Lifecycle scarring and cohort longevity: health, income, and neighborhoods

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Draft

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Abstract:

We argue for the usefulness of a cohort-based measure of longevity and demonstrate that our methodology can produce reliable and sensible results for cohorts as recent as the 1965 year of birth. Using Canadian administrative tax data, we recreate and extend income gradient findings from earlier work, showing that longevity improvements in Canada arise across the income distribution—at sharp contrast to the increasing inequality found in the United States. We then introduce six lifecycle scars that we are able to measure in our data for ages 35-54, including health shocks, benefit income receipt, and low-income neighborhood residency. Our results reveal a very large drop in longevity for those who claim a disability pension or the disability tax credit, modest longevity effects for benefit income receipt, and very modest impacts for living in a low-income neighborhood. For the Canada Quebec Pension Plan disability pension, men with no exposure at ages 45-54 live 12 years longer than men with heavy exposure. For women, the gap is 9 years. Looking at both the timing and intensity of shocks, arriving at older ages with a disability appears to have by far the largest impact on later-life survival.

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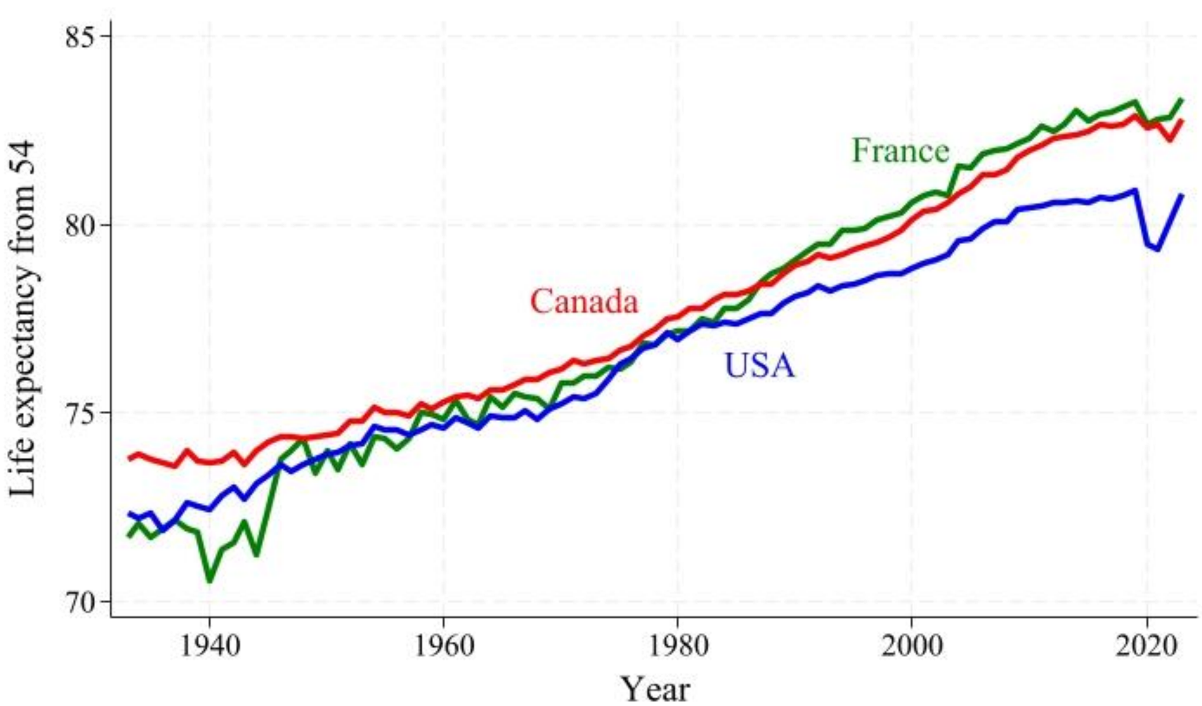
1.0 Introduction

The international literature linking socioeconomic status and longevity has grown in recent years. Chetty et al. (2016) is a pivotal paper in this literature, having used tax records to construct period mortality rates and analyze differential longevity in the United States. Similar analyses have appeared for other countries, including Denmark (Dahl et al. 2024), Germany (Haan et al. 2021), Norway (King et al. 2019), Sweden (Fors et al. 2021 and Hagen et al. 2025), and Canada (Milligan and Schirle 2021; Milligan 2024).

Figure 1: Period Life Expectancy from Age 54



Notes: All-gender period mortality data taken from the Human Mortality Database, with life expectancies calculated by the authors.

The motivation for this broad interest in international differences in longevity can be observed in Figure 1, which graphs period life expectancy conditional on reaching age 54 in Canada, the United States, and France. (France is chosen here as a typical example of the experience in another high-income country.) From 1950 to 1980, the three countries saw steady improvements at approximately the same pace. After 1980s, the pace of improvement in the United States began to lag other high-income countries. France and Canada followed a similar path, although with slightly better performance in France than in Canada.

In the Canadian context, Milligan and Schirle (2021) developed a methodology for producing cohort-based life expectancy estimates using administrative data from the Canada Pension Plan. They were able to demonstrate significant differences in life expectancy across the income distribution, finding that Canadian men within the top ventile of mid-career earnings were likely to live 8 years longer than men within the lowest ventile of mid-career earnings. Moreover, in sharp contrast to the United States, Canadian longevity gradients improved at a fairly uniform pace across the income distribution. Milligan (2024) extends the Canadian work by using administrative data from tax records and includes an analysis of geographical variation in longevity in Canada.

Milligan and Schirle (2021) provided a comparison of period and cohort measures of longevity. Period methods take observed deaths in any given year and compare to the population at risk, then aggregating cross-sectionally across ages to form survival rates and life expectancy. As such, the observed mortality rates of older cohorts are used to approximate the future mortality of younger cohorts. In contrast, cohort methods follow the experience of a given birth cohort over its lifecycle. Milligan and Schirle (2021) find that the steepness of the Canadian earnings-longevity gradient is understated when using a period life expectancy approach and argue for the expanded use of cohort methods for understanding how socio-economics forces may change life trajectories and future demographic trends.

In this study we use cohort-based methods for estimating life expectancy to investigate how several life challenges may affect life expectancy after age 54. Previous work (ours included) often uses mid-life income or earnings as an index to categorize the population into groups in order to study longevity gradients. Underlying this index, however, is an understanding that life events preceding the moment of indexation are the driving factors in observed differential longevity. These life events could range from pre-birth genetic factors to the circumstances of birth to education to various health, income, and employment shocks experienced over the lifecycle. Our data are not well suited to study of education or childhood events. However, we can produce measures of ‘scars’ that might hit a person through their adult life that could influence their longevity. Our analysis of lifecycle scarring can prove useful by helping to ‘unpack’ some of the reasons why people might arrive at the point of mid-life indexation with lower income.

We use Canadian administrative tax data to see how periods of disability, benefit income receipt, and residence in relatively low-income neighborhoods might affect the life expectancy of individuals across the (mid-life) income distribution. We examine cohorts of Canadians born between 1938 and 1965, investigating how scarring between ages 35 and 54 may impact their life expectancy and survival rates from ages 55 to older ages.

We find that all three types of lifecyle scarring we study (disability, benefit income receipt, and low-income neighborhood residency) lower longevity compared to those without the scars. The patterns of scarring are distinct, however, as the impact of some measures increases with intensity of exposure while for other scars it is only whether there is any exposure at all that matters. In particular, we show that indicators of disability have the largest impact on longevity. Life expectancy for those with no exposure to the Canada/Quebec Pension Plan disability pension compared to those with heavy exposure is 12 years longer for men and 9 years longer for women.

The paper begins by laying out the case for using cohort longevity and presenting our methodology. We then present longevity gradients by income decile to set the stage for our main analysis of lifecycle scarring and how longevity varies across those with different intensity and age patterns of lifecycle scarring. We then conclude.

2.0 Projecting Cohort Longevity

In this section we begin by describing the use cases for period and cohort longevity measures, arguing that for many common applications a cohort measure is preferrable. We then describe our cohort longevity projection methodology.

2.1 Period and Cohort Measures

Period life expectancy is the most commonly used measure of lifespans. Period life expectancy is calculated using a cross-section of age-specific mortality rates for a given population in a given year. By summing survival rates (calculated as one minus mortality) from any particular age forward, a measure of life expectancy can be formed.

Period life expectancy has an obvious advantage in being easy to calculate, as only one year of data is needed. It may also serve as a useful summary of a time-period shock such as the impact of a major war or a pandemic. Both of these use cases can be seen in Figure 1, with the impact of World War II in France and the pandemic (particularly in the United States) in 2020 and 2021. On the other hand, no person actually experiences the life expectancy projected by this period method unless age-specific mortality rates are constant over time.

Another approach to longevity takes the point of view of a given cohort and asks how long on average members of that cohort live. The potential advantages of this approach are clear: by measuring the lifepaths of real people, cohort longevity allows for the study of important and interesting policy questions like the long-term impact of policies or health shocks, and planning for private or public pensions and insurance which depend on the future longevity of today's living people. The major shortcoming of cohort longevity is that one must presumably wait until a cohort has completed its lifespan before assessing impacts—waiting for 50 years or more to assess the impact of a policy or a shock is a serious constraint on the use of cohort longevity.

We argue this shortcoming can be reliably and easily overcome by projecting cohort mortality to older ages using the experienced path of mortality for each cohort at younger ages. Gompertz's Law asserts that the age-mortality path is log-linear. In previous work (Milligan and Schirle 2021; Milligan 2024) we have developed an application of Gompertz's Law and shown that it produces both accurate and useful projections for cohort longevity. In the balance of this section, we lay out our methodology.

2.2 Cohort Longevity Projection

Our method first projects forward survival rates for a given population and then aggregates them across ages to form a cohort longevity projection. The survival rate projections are calculated from age-specific mortality rate estimates built around Gompertz's Law, which asserts a log-linear relationship between log mortality and age.[1] Empirically, a Gompertz projection for a population with data on age-specific mortality at each age *a* could take the form:

$$\log(mortality\ rate_a) = \beta_0 + \beta_1 age_a + e_a. \quad (1)$$

In principle, this projection could be run separately for any population defined on the basis of birth cohort, income group, or lifecycle scarring. In practice, Milligan (2024) argues for a cohort-pooled Gompertz projection that allows each year of birth cohort to have a separate intercept term and allows the age coefficient to drift linearly across years of birth. This augmentation provides some stability for years of birth with fewer observations while still allowing year-of-birth differences to emerge in the projections with a high degree of flexibility.

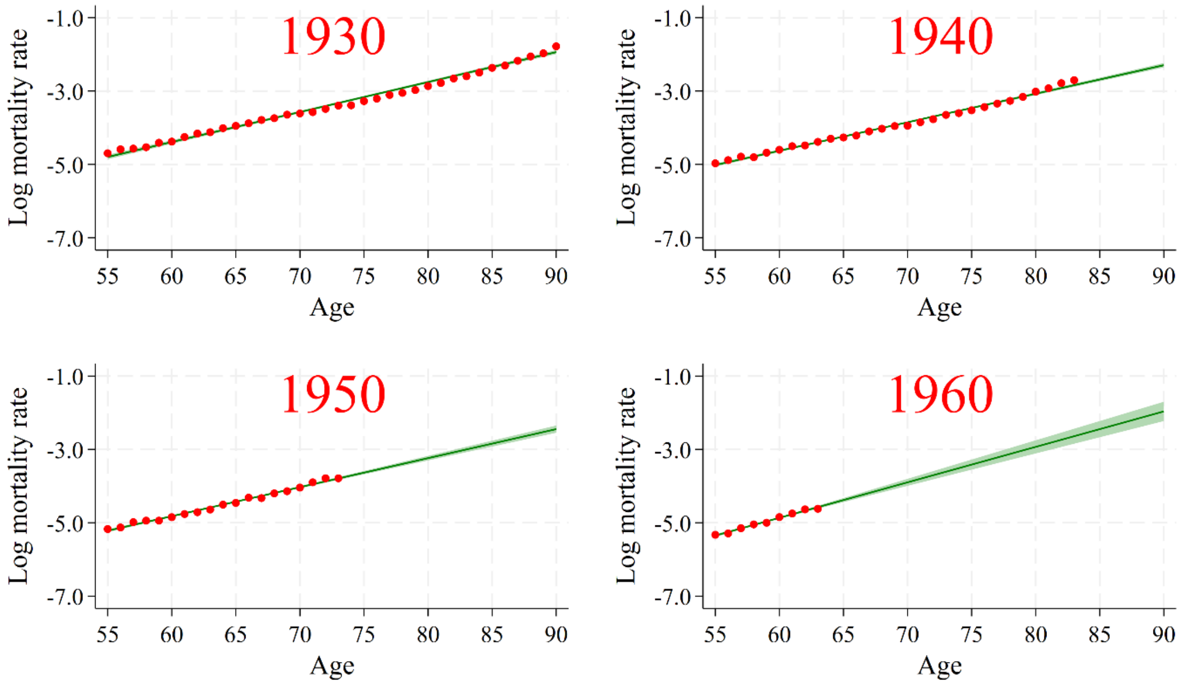
This pooled Gompertz projection for a year of birth cohort *y* observed at age *a* therefore takes the form:

$$\log\left(mortality\ rate_{ay}\right) = \beta_0 + \sum \gamma_y + \beta_1 age_a + \beta_2 age_a \times coh_y + e_{ay}. \quad (2)$$

These Gompertz projections perform very well, as can be seen in Figure 2. Each panel of the graph shows the realized mortality rates and estimated regression line (with associated 95% confidence interval) for a given year-of-birth cohort. The estimation uses the population-wide mortality rates for Canadian men from the Human Mortality Database, running pooled regressions of the form of equation (2) above. For the earlier birth years, the standard error of the estimate is very small, leaving it hard to distinguish the shaded confidence interval from the regression line. For the 1960 birth cohort, data up to 2023 (age 63) are available, which is a smaller base on which to base the estimation. This results in visibly larger confidence intervals for the estimates at older ages; although smaller than they would be if an unpooled sample based on equation (1) were employed.

[1] See Gompertz (1825).

Figure 2: Gompertz cohort mortality projections



Notes: Data from Human Mortality Database for Canadian males. Each panel shows results for the indicated year of birth cohort. The dots show the actual mortality rates. The line shows the regression estimate, with shading to indicate the 95% confidence interval.

To move from mortality rates to life expectancy, we sum survival rates (calculated as 1 minus the mortality rate) from age 55 to age 100, with different mortality rates used in three different ranges.

i) Observed data: From age 55 to the last observed age for a cohort we use experienced mortality rates. (E.g. up to age 63 in 2023 for the 1960 birth cohort.)

ii) Gompertz projections: From the age after the last observed age up to age 89 we use the Gompertz projection following equation (2) above.

iii) Population data: For ages 90 plus we use the population average age-specific mortality rates from the Human Mortality Database for 2019.

This three-range calculation follows the practice established by Chetty et al. (2016) and is based on evidence that Gompertz projections perform poorly after age 90.[2] To the extent this introduces bias, it serves to attenuate the slope of longevity gradients.

3.0 Income gradients for cohort longevity

We begin the analysis with a brief presentation of the evolution of cohort longevity by income decile. This builds on our previous work in Milligan and Schirle (2021) and Milligan (2024). The presentation of this analysis both serves as a benchmark to our earlier work and lays the foundation for the lifecycle scarring analysis which is the main contribution of this paper. Compared to the previous work, we extend the income decile analysis to more years of data.[3]

The data we employ is the Longitudinal Administrative Databank (LAD) for the years 1982 to 2022. In 1982 (the first year the LAD is available) a 20% sample of tax filers from the T1 Family File were drawn and for each year thereafter a sample of new tax filers are added so that LAD represents a 20% sample of Canadian tax filers each year. For individuals sampled, information from their tax files is updated each year, however we are limited with respect to demographic information. We can observe an individual's sex, age and marital status, the postal code of their residence (as of December 31st of the year), and whether and what year an individual dies. Otherwise, we are limited to information provided on tax forms and have little information regarding other individual or job characteristics.

In Milligan and Schirle (2021) we used the universe of Canada Pension Plan contributors from an administrative database available for years from 1966 to 2015. That data source had the advantage of universal and long-term coverage. On the other hand, that paper was restricted to individual earned income in that data source, and adding more years of data was difficult. Milligan (2024) showed that the LAD sample produces very similar results to what was found in

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2 See evidence in Gavrilov and Gavrilova (2011) and Gavrilova and Gavrilov (2014). After age 90, Gompertz projections tend to under-estimate experienced mortality.

3 In Milligan (2024), LAD up to 2021 was used. We will update this to 2023 before finalizing this paper. We were unable to get the updated income-decile results out of the data centre in time for this draft, so we simply take the data from Milligan (2024) for producing this income-decile analysis.

the universal sample of CPP contributors, which should increase confidence in using the LAD for the purpose of studying longevity.

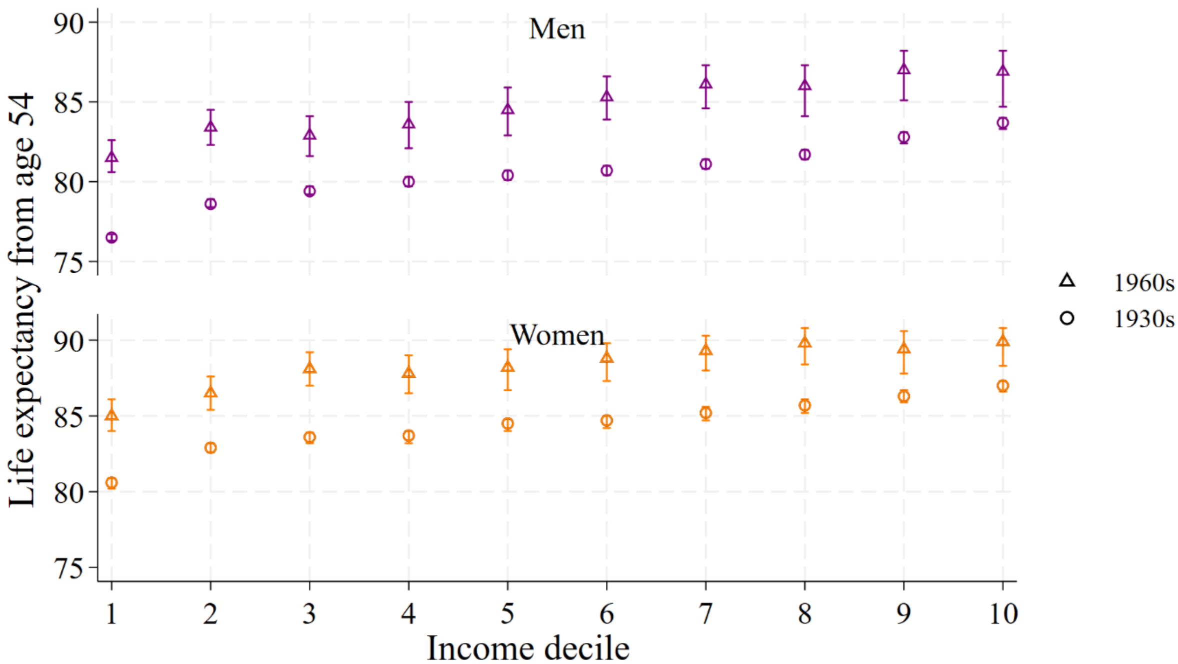
Our sample only includes individuals who have lived to age 54, and for whom we can observe the total after tax family income (adjusted for family size and inflation) from ages 52 to 54. We use an average of income over ages 52-54 to assign individuals to income deciles, within gender and year of birth groups. Various options for measuring income (both age ranges and income measurement) are available and the robustness of this choice is evaluated in Milligan (2024). We also develop several indicators for lifecycle scarring that we describe in the next section.

We plot in Figure 3 our estimates of life expectancy by gender, deciles of after-tax adjusted family income, and decade of birth (1930-1939 and 1960-1965). We show a simulated 95 percent confidence interval for each estimate—although they are small and therefore obscured by the point estimate for the 1930s data points.[4] For women, in the lower panel, life expectancy spans 80.6 to 87.0 for 1930s births and 85.0 to 89.9 for 1960s births, for a top-bottom decile gradient slope of 6.4 years in the 1930s and 4.9 years in the 1960s. For men, in the top panel of Figure 3 shows a top-bottom decile difference of 7.2 years in the 1930s and 5.4 years in the 1960s. So, looking just at the top and bottom decile there appears to be a lessening of the gradient over these 30 years of births. Looking more generally across all deciles in Figure 3 the movement can best be characterized as a fairly uniform shift across the income distribution. This is in sharp contrast to the findings in the United States, which show a strong steepening of longevity gradients with respect to income, and almost no growth in longevity in the bottom half of the income distribution.[5]

[4] We draw disturbances using the empirical standard errors for the mortality estimates from the Gompertz estimation. The perturbed mortality rates are then put through our procedure. The cutoff points for the confidence interval are found from the empirical distribution of 1000 replications. The confidence intervals are not necessarily symmetric as even extreme mortality disturbance draws may not move the upper estimates of life expectancy estimates. (Consider a comparison to an asymmetric '95% hurricane projection cone' that hits against a hard geographical barrier such as a mountain.)

[5] See, among others, Chetty et al. (2016) and National Academies of Sciences, Engineering, and Medicine (2015).

Figure 3: Life Expectancy Gains Across Birth Cohorts and Income



Notes: Data from LAD. Graph shows estimated life expectancy by decade of birth cohort (1930s and 1960s), gender, and decile of after-tax adjusted family income. A simulated 95 percent confidence interval is displayed around each estimate.

This finding of a strong (although not-increasing) gradient of longevity with respect to income motivates many questions about what drives the gradient. While income at ages 52-54 is used here as an index to sort the population into deciles to understand who is living short and longer lives, the analysis is not intended to be causal—it is not the level of income at ages 52-54 itself which is thought to drive these differences. Analysis in Milligan and Schirle (2021) and elsewhere shows that absolute income differences across cohorts are not enough to explain the gains in longevity either within country or across countries.

In the next section, we take the next step in this investigation of longevity gradients by examining how much different health, income, and neighborhood scars across the lifecycle might be associated with differences in longevity.

4.0 Lifecycle scarring and longevity

This section presents our new results on lifecycle scarring and longevity. We being by describing the measurement of the scars we are able to capture in our data. We then show the longevity of those experiencing differing intensity of scarring over their lifecycles. Finally, we present regressions exploring how differences in the timing of scars affect the probability of survival. Throughout the analysis, we avoid making definitive causal conclusions. The point of our work here is to begin the unpacking of longevity gradients by income; a way-station that may prove helpful in pointing the way toward more definitive causal analysis.

Longevity gradients across some index of midlife income are potentially driven by causal factors from pre-birth genetic inheritances to childhood environment to education to midlife health, income, and living conditions. In our LAD data, we are constrained in two ways. First, we can only see what is observable in administrative tax data: claims for tax credits and deductions, family relationships, income types, and location. The second constraint is time: we have LAD data only for years 1982 to 2022. This constraint limits the age range over which we can observe potential scars and still have sufficient data to project longevity.

For example, if we collect information on scars from ages 25 to 54, the first cohort we can analyze is 1957 births (age 35 in 1982) that reach only age 65 by 2022. On the other hand, if we collect information on scars from ages 45 to 54 we can now analyze cohorts as far back as 1937 births, but we miss everything that happens to an individual before age 45. In the analysis below, we balance these concerns by focusing on ages 35-54 as the lifecycle scar window.

For each of these lifecycle scar measures, we can characterize both the intensity (how many years the scars are observed between 35-54) and the timing (which particular ages between 35-54) of the scars.

4.1 Measures of lifecycle scarring

The LAD allows us to construct measures of several potentially interesting lifecycle scars. These can be put into three groups. First is health: we observe incidence of Canada/Quebec Pension

Plan Disability benefit income as well as claims for the disability tax credit.[6] The second group is measures of low income: social assistance (welfare) income, workers compensation, and employment insurance income. The third group is the income level of the neighborhood in which the individual has been living. Below we describe the construction of each of these measures.

CQPP-D: Canada and Quebec Pension Plan Disability

For the full run of the LAD (1982 to 2022) we can observe the receipt of income from Canada and Quebec Pension Plan benefits. Recipients of these income sources are issued a T4A(P) by the Canada Revenue Agency, so the benefit amounts included in the LAD result from administrative records. The Canada Pension Plan is a contributory public pension scheme that pays a disability, a retirement benefit, and a survivor benefit (as well as some smaller benefit programs). The Quebec Pension Plan is a similar program operating in the province of Quebec with slightly different contribution and benefit parameters but the same tax treatment as the Canada Pension Plan. From 1992 onward we see benefits from the disability programs specifically. Before 1992, we assume that for the age group 35-54 we are looking at that the large majority of benefits are disability and not retirement or survivor.

Beyond changes in what income is captured in the LAD, the entry criteria into the Canada and Quebec Pension Plan Disability benefit (CQPP-D) have changed over time.[7] Workers must have suffered a prolonged mental or physical disability which prevents work, as well as having made sufficient contributions to the CQPP scheme over their work career. The exact interpretation and meaning of these criteria have changed over time, however, and in particular became more strict in the 1990s (Campolieti 2001, 2002, 2006). This weakens the use of CQPP-D as an indicator of health status since it will pick up different thresholds of health incapacity in different years.

DTC: Disability Tax Credit

For every year since 1983, the LAD reports whether the disability tax credit (DTC) was claimed by each individual in the sample. The DTC is a non-refundable tax credit available to individuals with severe and permanent disabilities. We note the DTC was expanded in 2005 to include those

[6] We have also explored using claims for the Medical Expense Tax Credit, but that analysis is incomplete and ongoing.

[7] See Baker and Milligan (2012) and Milligan and Schirle (2016) for overviews and analysis of CQPP-D. Milligan and Schirle (2019) compare US Social Security Disability Insurance and CQPP-D.

with multiple significant limitations or receiving life-sustaining therapy. Eligibility requires certification from a medical practitioner. In 2022, approximately 1.1. million people claimed all or some portion of the credit for themselves (Department of Finance Canada 2025). As Leanage, Jeon, and Arim (2025) report, however, only a small fraction of persons with disabilities claim the DTC. By matching the 2017 Canadian Survey on Disability to Statistics Canada's T1 Family Files, they found that about 6 in 10 persons with very severe disabilities had neither claimed the DTC or received disability benefits from the Canada and Quebec Pension Plan Disability systems. Dunn and Zwicker (2018) have suggested a lack of take-up relates to the non-refundable nature of the tax credit since the DTC does not provide tax relief for those whose income does not exceed the threshold where taxes would be owing (because of other credits and deductions which have already lowered the tax liability to zero).

WC: Workers Compensation Income

The LAD has reported receipt of benefits from workers' compensation plans since 1992. Workers compensation pays benefits for injuries sustained in the workplace that inhibit ongoing employment. In Canada, workers compensation is organized as a public plan by provincial governments. So, benefit levels and rules vary across the country. However, across Canada those receiving income from these programs receive a T5007 from the Canada Revenue Agency based on provincial administrative records. For a description of how workers compensation is set up in Ontario, see Campolieti et al. (2007).

SA: Social Assistance Income

As an indication of general financial hardship, we look for whether a person has received social assistance payments. This information is available in LAD since 1992. Social assistance (SA) is the general term for provincially financed and operated cash welfare programs for those without other sources of income. Eligibility and qualification rules, as well as benefit levels, vary substantially across provinces. But, in all cases a T5007 is issued by the Canada Revenue Agency based on administrative records from the paying province. Time trends in incidence and program rules are analyzed in Kneebone and White (2009) and Finnie et al. (2004).

EI: Employment Insurance Income

For all years since 1982 we can observe in LAD whether a person received Employment Insurance benefits (EI). Prior to 1996 this program was known as Unemployment Insurance. We view use of EI as an indicator of a more volatile work career. For qualification, a period of unemployment must last at least 2 weeks for a person to be eligible for benefits. Benefit receipt does not capture all unemployment or joblessness, however, as individual who left their jobs (quit), were dismissed with cause (fired), or had insufficient work histories would not be eligible for benefits. Rules have varied through time (e.g. weeks of work in the previous UI regime; hours of work in the current EI regime) and across EI regions (fewer hours needed to qualify in high-unemployment EI regions). In addition, we cannot distinguish between 'regular' EI benefits or parental leave benefits—which can be quite generous in Canada, lasting 50 weeks in most provinces (see Baker and Milligan 2008 for the evolution of EI parental leave in Canada). Banting and Medow (2012) provide a comprehensive analysis of how EI works and the trends and changes in coverage over time.

Low FSA: Low-income neighborhoods

Neighborhoods can affect long-run longevity outcomes in several ways, from the quality of schools and hospitals to the influence of peers to safety and the built environment. Milligan (2024) takes the mean income by neighborhood and ranks neighborhoods to form equal-population deciles. For neighborhood, the first three digits of the six-digit postal code are used. These first three digits (known as the Forward Sortation Area or FSA) characterize a geography that reaches 50-60 thousand in urban areas, but much smaller in rural areas.[8] We take the reported FSA at each age and tag whether it is in the bottom quintile of FSAs as ranked by income. We characterize any such years as a year living in a low-income FSA.

Milligan (2024) finds substantial longevity differences across low-income and high-income FSAs. If a man is in the highest country-wide income decile himself but lives in a low-income FSA, the life expectancy is the same as a man in the 5th national decile of income in the high-

[8] As one example, the City of Vancouver has about 750,000 population and is divided into 28 FSAs, for an average of about 27,000 per FSA.

income FSA. Wolfson et al. (2024) also looks at local geographies, finding less differences across low- and high-SES neighborhoods in Canada than in the United States.

4.2 Longevity gradients and lifecycle scarring

We now turn to our main analysis of the impact of lifecycle scarring on life expectancy. For each of the six scars we observe up to 20 years of lifecycle scarring, from ages 35-54. For the scars that are observed only since 1992 (WC and SA) we are more limited in birth cohorts that are available, but for the others we can observe a deeper selection of birth cohorts.[9] We place each person into gender-specific bins by the intensity of the scarring: no scars, 1-5 years…up to 16-20 years. Data are pooled across all available years of birth. For those in each scar-intensity-gender bin, we apply our cohort life expectancy methodology and report the estimated life expectancies.

The results are shown in Figure 4 for males. The point estimates are shown in the height of the bars for each intensity level, with the simulated 95 percent confidence interval shown with the capped line. The larger confidence intervals on some estimates reflect small sample sizes within that bin.

We start with CQPP. There is a sharp difference between those with no CQPP disability benefit income and those with at least one year. With no scar, the estimated life expectancy is 84.9 years; with 1-5 years it is 5.5 years less at 79.4 years of life. Still, there is a further dose-response relationship with more years leading to a further drop in the point estimates; although the simulated confidence intervals grow with the smaller sample sizes within the higher-scarred bins.[10] For the 16-20 year bin, estimated life expectancy is only 73.1 years; almost 12 years less than those without any CQPP-D benefit income. Because CQPP-D is meant for those with permanent disabilities that leave them unable to work, for most people once they start CQPP-D they do not exit the program.[11] So, those with more years on CQPP-D may have earlier onset of disability, which may lead to a greater accumulated scarring of their health.

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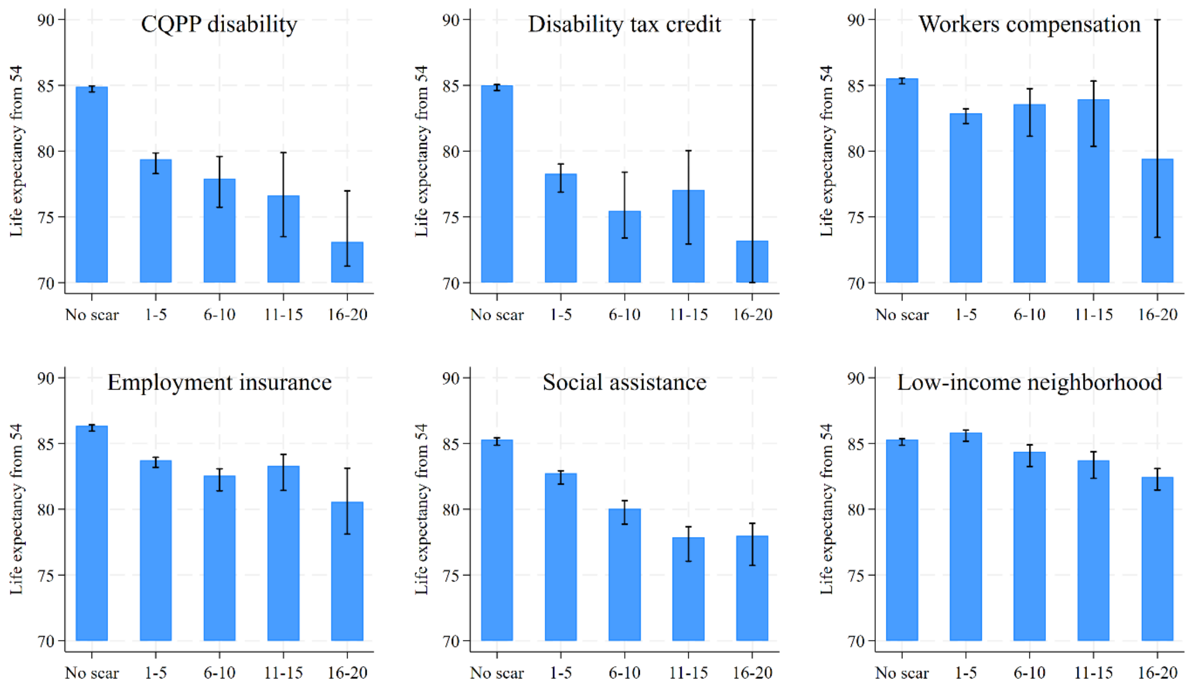
[9] The 1957 birth cohort is age 35 in 1992 and 54 in 2011. We observe them up to age 65 in 2022. For the 1947 birth cohort, they are age 35 in 1992 and 54 in 2001. We observe them up to age 75 in 2022.

[10] For reference, there are 4,920,720 males in the 'no scar' bin for CQPP-D, 82,440 in the "1-5 year" bin, and only 17,320 in the "16-20 year" bin.

[11] According to an internal evaluation reported in Employment and Social Development Canada (2021), 1.6% of beneficiaries were reassessed during the evaluation period, with 41% of these having their benefits stopped.

Figure 4: Intensity of Lifecycle Scarring and Men's Life Expectancy



Notes: Data from LAD. Reported are the estimated life expectancies from the indicated scar-intensity grouping for males, with "1-5" indicating 1-5 years of incidence and so on.

For the other two measures of health-related scarring, there is also a strong difference between those with no scarring and those with at least one year of scarring; however there is less evidence of a dose-response relationship for deeper intensity of the scarring. For the disability tax credit, the initial drop between those with no scarring and 1-5 years is similar to what was seen for CQPP-D. For workers compensation, however, the drop is much smaller, from 85.5 years for those with no years to 82.9 life years for those with 1-5 scar years. This may result from the source of the health issue—workers compensation covers only workplace-related injuries. If you are injured at work that may be less correlated with previous lifestyle choices, genetic predisposition to disease or disability, or earlier-life scars before age 35. That said, it is also possible that disabilities covered by workers compensation are less severe than with CQPP-D or the DTC.

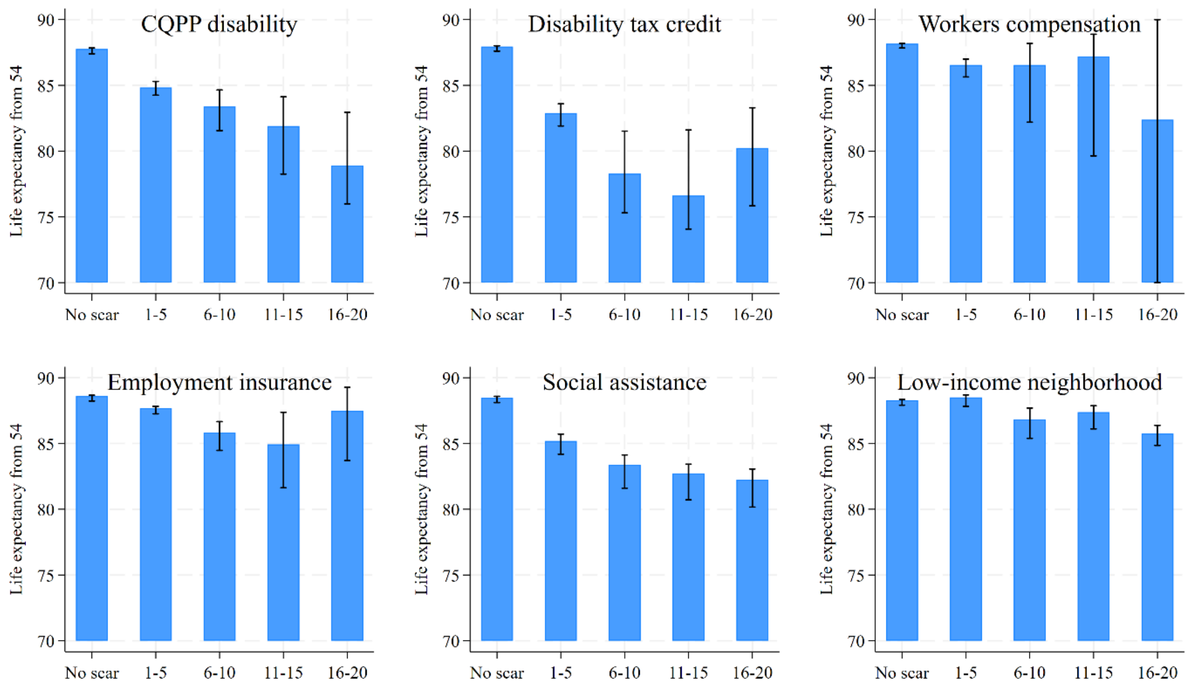
We now turn to the two employment-based measures of scars, EI and SA receipt. There is a 2.6 year drop in life expectancy comparing those with no years of EI receipt and those with 1-5 years, from 86.3 to 83.7 years. This may reflect the impact of a more volatile work career; or the underlying causes of experiencing a more volatile work career that are also correlated with lower life expectancy. For SA, there is a larger initial drop for having some amount of lifecycle scarring, and also a significant decline in the point estimate with more lifecycle exposure. Again, this isn't evidence of a causal relationship because there may be underlying causes that drive both SA and life expectancy. But, we can say that those men who tend to have a lot of time spent on SA benefits have significantly lower life expectancy. Of note, the impact of the two disability scarring measures (CQPP-D and DTC) is much larger than the income-based scarring measures (SA and EI).

The final lifecycle scarring measure we examine is living in a low-income neighborhood. Here, there is no significant difference between those with zero years and those with 1-5 years—and the point estimate for having 1-5 years is actually higher. There is a significant drop for those with long exposure to low-income neighborhoods, with life expectancy dropping to 82.5 for those with 16-20 years of scarring. Long tenures in low-income neighborhoods are likely correlated with lower lifetime earnings and other underlying factors common to those driving low life expectancy. But it is interesting to note the magnitudes here; some exposure has no difference and even long exposure has less of an impact on life expectancy than the health and income shocks examined above.

The analogous results for women are presented in Figure 5. The results in almost all cases are similar to males both in intensity pattern and magnitude. For CQPP-D scarring, those with no years of receipt have a life expectancy of 87.8 years while those with 16-20 years are at 78.9, for a gap of 8.9 years. The one exception is EI, which may reflect the higher use of EI parental leave benefits for women.[12] There is only a 0.9 year drop in life expectancy for having 1-5 years of scarring compared to having no years. Moreover, the point estimate for having 16-20 years is higher than for the intermediate bins (although with a large confidence interval).

[12] For EI, there are more women who received 1+ years of benefits than received zero years. This is not true for men.

Figure 5: Intensity of Lifecycle Scarring and Women's Life Expectancy



Notes: Data from LAD. Reported are the estimated life expectancies from the indicated scar-intensity grouping for females, with “1-5” indicating 1-5 years of incidence and so on.

Taking the evidence from both genders together, Both the magnitude of the life expectancy drop and the dose-response relationship is much stronger for the health shocks (particularly CQPP-D and DTC) than for the income shocks. Exposure to low-income neighborhoods appears to have little impact.

4.3 Effects of intensity and timing of scars on survival

The results presented graphically above show the impact of different intensities of lifecycle scarring on life expectancies. The change in life expectancies is an aggregation of changes to each age-specific survival rate. In this section, we turn to regressions on a binary variable representing survival to a specific age. This provides three additional insights for our analysis. First, it allows us to formalize the patterns of dose-response relationship seen in the life expectancy figures. Second, we can see if the impact on survival rates to different ages is similar.

Third, we can examine the importance of scarring at specific ages within the 35-54 window to see if there are particularly sensitive ages to be subject to scarring.

Table 1: Females Scar Intensity Regressions

	CQPP -D	DTC	WC	EI	SA	Low-inc FSA
			Specification 1			
Constant	0.909***	0.906***	0.906***	0.907***	0.914***	0.909***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0003)
Years (continuous)	-0.015***	-0.018***	-0.003***	-0.001***	-0.018***	-0.001***
	(0.001)	(0.001)	(0.0003)	(0.0001)	(0.001)	(0.0001)
			Specification 2			
Constant	0.911***	0.908***	0.906***	0.910***	0.916***	0.911***
	(0.0004)	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0004)
Years (continuous)	-0.005***	0.00004	-0.0001	-0.001***	-0.014***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)	(0.0001)
Years >0	-0.091***	-0.189***	-0.015***	-0.008***	-0.040***	-0.037***
	(0.007)	(0.007)	(0.002)	(0.001)	(0.003)	(0.006)

Notes: Data from LAD. Shown are the regression coefficients and standard errors of a regression of a binary variable indicating survival to age 70 on a constant, a set of year of birth dummies, and the indicated scar intensity variables. Robust standard errors are clustered in year of birth. Three stars indicates significance at the 1% level; two stars for 5%; 1 star for 10%.

Our first set of regression results for females is reported in Table 1. The dependent variable in each case is survival to age 70, and the sample only includes those who are alive at age 54. Each column shows the result for one of the six different scars. The first panel has a basic specification with a constant, year of birth dummies, and a variable with the number of years (between 0 and 20) that the scar appears between the ages 35-54. The second panel has a second specification that adds a dummy for having a positive number of years, so that the impact of having any exposure to the scar and the linear impact of the scar between 1 and 20 years is separated. Robust standard errors clustered on year of birth are shown beneath in parentheses.

In specification 1 in the top panel, the estimated constant term shows a baseline survival rate which corresponds to the first year of birth in each sample.[13] The constant's value is about 0.91 across all specifications, indicating that about 91 percent of respondents survived from ages 54 to 70. The coefficient for the number of continuous years of scarring is negative and significant in all cases, but the magnitude is large for CQPP-D, DTC, and SA. The -0.015 coefficient for CQPP-D can be interpreted as meaning that those with 10 years of scarring have a 15 percentage point less chance of survival to age 70 as the baseline. This magnitude is a significant drop from the 90.9 percent chance of survival in the baseline; with the probability of dying increasing from about 9 percent to 24 percent. WC, EI and exposure to a low-income FSA show modest impacts.

The second specification attempts to separate the impact of having any (>0) scarring from the continuous impact between 1 and 20 years. The estimates here largely align with the lessons of Figure 5. There is a very large decrease in the probability of survival for having a positive number of years of scarring for the DTC (-0.189 estimate) and CQPP-D (-0.091 estimate), while there are more modest effects for the other scars. For SA and CQPP-D there are still dose-response effects for CQPP-D and SA in the second specification, but for DTC the regression shows that all of the impact is on the zero vs. positive distinction. For SA, the linear response is especially strong, at -0.014 per year of scarring.

We present the analogous regression results for males surviving to age 70 in Table 2. The results are very similar to what is seen for life expectancy in Figure 4. The baseline level of survival probability as indicated by the coefficient on the constant term is slightly lower here, at around 0.86, which reflects the lower survival probabilities of males. The pattern of coefficients for the males here is very similar to the female regression results in Table 1.

[13] The first year is 1982, so 35 year olds were born in 1947.

Table 2: Males Scar Intensity Regressions

	CQPP -D	DTC	WC	EI	SA	Low-inc FSA
			Specification 1			
Constant	0.860***	0.857***	0.858***	0.868***	0.868***	0.862***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0007)	(0.0002)
Years (continuous)	-0.022***	-0.020***	-0.007***	-0.005***	-0.027***	-0.002***
	(0.0004)	(0.0008)	(0.001)	(0.0001)	(0.001)	(0.0001)
			Specification 2			
Constant	0.864***	0.860***	0.860***	0.883***	0.873***	0.866***
	(0.0003)	(0.0002)	(0.0001)	(0.001)	(0.001)	(0.001)
Years (continuous)	-0.005***	0.0002	-0.004***	-0.001***	-0.017***	-0.0005**
	(0.001)	(0.002)	(0.001)	(0.0001)	(0.001)	(0.0002)
Years >0	-0.184***	-0.229***	-0.027***	-0.052***	-0.079***	-0.027***
	(0.012)	(0.015)	(0.002)	(0.001)	(0.006)	(0.003)

Notes: Data from LAD. Shown are the regression coefficients and standard errors of a regression of a binary variable indicating survival to age 70 on a constant, a set of year of birth dummies, and the indicated scar intensity variables. Robust standard errors are clustered in year of birth. Three stars indicates significance at the 1% level; two stars for 5%; 1 star for 10%.

The regression results shown so far look at survival to age 70. Of course, the life expectancy estimates represent an aggregation of all survival rates after age 54. So, it is useful to check if the different scars have varying impact for survival to different ages. We check on this possibility in Table 3. We show survival to age 65, 70, and 75 for the CQPP-D scarring, focusing on specification 2 (with a binary >0 variable and a linear term). The table shows results for females on the top and males on the bottom, although the results are very similar. There are large impacts on the binary incidence (years>0) variable that are fairly similar across different survival ages. However, the linear term is systematically stronger for survival to age 75 compared to survival to age 65.

Table 3: Survival Age Regressions for CQPP-D

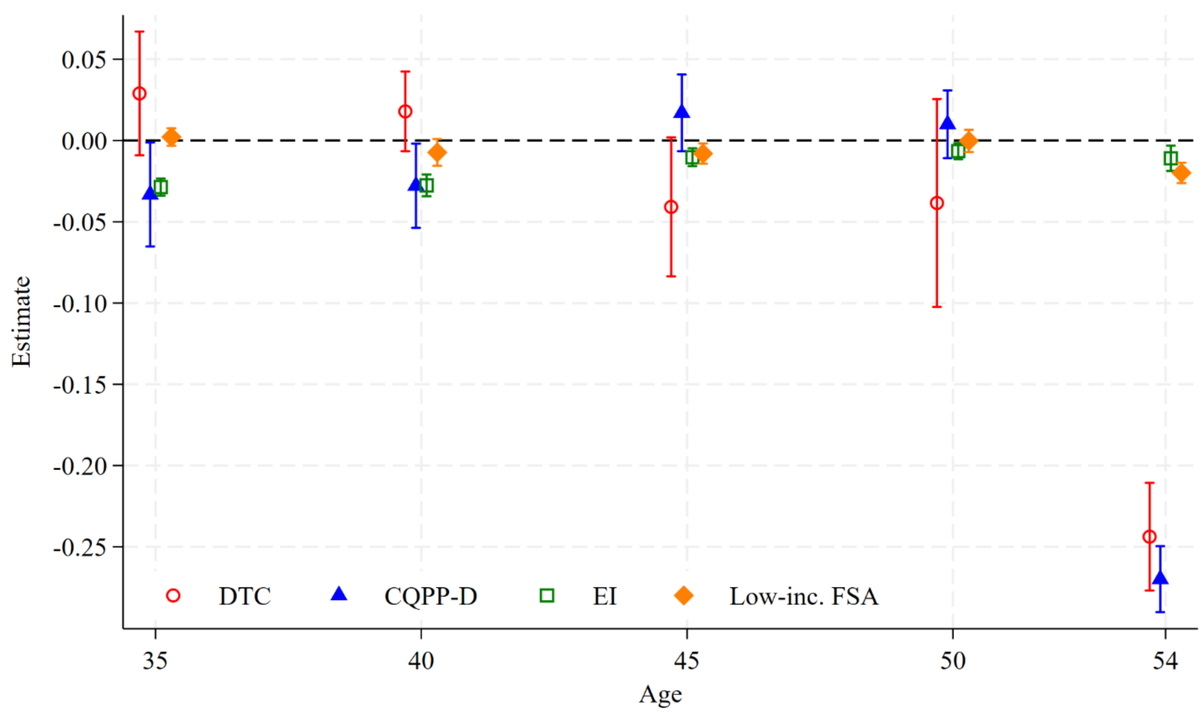
	Age 65	Age 70	Age 75
Females			
N	2,683,165	1,360,510	224,680
Constant	0.952***	0.911***	0.850***
	(0.0003)	(0.0004)	(0.002)
Years (continuous)	-0.002***	-0.005***	-0.005**
	(0.0005)	(0.001)	(0.002)
Years >0	-0.084***	-0.091***	-0.094***
	(0.007)	(0.007)	(0.015)
Males			
N	2,715,280	1,379,385	229,115
Constant	0.924***	0.864***	0.782***
	(0.0002)	(0.0003)	(0.00200)
Years (continuous)	-0.002**	-0.005***	-0.010***
	(0.0008)	(0.001)	(0.002)
Years >0	-0.149***	-0.184***	-0.173***
	(0.008)	(0.012)	(0.017)

Notes: Data from LAD. Shown are the regression coefficients and standard errors of a regression of a binary variable indicating survival to the age indicated on a constant, a set of year of birth dummies, and the indicated scar intensity variables. Robust standard errors are clustered in year of birth. Three stars indicates significance at the 1% level; two stars for 5%; 1 star for 10%.

Our third and final set of regression results looks at the age at which scarring incidence happens. Does it matter, for example, if you live in a low-income FSA when you are 35 compared to age 45? Which has the larger impact? We show the results for males in Figure 6 and for females in Figure 7. We have four different scars we examine here: DTC, CQPP-D, EI, and low-income FSA. The dependent variable is a binary for survival to age 70. For each scar there is a separate regression which includes year of birth dummies, a constant, and dummies for the incidence of a scar at five different ages: 35, 40, 45, 50, and 54. The figures plot the regression coefficients along with the 95 percent confidence interval associated with the robust standard errors clustered on year of birth.

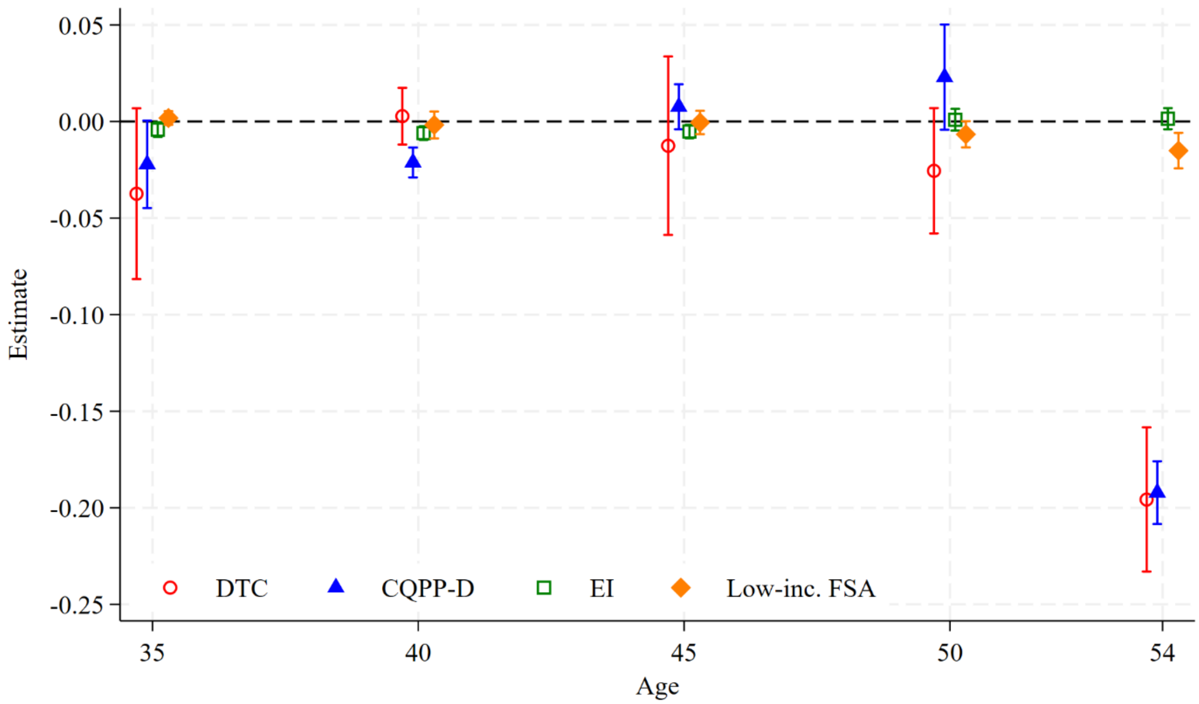
For males in Figure 6, the sharpest pattern is the dominance of incidence at age 54 for DTC and CQPP-D. It appears to matter little if there was a disability at earlier ages that stopped. What matters most for age 70 survival is the presence of a disability at age 54. Living in a low-income FSA at age 54 is worse than at younger ages and drawing on EI at younger ages is worse than older ages. But the magnitudes of these effects, while statistically significant, is small.

Figure 6: Regression coefficients for age at scarring, Males



Notes: Data from LAD. Reported are the estimated coefficients on regressions on a binary dependent variable indicating survival to age 70. The reported coefficients are from a single regression for each scar, with dummies for the incidence of the scar at single ages 35, 40, 45, 50, and 54. The 95 percent confidence interval based on robust standard errors clustered on year of birth are noted with lines.

Figure 7: Regression Coefficients for Age at Scarring, Female



Notes: Data from LAD. Reported are the estimated coefficients on regressions on a binary dependent variable indicating survival to age 70. The reported coefficients are from a single regression for each scar, with dummies for the incidence of the scar at single ages 35, 40, 45, 50, and 54. The 95 percent confidence interval based on robust standard errors clustered on year of birth are noted with lines.

The results for women in Figure 7 are very similar to men. The dominant impact is the presence of a disability at the end of the scarring window (ages 35-54) and not much what happens before then.

4.4 Future work

We are now working on regressions exploring how the lifecycle scars affect the income gradient of longevity. In particular, consider a regression of survival to age 70 on age 52-54 after-tax adjusted family income decile dummies. Then, in a second specification we can add variables capturing scarring between ages 35 and 54. We can then look at how the coefficients on income deciles change to learn about how much of the income gradient can be explained by the scars we are able to measure.

5.0 Conclusions

In this paper we argue for the usefulness of a cohort-based measure of longevity and demonstrate that our methodology can produce reliable and sensible results for cohorts as recent as the 1965 year of birth. Using Canadian administrative tax data, we recreate and extend income gradient findings from earlier work, showing that longevity improvements in Canada arise across the income distribution—at sharp contrast to the increasing inequality found in the United States. We then introduce six lifecycle scars that we are able to measure in our data for ages 35-54, including health shocks, benefit income receipt, and low-income neighborhood residency. Our results reveal a very large drop in longevity for those who claim a disability pension or the disability tax credit, modest longevity effects for benefit income receipt, and very modest impacts for living in a low-income neighborhood. For the Canada Quebec Pension Plan disability pension, men with no exposure at ages 45-54 live 12 years longer than men with heavy exposure. For women, the gap is 9 years. Looking at both the timing and intensity of shocks, arriving at older ages with a disability appears to have by far the largest impact on later-life survival.

Our results are descriptive in nature. Papers from many countries showing how longevity varies across income groups do not argue for the causality of the relationship; income is being used as an available index to categorize who is living longer lives. Our results on lifecycle scarring in this paper begin to unpack the earlier-life circumstances that are associated with shorter or longer lives, but we cannot rule out selection-based explanations of why those who live in low-income neighborhoods or receive benefit income live shorter lives. That said, our results do point researchers in directions that may prove useful for further analysis. In particular, the large impact of disability compared to benefit income or low-income neighborhood residency should be at the top of the list for further investigations seeking to understand why some live longer than others.

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