

Forecasting the age structure of the scientific workforce in Australia

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Summary

Planning for a future workforce requires forecasts of age structure changes to inform policy decisions, particularly related to universities and immigration. We propose a new dynamic statistical model for forecasting the age structure of a workforce. Our approach is inspired by a stochastic model used in population forecasting, replacing births with graduate entry, modelling exits through death and retirement, and including a remainder term that captures migration and career changes. Functional data models are used to model age-specific components, while ARIMA models are used for time series components. Simulation is employed to generate forecast distributions, capturing uncertainty from all components. The approach is illustrated using data on Australia's scientific workforce, allowing us to forecast the age distribution of various scientific disciplines for the next ten years. This analysis was central to an Australian Academy of Science initiative examining the capability of Australia's science system and identifying workforce gaps.

Key words: cohort analysis; demographic modelling; functional data models; labour market; workforce planning

1. Introduction

8 In planning for the future labour market, it is necessary to forecast the age structure
9 of the workforce in order to enable informed decision-making on policies, especially
10 concerning universities and immigration. We propose a statistical modelling approach
11 to this problem, illustrated using various scientific disciplines in Australia, forecasting
12 future workforce age structures over the next decade. The forecasts described have been

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13 used by the Australian Academy of Science as part of *Australian Science, Australia's Future: Science 2035*, an initiative assessing the capability of the national science
14 system and its role in achieving Australia's ambitions ([Australian Academy of Science 2025](#)).
15

16
17 The economic implications of workforce age structure shifts are well-documented (e.g.,
18 [Bloom et al. 2007](#)), affecting productivity, pensions and superannuation, and skill
19 shortages ([Productivity Commission 2013; OECD 2019a,b](#); [Hyndman, Zeng & Shang 2021](#)). The social implications are also significant, with an aging workforce leading to
20 changes in workplace dynamics, potential problems with intergenerational knowledge
21 transfer, and the need for policies that support older workers. Yet this problem does
22 not appear to have been previously addressed from a statistical modelling perspective.
23

24 Our approach builds on functional data models, introduced to demographic modelling
25 by [Hyndman & Ullah \(2007\)](#). They combined nonparametric smoothing and functional
26 principal components for age-specific demographic rates. These models were then used
27 by [Hyndman & Booth \(2008\)](#) for mortality, fertility, and migration rates, providing
28 stochastic data generating processes for the components of demographic balance
29 equations. These separate component models were then simulated to form future
30 sample paths, leading to age- and sex-specific stochastic population forecasts. The
31 modelling framework was later extended by [Hyndman, Booth & Yasmeen \(2013\)](#) to
32 ensure coherence of forecasts between sexes or other demographic groups.

33 We propose a related approach for modelling workforce dynamics by redefining the
34 demographic components in two ways. First, we replace fertility with workforce entry,
35 which functions more like a migration process than a birth process because graduates
36 can enter the workforce at any age. Second, we *explicitly* model workers leaving the
37 workforce through two processes: retirement and death. Of course, people may also
38 leave the workforce for other reasons, such as a career change or family commitments,
39 but since we do not have data on these processes, we model them *implicitly* via a
40 remainder term.

41 We describe the methodology in Section 2. By way of illustration, we apply the
42 methodology to major scientific disciplines in Australia, focusing on the Natural and

43 Physical Sciences. We describe the data sources in Section 3, with the results provided
 44 in Section 4. The aim of this analysis is to inform future workforce planning and policy
 45 decisions to support the growth of Australia’s scientific community. Finally, we provide
 46 some discussion and conclusions in Section 5.

47 2. Methodology

48 Suppose our workforce is divided into I groups, indexed by $i = 1, \dots, I$. In our
 49 application, these are scientific disciplines, but in principle they could refer to any
 50 subdivision of workers. Let $P_{i,x,t}$ denote the number of equivalent full-time workers
 51 in group i who are aged x at the start of year t , where $x = 15, 16, \dots$. The starting
 52 age of 15 is chosen because it is the minimum age at which individuals are counted
 53 as part of the labour force in the Australian Census ([Australian Bureau of Statistics
 54 2021b](#)). We assume that data are available for years $t = 1, \dots, T$, and that forecasts
 55 are required for $P_{i,x,T+h}$ across all ages and groups, for some forecast horizon $h > 0$.

56 People can leave the workforce of a group through death, retirement, emigration, family
 57 responsibilities, or career change; they can enter the workforce through graduation,
 58 immigration, changes in family responsibilities, or career change. Unfortunately, we
 59 typically do not have data on many of these processes, so we will combine changes due
 60 to family responsibilities, career changes, emigration and immigration into a remainder
 61 term, which we denote as $E_{i,x,t}$. Let $D_{i,x,t}$ denote the number of deaths of workers
 62 in group i of age x in year t , $R_{i,x,t}$ denote the number of retirements from the same
 63 group of workers, and $G_{i,x,t}$ denote the number of new graduates of age x in year t
 64 who take up work in group i . The numbers in each case are for people aged x at the
 65 *start* of year t . Then population changes can be described using the following model:

$$P_{i,x+1,t+1} = P_{i,x,t} - D_{i,x,t} - R_{i,x,t} + G_{i,x,t} + E_{i,x,t}, \quad (1)$$

66 where

- 67 • $D_{i,x,t} \sim \text{Binomial}(P_{i,x,t}, q_{i,x,t})$, with $q_{i,x,t}$ being the probability of death for
 68 group i at age x in year t ; and

- 69 • $R_{i,x,t} \sim \text{Binomial}((P_{i,x,t} - D_{i,x,t}), r_{i,x,t})$, with $r_{i,x,t}$ being the probability of
70 retirement from group i at age x in year t .

71 That is, the population each year is equal to the population from the previous year
72 having aged 1 year, minus the deaths or retirements that occurred during the previous
73 year, plus the new graduates, plus any other changes due to migration or career change
74 (which may be negative). We assume that $E_{i,x,t} = G_{i,x,t} = 0$ above some age threshold
75 (say $x = 100$). Once $P_{i,x,t} = 0$ when x is above that threshold, all future populations
76 $P_{i,x+k,t+k} = 0$, for $k = 1, 2, \dots$. That is, when the cohort aged x in year t has all retired
77 or died, and x is above the threshold, they will not be replaced by new workers of the
78 same age.

79 While our model was inspired by the stochastic population model of [Hyndman &](#)
80 [Booth \(2008\)](#), that model has different inputs (births and immigration) and fewer
81 outputs (deaths and emigration). Labour market forecasting is more complicated with
82 no birth process, several more inputs (graduates, immigration, career changes, career
83 renewal), and several more outputs (deaths, retirements, emigration, career disruption
84 and career changes).

85 As a first approximation, the components q , r , E and G can be assumed to behave
86 independently for each combination of i , x and t . In reality, there may be some
87 negative correlation between G and E as insufficient graduates would probably lead
88 to employers finding people from overseas, while too many graduates would lead to
89 scientists seeking work elsewhere.

90 The choice of a Binomial rather than a Poisson distribution (in contrast to [Brillinger](#)
91 ([1986](#))) for deaths and retirements is because the Binomial distribution ensures that
92 the number of deaths and retirements cannot exceed the population at risk. In a
93 simulation context, with very small populations, this is important to avoid nonsensical
94 results.

95 It is unlikely that we have available separate death and retirement counts for each group,
96 and retirement data is not available in all years. So we will let $q_{i,x,t} = q_{x,t}$ and $r_{i,x,t} = r_x$,
97 assuming that death rates and retirement rates are the same across all groups, and
98 that retirement rates do not change over time. Similarly, graduation numbers are

99 rarely available by discipline and age, so we will approximate $G_{i,x,t} = g_x G_{i,t}$ where
100 $G_{i,t}$ is the total number of graduates in year t and g_x is the proportion of graduates
101 by age across all disciplines.

102 This leads to the simpler model

$$P_{i,x+1,t+1} = P_{i,x,t} - D_{i,x,t} - R_{i,x,t} + g_x G_{i,t} + E_{i,x,t}, \quad (2)$$

103 where

- 104 • $D_{i,x,t} \sim \text{Binomial}(P_{i,x,t}, q_{x,t})$; and
105 • $R_{i,x,t} \sim \text{Binomial}((P_{i,x,t} - D_{i,x,t}), r_x)$.

106 For the age-specific time-varying components $q_{x,t}$ and $E_{i,x,t}$, we will use functional
107 data models (Hyndman & Ullah 2007). For $q_{x,t}$, this is of the form

$$\log(q_{x,t}) = \mu(x) + \sum_{k=1}^K \beta_{k,t} \phi_k(x) + \varepsilon_{x,t}, \quad (3)$$

108 where $\mu(x)$ is the mean function, $\phi_k(x)$ are functional principal components, $\beta_{k,t}$ are
109 the principal component scores, and $\varepsilon_{x,t}$ is an error term. Each $\beta_{k,t}$ is then modelled
110 using a univariate time series model, such as an ARIMA model. A log-link function is
111 used to ensure that the probabilities remain positive. An inverse logit link function
112 could also be used, if the probabilities are close to 1 for some ages. A similar model is
113 used for $E_{i,x,t}$, with separate mean functions and principal components for each group
114 i . The number of components $K = 6$, for the reasons outlined in Hyndman & Booth
115 (2008).

116 Because the $\beta_{k,t}$ values are principal component scores, they are uncorrelated by
117 construction. While it is possible for there to be some cross-correlations between the
118 series at lags other than zero, these are usually not large enough for a multivariate
119 model to give more accurate forecasts (see, Hyndman & Ullah 2007) except in contrived
120 simulated examples. On the other hand, Aue, Norinho & Hörmann (2015) did use
121 multivariate models to capture these cross-correlations, although they did not compare
122 them on real data.

123 Functional data models have been widely used in demography and other fields, and
 124 have been shown to work particularly well for age-specific demographic processes
 125 ([Hyndman & Booth 2008](#); [Booth et al. 2006](#)). They enable the inherent smoothness
 126 over age to be captured, while modelling the autocorrelation over time using relatively
 127 simple univariate time series models applied to the principal component scores. In
 128 our application, we use univariate ARIMA models for the $q_{x,t}$ scores, and ARMA
 129 models for the $E_{i,x,t}$ scores, each estimated using maximum likelihood estimation.
 130 The assumption of stationarity for the $E_{i,x,t}$ scores is validated for the disciplines we
 131 consider, but is not a requirement in general.

132 For the time-varying component, $G_{i,t}$, we use a global ARIMA model ([Hyndman](#)
 133 & [Montero-Manso 2021](#)) to capture the dynamics over time and across disciplines.
 134 This is estimated using least squares estimation. The global model pools information
 135 across disciplines to improve forecast accuracy, especially for disciplines with limited
 136 historical data.

137 To forecast future working population numbers, $P_{i,x,t}$, $t > T$, we simulate future
 138 sample paths of each of the components $G_{i,t}$, $q_{x,t}$, and $E_{i,x,t}$, simulate $D_{i,x,t}$ and
 139 $R_{i,x,t}$ from their respective Binomial distributions, and then use the demographic
 140 growth-balance equation Equation 2 iteratively to obtain $P_{i,x,t}$ for $t = T + 1, T + 2, \dots$
 141 This simulation-based approach allows us to capture the uncertainty in each of the
 142 components, leading to a distribution of possible future outcomes for $P_{i,x,t}$.

143 This model is somewhat pragmatic given the data available in our specific application.
 144 If better data were available, other variations on Equation 1 could be used. For
 145 example, if death rates were available by discipline, then we would replace $q_{x,t}$ by
 146 $q_{i,x,t}$ in the Binomial deaths distribution. If retirement rates were available by year, or
 147 by discipline, we could similarly replace r_x by a more specific retirement rate in the
 148 Binomial retirements distribution. If we had data on graduations by age and discipline,
 149 we could replace $g_x G_{i,t}$ by $G_{i,x,t}$. If we had data on migration, we could split the
 150 remainder $E_{i,x,t}$ into several components, and model them separately. None of this
 151 changes the overall modelling framework we are proposing.

152 Fortunately, there is no reason to think scientists of different disciplines would have
153 different mortality experiences. A century ago, the dangers of radiation did increase
154 mortality rates amongst chemists and physicists compared to other sciences, but
155 modern science is conducted in extremely safe environments, so it seems reasonable to
156 assume that all science disciplines share similar mortality profiles.

157 There has been a small increase in average retirement age over the last ten years due to
158 an increase in the age at which the old age pension can be accessed ([Hyndman, Zeng
& Shang 2021](#)), and a steady increase in the preservation age at which superannuation
159 can be accessed ([Kingston & Thorp 2019](#)). However, there is no existing policy proposal
160 to change either of these in the future, so it is reasonable to take the retirement age
161 distribution in recent years as valid for the foreseeable future. Further, we know of no
162 evidence that the socio-economic status of scientists varies with discipline, so there is
163 no reason to think retirement intentions would change with discipline either.

165 We assume the age distribution of graduates is a product of age-dependent and time-
166 dependent variables, g_x and $G_{i,t}$. Primarily, this is a pragmatic choice because we
167 do not have more detailed data available. We can get age distributions of graduates
168 across all disciplines in Australia, but not for each discipline; and we can get the
169 numbers of graduates by discipline and year in Australia, but with no age breakdown.
170 The most likely consequence of this simplifying assumption is that the variability in
171 graduate numbers by age and time could be underestimated. It is conceivable that
172 older graduates are drawn to different disciplines than younger graduates, or that
173 fashionable disciplines change over time, resulting in different age distributions of
174 the graduates over time. But without specific data related to this issue, we can only
175 speculate.

176 It is also worth pointing out that the remainder term $E_{i,x,t}$ will absorb any inaccuracies
177 that result from simplifying model assumptions in the other components, and we
178 forecast the remainder allowing for changes over time, age and discipline. In fact,
179 we could ignore all the model components and just forecast $P_{i,x,t}$ directly using
180 a functional time series model, but that would fail to separate out the competing
181 dynamics at play, and lead to much wider prediction intervals. By trying to model the

182 individual components where we have available data, even if imperfectly, we capture
 183 more of the inherent uncertainty and obtain narrower prediction intervals.

184

3. Data

185 To illustrate the methodology, we consider the Natural and Physical Sciences as defined
 186 in the Australian Standard Classification of Education (ASCED) by the [Australian](#)
 187 [Bureau of Statistics \(2001\)](#). We refer to ASCED's Narrow Fields as “disciplines”; these
 188 comprise Physics and Astronomy, Mathematical Sciences, Chemical Sciences, Earth
 189 Sciences, Biological Sciences, Other Natural and Physical Sciences, and Natural and
 190 Physical Sciences not further defined (n.f.d.). Table 1 lists the detailed fields within
 191 each scientific discipline.

Table 1. Classification of scientific disciplines, based on the ASCED Narrow Fields of Education within the Broad Field of Natural and Physical Sciences. The table lists their corresponding Detailed Fields. “n.e.c.” stands for “Not Elsewhere Classified.”

Narrow Fields	Detailed Fields
Physics and Astronomy	Physics, Astronomy.
Mathematical Sciences	Mathematics, Statistics, Mathematical Sciences, n.e.c.
Chemical Sciences	Organic Chemistry, Inorganic Chemistry, Chemical Sciences, n.e.c.
Earth Sciences	Atmospheric Sciences, Geology, Geophysics, Geochemistry, Soil Science, Hydrology, Oceanography, Earth Sciences, n.e.c.
Biological Sciences	Biochemistry and Cell Biology, Botany, Ecology and Evolution, Marine Science, Genetics, Microbiology, Human Biology, Zoology, Biological Sciences, n.e.c.
Other Natural and Physical Sciences	Medical Science, Forensic Science, Food Science and Biotechnology, Pharmacology, Laboratory Technology, Natural and Physical Sciences, n.e.c.

192 We define the population of workers in a discipline as those who are active in the labour
 193 market and hold a bachelor’s degree or higher in that discipline. For the purposes of
 194 this analysis, we will omit “Other Natural and Physical Sciences” and “Natural and
 195 Physical Sciences n.f.d.”.

196 **3.1. Working population**

197 Data on the working population were sourced from the *Census of Population and*
 198 *Housing* ([Australian Bureau of Statistics 2023](#)) for census years 2006, 2011, 2016, and

2021. This dataset encompasses one-year age groups, the highest level of completed
 non-school qualification level (QALLP), the corresponding field of study (QALFP,
[Australian Bureau of Statistics 2021c](#)), and the industries in which individuals work.
 However, labour force participation status ([Australian Bureau of Statistics 2021a](#)) is
 available only for 2016 and 2021. To estimate worker numbers for 2006 and 2011, the
 average participation rates from 2016 and 2021 were applied, assuming overall age
 distributions remain consistent.

The resulting estimates of the number of scientists who are active in the Australian
 labour market is shown in Figure 1 as the thick lines. Cohort interpolation ([Stupp 1988](#)),
 applying linear interpolation within each age cohort between census years, is
 used to estimate values for the intercensal years (shown as thin lines), giving $P_{i,x,t}$ for
 each discipline i , age x , and year t .

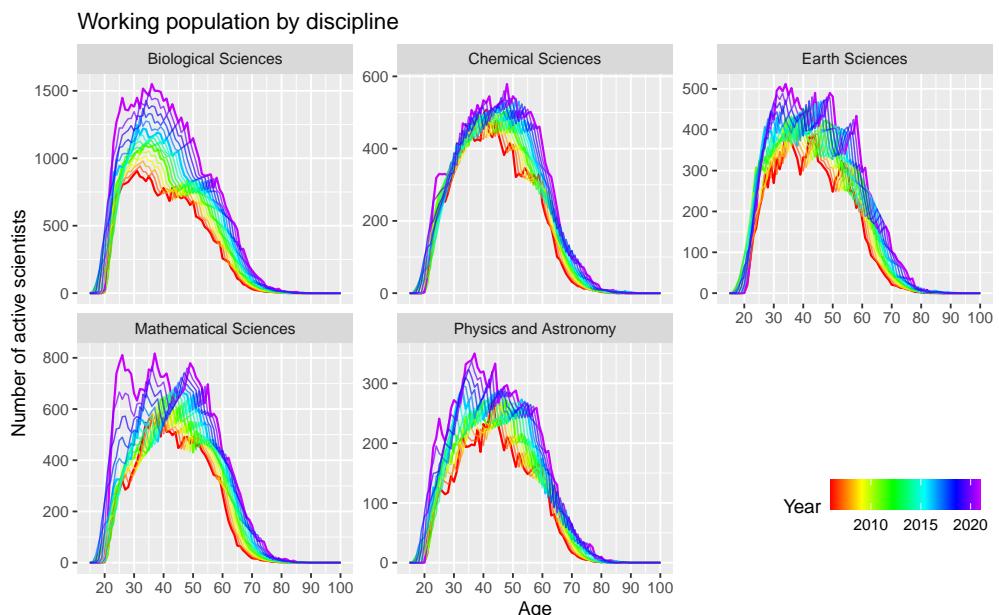


Figure 1. $P_{i,x,t}$: Estimated number of working scientists in Australia by discipline and age, 2006–2021. Thicker lines are used to denote census years.

211 3.2. Retirements

Retirement data was sourced from the *Retirement and Retirement Intentions* dataset
 (Catalogue 6238) for the 2022–2023 financial year ([Australian Bureau of Statistics](#)

2024). The data are categorised by the industry of an individual's main job, and are provided in four broad age groups (45–59, 60–64, 65–69 and 70+). There are 19 industry categories, with the largest numbers of scientists working in Education and Training (15.8%), Professional, Scientific and Technical Services (15.5%), and Health Care and Social Assistance (14.6%). The proportions in other industries are much smaller. We take a weighted average of retirement intentions using these top three industries, with proportions rescaled to sum to 1. The resulting values are shown in Figure 2 as the gray line. To obtain a single-year-of-age retirement distribution, we disaggregate the data using a monotonic cubic spline applied to the cumulative values of these age groups (Smith, Hyndman & Wood 2004). The resulting smoothed distribution (r_x) is shown as the black line in Figure 2.

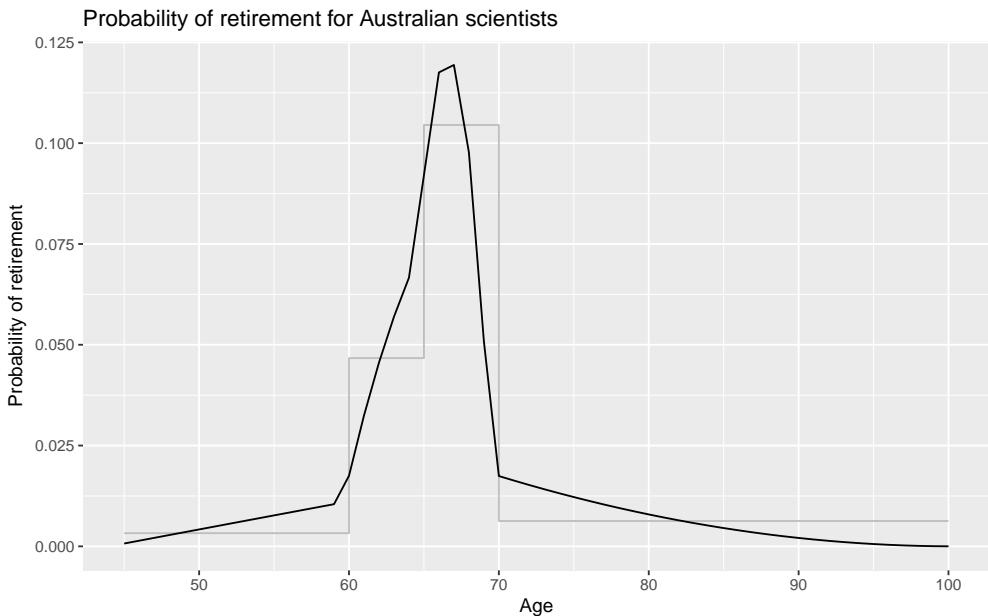


Figure 2. r_x : Age distribution of retirement intentions, based on data from the 2022–2023 Australian financial year. The grey line shows the age-group probabilities; the black line shows the smoothed probabilities.

3.3. Deaths

Age-specific mortality rates from 1971 to 2021 were obtained from the [Human Mortality Database \(2024\)](#). Using standard life table methods, these rates are converted into age-specific probabilities of death, as shown in Figure 3. Over time, mortality probabilities

229 have generally declined across all age groups, reflecting improvements in Australian
 230 life expectancy.

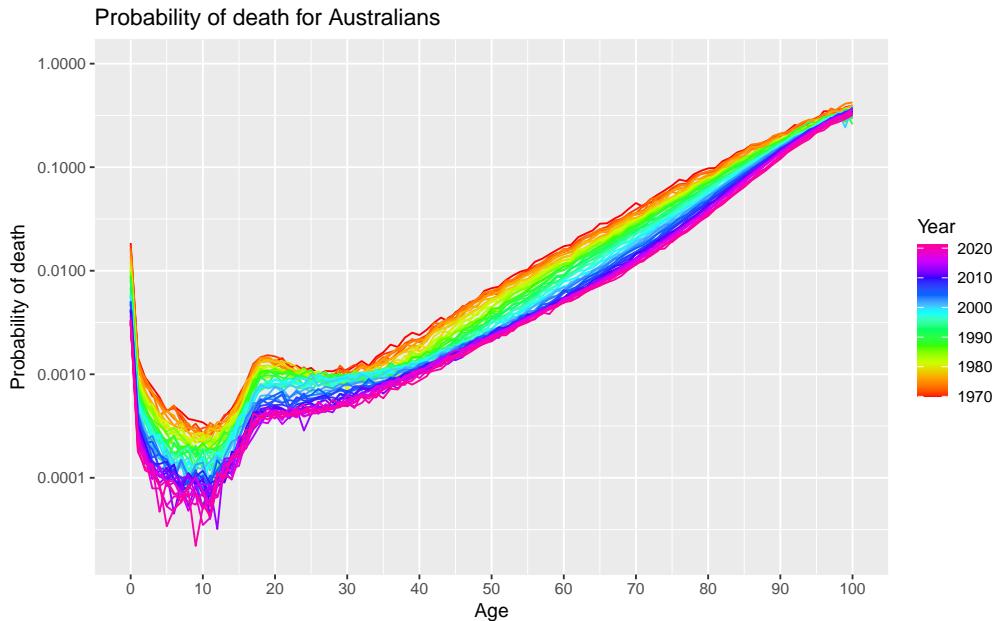


Figure 3. $q_{x,t}$: Age-specific probabilities of death (on a logarithmic scale) for each year from 1971 to 2021.

231 No data are available for specific industry groups, so we assume that all scientists have
 232 the same mortality probabilities as the general population. These probabilities serve
 233 as estimates of $q_{x,t}$.

234 3.4. Graduate completions

235 Graduate completion statistics were obtained from the *Award Course Completions*
 236 dataset ([Department of Education 2024b](#)). Figure 4 shows the distribution of graduate
 237 completions with a bachelor's degree or higher, by age for each year from 2006 to
 238 2023. Some missing values result in gaps in certain lines, but the overall pattern
 239 remains highly consistent across years. Given this consistency, the data is averaged
 240 across all available years, and then smoothed by applying monotonic cubic splines
 241 to the cumulative values ([Smith, Hyndman & Wood 2004](#)). The resulting averaged
 242 distribution, shown as the black line in Figure 4, smooths out year-to-year fluctuations
 243 and provides an estimate of g_x .

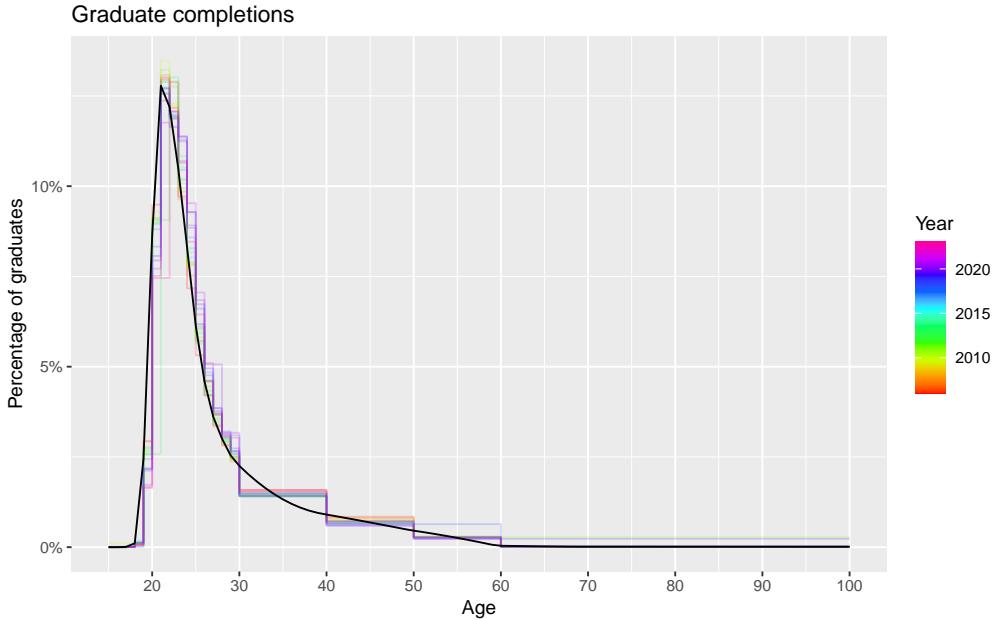


Figure 4. g_x : Estimated distribution of graduate completions by age (black). This is estimated by averaging and smoothing the data for the years 2006 to 2023 (coloured).

244 The Department of Education provides data on the number of graduates with
 245 a bachelor's degree or higher, categorised by discipline and year ([Department of](#)
 246 [Education 2024a](#)). This dataset includes both domestic and international students.
 247 The total number of graduates, $G_{i,t}$, in each discipline i and year t , are shown in
 248 Figure 5.

249 The large increase in the working population observed in the 2021 Census for
 250 Mathematical Sciences (Figure 1) can be partly attributed to the sharp rise in graduate
 251 numbers between 2016 and 2021. This is probably due to the impact of data science,
 252 and the growing importance of statistics and machine learning in many areas of
 253 employment.

254 3.5. Remainder

255 The demographic growth-balance equation (Equation 2), when rearranged, provides
 256 an expression for the remainder including net migration and career changes:

$$E_{i,x,t} = P_{i,x+1,t+1} - P_{i,x,t} - D_{i,x,t} - R_{i,x,t} - g_x G_{i,t}, \quad (4)$$

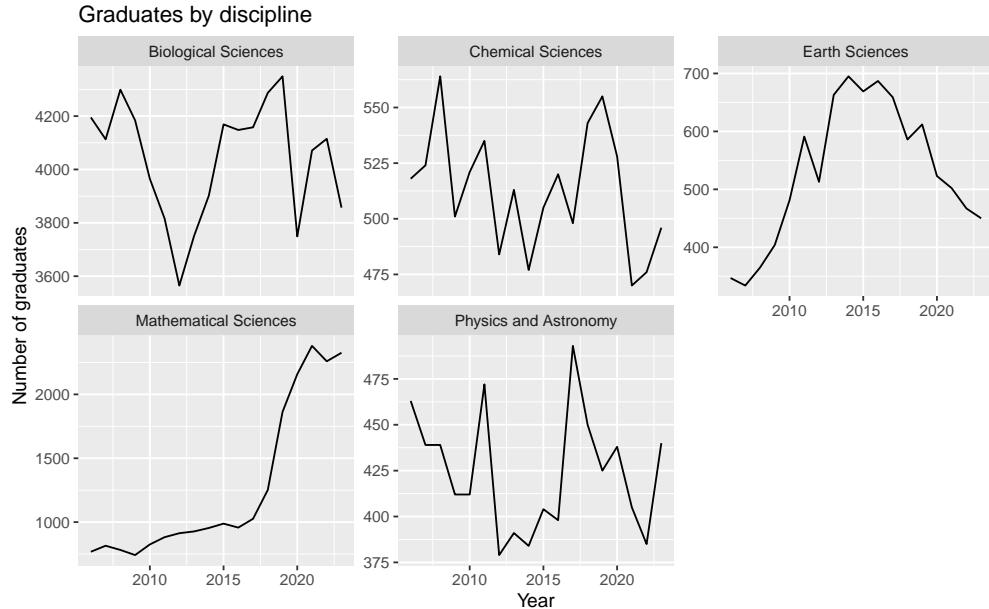


Figure 5. $G_{i,t}$: Total number of graduates with a bachelor's degree or higher by discipline from 2006 to 2023.

- 257 However, we do not have data on $D_{i,x,t}$ and $R_{i,x,t}$, so we replace these by their expected
 258 values, $P_{i,x,t}q_{x,t}$ and $P_{i,x,t}(1 - q_{x,t})r_x$, respectively. We can only estimate remainders
 259 up to 2020 because we need data for both year t and year $t + 1$ in Equation 4, and our
 260 working population data only extends to 2021. The estimated remainders are shown
 261 in Figure 6.
- 262 The inclusion of international students in the graduate data leads to large positive
 263 values of the remainder for the teenage years, followed by large negative values when
 264 these students return to their home countries after graduation.

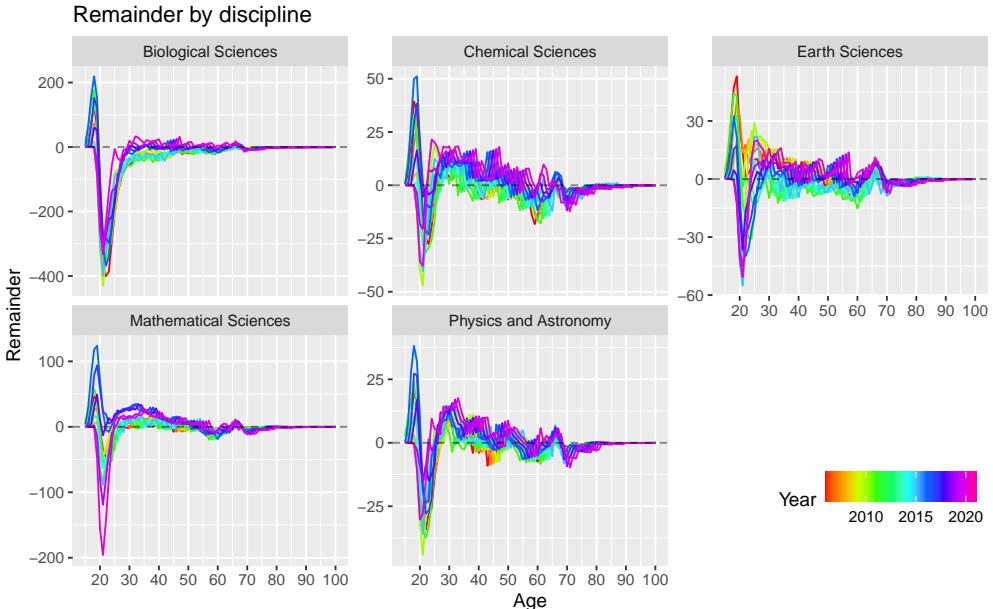


Figure 6. Estimated remainder $E_{i,x,t}$ by discipline, age and year (2006–2020).

265

4. Results

266 4.1. Graduate completions

267 To forecast future graduate numbers, $G_{i,t}$, a global ARIMA model was employed,
 268 following the principles outlined by [Hyndman & Montero-Manso \(2021\)](#). The global
 269 model captures overall trends across disciplines by scaling graduate data within
 270 each discipline, ensuring proportional contributions from all disciplines before fitting
 271 the global ARIMA model. This improves the numerical stability of the model by
 272 incorporating information across disciplines. The forecast distributions are shown in
 273 Figure 7, with the mean forecast represented by the solid line and 90% prediction
 274 intervals indicated by the shaded area.

275 4.2. Death probabilities

276 The death probabilities shown in Figure 3 were first smoothed using the partially
 277 monotonic penalised spline approach of [Hyndman & Ullah \(2007\)](#). Then the functional
 278 data model Equation 3 was estimated, with ARIMA models fitted to the coefficients.
 279 The forecasts for one year are shown in Figure 8, with the mean forecast represented

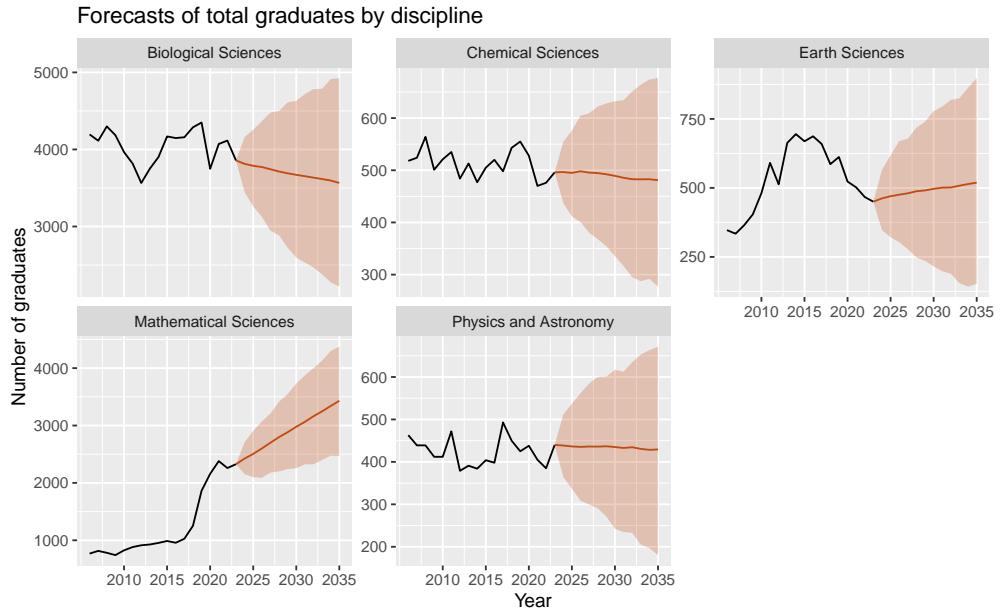


Figure 7. Forecast of $G_{i,t}$: the number of graduates by discipline, 2024–2035, based on historical data from 2006–2023. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.

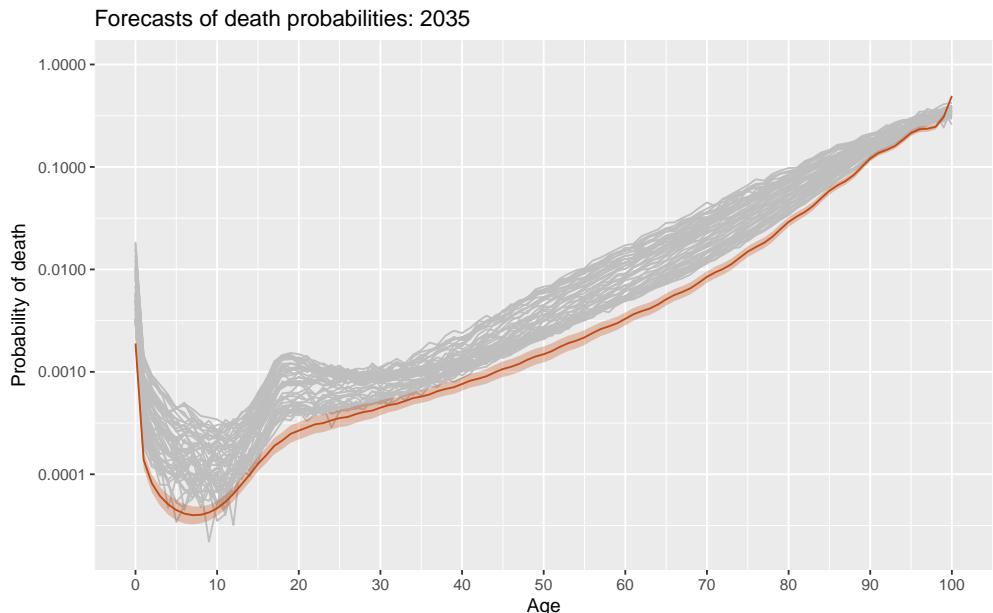


Figure 8. Forecasts of $q_{x,t}$: age-specific probabilities of death (on a logarithmic scale) for 2035, based on historical data from 1971–2021. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimate.

280 by the solid line and 90% prediction intervals indicated by the shaded area. Note that
 281 the historical data (shown in gray) represent unsmoothed values, while the forecasts
 282 are based on the smoothed functional data model. The additional variation seen in
 283 the historical data is captured in the model through the Binomial death process.

284 **4.3. Remainder**

285 The remainder, $E_{i,x,t}$, is also modelled using a functional data model ([Hyndman &](#)
 286 [Ullah 2007](#)), with ARIMA models fitted to the principal component scores. In this
 287 case, all scores were found to be stationary using the KPSS test ([Kwiatkowski et al.](#)
 288 [1992](#)), so ARMA models are used. The forecasts for one year are shown in Figure 9,
 289 with the mean forecast represented by the solid line and 90% prediction intervals
 290 indicated by the shaded area.

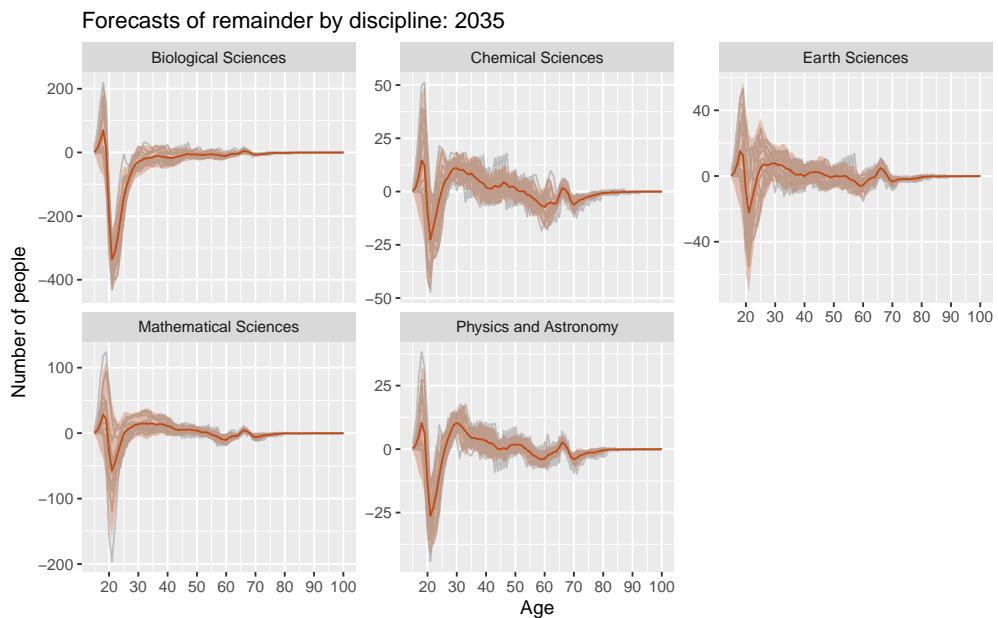


Figure 9. Forecasts of $E_{i,x,t}$: the remainder by discipline for 2035, based on historical data from 2006–2020. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.

291 **4.4. Simulating future populations**

292 We use the demographic growth-balance model Equation 2 to iteratively simulate
 293 future populations, using the models described above for the components. The following
 294 steps outline the process.

295 A total of 1000 simulations are run to obtain a distribution of future age-specific
 296 population scenarios. The average of the 1000 simulations provides the mean age-
 297 specific forecast, while quantiles estimate forecast uncertainty. Figure 10 presents the
 298 mean and 90% prediction intervals for 2035.

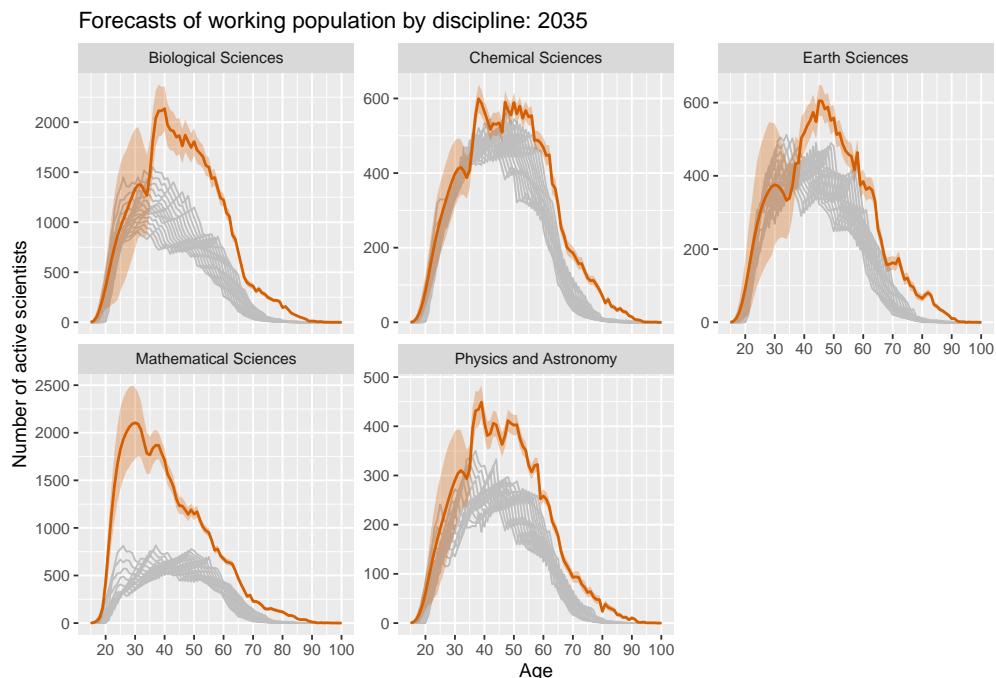


Figure 10. Forecasts of $P_{i,x,t}$: the working population by discipline for 2035. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.

299 In 2035, forecast variability is highest in the age period 20–35 years, before gradually
 300 narrowing as the workforce ages. This is due to the relatively high uncertainty in
 301 the new graduates component compared to the other components. Mid-to-late career
 302 estimates primarily reflect the aging of existing cohorts. The prediction intervals become
 303 especially narrow during the retirement phase, where the workforce dynamics become
 304 more predictable. Since retirements increase after the late 50s, workforce participation

beyond 60 serves as a benchmark for identifying trends in delayed retirement and extended career duration. Over the next ten years, we expect an aging workforce in all but the Mathematical Sciences, where a large increase in the population is forecast.

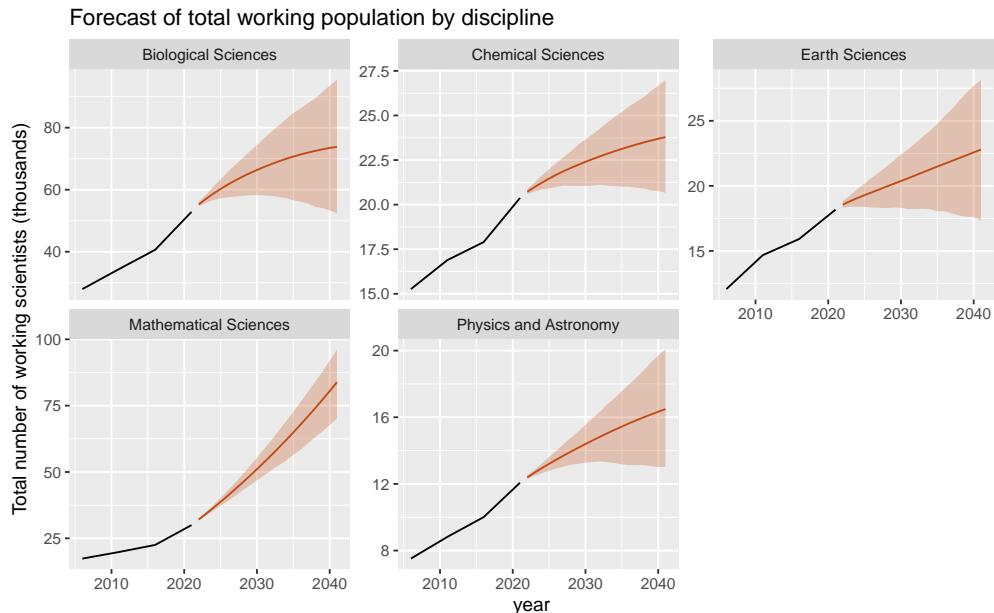


Figure 11. Forecasted total number of working scientists across scientific disciplines from 2022 to 2041. The shaded region represents the 90% prediction interval, the coloured line indicates the mean estimate, and the black line represents historical data.

Cohort effects are also visible in Figure 10, where fluctuations in earlier ages and years propagate through to later ages and years. This is particularly evident in the mid-career years because there are few deaths and retirements, few graduates older than 30, and the variation due to the remainder term is relatively small after age 30. Summing over ages allows for estimating the forecast distribution of the total number of working scientists in each future year, as shown in Figure 11. The forecasts indicate continued growth, but at a gradually slower pace for all disciplines other than the Mathematical Sciences. Where the lower bound is nearly flat, workforce stagnation is possible in a conservative scenario. Even in the optimistic scenario (corresponding to the upper bound), growth only slightly exceeds the current pace, except for the Mathematical Sciences. As noted earlier, the divergent behaviour of the Mathematical Sciences is likely driven by the growing importance of data science and related fields.

320 The wide prediction intervals reflect the uncertainty in the forecasts, and show that
321 caution is needed when interpreting the results. The only discipline where there is clear
322 evidence of growth or decline is the Mathematical Sciences. For all other disciplines,
323 the prediction intervals include the current level, indicating that stagnation, increase,
324 or decline is possible.

325

5. Discussion

326 While these forecasts provide a foundation for workforce planning, it is important to
327 note that they are entirely driven by historical trends and do not account for possible
328 new developments, such as the impact of AI and other emerging technologies on the
329 labour market in different scientific disciplines. Other factors, such as policy changes or
330 global economic shifts, may also influence workforce trends. These exogenous factors
331 could be accounted for by adding covariates into the time series models used, provided
332 relevant data are available.

333 Evaluating and validating these forecasts is challenging due to the relatively long
334 forecast horizon compared to the available historical data. While time series cross-
335 validation (Hyndman & Athanasopoulos 2021) could be used to assess forecast accuracy
336 for shorter horizons, the benefit of the forecasts is primarily for longer horizons, where
337 such validation is not possible. The uncertainty in the forecasts, as reflected in the
338 wide prediction intervals, highlights the need for caution when interpreting the results.

339 If more detailed data were available, the model could be refined further by including,
340 for example, discipline-specific death rates, retirement data by year and/or discipline,
341 graduate data by age and discipline, and data on migration and career changes. It
342 is not clear how much these refinements would improve forecast accuracy, but they
343 would likely reduce uncertainty in the forecasts.

344 Forecasts are often designed not just to predict the future, but also to inform policy
345 decisions, and so modify the future. In this context, these forecasts could be used to
346 identify potential skill shortages or surpluses in specific disciplines, guiding decisions on
347 university and immigration policy, and thus changing the future outcomes (Hyndman

348 2023). Consequently, forecast accuracy may be less important than understanding the
 349 range of possible outcomes and their implications for policy.

350 While this analysis has focused on the scientific workforce in Australia, the methodology
 351 could be applied to other countries or workforce sectors, provided similar data are
 352 available. The specific components of the demographic growth-balance equation may
 353 need to be adapted to reflect the available data in other applications.

354 6. Software and reproducibility

355 All results presented here can be reproduced using the code available at https://github.com/robjhyndman/age_structure_forecasts. The analysis was
 356 conducted using R version 4.5.1 (R Core Team 2025), with the following R packages:
 357 vital (Hyndman et al. 2025), tsibble (Wang et al. 2025), fable (O'Hara-Wild et al.
 358 2024), targets (Landau 2025, 2021), ggplot2 (Wickham et al. 2025; Wickham 2016),
 359 and other tidyverse (Wickham et al. 2019) packages.
 360

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