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Abstract

Planning for a future workforce requires forecasts of age structure changes to inform policy decisions, particularly related to universities and immigration. We modify the traditional demographic growth-balance equation to account for workforce-specific dynamics, replacing births with graduate entry, modeling 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, supporting strategic workforce planning and policy development for Australia's scientific community.

Keywords: cohort analysis; demographic modelling; functional data models; labour market; workforce planning.

1 Introduction

In planning for the future labour market, it is necessary to forecast the age structure of the workforce, in order to enable informed decision-making on policies, especially concerning universities and immigration. We propose a statistical modelling approach to this problem, illustrated using various scientific disciplines in Australia, forecasting future workforce age structures over the next decade. The forecasts described have been 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 system and its role in achieving Australia's ambitions (Australian Academy of Science 2025).

The economic implications of workforce age structure shifts are well-documented (e.g., Bloom et al. 2007), affecting productivity, pensions and superannuation, and skill shortages (Productivity Commission 2013; OECD 2019a,b; Hyndman, Zeng & Shang 2021). The social implications are also significant, with an aging workforce leading to changes in workplace dynamics, potential problems with intergenerational knowledge transfer, and the need for policies that support older workers.

Yet this problem does not appear to have been previously addressed from a statistical modelling perspective.

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

We propose to adapt this framework to workforce dynamics by redefining the demographic components in two ways. First, we replace fertility with workforce entry, which functions more like a migration process than a birth process because graduates can enter the workforce at any age. Second, we allow workers to leave the workforce through two processes: retirement and death. Of course, people may also leave the workforce for other reasons, such as a career change or family commitments, but since we do not have data on these processes, we model them implicitly via a remainder term.

We describe the methodology in Section 2. By way of illustration, we apply the methodology to major scientific disciplines in Australia, focusing on the Natural and Physical Sciences. We describe the data sources in Section 3, with the results provided in Section 4. The aim of this analysis is to inform future workforce planning and policy decisions to support the growth of Australia's scientific community. Finally, we provide some discussion and conclusions in Section 5.

2 Methodology

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

People can leave the workforce of a group through death, retirement, emigration, or career change; they can enter the workforce through graduation, immigration, or career change. Unfortunately, we typically do not have data on many of these processes, so we will combine career change, emigration and immigration into a remainder term, which we denote as $E_{i,x,t}$. Let $D_{i,x,t}$ denote the number of deaths of workers in group i of age x in year t, $R_{i,x,t}$ denote the number of retirements from the same group of workers, and $G_{i,x,t}$ denote the number of new graduates of age x in year t who take up work in group i. The numbers in each case are for people aged x at the *start* of year t. Then population changes can be described using a model similar to the stochastic population model of Hyndman & Booth (2008), excluding the birth process:

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

where

- $D_{i,x,t} \sim \text{Binomial}(P_{i,x,t}, q_{i,x,t})$, with $q_{i,x,t}$ being the probability of death for group i at age x in year t; and
- $R_{i,x,t} \sim \text{Binomial}((P_{i,x,t} - D_{i,x,t}), r_{i,x,t})$, with $r_{i,x,t}$ being the probability of retirement from group i at age x in year t.

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

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

It is unlikely that we have available separate death and retirement counts for each group, and retirement data is not available in all years. So we will let $q_{i,x,t} = q_{x,t}$ and $r_{i,x,t} = r_x$, assuming that death rates and retirement rates are the same across all groups, and that retirement rates do not change over time. Similarly, graduation numbers are rarely available by discipline and age, so we will approximate $G_{i,x,t} = g_x G_{i,t}$ where $G_{i,t}$ is the total number of graduates in year t and g_x is the proportion of graduates by age across all disciplines.

This leads to the simpler model

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

where

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

We use functional time series models (Hyndman & Ullah 2007) for $q_{x,t}$ and $E_{i,x,t}$, a global ARIMA models for $G_{i,t}$, and univariate ARIMA models for the principal component scores of the functional time series models.

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

3 Data

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

We define the population of workers in a discipline as those who are active in the labour market and hold a bachelor's degree or higher in that discipline.

3.1 Working population

Data on the working population were sourced from the *Census of Population and 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

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.

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.

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.

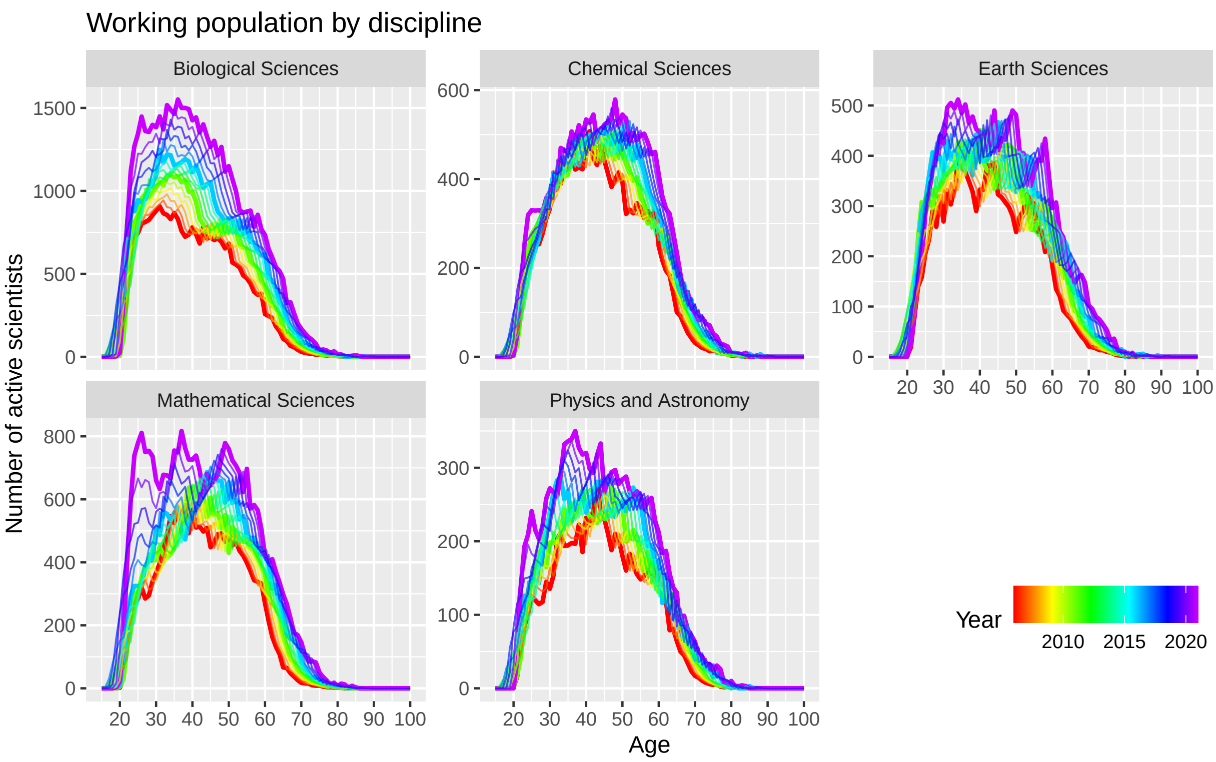

Figure 1: $P_{i,x,t}$: *Estimated number of working scientists in Australia by discipline and age, 2006–2021. Thicker lines are used to denote census years.*

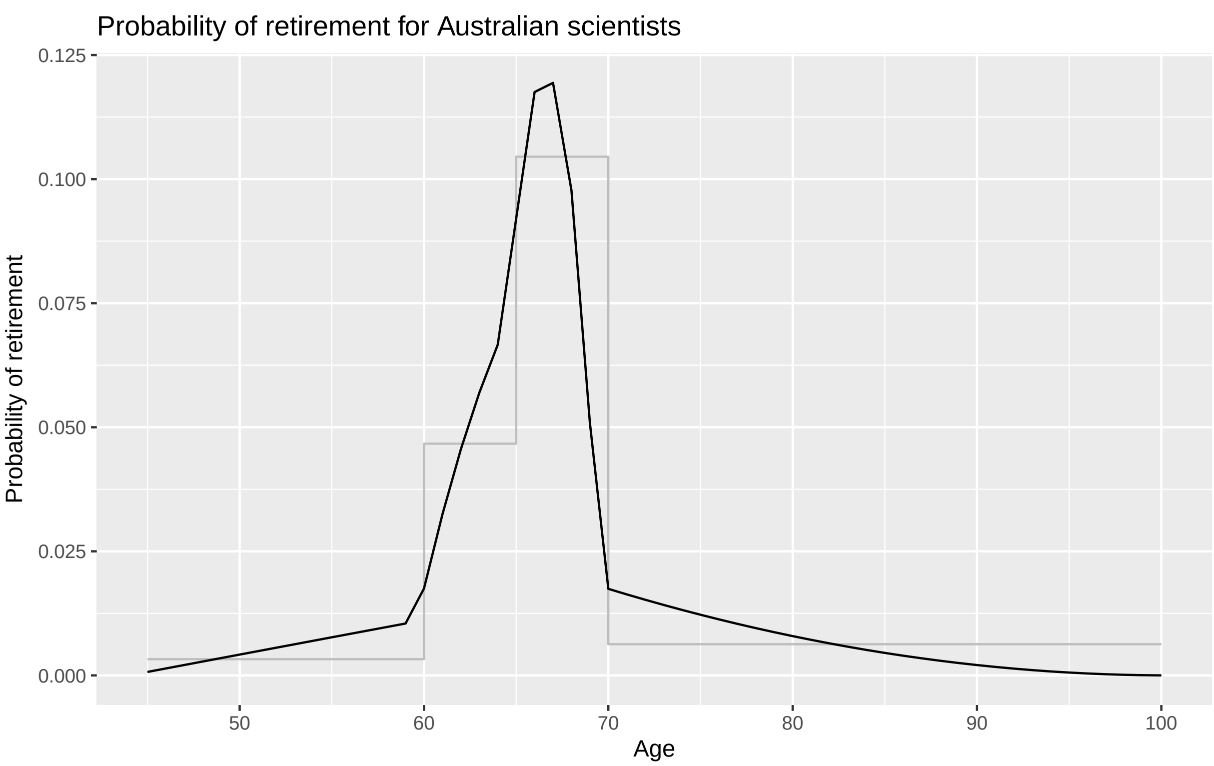

Figure 2: r_x: *Age distribution of retirement intentions, based on data from the 2022–2023 Australian financial year. The blue line shows the smoothed probabilities.*

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

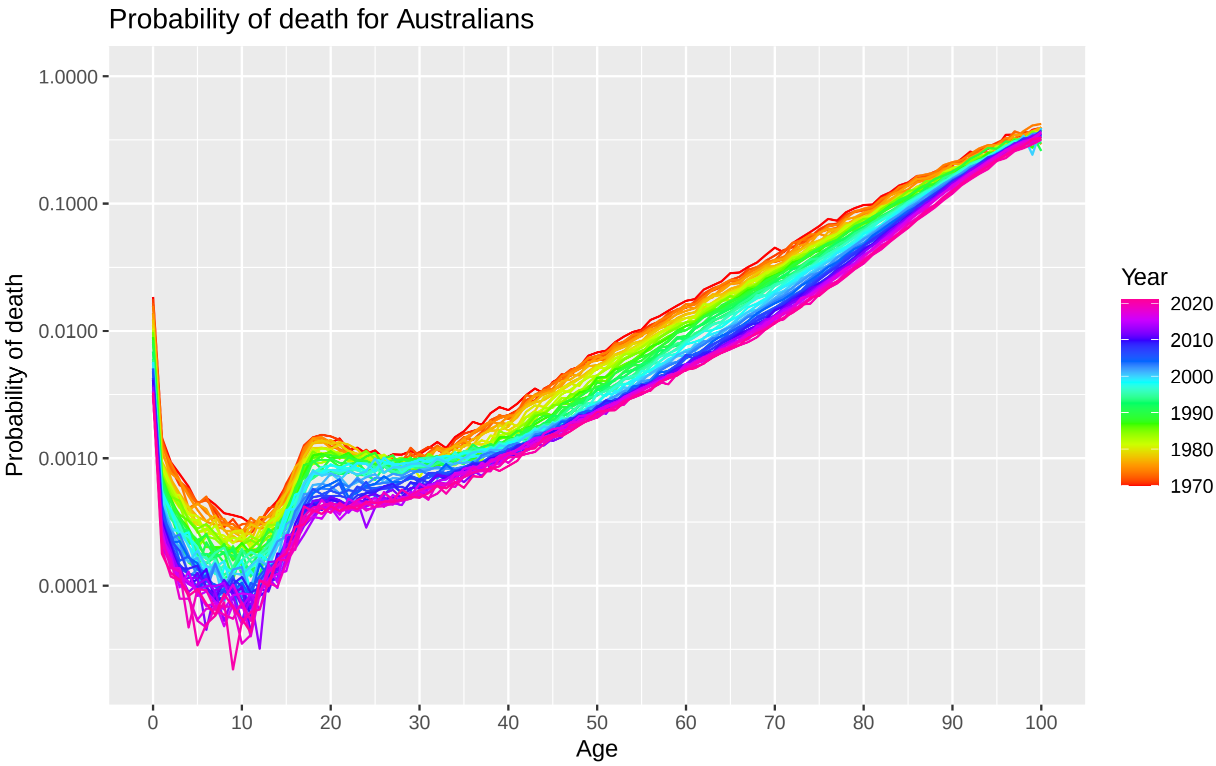

Figure 3: $q_{x,t}$: *Age-specific probabilities of death (on a logarithmic scale) for each year from 1971 to 2021.*

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

3.4 Graduate completions

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

The Department of Education provides data on the number of graduates with a bachelor's degree or higher, categorised by discipline and year (Department of Education 2024a). This dataset includes

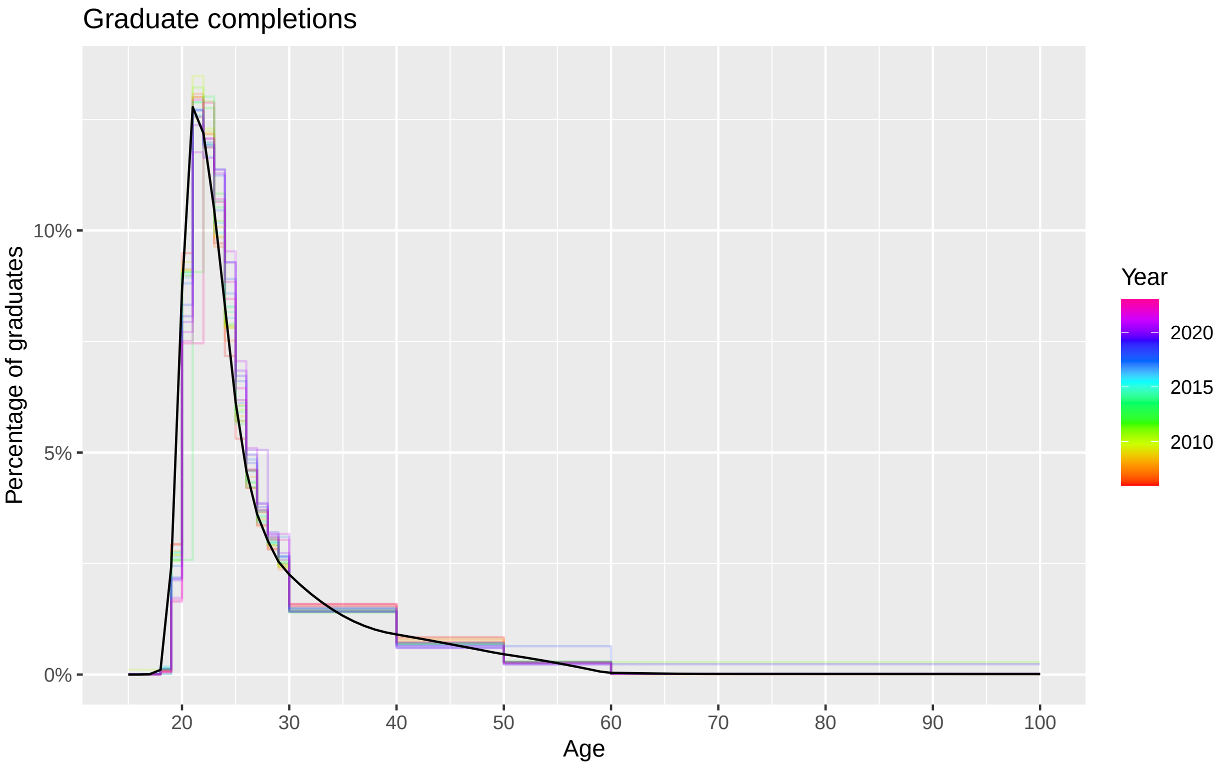

Figure 4: g_x: *Estimated distribution of graduate completions by age (black). This is estimated by averaging and smoothing the data for the years 2006 to 2023 (coloured).*

both domestic and international students. The total number of graduates, $G_{i,t}$, in each discipline i and year t, are shown in Figure 5.

The large increase in the working population observed in the 2021 Census for Mathematical Sciences (Figure 1) can be partly attributed to the sharp rise in graduate numbers between 2016 and 2021.

3.5 Remainder

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

$$E_{i,x,t} = P_{i,x+1,t+1} - P_{i,x,t} - D_{i,x,t} - R_{i,x,t} - g_x G_{i,t}, \tag{3}$$

However, we do not have data on $D_{i,x,t}$ and $R_{i,x,t}$, so we replace these by their expected 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 up to 2020 because we need data for both year t and year $t+1$ in Equation 3, and our working population data only extends to 2021. The estimated remainders are shown in Figure 6.

The inclusion of international students in the graduate data leads to large positive values of the remainder for the teenage years, followed by large negative values when these students return to their home countries after graduation.

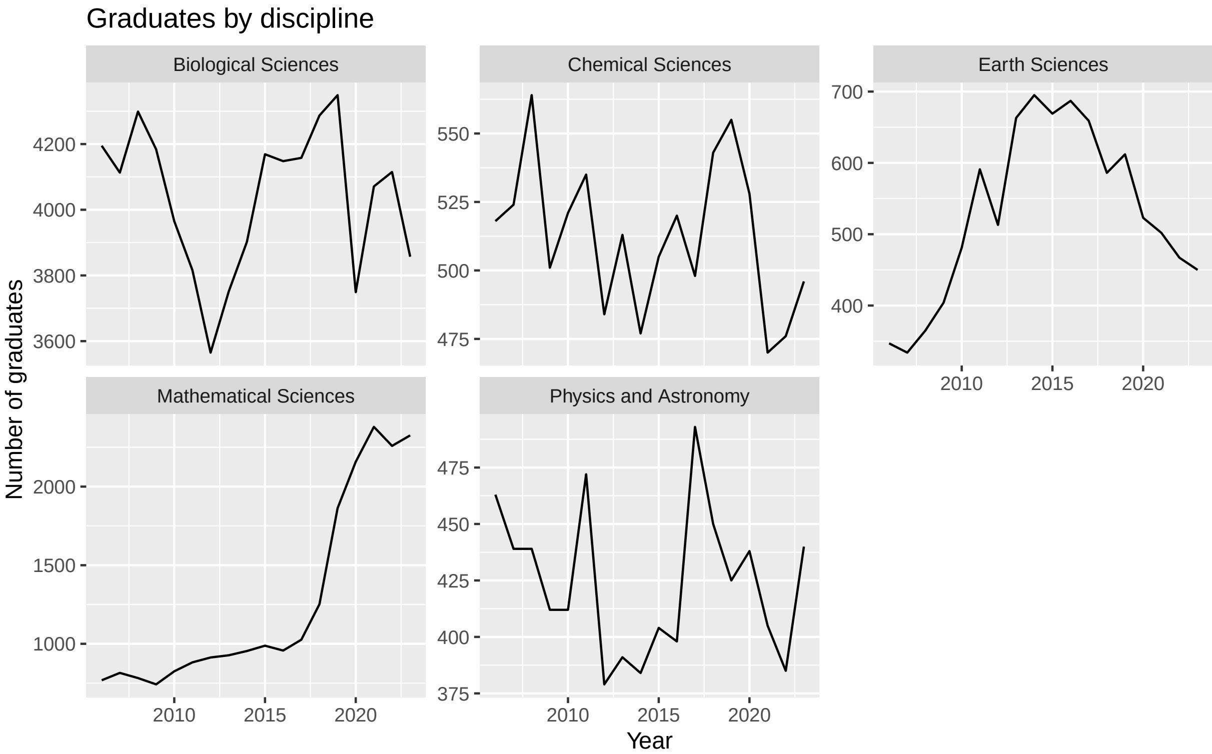

Figure 5: *$G_{i,t}$: Total number of graduates with a bachelor's degree or higher by discipline from 2006 to 2023.*

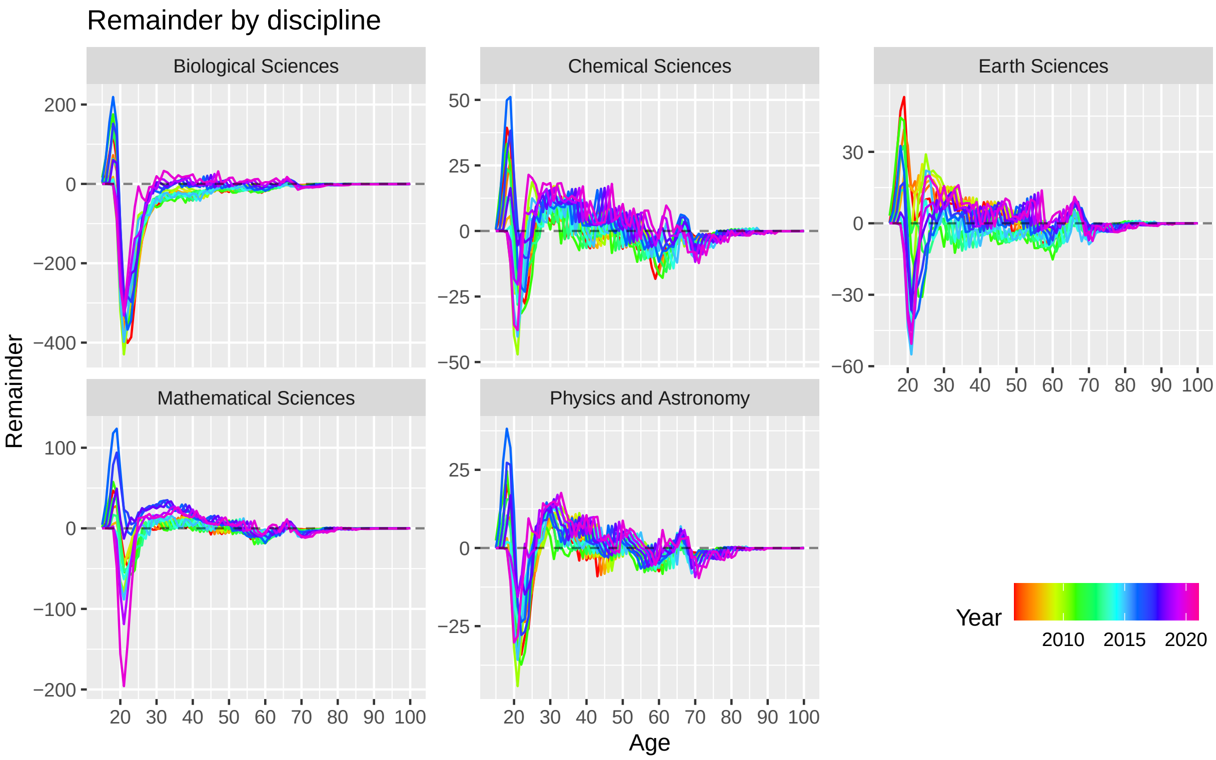

Figure 6: *Estimated remainder $E_{i,x,t}$ by discipline, age and year (2006–2020).*

4 Results

4.1 Graduate completions

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

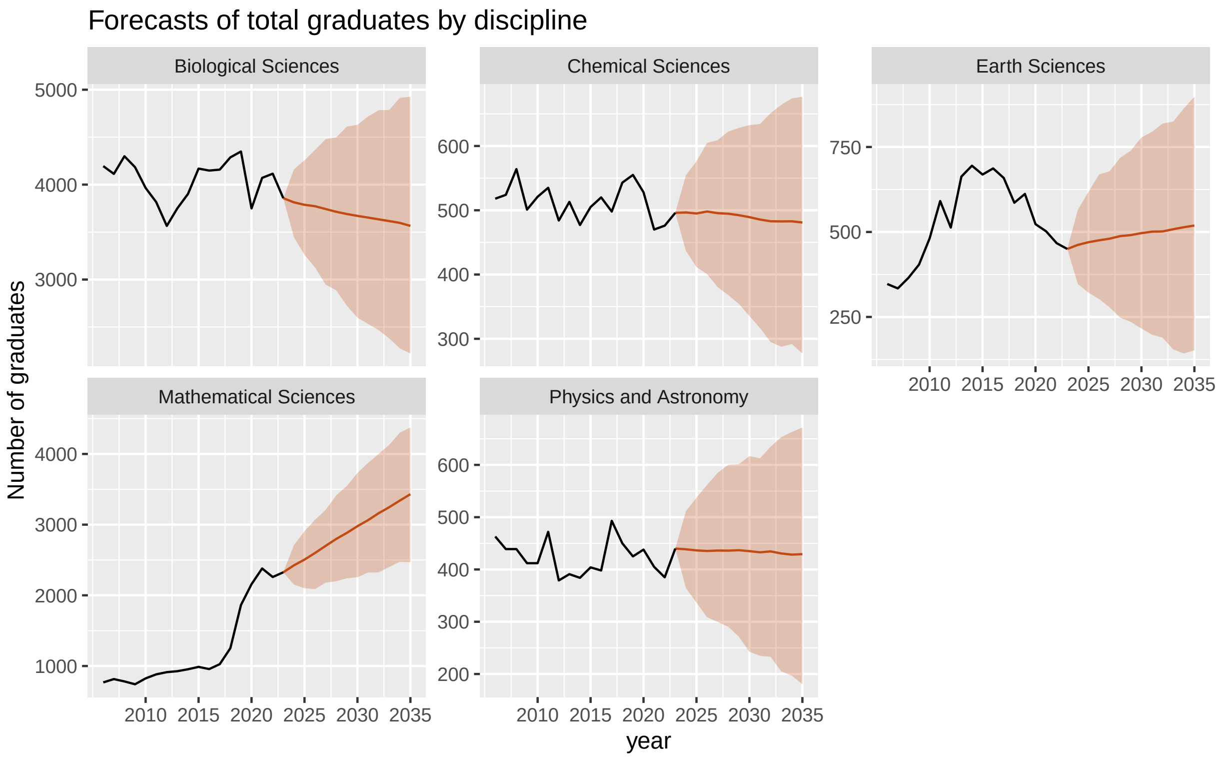

Figure 7: *Forecast of $G_{i,t}$: the number of graduates by discipline, 2024-2035, based on historical data from 2006–2023. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.*

4.2 Death probabilities

The death probabilities, $q_{x,t}$, were forecast using a functional data model (Hyndman & Ullah 2007), with ARIMA models fitted to the coefficients. The forecasts for one year are shown in Figure 8, with the mean forecast represented by the solid line and 90% prediction intervals indicated by the shaded area. Note that the historical data (shown in gray) represent unsmoothed values, while the forecasts are based on the smoothed functional data model. The additional variation seen in the historical data is captured in the model through the Binomial death process.

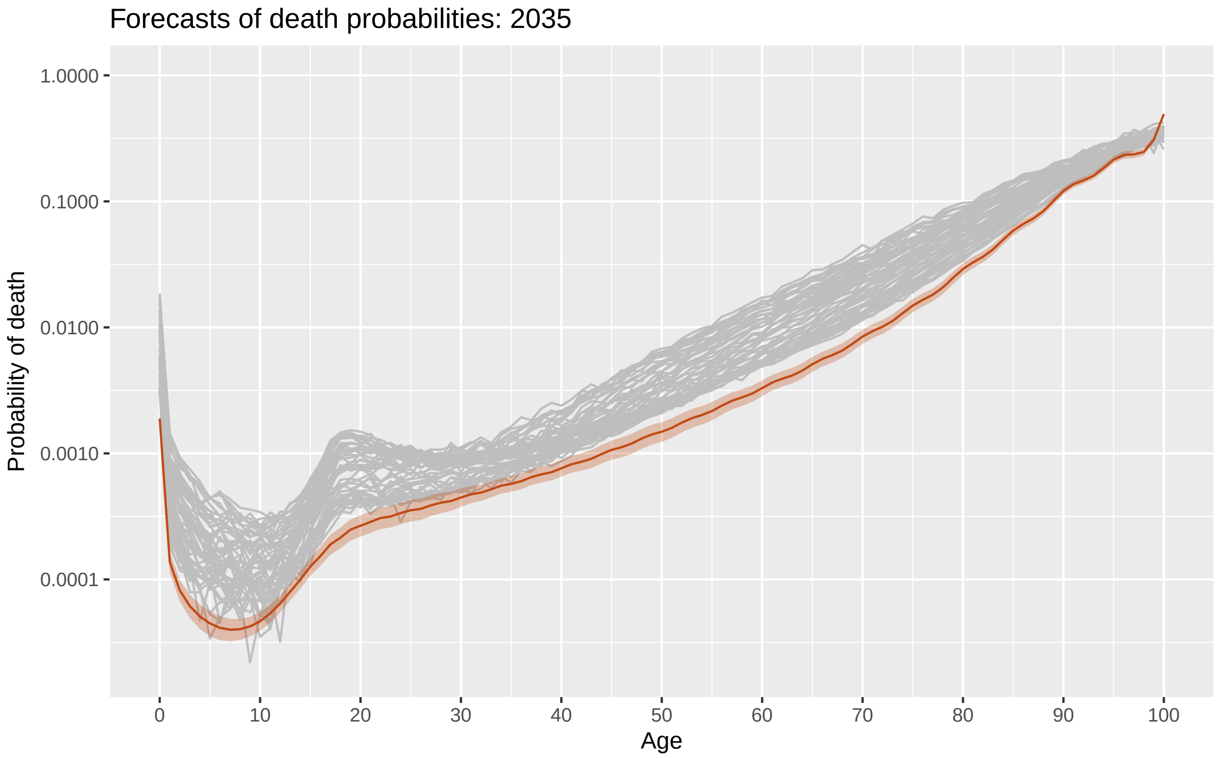

Figure 8: *Forecasts of $q_{x,t}$: age-specific probabilities of death (on a logarithmic scale) for 2035, based on historical data from 1971–2021. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimate.*

4.3 Remainder

The remainder, $E_{i,x,t}$, is also modelled using a functional data model (Hyndman & Ullah 2007), with stationary ARMA models fitted to the coefficients. The forecasts for one year are shown in Figure 9, with the mean forecast represented by the solid line and 90% prediction intervals indicated by the shaded area.

4.4 Simulating future populations

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

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

In 2035, forecast variability is highest at younger ages, starting from 15 and widening before gradually narrowing as the workforce ages. The prediction interval becomes especially narrow during the retirement phase, where the workforce dynamics become more predictable, indicating greater certainty in this portion of the forecast.

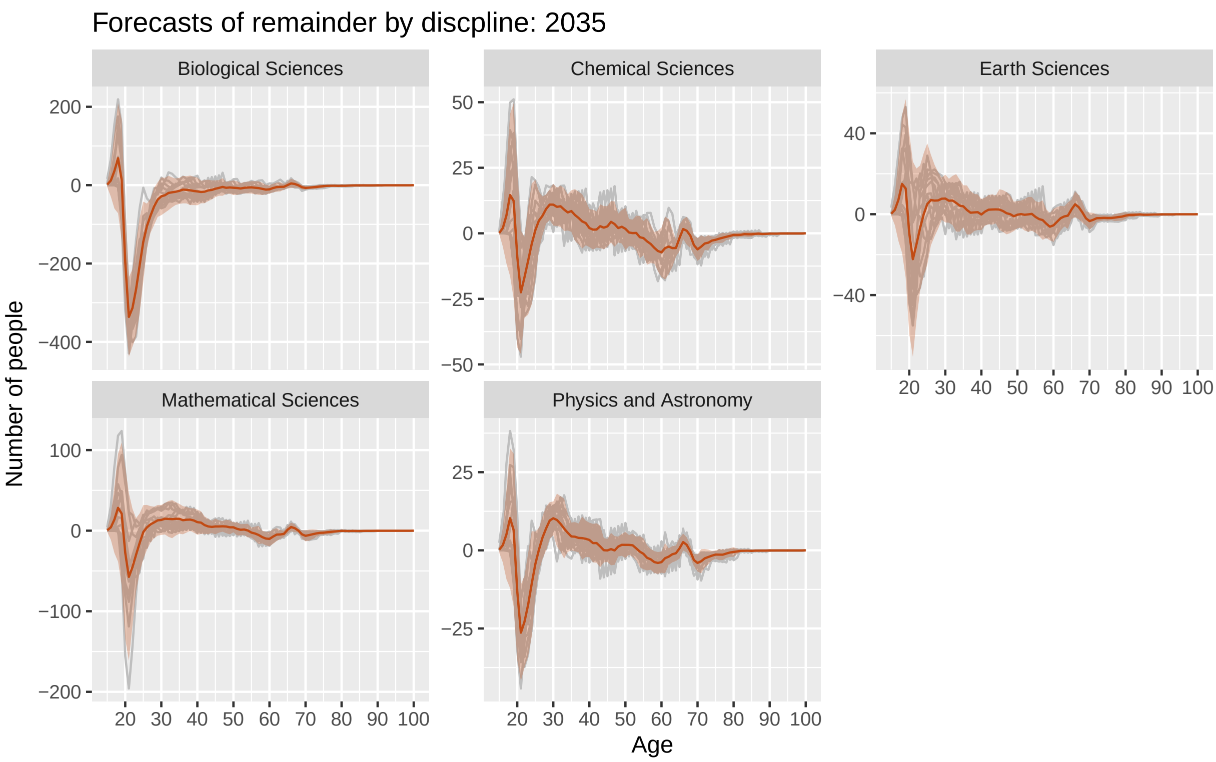

Figure 9: *Forecasts of $E_{i,x,t}$: the remainder by discipline for 2035, based on historical data from 2006–2020. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.*

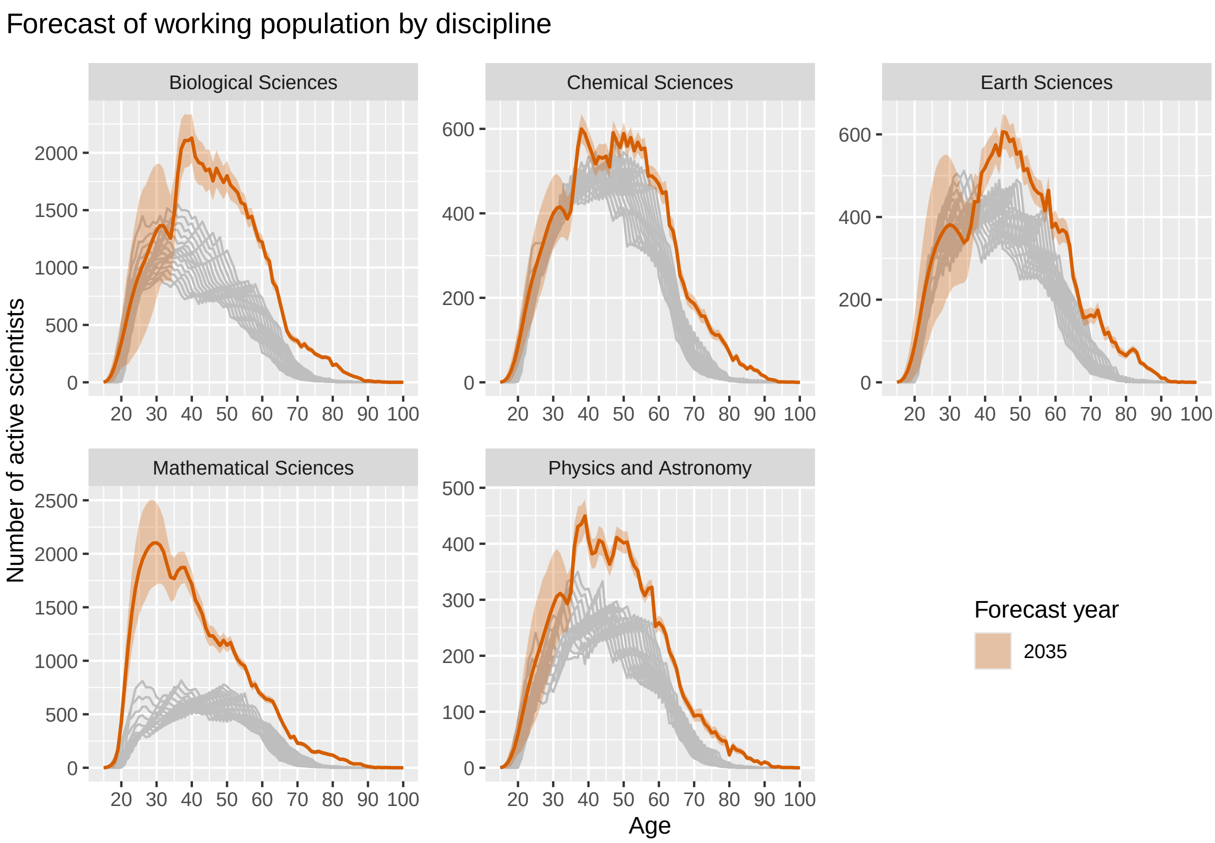

Figure 10: *Forecasts of $P_{i,x,t}$: the working population by discipline for 2035. The shaded regions represent the 90% prediction intervals, and the solid lines indicate the mean estimates.*

Prediction intervals are also shown for 2025, as it represents a forecast rather than observed workforce data. This comparison helps illustrate how the age distribution is expected to evolve over the next decade.

Between 2025 and 2035, the forecasts indicate an aging workforce, with increases in the number of scientists in their late 30s, and from ages 45 to 80. This trend is particularly evident in the wider gap at ages 45–60 between the forecasted distributions over the ten-year period.

Additionally, patterns in the age distribution persist over time. A dip or trough observed at a given age in 2025 reappears 10 years later as the same cohort progresses through the workforce. While these shifts may be harder to distinguish due to the structure of single-year age cohort data, they reveal how workforce cohorts evolve and how observed patterns carry through in future projections.

Summing over age groups allows for estimating the total number of working scientists in each future year, as shown in Figure 11. This highlights whether the workforce is growing, stabilising, or declining. On average, projections indicate continued growth, but at a gradually slower pace. The lower bound remains nearly flat, suggesting workforce stagnation in a conservative scenario. Even in an optimistic scenario, growth only slightly exceeds the current pace.

After 500 simulations of the future population for each discipline, the projections ten years apart (2025 and 2035) shown in Figure 10 provide a basis for comparing estimates of the current and future workforce.

The projections indicate wider prediction intervals for younger age groups due to uncertainty in future graduate numbers, while mid-to-late career estimates primarily reflect the aging of existing cohorts. Across disciplines, the typical working population spans from the mid-to-late 20s (10th percentile) to the mid-50s and early 60s (90th percentile). 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.

The key findings from Figure 10 are summarised below:

- **Physics and Astronomy** *(Aging Workforce):* The 35–45 age group shows a higher average than the previous 2025 cohort. There is a growing number of scientists aged 45 to 60, and more individuals aged 60+ are remaining in the workforce longer. These patterns indicate a gradual transition toward an older age structure, reflecting an aging workforce.
- **Mathematical Sciences** *(Expansive Workforce):* Workforce growth is evident across a broad range of ages, particularly among individuals aged 25 to 70. The most significant increase occurs before 60, though there is also a clear rise in older workers (60+) remaining in the

workforce rather than retiring. Overall, workforce growth is strong and evident across age groups.

- **Chemical Sciences** *(Stationary Workforce):* The average workforce size remains stable, with a relatively narrow prediction interval, indicating a predictable pattern of stability over time. While there is a minor increase in the number of workers aged 70, this change is not substantial enough to suggest a broader shift in workforce dynamics.
- **Earth Sciences** *(Aging Workforce):* Early-career workforce projections are more uncertain relative to its size. A decline in the working population is observed in the mid-thirties, followed by an increase throughout the forties, though both remain modest. While the overall workforce remains relatively stable, these patterns indicate a slow shift toward an older age distribution.
- **Biological Sciences** *(Aging Workforce):* The number of workers aged 50 to 65 is increasing, indicating growth in later-career participation.
- **Other Natural and Physical Sciences** *(Expansive Workforce):* Workforce growth is strong across ages 30 to 70, characteristic of an expanding workforce.
- **Natural and Physical Sciences (n.f.d.)** *(Aging Workforce):* Growth is primarily concentrated in the 55–70 age range, indicating delayed retirement and an aging workforce.

These trends are further validated by the total workforce projections shown in Figure 11. This figure presents the total number of working scientists by discipline at each point in time, illustrating changes in workforce size over the forecast period. While all disciplines exhibit widening prediction intervals resembling an open funnel, this primarily reflects increasing uncertainty over time as forecasts extend further into the future. The extent of this uncertainty varies by discipline, with some exhibiting more stable trends while others show greater variability in potential workforce outcomes.

From the plot, Mathematical Sciences, Other Natural and Physical Sciences, and Natural and Physical Sciences (n.f.d.) are projected to grow at an accelerating pace. Chemical Sciences, on the other hand, is more likely to decline, while the remaining disciplines are expected to experience more stable growth. However, it is important to consider the prediction intervals when interpreting these trends. These patterns are largely consistent with workforce structure classifications, with expansive disciplines experiencing faster growth, aging disciplines maintaining more stable trends, and constrictive disciplines showing signs of decline.

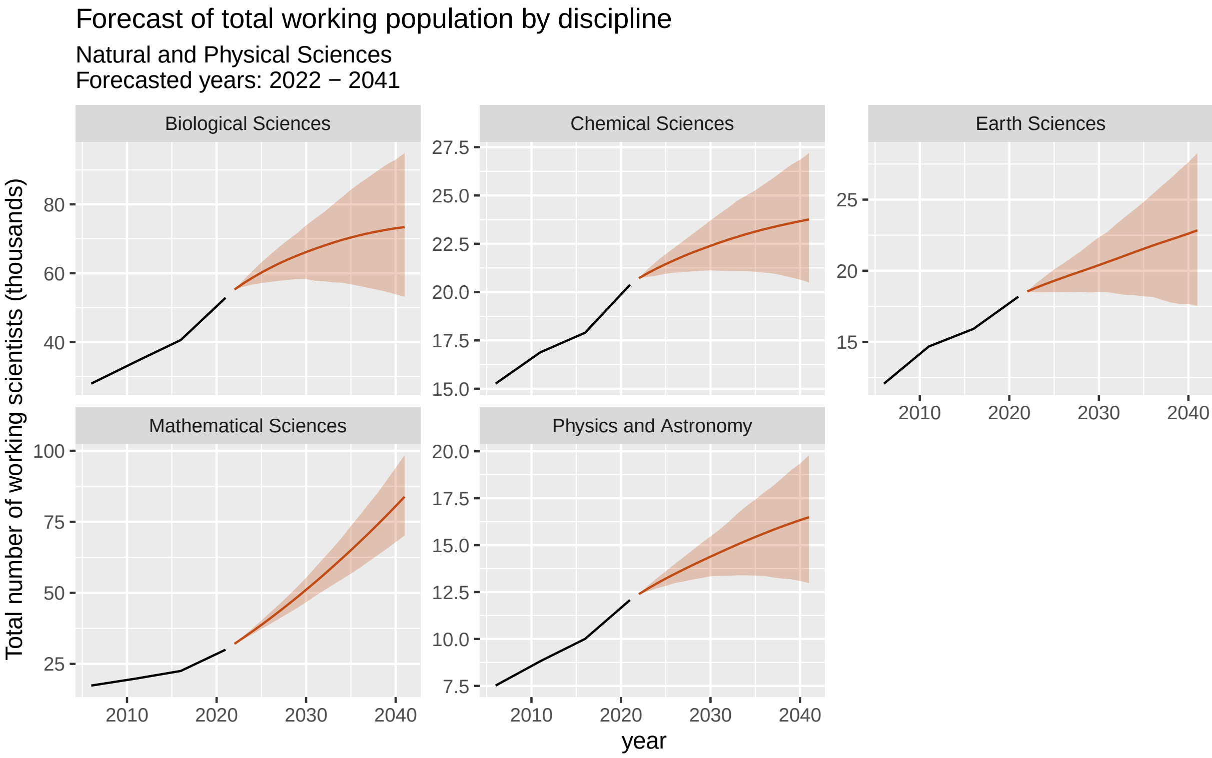

Figure 11: *Forecasted total number of working scientists across scientific disciplines from 2022 to 2041. The shaded region represents the 90% prediction interval, the coloured line indicates the mean estimate, and the black line represents historical data.*

5 Conclusion

This report provides data-driven forecasts of Australia's science workforce age structures, outlining expected changes across disciplines by 2035. The Natural and Physical Sciences, along with Engineering, are projected to experience workforce aging, with growth concentrated in older age groups. Information Technology is expected to expand, though some disciplines remain uncertain due to high graduate numbers not translating into workforce participation. Smaller disciplines within Agriculture and Environmental Studies are projected to decline.

When interpreting these projections, policymakers should consider data limitations, particularly in discipline classification and reporting. Variations in self-reporting and ASCED categorisation may not fully capture industry or education changes, impacting accuracy, especially in smaller or evolving disciplines.

Additionally, while these projections provide a solid foundation for workforce planning, it is important to note that they are entirely driven by historical trends and do not account for possible new developments, such as the impact of AI and other emerging technologies on the labour market in different scientific disciplines. Other factors, such as policy changes or global economic shifts, may also influence workforce trends and should be taken into account.

While alternative demographic methodologies, such as the Lee-Carter model, could be considered for estimating demographic components, the methods employed in this report, including the functional data model, ARIMA model, and demographic growth-balance equation, are better suited to the specific characteristics of the data and the goals of this analysis.

Other quantitative studies, such as job market forecasting, may offer complementary insights into broader trends in the scientific workforce. Qualitative studies can also uncover latent factors that go beyond historical data. While this report focuses on forecasting based on past trends, these alternative approaches can provide additional perspectives on the scientific workforce in Australia.

Future work could enhance the accessibility of these projections through interactive visualisations, improve accuracy with new Census data, and broaden the analysis to additional ASCED fields. Refining estimation methods would further strengthen projection reliability and robustness.

This analysis contributes to the Australian Academy of Science's initiative *Australian Science, Australia's Future: Science 2035* by identifying shifts in the workforce, helping anticipate future demand for science capabilities, and highlighting potential workforce gaps as aging and retirement reshape workforce dynamics.

6 Acknowledgements

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