Appendix B: Robustness Checks

I conduct robustness checks of the results presented in the main text in Appendix B. First, I present trends in lifetime employment probabilities. Second, I show that changing the age group does not affect either population-level trends or trends by sex. Third, I investigate explanations for male-female parity in tenure at the time of hiring. I show that it holds within education groups. I also show that there has been convergence in the fraction of the male and female population of a given birth cohort who reach retirement ages with a lifetime job.

B.1. Lifetime Employment Analysis

I investigate the conditional probability of lifetime employment for the population as a whole and across the groups investigated in the main text. I do so by plotting the term $\frac{l_{20}}{l_5}$ from the tenure tables described in the main text.

Figure B.2.1 presents the trend in the conditional probability of having a lifetime job. Figure B.2.1 shows that, besides some sharp drops during the recessions, the probability of lifetime employment with an employer given that one has already spent 5 years with that employer exhibits no trend in the period. It averages around 18 percent, which is smaller than that reported in previous research (Hall 1982; Ureta 1992).

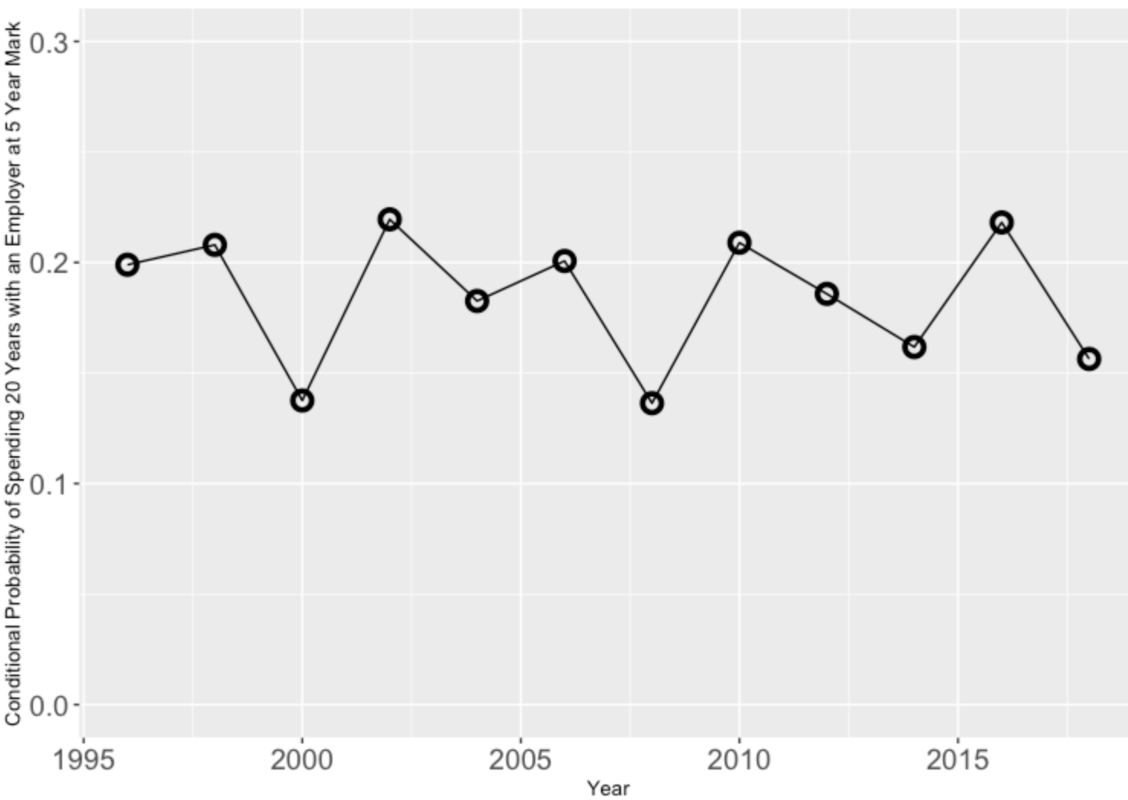
Figure B.2.2 presents between survey estimates of the conditional probability of a lifetime job estimated separately by sex. Given men's conditional expected tenure advantage, it is perhaps unsurprising that in most periods men also have higher probabilities of lifetime employment. Over the whole period, men have just under a 20-percentage point likelihood of making it to 20 years on the job given that they have spent 5 years with an employer compared to women's 17 percentage point likelihood. There is no clear trend in the conditional probability of lifetime employment over the period.

Figure B.2.3 presents between survey estimates of the conditional probability of a lifetime job estimated separately by race. In contrast to previous results like Ureta (1992), I find an inconsistent and modest difference between white and black workers' propensity to spend 15 additional years with an employer who they have already spent 5 years with. Taking simple means across all periods, I find that white workers who have spent 5 years with an employer have a 19 percent chance of spending the next 15 years with the same employer. Black workers' corresponding probability is 15 percent. Overall, racialized differences in the employment tenure distribution are persistent and exhibit no obvious trend toward equality.

Figure B.2.4 presents between survey estimates of the conditional probability of a lifetime job separately by ethnicity. I find an inconsistent and modest difference between Hispanic and non-Hispanic workers' propensity to spend 15 additional years with an employer who they have already spent 5 years with. Taking simple means across all periods, I find that Hispanic workers who have spent 5 years with an employer have a 20 percent chance of spending the next 15 years with the same employer. Non-Hispanic workers' corresponding probability is 19 percent. Overall, U.S. ethnic differences in job stability appear unstable and exhibit no obvious trend.

Males, whites, and Hispanics have slight advantages in conditional lifetime employment relative to females, blacks, and non-Hispanics. Variation in lifetime employment by group was small. No group differed by more than 4 percentage points from the other on average over the entire period. The largest differences were by race followed by sex followed by ethnicity. There was no clear trend in the conditional probability of lifetime employment for either the population as a whole or any group in the period I investigated.

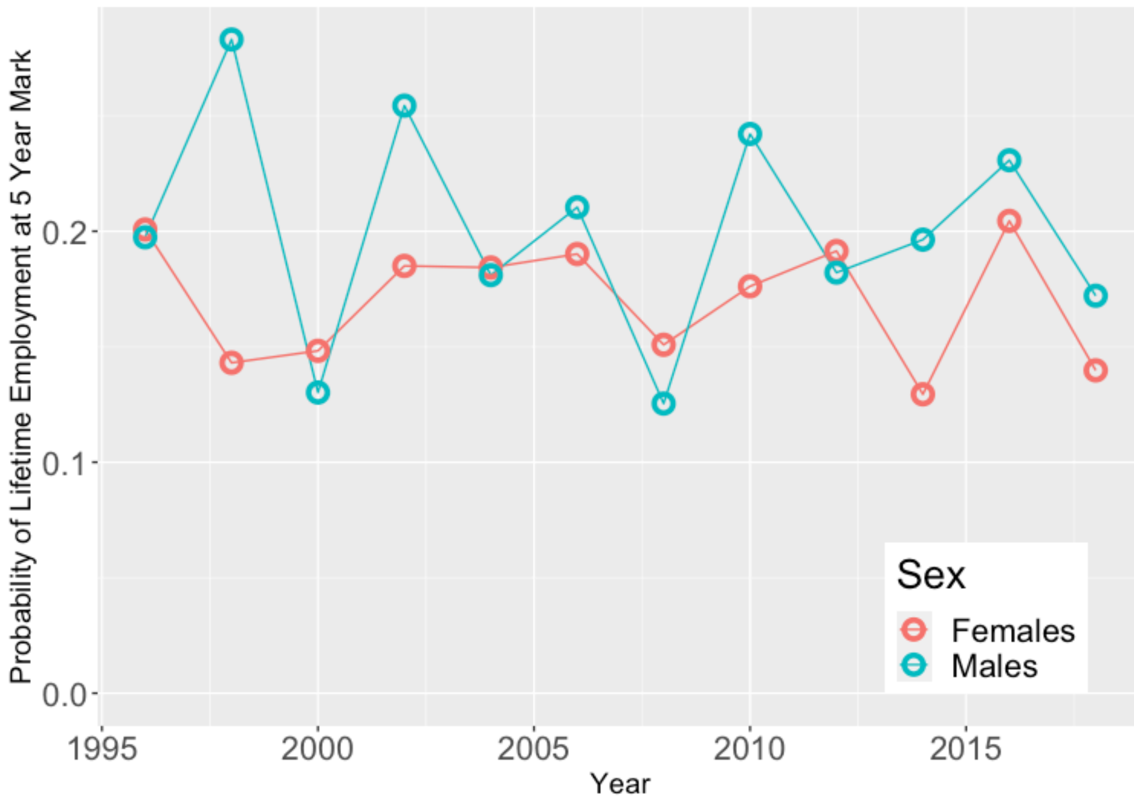
Figure B.1.1. Conditional Probability of Lifetime Employment for the U.S. Population, 1996 – 2020



Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for workers working in privately owned firms aged 14 to 99 from 1996 to 2019.

Notes: Figure B.1.1 graphs the conditional probability of reaching 20 years of job tenure for workers who have reached 5 years of job tenure during each between survey period from 1996 to 2020. The probability of reaching 20 years of job tenure hovered between 0.14 and 0.22 over the period and exhibited no trend over time. As with the expected employment duration calculations, one can see that there are drops in the conditional probability of lifetime employment during recessions. For instance, in the between survey period from 1998 to 2000 versus 2000 to 2002, the conditional probability of lifetime employment dropped seven percentage points, from 0.22 to 0.14.

Figure B.1.2. Conditional Probability of Lifetime Employment by Sex, 1996 – 2020



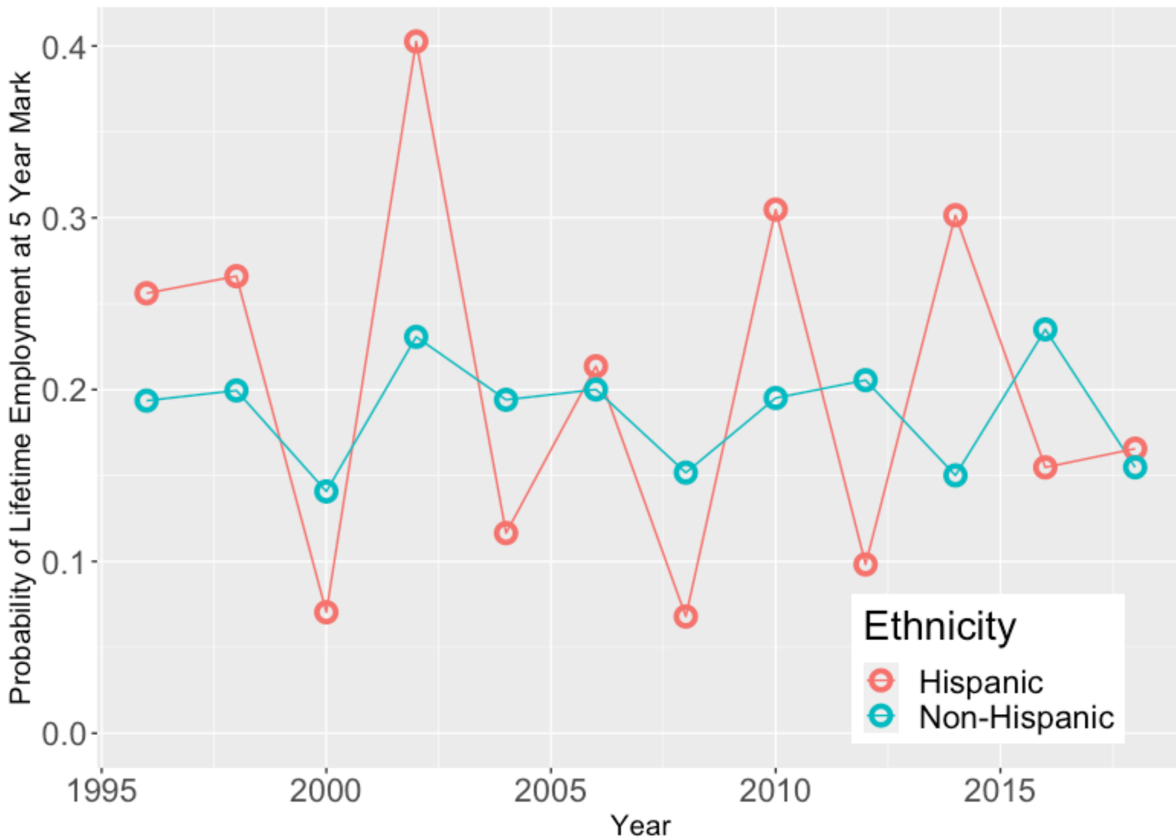
Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for male and female workers aged 14 to 99 working in privately owned firms from 1996 to 2019.

Notes: Figure B.1.2 graphs the computed conditional probability of lifetime employment for males and females for each between survey period from 1996 to 2020. Neither series exhibits any clear trend. Males maintain a mean advantage over women of about 3 percentage points over the period and an advantage in lifetime employment in most periods. Nonetheless, sometimes females have an advantage in lifetime employment. For instance, at the rates prevailing during the 2009 Great Recession, males (females) who had spent 5 years with their employer had a 15 percent (13 percent) chance of making it to 20 years with their employer.

Figure B.1.3. Conditional Probability of Lifetime Employment by Race, 1996 – 2020

Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for black and white workers aged 14 to 99 working in privately owned firms from 1996 to 2019.
Notes: Figure B.1.3 graphs the computed conditional probability of lifetime employment for blacks and whites for each between survey period from 1996 to 2020. Neither series exhibits any clear trend. Whites maintain a mean advantage over blacks of about 4 percentage points over the period, but the advantage is clearly inconsistent over time. For instance, at the rates prevailing during the 2011 recovery from the Great Recession, blacks (whites) who had spent 5 years with their employer had a 25 percent (19 percent) chance of making it to 20 years with their employer.

Figure B.1.4. Conditional Probability of Lifetime Employment by Ethnicity, 1996 – 2020



Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for Hispanic and non-Hispanic workers aged 14 to 99 working in privately owned firms from 1996 to 2019.

Notes: Figure B.1.4 graphs the computed conditional probability of lifetime employment for Hispanics and non-Hispanics at each between survey period from 1996 to 2020. Neither series exhibits any clear trend. Hispanics maintain an advantage over non-Hispanics of about 2 percentage points over the period, but the advantage is clearly inconsistent over time. For instance, at the rates prevailing during the 2009 Great Recession, Hispanics (non-Hispanics) who had spent 5 years with their employer had a 7 percent (15 percent) chance of making it to 20 years with their employer.

B.2. Changing the Age Group Under Consideration

I show that the trends reported in the main text for those aged 15 and above hold when using a narrower definition, those aged 19 to 64, in the IPUMS CPS JTS. The estimand for this population is the expected job tenure before age 64 for an employment relationship that began after age 19. Hiring by race and ethnicity are only available for the population aged 14 and over in the QWI and so I am unable to robustness check those results. Table B.2.1. presents case counts from the IPUMS CPS JTS in our analytic sample for the population aged 19 to 64. Our year-subpopulation cells are smaller than in the main text by construction. Nonetheless, cell sample sizes typically in the thousands.

B.2.1 Example Tenure Table

I present an example tenure table, Table B.2.2 for this narrower age group analogous to Table 3 in the main text. Hiring data by race and ethnicity are not available for the age range analyzed and so I include males instead.

Table B.2.1: IPUMS CPS JTS Narrow Age Group Analytic Sample Case Counts

Year	Total	Male	Female	[0, 1)	[1, 2)	[2, 5)	[5, 10)	[10, 15)	[15, 20)	20+
1996	31,195	16,109	16,109	7,455	3,803	6,482	6,184	3,039	1,977	2,255
1998	33,742	17,411	17,411	8,515	3,960	7,361	6,147	3,518	1,823	2,418
2000	34,324	17,922	17,922	8,306	4,033	7,705	6,117	3,604	1,876	2,683
2002	39,157	20,078	20,078	8,349	4,861	9,277	7,251	4,024	2,182	3,213
2004	37,537	19,292	19,292	7,490	4,152	9,296	7,701	3,665	2,216	3,017
2006	37,735	19,634	19,634	8,248	4,162	8,518	7,958	3,560	2,335	2,954
2008	36,921	18,966	18,966	7,408	4,271	8,584	7,508	3,796	2,103	3,251
2010	34,813	17,533	17,533	5,801	3,763	8,704	7,227	4,175	1,988	3,155
2012	34,159	17,676	17,676	6,435	3,534	7,452	7,423	4,101	2,003	3,211
2014	34,085	17,638	17,638	6,365	3,549	7,631	7,261	3,998	2,069	3,212
2016	32,843	17,024	17,024	6,473	3,641	7,621	6,400	3,626	2,131	2,951
2018	31,137	16,184	16,184	5,893	3,398	7,385	5,984	3,568	2,011	2,898
2020	29,861	15,553	15,553	5,661	3,276	7,126	6,045	3,143	1,800	2,810

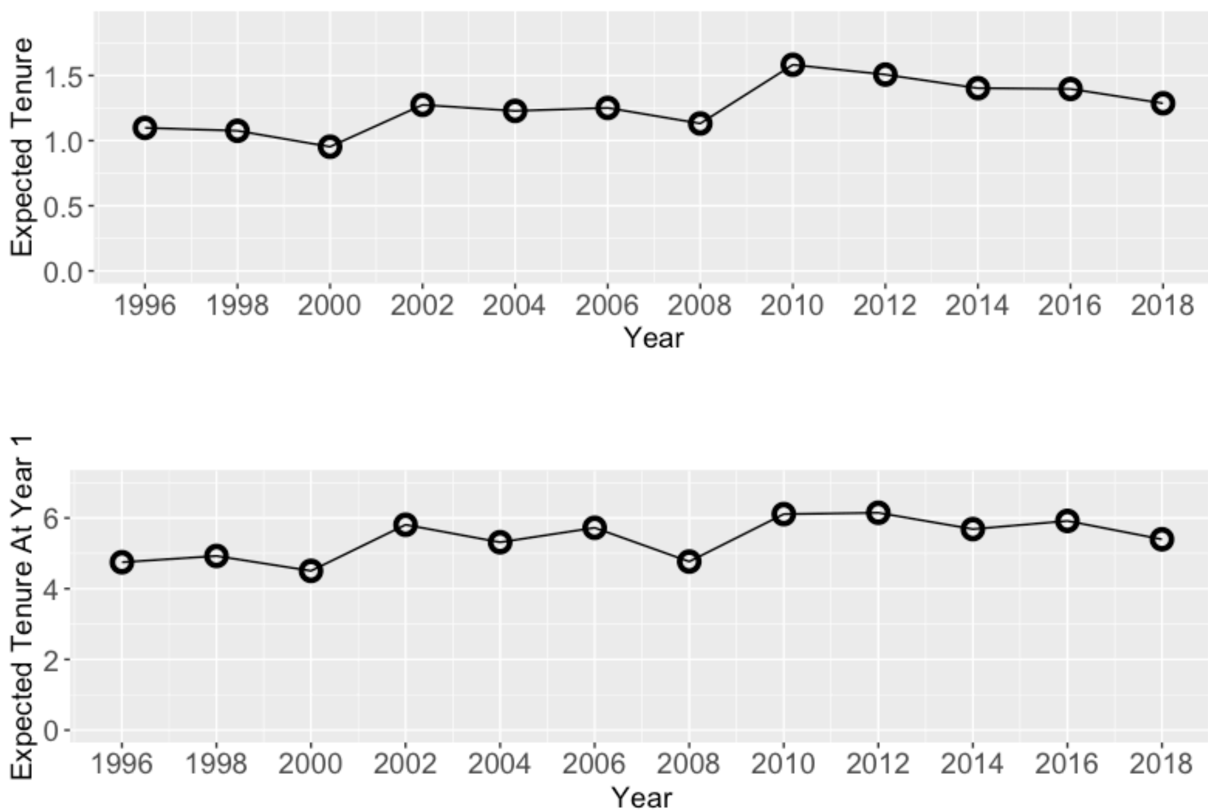
Source: IPUMS CPS JTS (Flood et al. 2022).
Notes: I drop all missing, ineligible, unincorporated self-employed, and unpaid worker cases before computing case counts. The age group considered is 19 to 64. Hiring data by race and ethnicity is not available for this age range and thus could not be analyzed using the formal demographic method used in the main text.

Table B.2.2: U.S. Period Tenure Table Examples for Age 19 to 64 for the Population and Selected Subpopulations, 2005 – 2006

Job tenure x	2004 J(x)	2006 J(x)	l_x	$p(x)$	e_x
Panel A: Population					
0	18,424,393	20,615,236	83,519,683	1.00	1.23
1	10,199,143	10,499,235	15,534,976	0.19	5.31
2	22,788,785	21,711,497	10,187,712	0.12	7.02
5	18,370,608	19,786,861	6,362,009	0.08	7.63
10	8,411,078	8,383,023	3,092,754	0.04	8.93
15	5,018,232	5,451,575	1,696,111	0.02	10.37
20	3,134,296	3,119,785	1,146,996	0.01	9.30
25	1,908,786	2,149,598	796,203	0.01	7.68
30	1565,846	1,462,372	611,402	0.01	4.43
Panel B: Females					
Job tenure x	2004 J(x)	2006 J(x)	l_x	$p(x)$	e_x
0	8,852,823	9,921,856	38,324,595	1.00	1.24
1	4,953,917	4,948,025	7,441,445	0.19	5.10
2	10,843,134	10,273,881	4,823,575	0.13	6.77
5	8,653,254	9,205,053	2,939,919	0.08	7.47
10	3,743,900	3,758,599	1,370,192	0.04	9.15
15	2,294,600	2,574,313	752,074	0.02	10.97
20	1,303,772	1,308,773	523,999	0.01	9.58
25	704,282	902,468	369,508	0.01	8.14
30	488,575	472,697	300,941	0.01	4.41
Panel C: Males					
Job tenure x	2004 J(x)	2006 J(x)	l_x	$p(x)$	e_x
0	9,571,570	10,693,381	45,195,029	1.00	1.22
1	5,245,227	5,551,209	8,093,046	0.18	5.53
2	11,945,651	11,437,617	5,363,905	0.12	7.27
5	9,717,355	10,581,808	3,424,907	0.08	7.79
10	4,667,178	4,624,424	1,728,141	0.04	8.78
15	2,723,632	2,877,262	948,336	0.02	9.90
20	1,830,524	1,811,012	623,236	0.01	9.14
25	1,204,504	1,247,130	429,981	0.01	7.34
30	1,077,271	989,675	315,482	0.01	4.42

Source: Author's calculation using the IPUMS CPS JTS (Flood et al. 2022) and QWI Hires. Series for the population of tenured workers aged 19 to 64.
Notes: The IPUMS CPS JTS excludes those who started working prior to age 19. The two columns are the number of jobs in each tenure group for each subpopulation. The radix l_0 for each panel is the number of between survey hires for each period divided by the length of the between survey period (2 years).

Figure B.2.1. Expected Employment Tenure and Conditional Expected Tenure for the U.S. Population Aged 19 to 64, 1996 – 2020



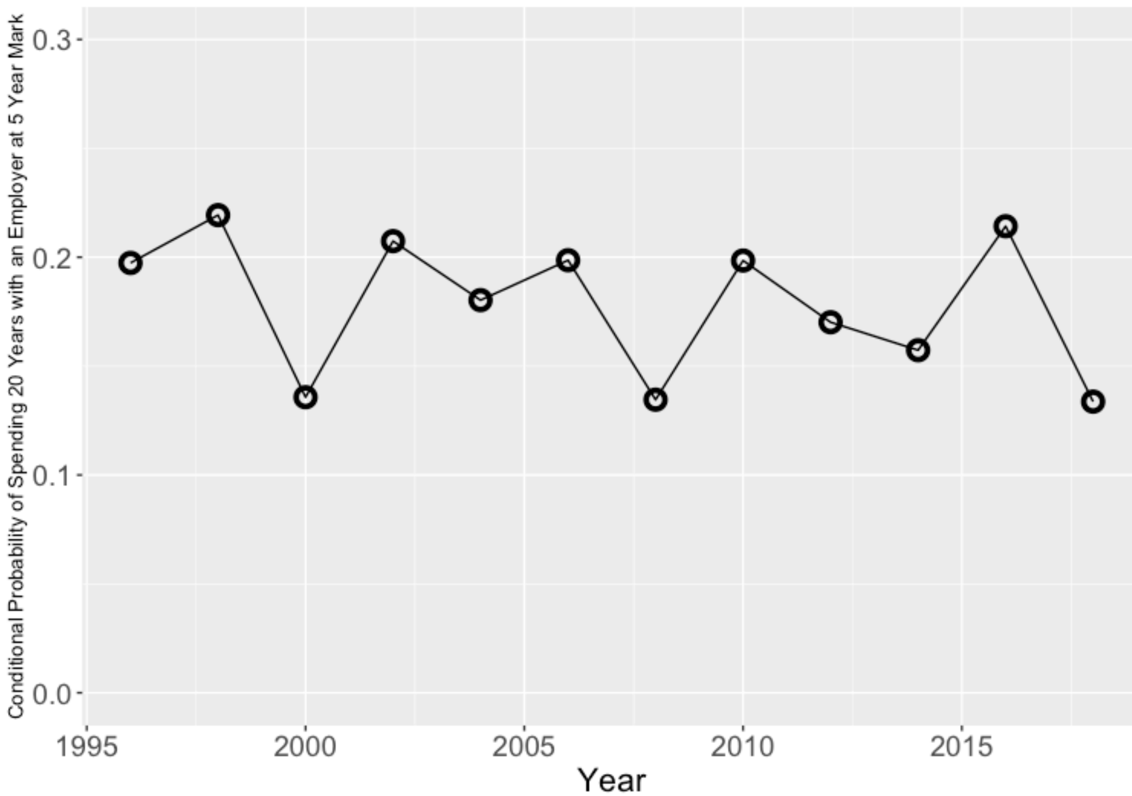
Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for workers working in privately owned firms aged 19 to 64 from 1996 to 2019.

Notes: Figure B.1.1's top panel graphs the computed expected job tenure for workers in each between survey period for the IPUMS CPS JTS. The top panel shows a slight increase in expected job tenure over time. Expected job tenures rose from 1.10 for the 1996 –1998 between survey period to 1.29 for the 2018 to 2020 between survey period. The population minimum (maximum) expected job tenure was 0.95 (1.58) from 2000 to 2002 (2010 to 2012). Figure B.1.1's bottom panel shows that the rise in workers' expected job tenure advantage also exists at the 1-year tenure mark. Conditional expected job tenures rose more half a year over the period, from 4.75 in the 1996 to 1998 between survey period to 5.40 in the 2018 to 2020 between survey period. The population minimum (maximum) conditional expected job tenure was 4.50 (6.15) during the 2000 to 2002 (2012 to 2014) between survey period.

Figure B.2.2. Expected Employment Tenure and Conditional Expected Employment Tenure for the U.S. Population Aged 19 to 64 by Sex, 1996 – 2020

Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for male and female workers working in privately owned firms aged 19 to 64 from 1996 to 2019.
Notes: Figure B.1.2's top panel graphs the computed expected job tenure for male and female workers for each between survey period for the IPUMS CPS JTS. The top panel shows an inconsistent expected job tenure advantage for male workers at the time of hiring of about 2 days. Figure B.1.2's bottom panel graphs the expected job tenure conditional on spending one year with an employer for male and female workers for each between survey period from 1996 to 2020. The bottom panel shows that male advantage grows to about 0.58 years of expected tenure after 1 year with an employer.

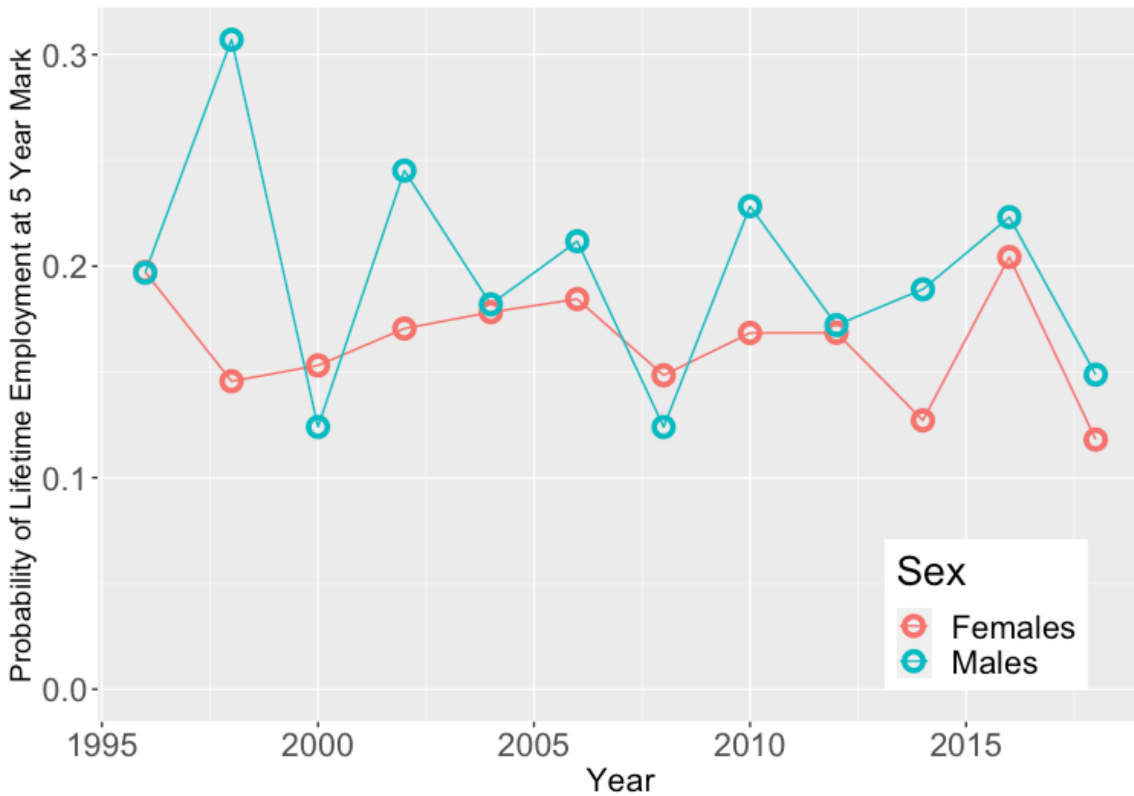
Figure B.2.3. Conditional Probability of Lifetime Employment for the U.S. Population Aged 19 to 64, 1996 – 2020



Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for workers aged 19 to 64 working in privately owned firms from 1996 to 2019.

Notes: Figure B.2.3 graphs the conditional probability of reaching 20 years of job tenure for workers who have reached 5 years of job tenure during each between survey period from 1996 to 2020. The probability of reaching 20 years of job tenure hovered between 0.13 and 0.22 over the period and exhibited no trend over time. As with the expected employment duration calculations, one can see that there are drops in the conditional probability of lifetime employment during recessions. For instance, in the between survey period from 1998 to 2000 versus 2000 to 2002, the conditional probability of lifetime employment dropped seven percentage points, from 0.22 to 0.14. Overall, the conditional probability of lifetime employment for those aged 19 to 64 strongly resembles the age 14 to 99 group.

Figure B.2.4. Conditional Probability of Lifetime Employment for the U.S. Population Aged 19 to 64 by Sex, 1996 – 2020



Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for male and female workers aged 19 to 64 working in privately owned firms from 1996 to 2019.

Notes: Figure B.2.4 graphs the computed conditional probability of lifetime employment for males and females for each between survey period from 1996 to 2020. Neither series exhibits any clear trend. Males maintain a mean advantage over women of about 3 percentage points over the period, but the advantage is not maintained over all periods. For instance, at the rates prevailing during the 2009 Great Recession, males (females) who had spent 5 years with their employer had a 15 percent (12 percent) chance of making it to 20 years with their employer.

Appendix B.3. A Second Look at Male and Female Job Tenures

The results in this paper, both in the main text and in Appendix B.1, show that sex differences in expected job tenure are small.[1] I check the robustness of my main text results in two ways. First, I break out my main findings by education group. Finally, I briefly investigate whether long-term employment relationships for men and women are converging across birth year cohorts (Molloy, Smith, and Wozniak 2024: 46, 54).

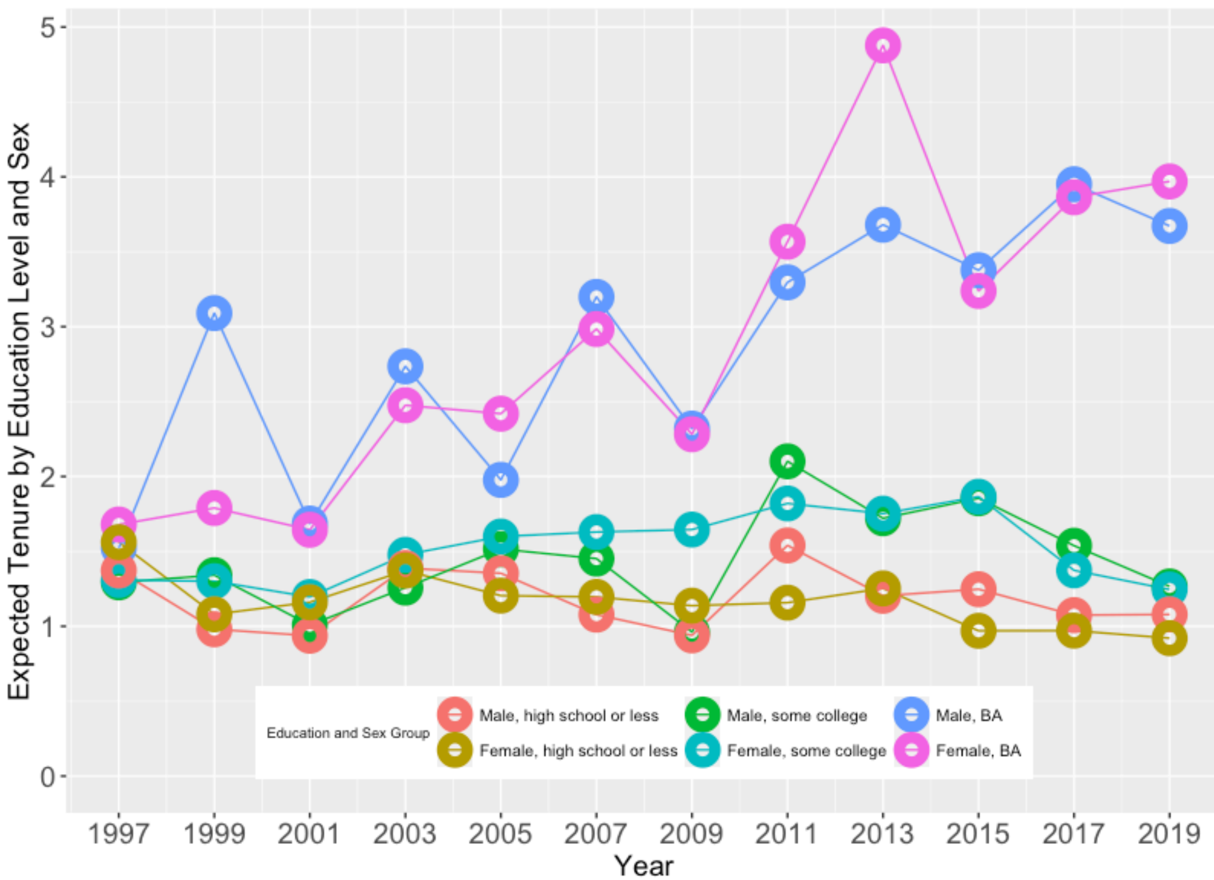
Baum (2022) points out that, in their early careers, female high school graduates have greater job stability than their male counterparts. Does this advantage extend to later career female high school graduates? I address this question in Figure B.3.1, which graphs the expected job tenure at hiring for males and females for three education groups: high school and less, some college, and BA. I do this with an age range of 25 to 99 because the QWI does not report hires by education and sex groups for those younger than 25 and I want to keep the estimand as comparable with that presented in the main text as possible. The estimand in Figure B.3.1 is the expected years spent in a role for a job that started after age 25.[2] There has been a divergence in expected job between the college-educated and non-college educated working populations' expected job tenures, but within an education category sex differences are small.

Although the main text focuses on early career differences between men and women, I also investigated to what extent men and women are converging in their later careers. To do this, I computed how the share of the population with lifetime employment (20 years or more with a single employer) varied by birth cohort and sex. In Figure B.3.2 below, I plot the fraction of each birth cohort at near retirement ages (55 to 65) who report having achieved lifetime employment, broken down by sex. I exploit all CPS JTS surveys available from IPUMS (1983, 1987, 1996 – 2020 biennially) to obtain population representative samples from birth year cohorts ranging from 1925 to 1967 (Flood et al. 2022). Figure B.3.2 shows that, at ages near retirement, the fraction of men and women with high tenures start far apart but exhibit near convergence for cohorts born nearer to the present. The fraction of males reporting lifetime employment near retirement ages has declined throughout the period. The fraction of females reporting lifetime employment near retirement rises from 1925 to the early 1960s, when it begins falling again. This supports the notion that, in the last quarter century, job tenure trajectories have been converging over time, but shows that there are both early and late career mechanisms contributing to this. Males have a slightly smaller likelihood of making it to one year of tenure. Later in the career, men and women's job tenure trajectories are converging because women are increasingly likely to have long-careers at retirement ages and men are increasingly less likely to have long-careers at retirement ages. Overall, these facts support the claim made in the main text that, in the last quarter century, males and females have similar expected job tenure at hiring.

[1] The main text explains that the expected tenure parity arises because male employment relationships with tenures less than one year typically end earlier than female relationships. In recent years, the female advantage in job survival in the early years appears to substantially offset the female disadvantage in expected job tenure generated by childbirth.

[2] This estimand is different from that reported in either the main text or Appendix B.1. It is also older than the population studied by Baum (2022) in the NLSY '97.

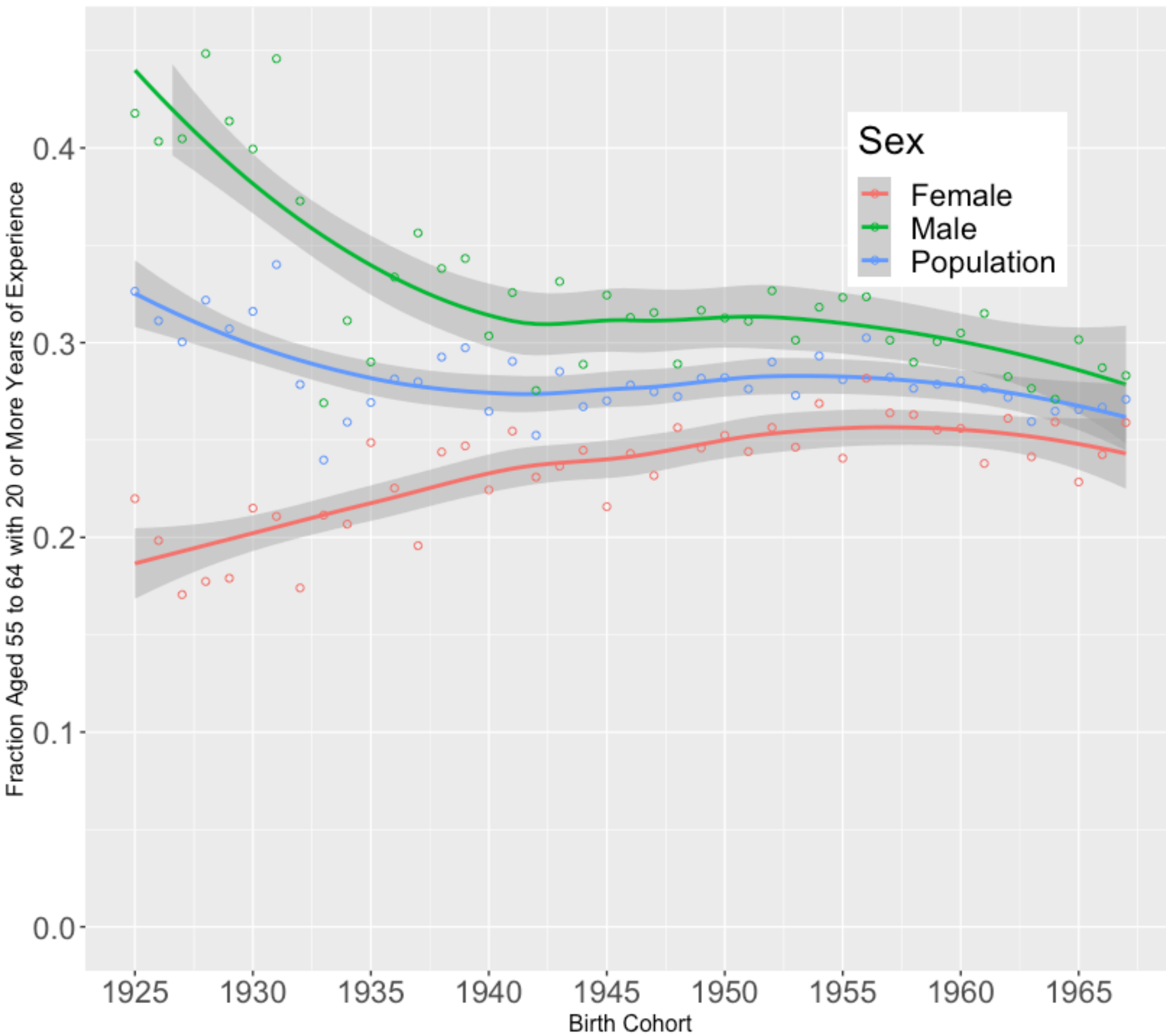
Figure B.3.1. Expected Tenures by Education and Sex



Source: Author using IPUMS CPS JTS 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, and 2020 (all non-government, non-self-employed employees) and the Quarterly Workforce Indicators hiring series for Hispanic and non-Hispanic workers aged 25 to 99 working in privately owned from 1996 to 2020.

Notes: Figure B.3.1 graphs the computed expected job tenure for workers of each sex and education combination for the between survey period from 1996 to 2020. The college educated go from a slight disadvantage to an advantage starting in in the 1998 to 2000 between survey period, but within an education category both sexes have similar expected job tenure. Across all years, the mean differences in expected tenure between the sexes are 0.02 years for the high school or less group in favor of men, 0.08 years for the "some college" group in favor of women, and 0.02 years for the college educated group. Overall, the differences between the sexes are small within education groups. Therefore, differential experiences within an education group are not plausible contributors to male-female parity at the population level. Females with a high school education or less had greater expected job tenure in most periods, especially prior to 2016. This corresponds with the result by Baum (2022). Nonetheless, within educational categories male-female differences were small and noisy.

Figure B.3.2. Fraction of Workers Nearing Retirement with 20 Years or More of Employment Tenure



Source: Author's calculation using the IPUMS CPS JTS series from 1983, 1987, 1996 – 2020 (biennially).

Notes: Male cohort fractions aged 55 to 64 with 20 years or more with an employer are plotted in the green line. Female cohort fractions aged 55 to 64 with 20 years or more with an employer are plotted in the red line. The population fractions of workers nearing retirement with 20 years or more of employment tenure are shown as the blue line. The shaded area is a 95 percent confidence interval for line obtained from a loess smoother.

Appendix C: A Microsimulation of Labor Market Processes

I conducted a highly stylized microsimulation of the population of jobs using the tenure-specific job hazards that Baum (2022) estimated from real job vintages in the NLSY '97. I compute empirical survival probabilities and expected job durations at various tenures from the raw distribution and compare those to the survival probabilities and expected job durations that I would estimate using the variable-r life table estimation algorithm. To document the performance of the variable-r algorithm in various realistic scenarios, I apply a specific digit-bias in tenure reporting similar to that documented in prior research (Diebold, Neumark, and Polsky 1997; Neumark, Polsky, and Hansen 1999, S59). The bias causes the survey respondent to misreport their true employment tenure according to a reporting function, described in detail below.

There are four reasons to conduct and report such a simulation. First, although the variable-r algorithm for life table estimation has been tested extensively with both real and simulated data, I am not aware that any results from the latter tests have made their way into the peer-reviewed literature (Preston and Bennett 1983; Preston 1987; Preston, Heuveline, and Guillot 2001, 186). Perhaps due to limited journal space, authors sometimes refer to properties of the intercensal life table estimation algorithms that they have observed in simulations without presenting the detailed results or even the basic parameters of the simulations themselves (Coale 1984, 206; Coale, John, and Richards 1985, 622; Preston, Heuveline, and Guillot 2001, 186). Second, a reasonably close recovery of the true survival function when data are reported accurately in single-year intervals should engender confidence in the reader that I have implemented the variable-r method correctly. Third, one might be concerned that there are special features of the hazard function, e.g., that jobs survive for far less long than human lives, that may hamper the variable-r algorithm in estimating survival curves, expected employee tenures, and group differences in these quantities. Fourth, the code and microsimulation results I provide set a benchmark against which one can evaluate various pre- or post-processing procedures to complement the variable-r algorithm as well as future innovations in organizational demography.

C.1 Microsimulation Details

The labor market starts with zero jobs. Every two weeks, the economy generates hires from a Poisson distribution with mean 1000. Jobs are destroyed at tenure-specific rates implied by the piecewise exponential job hazard function for 18 – 36-year-old females with a high school education and no dual employment estimated using the NLSY '97 (Baum 2022, 550, 556 – 558, Figure 1, Panel B).[3] The tenure-specific hazard rate is constant from year 15 onwards. Jobs are assigned a tenure-at-job destruction immediately upon creation based on the job survival curve. A hypothetical organizational demographer takes a census of this economy at period 50 and 52 and has perfect information on the number of hires in the intervening period. The open interval for this census of jobs begins at year 35.[4] That organizational demographer feeds counts of the jobs indexed by tenure and hires into the variable-r algorithm and uses this to estimate the job tenure survival curve and expected job duration curve. This exercise is repeated 30 times to

[3] Baum did not respond to emailed requests for code, data, or coefficients from his survival analysis. I used the R function metaDigitise to extract estimates of the hazard function for job destruction directly from the graphic. I include the scraped data with the replication kit.
[4] I chose this open interval to avoid the problem of having single-year tenure cells with zero employees in them.

generate a range of variation. Variation in the simulation comes both from individual variation in job survival as well as the intercensal total hiring. I conduct a second labor market simulation assuming that all job separation hazards at all tenures are reduced by 15 percent. This would be a modest reduction in the job separation hazard, smaller than the hazard ratio of high school graduates' job separation rates to college graduates' job separation rates calculated in Baum (2022).

I consider 4 scenarios. In the first scenario, the variable-r algorithm uses single year tenure data, and the analyst has access to true job tenures. The second scenario is the same as the first except that I first abridge the data to the intervals [0, 1), [1, 2), [2, 5), [5, 10), [10, 15), [15, 20), [20, 25), [30, 35), and $[35+)$. In the third and fourth scenarios, the data are subject to a digit-bias. I study the potential effects of digit-preference on my estimates by imposing a digit-bias inspired by that documented in Neumark, Polsky, and Hansen (1999, S59 – S60). Specifically, let the individual respondent report the true tenure to the hypothetical census taker with probability p and report a nearby multiple of 5 with probability $1-p$. The digit-bias I impose is more severe the longer the length of t, the true tenure spell: $p = 0.94 - 0.008t$.[5] In the third scenario, the data are analyzed in single-year intervals. In the fourth scenario, the data are analyzed after abridging to the intervals used in the second scenario.

I take 25,000,000 draws from the data generating processes described above and use the empirical distribution of job survival times from those draws to approximate the true job survival curves and conditional expected job duration curves for both labor markets. I compare the approximated true job survival curve and approximated true expected job duration curve with the same curves estimated via variable-r methods as described above. I plot the job survival and conditional expected job duration curves from 0 to 30 years of tenure. The results are presented across four different scenarios, with each scenario representing a different combination of whether errors in the data are present (yes/no) and whether the analyst has abridged the tenure data before analysis (yes/no).

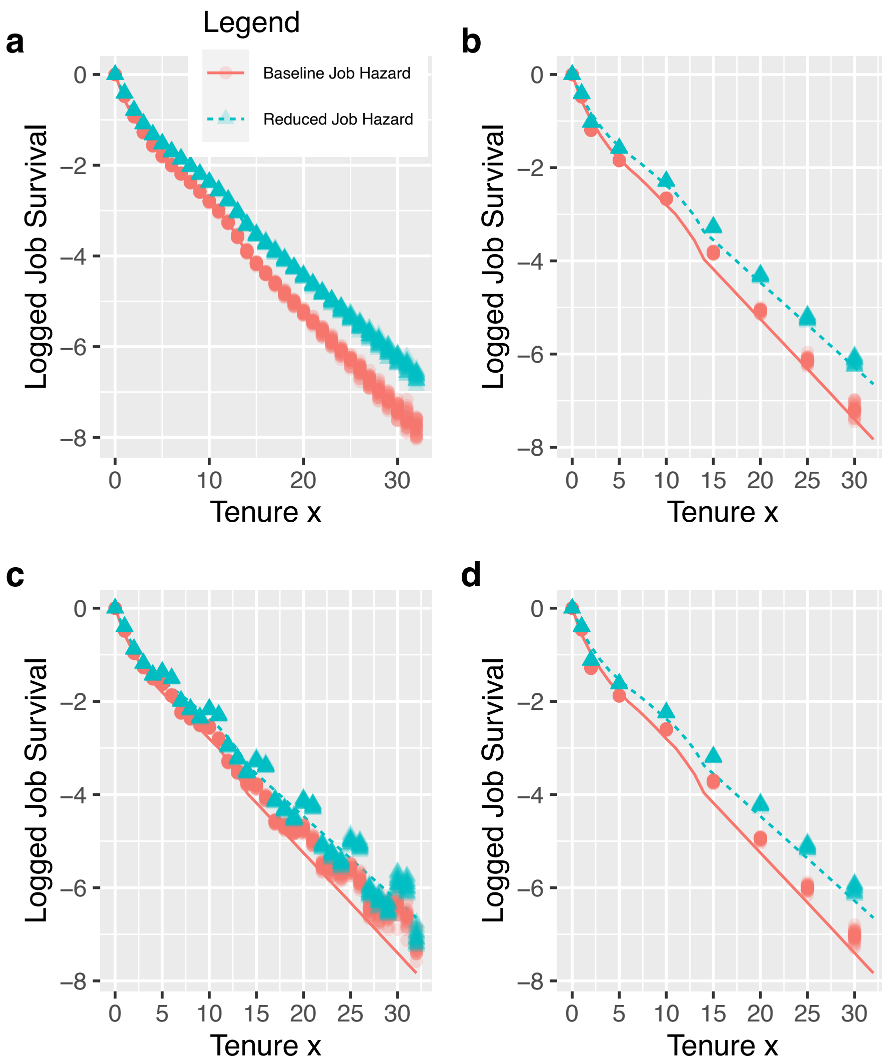
The results are presented across Figures A1 and A2. Figure A1 plots results comparing logged job survival probability estimate from variable-r with those obtained from the approximate underlying distribution. Figure A2 plots results comparing expected job tenures from variable-r with those obtained from the approximate underlying distribution. In both Figures, Panels a, b, c, and d graph the baseline and reduced hazard processes for the first, second, third, and fourth scenarios, respectively.

For each panel, the red solid line graphs results from the labor market constructed using Baum's (2022) estimates and a blue dotted line graphs results from the labor market in the hypothetical world in which job separation hazards were reduced by 15 percent for all tenures. Each point corresponds to an extracted variable-r estimate of the job survival curve or conditional expected job tenure curve; red open circles correspond to the estimates extracted from data generated from original economy's simulation while blue open triangles correspond to estimates derived from the economy in which tenure-specific hazards drop by 15 percent. The

[5] Neumark, Polsky, and Hansen (1999) found that in their sample, letting t' be the *reported* job tenures and p' be the probability that t was rounded to a nearby multiple of 5 to generate t', grid search yielded parameter estimates of $\gamma \in [0.94, 0.99]$ and $\delta \in [-0.008, -0.005]$ in the formula $p' = \gamma + \delta t'$. In the simulation, I start by simulating the true tenure t. I subsequently impose the most severe form of heaping consistent with respondents' having a reporting function in which they round their tenure to a multiple of 5 with probability $1-p$ and report their true tenure with probability $p = \gamma + \delta t$ with $\gamma \in [0.94, 0.99]$ and $\delta \in [-0.008, -0.005]$.

main goal of the simulation is to see whether this change would be detectable using the variable-r algorithm.[6]

Figure C1: Empirical and Variable-r Estimated Logged Job Survival Probabilities from a Simulated Labor Market



Note: Red circles represent point estimates of tenure-specific logged job survival probability from the variable-r algorithm under baseline hazard rates. Green triangles represent point estimates of tenure-specific logged job survival probability from the variable-r algorithm when hazard rates are reduced by 15 percent. The solid lines represent empirical logged job survival probabilities drawn from a simulated labor market of 25,000,000 jobs. In the first scenario, presented in Panel a, the variable-r algorithm uses single year tenure data, and the analyst has access to true job tenures. The second scenario, presented in Panel b, is the same as the first except that I first abridge the data to the intervals [0, 1), [1, 2), [2, 5), [5, 10), [10, 15), [15, 20), [20, 25), [30, 35), and [35 +). In the third and fourth scenarios, presented in Panels c and d respectively, the data are subject to a digit-bias inspired by that documented in Neumark, Polsky, and Hansen (1999, S59 – S60). In the third scenario, presented in Panel c, the data are analyzed in

[6] I also considered an alternative abridging strategy that crudely bucketed the data at [0, 1), [1, 5), [5, 10), [10, 15), [15, 20), [15, 20), [20, 25), [25, 30), and [30, ∞) as well as a heaping scenario in which hires grew at 0.1 percent biweekly. Neither of these scenarios changed the qualitative conclusions of this section.

single-year intervals. In the fourth scenario, presented in Panel d, the data are analyzed after abridging to the intervals used in the second scenario presented in Panel b.
Source: Author's calculations using the hazard process from Baum (2022) and a digit-preference bias like that documented by Neumark, Polsky, and Hansen (1999).

C.2 Microsimulation Results and Evaluation

In general, the variable-r algorithm could always estimate the expected job duration with fidelity. Across scenarios 1, 2, and 4, for both baseline and reduced hazard, the mean estimated expected job duration was within 1 percent of the ground truth. Even when heaping was imposed with no adjustment, the expected employee tenure was with 5 percent of the ground truth. Visually, it is also clear that the variable-r method's extracted job survival and expected job tenures could distinguish the baseline and reduced hazard scenarios. Only under the third scenario, and only at tenures 6 and 11, was it the case that the variable-r expected eventual tenure estimates were typically higher for the reduced hazard group. The variable-r method as a point estimation technique appears well-suited for the detection of modest group differences in expected employee tenure under realistic job separation conditions.

The variable-r methods point estimates also captured the approximate true job survival curve and the conditional expected job duration curve the data are analyzed in single-year intervals and reported without error. The conditional expected job durations probabilities with single-year intervals and no digit-preference were typically within 5 percent of the ground truth at the tenures tested. Estimation error nonetheless arises from sampling error, the discretization of the "hiring" process, and discretization of the variable-r implementation (Kim 1986; Preston, Heuveline, and Guillot 2001). Expected job duration estimates fan out at higher levels of tenure under all scenarios for both hazards. The hypothetical census-taker has less data to work with at higher tenures as more jobs are lost to attrition. An analyst should expect the eventual tenure to be more uncertain at higher employee tenures as a rule. Provided an analyst has access to accurate surveys of job tenures and between-survey hiring data, estimating the survival curve and conditional expected job duration poses no special estimation difficulties for the variable-r algorithm as I have implemented it.

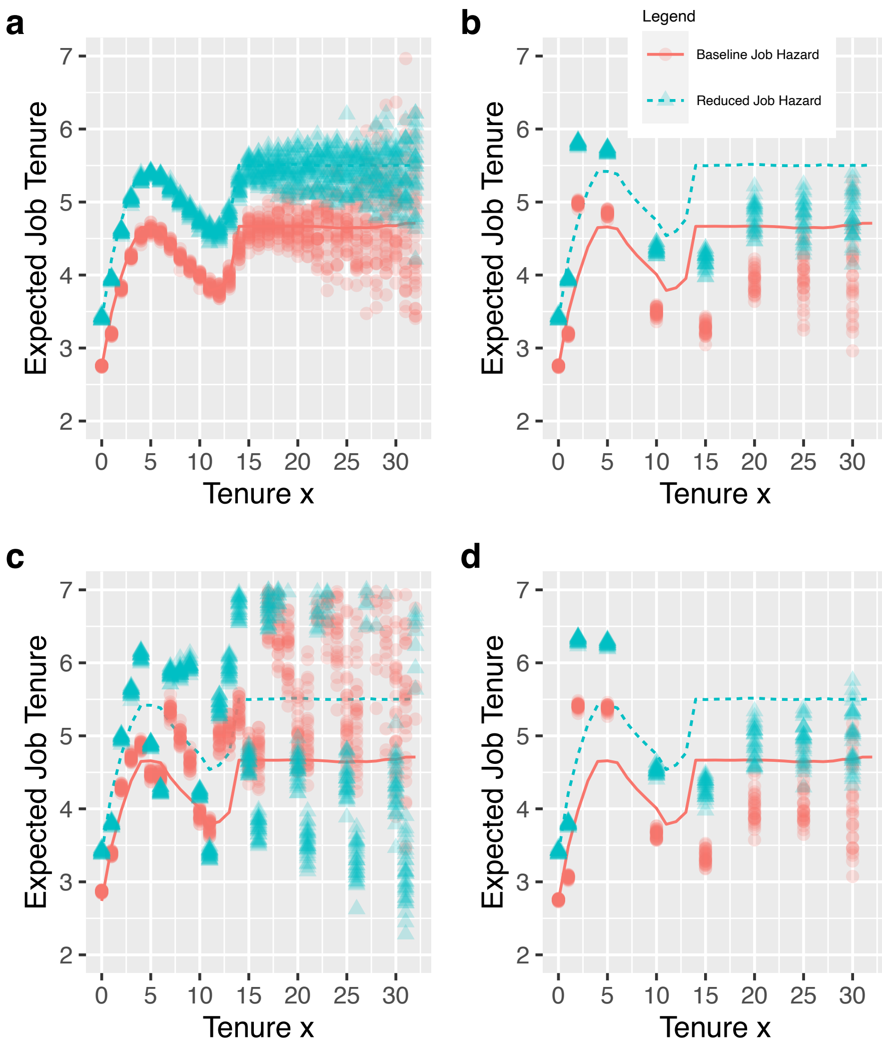
Turning to scenario 2, presented in Panel b, abridging accurate data induces small absolute errors in the job survival curve and larger errors in conditional expected employee tenure. Across both hazard categories, at tenures ranging from 2 to 15 years, the error in conditional expected employee tenure estimates ranged from 5 to 42 percent. The simulation suggests that abridging, when the data are accurately reported, has considerable potential costs when hazard varies with tenure. Those costs appear in the form of biased estimated eventual tenure estimates at policy-relevant conditional expected tenures. This motivates a focus on e_0 and e_1 in the main text.

In scenario 3, presented in Panel c, heaping induces incoherent life tables as discussed in the main text. The typical tenure table estimate has an upward sloping period survival curve around multiples of 5, e.g., at 6, 11, 16, and 21 on my run of the data. As shown in scenario 4, presented in Panel d, abridging was sufficient to eliminate upward sloping period survival in general. On the other hand, abridging appears to induce larger errors in conditional expected tenure levels than for estimates based on single-year data even when digit-bias distorts the estimated survival distribution to the point of incoherence. When estimating conditional expected job duration at high tenures, e.g., more than 10 years, abridging usually increased the distance between the variable-r's output and the empirical distribution of tenures that I have been treating as the ground truth throughout this exercise. Abridging reduced the variance of the variable-r conditional expected job tenure estimates.

I conclude that, as with human populations, combining abridging with variable-r algorithms enables a reasonable approximation of the job survival curve under realistic levels of heaping. Abridging should be especially considered by an analyst that places a high value on tenure table coherence. Abridging generates likely generates fewer benefits for an analyst only concerned with conditional expected job tenures even when moderate levels of digit-bias are present. For the expected job tenures, errors were indeed slightly smaller under abridging. At medium tenure levels (such around 2 and 5 years of tenure), abridging sometimes yielded larger errors in the expected eventual tenure estimate than were found in single-year data even under digit-preference biases. At high tenures, abridging usually reduced the error in the estimated conditional expected job tenure. Overall, these results inspire confidence that expected employee tenure at low tenures will be well approximated using variable-r methods.

Modest group differences in conditional expected job duration can be reliably detected by the algorithm at short and medium tenures under realistic levels of digit-bias. In the simulation, across the scenarios, the estimated conditional expected job duration distributions from the two different groups only began to visually overlap near or after 20 years of tenure. At higher tenures, point estimation of group differences may need to be supplemented with statistical inference to establish their existence and plausible size. Not all experiments were unequivocally successful: the variable-r method did not perform well at estimating the level of conditional expected job tenures at high tenures under the heaping conditions imposed in the simulation regardless of whether the data was abridged or analyzed in single-year intervals. This likely arises for at least two reasons. First, the digit bias I impose becomes more severe at higher tenures. Second, less data is available at higher tenures. Nonetheless, the variable-r estimates appeared to be converging to the correct conditional expected tenure levels as x increased when job separation hazard was flat.

Figure C2: Empirical and Variable-r Estimated Conditional Expected Job Tenures from a Simulated Labor Market



Note: Red circles represent point estimates of tenure-specific logged job survival probability from the variable-r algorithm under baseline hazard rates. Green triangles represent point estimates of tenure-specific logged job survival probability from the variable-r algorithm when hazard rates are reduced by 15 percent. The solid lines represent empirical logged job survival probabilities drawn from a simulated labor market of 25,000,000 jobs. In the first scenario, presented in Panel a, the variable-r algorithm uses single year tenure data, and the analyst has access to true job tenures. The second scenario, presented in Panel b, is the same as the first except that I first abridge the data to the intervals [0, 1), [1, 2), [2, 5), [5, 10), [10, 15), [15, 20), [20, 25), [30, 35), and [35 +). In the third and fourth scenarios, presented in

Panels c and d respectively, the data are subject to a digit-bias inspired by that documented in Neumark, Polsky, and Hansen (1999, S59 – S60). In the third scenario, presented in Panel c, the data are analyzed in single-year intervals. In the fourth scenario, presented in Panel d, the data are analyzed after abridging to the intervals used in the second scenario presented in Panel b.
Source: Author’s calculations using the hazard process from Baum (2022) and a digit-preference bias like that documented in Neumark, Polsky, and Hansen (1999).