming literature (see e.g., Van de Ven (2022)).

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 **DS**: Appendix D.[Update]

3.3.1 Specification of preference parameters

The utility function parameters described above were adjusted to match model projections for 2019 to selected statistics estimated from UKHLS survey data. Use of UKHLS data to parameterise preferences is consistent with the data used to estimate most of the other model parameters, as discussed in Bronka et al. (2025). Use of data for a single population cross-section to parameterise the preference parameters of the model follows Van de Ven (2022). Data for 2019 were considered, as this is the first year from which projections are made, so that most agent characteristics (model state variables) are based on survey data from this year.

The value of γ (the coefficient of relative risk aversion) was exogenously set to 2.0, based on meta-analyses reported by Elminejad et al. (2022) and Havranek et al. (2013). Elminejad et al. (2022) explore 1,021 estimates for relative risk aversion from 92 studies. They report that mean risk aversion is equal to 1 in economics and between 2 and 7 in finance contexts. In a similar vein, Havranek et al. (2013) analyse 34 studies that report 242 estimates for the intertemporal elasticity of substitution calculated on UK data. The mean of these estimates is 0.487 and the standard deviation is 1.09. In our case, adoption of CES intertemporal preferences implies that the intertemporal elasticity of substitution is (approximately) equal to the inverse of relative risk aversion, suggesting a value for γ in the region of 2.0.

Given the assumed value for γ, α (utility price of leisure) was adjusted to match the model to the proportion of people aged 18 to 74 who were reported by the UKHLS to be not employed in 2019.

Following Van de Ven (2022), ϵ (elasticity of substitution between equivalised consumption and leisure) was adjusted to match the model to distributional variation observed for the ratio between equivalised consumption and leisure. Specifically, the preference relation described by Equation 2 implies that, as ϵ increases, so too does the ratio of equivalised consumption to leisure of high incomehigh-income people (graduates) relative to lower income people (non-graduates).

δ (constant exponential discount factor) and ζ_0 (warm glow model for bequests) were adjusted to reflect the ratio of average equivalised expenditure by benefit units with heads aged 55 to 74, relative to benefit units with heads aged 18 to 54.[9]

The above parameters were manually adjusted until the disparity between statistics evaluated from simulated and survey data for each of the moments noted above were reduced to less than one percentage point. Specifically, the following parameters were identified for analysis:

$\gamma = 2.0$; $\alpha = 1.26$; $\epsilon = 0.34$; $\delta = 0.98$; $\zeta_0 = 17$; $\zeta_1 = 0.4$.

With these preference parameters, the model projects: 37.45% people aged 18 to 74 not in employment, compared with 38.08% described by survey data; the ratio of

[9] As the UKHLS does not report comprehensive measures of household expenditure, these statistics were evaluated using data reported by the Living Costs and Food (LCF) survey from 2019. Use of the ratio of consumption, rather than consumption in levels was done to accommodate any fundamental differences in financial flows described by the LCF and UKHLS.

equivalised consumption to leisure of graduates 1.3541 times that of non-graduates, compared with 1.3614 described by survey data ; average equivalised consumption among people aged 18 to 54 equal to 0.7972 times that of people aged 55 to 74, compared with 0.7896 described by survey data.

Further analysis revealed that the assumed preference parameters implied a population average intertemporal elasticity of substitution of consumption equal to 0.3501, which lies well within the range of estimates reported by Havranek et al. (2013). This is consistent with the motivation underlying the assumed value for γ. Similarly, the population average (Marshallian) labour supply elasticity implied by the parameterised model was evaluated at 0.1789. This property of the model is also in common with estimates reported in the associated empirical literature, which are typically between -0.12 and +0.28.[10]

4 Results

5 Conclusions

[10] Based on estimates reported in the review by Keane (2011) and the meta-analysis of Bargain and Peichl (2016); see **DS**: Appendix A.6.[Update]

References

Albuquerque, P. (2022). Met or unmet need for long-term care: Formal and informal care in southern Europe. *Journal of the Economics of Ageing*, (23).

Bargain, O., & Peichl, A. (2016). Own-wage labor supply elasticities: Variation across time and estimation methods. *IZA Journal of Labor Economics*, (5), 1–31.

Bronka, P., van de Ven, J., Kopasker, D., Katikireddi, S., & Richiardi, M. (2025). Simpaths: An open-source microsimulation model for life course analysis. *International Journal of Microsimulation*, *1*(18), 95–133.

Carlesworth, A., Firth, Z., Gershlick, B., Roberts, A., & Watt, T. (2018). Securing the future: Funding health and social care to the 2030s. *Institute for Fiscal Studies, ISBN 978-1-911102-98-4.*

Elminejad, A., Havranek, T., & Irsova, Z. (2022). Relative risk aversion: A meta-analysis. *ZBW - Leibniz Information Centre for Economics.*

European Commission, E. U. (2021). The 2021 Ageing Report: Economic and budgetary projections for the EU member states (2019-2070). *European Commission Institutional Paper*, (148).

Havranek, T., Horvath, R., Irsova, Z., & Rusnak, M. (2013). Cross-country heterogeneity in intertemporal substitution. *William Davidson Institute Working Paper*, (1056).

Keane, M. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature*, *49*(4), 961–1075.

OBR. (2024). *Fiscal risks and sustainability.* HM Stationary Office. ISBN 978-1-5286-4904-9.

OECD. (2022). Health at a Glance: Europe 2022: State of Health in the EU Cycle. *OECD Publishing, Paris.* https://doi.org/10.1787/507433b0-en.

OECD. (2024). *Elderly population.* Retrieved January 16, 2026, from https://www.oecd.org/en/data/indicators/elderly-population.html.

Richiardi, M., & Richardson, R. (2017). Jas-mine: A new platform for microsimulation and agent-based modelling. *International Journal of Microsimulation*, (10), 106–134.

Rocks, S., Boccarini, G., Charlesworth, A., Idriss, O., McConkey, R., & Rachet-Jacquet, L. (2021). Health and social care function projections 2021. *Health Foundation*. https://doi.org/10.37829/HF-2021-RC18

Van de Ven, J. (2022). Parameterising a detailed dynamic programming model of savings and labour supply using cross-sectional data. *International Journal of Microsimulation*, (10), 135–166.

Wittenberg, R., Comas-Herrera, A., King, D., Malley, J., Pickard, L., & Darton, R. (2006). Future demand for long-term care, 2002 to 2041: Projections of demand for long-term care of older people in england. *PSSRU Discussion Paper 2330*.

Appendices

A Social Care Processes

A.1 Need and Receipt of Social Care for Population Aged Under 65

All individuals under age 65 who are identified as long-term sick and disabled are assumed to have a need for social care. Furthermore, any individual in need of social care is assumed to be unable to work, so that long-term sick and disabled are omitted from employment. These assumptions reflect the adoption of an employment status identifier (FRS variable `empstati`) for the empirical specification of disability, and the high incidence of social care receipt reported among people with a disability as discussed in **DS**: Section 2.2.1.[Update] Note that use of an employment status identifier also omits the incidence of social care to children from the analysis.[11] Hence, the "social care" considered for analysis is shorthand for "adult social care", in common with popular discussion.

Receipt of social care among individuals under age 65 focusses exclusively on informal social care. At the time an individual under age 65 is projected to enter a disabled state, a probit equation (Table A.1) is used to identify whether the individual receives informal social care. In the absence of longitudinal data to parameterise persistence, this projection is assumed to continue for as long as the person remains ill or disabled. If an individual under age 65 is identified as receiving social care, then care is assumed to be provided by a single person, with the time of care described by a linear equation (Table A.2). The (informal) carer is identified deterministically, using a hierarchical approach falling first to a spouse under age 75 (if one exists), then to parents under age 75, and finally to "other" adults aged between 25 and 74 years.

Table A.1: Probit regression estimates for receipt of informal social care services among people aged 16 to 64 with a long-term illness or disability.

	Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by FRS at annual intervals between 2015/16 and 2019/20, and 2021/22.
Notes. Sample limited to individuals between age 16 and 64 with a long-term illness or disability. Robust standard errors reported. Long term illness or disability identified as code 9 of variable `empstati`.

[11] Children's social care includes support for children with disabilities, requiring protection from harm, or being looked after by local authorities.

Table A.2: Linear least squares regression estimates for hours of informal care per week received by people aged 16 to 64 years, with a long-term illness or disability, and in receipt of some informal social care

	Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by FRS at annual intervals between 2015/16 and 2019/20, and 2021/22.

Notes. Sample limited to individuals between age 16 and 64 with a long-term illness or disability. Robust standard errors reported. Long term illness or disability identified as code 9 of variable `empstati`.

A.2 Need and Receipt of Social Care for Population Aged 65 and over

Social care provisions for individuals aged 65 and over are projected using the following process. First, the incidence of needing care is modelled following probabilities described by a probit equation (Table A.3). Second, the incidence of receipt of care is also modelled as a probit equation (Table A.4). If in receipt of care, a multinomial logit equation (Table A.5) is used to determine if the individual receives: i) only informal care; ii) formal and informal care; or iii) only formal care. If in receipt of informal care, a multi-level model is used to distinguish between alternative providers of informal care. The first level (Table A.6) considers whether a partner provides informal care, for individuals with partners and in receipt of some informal care. For individuals who receive social care from their partner, the second level uses a multinomial logit (Table A.7) 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 (Table A.8) considers six alternatives that allow for up to two carers from "daughter", "son", and "other". For each carer, a log linear equation (Tables A.9 to A.13) is used to project number of hours of care provided. Finally, hours of formal care are converted into a cost, based on the year-specific mean hourly wages for all social care workers, **DS**: as reported in Table 2.5.[Update][12]

Table A.3: Probit regression estimates for "in need of care" for people aged 65+

	Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.

Notes. Sample limited to individuals aged 65 and over without missing variables. Weighted estimates with robust standard errors. "Need care" defined as requiring assistance with at least two activities of daily living reported by the UKHLS (including instrumental activities). "lag" defined as preceding year.

[12] Where the simulated year lies outside the time-series reported in the table, the series is extended assuming a (geometric) growth rate of 3.1% per annum. This growth rate is the average reported between 2011 and 2022 in Table 3.5, and is greater than the rate assumed for inflation of 2.6% per annum.

Table A.4: Probit regression estimates for receipt of social care for people aged 65+

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and over without missing variables. Weighted regression with 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. "lag" refers to preceding year.

Table A.5: Multinomial logit regression estimates for formal and informal social care of population aged 65 and over in receipt of some care (reference group: only informal care)

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and over receiving social care without missing variables. Weighted regression with robust standard errors reported. "lag" refers to preceding year.

Table A.6: Probit regression estimates describing incidence of partners providing social care for people aged 65 and over receiving care and with a partner

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and over receiving social care, with a partner, and without missing variables. Weighted estimates with robust standard errors reported. Explanatory variables describe characteristics of person in receipt of care. "lag" is defined as preceding year.

Table A.7: Multinomial logit regression estimates for receipt of supplementary care for population aged 65 and over who receive care from their partner (reference group: none)

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and over receiving social care from their partner and without missing variables. Regression considers four alternatives for supplementary carers: none (reference), daughter, son, and other. Weighted regression with robust standard errors reported. "lag" defined as preceding year.

Table A.8: Multinomial logit regression estimates for informal carer(s) for population aged 65 and over who receive care but not from a partner (reference group: daughter only)

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care but not from a partner and without missing variables. Regression considers six possible alternatives: none daughter only (reference), daughter and son, daughter and other, son only, son and other, and other only. Weighted estimates with robust standard errors reported. "lag" refers to preceding year.

Table A.9: Linear least squares regression estimates for log hours of informal care per week provided by partner to people aged 65 and over

	Coefficient	**Standard Error**	**p¿z**

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care from a partner and without missing variables. Robust standard errors reported. Explanatory variables describe characteristics of person in receipt of care.

Table A.10: Linear least squares regression estimates for log hours of informal care per week provided by daughter to people aged 65 and over

	Coefficient	**Standard Error**	**p¿z**

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care. Robust standard errors reported.

Table A.11: Linear least squares regression estimates for log hours of informal care per week provided by son to people aged 65 and over

	Coefficient	**Standard Error**	**p¿z**

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care. Robust standard errors reported.

Table A.12: Linear least squares regression estimates for log hours of informal care per week provided by others to people aged 65 and over

	Coefficient	**Standard Error**	**p¿z**

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care from a partner and without missing variables. Explanatory variables describe characteristics of person in receipt of care. Robust standard errors reported.

Table A.13: Linear least squares regression estimates for log hours of formal care per week provided to people aged 65 and over

	Coefficient	**Standard Error**	**p¿z**

Source. Authors' calculations on pooled data reported by waves "g", "i", and "k" of UKHLS.
Notes. Sample limited to individuals aged 65 and receiving social care from a partner and without missing variables. Robust standard errors reported.

The probit equations describing need and receipt of social care for individuals aged 65 and over were estimated in a similar fashion, using pooled data reported by waves "g", "i", and "k" of the UKHLS. Individuals were identified as "needing care" if they reported requiring help with at least two of the activities of daily living (ADL) or instrumental activities of daily living (IADL) reported by the survey. The focus on ADLs to identify "need of care" is common in the associated literature (e.g., Albuquerque (2022)), and the focus on two ADLs reflects observations discussed in **DS**: Section 2.2.1 (especially Table 2.2)[Update] and associated terms set out by the Care Act 2014. Similarly, individuals were identified as "receiving care" if they reported receiving some assistance with at least one ADL or IADL in the week preceding the survey.

The same set of explanatory variables are considered for the probit equations governing need and receipt of social care discussed above. These variables include gender, education status, relationship status, self-reported health status, age, and geographic region. Each regression also included a one-year lag of the dependent variable (imputed as discussed in Appendix A.5.1). This set of covariates corresponds to pre-determined variables for social care in the schedule used by SimPaths to project data for any given year.

Coefficient estimates reported in Tables A.3 (need for care) and A.4 (receipt of care) share close similarities, alluding to the close correspondence between reported need for and receipt of social care. The incidence of social care tends to be lower for men than for women, after controlling for the remaining set of covariates. Caution should be exercised in interpreting this result, which may reflect under-reporting of gender biases in informal care among partner couples later in life. It is nevertheless consistent with estimates reported elsewhere in the literature (e.g., Albuquerque (2022)).

Rates of social care tend to be inversely proportional to education level, which is also consistent with findings generally reported in the associated literature. Although self-reported health status is included in the set of covariates, this result may reflect a higher incidence of physically demanding work history among lower educated survey respondents. This interpretation is also consistent with the inverse relationship identified between rates of social care and self-reported health.

Unsurprisingly, the estimated coefficients describe significant persistence for rates of social care, which rise appreciably with age. The estimates also indicate a positive relation between social care of having a partner, which reflect the predominant role of partners in provision of informal care as discussed in Section 2.2. While the coefficients that allow for regional variation are mixed, they tend to suggest higher rates of social care in London (the reference group), relative to the remainder of the UK.

The simulation reported in Section 4 uses a Monte Carlo approach to project need of care, based on probabilities described by the probit model reported in Table A.3 A similar approach is used to project receipt of care based on probabilities described by

Table A.4. Importantly, projections for need and receipt of care are based on the same random draw from a uniform [0,1] distribution. This implies that, where the probability of needing care (Table A.3) exceeds the probability of receiving care (Table A.4), then care will only be simulated where it is needed. Hence, in the current context unmet care needs reflect the degree to which probabilities describing needs for care exceed those of receiving care.

Table A.5 reports multinomial regression coefficients for the split between informal and formal social care for the population aged 65 and over in receipt of some care. The covariates included in this equation were selected after noting that coefficient estimates were insignificant for gender, self-reported health, and age under 85. The coefficient estimates reported in Table A.5 indicate that individuals receiving social care via the formal market tend to be higher educated, without a partner, or at an advanced age.

Table A.6 indicates that, for individuals aged 65 and over, who receive some social care and have a partner, men are more likely than women to receive informal care from their partner. This is notable, as estimates reported in Tables A.3 and A.4 indicate that men are generally less likely to report receiving care. Table A.6 also highlights the persistence of care arrangements, and that care from partners is less prevalent toward the end of the life course.

Tables A.7 and A.8 report multinomial logit regression estimates for the set of informal carers where an individual is identified as receiving some informal care. In this case, covariates are limited to the lagged dependent variable (and a constant) to facilitate reflection of persistence in caring arrangements, subject to the limited data available for estimation.

Tables A.9 to A.13 report linear regression estimates for hours of care received, distinguished by type of provider. Inspection of these tables indicates that the most precise estimates were evaluated for informal care hours provided by partners, for which the largest survey sample is available. The estimated statistics for care provided by partners indicate that hours of care tend to be higher for men, who are lower educated, in poor health, and who also have daughters that care for them. Other regression estimates reveal substantial uncertainty concerning coefficient estimates, with the positive relationship between hours of care and poor health being a notable exception.

A.3 Simulating Provision of Social Care

The approach adopted for simulating receipt of social care described in Appendices A.1 and A.2 identifies the incidence and hours of informal social care that individuals are projected to receive. In the case of people aged 65 and over, 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 input data considered for SimPaths – with the notable exception of partners – 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 not recorded by the input data. The method that is used to project informal provision of social care is designed to accommodate limitations of the available survey data in a way that broadly reflects projection of social care receipt.

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 3.2, a probit equation (Table A.14) is used to distinguish between alternatives (ii) and (iii). Similarly, for the remainder of the population, another probit equation (Table A.15) is used to distinguish between alternatives (i) and (iv). A log-linear equation (Table A.18) is then used to project number of hours of care provided, given the classification of who care is provided to.

Table A.14: Probit regression estimates for the incidence of providing informal care to non-partners among people aged 18 and over who supply informal care to their partners

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS.
Notes. Sample limited to individuals aged 18 and over with partners to whom they provide informal care and without missing variables. Weighted estimates with robust standard errors. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity (available from authors upon request).

Table A.15: Probit estimates for the incidence of providing informal care to non-partners among people aged 18 and over who do not supply informal care to a partner

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS.
Notes. Sample limited to individuals aged 18 and over who do not provide informal care to a partner and without missing variables. Weighted estimates with robust standard errors. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity (available from authors upon request).

Table A.16: Probit regression estimates for the incidence of providing informal care among people aged 18 and over who do not have a partner

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS.
Notes. Sample limited to individuals aged 18 and over who do not have a partner and without missing variables.

Table A.17: Multinomial logit regression estimates for the incidence of providing informal care among people aged 18 and over with a partner

only care for partner (4.9%)	care for partner and other (1.3%)	only care for other (13.0%)

Source. Authors' calculations on pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS.
Notes. Notes: Sample limited to individuals aged 18 and over who have a partner and without missing variables comprising 112,579 observations. Pseudo R2 equals 0.3560. Reference group is people not providing social care. Population shares reported in brackets. Weighted estimates with robust standard errors. "lag" defined as preceding year. Regional dummy variables generally not significant, and omitted from table for brevity.

Table A.18: Linear least squares regression estimates for log hours of informal care per week provided by people aged 18 and over

Coefficient	Standard Error	p¿z

Source. Authors' calculations on pooled data reported between 2015 and 2020 by waves "f" to "l" of the UKHLS.
Notes. Sample limited to individuals aged 18 and over supplying some social care and without missing variables. See table A.17 for further details.