We are our memory: A flexible framework for quantifying the demographic imprints of the past

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Abstract

Populations have demographic connections to history: people who were exposed to the past may still be alive or may at least have living kin. Denton & Spencer (2021) and Alburez-Gutierrez (2022) have articulated the concept of "demographic memory" to refer to how the memory of single events lingers in populations through their age or kinship structure. This article works to clarify and further demonstrate the usefulness of this concept. Theoretically, it argues for demographic memory as an idea that unifies and makes rigorously quantifiable many of the scattered ideas of historical embeddedness that exist across the social and biological sciences, including in economics, epidemiology, political science, and genetics. Methodologically, this article offers a flexible and widely applicable model of demographic memory defined by cohort survivorship. This model can estimate the memory of events, eras, and continuously varying conditions of interest, such as socioeconomic, political, and environmental variables, and it allows for social stratification in both the conditions of interest and how they are forgotten. As a proof of concept, this new model is applied to the memory of recent prime ministers in the United Kingdom and the memory of liberal democracy across the world.

"We are our memory,
we are this chimerical museum of shifting forms,
this heap of broken mirrors."
—Jorge Luis Borges (1975: 23)

1. Introduction

Many concepts in the social and biological sciences centre on the idea that people absorb the past and carry it forward, influencing the social and health outcomes of future populations as a result. Social scientists often study the cognitive or cultural memory of individuals and populations, while biological and health scientists analogously study how past exposures to infections, toxins, and other stressors are remembered by the body. These diverse forms of memory all operate through similar mechanisms of embodiment, but they are usually studied in isolation. Additionally, even though mortality, fertility, and migration determine the occurrence of the bodies that carry memory forward, the role of demography is often unacknowledged in studies of how the past influences the population-level outcomes of the future. The lack of a unifying, interdisciplinary framework that explicitly accounts for demography's role in memory leads to measurement error and missed opportunities for prediction in many existing studies of memory. Being able to systematically and more accurately model the expected levels of how the past persists into the future would allow for new insights into social and health problems and for policies to be targeted to support populations scarred by the past.

A new concept in demography has the potential to build a solid methodological bridge between the many biological, health, and social literatures in invoke "memory" of some kind. At least as early as Ryder (1965), sociologists have argued that historical events leave psychological imprints on birth cohorts and that those imprints influence the development of society partly as a function of how long those cohorts remain alive. Based on this idea, Denton & Spencer (2021) and Alburez-Gutierrez (2022) have recently coined the term "demographic memory" to refer to the ways in which the past is remembered either through the survival of the people who lived through the past, or through the survival of those individuals' family members. Not all types of "memory" in the social and biological sciences operate through survivorship or kinship ties—for example, a large literature in political science, economic history, and sociology focuses on the role of community institutions in sustaining cultural persistence (Cirone & Pepinsky, 2022; Zucker, 1977)—but many remembered phenomena do, in fact, operate through simple demographic ties. Therefore, demographic memory has the power to offer an elegant framework that unifies and refines concepts of historical embeddedness across many disparate fields, while also stressing the primacy of demographic forces in shaping how populations' past influences their present and future. As will be discussed, fields that could immediately benefit from the application of models like those in Denton & Spencer (2021) and Alburez-Gutierrez (2022) include political sociology, population epigenetics, environmental epidemiology, and the economics of inflation.

However, if demographic memory is to provide this unifying framework, more elaborate formal models of demographic memory are needed. Denton & Spencer's (2021) model of demographic memory can only be used to model the legacy of single events. A more general model would allow one to consider the memory of single events, eras, and continuously varying historical conditions, e.g. economic development, climate, or disease burden. Denton & Spencer's (2021) model also estimates demographic memory within a stable population framework. This allows the model to clearly demonstrate how the demographic memory of single events responds to changes in key demographic variables. However, this limits the model's applicability to empirical and more complex theoretical work. It also does not allow for any concept of individual-level forgetting; it assumes that, at the population level, demographic memory is only lost through mortality and emigration.

This article, first, provides a broad theoretical foundation for research into demographic memory, and then, it presents and illustrates a general, flexible framework for estimating demographic memory that expands on the work of Denton & Spencer (2021). In the background section of this article, a definition of demographic memory is articulated, in light of the competing presentations in Denton & Spencer (2021) and Alburez-Gutierrez (2022) and the competing idea of "demographic metabolism". Then, related concepts across the social and biological sciences are considered, in order to motivate what properties a model of demographic memory with interdisciplinary appeal should have. The methodological section of this article presents a flexible model for estimating demographic memory in the context of continuously varying conditions of interest, non-stable population dynamics, various processes of forgetting, and social stratification. In the application section of this article, this model is applied to the memory of recent prime ministers in the United Kingdom and the memory of the strength of liberal democracy throughout the world. Finally, the importance of considering social and cultural contingencies when modelling memory and some practical considerations for future work are discussed.

2. Background

2.1. Two concepts of demographic memory

Denton & Spencer (2021) and Alburez-Gutierrez (2022) offer two different conceptualizations of demographic memory. They both articulate “memory” in terms of the survival of subpopulations of people who are connected to past events of interest in a specified way, but they define their subpopulations based on different types of demographic connections to the past: cohort life courses and kinship ties, respectively.

Denton & Spencer (2021) frame demographic memory in terms of how the past is embedded within population age structures. Specifically, they present a general model for computing the proportion of a stable population that can be assumed to remember a historical event, by virtue of them having been alive and older than the age at which lasting memories begin to form when the event of interest happened (and them living at the time in a population in which the event was socially meaningful). They note that, at a certain point in the future, the entire subpopulation of people who live through any event will have died, and therefore, there will no longer be any first-hand witnesses of that event. Therefore, in their conceptualisation, demographic memory is extinguished with the death of the last first-hand witness. To differentiate this concept from the work of Alburez-Gutierrez (2022), this can be called “survivorship memory”.

The idea of survivorship memory is closely related to the existing concept of demographic metabolism (Lutz, 2013; Ryder, 1965). Demographic metabolism describes how individuals acquire certain characteristics throughout their lives that are either stable or semi-stable (like one’s highest educational attainment)—and then how long-term social change happens partly as a function of cohort turnover; individuals who acquired their characteristics in one period replace those who acquired their characteristics in an earlier period when the characteristics that tended to be acquired were different. Meanwhile, the concept of survivorship memory describes the very distribution of the historically acquired characteristics of the people who are present in a population at a specific point in time. Therefore, survivorship memory is the quantity whose change is being measured in studies of demographic metabolism.

Alburez-Gutierrez (2022) makes the innovation of analysing the demographic embedding of the past within kinship structures, instead of within age structures. In his initial work on this concept, he calculated what proportion of Río Negro, an indigenous community in Guatemala, has been a close relative of a victim of a genocide that the community experienced, from the time of the genocide in 1982 to the present. This work theorises how the legacy of past events is influenced by populations' kinship ties to individuals who experienced those events, and it has been expanded upon in other analyses of the prevalence of kin loss and grief (Acosta et al., 2025; Alburez-Gutierrez et al., 2024; Schlüter et al., 2024; Snyder et al., 2022; see also Alburez-Gutierrez et al., 2021; Smith-Greenaway et al., 2021). However, this alternate conceptualization of demographic memory—which can be termed "kinship memory"—has many possible uses beyond its ability to quantify bereavement.

2.2. Interdisciplinary uses of demographic memory

The ideas of survivorship and kinship memory map onto a large number of concepts independently developed across the social and biological sciences. Given sufficiently detailed data, flexible models of demographic memory could make all of those concepts rigorously quantifiable, either to a greater extent than literature currently does or for the first time ever. Therefore, before developing new models, it is worth considering the wide range of phenomena that we might want new models to be able to describe.

One example of an existing "memory" model that would benefit from more attention to demographic processes is Malmendier & Nagel's (2016) model of inflation. They develop a microeconomic model in which cohorts carry their past experiences of inflation with themselves, thereby influencing future inflation expectations and causing future inflation rates to trail past inflation rates; macroeconomists have long suggested that similar mechanisms cause "long memory" phenomena in other economic indicators (see Guégan, 2005). However, the conceptualisation of cohorts in this work is usually unrealistic. Even in Malmendier & Nagel's (2016) detailed model, cohorts in the United States are assumed to contain no migrants and it is assumed that the composition of each cohort with respect to past experiences of inflation does not change over time, despite lower socioeconomic groups usually having higher mortality and often also experiencing higher-than-average inflation rates (Angelico & Di Giacomo, 2019; Klick & Stockburger, 2021; Office for National Statistics, 2022). Estimating a population's average past exposure to inflation within an explicitly demographic model would bring these problems to the fore and therefore improve the accuracy of predictions of future inflation rates.

There are similar opportunities for survivorship memory models in epidemiology. Levels of immunity in a population are often modelled without accounting for the mortality and migration of the vaccinated and unvaccinated, and this is increasingly understood to lead to the mistargeting of vaccination campaigns (MacIntyre et al., 2018; Peak et al., 2018; Rimoin et al., 2010). Immunity also seems to be estimated without attention to immune individuals ageing into or out of the age ranges in which they are most likely to be part of disease transmission chains, as the lack of life course smallpox vaccination among people suffering from recent mpox outbreaks has made salient. The need to pay attention to the past demography of a population when considering its current health is also underlined by the finding that the migration into Northern cities of Black Americans who were not imprinted by the

1889 influenza pandemic from the American South may explain the unusually low excess mortality rate of the Black population of Northern cities during the 1918 influenza pandemic (Eiermann et al., 2022). In environmental epidemiology, McFarland et al. (2022) have developed a model of the proportion of the United States population imprinted with lead exposure in childhood, but like Malmendier & Nagel (2016), it does not account for the differential lead exposure of migrants and the differential mortality of individuals with different levels of lead exposure. Overall, the development of more detailed models of survivorship memory could be a particularly great benefit to environmental epidemiology, complimenting existing work on life course exposures to lead, air pollution (Baranyi et al., 2022), and violence (Canudas-Romo et al., 2017; Lanfear et al., 2023).

Otherwise, there is a range of concepts that survivorship and kinship memory models could quantify better, or for the first time. Political scientists have found that popular political beliefs imprint onto young adults in a way that influences election outcomes for decades (Ghitza et al., 2022), but this finding could be used to forecast future political beliefs using population projections. Health economists already study how foetal shocks cause adverse effects on birth cohorts' health (Almond & Currie, 2011), but they could use survivorship memory models to consider how any number of consecutive foetal shocks persist in populations over time. Demographers may be similarly interested in modelling the interplay between the cumulative mortality burden in a population and individuals' fertility behaviours (see Gaddy & Mølbak Ingholt, 2024; Newmyer et al., 2025). By modelling the memory of environmental hazards, researchers could also put quantitative bounds on medical anthropologists' concepts of populations that are constituted by shared exposure to toxic hazards, sometimes called "chemical kin" or "biological citizens" (see Dow & Lamoreaux, 2020). Meanwhile, more orthodox scholars of citizenship may be interested in modelling the populations of people eligible to become citizens of different countries by virtue of ancestral descent (see Dumbrava, 2014) or to similarly enrol as a member of a Native American tribe (see Thornton, 1997). Additionally, kinship memory models could estimate the distribution of epigenetic markers that impact health. Identifying the effects of intergenerational epigenetic inheritance is empirically difficult in humans (Horsthemke, 2018). However, estimating the population distribution of those effects is valuable for targeting medical interventions, to the extent that those effects do seem to be real (Costa, 2024; Perez & Lehner, 2019) and that research into them is not used to legitimise eugenic thinking (see Phelan et al., 2013; Sear, 2021). These examples of areas for future work show the wide-ranging promise of demographic memory models.

3. A flexible model of survivorship memory

If demographers and non-demographers alike are to estimate and make projections of different forms of demographic memory, more elaborate formal models are needed.

Several tools for estimating kinship memory already exist. When thinking about the kin of a small number of imprinted individuals, it can make sense to apply an egocentric approach to each individual. One can use matrix models, like in Caswell & Song (2021), to estimate the number and characteristics of the kin of each individual, if it is not possible to actually observe those kin. Alternatively, it is now possible to empirically estimate the answers to many questions about long-term demographic processes by using crowdsourced genealogies (e.g. Blanc, 2021; Fletcher et al., 2022; Hsu et al., 2021; Minardi et al., 2023). When existing genealogies are systematically biased in a way that obscures demographic processes (see Calderón-Bernal et al., 2023; Stelter & Alburez-Gutierrez, 2022), one can use demographic microsimulation to produce plausible whole-population genealogies instead. One can also use kinship equations to estimate the prevalence of people with particular types of kin as a proportion of the whole population (Alburez-Gutierrez et al. 2021). Therefore, although kinship memory is a new concept, existing kinship models can be easily repurposed in order to estimate it.

In contrast, significant progress remains to be made toward developing models of survivorship memory. Therefore, this article presents a flexible formal framework for estimating survivorship memory, building on the work of Denton & Spencer (2021).

A flexible understanding of life course memory starts with the observation that, at the individual level, memory can be gained and lost at a variety of rates. Figure 1 shows the trend in some hypothetical condition of interest over time, *c(t)*—in this case, the number of annual net international migrants to Germany, estimated in the 2024 revision of the UN World Population Prospects (UN Population Division, 2024). Then, the figure shows two possible trajectories for how the memory of net migration accumulates in the mind of a person born in Germany in 1980. We can imagine that the first five years of exposure to *c(t)* leaves no lasting impact, but from age 5—the "age of awareness" in Denton & Spencer (2021)—some memory of migration levels takes shape. If the individual is like a sponge and remembers everything after age 5 equally ("trajectory 1" in Figure 1), their memory becomes an increasingly lagging indicator of the current level of *c(t)*. Their average remembered level of *c(t)* rises fairly quickly with the high migration around 1990, but by the time of the Syrian and Ukrainian migration waves of 2015 and 2021, their memory is not as immediately responsive. This because, when they turned 10, the previous year was 20% of everything they remembered, but when they turned 35, the previous year only occupied 4% of their memory.

However, not everyone remembers everything forever, nor is the past always remembered equally. "Trajectory 2" shows an example of alternate way in which the *c(t)* of net migration in Germany could be remembered: individuals remember the average of what they lived through in just the last 10 years. This trajectory is more reactive: falling below "trajectory 1" in the low net migration period of the 2000s and rising above "trajectory 1" in the higher migration period from 2015 to 2025.

There are myriad other trajectories that memory can take as a function of the past. The age at awareness can be different for different people, or awareness can

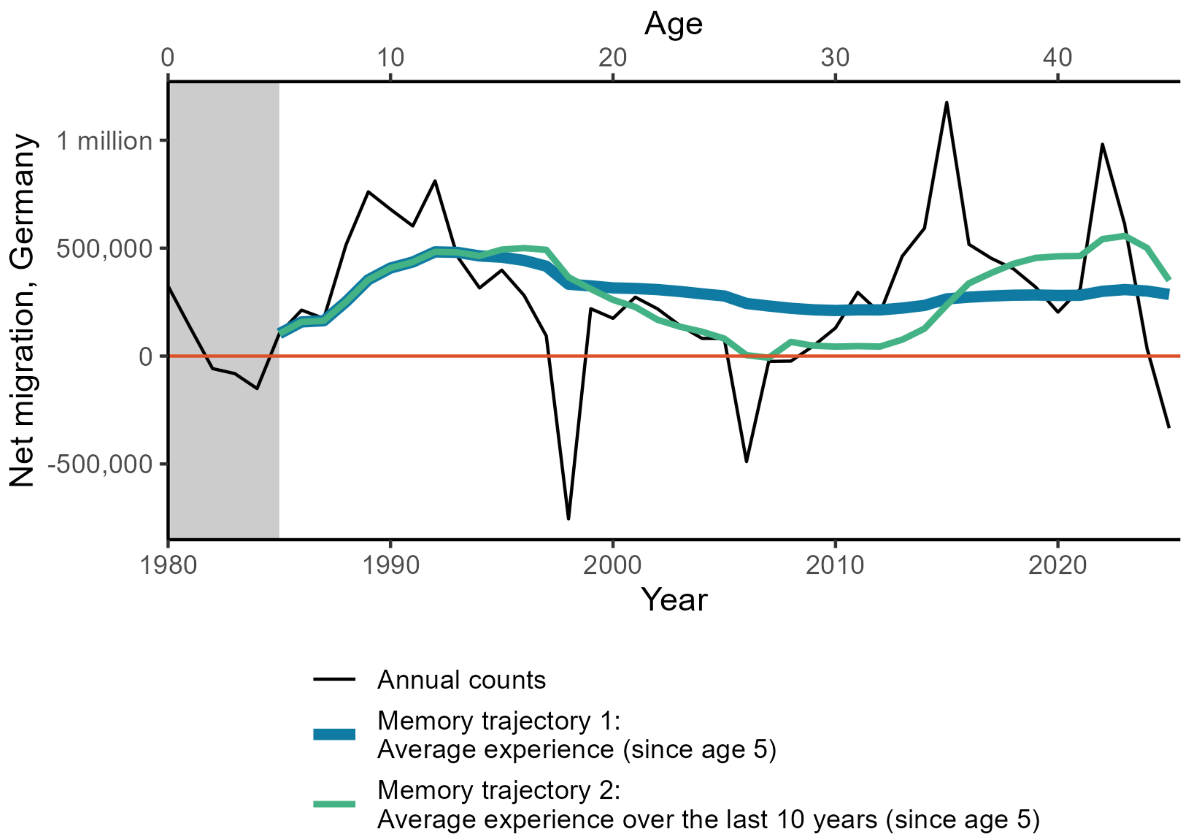

Figure 1. The estimated level of annual net migration to Germany from 1980 to 2025, and two possible trajectories of the memory of the level of annual net migration for someone born in 1980.

gradually emerge, rather than starting all at once. Meanwhile, the past can be forgotten because of what age it occurred at (even after an individual's age of awareness). The past can also be forgotten because what happened itself was not very memorable. Conversely, an event can come to be better remembered with the passage of time, either because people are slow to absorb the changes they live through or because that event has come to "live large" in people's minds, through its effects or its memorialisation. For example, Ehrmann & Tzamourani (2012) find that very high levels of past inflation are remembered disproportionately more easily than levels of inflation that were only moderately high. Individuals' ability to recall the past, literally or metaphorically, can also be influenced by their cohort and the period in which the past is being recalled. A flexible model of survivorship memory would allow for all of these many effects to be specified jointly.

Then, at the population level, the average memory of *c(t)* depends on the historical levels of *c(t)*; the profile of how individuals absorb (and forget) *c(t)* as a function of their age, period, and cohort; and the age structure of the population. Figure 2(a) shows a different *c(t)*, the extent of global warming in the Northern Hemisphere from 1900 to the present, as the difference in the average annual temperature from the 1861–90 average, as calculated by Our World in Data and the

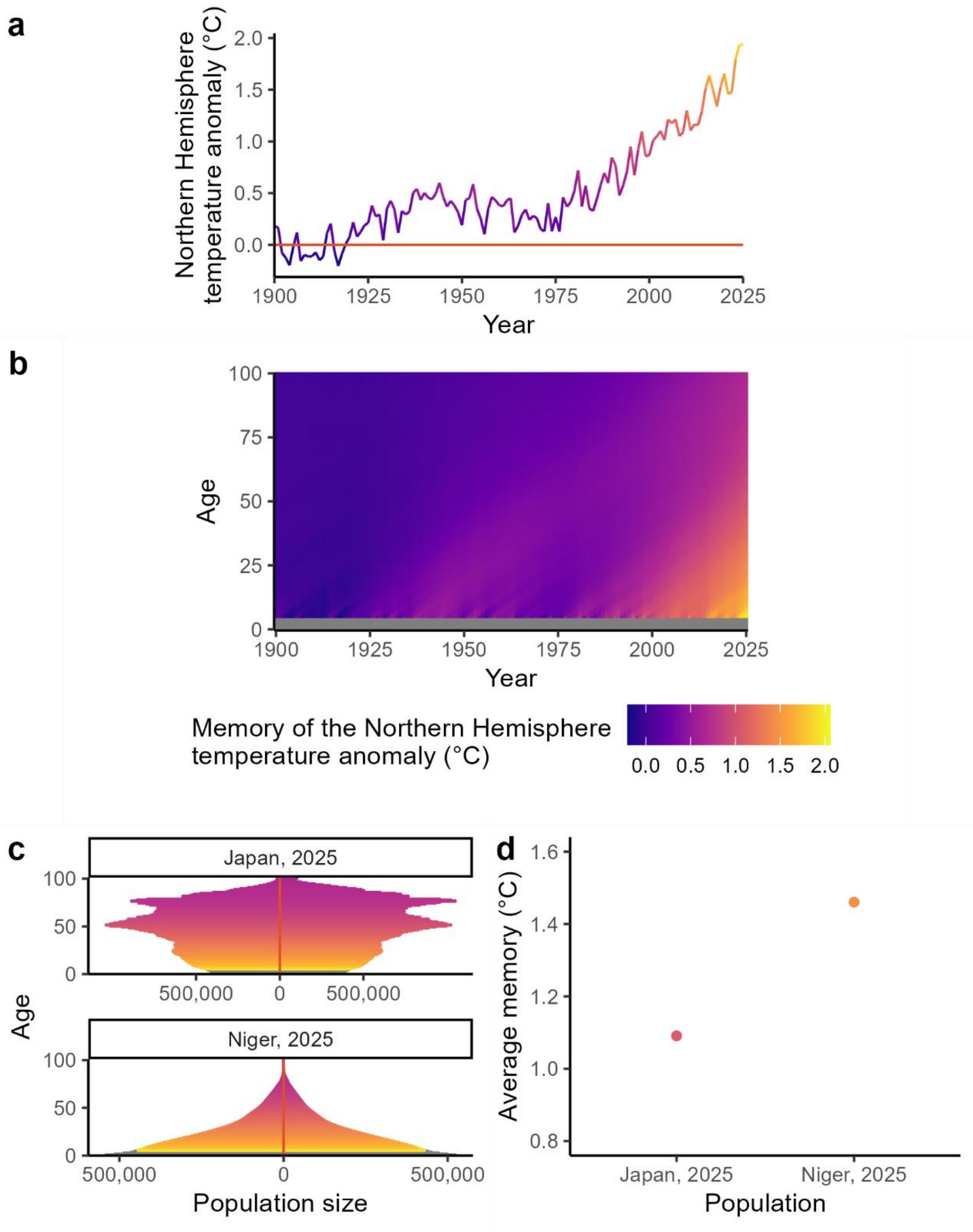

Figure 2. The estimated annual level of global warming in the Northern Hemisphere from 1900 to 2025, compared to the 1861–90 average (panel a); a Lexis surface of the average memory of global warming from 1900 to 2025, in terms of average experience of warming after age 5 (panel b); population pyramids of Japan and Niger in 2025 with cohorts coloured by their average memory of warming in 2025 (panel c); and the average memory of warming in Japan and Niger in 2025 across all cohorts since age 5 (panel d).

Met Office Hadley Centre (Morice et al., 2021; Ritchie et al., 2025). Figure 2(b) shows the remembered level of global warming over a Lexis space, assuming that a cohort's memory at any point in time is the average experience of global warming from age 5 to the current age, like "trajectory 1" in Figure 1. This Lexis space of memory will be the same in any population with the same profile of memory gain and loss, but different populations will have different average memories of global warming, since some are relatively young or old on average. Figure 2(c) shows the 2025 population pyramids of Japan and Niger, an old and a young national population, respectively. Figure 2(d) shows how this age difference results in the average person in Japan in 2025 having a memory of 1.09°C warming above late 19^{th} century levels compared to 1.46°C for the average person in Niger. This analysis does not account for the fact that warming has not been globally homogenous (Chung et al., 2024; Maclean et al., 2017), but this does illustrate the general point that populations with young age structures like Niger will absorb changes in $c(t)$ more quickly than populations with old age structures like Japan.

Building on this analysis, one could weight the cohorts in a population by their current size or by some additional variable, like their propensity to experience some behaviour of interest. For example, if one wanted to use exposure to global warming as a proxy for exposure to health effects due to climate extremes but one thought that experiencing extremes at different ages had differential effects on health, one could weight cohorts differently based on the ages at which they experienced different amounts of cumulative warming. Alternatively, if a researcher wants to quantify political memory with an eye on how political legacies affect contemporary voting behaviour, they could weight cohorts by their propensity to vote; or if a researcher wants to study the effect of some toxin on newborns via breastfeeding, they could weight maternal cohorts by their period age-specific fertility rates. Additionally, one could recognise that there is social stratification in exposure to $c(t)$ within cohorts in terms of their gender, ethnicity, class, or some other social marker and then jointly weight individuals by their cohort and social group.

Overall, a flexible approach to quantifying survivorship memory is to express the memory of any event, era, or continuously varying condition of interest as the product of four functions. $c(t, x_t, s_t)$ is the level of the condition of interest (c), as a function of historical time (t), an individual's age at historical time t (x_t), and an individual's socially defined subgroup at historical time t (s_t), if relevant. $r(p, t, x_t, s_t)$ is the proportional extent to which an exposure to c at historical time t and age x_t is remembered at present time of interest p at age x_p, depending on the individual's subgroup at time t, s_t. $k(p, t, x_t, s_t)$ is the number of people in a population at present time p who were in subgroup s_t at age x_t and time t. $w(p, t, x_t, s_t)$ is the weight given to people at time p who were in subgroup s_t at age x_t and time t.

After defining these functions, the next step towards estimating survivorship memory is to recognise that the extent to which c is remembered by any cohort at a particular time p is jointly determined by r (which affects the rate of memory gain and loss), w (which affects the weight of different subgroups across the life course), and k (which encodes the share of the cohort in different social subgroups over time).

Therefore, these terms should be combined and normalised for each age x_p and for each cohort. If, within each cohort, the rate of memory gain and loss by age (*r*) and the social weighting by age (*w*) is the same across all subgroups (s_t), one can combine these three functions in straightforward way to calculate the total relative contribution of each age and subgroup (θ) to the overall memory of *c* in that cohort at time *p* using:

$$\theta(p,t,x_t,s_t) = \frac{k(p,t,x_t,s_t)\cdot w(p,t,x_t,s_t)\cdot r(p,t,x_t,s_t)}{\int_{x_t=0}^{\infty}\int_{s_t\in S} k(p,t,x_t,s_t)\cdot w(p,t,x_t,s_t)\cdot r(p,t,x_t,s_t)\,ds_t\,dx_t} \tag{1}$$

where *S* is the set of all subgroups.

Following this, the average memory of *c* for any individual or group of people at time *p* and age x_p can be written as:

$$M(p,x_p) = \int_{t=p-x_p}^{p}\int_{s_t\in S} c(t,x_t,s_t)\cdot\theta(p,t,x_p-p+t,s_t)\,ds_t\,dt \tag{2}$$

and the average memory of *c* for an entire population at time *p* can be written as:

$$\bar{M}(p) = \int_{x_p=0}^{\infty} M(p,x_p)\cdot k(p,x_p)\,dx_p \tag{3}$$

where $k(p, x_p)$ is the population at time *p* by age x_p, which can come from integrating over $k(p, t, x_t, s_t)$ where $t = p$.

This approach to quantifying survivorship memory has several desirable characteristics. It extends Denton & Spencer's (2021) observation that the migrant and locally-born parts of a population will both have the exposure to some "universal" event but only the latter will remember "local" events; by allowing an arbitrary number of population subgroups to be defined, one can account for a greater amount of stratification in exposure to *c(t)*—between and within populations. It also extends the concept of a static "age at awareness" to frame memory gain and memory loss as two dynamic and interrelated processes; with its flexibility, *r* can jointly capture the fact that cohorts gradually become aware of *c(t)* at some distribution of x_t ages in childhood, adolescence, or young adulthood, while with further ageing, *c(t)* is forgotten at some average rate that can be specified. Overall, *c*, *r*, and *w* can be specified to allow for a variety of interesting age, period, and cohort patterns.

The approach in eqs. 1–3 has been formulated with a continuously varying condition of interest in mind, such as an environmental or socioeconomic variable, but it can be easily adapted to modelling the memory of an era or a single event. When thinking about a well-defined era, *c(t)* should be defined as a piecewise function that equals 1 for the duration of the era and equals 0 at all other points in time—with no variation by x_t and the only variation in s_t coming from residence in locations and socially-defined groups in which the era was or was not socially meaningful. Then, $\bar{M}(p)$ will have the interpretation of being the proportion of the population's memory at time *p* taken up by that era. When thinking about an era with fuzzy borders, e.g. the Cold War, *c(t)* can gradually increase and decrease but should stay bounded between 0 and 1. When thinking about the memory of a particular event, one can define *c(t)* as equal to 1 at $t \leq a$ and equal to 0 at $t > a$, for an event of interest at time *a*. Then, the proportion of the population alive at time *p* who remembers the event is a piecewise function equal to 0 at $p < a$ and equal to $\bar{M}(p)$ at $p \geq a$.

A simple tutorial is useful for demonstrating how eqs. 1–3 provide estimates of survivorship memory. Table 1 calculates the $\bar{M}(p)$ of a hypothetical *c(t)* for a population that only comprises two cohorts and two subgroups. Cohort 1 is born at $t = 2000$ and cohort 2 is born at $t = 2005$. *c* is increasing at a variable rate over the period of 2000 to 2010. *c(t)* does not vary by age but is always twice as high for subgroup s_2 than for s_1. All cohorts and subgroups uniformly experience their age at awareness at age 2, but cohort 1 forgets their past exposure to *c(t)* at a rate of 10% per year and cohort 2 does so at 15% per year. The number of survivors to 2010 in cohort 2 is twice the number in cohort 1 (which could be due to cohort 2 having a larger l_0 starting size and having experienced less cumulative exposure to mortality), but both cohorts have experienced the same age-specific rate of net mobility from s_2 to s_1. All cohorts, ages, and subgroups alive at time *p* are weighted equally so that *w* invariantly equals 1. As in eq. 1, *r*, *k*, and *w* are multiplied and normalised to get θ for each cohort; then, θ and *c* are multiplied to get the average memory of *c* for each cohort at time *p* (*M*); finally, the two cohorts are weighted by their size at time *p* to get the overall memory ($\bar{M}$).

The tutorial presented in Table 1 considers a small and quite simple case of survivorship memory, but eqs. 1–3 have the flexibility to model much more complex scenarios. There are aspects of quantifying survivorship memory that are empirically difficult, but this model draws explicit attention to them, so that they can be handled with care and so that assumptions regarding those difficult aspects can be made explicit. For example, one wants to estimate the $\bar{M}(p)$ of the proportion of an average person's life spent in poverty, the framing of *c* as potentially varying over x_t and s_t, in addition to *t*, reminds the researcher to consider social variation in the poverty rate over time. Additionally, it is helpful that the function that weights populations by their past exposure to *c* (*k*) is explicitly defined in terms of the age and subgroup trajectory of the survivors to time *p*, as this draws attention to the potential role of mortality and migration selection on memory. If 30% of 5-year-olds in 1960 were in some high-*c* s_1 and 70% in some low-*c* s_2, that does not necessarily mean that 70% of 80-year-olds in 2035 will have been in s_2 at age 5. Higher survival and/or net migration rates for former members of s_2 relative to former members of s_1 could mean that the proportion rises to 90%. Failing to account for this will bias one's estimate of $M(p = 2035, x_p = 80)$ upwards. A example of this bias in existing literature comes from the survivorship model of the imprinted childhood lead exposure in the

Table 1. Example calculation estimating survivorship memory using eqs. 1–3

c(t = 2000–10, s_t = s_1, s_2)

t =	2000	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10
s_1	10	12	13	15	16	19	20	20	22	25	28
s_2	20	24	26	30	32	38	40	40	44	50	56

Cohort 1 (born 2000)

r(p = 2010, t = 2000–10, x_t = 0–10, s_t = s_1, s_2)

t =	2000	'01	'02	'03	'04
$s_{1,2}$	0	0	.43	.48	.53

t =	2005	'06	'07	'08	'09	'10
$s_{1,2}$	.59	.66	.73	.81	.90	1

k(p = 2010, t = 2000–10, x_t = 0–10, s_t = s_1, s_2)

x_t =	0	1	2	3	4
s_1	15	16	17	18	19
s_2	15	14	13	12	11

x_t =	5	6	7	8	9	10
s_1	20	21	22	23	24	25
s_2	10	9	8	7	6	5

Cohort 2 (born 2005)

r(p = 2010, t = 2005–10, x_t = 5–10, s_t = s_1, s_2)

t =	2005	'06	'07	'08	'09	'10
$s_{1,2}$	0	0	.61	.72	.85	1

k(p = 2010, t = 2005–10, x_t = 5–10, s_t = s_1, s_2)

x_t =	0	1	2	3	4	5
s_1	30	32	34	36	38	40
s_2	30	28	26	24	22	20

w(p, t, x_t, s_t) = 1

Cohort 1

θ(p = 2010, t = 2000–10, x_t = 0–10, s_t = s_1, s_2)

t =	2000	'01	'02	'03	'04
s_1	.00	.00	.05	.06	.06
s_2	.00	.00	.02	.02	.02

	2005	'06	'07	'08	'09	'10
s_1	.07	.08	.09	.11	.12	.14
s_2	.02	.02	.03	.03	.03	.03

M(p = 2010, x_p = 10) = 26.42
k(p = 2010, x_p = 5) = 30

Cohort 2

θ(p = 2010, t = 2005–10, x_t = 5–10, s_t = s_1, s_2)

t =	2005	'06	'07	'08	'09	'10
s_1	.00	.00	.11	.14	.17	.21
s_2	.00	.00	.08	.09	.10	.10

M(p = 2010, x_p = 5) = 33.34
k(p = 2010, x_p = 5) = 60

$\bar{M}$(p = 2010) = 31.03

United States by McFarland et al. (2022) mentioned before. That model arguably overestimates the memory of lead exposure and its effects on average American cognitive ability because lead exposure is assumed to have no effect on life course mortality; in reality, the lead exposure itself increases the probability of death and the lead exposure is confounded with various social determinants of health that further increase mortality.

The main technical limitation of the model in eqs. 1–3 is that there can be no subgroup variance in *r* and *w* within cohorts. This is because the weighting formula in eq. 1 does not explicitly normalise individuals' memory gain/loss and social weighting trajectories across their life courses. It only has the effect of doing so when there is no subgroup variance in *r* and *w*. Meanwhile, if s_2 forgets the past at a faster rate than s_1 (or has a latter age at awareness), eq. 1 treats people who have spent more time in s_2 as having less memory than people who have spent more time in s_1. In most demographic memory applications, each individual alive at time *p* should probably be thought of as having at equal amount of memory; they just remember different parts of their lives to different extents. Table S1 demonstrates a 13% error in the estimation of $M(p, x_p)$ that results from applying eq. 1 to some example data that contains subgroup variance in *r*. Table S1 also shows that it is trivial to manually calculate the correct θ when dealing with very small datasets, but a model that expands the flexible approach in eqs. 1–3 so that one can formally account for the individual memory trajectories implied by aggregate *r*, *w*, and *k* functions is left for future work. A general approach will need to account for the age-specific transition probabilities between the subgroups and therefore a simulation approach may be the most parsimonious option.

4. Estimating the survivorship memory of politics

4.1. The shadow of British prime ministers

The flexible framework of survivorship memory presented in eqs. 1–3 can be used to estimate a population's average exposure over time to a range of past phenomena. One task it is well-suited to is to estimate the rise and fall of a series of successive eras in the public's mind. As a demonstration of this, one can estimate the survivorship memory of the three female British prime ministers to date (Margaret Thatcher, Theresa May, and Liz Truss), relative to each other and to their male counterparts. Specifically, one can ask: what proportion of the average UK resident's life over the age of 18 has been lived under Thatcher's, May's, Truss', or a male prime minister's leadership—or outside of the UK?

To estimate this, one only needs data on the dates of the different premierships; age-specific estimates of the UK population over time; and estimates of what proportion of each cohort of the UK population over time was living abroad at different ages. The first of these datasets is readily available: Thatcher was prime minister for 11 years, 7 months from 1979 to 1990; May was prime minister for just over 3 years from 2016 to 2019; and Truss was prime minister for 49 days in 2024. Men have served at all other points in time to the present, and it can be assumed that Keir Starmer remains prime minister until the next general election, which must be held by August 2029, after which point the gender of the prime minister is unknown. Population data stratified by migration history is difficult to estimate exactly but can be very crudely approximated for the period of 1950 to 2100 (Appendix S1). Then, ince the estimand of interest is simply the proportion of lives lived in different states over age 18, $r(p, t, x_t, s_t)$ can simply be equal to 0 at $x_t < 18$ and equal to 1 at $x_t \geq 18$ and $w(p, t, x_t, s_t)$ can simply be 1 at all points.

Applying eqs. 1–3, Figure 3 estimates the proportion of the average UK resident's life over age 18 taken up by a specific female British prime minister, any male British prime minister, a future British prime minister of unknown gender, or any non-UK leader. The estimates show that as an era lasts longer, it rises to larger stature in the survivorship memory of a population. Then, after an era ends and the people who lived through it exit the population through death and those who survive become exposed to new eras, the era becomes less prominent. For example, at the end of Thatcher's 11-year premiership, if one selected a random British resident, Thatcher was most likely to have taken up 53.2% of the time since that person turned 18. At the time of her resignation, all British-born residents between age 18 and 30 had memory only of her premiership, those between age 18 and 41 had spent at least half of their adult lives during her premiership, and even people aged

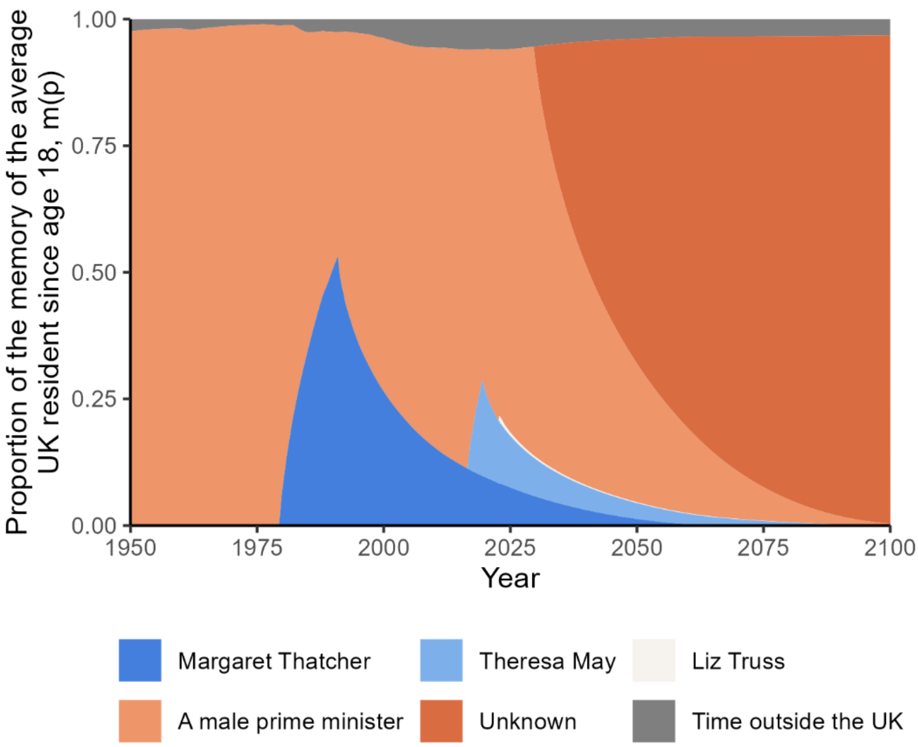

Figure 3. The proportions of the average British resident of their life lived after age 18 (survivorship memory without individual-level forgetting) under the premiership of Margaret Thatcher, Theresa May, Liz Truss, a male prime minister, an unknown prime minister (from August 2029 onwards), or outside the UK.

64 had spent a quarter of their lives with Thatcher as their leader. Meanwhile, at the start of 2025, the duration of the average British resident's adult life spent under Thatcher has fallen to 7.5%.

Comparing the difference in the *m(p)* for different prime ministers gives further insights into the nature of demographic memory defined by survivorship. For example, it is estimated that Liz Truss will not overtake Margaret Thatcher in the survivorship memory of the British population until roughly January 2064, when the youngest person to have been age 18 during the premiership of Thatcher will be 91 years old. This is because, even though Truss' premiership is a much more recent memory than Thatcher's premiership is, the latter lasted 86 times longer than the former. Additionally, one finds that there was greater survivorship memory of a female prime minister than a male prime minister for the period between April 1989 and May 1991, i.e. starting from when Thatcher had been in power for 10 years and continuing for 6 months after her premiership ended. If women were to become prime minister continuously from August 2029, that situation would happen again after only 8 years in power passed, due to memory of the first three female prime ministers still existing in the population.

However, the rate at which past and future prime ministers claim their space in the survivorship memory of the United Kingdom changes over time. After the first two years of her premiership, Thatcher accumulated an *m* of 0.168, whereas May gained an *m* of only 0.141 over her first two years in office. This is because of the ageing of the British population between the 1980s and 2010s. New eras take up a smaller proportion of the period of awareness of older individuals. Therefore, since the demographic transition causes population ageing, eras that take place later in the transition take longer to dominate populations' survivorship memory compared to ones that took place earlier.

Yet, there is a limit to how much population ageing causes a population to hold on to its past. The population of the UK is projected to have a mean age of 48 in 2100, compared to the relative youth of 41 years in 2025 and 35 years in 1950, but the vast majority of the memory of the British population in 2100 is still in our future. Out of the proportion of the life of the average British resident in 2100 that will have taken place in the UK, 99.6% will occur under a prime minister who is currently unknown. Even as soon as 2050, 66.7% of the average time lived in the UK for a British adult will be under an unknown prime minister.

4.2. Period versus remembered democracy

Further insights into how political regimes and institutions loom in the memory of a population can be derived from another case study. The Varieties of Democracy (V-Dem) project produces indices that attempt to quantify the strength of democracy and its different attributes in countries over time (Coppedge et al., 2025). The time series for many current countries begins in the 19th century, so despite reasonable critiques of the indices' construct validity (Wolff, 2023), V-Dem indices can be used to estimate changes in the demographic memory of democratic strength over time, when paired with the age-specific population estimates and projections in the 2024 revision of the UN World Population Prospects (UN Population Division, 2024).

In a country with a very stable democracy, or one that has strengthened or weakened very gradually, the average resident's experience of democracy will closely follow the current level of democracy over time. In contrast, erratic changes in democratic strength will cause a country's population to have either more or less experience with democracy than the present provides. Paraguay and Hungary are two countries that have had very similar erratic changes in the development of their democracy, as measured by V-Dem's liberal democracy index: the 1870s to 1930s were a time of very limited democracy, followed by authoritarian repression from the 1940s to 1980s, a surge in democratic power in the 1990s, and democratic backsliding since the early 2010s. However, Figure 4(a) shows that the recent backsliding in the two countries looks very different against the backdrop of each country's remembered level of democracy. The backsliding in Paraguay up to 2024, starting with the impeachment of President Fernando Lugo in 2012, has only brought Paraguay back down to the average level of democracy experienced by Paraguayans since age 18. On the other hand, the backsliding in Hungary up to 2024, starting with the second government of Viktor Orbán in 2010, has brought the period level of democracy 35% below the remembered level of democracy.

Figure 4(b) shows the range of countries with democracies that have also backslid in period terms below their remembered averages. The largest outliers in 2024 are Mauritius (–0.184, or –33%), El Salvador (–0.183, or –67%), and Hungary (–0.174, or –35%). On the other side of the line of equality are recent democratic success stories. Seychelles has a liberal democracy index of 0.659 as of 2024, which is +0.208 or 46% above its remembered average. This is thanks to a rapid, steady transition to democracy that began in the 1990s. The next largest positive outliers are the Gambia (+0.178, or 54%) and the Maldives (+0.142, or 50%), following fateful elections in 2016 and 2018, respectively.

The difference between countries' period and remembered levels of democracy depends, in the first instance, on the rate of change in the period level. However, it also depends on the rate of change in the remembered level, which is fundamentally constrained by the age structure of the population. As discussed in Section 4.1., older populations lose their past more slowly that younger ones. To demonstrate this in the case of changes in liberal democratic strength, Figure 5 shows the projected change in the remembered level of memory that would result if two groups of countries—one with very low (0.00 to 0.10) and one with moderately high (0.60 to 0.70) levels of remembered democracy in 2024—hypothetically reverted to the global population-weighted period level of democracy in 2024 (0.289) for the period of 2025 to 2029. The low democracy populations would experience large increases in their remembered levels of democracy and the high democracy populations would experience large decreases, but the effects in either direction would be largest in the populations with the youngest age structures. Among the initially high democracy populations, Vanuatu (with a projected average age of 25.8 in 2029) would experience 65.9% more backsliding in the remembered level of

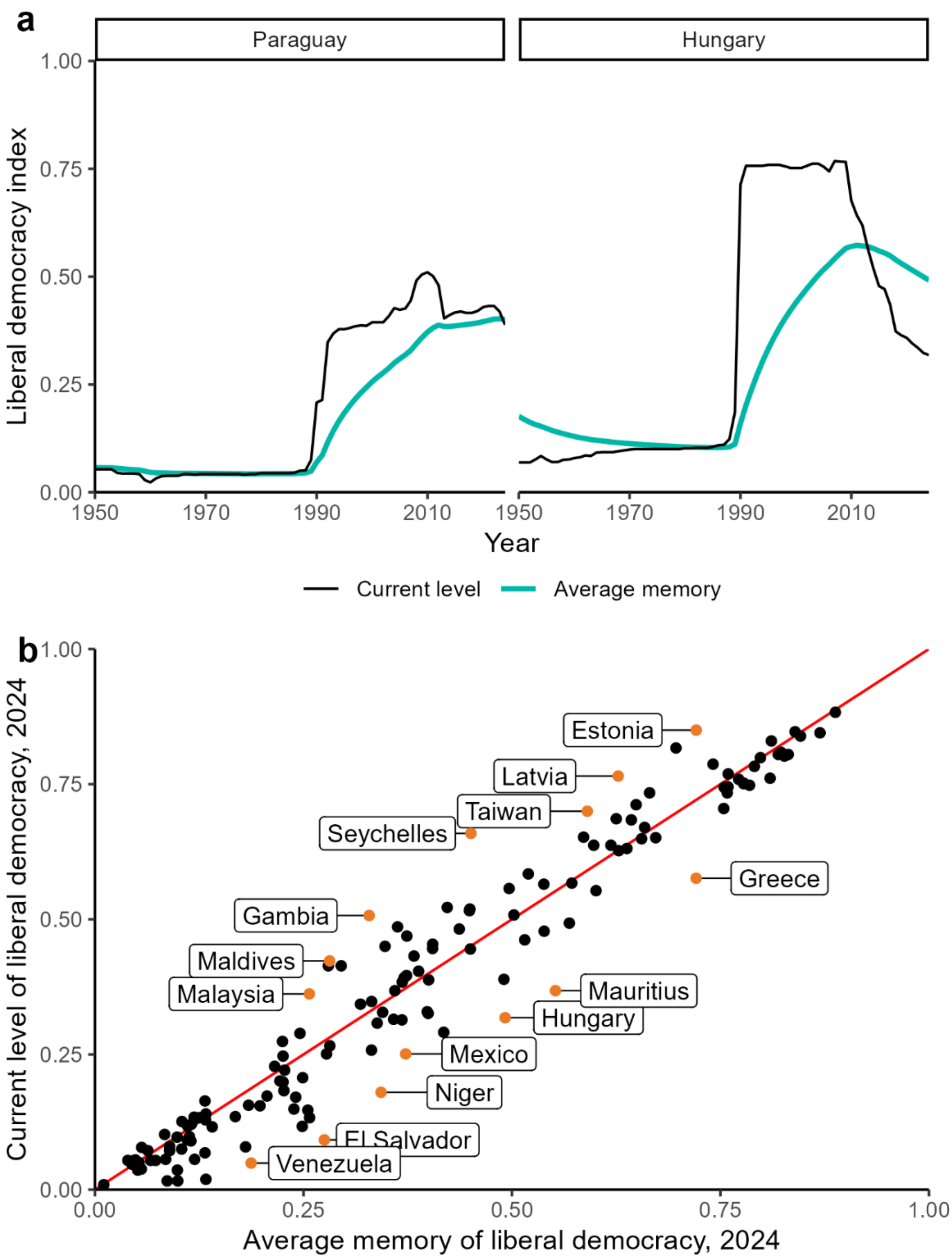

Figure 4. The V-Dem liberal democracy index for Hungary (the period level of democracy) and the average level of the liberal democracy index that the average Hungarian resident has lived through since age 18 (the remembered level of democracy) from 1950 to 2024 (panel a); and the remembered versus period level of democracy in 146 countries and territories in 2024 with select outliers highlighted (panel b).

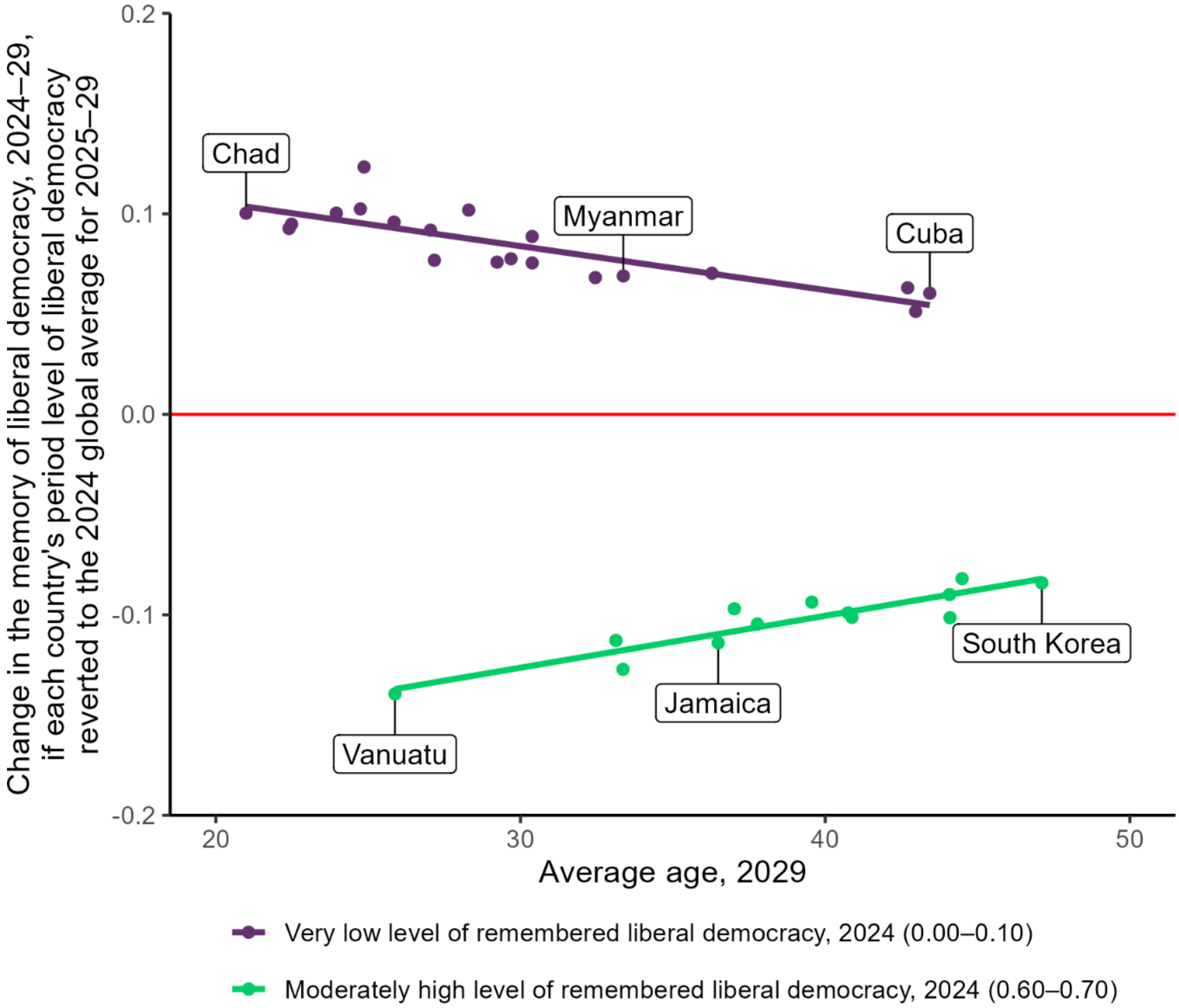

Figure 5. The projected change in select countries' remembered level of liberal democracy (since age 18) between 2024 and 2029, if each country's period level of liberal democracy reverted to the global population-weighted average in 2024 of 0.29 for the period of 2025 to 2029, as a function of the countries' average age in 2029 and whether they had a very low (0.00 to 0.10) or moderately high (0.60 to 0.70) remembered level of liberal democracy in 2024.

Democracy than South Korea (with its projected average age of 47.1). Among the initially low democracy populations, the young populations of Chad, Afghanistan, and Burundi would incorporate much more democratic strength in those five years than the older populations of Cuba, Belarus, and China.

There is a large and conflicting literature that links the demographic transition to democratic strength and weakness. In political science, there is a common argument that the population ageing that comes from the demographic transition can lead to intergenerational injustice and resulting resentment of democracy by younger adults, as the average voter gets older and potentially votes for policies with adverse consequences that younger people may have to live with for a long time (Berry, 2014; Huang, 2023; Lindh & Lundberg, 2008; Seo, 2017). This hypothesis is often explored in the context of direct democracy, with a particular focus on popular referenda like the UK's 2016 Brexit vote (Eichengreen et al., 2021; Frese et al., 2024). In contrast, others have argued that an late-transition age structure is preferable to a younger one in terms of democratic tendencies, as the presence of large numbers of young people (or men in particular) in society can be a destabilising force (Urdal, 2006; Weber, 2013). The idea that excessive numbers of men are inherently problematic for societal cohesion is under-theorised and empirically contested by behavioural ecologists (Schacht et al., 2014), but there are other arguments in support of a link between healthy democracy and old demography. Wilson & Dyson (2017) argue sweepingly, linking many supposed effects of the demographic transition—including female labour force participation, the social maturity of the average citizen, a shift from short-term to forward-thinking priorities, and an increase in living standards due to demographic dividends—to the emergence and strengthening of democracy (see also Dyson, 2010).

Figure 5 contributes to this literature by suggesting that there may be a particular link between population ageing to resistance to democratic backsliding. When democracies experience a weakening of their institutions, their populations will remember their past levels of high democratic strength for longer if they have a relatively old age structure. In turn, if a greater memory of democracy fosters a greater desire for democracy, then older populations should mount a greater defence of democracy in the face of backsliding. However, it is conversely true that, when a less democratic population has already undergone significant population ageing, such as in China, a new movement for democracy may need longer to take root than if that movement had occurred earlier, all else being equal. These observations that tie old age to a lack of readiness for political change will be even more true if individuals' preferences for different political regimes are disproportionately set early in life, rather than only being some lagging indicator that accumulates over the course of their lives. There is data to support the existence of strong cohort effects in political preferences in the United States (Ghitza et al., 2022), for example, and this data could be used to re-specify the r function of memory gain and loss that underlies Figures 4 and 5.

5. Discussion

When data is available to make full use of eqs. 1–3, demographers and non-demographers alike can come to significant insights about how the social and biological conditions of the past are embedded in populations. This flexible framework can allow to estimate the answers to new descriptive research questions or to refine their existing estimates with a clear attention to the demographic processes that shape their phenomenon of interest. Answering these descriptive questions will already allow researchers to better target policy interventions to communities of need, as for example, the work on the "memory" of childhood exposure to lead by McFarland et al. (2022) has shown. Additionally, when there is a clear link function between the embeddedness of the past in a population and that population's behaviour, applying models of demographic memory can allow researchers to reliably predict and plan for future outcomes. Malmendier & Nagel (2016) have shown this with respect to past experience of inflation predicting future consumer behaviour. Deploying the related idea of demographic metabolism, Lutz & Muttarak (2017) have shown that the past accumulation of education in a population can improve its future ability to adapt to climate change. Ultimately, the analyses related to climate change in Figure 2 and political memory in Figures 3–5 are only a few modest examples of the type of work that can be done. The idea of survivorship memory is expansive, with potential applications in fields as disparate as environmental epidemiology, political economy, and developmental psychology. Building on the existing work of Denton & Spencer (2021) and Alburez-Gutierrez (2022), as well as the work of Ryder (1965) and Lutz (2013) on the related idea of demographic metabolism, survivorship memory has the power to unify concepts that have existed outside of demography for decades by giving them a rigorously quantifiable and deeply demographic basis. In this sense, demographic memory is not a new idea, but the clear formulation of the concept—mathematically and theoretically—represents an innovation.

The concept of demographic memory, expressed in terms of age or kin structure, does have its limits. It is only a complement to other ways of thinking about memory in the social and biological sciences. Human memory has many forms, including institutional and technological ones (Finley, 2025), that do not correspond well to the metaphor of the past being embedded in the body or its bloodline. In particular, it is important to delineate demographic memory from the concept of collective memory. Here, “collective memory” refers to the concept that frames a population as a whole as remembering its past because a large proportion of its members have an awareness of that past, especially in a way that consciously or unconsciously influences their identity or their view of the world at large.

The common view in sociology, history, psychology, and political science is that collective memory (sometimes called “social memory” or “historical memory”) is produced, sustained, and forgotten through social, often political, processes (Olick, 1999; Giesen & Junge, 2003; Green, 2011; Hite, 2011; Hirst et al., 2018)—rather than simply increasing and decreasing “naturally” through demographic processes like mortality, migration, fertility, or ageing. Instead, collective memory is shaped, through direct and indirect pathways, by education (Seixas, 2005; Roediger & DeSoto, 2014; Staff et al., 2018), practices of remembrance (Cole, 2004; Fowler, 2007; West, 2008; Bilbija & Payne, 2011), and formal policies and prevailing social conditions that work to suppress, uncover, or reshape memories of the past (Chirwa, 1997; Esposito, 2008; Renshaw, 2016; Hackmann, 2018). In fact, Halbwachs (1941) originally conceived of *mémoire collective* in explicit rejection of the essentialist notion that individuals have a memory of the past that emerges in a straightforward way from their demographic characteristics, e.g. through a mystical or Jungian collective unconscious (see Assmann & Czaplicka, 1995; Erll, 2011).

For this reason, it may not be advised for researchers to try to use models of demographic memory to directly quantify what is actually the domain of collective memory. When scholars of collective memory itself have tried to bring explicit quantification into their work, they have often concluded that numerical representations of memory fail to consider the social and political processes that shape and contextualise memory. For example, one quantitative method that can be used to study collective memory is to ask a representative sample of individuals whether they remember or are aware of a historical event or figure (e.g. Harris, 2006; Roediger & DeSoto, 2014; Schuman & Scott, 1989; Yamashiro et al., 2022). These surveys can reveal interesting social patterns in individual-level memory, but Olick (1999) argues that even “survey research on social memory excludes much of what is genuinely social about memory” (p. 342). This is because collective memories reflect what the past means to a group, rather than what actual past they (or their kin) have experienced or been taught about. Moreover, a simple quantitative approach can easily overlook how collective understandings of the past can be distorted or outright false, even if the past in question is within respondents’ lifetimes.

Instead, models of demographic memory are well-suited to asking questions like, what is the average exposure in a present population to a particular historical event, era, or phenomenon; or what are the length and type of kinship ties that connect a current population to a historical one that experienced some phenomenon of interest? The development of models that improve researchers’ ability to estimate answers to questions like these is unlikely supplant the qualitatively rich concept of collective memory, but the idea of demographic memory has a richness in its own right. Moreover, part of that richness can and should come from an awareness of the social and cultural complexity of obtaining accurate answers to questions like these. For example, Denton & Spencer (2021) consider the importance of age effects and shared geography in their framing of survivorship memory. In turn, the conceptual development of kinship memory by Alburez-Gutierrez (2022) explicitly recognises the importance of social ties like kinship as a unique way in which populations are bound to the past. The development of more elaborate formal models of demographic memory, like those in Section 3 of this article, will allow for further social contingencies of “memory” to be explicitly modelled.

Additionally, other types of demographic memory can be imagined. There are ways of being connected to the past through demographic characteristics besides one’s cohort or family membership. One way comes from speaking a language; having access to the oral and written traditions of a particular language connects individuals to the past and consequently shapes the futures of the populations they belong to. Another type of memory comes from one’s racial or ethnic group. Being racialised and essentialised in a particular way by outsiders can lead to a group’s oppression and deprivation, but strategic essentialism by the ingroup allows one to lay claim to a particular history or tradition, even without direct experience of that history, and thereby to wield that history in the resistance of oppression (hooks, 1991; Spivak, 1996; Su, 2009). Similarly, national identity brings with it ideas of history and myth that individuals carry forward into the future. Future work in the field of demographic memory might not only expand models of survivorship or kinship memory to existing ideas in other disciplines; they might also see to quantify previously unexplored ways in which demography shapes “memory” and its importance for societal continuity and change.

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Data availability

No data was collected for this work, and the data underlying the illustrative figures in the article are publicly available from the sources cited. The R code underlying analyses can be requested from the author.

Supplementary materials

Table S1. Example calculation demonstrating the effect of subgroup variance in *r* on eqs. 1–3

c(t = 2000–01, s_t = s_1, s_2)

t =	2000	‘01
s_1	10	20
s_2	80	40

r(p = 2001, t = 2000–01, x_t = 0–1, s_t = s_1, s_2)

t =	2000	‘01
s_1	1	1
s_2	0.2	1

k(p = 2001, t = 2000–01, x_t = 0–1, s_t = s_1, s_2)

t =	2000	‘01
s_1	1	1
s_2	1	1

w(p, t, x_t, s_t) = 1

Incorrect (applying eq. 1):

θ(p = 2001, t = 2000–01, x_t = 0–1, s_t = s_1, s_2)

t =	2000	‘01
s_1	.31	.31
s_2	.06	.31

M(p = 2010, x_p = 1) = 26.88

Correct (with *θ* estimated manually):

θ*(p = 2010, t = 2005–10, x_t = 5–10, s_t = s_1, s_2)

t =	2000	‘01
s_1	.25	.25
s_2	.08	.42

M*(p = 2010, x_p = 1) = 30.83

Appendix S1. Estimating UK population counts by migration history

Several data sources can be combined to estimate the necessary population data to conduct the analysis in Section 4.1. The 2024 revision of the UN World Population Prospects provides annual age-specific population estimates and projections for the UK from 1950 to 2100 in one-year age groups up to 100+ and annual total net migration estimates and projections over the same period (UN Population Division, 2024). The 2020 revision of the UN International Migrant Stock dataset offers estimates of the migrant stock in the UK from 1990 to 2020 in five-year age groups up to 75+ (UN Population Division, 2020). The UK Office for National Statistics provides annual estimates of immigration from 1991 to 2019 in irregular age groups (0–14; 15–24; 25–44; 45–59 for women and 45–64 for men; 60+ for women and 65+ for men) (Office for National Statistics, 2020).

Multi-year age intervals can be smoothed to one-year intervals using a penalised composite link model (Rizzi et al., 2015). Then, estimates of migration stock by age can extrapolated backwards to 1950 and forwards to 2100 by assuming that the age-specific proportion of the population with a migration background is the same in 1950–89 as in 1990 and the same in 2021–2100 as in 2020. Then, for each the migrants in each cohort, a probability distribution of age at migration conditional on having migrated by their current age can be approximated by plotting the average distribution of ages at immigration between 1991 and 2019 scaled upwards or downwards by the total net migration in the current period on a Lexis scale, then taking the rates along the cohort's diagonal prior to their current age and normalising them to sum to 1. To do this for cohorts born before 1950, it can be assumed that the total net migration in each year from 1850–1949 was the average level in the 1950s. Then, that age-specific probability distribution can be converted to a cumulative distribution of the probability of having migrated to the UK by a particular age. Finally, this cumulative distribution can be used to model the life course transition of the migrant population aged x_p at present time p from a subgroup s_2 outside the UK (where they are exposed to non-UK leaders) to s_1 inside the UK (where they are exposed to UK leaders).

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