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Attenuation and reinforcement mechanisms over the life course☆

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We analyse the complex dynamic feedback effects between different life domains over the life course, providing a quantification of the direct (not mediated) and indirect (mediated) effects. To extend the analysis in scope and time beyond the limitations of existing data, we use a rich dynamic microsimulation model of individual life course trajectories parameterised and validated to the UK context. We interpret findings in terms of the implied attenuation or reinforcement mechanisms at play, and discuss implications for health and economic inequalities.

1. Introduction

Individual life domains are highly interconnected, and events occurring in one domain generally affect other domains.[1] This interconnectedness determines whether the impact of an event gets amplified or dampened when attention is broadened from the event in isolation to the life course as a whole. In turn, the interplay between attenuation and reinforcement mechanisms determines individual resilience and vulnerability, with important bearings on economic and health inequalities. While studies abound that take into account the role of mediators in the determination of outcomes, they often lack an integrated approach that considers *all* factors under analysis as both potential mediators and outcomes, in a dynamic context.

Most studies perform mediation analysis on *observed* data. The increasing use of computational models (specifically: in the social sciences and public health) opens up new research possibilities that take advantage of the potential to experiment with interacting causal pathways. Protocols and procedures for manipulating causal pathways and analysing counterfactuals in computational models are however not yet established.

In this paper, we propose a computational procedure to isolate direct and indirect (mediated) effects in a microsimulation framework. The paper explores the feedback loops between health, family and labour market outcomes, and the associated implications for income and health inequalities over alternative time horizons. To construct the relevant counterfactuals, we use a rich dynamic microsimulation model parameterised for the United Kingdom, which projects individual life course trajectories over the

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[1] Just think of the last time you came home after a frustrating day at work.

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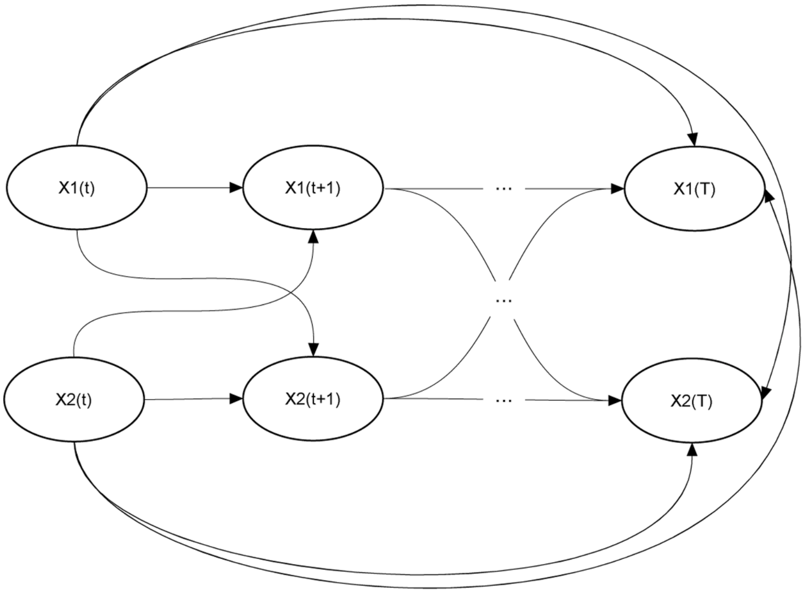

Fig. 1. Dynamic determination of individual outcomes.

three inter-related domains of work, family and health. The model is linked to an underlying tax-benefit calculator, which provides a realistic description of the impact of taxes and benefits at both the individual and population level.

The structure of the model accommodates dynamic interactions between all simulated variables. Given this underlying structure, we offer a model-based decomposition of the overall effect of specific events in terms of their *direct* effect – the un-mediated, self-reflective impact of (changes of) one variable on the future evolution of the same variable – *cross*-effect (the impact on the future evolution of other variables), and *indirect* effect (the mediated impact on the same variable, coming from the impact on other variables). Our primary focus of interest is the comparison of the direct and indirect effects, which we use to construct a synthetic indicator of the complex interactions that shape individual trajectories. This in turn permits quantification of the importance of attenuation and reinforcement mechanisms over time.

As an illustration of the methodology, we consider the impact of two different exogenous events: a partnership dissolution, and a sudden health deterioration. These scenarios have been selected as two polar cases in our empirical and modelling context. Our 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 dissoliution. 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.

To the best of our knowledge, this paper is the first empirical study investigating the feedback loops between multiple life domains and their implications for income and health inequalities over the life cycle. The detailed calibration of the model to a real-world setting allows us to explore quantitatively multiple sources of inequalities, at an individual level and over multiple time horizons.

The structure of the paper is as follows. Section 2 frames our work in the context of life course analysis. Section 3 describes the microsimulation approach. Section 4 introduces the counterfactual analysis that underpins our decomposition. Sections 5 presents our microsimulation model. Section 6 explains the two conceptual experiments. Sections 7 and 8 present the results for the two experiments in turn. Section 9 discusses implications for inequality and resilience. Section 10 summarises and concludes.

2. The impact of shocks

Fig. 1 shows the possible links (direct acyclic graph, DAG) between variables of interest – for simplicity, the diagram includes only two variables at different observational times – for illustration, say socio-economic status (X_1), and health (X_2). Each variable possibly has an un-mediated impact on its future values and on the future values of the other variables, as well as mediated effects.

The figure helps classifying the related literature. We focus in particular on studies that have looked at the impact of specific events – economic events, health events, family-related events – rather than specific individual characteristics. This is because events – also referred to as *shocks* – can sometimes lead to quasi-natural experiments, facilitating identification of the associated effects. Examples of shocks examined in the literature include job displacement (often following mass layoffs), acute hospital admissions (due to road accidents or strokes, for example), partnership dissolution and divorce. The literature is vast.

For example, some studies of job displacement consider the implications for prospective labour market circumstances (e.g. Farber, 2017); the effects of $X_1(t)$ on $X_1(T)$ in Fig. 1. Other studies explore the influence of job displacement on domains beyond the labour market, such as cardiovascular health (Black et al., 2015), mental health (Paul et al., 2018), and fertility (Huttunen and Kellokumpu, 2016); the effects of $X_1(t)$ on $X_2(T)$ in Fig. 1. When exploring family composition (X_1 variables measured at t), Preetz (2022) investigates the effects of partnership dissolution on life satisfaction and mental health, while Glaser et al. (2008) look at the impact on support in later life, and Barbuscia et al. (2022) focus on a number of health conditions, including self-rated health, depressive mood, and sleep disorder (X_2 variables measured at T). Some studies consider the influence of modifiers (and potential mediators), e.g. how family structure has a bearing on job displacement and subsequent recovery (Attewell, 1999); $X_2(t)$ on $X_2(T)$, mediated by $X_1(t+\tau)$.

Public health studies focus more on cross-effects of health shocks on other domains (the effects of $X_2(t)$ on $X_1(T)$ in Fig. 1). For instance, García-Gómez et al. (2013) consider the impact of acute hospital admissions on employment and income, while Lenhart (2019) analyses the impact of declines in self-reported health status and the onset of health conditions on subsequent labour market outcomes, and Bonekamp and Wouterse (2023) study the impact of hospital admissions on wealth. Most of these studies are based on longitudinal panel surveys, with some using cohort data (e.g. Griffiths et al., 2021, or Wörn et al., 2023, consider the effects of job loss on mental and physical health during the Covid-19 pandemic) and others using administrative data (e.g. Fadlon and Nielsen, 2021, exploring family labour supply responses to severe health shocks).

Our objective is to broaden the view presented by the extant literature, allowing the distinction between determinants and outcomes to blur, and all state variables to co-evolve. To facilitate that analysis, we turn to dynamic microsimulation.

3. Microsimulation as data enrichment

Empirical studies are constrained by the available data. Household panel surveys provide rich information on a number of individual characteristics, but their longitudinal dimension is limited (e.g. the EU-SILC, the main survey for the European Union, was characterised until 2018 by a rotational structure of only 4 years - extended to 6 years since). Even long-standing surveys such as the PSID, introduced in 1968, report complete life histories only for a highly selected (older, native, less mobile etc.) sub-sample of the US population. Cohort surveys share similar limitations to panel surveys, subject to further limitations imposed on the segment of the population for whom data are reported. While administrative data sometimes help to fill gaps of respondent surveys, public access to such resources is often restricted, and they generally describe a relatively limited set of characteristics, thus precluding the broad analysis that is required to disentangle complex feedback effects between alternative life domains.

Dynamic microsimulation (O'Donoghue, 2014; O'Donoghue and Dekkers, 2018) offers a way to integrate empirical evidence potentially derived from multiple sources into a coherent and consistent framework, allowing extrapolation of the implied dynamics beyond the temporal limits of the observational data.

In microsimulation, the state of micro units (for example, individuals, households, firms) is modified starting from some initial configuration, on the basis of 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 – in the case of individuals – related to education, household composition, fertility, labour supply, lifestyle and health behaviour, retirement.

Microsimulations can be considered as synthetic databases containing detailed information about a population of interest. The 'initial configuration' of a microsimulation database is typically augmented by projecting new variables not described by the initial configuration, or extending the reported time horizon. An example of the former of these cases is when disposable household income is projected by combining market income described by the initial configuration with a description of the corresponding tax-benefit rules. Where data are projected through time, then dynamic microsimulations involve the simulation of panel data that can be subject to subsequent empirical analysis.

Mathematically, dynamic microsimulation models are Markov chains, where at each time t an agent $i \in \{1, \ldots, N\}$ is fully described by some set of state variables $\boldsymbol{x}_{i,t} \in \mathbb{R}^K$. When the model is cast in discrete time (i.e. sampled at regular intervals, for instance yearly) 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 (potentially including past, present, and anticipated 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 consistent reflection of the "real-world" environment. Finally, the notation can 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 $\{i,j,h, \ldots\}$ each defined by their own state variables $\boldsymbol{x}_{i,t}, \ \boldsymbol{x}_{j,t}, \ \boldsymbol{x}_{h,t} \ldots$ possibly depending on the state variables of all other agents of any type (as in an agent-based setting).

In this context, interaction between different life domains is simply defined as 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 respective laws of motion are specified as follows :[2]

[2] In terms of Figure 1, employment is X_1 and health X_2. The example easily generalises to more domains, and other variables.

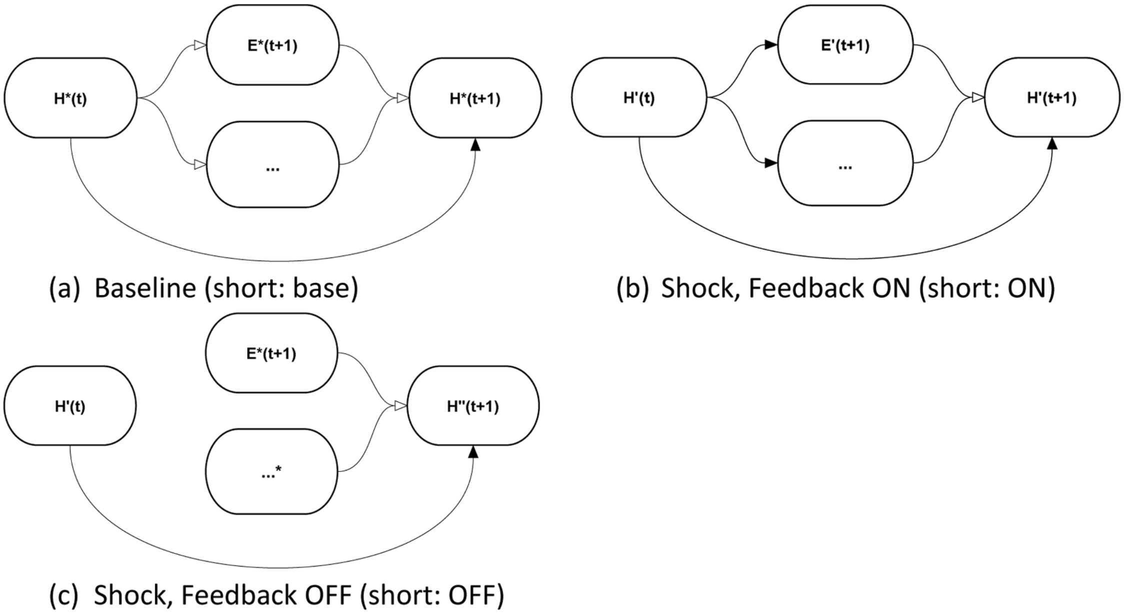

Fig. 2. Counterfactuals.

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

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

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.

Suppose we are interested in health outcomes at time T, and wish to evaluate the impact of a health event at time 0. In the model, there are two causal pathways: one goes directly from health at time t to health at time $t+1$, for all $t = 0,\ldots,T$; the other pathway is mediated by employment outcomes.

This modelling framework can be confronted with a reductionist approach, which would entail estimation of the following specifications, *in isolation*:

$$h_{i,t+1} = h'(h_{i,t}, \ldots, \boldsymbol{\theta}'_h, \boldsymbol{P}_t, \boldsymbol{\varepsilon}_{i,t}) \tag{4}$$

$$e_{i,t+1} = e'(e_{i,t} \ldots, \boldsymbol{\theta}'_e, \boldsymbol{P}_t, \boldsymbol{\varepsilon}_{i,t}) \tag{5}$$

If the time span is sufficiently long, indirect effects would be captured by the lagged dependent variable. For example, in eq. 4′ the coefficient on the lagged health variable in the reduced-form specification would pick up the effect on employment, and the subsequent effect of employment on future health. The reductionist approach would produce *on average* the same outcomes as the multidimensional approach, provided the estimators are well-behaved. However, in the reductionist specification the coefficient of the lagged health status would suffer from an omitted variable bias (employment), leading to a mis-representation of the true persistency effect of the health shock. This in itself could lead to incorrect policy implications.[3]

Moreover, a reductionist approach is by construction blind to what happens in other life domains. For instance, by using eqs 4′–5′, it would not be possible to predict the impact of an economic shock on health status, or the impact of increasing levels of education on future population health, with related implications for analysis of income inequality.

4. Analytical strategy

Dynamic microsimulation is generally used to project population aggregates, based on individual simulated outcomes. Here, we use it to construct differentiated individual counterfactuals that allow us to quantify how different causal pathways dynamically contribute to outcomes.

Our analytical strategy entails running three sets of simulations. The first simulation provides the *baseline* (short name: 'base'), with default parameterisation, and without any artificially imposed shock to initial conditions. This is stylised in Fig. 2, panel (a), with

[3] If, for example, a policy influenced health in a way that altered the coincident relationship with employment.

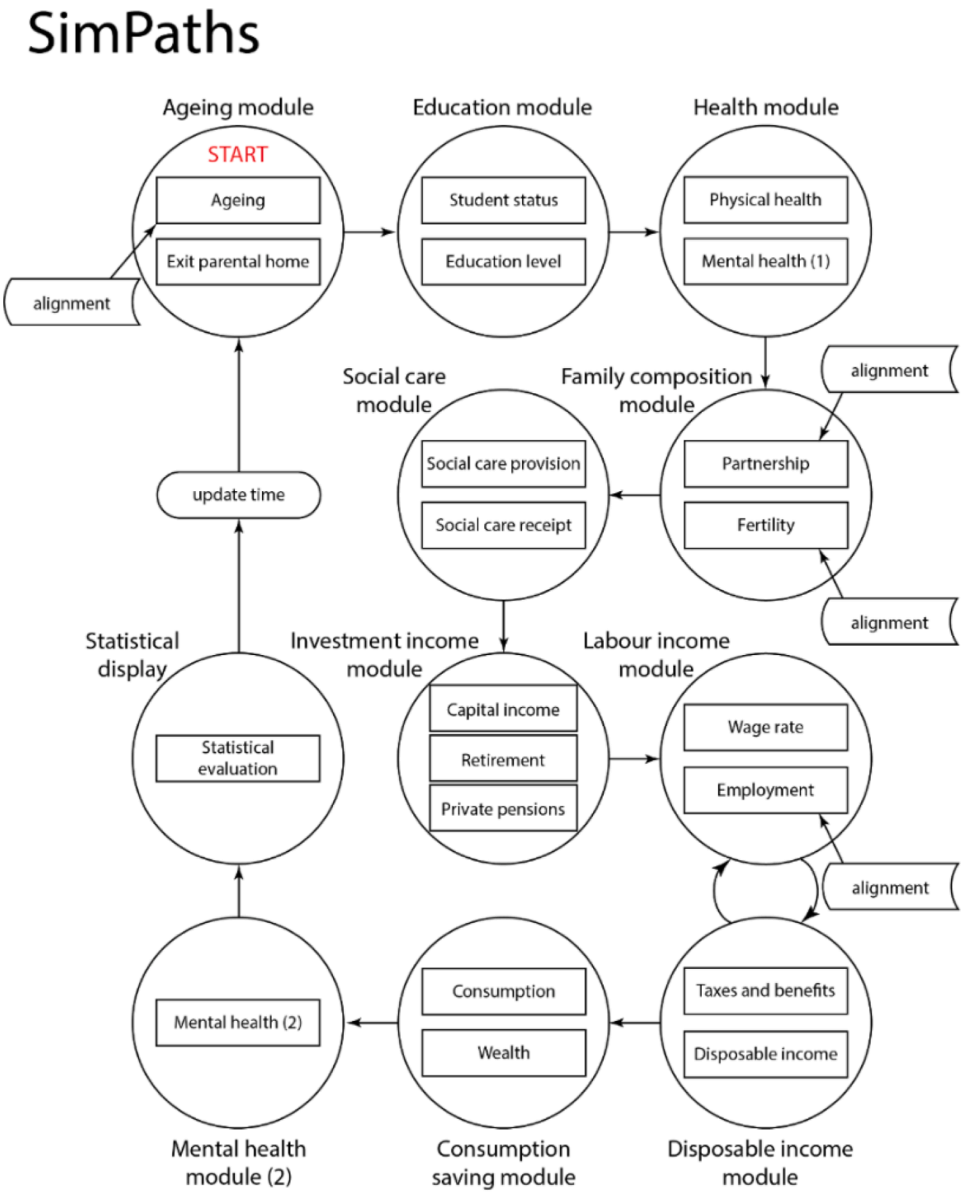

Fig. 3. Structure and order of processes modelled in SimPaths.

reference to the evolution of a single variable of interest, say health (H). Baseline values are identified with an asterisk. Health at time t has a direct impact on health at time $t+1$, and a mediated effect through its effects on employment (E) and other variables (not shown in the figure).

The second set of simulations entail shocking the initial conditions, for instance by decreasing the level of initial health. This is shown in panel (b), and referred to as '*Shock, Feedback ON*' (short name: 'ON'). The new values of the variables are indicated with a 'prime' sign.

Finally, panel (c) depicts counterfactual simulations where the initial shock is only allowed to have a direct impact on the future values of the shocked variable itself (health in our example), while the evolution of all the other variables is taken from the baseline ('*Shock, Feedback OFF*', short name: 'OFF').[4] This is indicated in panel (c), by the asterisks on "$E^*(t+1)$" and other variables, "…*", whereas the shocked value of $H'(t)$ is depicted as feeding through to a "feedback off" shocked value $H''(t+1)$.

The ON vs. base comparison answers the question: "*How would a shock in a given life domain broadly affect life trajectories?*" The OFF vs. base comparison answers the question: "*How would a shock in a given life domain affect life trajectories, if it did not spill over to other life*

[4] This requires matching the simulated individuals in the 'Feedback ON' scenario with their counterparts in the baseline.

domains?".

As already discussed, the overall effect of the shock involves a direct effect on the same domain where the shock occurred (health in the figure), a cross-effect on other domains (employment, etc.), and an indirect effect from the other domains back to the shocked domain.

In this framework, the direct (un-mediated) effect can be measured by comparing the 'Feedback OFF' scenario with the baseline, with respect to the evolution of the shocked variable. The cross-effect can be measured by comparing the 'Feedback ON' scenario with the baseline, with respect to the evolution of the other variables of interest. The indirect (mediated) effect can be measured, following a diff-in-diff approach, by contrasting differences between the 'Feedback ON' scenario and the baseline with differences between the 'Feedback OFF' scenario and the baseline.

It is not a priori clear whether the impact of the shock on the future evolution of the shocked variable itself should be greater under the ON or OFF scenarios. The case where the difference with respect to the baseline is higher in the 'Feedback ON' than in the 'Feedback OFF' scenario, that is when the total effect is higher than the direct effect, implies *reinforcement* mechanisms; the opposite indicates *attenuation* mechanisms.

We can then construct a feedback indicator as follows:

$$F_{x,t} = \frac{\text{total effect}}{\text{direct effect}} = \frac{(ON_{x,t} - base_{x,t})}{(OFF_{x,t} - base_{x,t})} \tag{6}$$

where x is the variable being considered. Values of $F > 1$ reveal reinforcement mechanisms, while $F < 1$ indicates attenuation mechanisms.

This indicator is related to the 'proportion mediated' (PM) indicator in mediation analysis (Ditlevsen, 2005; Ananth, 2019):

$$PM_{x,t} = \frac{\text{indirect effect}}{\text{total effect}} = \frac{\text{total effect} - \text{direct effect}}{\text{total effect}} = 1 - \frac{1}{F_{x,t}} \tag{7}$$

or $F_{x,t} = \frac{1}{1-PM_{x,t}}$. Our preference for the F indicator is due to its more straightforward interpretation in terms of the dominance of reinforcement vs attenuation mechanisms as discussed above.

5. The model

For this study, we use the SimPaths dynamic microsimulation model developed at the Centre for Microsimulation and Policy Analysis at the University of Essex (Bronka et al., 2025), estimated on UK data.[5] SimPaths implements a hierarchical architecture where individuals are structured in benefit units (for fiscal purposes), and benefit units are structured in households.[6] The model runs at a yearly frequency, consistent with the yearly frequency of the survey data on which the different processes are estimated. The model is composed of seven different modules: (i) Demography, (ii) Education, (iii) Health, (iv) Household composition, (v) Non-labour income, (vi) Labour supply, and (vii) Consumption. Each module is in turn composed of different processes or sub-modules; for example, the demographic module contains an ageing process and a process for leaving the parental home, and the labour supply module includes a wage setting process together with a process determining the number of hours of work supplied.

Simulated modules and processes are organised as displayed in Fig. 3. In each simulated year, agents are first subject to an ageing process (involving age and year specific probabilities of dying), followed by a population alignment process.

Population alignment adjusts the simulated population to match population projections produced by the Office for National Statistics (ONS). Specifically, the ONS reports population estimates for the UK distinguished single year of age and gender for 12 geographic regions for each year between 2011 and 2023 inclusive. The ONS also reports projections for the same disaggregated population subgroups for each year between 2024 and 2043.

In each simulated year, the alignment process begins by evaluating the population short-fall/excess associated with each age, gender and region category, relative to ONS population estimates/projections. The model then simulates internal migration by moving benefit units with baby girls from regions with an excess of females aged 0 to those with a short-fall until all short-fall or excess regions are exhausted. Any net differences that remain between the simulated and ONS reported numbers of females aged 0 by region are resolved by removing benefit units to reflect (implicit) international emigration, or cloning benefit units to reflect international immigration.

Having matched ONS estimates/projections for the number of females aged 0, the alignment process proceeds to consider males aged 0. The model allows for up to one birth each year, which ensures that no benefit unit includes both a female and male aged 0. This means that the same process as described for females aged 0 can be applied to align the simulated number of males aged 0, without risking distortion to the previously matched numbers for females.

Subsequent gender and age categories are considered in turn, where benefit unit migration is limited to the set of units in which the youngest member corresponds to the gender/age category under consideration. Closure of this procedure is facilitated by the fact that

[5] The model is coded in Java using the JAS-mine simulation library (Richiardi and Richardson, 2017).

[6] 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.

Table 1
Sample sizes.

Experiment	Shocked individuals
(a) Partnership dissolution	8,401
(b) Health shock	25,232

Note: Each of the initially shocked individuals is simulated from 2011 to 2050.

the incidence of benefit units comprised of a single individual increases as the gender/age category under consideration proceeds to higher ages.

Following alignment, the education module determines whether students should remain in education, or – for individuals who are no longer in education – re-enter education. 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 (for those who returned to education, their level of education can only go up) and can enter the labour market.

The health module calculates an individual's continuous health score, a measure of mental distress, and evaluates whether the individual is long-term sick or disabled (in which case, he / she is not at risk of work).[7]

The household composition module projects cohabiting relationship formation and dissolution. This aspect of the model is the principal source of interactions between simulated agents. When a relationship forms, the partners are selected via a matching process that is designed to reflect correlations observed in survey data. Females in couples can give birth to a (single) child in each simulated year, as determined by a fertility process. Fertility is modelled at the individual level, and is aligned to fertility rates implied by official population projections.

The labour supply module projects potential wages for each simulated adult in each year using a wage equation with parameters estimated using a Heckman-corrected regression on contemporary survey data. Given potential wages, hours of work supplied by all adult members of a benefit unit are evaluated by identifying the utility-maximising number of discrete hours of work, in a random utility model framework.[8] This calculation involves identifying disposable income for each feasible labour alternative, which is imputed from a detailed description of the contemporary UK tax and benefit system, as described in van de Ven et al. (2025).[9]

Finally, a simple consumption module transforms disposable income into consumption by applying an homogenous saving rate, calibrated to the data. The same saving rate is also used when calculating capital income.

Simulations can be initialised in any year between 2011 and 2017 – they start in 2011 for this study – based on a representative cross-section of the UK population in the respective year, and can run until 2060. The period of overlap with existing data is used for validation purposes.

The model structure, as well as the estimated parameters based on the UK Household Longitudinal Survey (UKHLS) and Family Resources Survey (FRS) data and validation to historical time series for the period 2011–2020, are described in Bronka et al. (2025), and summarised in Appendix 1.

6. The experiments

We consider two experiments: a partnership dissolution, and a health shock, applied to the cohort of men aged 30 in the initial year of the simulation (2011). Simulations are run until 2050, when the simulated individuals reach the age of 69.[10] In the first scenario, all partnerships involving men aged 30 in the initial year of the simulation are dissolved. In the subsequent periods, these men might decide to re-partner, thus entering the market for partnership, where they might (or might not) find a suitable partner. The comparison group in the baseline is therefore composed of all partnered men aged 30 in 2011 – the same group of men, in a world in which the shock did not occur.

In the second scenario, the self-rated health status of all men aged 30 in the initial year is reduced to 1 ("poor", on a five point self-reported scale varying from "poor" to "excellent").[11] The comparison group in the baseline comprises all men aged 30 in 2011 (irrespective of their partnership status) – again, the same group of men, in a world in which the shock did not occur.

Table 1 reports the sample size for each experiment (number of individuals shocked in 2011). Coming from the UKHS survey data, the individuals selected for our experiments are representative of the respective segments of the UK population (see Appendix 2 for a comparison of the characteristics of the two samples with alternative survey data).

To be noted, the focus on partnership dissolution requires a change with respect to the standard version of SimPaths described in

[7] The status of long-term sick / disabled is reversible though.

[8] *A' la* van Soest (1995). The structural labour supply module is replaced by a simpler probabilistic transition module for the Covid-19 years (2020 and 2021), during which it is considered that households were less able to choose their preferred level of hours worked.

[9] Imputations are based on data derived from UKMOD, a tax-benefit calculator for the UK; see Richiardi *et al.* (2021).

[10] Focussing on a specific cohort allows a better understanding of the simulated dynamics. Moreover, when shocking relationship status, the overall "market for partnership" is affected only marginally.

[11] In the sample, approximately 19% of men aged 30 in 2011 report excellent health, 53% very good, 21% good, 6% fair, 1% poor. The shock hits all of them and brings down their health status to 'poor'.

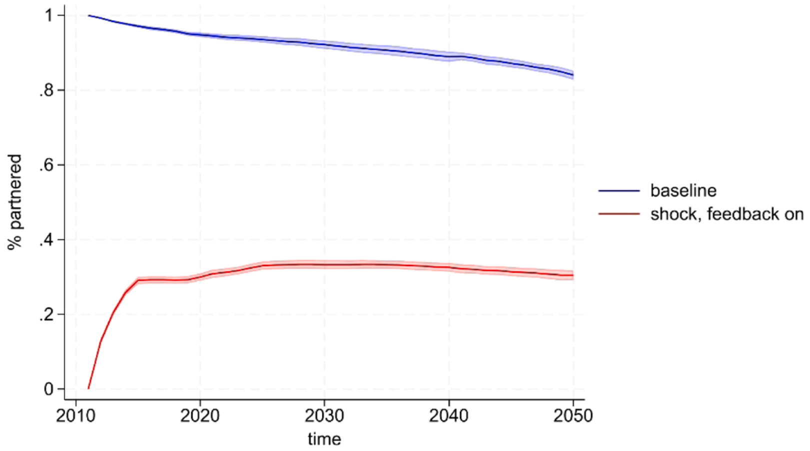

Fig. 4. Partnership dissolution: Total effects
Note: 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

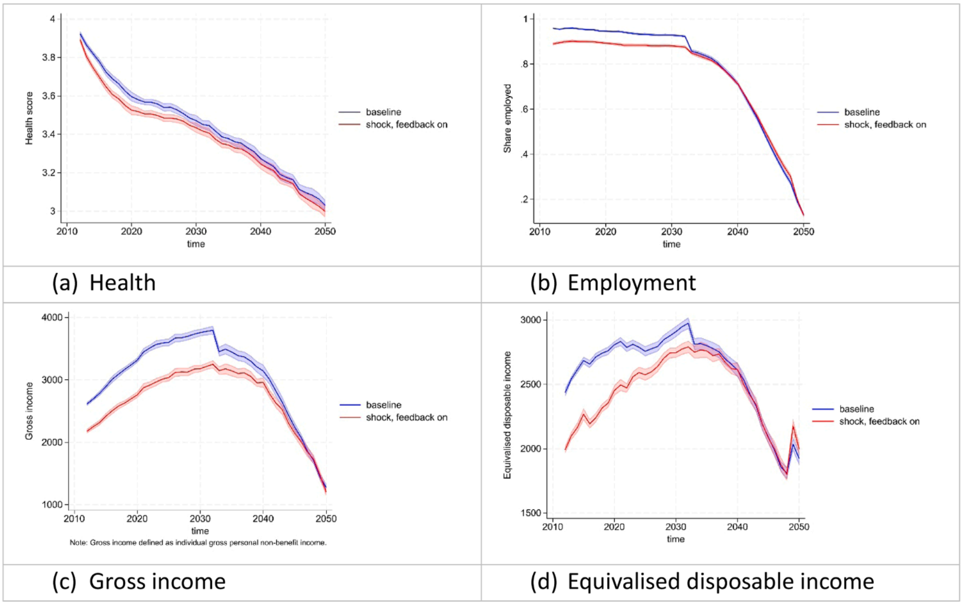

Fig. 5. Partnership dissolution: Cross-effects
Note: 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

Section 5, as population alignment to official demographic projections must be switched off. This is because population alignment in the model depends on household structure (see Bronka et al., 2025 for more details), which is obviously impacted by the partnership dissolution. Retaining population alignment would then imply that the simulated populations in the different scenarios are not the same, preventing us from matching individuals from the baseline in the 'Feedback OFF' scenario. For coherence, population alignment is switched off also for the health shock experiment.

What this implies is that the experiments are run on a closed and constant population. Without population alignment, the initial cohort of men remains representative of the UK male population aged 30 in 2011 (see Appendix 2), and their partners remain representative of the partners of the UK males aged 30 in 2011. However, no immigration or emigration is allowed.

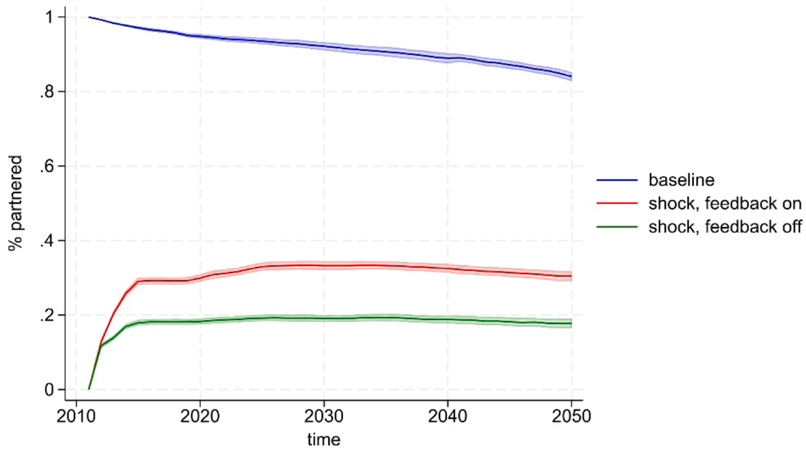

Fig. 6. Partnership dissolution: Total and direct effects
Note: Base vs. ON = total effect; Base vs. OFF = direct effect. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

7. Results: partnership dissolution

Fig. 4 shows the evolution of the partnership rate in the baseline and feedback ON scenarios, for the affected individuals (partnered men aged 30 in 2011). The share of partnered men declines over time in the baseline, mostly due to a regression to the mean (the sample is positively selected to start with). In the counterfactual, it takes about 3 years for the partnership rate to increase and reach an equilibrium level of about 30 %.[12]

The difference between the baseline and the feedback ON scenario is a measure of the *total* effect of the shock. Becoming unpartnered at age 30 increases the probability of being single at age 65 by almost 60 percentage points. This may contrast with the observation that partnership breakdowns are a common occurrence at all ages, and in particular for young adults, and they do not seem to lead to such drastic long-term consequences, in real life. This is because most individuals re-partner quite quickly and would therefore not be classified as ‘single’ in a survey, despite having gone through a partnership dissolution. In other words, as is well known, stock sampling leads to length-time bias, with a higher likelihood that the short duration spells will be omitted from the sample. Our experiment should therefore be interpreted as putting individuals in an un-partnered spell that is long enough to be recorded in a survey, that is in a long-term single status, with potentially larger long-term consequences.

Cross-effects on other variables are explored in Fig. 5. The partnership dissolution at 30 has a small negative effect on health (panel (a)) until approximately the age of 50. The effect on employment (panel (b)) is more pronounced, with a decrease in the probability of being employed of around 5 percentage points, again until the age of 50. After that, employment rates in the baseline drop. This is because estimated labour supply for men (and women) in couples is reduced after the age of 50, something that is also observed in the survey data. The drop in the baseline therefore reflects the higher percentage of partnered individuals.[13] The same composition issue (a higher percentage of partnered men) explains why employment rates in the baseline fall below those of the counterfactuals at older ages.

Panels (c) and (d) show the effects on income. Gross income (panel (c)) is higher in the baseline, reflecting higher employment rates and longer work hours – see Appendix 4 for more details. The same pattern is found for equivalised disposable income (panel (d)). The effects of the shock on equivalised disposable income however differ depending on household structure. Specifically, the simulations assume that children follow their mother when a relationship dissolves. In the period immediately after the separation, two effects are consequently at play: a mechanical change to the equivalisation factor, and the incidence of maintenance payments if the couple has children.

The equivalisation factor assumed for analysis is the modified OECD scale. This scale assigns a value of 1 to the first adult; 0.5 to the second and each subsequent person aged 14 and over; and 0.3 to each child aged under 14. A partnership dissolution will tend to reduce the equivalence scales of divorced men, which works to increase equivalised disposable income.

[12] The partnership rate in the counterfactual scenario levels off at around 30%. For comparison, age-specific partnership rates in the baseline are much higher for prime-age men, remaining approximately constant at around 80% between 30 and 65 years of age. The difference is explained by the fact that most of the transitions from single to partnered happen before the age of 30.

[13] All individuals in the baseline start as partnered, and all individuals in the scenario start as single. However, over time the initial partnerships might “naturally” (that is, as simulated by the behavioural equations rather than artificially imposed in the experiment) come to an end, while single individuals might re-partner.

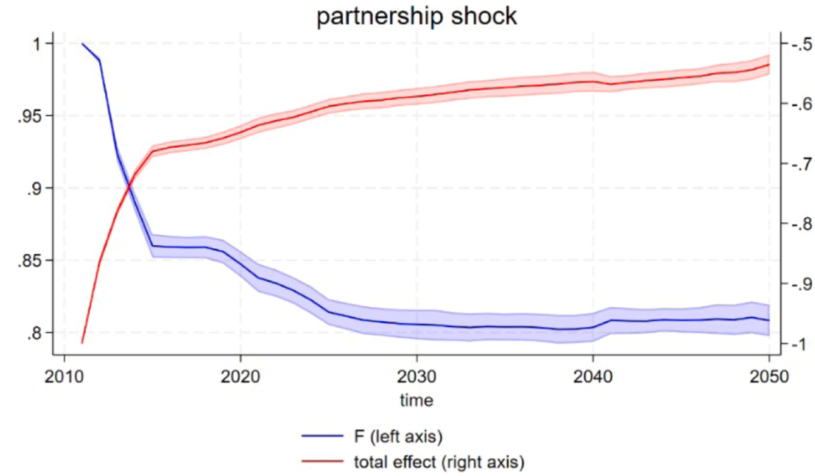

Fig. 7. Partnership dissolution: F index

Note: The F index (eq. (4)) measures the ratio of the total to the direct effect of the shock. Values above 1 indicate reinforcement mechanisms are at work, while values below 1 indicate attenuation mechanisms. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

In contrast, maintenance payments work to decrease the equivalised disposable incomes of men following relationship dissolution (where children are involved). The simulations project maintenance payments based on the rules in place from 2012 onwards (Child Maintenance Service, 2024). On average, maintenance payments reduce equivalised disposable income for men in the simulation, by 12 % (1st quartile: 9 %; 3rd quartile: 15 %).

On balance, panel (d) of Fig. 5 indicates that the influence of weaker employment and maintenance payments on average dominate reduced equivalence scales, resulting in lower measures of equivalised disposable income following the simulated shock to partnership status.

To understand the role of mediated effects, we bring in the 'Feedback OFF' scenario. Fig. 6 is the equivalent to Fig. 4, with the 'Feedback OFF' scenario added.

Comparing the blue ('baseline') to the green ('feedback OFF') series displayed in Fig. 6 indicates the influence of direct effects on projections. The figure indicates that the direct effect in isolation would see partnership increase from zero to 20 %, compared to >30 % when all the mediator effects are factored in ('Feedback OFF', red line).

Finally, Fig. 7 reports evolution of the F index, computed as per eq. (4). The F index (blue line) measures the ratio between the total and the direct effect of the shock on the shocked variable itself. The index starts at 1, as in the initial period the direct effect is the only one at work. The index then swiftly declines, reaching a plateau slightly above 80 %. This means that the complex dynamic interactions between life domains compensate for around 20 % of the initial impact of the shock. The figure also displays the total size of the effect (red line), to help contextualising the increased relative importance of the mediated effects.

8. Results: health shock

We contrast the results on the effects of a partnership dissolution with a second experiment, where we reduce the self-rated health score of all men aged 30 in the initial year of the simulation to 1.[14] Fig. 8 shows the evolution of health in the baseline and 'Feedback ON' scenario, our measure for the total effect of the shock. It takes approximately 10 years for the shock to be absorbed, on average, with big health gains obtained during the first 3–5 years after the shock. The main explanation for this simulated response is that the individuals receiving the shock are young. Despite some persistency in the process determining health (see Bronka et al., 2025 for

[14] Qualitative measures of self-reported health are associated with well-known problems of comparability and interpretation. The measures are nevertheless included for analysis as they are analytically convenient and strongly related to other health-related characteristics reported by the UKHLS. For example, the measures of self-reported health relate closely to associated measures for disability reported below. Furthermore, the average number of Activities of Daily Living (ADLs) that individuals aged 65 and over report needing help with in the UKHLS increases from 0.294 for those reporting Excellent health, 0.323 (Very Good), 0.614 (Good), 1.580 (Fair), to 3.835 for those reporting Poor health (averaged over waves "g", "i" and "k" of the survey).

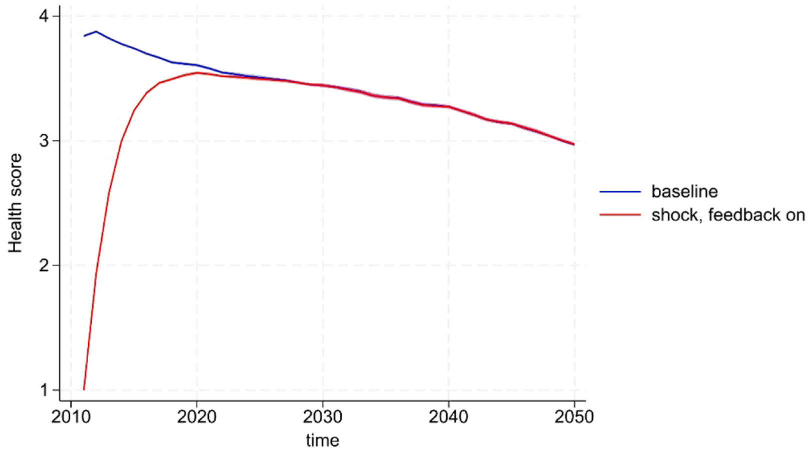

Fig. 8. Health shock: Total effects
Note: 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Men aged 30 in 2011.

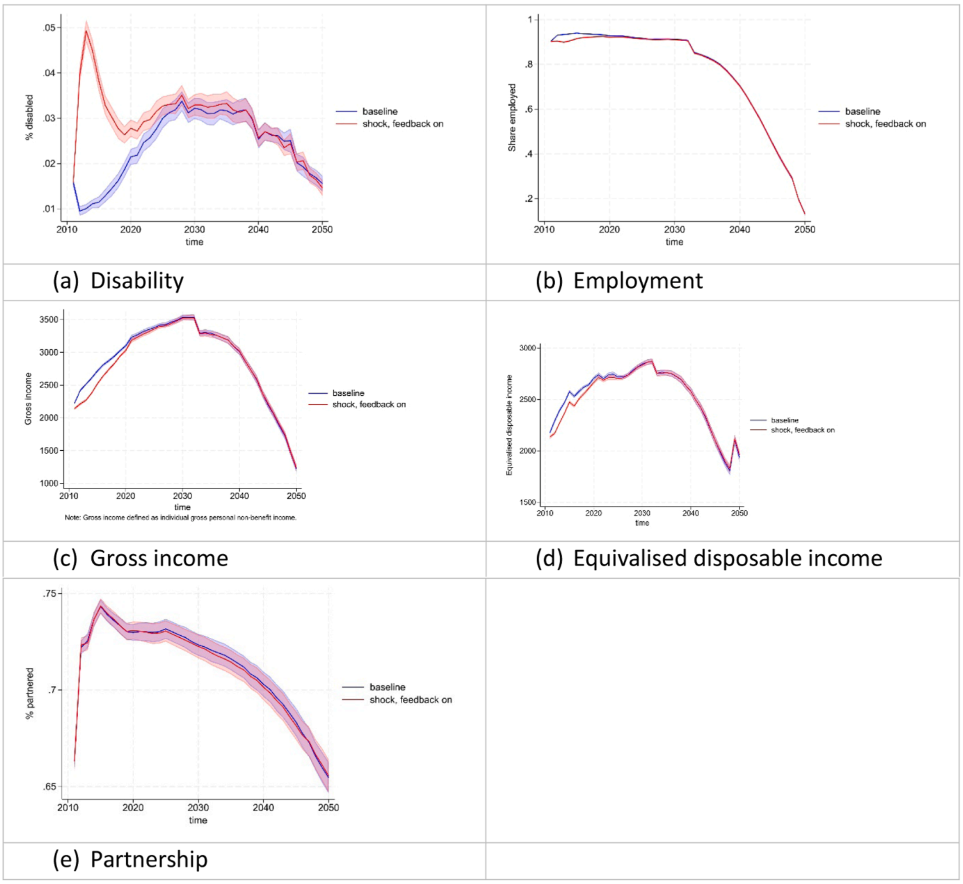

Fig. 9. Health shock: Cross-effects
Note: 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Men aged 30 in 2011.

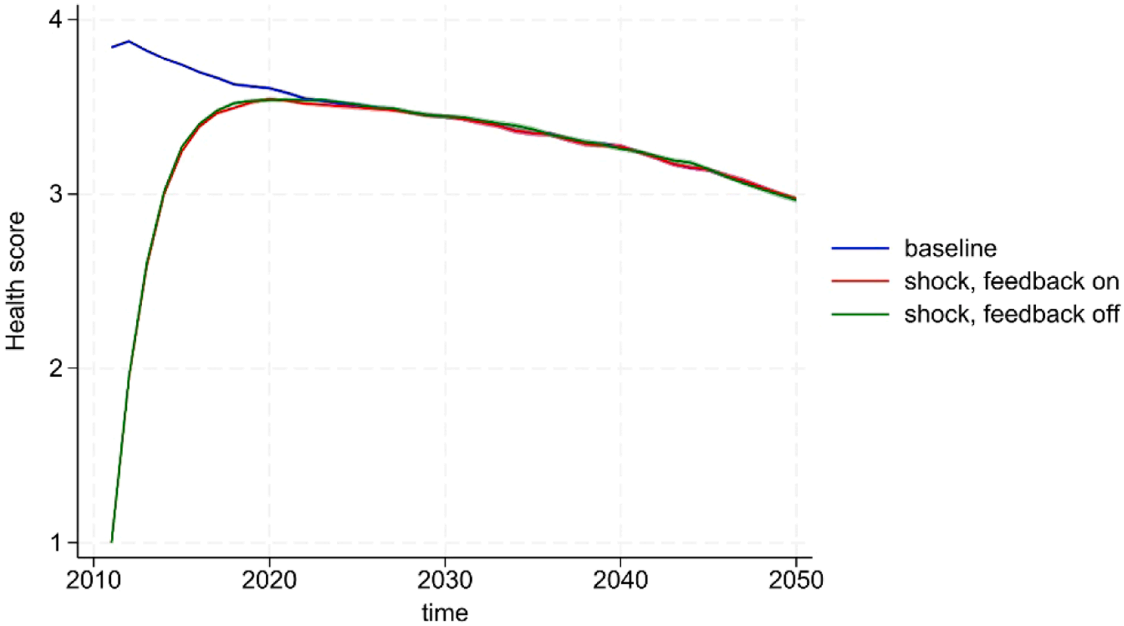

Fig. 10. Health shock: Total and direct effects
Note: Base vs. ON = total effect; Base vs. OFF = direct effect. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Men aged 30 in 2011.

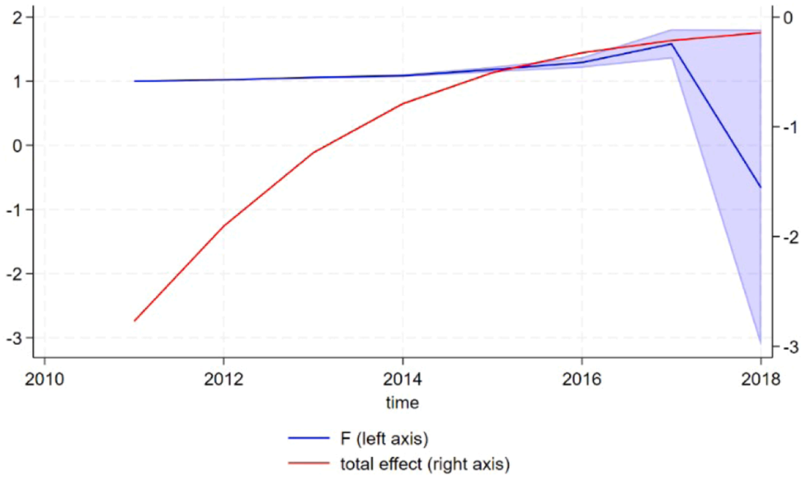

Fig. 11. Health shock: F index
Note: The F index (eq. (4)) measures the ratio of the total to the direct effect of the shock. Values above 1 indicate reinforcement mechanisms are at work, while values below 1 indicate attenuation mechanisms. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Men aged 30 in 2011.

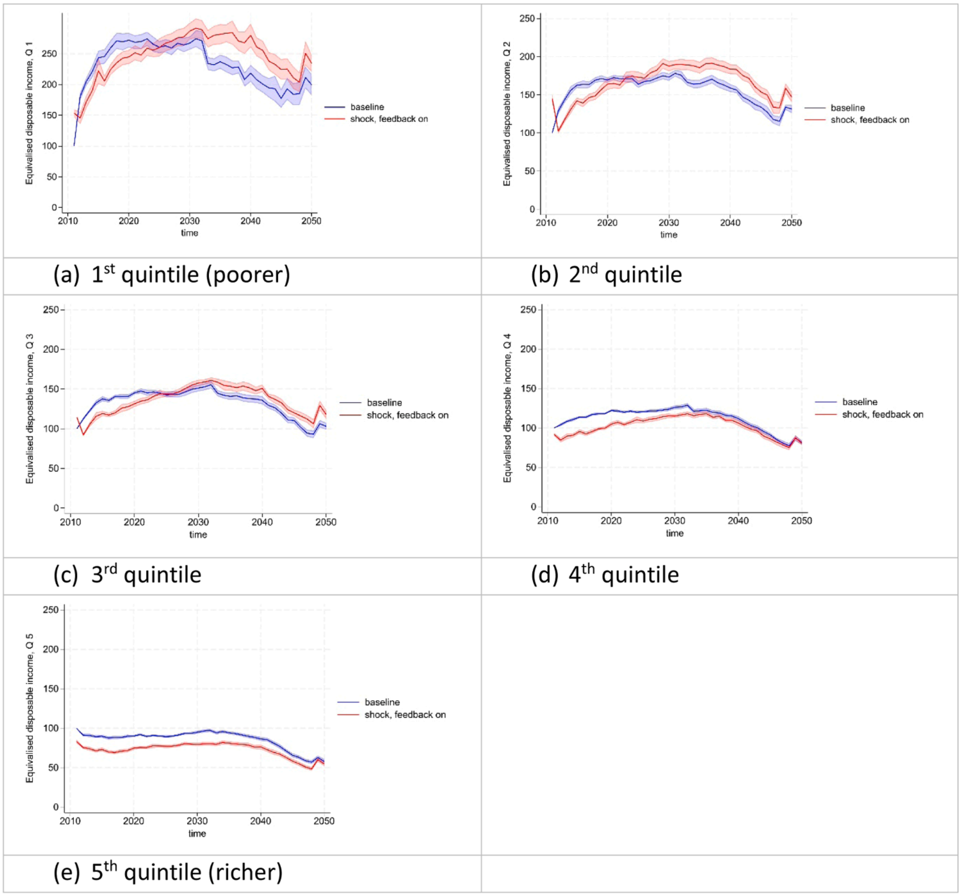

Fig. 12. Partnership dissolution: Cross-effects on equivalised disposable income, by income quintile in the initial year of the simulation
Note: Panels refers to different quintiles of equivalised disposable income in 2011, normalised to 100. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

details), their other determinants typically point to good health, hence increasing the chances of a recovery.[15]

The health shock has a large impact on the probability of being disabled (Fig. 9, panel (a)). Disability is simulated as a severe health condition but not an absorbing state; individuals can move into and out of disability, with probabilities estimated on survey data. These probabilities depend, amongst other things, on age, gender, education and socio-economic position (see Table A2 in Appendix 1). This explains why, as health gradually recovers, the probability of being disabled also returns to the simulated baseline.[16]

The model assumes that disabled people are not available to work.[17] Given that prime age men are typically observed to work despite poor health, it is the simulated increase in the disability rate that explains the small negative effects on employment projected for the health (panel (b) in the figure). The effects on employment carry over to effects on gross and net incomes (panels (c) and (d)). Interestingly, the health shock is not projected to influence partnership (panel (e)).

Given the limited spillovers to other domains, it is no surprise that the mediated effect is also limited, as implied by Fig. 10: the total effect substantially coincides with the direct effect.

This can also be seen in Fig. 11, which reports the evolution of the F index up to 2018: the index is mostly projected to be close to 1.

[15] For contrast, we also experimented with a simulated health shock to the cohort of men aged 50 in the initial year of the simulation. Given that the average health score for men aged 50 is lower than for men aged 30, the simulated shock is on average smaller. Despite this, and coherently with the intuition, we observe that it takes more for the shock to be absorbed, and for average health to return to the (declining) trajectory that is observed in the baseline. Appendix 5 describes the results of this exercise in more detail.

[16] The figure points to a counterintuitive lack of a clear age gradient in disability rates, in the baseline. This is because the disability variable is based on the 'long-term sick or disabled' response to the question related to current economic activity ('jbstat') in the UKHLS data. At older ages an increasingly proportion of the sample reports 'retired' as their economic status, even if they previously indicated 'long-term sick or disabled'.

[17] 'long-term sick or disabled' in the 'jbstat' classification is an alternative state to employment.

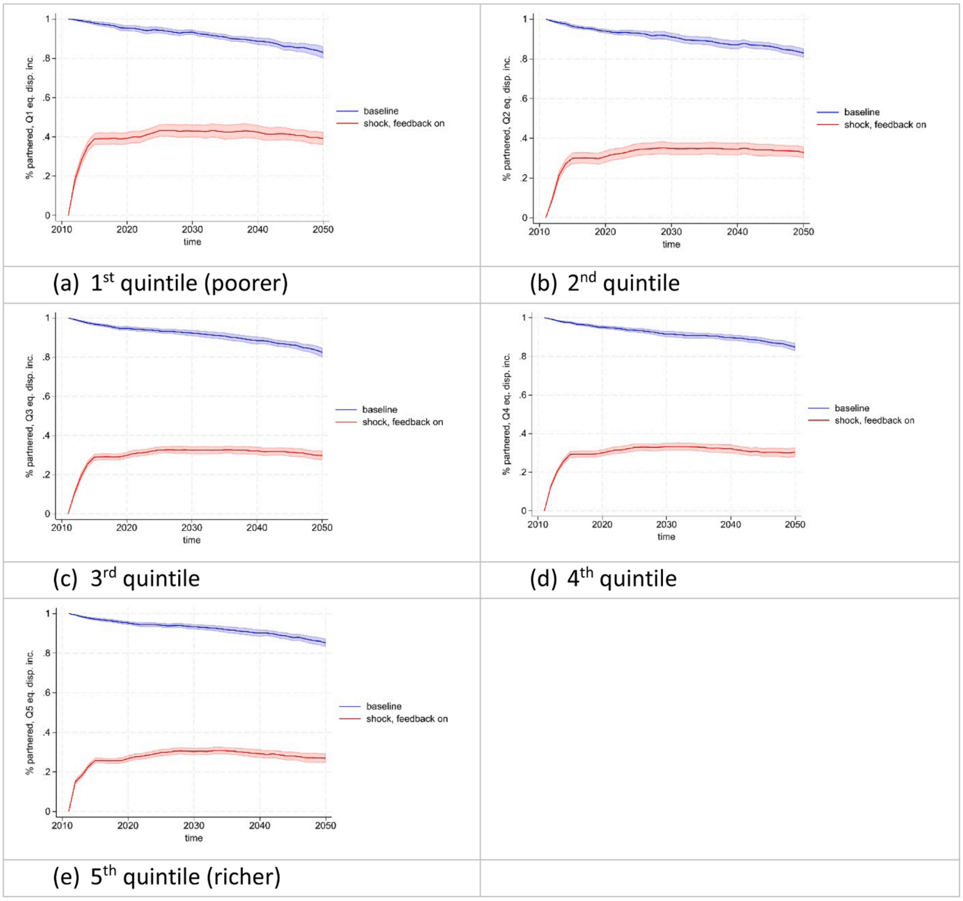

Fig. 13. Partnership dissolution: Direct effects on partnership rates, by income quintile in the initial year of the simulation.

Table 2
Distributional characteristics of the partnership shock sample, 2011.

Equivalised disposable income	Partners' employment rate	Partners' gross employment income (£/month, 2015 prices) (std. dev. in parenthesis)	Number of Children
1st Quintile	0.251	635.79 (362.56)	1.14
2nd Quintile	0.626	836.65 (477.02)	1.62
3rd Quintile	0.843	1175.16 (615.43)	1.32
4th Quintile	0.902	1645.88 (838.22)	0.90
5th Quintile	0.954	2429.90 (1383.04)	0.45

9. Distributional implications

Understanding how direct and indirect effects play out over multiple time horizons sheds new light on how inequalities unfold over the life course, and individual resilience to adverse events. For instance, we can analyse the cross-effects of a partnership dissolution on income distinguished by the initial socio-economic position.[18] Fig. 12 is a replica of Fig. 5d, by quintiles of equivalised disposable income in 2011. In each quintile, income is normalised to 100 in the initial year of the simulation to facilitate comparisons of associated distributional effects.

There are three interesting things to notice in Fig. 13. First, incomes tend to grow more, in percentage terms, for lower quintiles. Second, simulations show a cross-over, for quintiles 1–3, between the baseline and the scenario later in life, with average equivalised disposable income starting lower in the shocked scenario, but surpassing that of the baseline after around 15 years. Third, the impact of the partnership dissolution is more negative for higher earners.

To explain these dynamics, we begin discussion at the moment when partnerships are dissolved, in 2011. As Table 2 reports, the

[18] Given its more limited effect on variables other than health, we omit here a discussion of the distributional effects of the health shock.

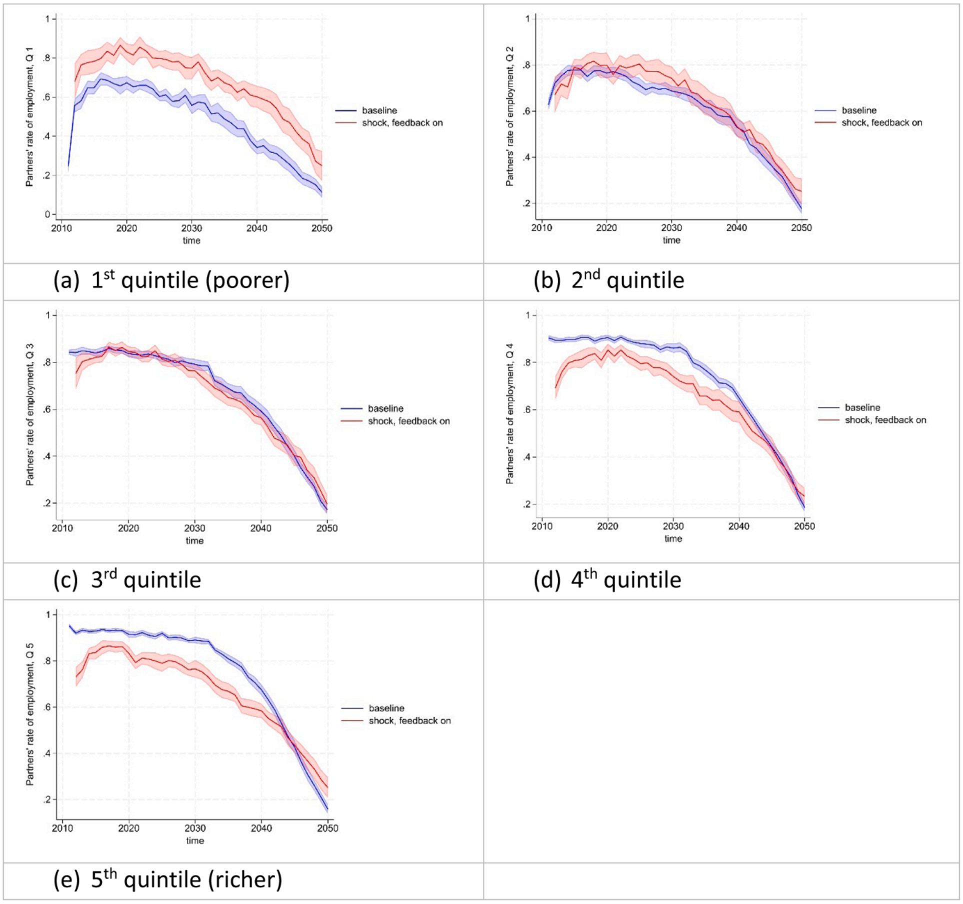

Fig. 14. Partnership dissolution: Cross effects on partnership rates of employment, by income quintile in the initial year of the simulation
Note: Panels refers to the fraction of partners who are in employment, for different quintiles of equivalised disposable income in 2011. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

proportion of shocked men whose partner was working, and their partner's earnings, increase with disposable income. This is partly by construction, as disposable income is computed at the benefit unit level, thus including earnings from both partners (as well as benefits that accrue to both the individual partners and the household). On the other hand, the average number of children – with the exception of the first quintile – decreases with income.

This explains why the shock to partnership affects men in the upper quintiles more, as we have explained when presenting Fig. 5d: lost partner earnings combined with smaller reductions in equivalence scales of men toward the top of the distribution dominate the relatively lower maintenance payments that they must typically pay, in relation to their income.[19]

Over time moreover, we observe a lower probability of re-partnering as we move up along the income distribution (Fig. 14). Given that being partnered is associated, on average, with higher equivalised disposable income, a lower probability of being re-partnered implies a more negative impact on income.[20]

Furthermore, there is a negative relationship in the simulated baseline between income quintile and the probability that a partner is employed (if one exists, Fig. 14). As noted previously, income quintiles are computed based on equivalised disposable income in 2011 and are thus lower by construction, ceteris paribus, if the partner is not working.

The fact that lower quintiles have a higher probability of re-partnering and a higher increase in the probability that the partner is working, with respect to the baseline, explains why their equivalised disposable income grows more. With a smaller initial loss and a higher rate of growth, equivalised disposable income in the lower quintiles surpasses that of the baseline.

[19] Richer individuals are charged a smaller fraction of their gross weekly income as maintenance payment. Moreover, they get fewer benefits, and have fewer children.
[20] The effect vanishes at very old ages as surviving individuals are more likely to be widowed, if previously partnered.

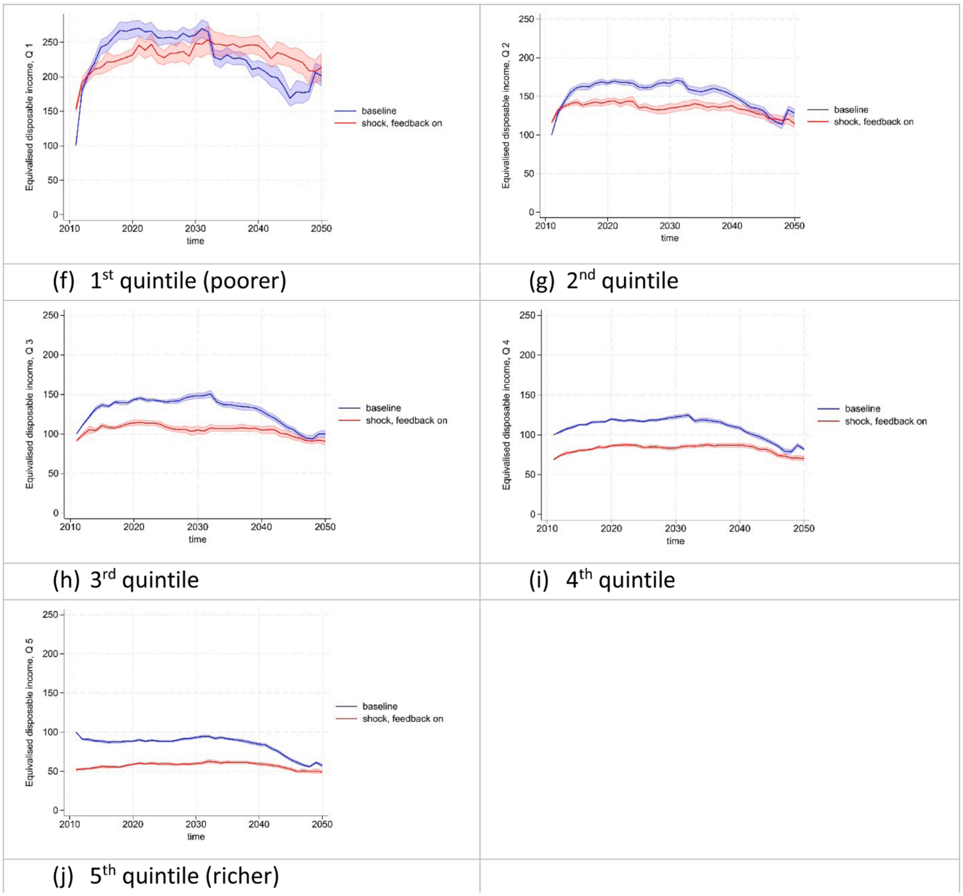

Fig. 15. Partnership dissolution: Cross-effects on equivalised disposable income, by income quintile in the initial year of the simulation, for the female partners.
Note: Panels refers to different quintiles of equivalised disposable income in 2011, normalised to 100. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Female partners of men aged 30 in 2011.

The effects reported above for men are comparable to those of their female partners (Fig. 15).[21] The negative impact of the partnership dissolution is however larger for women, reflecting the gender pay gap.[22]

In addition to studying resilience to a specific shock, this analytical framework could also be used to determine an overall score of resilience for the population of interest, by considering the effects of multiple shocks weighted by the likelihood of their occurrence (as estimated in the data). To be noted, the result that a partnership dissolution lowers on average equivalised disposable income takes into account that adjustments are made on different life domains. However, the proportion of the total effect that is mediated is higher for individuals with lower level of education, suggesting that attenuation mechanisms – including the safety net provided by the welfare state – are stronger for this group (Fig. 16).

10. Conclusions

In this paper we have illustrated a new approach to the study of the complex interactions between life domains, which allows researchers to move beyond the limitations of existing data sources. The approach relies on a structural model projecting life trajectories over time, with a consideration of the heterogeneity of individual characteristics and experiences. This allows to investigate the overall impact of specific life events on any of the outcomes included in the model, as well as the construction of specific counterfactuals to disable individual causal pathways. Exploiting this feature, we have derived a framework for characterising feedback between life domains in terms of their attenuating or reinforcing mechanisms. An illustrative application to young adult men in the UK

[21] The female partners affected by the experiment are obviously not constrained to be aged 30.
[22] Even more than for men, at very old ages only few women are partnered, so, the impact of the initial shock becomes negligible.

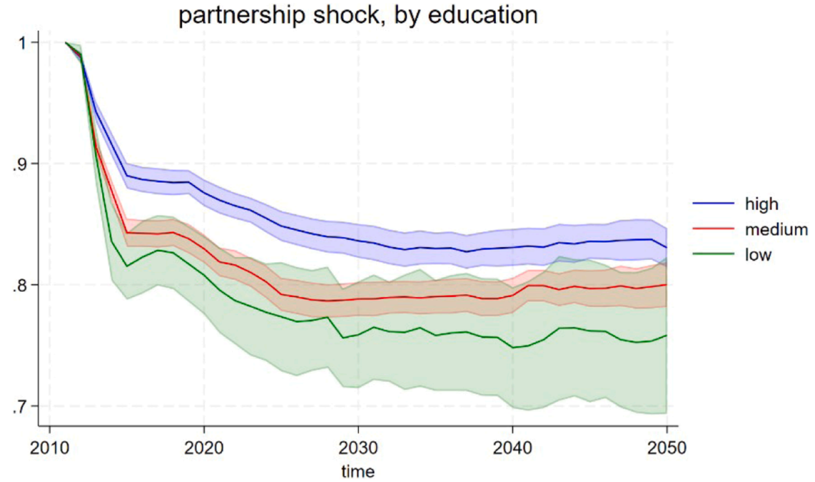

Fig. 16. Partnership dissolution: F index, by level of education
Note: The F index (eq. (4)) measures the ratio of the total to the direct effect of the shock. Values above 1 indicate reinforcement mechanisms are at work, while values below 1 indicate attenuation mechanisms. Lines refers to different level of education. 90 % confidence intervals are shown as shaded areas. Confidence intervals are based on 40 simulation runs. In each run, coefficients are bootstrapped from their estimated variance-covariance matrix before the simulation starts - separately for each process - and kept constant for the entire duration of the simulation. See Appendix 3 for more details. Sample: Partnered men aged 30 in 2011.

shows that partnership status is closely linked to most other life domains, with attenuating mechanisms that absorb around 20 % of the total effect of a shock. On the other hand, health has fewer connections to other life domains, and shocks to health on average do not get attenuated or reinforced by the web of complex interactions governing life trajectories.

Declaration of competing interest

We declare no competing interests for the research underlying our submitted paper "Attenuation and reinforcement mechanisms over the life course".

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2025.106911.

Data availability

The authors do not have permission to share data.

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