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Birth cohort data and life-course social risks: Insights and examples from the Dunedin Multidisciplinary Health and Development Study in New Zealand

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Abstract

Policymakers in OECD countries are increasingly asking for better evidence on how social and economic risks unfold over the life course. Using data from the Dunedin Multidisciplinary Health and Development Study, this paper illustrates the potential of one tool – birth cohort data – for providing life-course evidence through three illustrative use cases. The first analysis maps and explores life-course social risks for participants in the Dunedin Study between age 18 and 45. The second analysis zooms in on a critical life point – the school-to-work transition – to examine the pathways Dunedin Study members followed as they left education and moved into employment. The third uses integrated administrative data to explore unemployment benefit dynamics among the Study cohort and finds limited links with early life factors.

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The authors would like to acknowledge the late Richie Poulton, previous Dunedin Study Director and Emeritus Distinguished Professor, for his leadership during the Study's research transition from young adulthood to aging (2000-2023) and for donating the Royal Society Te Apārangi Rutherford Medal award to create this partnership study between the OECD and the Dunedin Study. Richie wanted to prove both the value of collaboration and of using birth cohort data in social policy research to inform the international social policy debate. The OECD hopes this project will offer lessons and inspiration to other countries to invest in good-quality data to better understand – and address – risks over the life course.

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1 Introduction and key findings

Policymakers are increasingly asking for better evidence on how social and economic outcomes unfold over the life course. At the 2018 Organisation for Economic Cooperation and Development (OECD) Ministerial Meeting on Social Policy, OECD Ministers called on the OECD to further advance a life-course perspective in its research to better inform the design of social policies that ensure "people have the necessary foundation to live fulfilling lives from infancy to old age" (OECD, 2018[1]). While recognizing the OECD's existing body of life-course-related research, including the Organisation's 2017 flagship *Preventing Ageing Unequally* report (OECD, 2017[2]), Ministers stressed a need for further research on how inequalities and disadvantage compound over the life course, and on what policies can do to tackle inequality and open opportunities at different stages of life. They also highlighted a specific need for new and better data to help governments "assess how different life events can change the trajectory of women's and men's lives" (OECD, 2018[1]).

A life-course approach offers several advantages for social research. Life-course research acknowledges that peoples' lives unfold over time and that events and conditions in the past are important in shaping outcomes in the present and the future (George, 2003[3]). It looks to move beyond static snapshots and treats life as a series of linked developmental stages, transitions, and cumulative experiences. Life-course research is often used to highlight how (dis)advantage can accumulate and compound over time, with the goal to help design policies that intervene early before problems become entrenched (Mayer, 2009[4]) It can also be used to identify the impact of unexpected events (e.g. the onset of illness or disability, death of a family member) on people's life trajectories. Life course research ultimately aims to help policymakers take preventive action to treat the causes of social problems, rather than the symptoms. It can help illustrate the benefits of taking an investment approach to social issues, spending and intervening early to give all members of society the opportunity to thrive.

Long-term birth cohort data provide one tool for conducting life-course research (Bynner and Joshi, 2007[5]). Birth cohort studies follow the same group of people from birth, collecting detailed, repeated measurements often long into adulthood. In doing so, they can inform how the timing and sequence of life events can affect later outcomes. Researchers using birth cohort data can examine whether an early-life event or condition precedes a later outcome, strengthening inference in ways not often possible with cross-sectional data (Bynner and Joshi, 2007[5]; VanderWeele, 2021[6]). Birth cohort data can also help highlight how issues accumulate and can identify important turning points that shape later outcomes.

Like all types of data collection, birth cohort data have their limits. Many birth cohort studies are limited in size, take many years to collect, and require substantial resources (Lawlor, Andersen and Batty, 2009[7]; O'Connor et al., 2022[8]). Participant drop-out and attrition is a particular threat and can bias results if those who remain in the study are not representative of the initial sample. Most birth cohort studies are also specific to a particular place and cohort, limiting the ability of findings to be generalised to other contexts or cases and the extent to which they can inform on the influence of macro-level factors. Nonetheless, in combination with other evidence, the depth and quality of the data produced can provide critical insights for policy.

In this paper, we aim to illustrate the value of taking a life-course approach and the potential of birth cohort data for informing on social risks. We use data collected by the Dunedin Multidisciplinary Health and Development Study (Dunedin Study) – a birth cohort study that follows the lives of more than 1 000 babies born in Dunedin, New Zealand, in 1972-1973 (Box 1.1) – to produce three illustrative use cases for birth cohort data in social research. These use cases range from broader and wider to narrower and more specific, and demonstrate just a few of the many ways that birth cohort data can help inform social risks. The first use case, in Section 2, explores life-course social risks, such as low education, non-employment, less-than-very-good self-rated health and diagnosed mental health conditions. It traces Dunedin Study members' exposure to social risks over their lives between 18 and 45. The second analysis, in Section 3, zooms in on a critical life point – the school-to-work transition – to examine the pathways Dunedin Study members followed as they left education and moved into employment. The third analysis, in Section 4, uses integrated administrative data to examine unemployment benefit dynamics among the Study cohort and possible links with early life factors. Examples of further use cases from the research literature are given in Box 1.2.

1.1 Life-course social risk trajectories

For the first use case, in Section 2, we use data from the Dunedin Study to examine Study members' exposure to social risks over the life course up to age 45. Adopting a method called Group-Based Trajectory Modelling (GBTM) (Nagin and Odgers, 2010[9]; Nagin, 2014[10]), we track Study members' exposure to four key social risks between age 18 and 45 and identify groups following similar, distinct trajectories over time – in other words, stylised patterns of social risk exposure over the life course. The four key social risks are:

- low skills
- non-employment
- poor general health
- poor mental health

We then explore whether early-life factors can help predict Study participants' membership of the different social risk trajectories. The early-life predictors used cover areas including family background (e.g. parents' education and occupational status), childhood health (e.g. child physical and mental health), childhood development (e.g. childhood IQ, childhood self-control) and adverse childhood experiences (e.g. abuse and neglect, household substance abuse, household partner violence). The overarching aim of the analysis is to identify distinct patterns of life-course social risk exposure and the early-life events and conditions associated with different risk patterns in later life. While not causal evidence Box 1.1, these early-life predictors may help provide insight into the reasons why different people face different social risks over the life course.

We find that Dunedin Study members differed considerably in their exposure to social risks, identifying eight distinct lifetime social risk trajectories:

- **Overall low social risk**: Just under a quarter of the Dunedin Study cohort (23%) experienced little exposure up to age 45 in the four risks examined. These Study members were not low educated, were rarely out of work, and were unlikely to report poor general health or to hold a mental health diagnosis. We label this trajectory "*Overall low social risk*".
- **Persistent low skill**, **Persistent poor general health**, and **Persistent poor mental health**: Slightly more than one-third of the Dunedin Study cohort (36%) experienced persistent exposure to one of the four examined social risks. For example, about 12% of the cohort were unlikely to have low education, to find themselves frequently out of work, or to have a mental health diagnosis, but were relatively likely to report less-than-very-good general health throughout. We label this group "*Persistent poor general health*". We also identify groups with persistent low education ("*Persistent low skill*", 12%) and persistent poor mental health ("*Persistent poor mental health*", 13%) but limited exposure to other social risks.

Box 1.1. The Dunedin Multidisciplinary Health and Development Study

The Dunedin Multidisciplinary Health and Development Study (the Dunedin Study) is a prospective birth cohort study that follows a sample of 1 037 individuals (52% men, 48% women) born in Dunedin on New Zealand's South Island between April 1972 and March 1973. The Study began as an investigation into early childhood health and development and has evolved into a multidisciplinary life-course study spanning physical health, mental health, and social and economic outcomes. Study members have been assessed at ages (labelled "phases") 3, 5, 7, 9, 11, 13, 15, 18, 21, 26, 32, 38, and 45. The cohort is representative of New Zealand's South Island on socioeconomic status, and is primarily of New Zealand European ethnicity, with 8.6% self-identifying as being Māori, the Indigenous People of New Zealand.

The Dunedin Study uses a multi-method, multi-informant approach. Data collection combines self-reports, teacher and parent assessments (in childhood), clinical interviews, behavioural observations, medical examinations, and biological samples. Researchers collect extensive physiological data, including cardiovascular, respiratory, dental, and metabolic health markers. Psychological measures include personality traits, cognitive function, and psychiatric diagnoses using structured interviews. Interviews and life history calendars (see Section 3) capture family background, education, employment, relationships, and financial well-being. Over time, the Study has expanded to include genetic and epigenetic analyses, as well as official records and administrative data on topics including benefit receipt (see Section 4).

The Study benefits from exceptionally high retention rates (over 90% across all phases except one (age 13)). The Study team puts sustained effort into tracking and maintaining contact with participants, including those who have moved abroad, and issue participants with regular updates on Study findings. Travel expenses, accommodation, and meals are provided during assessments, and Study participants who cannot travel are visited by field interviewers. The Study team seeks to foster a sense of participant ownership and trust, which has contributed to sustained commitment over decades.

Analytically, the Study uses an observational, prospective-longitudinal design. While subject to the usual limitations of observational studies in the extent to which it can produce definitive causal statements, the Study's temporal design and use of repeated observation strengthen the ability to make causal inference in ways rarely possible with cross-sectional or shorter-duration longitudinal studies. Given that many conditions in both health and social sciences have their roots in early childhood, a particular advantage of the Study is its ability to combine information on development and later life outcomes with the initial conditions faced by respondents at birth and in the early years. The addition of administrative data also provides unique opportunities to produce analyses that combine administrative outcomes (like benefit receipt) with the Study's rich health and development data.

The Dunedin Study overall offers a best practice example in the OECD of the development and administration of a birth cohort study. Now in its fifth decade and having fed into more than 1300 publications and reports, the Study continues to provide evidence to inform public policy in New Zealand, the OECD and beyond.

Source: (Poulton, Moffitt and Silva, 2015[11]; Poulton et al., 2023[12])

- **Late non-employment** and **Late educational attainment**: We identify two groups that experienced large changes in social risk exposure over the period to age 45. One group ("*Late non-employment*", 14%) were unlikely to be low educated, to report less-than-very good general health or to have a mental health diagnosis, but from age 26 to 38 were increasingly likely to find themselves frequently out of work. Women are heavily over-represented in this group, which likely reflects the impact of parenthood and women's often disproportionate responsibility for care and unpaid work. Another group ("*Late educational attainment*", 8%) represents cohort members who attained at least medium-level education at some point after age 18.

- **Educated high social risk** and **Overall high social risk**: Finally, we identify two groups that experienced persistent exposure to multiple social risks. This includes a group ("*Educated high social risk*", 7%) with medium- or high-level education but persistent exposure to non-employment, relatively poor general health and poor mental health, and another group ("*Overall high social risk*", 11%) persistently exposed to all four. These Study members may be particularly vulnerable to disengagement and social exclusion. Together, they make up just under one-fifth (18%) of the total Dunedin Study cohort.

Examining early-life predictors reveals important links between childhood circumstances and development and later social risk trajectories. Childhood IQ is a frequent predictor, including of both the group with limited lifetime exposure to social risks ("*Overall low social risk*") and of those exposed to multiple persistent social risks ("*Overall high social risk*"). This underlines the importance of supporting early cognitive development for later opportunities and outcomes. Additionally, childhood mental health conditions and adverse childhood experiences are both linked with a higher likelihood of trajectories involving multiple persistent social risks ("*Overall high social risk*"). Gender is also frequently predictive of group membership, reflecting structural gender inequalities within broader society. Specifically, being a woman reduces the chances of escaping lifetime exposure to any of our four social risks (i.e. "*Overall low social risk*").

1.2 Pathways out of education and into work

In Section 3, we zoom in and take a detailed look at a critical period in many people's lives – the transition out of education and into work. Using detailed monthly education and employment status data from the Dunedin Study's Life History Calendar, we provide a granular account of the school-to-work pathways followed by the Dunedin Study cohort between the ages of around 16 and 26. We use Sequence Analysis to identify patterns of school-to-work transition and group Study members according to the pattern followed. We then provide analyses of the early-life factors predicting, and later-life outcomes associated with, membership of each identified school-to-work transition pathway. Examples of the later life outcomes covered include economic outcomes (e.g. non-employment, low occupational status) and health and well-being outcomes (e.g. low self-rated general health, low life satisfaction).

Our findings point to eight distinct pathways followed by the Dunedin Study cohort as they left school, which we group here into three clusters. It should be noted that this is a separate analysis to the life-course social risk analysis summarised in Section 1.1 and these pathways are independent of the trajectories outlined in the previous section.

- Just under one-third (29%) of the Dunedin Study cohort left education comparatively early, in many cases without attaining upper-secondary education or above. Among these, a small subgroup (6% of the cohort) left school around or before age 18 and spent most of the period up to age 26 not in education, employment, or training (NEET). We label this group "*Early school leaving and long-term NEET*". A slightly larger group (13%) left school similarly early but were more successful at integrating into the labour market. Members of the groups were likely to move into continuous full-time employment and in fact spent less time as NEET than almost all other identified groups. We label this group "*Early school leaving to full-time work*". Lastly, we identify a group ("*Insecure employment*", 10%) who remained in education slightly longer but in many cases still left without upper-secondary education (or similar) and often struggled to secure stable full-time employment.
- Slightly over one-third (38%) of the Dunedin Study cohort followed "Upper secondary education" pathways, remaining in education until approximately age 18-19 before in most cases moving into full-time employment. Among this cluster, we identify groups that moved from full-time upper

secondary education to full-time work ("*Upper secondary education to full-time work*", 13%), that combined upper secondary education (or similar) with part-time work before moving into full-time work ("*Upper sec. ed. and part-time work to full-time work*", 18%), and that combined full-time work with periods in education across their early-to-mid-20s ("*Upper sec. ed. to full-time work and later education*", 7%).

- The final third (33%) of the Dunedin Study cohort followed "Higher education" pathways, continuing their studies until their early 20s. This cluster can be split into a group that concentrated mostly on their education only ("*Higher education*", 12%), and a larger group that combined education with part-time work ("*Higher education and part-time work*", 21%).

Early-life analysis again highlights factors associated with group membership. Childhood IQ once more stands out as a frequent predictor: Study members who had higher childhood IQs were less likely to experience difficult school-to-work transitions (e.g. "*Early school leaving and long-term NEET*") and more likely to follow a "Higher education" pathway. Members with stronger childhood self-control – the ability in early life to control one's own emotions, thoughts, and behaviours – were similarly less likely to follow the most difficult school-to-work pathways, echoing earlier Dunedin Study evidence on the importance of self-control for later outcomes (Moffitt et al., 2011[13]). However, we find that family background (e.g. parents' education, parents' occupational status) and childhood health are only weakly associated with the different school-to-work pathways.

Lastly, our later-life outcome analysis shows that Dunedin Study members who experienced more difficult school-to-work transitions consistently faced poorer economic, health and well-being outcomes into mid-adulthood. Mirroring findings elsewhere on the scarring effects of being NEET (Carcillo et al., 2014[14]) outcomes were especially difficult for the small subgroup who left school early and spent an extended period as NEET (i.e. "*Early school leaving and long-term NEET*"). Compared to most other Study members, across their 30s and into their 40s, this subgroup was more likely to experience frequent non-employment and employment in low-status occupations, report financial difficulties, report poor general health, have a mental health diagnosis, and, to a lesser degree, report lower life satisfaction. In many cases these outcome gaps persisted over time, with associations between school-to-work transitions and later outcomes nearly as apparent when members reached their mid-40s as when they were in their mid-20s or early-30s.

1.3 Early-life factors and unemployment benefit receipt dynamics during early adulthood

Finally, in Section 4, we make use of administrative benefit receipt data integrated into the Dunedin Study to explore unemployment benefit receipt dynamics among the Study cohort and possible links with early-life factors. Using discrete-time event history analysis (pooled and random effects complementary log-log regression models), we explore the issue of "duration dependence"; that is, the idea that benefit recipients can become "stuck" on benefits with time spent on benefits making future receipt more likely. We find that receipt patterns among the Dunedin Study cohort are consistent with "duration dependence" – the longer the unemployment benefit spell, the lower the chances of exit – but also that much of this apparent "dependence" is driven by differences between recipients, with recipients with better labour market prospects likely to exit first. Accounting for observed and unobserved heterogeneity between recipients sees the degree of duration dependence fall by more than half – a level similar to several other studies (Mood, 2013[15]; Ilmakunnas, 2023[16]). Our final corrected estimate points to modest duration dependence, with the probability of leaving unemployment benefit receipt falling by about 5% for each week of receipt.

Box 1.2. Further examples of life-course research on social risks and social policy issues

Increasing data availability provides increasing options for life-course research into social risks and social policy. Further examples of research using longitudinal data and taking a life-course approach to issues relating to social risks and social policy include:

- **Poverty dynamics and long-term outcomes:** Low income may have different and more damaging effects on life outcomes when it is recurrent or persistent. While some households may be able to bridge a short-term loss of income by drawing on savings or other resources, extended periods of low income are likely to see assets depleted and disadvantage compounded. Longitudinal data allow researchers to examine whether poverty is typically a transient or persistent condition, and whether and how the two have different impacts on outcomes. For example, focusing on children, Lai et al (2019[17]) use birth cohort data from the UK Millennium Cohort Study to examine different child poverty trajectories and their association with adolescent physical and mental health. They find that just under one-fifth of the cohort experienced persistent poverty, and that compared with children who never experienced poverty, those who lived in persistent poverty were at increased risk of mental ill health, obesity and longstanding illness as teenagers.
- **Unemployment dynamics and long-term "scarring":** Job loss can leave lasting damage on careers. Studies show that experiencing unemployment, especially long-term unemployment early in the career, increases the probability of future unemployment and reduces future earning compared to similar individuals who avoided unemployment (Fondeville and Ward, 2014[18]). Longitudinal data make it possible for researchers to follow those experiencing unemployment and their subsequent career outcomes. For example, Jarosch (2023[19]) uses a panel dataset extracted from German Social Security data to examine the extent to which unemployment spells lead to further unemployment and earnings losses. They find major persistent "scars" from job loss, equivalent in present value to about 18% of earnings on average, primarily because those returning from unemployment find themselves lower down the "job ladder" and more susceptible to further job loss.
- **Gender differences in earnings and the motherhood penalty**: What drives the gender pay gap? While cross-sectional data are helpful for highlighting gender differences in employment outcomes at a given point in time, life course studies are useful for informing on when and where women's and men's careers often diverge. Many studies point to the moment they become parents (England et al., 2016[20]; Cukrowska-Torzewska and Matysiak, 2020[21]). For example, Kleven, Landais and Søgaard (2019[22]) use an event-history approach and a panel dataset built on Danish administrative data to examine the impact of first childbirth on long-run earnings. They find that child arrival leads to a long-run 20% drop in mothers' earnings, with no comparable effect for fathers. This "motherhood penalty" is driven by reduced hours, lower labour force participation, and differential occupation, sector and firm choices for women.
- **Life-cycle impact of social programmes**: From a policy perspective, one important use for longitudinal data and a life-course approach is tracking the (long-term) impact of policy interventions. Recent advances in forecasting even allow for the estimation of full life-cycle impact long before participants have lived out their lives. As one example, García et al. (2020[23]) use a life-course approach to assess the life-cycle returns to two well-known, high-quality early childhood intervention programmes – the Carolina Abecedarian Project (ABC) and the Carolina Approach to Responsive Education (CARE). Merging the trial data with synthetic cohort data produced using population surveys, Garca et al. project each trial participant's lifetime outcomes and costs. They forecast that over the lifetime, for every dollar spent, the programmes are likely

to yield about seven dollars in benefits when accounting for long-term gains in education, earnings, health, and crime reduction.

We also examine whether early-life factors can help predict the benefit durations. The Dunedin Study data are uniquely well suited to the latter task: while many studies examining benefit receipt dynamics make use of benefit history data from administrative or survey sources, few have access to the rich data on family background and childhood conditions and development available in the Dunedin Study. We find only limited evidence of links between early-life factors and benefit receipt dynamics, with the important exception of childhood self-control (see above). We find that childhood self-control is associated with quicker exit from benefit receipt: once in receipt of unemployment benefit, Dunedin Study members with greater childhood self-control tend to exit benefit receipt sooner. This is consistent with previous work by the Dunedin Study which shows that Study members with lower childhood self-control have spent a larger proportion of their lives receiving social benefits.

2 Life-course social risk trajectories

Understanding the prevalence and distribution of social risks is central to designing and implementing effective social policies. Typical cross-sectional data sources, such as household surveys, provide valuable insights into the prevalence of social risks, including for marginalised groups, but offer only limited information on the dynamics of these risks and how individual experiences evolve over the life course. The potential for people to experience persistent or repeated social risk exposures (e.g. long-term or repeated non-employment) is a particular concern, as is the potential for people to experience multiple social risks, either simultaneously or at various points over the life course. These people are likely to be at higher risk of disengagement and social exclusion, among other adverse outcomes.

Birth cohort data can provide valuable insights into how social risks change, persist and accumulate over the life course. By tracking the same individuals over time, cohort data allow for the differentiation of temporary risk exposure from chronic or recurrent experiences. Birth cohort data help trace the root causes of these risks by collecting information on people's lives and circumstances from their early years onwards.

In this section we use data from the Dunedin Study to illustrate one way in which birth cohort data can be used to better understand social risks over the life course. Taking a "person-centred" approach to social risks, we use Group-Based Trajectory Modelling (GBTM) (Nagin and Odgers, 2010[9]; Nagin, 2014[10]) to examine Study members' exposure to social risks over the life course up to age 45 and to identify distinct groupings for life-course social risk exposure. We consider exposure on four key social risks (see Section 2.1.1 and Figure 2.1): low skills, measured by low education, which reduce employment opportunities and often lead to low earnings (Bonoli, 2005[24]; OECD, 2024[25]); non-employment, which, in addition to lost income, harms skills and abilities, reduces opportunities for social connections, and can damage physical and mental health (Llena-Nozal, 2009[26]; Picchio and Ubaldi, 2024[27]; Virgolino et al., 2022[28]); and poor general health and poor mental health, which both restrict access to work and limit participation in valued social activities (Devaux and Sassi, 2015[29]).

We then use the resulting grouping variable as the dependent variable in an analysis of early-life factors predicting trajectory group membership. The predictors used cover areas including family background (e.g. parents' education and occupational status), childhood health (e.g. child physical and mental health), childhood development (e.g. childhood IQ, childhood self-control) and adverse childhood experiences (e.g. abuse and neglect, family incarceration, household substance abuse, household mental illness, loss of a parent, and household partner violence).

Key findings from this section are as follows:

- Dunedin Study members differ in their exposure to life-course social risks. An important minority of the cohort (23%) have little exposure to the four covered risks up to age 45, but the remainder (77%) follow trajectories that see them frequently exposed to at least one social risk, and in many cases, this exposure is persistent over time.
- Just over one-third of the Dunedin Study cohort (36%) are persistently exposed to one of the four covered social risks, and just under one-fifth (18%) are persistently exposed to multiple social risks. These Study members are likely to be at particular risk of disengagement and social exclusion.
- Early-life predictors reveal important associations between childhood circumstances and development and later social risk trajectories. Childhood IQ emerges as a frequent predictor,

including of both the lowest- and highest-risk trajectories, reflecting the significance of supporting childhood cognitive development for later opportunities and outcomes. Childhood mental health and adverse childhood experiences also have potential long-lasting effects, with both associated with a higher chance of membership in groups that experience multiple persistent social risks.

- Gender is another frequent predictor of group membership, reflecting structural gender inequalities in wider society (OECD, 2023[30]). Most notably, being a woman significantly reduces cohort members' chances of being part of the group with limited exposure to the four social risks over the life course. This mirrors women's greater exposure to many social risks (including economic inactivity and many common mental health disorders) more generally.

2.1 Data and methods

2.1.1 Adult social risk outcomes

We measure social risks using four binary indicator variables covering low skills, non-employment, poor general health and poor mental health:

- *Low education*: We measure skills based on educational attainment, with "low education" referring to Study members with a highest qualification equal to or below a New Zealand year 11-equivalent qualification (i.e. the "School Certificate" for the Dunedin Study cohort) (Scott and Gini, 2010[31]; Scott and Ali, 2024[32]). This variable is available for all Study phases between age 18 and 45.
- *Frequent non-employment*: The Dunedin Study collected detailed information on employment status through its Life History Calendar – a tool to collect retrospective information on important life events and their timing, including movements in and out of work (see Section 3). "Frequent non-employment" refers to members who spent 10% or more of the period between the previous and current assessment phase out of employment or education. This variable is available for all Study phases between age 18 and 45.
- *Less-than-very-good self-rated general health*: From phase 26 onwards, the Dunedin Study collected information on self-rated general health using the question "In general, would you say your health is…" with the response options "Excellent", "Very good", "Good", "Fair" or "Poor". "Less-than-very-good self-rated general health" refers to Study members who report being in "poor", "fair" or "good" health. We classify "good" health alongside "poor" and "fair" health because the response scale used is known to introduce a bias towards a positive self-rating of health (OECD, 2023[33]).
- *Any mental health diagnosis*: At each phase, the Dunedin Study collected information on past-year symptoms of mental disorders through private interviews by trained interviewers using the Diagnostic Interview Schedule (Caspi et al., 2020[34]). Diagnoses were made using the Diagnostic and Statistical Manual of Mental Disorders (DSM) current at each stage. "Any mental health diagnosis" refers to members who could be diagnosed with at least one mental disorder based on their past-year symptoms at the given phase. This variable is available for all Study phases between age 18 and 45.

Figure 2.1 shows the overall prevalence of each risk at each Study phase. Except for less-than-very-good self-rated health, prevalence generally falls across phases. The share of Study members in frequent non-employment falls particularly sharply, from almost half (48%) in the period leading up to "phase 18" (approximately age 18) to about one-third (34%) at phase 26 and just over one-quarter (27%) at phase 45. This mirrors improvements in labour market conditions as the Dunedin Study cohort move from early- to middle-adulthood (see Box 2.1) and the difficulties many young people have gaining a foothold in employment (OECD, 2016[35]; OECD and ILO, 2024[36]), as well as the fact that while in education, many cohort members recorded themselves as outside both education and employment during the December-January end-of-year holidays (see Section 3). The prevalence of low education falls by about 10 percentage points between phase 18 (33%) and phase 45 (22%), while the prevalence of mental health diagnoses falls by slightly less, from 50% at phase 18 to 44% at phase 45.

Figure 2.1. Except for general health, social risk prevalence falls as the cohort ages

Prevalence (%) of each social risk, 1972-1973 Dunedin Study birth cohort, phase 18 to phase 45

Note: "Low education" is defined as a highest qualification equal to or below a New Zealand year 11-equivalent qualification (i.e. the "School Certificate" for the Dunedin Study cohort). "Frequent non-employment" refers to having spent 10% or more of the period between the previous and current assessment phase out of employment or education. " Less-than-very-good self-rated general health" refers to the responses "poor", "fair" or "good" when asked "In general, would you say your health is…". Other response options were "very good" and "excellent". "Any mental health diagnosis" refers to members who could be diagnosed with at least one mental disorder based on their past-year symptoms at the given phase.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

2.1.2 Early-life predictors of social risk outcomes

2.1.2.1 Family background

Life chances are tied closely to family background. Parents' socio-economic status is a strong predictor of their children's education and employment outcomes (OECD, 2018[37]; Blanden, Doepke and Stuhler, 2022[38]; Clarke et al., 2024[39]), as well as later health (Flores and Kalwij, 2014[40]; Clarke et al., 2024[39]). We measure parents' socio-economic status using parental education and an occupation-based index measure:

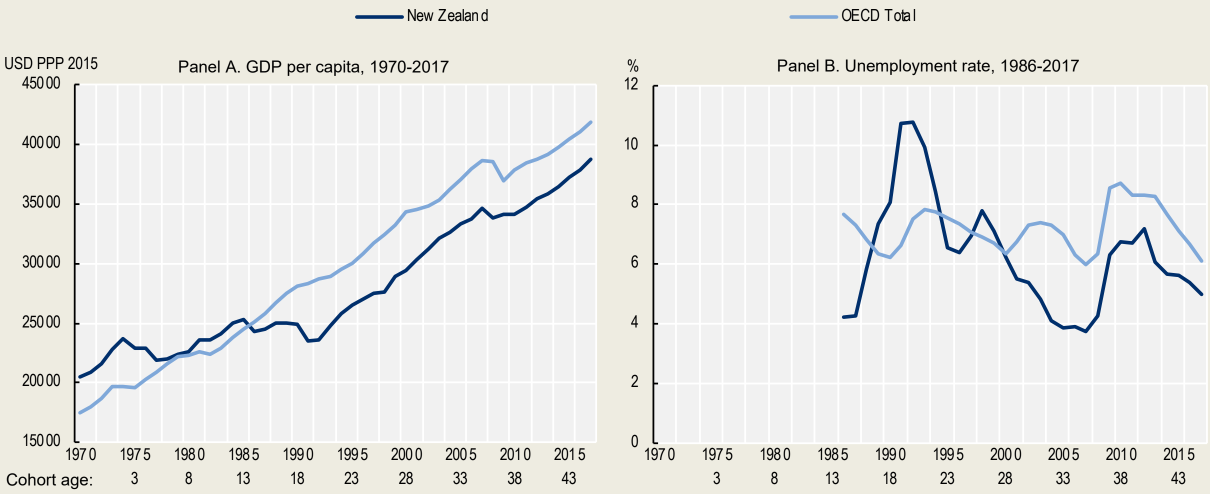
- *Parental education*: The Dunedin Study collected information on parents' educational attainment up to the assessment at phase 15. We use information on the highest level of educational attainment of either parent to produce a three-part ordinal education variable: low parental education (no school qualification); medium parental education (school certificate, high school graduate, or equivalent, plus vocational education); and high parental education (university degree or higher).
- *Parental occupational status*: The Dunedin Study measured parental occupational status repeatedly from birth through to phase 15 using a scale that classified parental occupations on a six-part categorical variable based on the educational attainment and income associated with that occupation in the New Zealand Census (Poulton et al., 2002[41]). We use the mean across assessments of the highest status of either parent to produce a continuous measure of parental occupational status with higher values representing higher occupational status.

Box 2.1. The Dunedin Study cohort came of age at a time of economic uncertainty

Starting in 1972, the Dunedin Study cohort grew up at a time of large-scale social and economic change (Carroll, 2012[42]; Grimes, 2023[43]). Their first years coincided with the tail-end of New Zealand's period of post-war stability but a series of external shocks, including the 1973 oil crisis and the loss of the United Kingdom as a key export market following its entry into the European Economic Community, saw economic conditions weaken quickly (Carroll, 2012[42]). Growth stagnated from the middle of the 1970s onwards (Figure 2.2, Panel A), while inflation increased quickly and remained persistently high: price rises exceeded 10% per year through most of the 1970s and early 1980s, to the extent that prices nearly quadrupled in the decade between 1974 and 1984 (Statistics New Zealand, 2015[44]; OECD, 2024[45]). Unemployment, which had been as low as 2% in 1971, rose steadily to 3% in 1976 and 5% by 1981 (Statistics New Zealand, 2015[44]).

Figure 2.2. GDP per capita growth stalled between the mid-1970s and early 1990s, and unemployment spiked in the early 1990s

GDP per capita, USD PPP 2015 (Panel A), and unemployment rate, % (Panel B), New Zealand and OECD Total, 1970-2017



Source: OECD National Accounts database, https://www.oecd.org/sdd/na/, and OECD Data Explorer, https://www.oecd.org/en/data/datasets/oecd-DE.html

In 1984, in response to persistent poor economic performance, the newly elected Labour government initiated a series of market-oriented reforms. Known as "Rogernomics" after Roger Douglas, the Minister of Finance at the time, these measures included floating the exchange rate, financial market deregulation, the privatisation of state-owned enterprises, removing subsidies for industries including agriculture, reducing the top rate of income tax, and reducing government expenditure (Grimes, 2023[43]). The subsequent adjustment and reallocation period saw widespread job losses and a continued deterioration in many economic indicators. GDP per capita fell during the second half of the 1980s, while unemployment grew quickly before peaking at just under 11% in 1992 (Figure 2.2), when the Dunedin Study cohort were age 19-20 and many were looking to enter the labour market. Joblessness disproportionately affected younger people (Statistics New Zealand, 2025[46]). Income inequality increased sharply over the same period, with New Zealand's Gini coefficient growing from 0.27 in the mid-1980s to approximately 0.33 by the mid-1990s, moving above the OECD average (Perry, 2019[47]). Income poverty also grew, with 15% of the population in after-housing-cost relative income poverty by the mid-1990s, up from 8-9% in the 1980s (Perry, 2019[47]).

The Dunedin Study cohort benefited from more favourable economic conditions as they moved into their mid-20s and early-30s. Inflation had fallen below 2% during the early 1990s (OECD, 2025[48]), and GDP per capita growth recovered from 1993 onwards (Figure 2.2). Indeed, growth averaged 2-3% annually from 1993 until the mid-2000s, faster than the OECD average. Unemployment fell quickly after its 1992 peak, reaching 6% by 1996 and about 4% by 2005 – the lowest in two decades – before increasing to just under 8% during the Global Financial Crisis (Figure 2.2). Inequality remained high but income poverty fell steadily, hitting 13% in 1998 and less than 10% on the eve of the Financial Crisis in 2008 (Perry, 2019[47]).

Financial Crisis aside, the Study cohort continued to enjoy a comparatively robust economy as they moved into their 40s. By 2018, as the cohort approached their most recent available assessment at phase 45, GDP per capita growth remained steady at around 2% annually with unemployment steady and falling at just under 6% (Figure 2.2). Real income grew steadily for much of the population across the 2010s, especially those towards the upper end of the income distribution, although inequality remained high and (after-housing-cost) relative income poverty remained steady at approximately 15-16% (Perry, 2019[47]).

2.1.2.2 Childhood physical and mental health

Childhood health is instrumental for later outcomes. In addition to direct links with adult health outcomes (Flores and Wolfe, 2023[49]), good health is central to children's education and development and an important predictor of later labour market success (Currie, 2009[50]; Jackson, 2015[51]; Burns and Gottschalk, 2020[52]; Currie, 2016[53]; Hale and Viner, 2018[54]).

- *Childhood physical health*: The Dunedin Study contains a wealth of information on participants' physical health in childhood, including clinician-rated health, motor ability, skinfold thickness, systolic and diastolic blood pressure, and fixed expiratory volume and forced vital capacity. We use an index measure constructed using a panel of these measures taken during assessments between birth and phase 11 (Belsky et al., 2015[55]). The final childhood health index is a standardised continuous variable with higher values representing better childhood health.
- *Childhood mental health*: The Dunedin Study collected information on past-year symptoms at ages 11, 13 and 15 through private interviews by trained interviewers using the Diagnostic Interview Schedule for Children (DIS-C) (Schaefer et al., 2017[56]). Diagnoses were made using the then-current Diagnostic and Statistical Manual of Mental Disorders 3rd edition (DSM-III). We use a binary measure indicating whether participants had no or at least one DSM-diagnosed mental disorder at ages 11-15.

2.1.2.3 Childhood cognitive functioning

Cognitive functioning and development share well-known links with adult outcomes, including in education and employment (Fergusson, Horwood and Ridder, 2005[57]; Hegelund et al., 2018[58]), physical health (Čukić et al., 2017[59]), oral health (Thomson et al., 2019[60]) and mental health (Koenen et al., 2009[61]; Wraw et al., 2016[62]). We use *childhood IQ* to measure several (if not all) important aspects of childhood cognitive functioning. The Dunedin Study collected information on childhood IQ through Wechsler Intelligence Scale for Children-revised (WISC-R) assessments at ages 7, 9, 11, and 13.[1] We use the standardised mean from across these four assessments.

[1] The WISC-R contains sub-tests in the following areas: 1. General Information; 2. Picture Completion; 3. Similarities; 4. Picture Arrangement; 5. Arithmetic; 6. Block Design; 7. Vocabulary; 8. Object Assembly; 9. General Comprehension;

2.1.2.4 Childhood social-emotional development

Social-emotional skills are increasingly recognised as central to children's development and later outcomes, including in work and in health (Moffitt et al., 2011[13]; Kautz et al., 2014[63]; OECD, 2021[64]; OECD, 2021[65]). We measure the development of one social-emotional skill – self-control – that has been highlighted as a particularly strong predictor of later outcomes (Moffitt et al., 2011[13]). Self-control is an umbrella term covering a series of social-emotional skills, including conscientiousness, self-discipline, and perseverance, and presenting in the ability to control one's own emotions, thoughts, and behaviours. The Dunedin Study gathered information on childhood self-control through nine measures collected up to age 11: observational ratings of children's lack of control at ages 3 and 5, and parent, teacher, and self-reports of impulsive aggression, hyperactivity, lack of persistence, inattention, and impulsivity at ages 5, 7, 9, and 11. We use a composite index built by Moffitt et al. (2011) that combines information from these reports into a single continuous measure, with higher values representing greater self-control.

2.1.2.5 Adverse childhood experiences

Adverse childhood experiences (ACEs) are potentially traumatic events during childhood. Examples include violence and abuse, physical and emotional neglect, and family instability and dysfunction (e.g. substance abuse). ACEs share important associations with a range of adult outcomes, including in education (Hardcastle et al., 2018[66]), employment (Metzler et al., 2017[67]) and health (Boullier and Blair, 2018[68]; Baldwin et al., 2021[69]). The Dunedin Study collected information on adverse childhood experiences based on archival records (e.g. interviewer and practitioner notes, social service records, etc.) gathered during the assessments carried out between phase 3 and 15 (Reuben et al., 2016[70]). These ACEs were categorised in line with the CDC Adverse Childhood Experiences Study (Felitti et al., 1998[71]) and cover five types of child harm (physical abuse, emotional abuse, physical neglect, emotional neglect and sexual abuse) and five types of household dysfunction (incarceration of a family member, household substance abuse, household mental illness, loss of a parent, and household partner violence). We use a binary variable indicating whether or not the Study member experienced at least one ACE up to phase 15.

2.1.3 Data analysis

We use multi-trajectory Group-Based Trajectory Modelling (GBTM) to identify groups of Study members following similar, distinct patterns for social risk over the life course up to age 45. Sometimes also called Latent Class Growth Analysis, GBTM is a parametric method for identifying groups of cases that follow similar trajectories on a given indicator over time (Nagin and Odgers, 2010[9]; Nagin, 2014[10]). Multi-trajectory GBTM is an extension that allows for the modelling of trajectories on two or more indicators simultaneously (Nagin et al., 2018[72]). The output includes estimates of each group trajectory on each indicator, the shape of the trajectories, and the probability that a given case belongs to a particular group.

We assessed GBTM models ranging from two to nine groups, starting first with quadratic shapes before simplifying where possible without sacrificing model fit. Following guidance by Nagin and colleagues (Nagin, 2005[73]; Nagin et al., 2018[72]), we assessed models based on the Bayesian Information Criterion (BIC) (with BIC values closer to zero representing a better fit), the average posterior probability of assignment (which as a rule of thumb should be greater than 0.7 for all groups), and the odds of correct group classification (which should be greater than 5 for all groups), plus visual inspection. Comparison

10. Coding; 11. Digit Span; 12. Mazes. Areas of cognitive functioning not well covered by the test include executive function (e.g. reasoning and problem solving), creative or divergent thinking (e.g. idea generation), and meta-cognition (e.g. strategising and self-monitoring).

suggests an eight-group model with mostly linear shapes offers the best fit (Online Annex Table A2.1).[2] Study members were assigned to the group for which they had the posterior probability of membership. Models were restricted to Study members who remained in the Study at phase 45 and had at least non-missing observations on all four social risk measures (n = 961). All GBTM was conducted using StataSE 18.5 and the traj plug-in (Jones and Nagin, 2013[74]).

We use multinomial logistic regression to examine associations between early-life predictors and social risk trajectory group membership. Models included all early-life predictors outlined above, plus gender as a covariate. We use multiple imputation (chained equations, 10 data sets) to account for missing data on early-life predictors.

2.2 Results

2.2.1 Social risk trajectories

Figure 2.3 summarises results from our preferred eight-group social risk trajectory model. It illustrates by group the actual and predicted probability of exposure to each social risk at each Study assessment phase. The model splits the Dunedin Study cohort into eight groups ranging in size from just over 7% of the cohort in Group 7 (n = 70) to 23% in Group 1 (n = 222). Most groups contain 10-15% of the cohort. We label each group based on the shape and combination of social risk trajectories.

Group 1, the largest group, contains a set of Study members that experience only limited exposure to social risks up to age 45. We label this group "Overall low social risk". These Study members are unlikely to report low education or less-than-very-good general health at any point, and a low and declining share have a mental health diagnosis. A relatively high share (42%) of the group experienced frequent non-employment when young, but this declines quickly as the cohort ages.

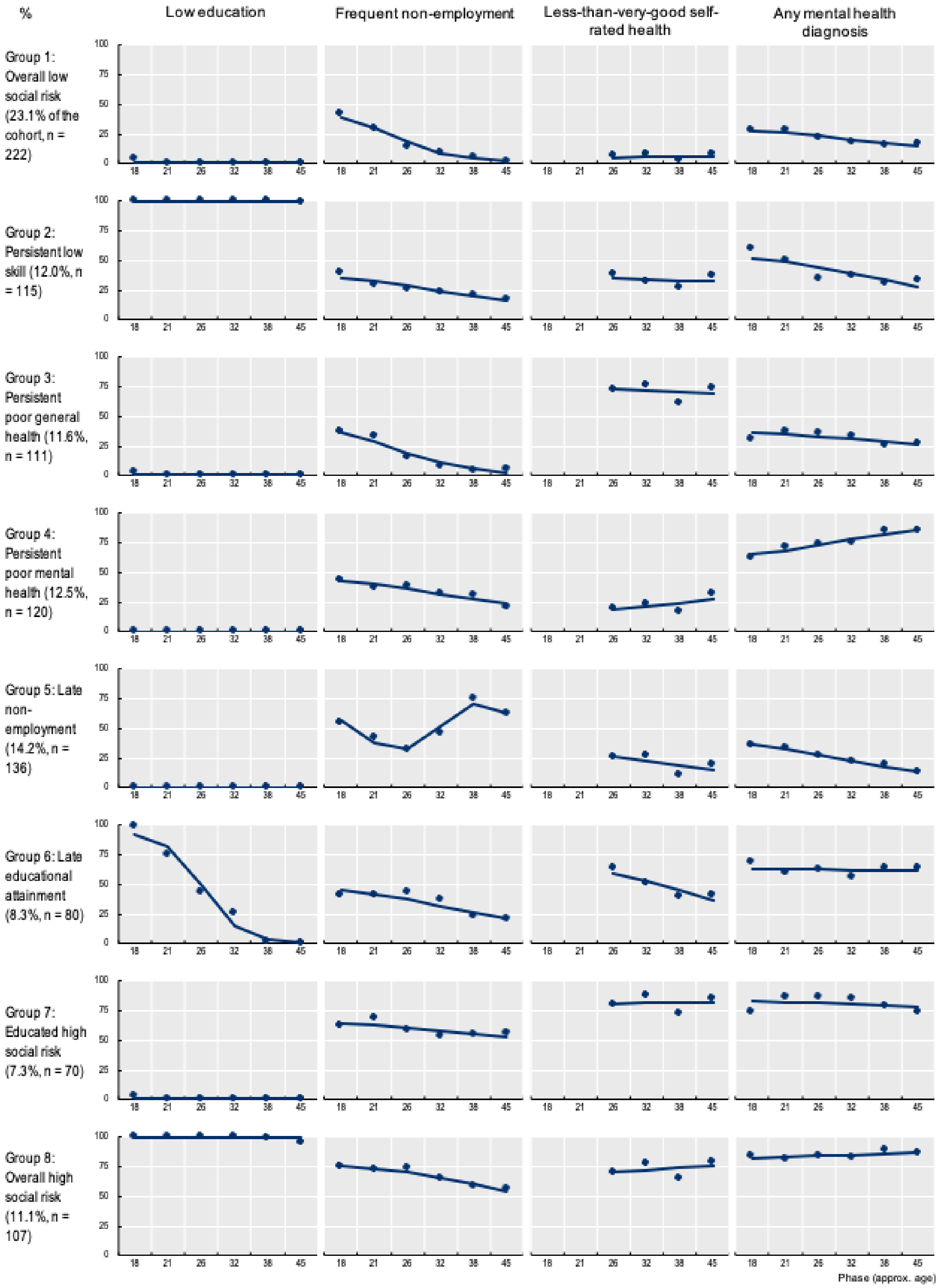
Members in Groups 2 ("Persistent low skill"), 3 ("Persistent poor general health") and 4 ("Persistent poor mental health") have low exposure on most measures but are persistently exposed on a single social risk. Members in Group 2, for example, have low education but are comparatively unlikely to experience frequent non-employment or report less-than-very-good general health. Their probability of a mental health diagnosis starts relatively high at over 50% but declines as they age. Members in Group 3 are unlikely to have low education, to find themselves frequently out of work or to have a mental health diagnosis but are likely to report less-than-very-good general health throughout the period studied. Those in Group 4 have a high and rising chance of a mental health diagnosis. Together, these three groups make up just over one-third (36%) of the Dunedin Study cohort, with each comprising about 12%.

Groups 5 ("Late non-employment") and 6 ("Late educational attainment") experience large changes in social risks over the period to age 45. Group 5 represents a set of members (14%) that are unlikely to be low educated, to report less-than-very-good general health or to have a mental health diagnosis but from age 26 to 38 are increasingly likely to find themselves frequently out of work. Women are strongly overrepresented in this group (see Online Annex Table A2.3), with the increasing probability of non-employment likely reflecting the impact of parenthood on access to paid work. Group 6 represents a smaller set of Study members (8%) that attain at least medium-level education qualifications at some point after age 18, most likely through participation in a foundation education programme. This group is decreasingly likely to report frequent non-employment or less-than-very-good general health as they age, although they remain relatively likely to hold a mental health diagnosis throughout the period studied.

[2] Our preferred model is an eight-group model with linear trajectories for all groups on "Less-than-very-good self-rated health" and "Any mental health diagnosis" and all but one group (Group 5) on "Frequent non-employment". It uses intercept-only (i.e. horizontal) terms for all but one group (Group 6) on "Low education" in part because a lack of variation for these groups prevented model convergence when we included linear or higher terms in the model.

Figure 2.3. Dunedin Study members differ in their exposure to life-course social risks

Actual and predicted probability (%) of exposure to each social risk by life-course social risk trajectory group, 1972-1973 Dunedin Study birth cohort, phase 18 to phase 45



Note: Estimates based on results from an eight-group Group-based Trajectory Model. See Online Annex Table A2.2 for full model parameters. “Low education” is defined as a highest qualification equal to or below a New Zealand year 11-equivalent qualification (i.e. the “School Certificate” for the Dunedin Study cohort). “Frequent non-employment” refers to having spent 10% or more of the period between the previous and current assessment phase out of employment or education. “Less-than-very-good self-rated general health” refers to the responses “poor”, “fair” or “good” when asked “In general, would you say your health is…”. Other response options were “very good” and “excellent”. “Any mental health diagnosis” refers to members who could be diagnosed with at least one mental disorder based on their past-year symptoms at the given phase.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Lastly, Groups 7 (“Educated high social risk”) and 8 (“Overall high social risk”) are strongly and persistently exposed to social risks. Members in Group 7 have attained medium- or high-level education qualifications but are likely to experience frequent non-employment, report less-than-very-good general health and have a mental health diagnosis across Study phases. Members in Group 8 are similar but have only low educational attainment. Study members in these two groups face multiple persistent social risks. Together, they make up just under one-fifth (18%) of the total Dunedin Study cohort.

2.2.2 Early-life predictors

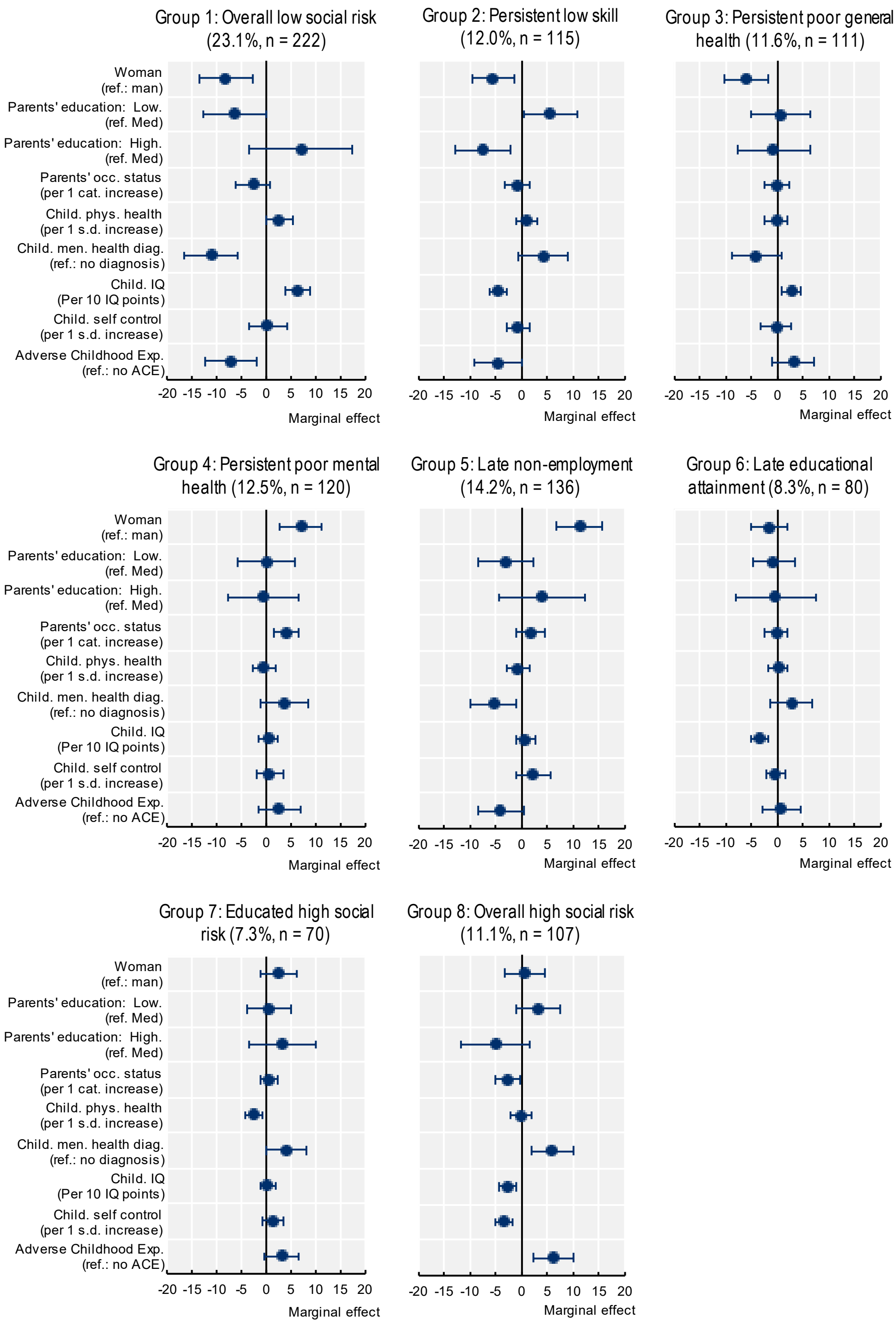
Figure 2.4 summarises associations between early-life predictors and social risk trajectory group membership. It shows the estimated average marginal effect of a unit change in each predictor on the probability of group membership, by trajectory group, controlling for other predictors.

Gender stands out as a frequent significant predictor of group membership. Being a woman is associated with a roughly 8-percentage point lower likelihood of being in the comparatively secure “Overall low social risk” group (Group 1), as well as 5- to 6-percentage point higher likelihood of being a part of Groups 2 (“Persistent low skill”) and 3 (“Persistent poor general health”). In contrast, being a woman is associated with a higher chance of being part of the “Persistent poor mental health” group (Group 4), consistent with evidence on the higher prevalence of some common mental health disorders for women (Vargas Lopes and Llena-Nozal, 2025[75]), and with being in the “Late non-employment” group (Group 5), in line with the explanation that this trajectory is driven by the impact of parenthood on employment (see above). Notably, gender is not a predictor of membership of either Group 7 (“Educated high social risk”) or Group 8 (“Overall high social risk”) – the two groups with members exposed to multiple persistent social risks.

Family background is not a frequent predictor of group membership, with some exceptions. Consistent with evidence on intergenerational persistence in education (OECD, 2018[37]; OECD, 2019[76]), having low-educated parents (those with no formal qualifications) is associated with a 6-percentage-point lower likelihood of being part of the “Persistent low skill” group (Group 2), while having parents with higher (university-level) education is negatively associated with the same group. Having low-educated parents is also associated with a lower chance of “Overall low social risk” group membership (Group 1). Higher parental occupational status is associated with a greater probability of being a member of the comparatively vulnerable Group 8 (“Overall high social risk”), as well as, notably, a higher chance of being part of the “Persistent poor mental health” group (Group 4). One possible reason for the latter is that higher socio-economic status may help moderate the negative impact of underlying mental health conditions on other outcomes (e.g. education) (Mikkonen et al., 2020[77]), and thus help keep these Study members in the persistent poor mental health-only Group 4, rather than in the groups facing multiple social risks (Groups 7 or 8).

Figure 2.4. Early-life predictors shared important associations with later social risk trajectories

Estimated marginal effect on the probability of group membership by a change in each independent variable, by life-course social risk trajectory group, 1972-1973 Dunedin Study birth cohort



Note: Marginal effects based on a multinomial logistic regression predicting membership of each life-course social risk trajectory group. Error bars set at the 95% confidence interval. Results based on a dataset that uses chained equation multiple imputation (10 imputations) for missing data. See Online Annex Table A2.4 for full estimates.

Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Childhood health also shares comparatively few associations with group membership. Childhood physical health is positively associated with membership of Group 1 ("Overall low social risk"), and negatively associated with membership of Group 7 ("Educated high social risk"), but notably shares no clear association with the chances of being a member of the "Persistent poor general health" group (Group 3): all else equal, Study members with worse childhood health are no more or less likely to be part of Group 3 than other Study members. Having had a mental health diagnosis in childhood is associated with an 11-percentage-point lower chance of being part of the "Overall low social risk" group (Group 1), and a 5-percentage-point higher chance of being part of "Late non-employment" (Group 5). A childhood mental health diagnosis is also associated with a higher chance of being part of Group 8, "Overall high social risk". This is consistent with evidence that early mental health conditions can have long-lasting effects in many areas of life, including education (Cornaglia, Crivellaro and McNally, 2015[78]) and employment (Egan, Daly and Delaney, 2015[79]).

Childhood IQ is a strong predictor of membership of several risk groups. Most notably, a 10-point increase in childhood IQ is associated with a 6-percentage-point higher likelihood of being part of the comparatively secure Group 1 ("Overall low social risk"), and a 3-percentage-point lower likelihood of being part of the generally insecure Group 8 ("Overall high social risk"). Childhood IQ is also negatively associated with membership of both Groups 2 ("Persistent low skill") and 6 ("Late educational attainment"), most likely due to its links with educational progression and attainment, as well as positively associated with membership of Group 3 ("Persistent poor general health"). Childhood self-control shares fewer links with most groups but is negatively associated with membership of Group 8, "Overall high social risk": all else equal, a 1-standard deviation higher score in measured self-control is associated with a 3-percentage-point lower chance of being part of Group 8.

Finally, adverse childhood experiences are associated with membership of both the comparatively secure Group 1 ("Overall low social risk"), and the comparatively vulnerable Group 8 ("Overall high social risk"). Controlling for other childhood characteristics, having experienced at least one adverse childhood experience is associated with a 7-percentage-point lower probability of membership of Group 1, and a 6-percentage-point higher probability of membership of Group 8.

3 Pathways out of education and into work

The transition from school to work represents a critical period in the lives of young people. While some move smoothly from education to employment, many others find the transition difficult (Carcillo et al., 2014[14]; OECD, 2016[35]). Finding a stable job can take time, and many young people experience periods of unemployment or insecure work before fully integrating into the labour market. Some may find themselves disengaged from both education and the labour market completely. Of particular concern to policymakers are the so-called NEETs, or those Not in Education, Employment or Training. The evidence on the "scarring" effects of being NEET when young suggests a difficult school-to-work transition may have long-lasting effects in multiple domains, including employment, earnings and health (Godfrey et al., 2002[80]; Maloney, 2004[81]; Carcillo et al., 2014[14]; Ralston et al., 2022[82]).

What pathways do young people follow after leaving school? And what factors shape the likelihood of following a given pathway? In this section we use detailed monthly education and employment status data from the Dunedin Study's Life History Calendar to provide a granular account of the school-to-work pathways followed by the Dunedin Study cohort between the ages of (approximately) 16 and 26. We use Sequence Analysis to identify patterns of school-to-work transition and group Study members according to the pattern followed. We also provide analyses of the early-life factors predicting, and later life outcomes associated with, membership of each identified school-to-work transition pathway.

A key advantage of using the Dunedin Study data for this analysis is the availability of (mostly prospective) data from across the life course. While alternative sources (e.g. administrative data) can provide options for tracing school-to-work transitions in similar detail (Lorentzen et al., 2019[83]; Levels et al., 2022[84]), few sources can match this information to detailed data on young people's backgrounds and early-life conditions, or their outcomes in later life. The richness of the Dunedin Study data allow us to examine associations between school-to-work transitions and a range of early-life predictors, including family background, childhood health and child development, as well as a number of later-life outcomes, including economic outcomes (e.g. non-employment, occupational status, financial difficulties) and health and well-being outcomes (e.g. self-reported health, mental health diagnosis, life satisfaction). Although we remain limited in our ability to make causal inferences (see Box 1.1), the depth and temporal ordering of the Dunedin Study data help strengthen inference by controlling for differences in background and initial conditions.

Key findings from this section are as follows:

- Dunedin Study members followed different school-to-work transition pathways. We identify eight distinct school-to-work transition groups, with pathways ranging from early school leaving and prolonged periods as NEET to extended periods in higher education.
- The majority (71%) of the Dunedin Study cohort followed pathways that saw them transition relatively smoothly from school to employment or higher education. Just over one-third (38%) of the cohort followed "Upper secondary education" pathways, remaining in education until around age 18-19 before moving into full-time employment. Another third (33%) followed "Higher education" pathways, staying in education until their early-20s. This combines cohort members

who either concentrated mostly on their education (12%) or, more likely, who combined higher education with part-time work (21%).

- The remaining one-third (29%) of the Dunedin Study cohort left education comparatively early, in most cases without attaining upper-secondary education or a vocational qualification. Many (but not all) of these early leavers experienced difficult school-to-work transitions. We identify a small group (6% of the Study cohort) who left school early and spent most of the period up to age 26 as NEET, and a slightly larger group (10%) who stayed in education often for another year but still frequently left without upper-secondary education (or similar) and in many cases struggled to find secure employment. Importantly, however, early school leaving did not always lead to disengagement. We identify a further group (13%) who left school early but had quick success in finding secure employment. Study members following this pathway spent less time as NEET than those following all other pathways.
- Some early-life factors help predict membership of the different school-to-work transition pathways. Childhood IQ is a predictor of several pathways: Study members who had higher childhood IQs were less likely to experience difficult school-to-work transitions and more likely to follow a "Higher education" pathway. Members with stronger childhood self-control – the ability to control one's own emotions, thoughts, and behaviours – were also less likely to follow the most difficult school-to-work transition pathway and more likely to pursue a (specific) higher education pathway. However, family background and childhood health have weaker associations.
- Study members who experienced more difficult school-to-work transitions consistently faced worse economic and health and well-being outcomes into mid-adulthood. Outcomes were particularly poor for the small group (6%) who left school early and spent a prolonged period as NEET. These Study members were more likely than most others to find themselves often out of work and in low-status occupations in their 30s and mid-40s, as well as to experience self-reported financial difficulties, self-reported poor general health, to hold a mental health diagnosis and, to a lesser extent, to report low life satisfaction. In many cases these outcome gaps were persistent with links between school-to-work transitions and outcomes almost as visible when Study members were in their mid-40s as they were when in their mid-20s or early-30s.

Overall, the findings help highlight how developments at one point in life can shape and influence outcomes later down the line. While we cannot rule out the possibility of unmeasured confounders, our results suggest at minimum that difficult school-to-work transitions can act as an indicator for those who are likely to face multiple and persistent poor outcomes in later life. Combined with evidence elsewhere on the scarring effects of being NEET (Carcillo et al., 2014[14]), findings from this section strengthen the suggestion that difficult school-to-work transitions can have important and long-lasting effects on young people's lives and might set a trajectory that is challenging to change, underlining the importance of supports to help young people find stable employment when entering the labour market.

3.1 Data and methods

3.1.1 Education and employment status

We measure Dunedin Study members' school-to-work transitions using monthly data on education and employment status from the Study's Life History Calendar (LHC). Since phase 21 (1993), Dunedin Study assessments have included a LHC that collects retrospective information on important life events and their timing and duration, including entry into or exit from relationships, childbirth and parenthood, spells in education (up to age 26), and spells in and out of employment (Caspi et al., 1998[85]). We simplify the information on employment into three possible states (not employed (including unemployed), employed part-time, and employed full-time) and on education to two states (not in education, and in education) and combine to produce a categorical monthly activity variable that can take six possible states:

1. NEET (Not employed and not in education)
2. In education
3. In education and part-time employed
4. In education and full-time employed
5. Part-time employed
6. Full-time employed

This six-part variable is available as time-ordered sequence for all Study members with non-missing LHCs between the ages of 15 and 26. We trim and synchronise the data so that each Study member's calendar starts and ends in the same calendar month (April 1988 and March 1998, respectively), which we justify on the grounds that most Study members were expected to leave education at a similar point in the year (e.g. December 1988 for those leaving after their School Certificate exams at the end of Form 5/Year 11) regardless of exact month of birth. The exceptions are Study members born in April or May 1972, who typically entered education one school year (grade) ahead of those born from June 1972 onwards, and therefore typically left education one year earlier. We shift calendars for these Study members back one year so that all members are "expected" to leave education in approximately the same calendar month.

We drop 96 Study members with missing LHCs at either phase 21 or 26, leaving a final sample of 941. The final dataset contains 10-year (120-month) long sequences for each of the 941 members and a total of 14 355 reported economic activity events (i.e. entry to or exit from education, entry to or exit from employment, changes from part- to full-time employment and vice versa).

3.1.2 Early-life predictors

We use the same set of early-life predictors as in Section 2. This includes the variables measuring Study members' family background (*Parental education* and *Parental occupational status*), their childhood health (*Childhood physical health*, and *Childhood mental health*), their cognitive development (*Childhood IQ*) and social-emotional development (*Self-control*), and any *Adverse Childhood Experiences*. See Section 2.1. for detail on variable definitions and construction.

3.1.3 Later-life outcomes

3.1.3.1 Economic outcomes

- *Frequent non-employment* at ages 32, 38 and 45: As in Section 2, "*Frequent non-employment*" refers to members who spent 10% or more of the period between the previous and current assessment phase out of employment or education. This variable is based on information from the Dunedin Study's LHC (see above).
- *Low status occupation* at ages 32, 38 and 45: The Dunedin Study measured occupational status at phases 32, 38 and 45 using a six-point scale for occupations based on the educational attainment and income associated with that occupation in the New Zealand Census (Davis, Jenkin and Coope, 2003[86]). Those without current or recent occupation data were rated on the basis of their educational achievement according to criteria in the New Zealand Socioeconomic Index 1996 (Davis, Jenkin and Coope, 2003[86]). "*Low status occupation*" refers to Study members in the lowest two occupational categories (e.g. Agricultural and Fishery Workers, Labourers and Related Elementary Service Workers, Salespersons, Demonstrators and Models, etc.) (Guiney et al., 2022[87]).

- *Financial difficulties* at ages 32, 38 and 45: At phases 32, 38 and 45, the Dunedin Study asked members a series of six questions about credit difficulties and seven about money management difficulties. We use an index measure built by standardising and then averaging counts from the two sets of difficulties (Moffitt et al., 2011[13]). "*Financial difficulties*" refers to Study members in the top tertile of the index.

3.1.3.2 Health and well-being outcomes

- *Less-than-very-good self-rated general health* at ages 26, 32, 38 and 45: As detailed in Section 2, from phase 26 onwards, the Dunedin Study collected information on self-rated general health using the question "In general, would you say your health is…" with the response options "Excellent", "Very good", "Good", "Fair" or "Poor". "*Less-than-very-good self-rated general health*" refers to Study members who report being in "poor", "fair" or "good" health. We classify "good" health alongside "poor" and "fair" health because the response scale used is known to introduce a bias towards a positive self-rating of health (OECD, 2023[33]).
- *Any mental health diagnosis* at ages 26, 32, 38 and 45: Also, as detailed in Section 2, the Dunedin Study collected information on previous-year symptoms of mental disorders through private interviews with diagnoses made using the Diagnostic and Statistical Manual of Mental Disorders (DSM) current at each stage. "*Any mental health diagnosis*" refers to members who could be diagnosed with at least one mental disorder based on their past-year symptoms at the given phase.
- *Low life satisfaction* at ages 38 and 45: At phases 38 and 45, the Dunedin Study collected information on life satisfaction using the statement "I am satisfied with my life" with responses options ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). "*Low life satisfaction*" refers to Study members responding either 1, 2 or 3.

3.1.4 Data analysis

We use Sequence Analysis (SA) (Ritschard and Studer, 2018[88]) to identify groups or patterns of school-to-work transition for Study members. SA is a non-parametric data-mining-type method for analysing sequence trajectories. Typically combined with some form of clustering method (e.g. cluster analysis), SA is most often used to identify a series of distinct trajectories on the given variable(s) that can be seen as typical and representative for a given sample. One advantage of SA over competing trajectory methods (e.g. Group-Based Trajectory Modelling, as used in Section 2) is that it is more readily able to handle sequences based on categorical variables, especially unordered categorical variables like our six-part monthly activity variable (see above).

The SA process consists of two main steps. The first is to calculate pairwise "distances" between each monthly activity status sequence. These distances measure how similar two sequences are to one another and are effectively the sum of the calculations needed to make two sequences identical by either inserting or deleting a given activity state at a given point in the sequence, or by substituting one activity state for another. There are a number of approaches available for calculating pairwise distances, each with its own advantages (Lesnard, 2010[89]; Studer and Ritschard, 2016[90]). Similar to several other studies in the area (Lorentzen et al., 2019[83]; Dicks, Levels and van der Velden, 2020[91]; Holmes et al., 2022[92]; Danner et al., 2022[93]), we use standard optimal matching (OM), a method that prioritises the length of time spent in given state over either the order or exact timing of states when calculating pairwise distances (Lesnard, 2010[89]; Studer and Ritschard, 2016[90]). We choose standard OM in part because we believe it is important to identify any Study members who spent prolonged periods as NEET. We also produce results using an alternative approach, Dynamic Hamming Distance (DHD), which is less sensitive to duration and more sensitive to the timing of events (Lesnard, 2010[89]; Studer and Ritschard, 2016[90]). This might be useful for distinguishing between cohort members who spend similar amounts of time in a given state (e.g. NEET) but at different points in their young adulthood (e.g. early NEET, later NEET) (Levels et al., 2022[84]). In practice, in this instance, the group classifications produced by OM and DHD are largely similar (see Online Annex Figure A3.1).

The second step is to cluster sequences based on the pairwise distance (or dissimilarity) matrix. We use Ward's Linkage Hierarchical Cluster Analysis. We consider solutions ranging from five to eight groups, and assess each based on group size, interpretability, and two main fit indices – the Calinski-Harabasz and Duda-Hart indices, both of which aim to reflect the degree of distinctiveness in the clustering (Halpin, 2016[94]) (Online Annex Table A3.1). We choose an eight-group solution on account of the substantive meaning of the groups identified and because it maximises the Duda-Hart index (Online Annex Table A3.1).

We use multinomial logistic regression to estimate associations between early-life predictors and school-to-work transition group membership. Models include all early-life predictors outlined above, plus gender as a covariate. We use multiple imputation (chained equations, 10 data sets) to account for missing data on early-life predictors.

Similarly, we use linear regression and logistic regression (as appropriate) to estimate associations between school-to-work transition group membership and later-life outcomes. Models include as independent variables the school-to-work transition group variable produced by the HCA, plus gender and all early-life predictors outlined above as covariates. We again use multiple imputation (chained equations, 10 data sets) to account for missing data on later-life outcomes as well as early-life predictors. We conducted all analysis in StataSE 18.5 with SA conducted using the user-written SQ-Ados (Brzinsky-Fay, Kohler and Luniak, 2006[95]).

3.2 Results

3.2.1 School-to-work transitions

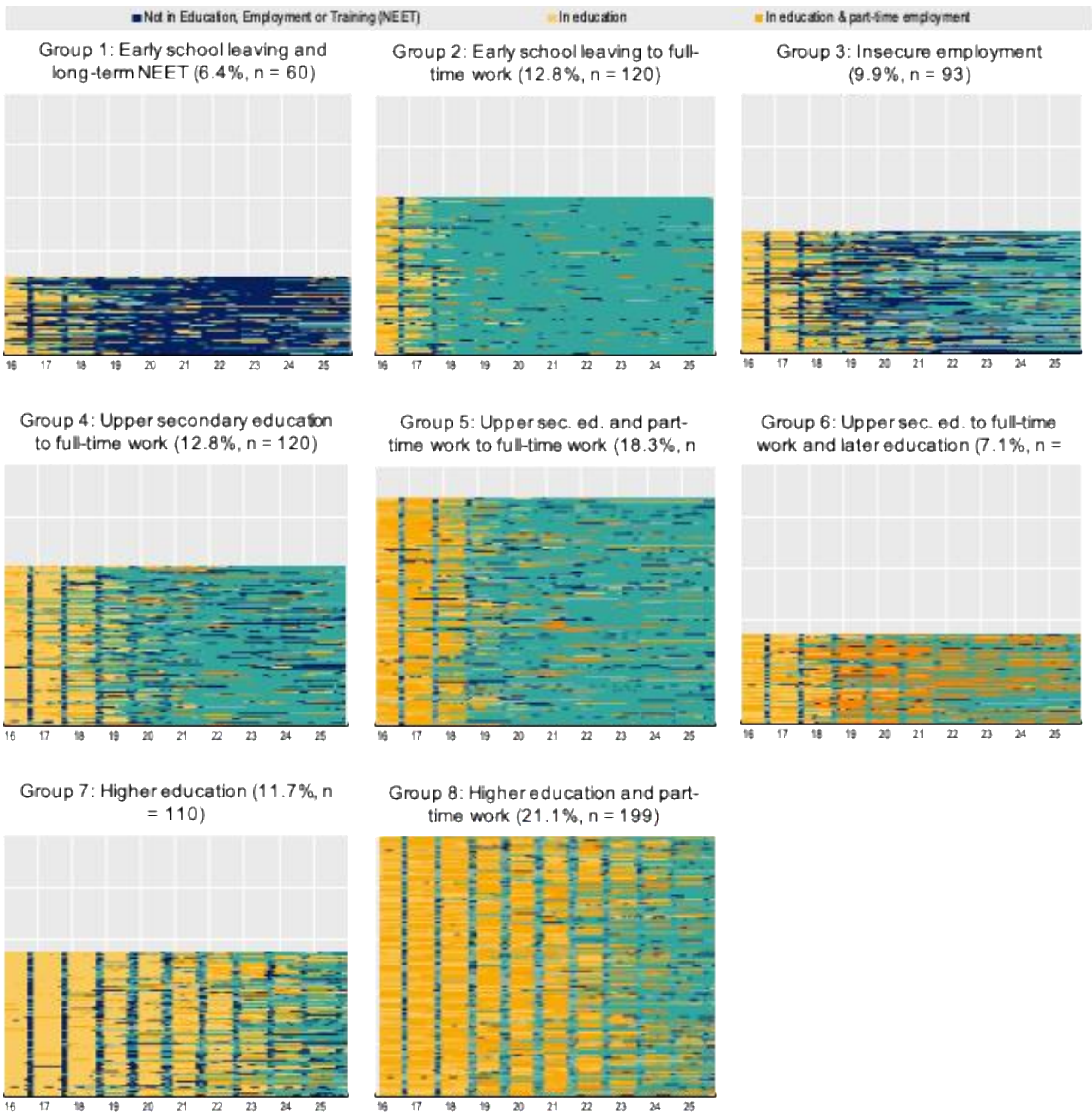
Figure 3.1 and Figure 3.2 summarise output from our Sequence Analysis and preferred eight-group solution for school-to-work transitions. Figure 3.1 is a "sequence index plot", showing by group the education and employment sequences followed by each Study member between April 1988 and March 1998. Figure 3.2 (a "state distribution plot") provides a different view of the same data, showing the distribution of group members across the six activity states at each point in time. Our preferred eight-group solution splits the Dunedin Study cohort into groups ranging in size from 6% to 21%. We label each based on the typical sequence followed, combined with supplementary information on typical education attainment at phase 26 (see Annex Table A3.3). For reference, Study Members were able to leave compulsory education at age 15.

Group 1 contains a small but important set of Study members (6.4%) who left education early and spent much of the period up to 26 out of both education and employment. We label this group "Early school leaving and long-term NEET". This majority of this group left education before age 18 (only 40% were in education when the first of the cohort turned 18, and just 15% by time they turned 21) with most (72%) attaining at most low educational attainment (i.e. a "School Certificate" or below) (Annex Table A3.3). Few found employment, especially full-time employment, even by their mid-20s. Indeed, 38% of the group were Not in Employment, Education or Training (NEET) when the first of the cohort turned 18, 75% when they turned 21, and 68% towards the end of the period when the first of the cohort turned 25. Across the ten years covered, members of Group 1 spent an average of 79 months (66%) as NEET, and just 11 months (10%) in full-time employment, either on its own (9% months) or in combination with education (1%) (Table 3.1).

Study members in Group 2 ("Early school leaving to full-time work", 12.8% of the cohort) also left education early but had early success in finding secure employment. As few as 20% of members in this group were in education when the first of the cohort turned 18, but as many as 78% were in work, all of which was full-time. Many stayed there for the duration. Indeed, across the ten years covered, Study members in Group 2 spent 100 months (82%) in full-time employment, and just 5 months (4%) as NEET (Table 3.1). This is the smallest share of time spent as NEET of the groups identified.

Figure 3.1. Dunedin Study members followed different school-to-work transition pathways

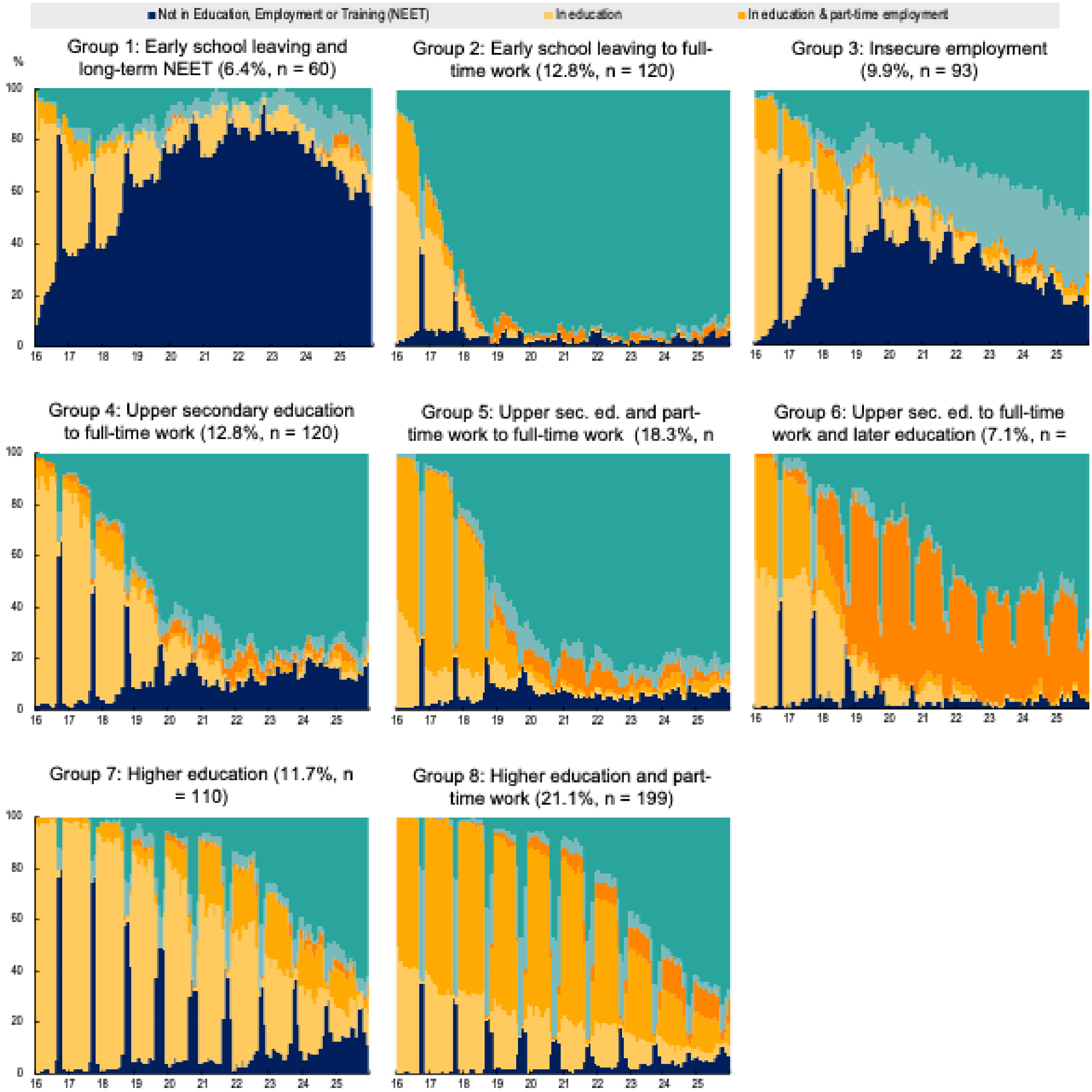
Sequence index plot for education and employment status, 1972-1973 Dunedin Study birth cohort, April 1988 (approx. age 16) to March 1988 (approx. age 26)



Note: Sequence index plot based on results from a Sequence Analysis using standard Optimal Matching and Ward's Linkage Hierarchical Cluster Analysis. Periods labelled using the age of the eldest cohort members. The periodic breaks in educational participation observed annually correspond to New Zealand's summer school holidays in December-January.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Figure 3.2. Dunedin Study members followed different school-to-work transition pathways (cont.)

State distribution plot for education and employment status, 1972-1973 Dunedin Study birth cohort, April 1988 (approx. age 16) to March 1988 (approx. age 26)



Note: State distribution plot based on results from a Sequence Analysis using standard Optimal Matching and Ward's Linkage Hierarchical Cluster Analysis. Periods labelled using the age of the eldest cohort members. The periodic breaks in educational participation observed annually correspond to New Zealand's summer school holidays in December-January.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Table 3.1. Dunedin Study members with the most difficult school-to-work transitions spent two-thirds of the period between age 16 and 26 as NEET

Average cumulative time spent in each state by school-to-work trajectory group, April 1988 to March 1998, 1972-1973 Dunedin Study birth cohort, months and % of months

	Not in education, employment or training (NEET)	In education	In education & part-time employment	In education & full-time employment	In part-time employment	In full-time employment
Months						
Group 1: Early school leaving and long-term NEET (6.4%, n = 60)	79.3	20.1	2.0	0.6	7.1	10.8
Group 2: Early school leaving to full-time work (12.8%, n = 120)	4.9	9.3	3.6	2.3	1.8	98.0
Group 3: Insecure employment (9.9%, n = 93)	37.3	21.8	6.8	1.3	21.7	31.2
Group 4: Upper secondary education to full-time work (12.8%, n = 120)	15.9	26.1	4.3	4.1	4.4	65.2
Group 5: Upper sec. ed. and part-time work to full-time work (18.3%, n = 172)	7.8	7.1	21.4	4.9	8.9	70.0
Group 6: Upper sec. education to full-time work and later education (7.1%, n = 67)	5.9	15.6	10.3	39.9	5.0	43.3
Group 7: Higher education (11.7%, n = 110)	17.0	56.7	12.4	1.5	5.9	26.4
Group 8: Higher education and part-time work (21.1%, n = 199)	6.3	19.7	44.9	5.4	11.0	32.5
% of months						
Group 1: Early school leaving and long-term NEET (6.4%, n = 60)	66.1	16.7	1.7	0.5	5.9	9.0
Group 2: Early school leaving to full-time work (12.8%, n = 120)	4.1	7.8	3.0	1.9	1.5	81.7
Group 3: Insecure employment (9.9%, n = 93)	31.0	18.2	5.6	1.1	18.1	26.0
Group 4: Upper secondary education to full-time work (12.8%, n = 120)	13.2	21.7	3.6	3.4	3.7	54.4
Group 5: Upper sec. ed. and part-time work to full-time work (18.3%, n = 172)	6.5	5.9	17.8	4.1	7.4	58.3
Group 6: Upper sec. education to full-time work and later education (7.1%, n = 67)	4.9	13.0	8.5	33.2	4.2	36.1
Group 7: Higher education (11.7%, n = 110)	14.1	47.3	10.4	1.3	5.0	22.0
Group 8: Higher education and part-time work (21.1%, n = 199)	5.3	16.4	37.4	4.5	9.2	27.1

Note: Groups based on results from a Sequence Analysis using standard Optimal Matching and Ward's Linkage Hierarchical Cluster Analysis.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Members in Group 3 ("Insecure employment", 9.9%) spent slightly longer in education but many left without attaining upper-secondary or vocational education or above and frequently struggled to find secure full-time employment. Just over half (54%) of Group 3 were still in education when the first of the cohort turned 18, but less than half (42%) attained upper-secondary (or vocational) education or above. Members of

Group 3 moved frequently between work, education and periods as NEET, especially between ages 18 and 21. Periods in part-time work were especially common for this group, although this was frequently intermittent and interrupted by periods in full-time work, in education, or as NEET. Full-time work became increasingly common as the group approached their mid-20s, with around half working full-time by the end of the period covered.

Groups 4 (”Upper secondary education to full-time work”, 12.8%), 5 (”Upper sec. ed. and part-time work to full-time work”, 18.3%) and 6 (”Upper sec. ed. to full-time work and later education”, 7.1%) cover Study members who stayed longer in education and frequently attained either upper-secondary education (e.g. Sixth Form Certificate) or vocational education. In all three cases more than 70% of the group were still in education when the first of the cohort turned 18, with around 75% attaining an upper-secondary or vocational qualification (Annex Table A3.3). Members of Group 5 frequently combined education with part-time work between the ages of about 17 and 19, whereas Group 4 more often focused on education alone. Notably, from around age 19 onwards, members of Group 4 were at consistently greater risk of spending time as NEET than members of Group 5: between 10% and 20% of members of Group 4 found themselves NEET in any given month from about age 19 onwards, compared to about 5% to 10% of Group 5. One possibility is that the early work experience gained by Group 5 through their part-time work helped protect them against later non-employment (Gottschalk Ballo et al., 2022[96]; Rahmani and Groot, 2023[97]). Group 6 notably combined full-time work with periods in education across their early- to mid-20s.

Lastly, Groups 7 (“Higher education”, 11.7%) and 8 (“Higher education and part-time work”, 21.1%) cover Study members who spent a prolonged period in education, most often progressing to higher (university-level) education. In both cases, more than 95% of the group were still in education when the first of the cohort turned 18, and more than 85% when they turned 21, with 60% or more attaining a university qualification (Annex Table A3.3). The major difference between the groups is that members in Group 8 more often combined education with part-time work: across the ten years covered, members of Group 8 spent more than one-third of their time (45 months, or 37%) combining education and part-time work, compared to about 10% (12 months) for Group 7 (Table 3.1). Members of Group 7 were also increasingly likely to find themselves NEET as they approached their mid-20s: between 10% and 20% of Group 7 members found themselves NEET in any given month from about age 25 onwards, compared to 5% to 10% of Group 8.

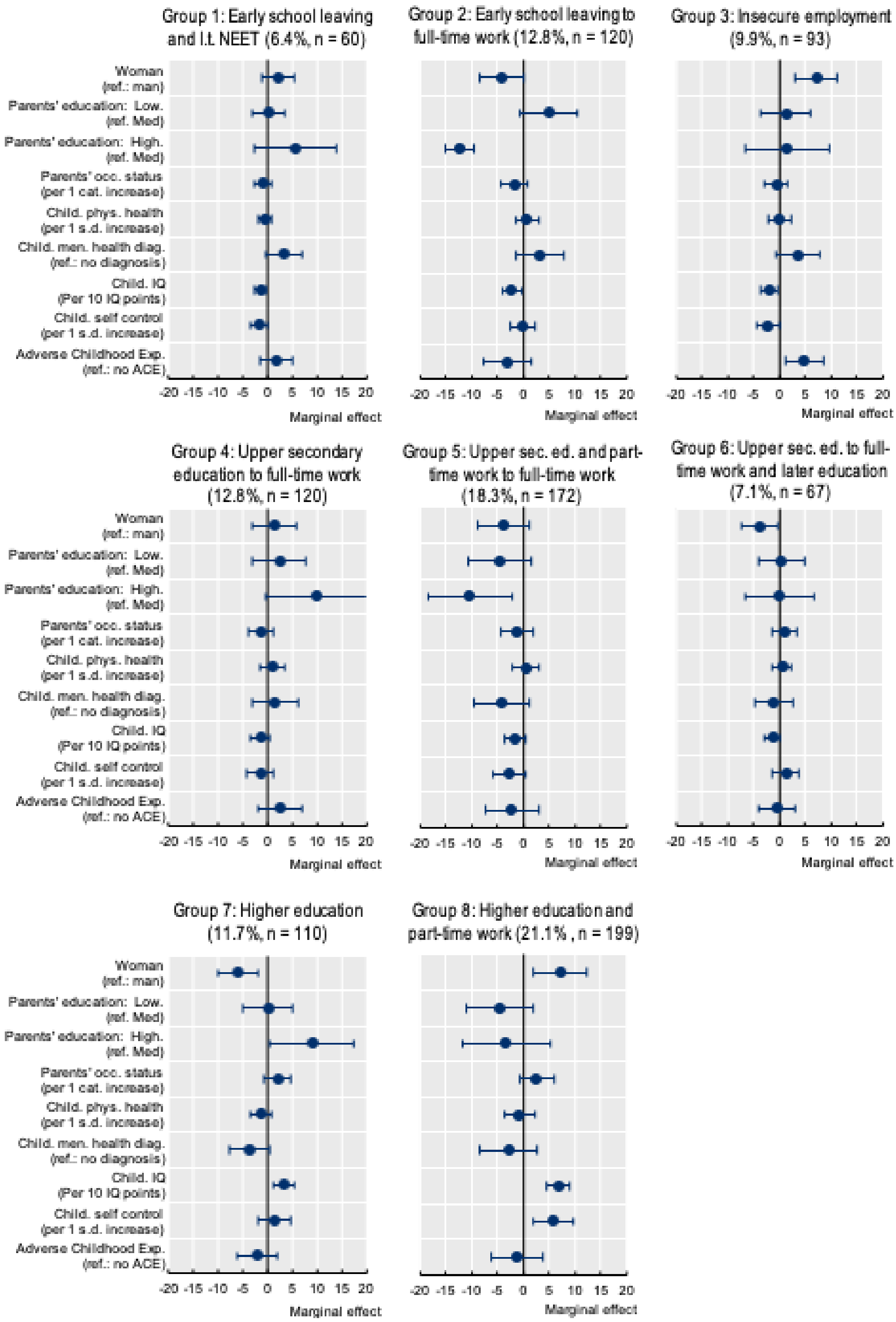
3.2.2 Early-life predictors

Figure 3.3 summarises associations between early-life predictors and school-to-work transition group membership. It shows the estimated average marginal effect of a unit change in each predictor on the probability of group membership, by transition group, controlling for other predictors. Overall, results suggest that links between our early-life measures and school-to-work transition group membership are frequently only weak and early-life factors predict group membership only in specific cases.

As was the case earlier for life-course social risks (Section 2), gender is a common predictor of group membership. For example, being a woman is associated with a 6-percentage-point higher probability of being a member of Group 7, “Higher education”, and a 7-percentage-point higher probability of being a member of Group 8, “Higher education and part-time work”. Women are under-represented in the group of Dunedin Study members who were able to concentrate solely on higher (university) education through their late-teens and early-20s, and over-represented in the group who combined higher education with part-time work. Being a woman is also associated with a 7-percentage-point higher chance of being a member of Group 3 (“Insecure employment”), reflecting that women are often less able to access secure employment more generally, and a 4-percentage-point lower chance of being a part of Group 6 (“Upper sec. ed. to full-time work and later education”).

Figure 3.3. Gender, childhood IQ and childhood self-control predict school-to-work transitions, but links with family background and childhood health are less clear

Estimated marginal effect on the probability of group membership by a change in each independent variable, by school-to-work transition group, 1972-1973 Dunedin Study birth cohort



Note: Marginal effects based on a multinomial logistic regression predicting membership of each school-to-work transition group. Error bars set at the 95% confidence interval. Results based on a dataset that uses chained equation multiple imputation (10 imputations) for missing data. See Online Annex Table A3.4 for full estimates.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Family background shares fewer clear associations with school-to-work transitions. Indeed, neither parents' occupational status nor having low educated parents share statistically significant associations with membership of any school-to-work transition group at the 5% level. As expected given intergenerational persistence in education (OECD, 2018[37]), having university-educated parents is positively associated with being part of Group 7, "Higher education": all else equal, Study members with high (university) educated parents are 9 percentage points more likely than others to follow the "Higher education" pathway. Having highly educated parents is also negatively associated with Group 5 ("Upper secondary education and part-time work to full-time work"), and most notably with Group 2 ("Early school leaving to full-time work"): Study members with high (university) educated parents are 12 percentage points less likely than others to leave school early and find themselves in stable full-time employment.

Despite the potential for poor health to disrupt learning and labour market integration, our two measures of childhood health also mostly fail to predict school-to-work transition group membership. Having a childhood mental health diagnosis is associated with slightly higher chance (by 3 percentage points) of being in Group 1 ("Early school leaving and long-term NEET"), and a slightly lower chance (by 4 percentage points) of being in Group 7 ("Higher education"). However, in both cases the associations are significant only at the 10% level. Childhood physical health shares no significant association with any of the school-to-work transition groups.

Childhood IQ is a frequent predictor of school-to-work transition group membership. Childhood IQ is negatively associated with the two early school leaving groups (Group 1 and Group 2), for example, with a 10-point increase in IQ associated with a 2-percentage-point chance of being a member of both Group 1 ("Early school leaving and long-term NEET") and Group 2 ("Early school leaving to full-time work"), all else equal. Childhood IQ is also negatively associated with membership of Group 3 ("Insecure employment") and positively associated with the two "Higher education" pathways: a 10-point increase in IQ is associated with a 3-percentage-point lower chance of Group 7 ("Higher education") membership, and a 7-point lower chance of being in Group 8 ("Higher education and part-time work"). Childhood self-control is similarly negatively associated with membership of Group 1 ("Early school leaving and long-term NEET") and positively associated with membership of Group 8 (("Higher education and part-time work").

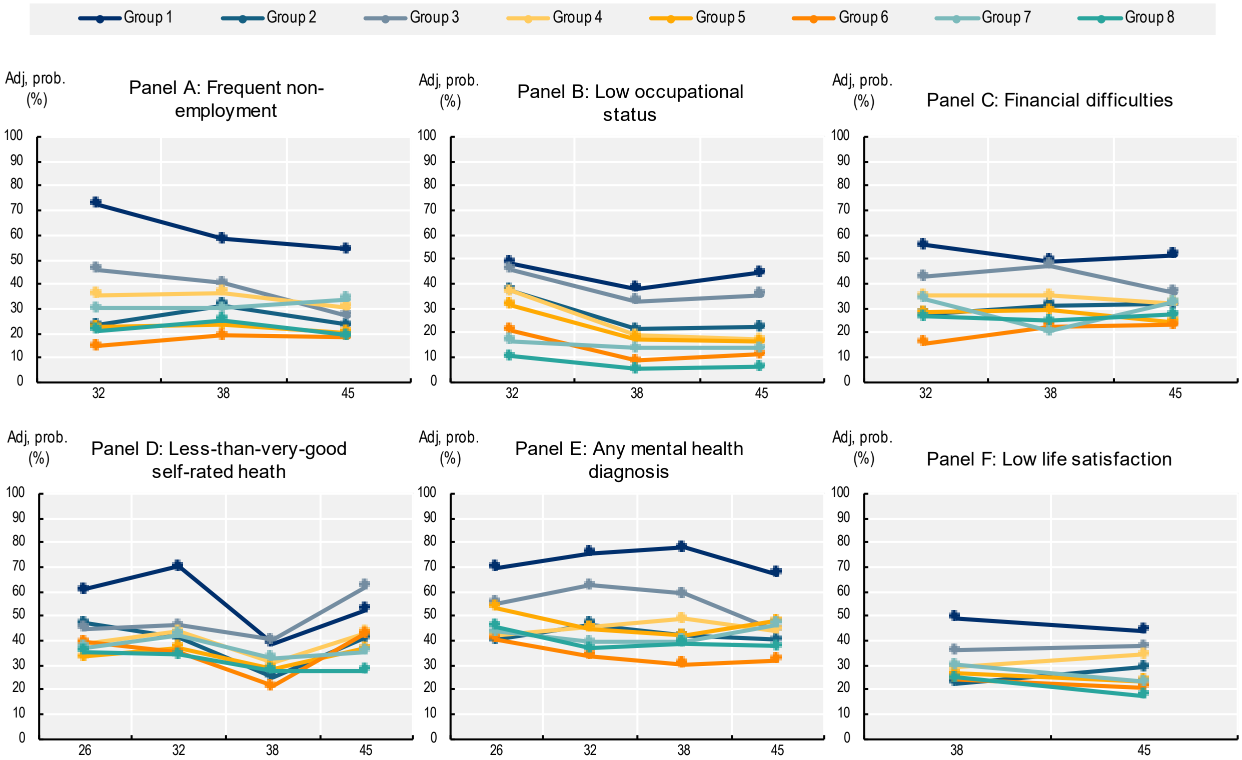
Lastly, adverse childhood experiences are associated with membership of the Group 3 ("Insecure employment"). Controlling for other childhood characteristics, having experienced at least one adverse childhood experience is associated with a 5-percentage-point lower chance of membership of Group 3, relative to all other groups.

3.2.3 Later-life outcomes

Figure 3.4 summarises associations between our school-to-work transition groups and later-life outcomes. It shows the estimated probability of each outcome at each available phase for members of each transition group after adjusting for gender and our early-life predictors (see Section 3.1.2 and 2.1.2). In other words, they show later-life outcomes for each school-to-work transition group after accounting for differences in family background and childhood health, development, and experiences. These estimates are based on results from logistic regressions. Tabulated summaries are given in Online Annex Table A3.5 and Annex Table A3.6.

Figure 3.4. Later-life outcomes differ substantially with school-to-work transitions

Average adjusted probability (%) of later-life outcomes by school-to-work transition group membership, phase 26 to phase 45, 1972-1973 Dunedin Study birth cohort



Note: Estimates based on results from logistic regression models. All models adjust for gender, parents' education and occupational status, childhood physical health and childhood mental health, childhood IQ, childhood self-control, and adverse childhood experiences. Results based on a dataset that uses chained equation multiple imputation (10 imputations) for missing data.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

There are clear differences in later-life outcomes for members of different school-to-work transition groups, with Study members who experienced the most difficult school-to-work transitions (Group 1) at significantly greater risk of poor outcomes between ages 26/32 and 45 (Annex Table A3.7). In comparison to members of most other transition groups, even after controlling for early-life factors, Study members in Group 1 were more likely to experience frequent non-employment at ages 32, 38 and 45 (Figure 3.4, Panel A), and when in work were more likely to find themselves in low status occupations (Panel B). They were also more likely than most to experience financial difficulties at ages 32, 38 and 45 (Panel C), more likely than most groups to report less-than-very-good general health at ages 26, 32 and 45 (Panel D), more likely than most to hold a mental health diagnosis at ages 26, 32, 38, and 45 (Panel E), and, to a lesser extent, were more likely to report low life satisfaction at ages 38 and 45 (Panel F). Members of Group 3 ("Insecure employment") also often experienced comparatively poor outcomes, especially regarding occupational status (Panel B). Members of Group 2 ("Early school leaving to full-time work"), who like Group 1 frequently left school early but who had greater success in finding secure employment, were less likely to experience poor later-life outcomes.

Differences in later-life outcomes between Group 1 and members of most other transition groups are fairly persistent over time. The gap in the probability of frequent non-employment between Group 1 and most others falls between phase 32 and phase 45 but remains large nonetheless (Figure 3.4, Panel A). Even by phase 45, members of Group 1 were almost three times as likely (35 percentage points, 282%) to experience frequent non-employment as members of the largest school-to-work trajectory group, Group 8 (“Higher education and part-time work”) (Panel A). The gap in self-rated general health also fluctuates over time (Panel D). However, on the remaining measures, gaps are largely stable. Comparing again with Group 8, between phase 32 and phase 45, members in Group 1 were consistently 30-40 percentage points more likely to find themselves in low status occupations (Panel B), 25-30 percentage points more likely to report financial difficulties (Panel C), 30 to 40 percentage points more likely to hold a mental health diagnosis (Panel E), and about 25 percentage points more likely to report low life satisfaction (Panel F). In many respects, the poorer outcomes associated with a difficult school-to-work transition remain almost as visible at phase 45 as they did earlier in life at phase 26 or phase 32.

4 Early-life factors and unemployment benefit receipt dynamics during early adulthood

Understanding benefit receipt dynamics is central to the design of efficient and effective social protection systems. Knowing more about the factors influencing the duration of, and exit from, benefit receipt can help policy-makers design benefits that better support people through adversity and in their return to self-sufficiency. However, despite considerable public and policy interest, relatively little is known about the micro-dynamics of benefit receipt, especially the characteristics that shape different receipt dynamics (Carcillo et al., 2014[98]; Immervoll, Jenkins and Königs, 2015[99]). There are only a limited number of studies that examine links between benefit receipt dynamics and family and early-life factors (Welch and Wilson, 2010[100]; Ilmakunnas and Moisio, 2019[101]; Ilmakunnas, 2023[16]; Vergunst et al., 2023[102]), in part because few datasets combine lengthy panel data and high-frequency information on benefit receipt with detailed information on recipients' background and early-life experiences.

This section examines dynamics among the Dunedin Study cohort in the receipt of New Zealand unemployment benefit – a means-tested, flat-rate benefit provided to jobseekers regardless of contribution history for an indefinite period (Box 4.1). It pays particular attention to the issue of "duration dependence", or the idea that the probability of leaving benefit receipt decreases as the length of receipt increases, as well as whether early-life factors can help predict the length of benefit use. In other words, among Dunedin Study members, do benefit recipients become "stuck" on benefits after a period of receipt, and do family and early-life factors shape the duration of benefit receipt and susceptibility to long-term benefit use? The analysis is based around administrative data on benefit histories from the Ministry of Social Development that have been integrated into the Dunedin Study. We measure benefit receipt in weeks and conduct the analysis using discrete-time event-history models (pooled and random effects complementary log-log regression models). As for the other use cases, the early-life predictors again cover domains including family background (e.g. parents' education and occupational status), childhood health (e.g. child physical and mental health), childhood development (e.g. childhood IQ, childhood self-control) and adverse childhood experiences (e.g. abuse and neglect, family incarceration, household substance abuse, household mental illness, loss of a parent, and household partner violence).

The Dunedin Study data are uniquely suited to this analysis. Many studies examining benefit receipt dynamics make use of administrative benefit history data (Bäckman and Bergmark, 2011[103]; Mood, 2013[15]; Immervoll, Jenkins and Königs, 2015[99]; Hohmeyer and Lietzmann, 2020[104]; Ilmakunnas, 2023[16]) but few have access to the rich data on family background and childhood conditions and development available in the Dunedin Study (see Vergunst et al. (2023[102]) for an exception). Previous work by the New Zealand Ministry of Social Development and the Dunedin Study team suggests that Dunedin Study members with adverse childhoods (e.g. low socio-economic status, family instability, childhood behavioural and mental health issues) spent more time receiving social benefits in general in young adulthood than those with less adverse childhoods (Welch and Wilson, 2010[100]). We build on this work to ask whether these kinds of early-life factors can be linked to the length of unemployment benefit receipt and the speed with which recipients move off of benefits.

Key findings from this section are as follows:

- Unemployment benefit receipt patterns among the Dunedin Study cohort are consistent with the idea that benefit recipients may become "stuck" on benefits as the length of receipt increases. The chances of leaving benefit receipt decline with spell length by about 13% for each additional week of receipt, so the longer the unemployment benefit spell, the higher the chances of remaining on the benefit.
- However, much of this apparent "duration dependence" is mechanical and driven by what are sometimes called "selection effects" and "composition effects": claimants with better labour market prospects tend to exit first, leaving behind group of claimants with characteristics that make exit less likely. Accounting for observed and unobserved differences between recipients sees the degree of duration dependence fall by more than half – a level similar to several studies on social assistance receipt (Mood, 2013[15]; Ilmakunnas, 2023[16]). Our final corrected estimate suggests that the probability of leaving unemployment benefit receipt declines by about 5% for each additional week of receipt.
- Childhood self-control – the ability to control one's own emotions, thoughts, and behaviours – is associated with quicker exit from benefit receipt: once in receipt of unemployment benefit, Dunedin Study members with greater measured childhood self-control tend to exit benefit receipt sooner than those with lower childhood self-control. This is consistent with previous work by the Dunedin Study, which shows that Study members with lower childhood self-control have spent a larger proportion of their lives receiving social benefits, and reinforces wider conclusions from the Study that emphasise the importance of supporting the growth and development of self-control.
- However, none of our remaining early-life factors shared a clear and statistically significant association with the duration of unemployment benefit receipt. This includes parental education and occupational status, childhood physical health, and childhood IQ.

4.1 Data and methods

4.1.1 Unemployment benefit receipt

We measure unemployment benefit receipt using data on benefit spells from the New Zealand Ministry of Social Development's (MSD) Benefit Dynamics Data Set matched to members of the Dunedin Study cohort. The MSD Benefit Dynamics Data Set is an administrative data set constructed from records in New Zealand's benefit payments system (Wilson, 1999[105]). As described in Welch and Wilson (2010[100]), information from the Benefit Dynamics Data Set was integrated into the Dunedin Study using full names, gender, date of birth, and residential location history, plus a range of additional data fields (e.g. full address histories, name change histories, household composition histories) in case of any partial or uncertain matches. Welch and Wilson (2010[100]) show that the integrated data provides information on benefit receipt that is largely representative of the general New Zealand population born in the same year as the Dunedin Study cohort (i.e. April 1972 and March 1973)

Box 4.1. Understanding the unemployment benefit in New Zealand

Unlike most OECD countries but similar to several other English-speaking countries (e.g. Australia, Ireland), New Zealand operates an unemployment benefit system based around what the OECD terms "unemployment assistance", as opposed to "unemployment insurance" (OECD, 2024[106]). Unemployment support is offered on a means-tested basis at a flat rate to all eligible jobseekers who are available and looking for work regardless of previous contributions or employment history. Payment rates are fixed at a comparatively modest level regardless of duration and, in contrast to many countries, there is no limit on the length of claim. Payments are also phased out as income (including partner income) rises.

As a result, in many respects, unemployment benefit in New Zealand performs a safety-net function similar to social assistance benefits in many other OECD countries (Immervoll, 2010[107]). For much of the working-age population, it provides the "benefit of last resort" should they find themselves with no alternative source of income.

The Dunedin Study cohort entered the labour market in the late 1980s and early 1990s and have seen unemployment benefits take two main forms during their working lives: Unemployment Benefit (UB) until 2013, and Jobseeker Support (JS) from 2013 onwards. In 2001, when the Study cohort were aged around 28-29, UB was available to all adult New Zealand citizens or permanent residents who had lived in New Zealand for at least 2 years at any one time, who were not in full-time work (30 or more hours per week) but who were available for and taking reasonable steps to find full-time work (OECD, 2024[106]). Payments were means-tested and removed at a taper rate of 70% on earnings (including partner's earnings) over NZD 80. All recipients were required to reapply every 12 months. UB was first introduced in 1938 and saw only minor changes to entitlement criteria and obligations until it was removed in 2013.

Jobseeker Support (JS) was introduced in July 2013. Established as part of a package of wider welfare reform, JS replaced Unemployment Benefit and incorporated several other benefits, including Sickness Benefits – a benefit for those temporarily ill or injured – and single parent benefits for women with children over age 14. Entitlement conditions and obligations are largely similar to those used previously for UB (New Zealand Work and Income, 2025[108]). As of 2019, the last year observed in our data set, JS was paid at a gross rate of NZD 245 (USD 147) per week for a single person aged 25 and over, or NZD 437 (USD 262) and NZD 408 (USD 245) per week for couples with and without children, tapered at 70% on earnings (including partner's earnings) over NZD 80 (OECD, 2024[106]). For a low-paid worker facing unemployment with no other income, and living in a single-person household, JS payments replaced 32% of previous net income for as long as the claimant remains eligible, i.e., irrespective of unemployment duration. At the start of the unemployment spell, this was considerably lower than the OECD average (e.g., 64% two months into unemployment, and 56% after six months. For very long unemployment spells, the JS replacement rate is similar to the OECD average (29% after five years) (OECD, 2025[109]).

The integrated data provides information on spells spent receiving what the MSD term "Main benefits", an umbrella term covering unemployment and training related benefits, student hardship benefits, single-parent benefits, and sickness and disability benefits, among others (Welch and Wilson, 2010[100]). Because dynamics are likely to differ between benefits with different purposes and target populations (Wilson, 1999[105]), we concentrate on receipt of three benefits linked specifically to unemployment: Unemployment Benefit (UB), which was historically New Zealand's main unemployment assistance benefit; Unemployment Benefit Training (UBT), which was a form of UB for individuals in approved training programs; and Jobseeker Support (JS), which replaced UB in 2013 and now represents the primary benefit for jobseekers in New Zealand, as well as certain other groups including those with temporary illnesses or injuries (Box 4.1). Despite its link to unemployment, we do not include Unemployment Benefit/Jobseeker Support Student Hardship, which provides temporary assistance to students looking for work during study breaks, as the length of receipt is always limited. Online Annex Table A4.4 provides results from alternative models that include receipt of all "Main benefits", including Unemployment Benefit/Jobseeker Support Student Hardship, as well as single-parent benefits (e.g. Domestic Purposes Benefit) and sickness and disability benefits (e.g. Invalids Benefit).[3]

The data set covers all benefit spells between January 1993 (when the Study cohort were aged 19-20) and November 2019 (when they were 46-47). We limit our analysis to spells started when the Study members were aged 21 or over, so as to correspond to the wider information collected on Study members at the phase 21 assessment. We also limit our analysis to spells spent as the primary benefit recipient, as opposed to the spouse or partner of the primary recipient.

The Benefit Dynamics Data Set provides information on the length of benefit receipt in days. However, inspection of the data shows regular spikes in spell frequency at seven-day intervals, especially for spells lasting around or less than one or two months, suggesting some rounding or censoring when duration was recorded. For this reason, we transform spell duration into weeks. We consider a break of at least one day as signifying the start of a new spell (Immervoll, Jenkins and Königs, 2015[99]).[4]

Overall, the integrated data provides information on 2 464 spells in receipt of Unemployment Benefit, Unemployment Benefit Training or Jobseeker Support spread across 578 Study members. Dropping spells where the partner was the primary recipient (239) or that started before age 21 (318) leaves a final sample of 1 907 spells across 503 Study members. We right censor the longest 1% of spells, leaving the effective maximum length of receipt as 210 weeks. We consider exits for any reason as exits from benefit receipt.[5] In the final sample, 1 866 (98%) of spells ended in "failure" (i.e. exit from unemployment benefit receipt), with the remainder (41, or 2%) right censored (i.e. recorded as ongoing).

4.1.2 Early-life predictors

We again use the same set of early-life predictors as in Section 2. This includes the variables measuring Study members' family background (*Parental education* and *Parental occupational status*), their childhood health (*Childhood physical health*, and *Childhood mental health*), their cognitive development (*Childhood*

[3] Results from these alternative models are largely similar to our main results for unemployment benefit as shown in Table 4.2. Estimates of raw duration dependence are identical, with each additional week of receipt is associated with a 13% lower chance of exit in both sets of results (Online Annex Table A4.4, and Table 4.2, Model 1). Including covariates and recipient random effects sees estimated duration dependence fall by 6 percentage points to 7% (Online Annex Table A4.4), slightly higher than our main results for unemployment benefit only (5%) (Table 4.2, Model 5). Childhood self-control is not a predictor of the speed of exit from main benefit receipt, suggesting weaker links to wider social assistance benefits (e.g. disability benefits, single-parent benefits) than for unemployment benefits.

[4] Online Annex Table A4.5 provides alternative results that treat two benefit spells as a single spell if there is a break of 14 days or less. This is consistent with the approach taken by the New Zealand Ministry of Social Development in their statistics on benefit receipt. These alternative results are close to identical to our main results in Table 4.2.

[5] One possible complication with this approach is that it is common in New Zealand and in the Dunedin Study cohort for adults (especially young adults) to move overseas and spend time living abroad (Milne et al., 2001[114]). Benefit spells that end with moves overseas may have different dynamics to those that end for other reasons (e.g. finding employment), which could bias our results of interest. Just over 5% of unemployment benefit spells in our database end with moves overseas. Online Annex Table A4.3 summarises results from a competing risks model that treats these spells as a separate type of exit. Estimates from this competing risks model are similar to those from our main (single risk) models outlined in Section 4.2.

IQ) and social-emotional development (*Self-control*), and any *Adverse Childhood Experiences*. See Section 2.1. for detail on variable definitions and construction.

4.1.3 Controls

All models include *calendar month* controls to account for seasonal variation in benefit exit, and most include *age at start of spell* controls. As the Dunedin Study cohort are all born within one year of one another, these *age at start of spell* controls also absorb any year effects in the likelihood of benefit exit. In many models, we also use *gender*, *educational attainment*, and *parent status* as additional controls:

- *Educational attainment* is a three-part variable corresponding to highest qualification attained. “Low education” refers to a highest qualification equal to or below a New Zealand year 11-equivalent qualification (i.e. the “School Certificate” for the Dunedin Study cohort) (Scott and Gini, 2010[31]; Scott and Ali, 2024[32]), “Medium education” to an upper-secondary level qualification (e.g. "Sixth Form Certificate", "New Zealand University Bursary") or vocational education, and "High education" to a university-level degree (e.g. Bachelor's) or higher. Education attainment is recorded for the start of the spell and is taken from information from the most recent preceding assessment.
- *Parent status* is a binary measure indicating whether the Study member has at least one child. Parent status is recorded for the start of the spell and is taken from information from the most recent preceding assessment.

4.1.4 Data analysis

We examine “duration dependence” in unemployment benefit receipt using discrete-time Event History Analysis (EHA) (Allison, 2014[110]). EHA, sometimes also called Survival or Duration Analysis or Hazard Rate Modelling, is group of methods for analysing time until an event, in this case exit from unemployment benefit receipt. The discrete time version of EHA is used in cases where the data are either intrinsically discrete (e.g. records based on annual tax returns) or is continuous but has either been measured at intervals or grouped in some way (Jenkins, 2005[111]). As discussed earlier in section 4.1.1, we have grouped the length of benefit spells into duration in weeks.

We conduct our discrete-time EHA using complementary log-log regression (Allison, 2014[110]). Complementary log-log regression is a type of generalized linear model often used for discrete-time event history data, and is particularly well suited to modelling discrete data that has been produced by grouping continuous data (Jenkins, 2005[111]), as is the case with our data on the length of benefit receipt (days, grouped into weeks). We model duration dependence by including the length of the unemployment benefit spell as an independent variable in the models. Based on inspection of the hazard function, we use spell length in linear form (i.e. as weeks) without transformation. When used in a complementary log-log regression, linear time variables produce a log-linear time function similar to the Gompertz hazard function popular in continuous-time EHA (StataCorp, 2024[112]). After exponentiating, the resulting estimates can be interpreted as the percentage change in the likelihood of exit from unemployment benefit associated with a one-week increase in the length of the unemployment benefit spell. Alternative results that model time using the natural logarithm of spell duration, plus its square, are given in Online Annex Table A4.2. Using the natural logarithm and its square produces a time function that approximates the lognormal distribution with the estimated hazard increasing, reaching a peak, and then decreasing over time.

A common issue in studies exploring benefit dynamics is properly controlling for characteristics that influence the length of benefit receipt. Some people are more likely than others to claim benefits, and some benefit recipients are more likely than others to stay on benefits for a long time, often for reasons that are difficult to capture with measured characteristics like age, gender, education or employment history (Jenkins, 2005[111]; Immervoll, Jenkins and Königs, 2015[99]). In EHA, failure to properly control for this kind "unobserved heterogeneity" between recipients can lead to the over-estimation of negative duration dependence (Jenkins, 2005[111]). We account for (potential) unobserved heterogeneity through the inclusion of "random effects", that is, recipient-level error terms that model variation in baseline hazard between benefit recipients. We first run pooled models to capture raw ("naïve") duration dependence, before adding random effects to isolate heterogeneity-adjusted dependence.

As in the analyses in sections 2 and 3, we use multiple imputation (chained equations, 10 data sets) to account for missing data on adult controls and early-life predictors. We conducted all analysis in StataSE 18.5 with the complementary log-log regressions run using the cloglog and xtcloglog commands (StataCorp, 2024[112]).

4.2 Results

Table 4.1 provides summary statistics on unemployment benefit receipt among the Dunedin Study cohort. Between the ages of 21 and 46-47, 49% of the Study cohort received unemployment benefit (either UB, UBT or JS) at least once, with the average number of spells among those ever-receiving unemployment benefit 3.8. 36% of those ever-receiving unemployment benefit received it only once over the period, 18% twice, and 47% three or more times. The median length of ended ("failed") spells in the sample was 12 weeks, and the mean 21 weeks.

Table 4.1. Summary statistics for unemployment benefit receipt among Dunedin Study members

Summary statistics for unemployment benefit spells, spells started May 1993-September 2019, 1972-1973 Dunedin Study birth cohort

Percentage of Dunedin Study members who received unemployment benefit at least once		(%)	48.5
Of which:	One spell	(%)	35.6
	Two spells	(%)	17.7
	Three or more spells	(%)	46.7
	Median no. of spells		2
	Mean no. of spells		3.8
Median length of ended spells		(Weeks)	12
Mean length of ended spells		(Weeks)	21.2

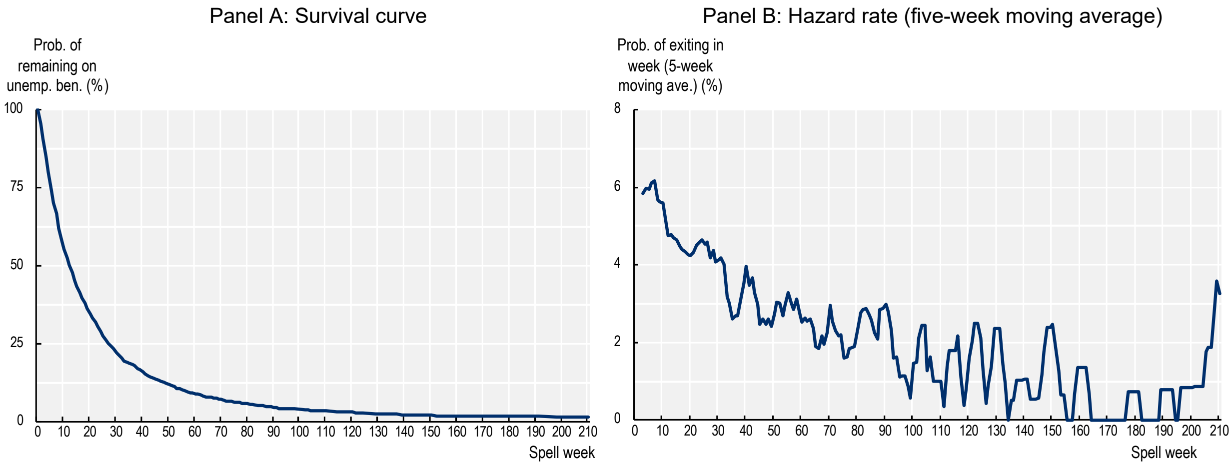
Note: "Unemployment benefit receipt" refers to spells receiving Unemployment Benefit (UB) or Unemployment Benefit Training (UBT) in years prior to 2013, or Jobseeker Support (JS) from 2013 on. Spells where Study member is registered as the primary recipient, only.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

4.2.1 *Duration dependence*

Are people who have been receiving unemployment benefit for longer less likely to leave benefit receipt? At surface level, the data for the Dunedin Study cohort suggest the answer might be yes. Figure 4.1, Panel A shows the probability of remaining in receipt of unemployment benefit beyond a given week in spell (a "survival curve"), and Panel B the five-week moving average exit rate for spells that have lasted up to the given point (the "hazard rate"). Panel A suggests that most spells end quickly. 25% of spells end by week 5, and 50% by week 12. Only one-third (33%) of spells last longer than 20 weeks. However, the chances of exit slow considerably as spell length increases (Panel B). While around 5-6% of ongoing claims end each week in the early weeks of a spell, this exit rate slows to just over 4% per week for spells that last to at least 20 weeks, 3% per week by around one year, and roughly 1-2% each week for spells that last two years or longer. Few spells (3.5%) last two years or longer, but those that get that far are much less likely to end in a given week than spells in their first few weeks.

Figure 4.1. Most benefit spells end quickly, but the pace of exit slows as spell length increases

Kaplan–Meier survival curve and five-week moving average hazard rate for unemployment benefit spells, spells started May 1993-September 2019, 1972-1973 Dunedin Study birth cohort



Note: The survival curve shows the probability that the spell will last beyond a given week. The hazard rate shows the five-week moving average probability of exiting in a given week, conditional on recipiency up to that point. "Unemployment benefit receipt" refers to spells receiving Unemployment Benefit (UB) or Unemployment Benefit Training (UBT) in years prior to 2013, or Jobseeker Support (JS) from 2013 on. Spells where Study member is registered as the primary recipient, only.
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

Estimates from our complementary log-log regressions provide a different angle on the same point. Table 4.2, Model 1 summarises results from a simple pooled model that includes only our time function (spell length in weeks) and controls for the calendar month. The estimated hazard ratio on spell length (0.987) suggests that each additional week of receipt is associated with a 13% lower chance of exit: among the Dunedin Study cohort, the longer the unemployment benefit spell, the lower the chances of exit.

A key policy question is to what extent this kind of "duration dependence" is caused by benefit receipt itself (through, for example, human capital deterioration), and to what extent by differences between recipients. Benefit recipients can differ from one another in their characteristics, and it is possible that declining chances of benefit exit reflect the fact that at longer lengths, those with the strongest skills and greatest earnings potential have already left benefit receipt. For example, Online Annex Figure A4.1 suggests that spells tend to be shorter for Study members with medium or high education than for those with low education. Adding education as well as age at start of spell, gender (man or woman) and parent status (no children or at least one child) to our complementary log-log model (Table 4.2, Model 2) increases the hazard ratio on spell length slightly compared to Model 1 (0.989, or an 11% decrease per week), suggesting that so-called "selection" by these factors helps drive at least a small part of observed duration dependence.

Table 4.2, Models 3-6 summarise estimates from our "random effects" models, models that more comprehensively account for (unobserved) heterogeneity between recipients. In line with several other studies on duration dependence in benefit receipt (Mood, 2013[15]; Hohmeyer and Lietzmann, 2020[104]; Ilmakunnas, 2023[16]), these results suggest that the degree of duration dependence falls sharply after dealing with unobserved heterogeneity. Estimates from Model 4, for example, suggest that each additional week of receipt is associated with just a 5% lower chance of exit – less than half the rate implied by the equivalent pooled model without random effects (Model 2). Among the Dunedin Study cohort, after accounting for differences between recipients, the length of time an individual has been on unemployment benefit seems to share only a modest-size association with the probability of leaving benefit receipt.

4.2.2 Early-life predictors

Can early-life factors help predict the length of unemployment benefit receipt? Table 4.2, Model 5 adds early-life predictors on family background and childhood conditions and development to our random effects model. Few of these early-life predictors are significant: among the Study cohort, conditional on already being an unemployment benefit recipient, none of parental education, parental occupational status, childhood physical health, childhood IQ or childhood adverse experiences are associated with the likelihood of exit from benefit receipt. Having a childhood mental health diagnosis is significant at the 10% level, providing a cautious suggestion that poor mental health in childhood may be linked to a lower chance (of around 13%) of leaving benefit receipt at any given point in time.

Childhood self-control is the exception. As noted earlier in Section 2, self-control is an umbrella term covering a series of social-emotional skills, including conscientiousness, self-discipline, and perseverance, and presenting in the ability to control one's own emotions, thoughts, and behaviours. Previous work by the Dunedin Study, together with New Zealand Ministry of Social Development, has shown that Study members with lower childhood self-control have spent a larger proportion of their lives receiving social benefits than those with greater childhood self-control (Caspi, Moffitt and Poulton, 2013[113]). Consistent with this, results in Table 4.2, Model 5 suggest that when in receipt of unemployment benefit, those with greater childhood self-control tend to exit benefit receipt more quickly than those with lower childhood self-control: conditional on already being an unemployment benefit recipient, a one-point higher score on the childhood self-control index is associated with a 15% lower chance of benefit exit. Notably, the effect associated with childhood self-control does not seem to change with spell length: our final model, Model 6, adds an interaction term between the childhood self-control index and our time function, spell length in weeks, which is not statistically significant. Instead, greater self-control in childhood is associated with a fixed proportional increase in the probability of moving off unemployment benefit regardless of how long the spell has lasted.

Table 4.2. Duration dependence in benefit receipt falls by more than half after accounting for heterogeneity between benefit recipients

Summary of results from discrete-time complementary log–log regressions predicting exit from unemployment benefit receipt, spells started May 1993-September 2019, 1972-1973 Dunedin Study birth cohort

		Pooled complementary log–log models				Random effects complementary log–log models							
			Model 1		Model 2		Model 3		Model 4		Model 5		Model 6
		Haz. Rat.	Std. Err.	Haz. Rat.	Std. Err.	Haz. Rat.	Std. Err.	Haz. Rat.	Std. Err.	Haz. Rat.	Std. Err.	Haz. Rat.	Std. Err.
Length of benefit spell	Weeks	0.987***	(0.001)	0.989***	(0.001)	0.994***	(0.001)	0.995***	(0.001)	0.995***	(0.001)	0.996**	(0.001)
Gender	Woman			0.973	(0.072)			1.046	(0.080)	0.987	(0.079)	0.993	(0.080)
Education	Low			0.742***	(0.054)			0.753***	(0.062)	0.841+	(0.075)	0.841+	(0.076)
	High			0.946	(0.074)			0.903	(0.084)	0.845+	(0.083)	0.844+	(0.083)
Parent status	At least one child			0.897	(0.080)			0.826*	(0.075)	0.860+	(0.078)	0.858+	(0.078)
Parents' education	Low									0.965	(0.089)	0.966	(0.090)
	High									0.992	(0.135)	0.998	(0.137)
Parents' occ. status	Parents' occ. status. index									0.947	(0.044)	0.945	(0.044)
Childh. physical health	Childh. phys. health index									0.994	(0.040)	0.994	(0.041)
Childhood mental health	Any men. health diag.									0.870+	(0.071)	0.867+	(0.072)
Adverse childhood exp.	At least one ACE									0.922	(0.076)	0.917	(0.077)
Childhood IQ	Childhood IQ									1.003	(0.034)	1.003	(0.034)
Childhood self-control	Childh.self-control index									1.155**	(0.051)	1.128*	(0.055)
Childhood self-control index * length of benefit spell												1.001	(0.001)
Constant		0.063***	(0.005)	0.068***	(0.006)	0.060***	(0.005)	0.060***	(0.007)	0.083***	(0.034)	0.081***	(0.034)
	Calendar month controls		Yes		Yes		Yes		Yes		Yes		Yes
	Age at start of spell controls		No		Yes		No		Yes		Yes		Yes
	Observations (spells)		45030		45030		45030		45030		45030		45030
	Study members		503		503		503		503		503		503

Note: ***: p < 0.001, **: p < 0.01, *: p < 0.05. +: p < 0.1. Results from complementary log–log models predicting exit from unemployment benefit receipt. Estimates expressed as hazard ratios and can be interpreted as the proportional change in the likelihood of exit from unemployment benefit receipt for a one-unit change in the given variable. Cluster robust standard errors in parentheses. Length of benefit spells is measured in weeks. "Unemployment benefit receipt" refers to spells receiving Unemployment Benefit (UB) or Unemployment Benefit Training (UBT) in years prior to 2013, or Jobseeker Support (JS) from 2013 on. Spells where Study member is registered as the primary recipient, only. Results based on a dataset that uses chained equation multiple imputation (10 imputations) for missing data..
Source: OECD Secretariat estimates based on data from the Dunedin Multidisciplinary Health & Development Study, https://dunedinstudy.otago.ac.nz

References

Allison, P. (2014), *Event History and Survival Analysis*, SAGE Publications, Inc., https://doi.org/10.4135/9781452270029. [110]

Bäckman, O. and Å. Bergmark (2011), "Escaping welfare? Social assistance dynamics in Sweden", *Journal of European Social Policy*, Vol. 21/5, pp. 486-500, https://doi.org/10.1177/0958928711418855. [103]

Baldwin, J. et al. (2021), "Population vs Individual Prediction of Poor Health From Results of Adverse Childhood Experiences Screening", *JAMA Pediatrics*, Vol. 175/4, p. 385, https://doi.org/10.1001/jamapediatrics.2020.5602. [69]

Belsky, D. et al. (2015), "Cardiorespiratory fitness and cognitive function in midlife: Neuroprotection or neuroselection?", *Annals of Neurology*, Vol. 77/4, pp. 607-617, https://doi.org/10.1002/ana.24356. [55]

Blanden, J., M. Doepke and J. Stuhler (2022), "Educational Inequality"*, NBER Working Paper No. 29979*. [38]

Bonoli, G. (2005), "The politics of the new social policies: providing coverage against new social risks in mature welfare states", *Policy & Politics*, Vol. 33/3, pp. 431-449, https://doi.org/10.1332/0305573054325765. [24]

Boullier, M. and M. Blair (2018), "Adverse childhood experiences", *Paediatrics and Child Health*, Vol. 28/3, pp. 132-137, https://doi.org/10.1016/j.paed.2017.12.008. [68]

Brzinsky-Fay, C., U. Kohler and M. Luniak (2006), "Sequence Analysis with Stata", *The Stata Journal: Promoting communications on statistics and Stata*, Vol. 6/4, pp. 435-460, https://doi.org/10.1177/1536867X0600600401. [95]

Burns, T. and F. Gottschalk (eds.) (2020), *Education in the Digital Age: Healthy and Happy Children*, Educational Research and Innovation, OECD Publishing, Paris, https://doi.org/10.1787/1209166a-en. [52]

Bynner, J. and H. Joshi (2007), "Building The Evidence Base From Longitudinal Data", *Innovation: The European Journal of Social Science Research*, Vol. 20/2, pp. 159-179, https://doi.org/10.1080/13511610701502255. [5]

Carcillo, S. et al. (2014), "NEET Youth in the Aftermath of the Crisis: Challenges and Policies"*, OECD Social, Employment and Migration Working Papers No. 164*, https://doi.org/10.1787/5js6363503f6-en. [14]

Carcillo, S. et al. (eds.) (2014), *Safety Nets and Benefit Dependence*, Emerald Group Publishing Limited, https://doi.org/10.1108/S0147-9121201439. [98]

Carroll, N. (2012), "Structural Change in the New Zealand Economy 1974-2012", Draft Paper for the Long-Term Fiscal External Panel. [42]

Caspi, A. et al. (2020), "Longitudinal Assessment of Mental Health Disorders and Comorbidities Across 4 Decades Among Participants in the Dunedin Birth Cohort Study", *JAMA Network Open*, Vol. 3/4, p. e203221, https://doi.org/10.1001/jamanetworkopen.2020.3221. [34]

Caspi, A., T. Moffitt and R. Poulton (2013), “Lifelong Impact of Early Self-Control”, *American Scientist*, Vol. 101/5, p. 352, https://doi.org/10.1511/2013.104.352. [113]

Caspi, A. et al. (1998), “Early Failure in the Labor Market: Childhood and Adolescent Predictors of Unemployment in the Transition to Adulthood”, *American Sociological Review*, Vol. 63/3, p. 424, https://doi.org/10.2307/2657557. [85]

Clarke, C. et al. (2024), “What are the economic costs of childhood socio-economic disadvantage? Evidence from a pathway analysis for 27 European countries”, *The Journal of Economic Inequality*, Vol. 22/2, pp. 473-494, https://doi.org/10.1007/s10888-023-09603-8. [39]

Cornaglia, F., E. Crivellaro and S. McNally (2015), “Mental health and education decisions”, *Labour Economics*, Vol. 33, pp. 1-12, https://doi.org/10.1016/j.labeco.2015.01.005. [78]

Čukić, I. et al. (2017), “Childhood IQ and survival to 79: Follow-up of 94% of the Scottish Mental Survey 1947”, *Intelligence*, Vol. 63, pp. 45-50, https://doi.org/10.1016/j.intell.2017.05.002. [59]

Cukrowska-Torzewska, E. and A. Matysiak (2020), “The motherhood wage penalty: A meta-analysis”, *Social Science Research*, Vol. 88-89, p. 102416. [21]

Currie, J. (2016), “The long-term consequences of children’s health and circumstance”, *Focus*, Vol. 3/1, pp. 11-16. [53]

Currie, J. (2009), “Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development”, *Journal of Economic Literature*, Vol. 47/1, pp. 87-122, https://doi.org/10.1257/jel.47.1.87. [50]

Danner, M. et al. (2022), “Patterns in NEET Statuses during the School-to-Work Transition in France”, in Levels, M. et al. (eds.), *The Dynamics of Marginalized Youth: Not in Education, Employment, or Training Around the World*, https://doi.org/10.4324/9781003096658. [93]

Davis, P., G. Jenkin and P. Coope (2003), *New Zealand Socio-economic Index 1996: An update and revision of the New Zealand Socio-economic Index of Occupational Status*, Statistics New Zealand. [86]

Devaux, M. and F. Sassi (2015), “The Labour Market Impacts of Obesity, Smoking, Alcohol Use and Related Chronic Diseases”, *OECD Health Working Papers*, No. 86, OECD Publishing, Paris, https://doi.org/10.1787/5jrqcn5fpv0v-en. [29]

Dicks, A., M. Levels and R. van der Velden (2020), “From school to where? How social class, skills, aspirations, and resilience explain unsuccessful school-to-work transitions”, *GSBE Research Memoranda 013*, Maastricht University, Graduate School of Business and Economics. [91]

Egan, M., M. Daly and L. Delaney (2015), “Childhood psychological distress and youth unemployment: Evidence from two British cohort studies”, *Social Science & Medicine*, Vol. 124, pp. 11-17, https://doi.org/10.1016/j.socscimed.2014.11.023. [79]

England, P. et al. (2016), “Do Highly Paid, Highly Skilled Women Experience the Largest Motherhood Penalty?”, *American Sociological Review*, Vol. 81/6, pp. 1161-1189. [20]

Felitti, V. et al. (1998), “Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults”, *American Journal of Preventive Medicine*, Vol. 14/4, pp. 245-258, https://doi.org/10.1016/S0749-3797(98)00017-8. [71]

Fergusson, D., J. Horwood and E. Ridder (2005), "Show me the child at seven II: childhood intelligence and later outcomes in adolescence and young adulthood", *Journal of Child Psychology and Psychiatry*, Vol. 46/8, pp. 850-858, https://doi.org/10.1111/j.1469-7610.2005.01472.x. [57]

Flores, M. and A. Kalwij (2014), "The associations between early life circumstances and later life health and employment in Europe", *Empirical Economics*, Vol. 47/4, pp. 1251-1282, https://doi.org/10.1007/s00181-013-0785-3. [40]

Flores, M. and B. Wolfe (2023), "The Influence of Early-Life Health Conditions on Life Course Health", *Demography*, Vol. 60/2, pp. 431-459, https://doi.org/10.1215/00703370-10579184. [49]

Fondeville, N. and T. Ward (2014), *Scarring effects of the crisis*. [18]

García, J. et al. (2020), "Quantifying the Life-Cycle Benefits of an Influential Early-Childhood Program", *Journal of Political Economy*, Vol. 128/7, pp. 2502-2541. [23]

George, L. (2003), "Life Course Research: Achievements and Potential", in Mortimer, J. and M. Shanahan (eds.), *Handbook of the Life Course*, Kluwer Academic/Plenum Publishers, New York. [3]

Godfrey, C. et al. (2002), *Estimating the Cost of Being "Not in Education, Employment or Training" at Age 16-18*, https://core.ac.uk/download/pdf/4154405.pdf. [80]

Gottschalk Ballo, J. et al. (2022), "Can adolescent work experience protect vulnerable youth? A population wide longitudinal study of young adults not in education, employment or training (NEET)", *Journal of Education and Work*, Vol. 35/5, pp. 502-520, https://doi.org/10.1080/13639080.2022.2099534. [96]

Grimes, A. (2023), *New Zealand: Lessons on economic reform from a distant relative*, Resolution Foundation, https://economy2030.resolutionfoundation.org/wp-content/uploads/2023/09/New-zealand-lessons-on-economic-reform.pdf#:~:text=the%20First%20World%20War%20and,reforms%20between%201984%20and%2019911. [43]

Guiney, H. et al. (2022), "Childhood sexual abuse and pervasive problems across multiple life domains: Findings from a five-decade study", *Development and Psychopathology*, pp. 1-17, https://doi.org/10.1017/S0954579422001146. [87]

Hale, D. and R. Viner (2018), "How adolescent health influences education and employment: investigating longitudinal associations and mechanisms", *Journal of Epidemiology and Community Health*, Vol. 72/6, pp. 465-470, https://doi.org/10.1136/jech-2017-209605. [54]

Halpin, B. (2016), "Cluster Analysis Stopping Rules in Stata", *University of Limerick Department of Sociology Working Paper Series WP2016-01*, University of Limerick. [94]

Hardcastle, K. et al. (2018), "Measuring the relationships between adverse childhood experiences and educational and employment success in England and Wales: findings from a retrospective study", *Public Health*, Vol. 165, pp. 106-116, https://doi.org/10.1016/j.puhe.2018.09.014. [66]

Hegelund, E. et al. (2018), "Low IQ as a predictor of unsuccessful educational and occupational achievement: A register-based study of 1,098,742 men in Denmark 1968–2016", *Intelligence*, Vol. 71, pp. 46-53, https://doi.org/10.1016/j.intell.2018.10.002. [58]

Hohmeyer, K. and T. Lietzmann (2020), “Persistence of Welfare Receipt and Unemployment in Germany: Determinants and Duration Dependence”, *Journal of Social Policy*, Vol. 49/2, pp. 299-322, https://doi.org/10.1017/S0047279419000242. [104]

Holmes, C. et al. (2022), “NEETs in England”, in Levels, M. et al. (eds.), *The Dynamics of Marginalized Youth: Not in Education, Employment, or Training Around the World*, Routledge, https://doi.org/10.4324/9781003096658. [92]

Ilmakunnas, I. (2023), “Is there a welfare trap? Duration dependence in social assistance recipiency among young Finns”, *Acta Sociologica*, Vol. 66/2, pp. 153-174, https://doi.org/10.1177/00016993221102510. [16]

Ilmakunnas, I. and P. Moisio (2019), “Social assistance trajectories among young adults in Finland: What are the determinants of welfare dependency?”, *Social Policy & Administration*, Vol. 53/5, pp. 693-708, https://doi.org/10.1111/spol.12413. [101]

Immervoll, H. (2010), “Minimum-Income Benefits in OECD Countries: Policy Design, Effectiveness and Challenges”*, OECD Social, Employment and Migration Working Papers*, No. 100, OECD Publishing, Paris, https://doi.org/10.1787/218402763872. [107]

Immervoll, H., S. Jenkins and S. Königs (2015), “Are Recipients of Social Assistance ’Benefit Dependent’?: Concepts, Measurement and Results for Selected Countries”*, OECD Social, Employment and Migration Working Papers*, No. 162, OECD Publishing, Paris, https://doi.org/10.1787/5jxrcmgpc6mn-en. [99]

Jackson, M. (2015), “Cumulative Inequality in Child Health and Academic Achievement”, *Journal of Health and Social Behavior*, Vol. 56/2, pp. 262-280, https://doi.org/10.1177/0022146515581857. [51]

Jarosch, G. (2023), “Searching for Job Security and the Consequences of Job Loss”, *Econometrica*, Vol. 91/3, pp. 903-942. [19]

Jenkins, S. (2005), *Survival Analysis.*, https://www.iser.essex.ac.uk/wp-content/uploads/files/teaching/stephenj/ec968/pdfs/ec968lnotesv6.pdf. [111]

Jones, B. and D. Nagin (2013), “A Note on a Stata Plugin for Estimating Group-based Trajectory Models”, *Sociological Methods & Research*, Vol. 42/4, pp. 608-613, https://doi.org/10.1177/0049124113503141. [74]

Kautz, T. et al. (2014), “Fostering and Measuring Skills: Improving Cognitive and Non-cognitive Skills to Promote Lifetime Success”, *OECD Education Working Papers*, No. 110, OECD Publishing, Paris, https://doi.org/10.1787/5jxsr7vr78f7-en. [63]

Kleven, H., C. Landais and J. Søgaard (2019), “Children and Gender Inequality: Evidence from Denmark”, *American Economic Journal: Applied Economics*, Vol. 11/4, pp. 181-209. [22]

Koenen, K. et al. (2009), “Childhood IQ and Adult Mental Disorders: A Test of the Cognitive Reserve Hypothesis”, *American Journal of Psychiatry*, Vol. 166/1, pp. 50-57, https://doi.org/10.1176/appi.ajp.2008.08030343. [61]

Lai, E. et al. (2019), “Poverty dynamics and health in late childhood in the UK: evidence from the Millennium Cohort Study”, *Archives of Disease in Childhood*, Vol. 104/11, pp. 1049-1055. [17]

Lawlor, D., A. Andersen and G. Batty (2009), “Birth cohort studies: past, present and future”, *International Journal of Epidemiology*, Vol. 38/4, pp. 897-902, https://doi.org/10.1093/ije/dyp240. [7]

Lesnard, L. (2010), “Setting Cost in Optimal Matching to Uncover Contemporaneous Socio-Temporal Patterns”, *Sociological Methods & Research*, Vol. 38/3, pp. 389-419, https://doi.org/10.1177/0049124110362526. [89]

Levels, M. et al. (2022), *The Dynamics of Marginalized Youth: Not in Education, Employment, or Training Around the World*, Routledge, https://doi.org/10.4324/9781003096658. [84]

Llena-Nozal, A. (2009), “The Effect of Work Status and Working Conditions on Mental Health in Four OECD Countries”, *National Institute Economic Review*, Vol. 209/1, pp. 72-87, https://doi.org/10.1177/0027950109345234. [26]

Lorentzen, T. et al. (2019), “Pathways to Adulthood: Sequences in the School-to-Work Transition in Finland, Norway and Sweden”, *Social Indicators Research*, Vol. 141/3, pp. 1285-1305, https://doi.org/10.1007/s11205-018-1877-4. [83]

Maloney, T. (2004), *Isolating the Scarring Effects Associated with the Economic Inactivity of Youth in New Zealand: Evidence from the Christchurch Health and Development Study: Report to the Labour Market Policy Group New Zealand Department of Labour*, University of Auckland. [81]

Mayer, K. (2009), “New Directions in Life Course Research”, *Annual Review of Sociology*, Vol. 35/1, pp. 413-433, https://doi.org/10.1146/annurev.soc.34.040507.134619. [4]

Metzler, M. et al. (2017), “Adverse childhood experiences and life opportunities: Shifting the narrative”, *Children and Youth Services Review*, Vol. 72, pp. 141-149, https://doi.org/10.1016/j.childyouth.2016.10.021. [67]

Mikkonen, J. et al. (2020), “Evaluating the Role of Parental Education and Adolescent Health Problems in Educational Attainment”, *Demography*, Vol. 57/6, pp. 2245-2267, https://doi.org/10.1007/s13524-020-00919-y. [77]

Milne, B. et al. (2001), “Brain drain or OE? Characteristics of young New Zealanders who leave”, *New Zealand Medical Journal*, Vol. 114/1141, pp. 450-453. [114]

Moffitt, T. et al. (2011), “A gradient of childhood self-control predicts health, wealth, and public safety”, *Proceedings of the National Academy of Sciences*, Vol. 108/7, pp. 2693-2698, https://doi.org/10.1073/pnas.1010076108. [13]

Mood, C. (2013), “Social Assistance dynamics in Sweden: Duration dependence and heterogeneity”, *Social Science Research*, Vol. 42/1, pp. 120-139, https://doi.org/10.1016/j.ssresearch.2012.07.005. [15]

Nagin, D. (2014), “Group-Based Trajectory Modeling: An Overview”, *Annals of Nutrition and Metabolism*, Vol. 65/2-3, pp. 205-210, https://doi.org/10.1159/000360229. [10]

Nagin, D. (2005), *Group-Based Modeling of Development*, Harvard University Press. [73]

Nagin, D. et al. (2018), “Group-based multi-trajectory modeling”, *Statistical Methods in Medical Research*, Vol. 27/7, pp. 2015-2023, https://doi.org/10.1177/0962280216673085. [72]

Nagin, D. and C. Odgers (2010), “Group-Based Trajectory Modeling in Clinical Research”, *Annual Review of Clinical Psychology*, Vol. 6/1, pp. 109-138, https://doi.org/10.1146/annurev.clinpsy.121208.131413. [9]

New Zealand Work and Income (2025), “Jobseeker Support”. [108]

O’Connor, M. et al. (2022), “Better together: Advancing life course research through multi-cohort analytic approaches”, *Advances in Life Course Research*, Vol. 53, p. 100499, https://doi.org/10.1016/j.alcr.2022.100499. [8]

OECD (2025), “Benefits in unemployment, share of previous income”, *OECD Publishing, Paris*. [109]

OECD (2025), *OECD Data Explorer*, OECD Publishing, Paris, https://data-explorer.oecd.org. [48]

OECD (2024), *Education at a Glance 2024: OECD Indicators*, OECD Publishing, Paris, https://doi.org/10.1787/c00cad36-en. [25]

OECD (2024), *National Accounts*, OECD Publishing, Paris, https://www.oecd.org/sdd/na/. [45]

OECD (2024), “OECD TaxBEN Policy Descriptions”, https://www.oecd.org/social/benefits-and-wages/. [106]

OECD (2023), *Health at a Glance 2023: OECD Indicators*, OECD Publishing, Paris, https://doi.org/10.1787/7a7afb35-en. [33]

OECD (2023), *Joining Forces for Gender Equality: What is Holding us Back?*, OECD Publishing, Paris, https://doi.org/10.1787/67d48024-en. [30]

OECD (2021), *Beyond Academic Learning: First Results from the Survey of Social and Emotional Skills*, OECD Publishing, Paris, https://doi.org/10.1787/92a11084-en. [65]

OECD (2021), *Measuring What Matters for Child Well-being and Policies*, OECD Publishing, Paris, https://doi.org/10.1787/e82fded1-en. [64]

OECD (2019), *PISA 2018 Results (Volume II): Where All Students Can Succeed*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/b5fd1b8f-en. [76]

OECD (2018), *A Broken Social Elevator? How to Promote Social Mobility*, OECD Publishing, Paris, https://doi.org/10.1787/9789264301085-en. [37]

OECD (2018), *Social Policy for Shared Prosperity: Embracing the Future OECD Ministerial Meeting on Social Policy Ministerial Policy Statement Social Policy for Shared Prosperity: Embracing the Future: Ministerial Policy Statement*, OECD Publishing, Paris, https://www.oecd.org/social/ministerial/ministerial-statement-2018.pdf. [1]

OECD (2017), “Preventing ageing unequally”, in *Preventing Ageing Unequally*, OECD Publishing, Paris, https://doi.org/10.1787/9789264279087-4-en. [2]

OECD (2016), *Society at a Glance 2016: OECD Social Indicators*, OECD Publishing, Paris, https://doi.org/10.1787/9789264261488-en. [35]

OECD and ILO (2024), *Youth at Work in G20 countries: Progress and policy action in 2023: Paper prepared under Brazil’s G20 Presidency (2024)*, OECD Publishing, Paris, https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/08/youth-at-work-in-g20-countries_1a1c9f65/8fd7f6b8-en.pdf. [36]

Perry, B. (2019), *Household incomes in New Zealand: Trends in indicators of inequality and hardship 1982 to 2018*, New Zealand Ministry of Social Development, http://www.msd.govt.nz/about-msd-and-our-work/publications-resources/monitoring/index.html. [47]

Picchio, M. and M. Ubaldi (2024), "Unemployment and health: A meta-analysis", *Journal of Economic Surveys*, Vol. 38/4, pp. 1437-1472, https://doi.org/10.1111/joes.12588. [27]

Poulton, R. et al. (2002), "Association between children's experience of socioeconomic disadvantage and adult health: a life-course study", *The Lancet*, Vol. 360/9346, pp. 1640-1645, https://doi.org/10.1016/S0140-6736(02)11602-3. [41]

Poulton, R. et al. (2023), "The Dunedin study after half a century: reflections on the past, and course for the future", *Journal of the Royal Society of New Zealand*, Vol. 53/4, pp. 446-465, https://doi.org/10.1080/03036758.2022.2114508. [12]

Poulton, R., T. Moffitt and P. Silva (2015), "The Dunedin Multidisciplinary Health and Development Study: overview of the first 40 years, with an eye to the future", *Social Psychiatry and Psychiatric Epidemiology*, Vol. 50, pp. 679-693, https://doi.org/10.1007/s00127-015-1048-8. [11]

Rahmani, H. and W. Groot (2023), "Risk Factors of Being a Youth Not in Education, Employment or Training (NEET): A Scoping Review", *International Journal of Educational Research*, Vol. 120, p. 102198, https://doi.org/10.1016/j.ijer.2023.102198. [97]

Ralston, K. et al. (2022), "Economic Inactivity, Not in Employment, Education or Training (NEET) and Scarring: The Importance of NEET as a Marker of Long-Term Disadvantage", *Work, Employment and Society*, Vol. 36/1, pp. 59-79, https://doi.org/10.1177/0950017020973882. [82]

Reuben, A. et al. (2016), "Lest we forget: comparing retrospective and prospective assessments of adverse childhood experiences in the prediction of adult health", *Journal of Child Psychology and Psychiatry*, Vol. 57/10, pp. 1103-1112, https://doi.org/10.1111/jcpp.12621. [70]

Ritschard, G. and M. Studer (eds.) (2018), *Sequence Analysis and Related Approaches*, Springer International Publishing, https://doi.org/10.1007/978-3-319-95420-2. [88]

Schaefer, J. et al. (2017), "Enduring mental health: Prevalence and prediction.", *Journal of Abnormal Psychology*, Vol. 126/2, pp. 212-224, https://doi.org/10.1037/abn0000232. [56]

Scott, D. and A. Ali (2024), *How does New Zealand's education system compare? New Zealand Summary Report of the OECD's Education at a Glance 2024*, New Zealand Ministry of Education. [32]

Scott, D. and P. Gini (2010), *How does New Zealand's education system compare? OECD's Education at a Glance 2010*, New Zealand Ministry of Education. [31]

StataCorp (2024), *Stata 18 Base Reference Manual*, College Station, TX: Stata Press. [112]

Statistics New Zealand (2025), *Stats NZ Infoshare*, Statistics New Zealand, https://infoshare.stats.govt.nz. [46]

Statistics New Zealand (2015), *100 years of the CPI*, Statistics New Zealand, https://statsnz.contentdm.oclc.org/digital/collection/p20045coll27/id/121/. [44]

Studer, M. and G. Ritschard (2016), “What Matters in Differences Between Life Trajectories: A Comparative Review of Sequence Dissimilarity Measures”, *Journal of the Royal Statistical Society Series A: Statistics in Society*, Vol. 179/2, pp. 481-511, https://doi.org/10.1111/rssa.12125. [90]

Thomson, W. et al. (2019), “Childhood IQ predicts age-38 oral disease experience and service-use”, *Community Dentistry and Oral Epidemiology*, Vol. 47/3, pp. 252-258, https://doi.org/10.1111/cdoe.12451. [60]

VanderWeele, T. (2021), “Can Sophisticated Study Designs With Regression Analyses of Observational Data Provide Causal Inferences?”, *JAMA Psychiatry*, Vol. 78/3, p. 244, https://doi.org/10.1001/jamapsychiatry.2020.2588. [6]

Vargas Lopes, F. and A. Llena-Nozal (2025), “Understanding and addressing inequalities in mental health”*, OECD Health Working Papers*, No. 180, OECD Publishing, Paris, https://doi.org/10.1787/56adb10f-en. [75]

Vergunst, F. et al. (2023), “Behaviors in kindergarten are associated with trajectories of long-term welfare receipt: A 30-year population-based study”, *Development and Psychopathology*, Vol. 35/1, pp. 119-129, https://doi.org/10.1017/S095457942100047X. [102]

Virgolino, A. et al. (2022), “Lost in transition: a systematic review of the association between unemployment and mental health”, *Journal of Mental Health*, Vol. 31/3, pp. 432-444, https://doi.org/10.1080/09638237.2021.2022615. [28]

Welch, D. and M. Wilson (2010), *Lifecourse factors associated with time spent receiving benefit in young adulthood: A note on early findings*, New Zealand Ministry of Social Development. [100]

Wilson, M. (1999), “The Duration of Benefit Receipt: New Findings from the Benefit Dynamics Data Set”, *Social Policy Journal of New Zealand*, Vol. 13. [105]

Wraw, C. et al. (2016), “Intelligence in youth and mental health at age 50”, *Intelligence*, Vol. 58, pp. 69-79, https://doi.org/10.1016/j.intell.2016.06.005. [62]