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Evolving Labor Market Transition Probabilities and Their Impact on Worklife Estimates

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Abstract

A panel of age-specific transition probabilities is developed for the three-decade period 1980 to 2010. Analysis shows that both male and female transition probabilities have evolved over the 30-year span. The transition probabilities are used to calculate both period and cohort worklives. The results differ starkly for men and women. For men, worklives are most affected for those with little education. For women, obtaining a college degree has the most impact on worklives. The results suggest that using historical period worklives may have mis-estimated worklives for these two groups relative to cohort estimates.

I. Introduction

A worklife is an estimate of the number of years a person is expected to remain active in the labor market. Worklife estimates are typically derived from first-order Markov models using observations of the labor force participation of populations of persons.[1] These models contain three mutually exclusive states: active, inactive and an absorbing state reflecting mortality. Underlying these Markov models are transition probabilities into and out of the active and inactive states, as well as transition probabilities into the absorbing state.

The standard methodology is to estimate worklives using *period* transition probabilities. Period transition probabilities are those experienced by current workers of different ages. The underlying assumption is that the transition probabilities individuals will face as they grow older are the same as those faced by currently older workers. For example, consider two individuals, one who is currently 25 years old and another who is currently 45. In 20 years, when the 25-year-old turns 45, she is assumed to have the same transition probabilities as the woman who is currently 45. Given trends in labor market activity, this may or may not be the case.

Worklife calculations can also be based on cohort transition probabilities. Cohort transition probabilities reflect projected future changes in labor market conditions that will be faced as the current cohort ages. Just as cohort life ta-

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[1]See, for example, Ciecka, et al., (1995, 2000), Krueger (2004), Skoog and Ciecka (2001a, 2001b, 2002, 2004) and Skoog, et al., (2011).

bles are often superior to period life tables for population predictions, we would expect cohort transition probabilities to be superior in projecting worklives.[2] Currently there are no published sources of projections of future transition probabilities. This paper moves towards that goal by providing a panel data set of transition probabilities for the past 30 years. We can use this historic record to test whether cohort transition probabilities faced by previous generations have differed from period transition probabilities.

This study follows the standard approach of using Current Population Survey (CPS) data from the Bureau of Labor Statistics to estimate transition probabilities. The CPS allows matching individuals at points in time one year apart. By observing an individual at two points in time, it is possible to observe transitions into and out of the labor force, as well as probabilities of remaining in either state during the year. In contrast to standard approaches, we construct a panel data set from March 1980 through March 2010. We are thus able to perform a 30-year longitudinal study of transition probabilities by age.

Because a major contribution of this paper is the construction of the data set, we devote Sections II, III and IV to a detailed description of the process used to extract and construct the panel data set. Extracting the data and matching individuals from one year to the next is complicated by the fact that the data format is inconsistent across years and documented changes in format over the years are fragmentary.

We then use the panel data set to estimate four relevant transition probabilities:

1) the probability of being inactive at age x+1 conditional on being inactive at age x, ${}^{i}p_x^{i}$;
2) the probability of being active at age x+1 conditional on being inactive at age x, ${}^{i}p_x^{a}$
3) the probability of being inactive at age x+1 conditional on being active at age x, ${}^{a}p_x^{i}$; and
4) the probability of being active at age x+1 conditional on being active at age x, ${}^{a}p_x^{a}$.

Transition probabilities are estimated for men and women by education in each year from 1980 through 2010.[3] This panel of transition probabilities allows for analysis of movements in transition probabilities over time as well as their impact on worklife calculations.

Over the 30-year span of this study, transition probabilities for men and women have evolved. The probability of remaining active has fallen for males under the age of 60, but risen for males over 60. That is, "working age" males are now more likely to exit the workforce but are more likely to remain active after traditional retirement ages. The probability of remaining inactive has risen for males below the age of 60, while remaining relatively stable over the age of 60. For women, the probability of remaining active has risen for all ages.

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[2]See Bell and Miller (2005).

[3]In a working paper, we examine the time series nature of transition probabilities.

The probability of remaining inactive has changed little for women under the age of 40, but has fallen for females over 40.

The evolving transition probabilities have changed period estimates of worklives. The results reveal an interesting contrast between male and female labor market activity. For young men as a whole, period worklife estimates in the late 2000s are slightly longer than period worklife estimates from the early 1980s, but are noticeably longer for older men. For women, worklives are longer for women at all ages.

When results are disaggregated by education, a richer picture emerges. College-educated men of any age have seen little change in worklives over the 30-year span. In contrast, men without a high school diploma have seen a sharp change in expected worklives. Young men without a high school degree have seen their worklives decrease by as much as three years, while older men without a high school degree have seen a small increase.

For women, we find that the increase in worklives is driven largely by changes in the experience of college-educated women. Between 1980 and 2010, worklives for young, college-educated women have increased by as much as five or six years. In contrast, worklives for women without high school degrees have gotten shorter.

We also examine how period worklife estimates from the early 1980s are compared to cohort estimates calculated using the 1980 to 2010 CPS data. Once again, contrasts between men and women are striking. For men, cohort worklives are shorter than 1980-1985 period worklives for younger, non-educated men and longer for older men with little education. In contrast, there is little difference between 1980-1985 and cohort worklives for college-educated men. For college-educated women, cohort worklives are much longer than 1980-1985 period worklives.

These results suggest that over this three-decade period, using 1980-1985 period worklives would have substantially biased worklife estimates for some groups. For men, little bias would occur for those with college educations, while for college-educated women, using period worklife estimates could have seriously biased results. For men with little education, earlier period worklives would not reflect their evolving labor market activity.

In the next section, the CPS data are described. Creating a dataset for the 1980-2010 periods requires merging data from two sources. Section III describes the process of merging this information. The fourth section discusses finding matches across years in the merged data. This is followed by a discussion of estimating transition probabilities in Section V, a comparison of transition probabilities in the sixth section and a comparison of resulting period and cohort worklives in Section VII. This is all followed by a conclusion.

II. The CPS Data

The Current Population Survey (CPS) is a household survey conducted annually for more than 50 years by the Bureau of the Census for the Bureau of Labor Statistics. The CPS provides a comprehensive body of demographic and labor force information for the nation's population. Surveys are conducted each month with approximately 60,000 households. The interviews ask for information about each individual in the household and among other data, ask for age, sex, race, education, and labor market status.

Households selected for the CPS are surveyed in a 4-8-4 survey month pattern: they are interviewed for four consecutive months, and eight months later, are interviewed for another four consecutive months. With the CPS's 4-8-4 survey month pattern, for each person it is conceivable to match up to four, one-year-apart interviews. When a match is found it is possible to discern that person's labor market status in a particular month of one year and the corresponding month of the next year. This allows estimating the number of people of a particular age and sex who have gone through any of the four following labor force transitions: 1) from active to active, 2) from active to inactive, 3) from inactive to inactive, and 4) from inactive to active.

There are two significant problems with using the raw CPS data for our research. The first is that the formats for the data are inconsistent across years, and clarifications of the changes in format over the years are scattered among various places. This makes aggregating the data difficult. Fortunately, a group of researchers at the University of Minnesota have compiled "[h]armonized data on people in the Current Population Survey, every March from 1962 to the present."[4] The harmonized CPS data are contained within the Integrated Public Use Microdata Series-CPS (IPUMS-CPS).[5] The IPUMS-CPS data have proven invaluable for consolidating CPS data definitions over the years, as well as automating the process of inserting the large CPS data stores into a usable format for analysis.

The second challenge is matching CPS data for individuals across years. The IPUMS-CPS data lack the requisite identifiers to link an individual's interviews carried out across years. Consequently, even with the CPS's 4-8-4 sampling procedure, there is no straightforward way within IPUMS-CPS to associate an individual's data from any of the initial four months they were surveyed to their data from any of the latter four months they were surveyed. Fortunately, we have been able to solve this association problem by linking an individual's identifiers in the raw CPS data with that same individual's demographic and employment information contained in the IPUMS-CPS dataset. This allows us to associate information across two years for most individuals surveyed in the CPS.

III. Merging IPUMS-CPS Data with Raw CPS Data

Merging the IPUMS-CPS data store with raw CPS data is a fairly subtle process. The first time a household is interviewed, a roster of families and persons within the household is developed. This roster is updated at each subsequent interview to take account of new or departed residents, changes in marital status, and similar items. The CPS data are then recorded hierarchically. A household record is followed by a record for the first family within that household. That family record is in turn followed by unique records for each person within that family. Additional sets of family and person records are included as

[4]See http://www.ipums.org/, downloaded 4 August 2011.
[5]See King, et al., 2010.

necessary for each particular household. A sample hierarchical structure is as follows:

Household record 1
    Family record 1
        Person record 1
        Person record 2
        Person record 3
    Family record 2
        Person record 1
        Person record 2
Household record 2.

The IPUMS-CPS data can be downloaded in either a hierarchical or rectangularized format. The rectangularized IPUMS-CPS data contains person records in the same order as the CPS file, only with the household and family records removed. A sample rectangularized structure for the household above would be represented as as follows:

Person(HH 1, Fam 1) record 1
Person(HH 1, Fam 1) record 2
Person(HH 1, Fam 1) record 3
Person(HH 1, Fam 2) record 1
Person(HH 1, Fam 2) record 2.

To consolidate the March data for any year, a database is defined with the relevant IPUMS-CPS variables.[6] The IPUMS-CPS comes with an associated command file which identifies the location and width of each field, as well as any codes used for enumeration. This associated command file is used to create that database.[7] It is essential in this process to maintain the order of the IPUMS-CPS person records. The data from a particular year are then inserted into the database, with the columns for the variables *HHID*, *HHNUM* and *LINENO* left as null.

We then turn to the CPS data corresponding to the same year and month.[8] Person records are isolated within the CPS data, keeping the records in their original relative order. The relevant individual identifiers (*HHID*, *HHNUM* and *LINENO*) are pulled from each CPS record and inserted into the corresponding record in the previously created IPUMS-CPS database.[9] By limiting

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[6]IPUMS-CPS data sets can be downloaded from the IPUMS-CPS site, http://www.ipums.org/.
[7]For performance reasons, it is recommended that a separate table be created for each survey year.
[8]CPS data can be obtained through the National Bureau of Economic Research (NBER). See its Web site http://www.nber.org/cps/data.html.
[9]Finding the actual variable positions in the original CPS data is tricky as well, as the names of the fields in the data dictionaries change often between years. These names of the fields in the CPS files across the different years are as follows: (see Madrian and Lofgren, 2000, Table B1):

	CPS Name	**Years**
HHID	HH-IDENT-NUM	77-88
	I-IDNUM	88B-95
	H-IDNUM	96-98
HHNUM	ITEM9	77-88
	H-HHNUM	88B-98
LINENO	LINENO	79-88
	A-LINENO	88B-98.

the update to individual fields, the database is filled one record at a time. Again, this can only be done because person records in the IPUMS-CPS rectangularized dataset and CPS hierarchical dataset are in the same order. Updating all of the records creates a well-organized database containing all of the IPUMS-CPS demographic and employment data harmonized with the individual identifiers needed to perform year-to-year matches.

IV. Matching CPS Entries across Years

Annual CPS matched individual datasets are developed from the March supplements for the years 1980 through 2010.[10] A variety of algorithms have been proposed to match CPS data across years, and each brings trade-offs in accuracy and sample size.[11] An algorithm checks for an initial correspondence across years by matching the *HHID*, *HHNUM* and *LINENO* from year t to year t+1. This, however, is not enough to be confident of a match across years. The CPS covers housing units, not households. A housing unit may be occupied by one set of households during the first four interview months, and by the time the second four months of interviews occur, there may be a different household living in that housing unit. Consequently, the same *HHID* and *LINENO* can refer to different households and people, producing false positives matches. Additionally, individuals may die, leave the household or simply refuse to answer in particular survey months. There may also be inadvertent errors in recording the data. Hence, additional checks are essential to ensure matches on individuals across years.

Additional checks look for consistencies in race, sex, age and education. For race and sex, there is a check for consistency between years t and t+1. For age, consistency requires that the age in year t+1 be between 0 and 2 years greater than the age in year t.[12] For educational attainment, the consistency check is that each person's education in year t+1 is at least that of year t.

Table 1 shows information about the number of potential and actual matches found in the data. Column (A) shows the number of individuals included in the CPS for each year. Note that these are the number of individuals included in the first year for each match. For example 181,488 people were included in the 1980 March CPS. Column (B) shows the potential number of matches possible given that only half the sample from any year is carried into the sample for the next year. Column (C) shows the actual number of matches found when the seven matching criteria are applied to the data. Column (D) shows the actual matches as a percent of total possible matches. These range from a low of 56% to a high of 74% and are consistent with results found by Madrian and Lofgren (2000). Finally, column (E) shows the number of matches for people over the age of 15.

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[10]It is not possible to use the IPUMS-CPS data to produce matched data for 1985-1986 and 1995-1996. For an explanation see Madrian and Lofgren (2000), footnote 3.

[11]For a good survey, see Madrian and Lofgren (2000) or Krueger (2004).

[12]Households to be interviewed in a particular month are contacted during the calendar week containing the 19th day of the month. Questions are asked about labor market activity during the reference week, the week containing the 12th day of the month. Hence, someone could be interviewed just after (before) his/her t^{th} birthday the first year in the sample and just before (after) his/her $t+1^{th}$ birthday the second year. Consequently, his/her age would change by zero (two) years.

Table 1
Matches by Year-Pair

Year-Pair	(A) Persons Included in the CPS for the Initial Year of Match	(B) Number of Potential Matches (A/2)	(C) Actual Matches Meeting All Criteria	(D) Actual Matches as Percent of Potential Matches (C/B)	(E) Number of Matches Meeting All Criteria and Over Age 15
1980-1981	181,488	90,744	63,979	71%	48,330
1981-1982	181,358	90,679	56,754	63%	42,870
1982-1983	162,703	81,352	56,993	70%	43,346
1983-1984	162,635	81,318	55,621	68%	42,426
1984-1985	161,167	80,584	52,588	65%	40,228
1985-1986	- - -	- - -	- - -	- - -	- - -
1986-1987	157,661	78,831	51,577	65%	39,616
1987-1988	155,468	77,734	50,388	65%	38,615
1988-1989	155,980	77,990	50,764	65%	38,693
1989-1990	144,687	72,344	51,288	71%	39,029
1990-1991	158,079	79,040	56,200	71%	42,529
1991-1992	158,477	79,239	49,929	63%	36,523
1992-1993	155,796	77,898	55,102	71%	41,914
1993-1994	155,197	77,599	53,894	69%	40,206
1994-1995	150,943	75,472	48,452	64%	36,121
1995-1996	- - -	- - -	- - -	- - -	- - -
1996-1997	130,476	65,238	48,321	74%	36,013
1997-1998	131,854	65,927	48,568	74%	36,475
1998-1999	131,617	65,809	48,547	74%	36,298
1999-1990	132,324	66,162	48,899	74%	36,667
2000-2001	133,710	66,855	46,277	69%	35,524
2001-2002	218,269	109,135	64,961	60%	47,475
2002-2003	217,219	108,610	70,151	65%	50,875
2003-2004	216,424	108,212	69,646	64%	50,732
2004-2005	213,241	106,621	59,754	56%	43,708
2005-2006	210,648	105,324	63,690	60%	46,618
2006-2007	208,562	104,281	60,618	58%	43,906
2007-2008	206,639	103,320	64,094	62%	47,083
2008-2009	206,404	103,202	63,602	62%	47,080
2009-2010	207,921	103,961	66,016	64%	48,889

V. Estimating Transition Probabilities

For worklife calculations, people are classified as active if they are in the civilian labor force and inactive if they are not in the labor force. Following this approach, all individuals with CPS data indicating that they are in the armed forces in year t are excluded from our analysis.[13] Individuals are active in the labor force in year t if the CPS employment status indicates they are employed or unemployed. Otherwise they are classified as inactive.

Thirty matched datasets are developed that follow individuals between years t and t+1 from 1980-1981 through 2009-2010. In each matched dataset,

[13]In all sample years except 2003, a value of 13 for the IPUMS-CPS variable *EMPSTAT* indicates employment in the armed forces. For 2003, a value of 984 for the IPUMS-CPS variable *OCC* indicates employment in the armed forces.

each individual has a weight associated with his/her information. The IPUMS-CPS variable *WTSUPP* is a person-level weight that IPUMS-CPS indicates should be used in analyses of individual-level CPS March supplement data. *WTSUPP* is based on the inverse probability of selection into the sample and adjustments for the following factors: failure to obtain an interview; sampling within large sample units; the known distribution of the entire population according to age, sex, and race; over-sampling Hispanic persons; to give husbands and wives the same weight; and an additional step to provide consistency with labor force estimates from the basic survey. *WTSUPP* values are aggregate by age and sex to obtain estimates of population numbers of individuals in different classifications.

Following Krueger's (2004) notation, for any particular matched dataset, let ${}^{a}N_{x}$ and ${}^{i}N_{x}$ respectively represent the number of individuals at age x that are active and inactive in the labor market. Also define:

- ${}^{a}N_{x}^{a}$ as the number of persons who are active in the labor force at age x and active in the labor force at age x+1,
- ${}^{a}N_{x}^{i}$ as the number of persons who are active in the labor force at age x and inactive in the labor force at age x+1,
- ${}^{i}N_{x}^{a}$ as the number of persons who are inactive in the labor force at age x and active in the labor force at age x+1, and
- ${}^{i}N_{x}^{i}$ as the number of persons who are inactive in the labor force at age x and inactive in the labor force at age x+1.

Let ${}^{a}p_{x}^{d}$ represent the probability that a person who is active at age x dies by age x+1. Similarly, let ${}^{i}p_{x}^{d}$ represent the probability that a person who is inactive at age x dies by age x+1. Since mortality data typically are not classified by labor market status, convention treats ${}^{a}p_{x}^{d} = {}^{i}p_{x}^{d} = {}^{\bullet}p_{x}^{d}$. The probability of dying between age x and x+1 is independent of labor market status. U.S. Centers for Disease Control and Prevention life tables are used to obtain values for ${}^{\bullet}p_{x}^{d}$. The life table from 1979-1981 is used for the 1980s, the life table from 1989-1991 is used for the 1990s and the life table from 1999-2001 is used for the years 2000 through 2010.[14]

Using the previous notation, two transition probabilities can be calculated. The probability of being inactive at age x+1 conditional on being inactive at age x, ${}^{i}p_{x}^{i}$, and the probability of being active at age x+1 conditional on being active at age x, ${}^{a}p_{x}^{a}$ are respectively calculated as[15]:

[14]Life Tables were downloaded from http://www.cdc.gov/nchs/products/life_tables.htm. Life expectancies changed modestly over this period. The life expectancy for a 40-year-old male, for example, went from 35.7 years in 1980 to 36.6 years in 2000.

[15]As expressed in equations (1) and (2), the probabilities are conditional on the beginning state and on surviving to age x+1.

$$(1) \qquad {}^{i}p_x^{i} = \left[\frac{{}^{i}N_{x-1}^{i} + {}^{i}N_x^{i}}{{}^{i}N_{x-1} + {}^{i}N_x} \right] \left(1 - {}^{\bullet}p_x^{d}\right)$$

$$(2) \qquad {}^{a}p_x^{a} = \left[\frac{{}^{a}N_{x-1}^{a} + {}^{a}N_x^{a}}{{}^{a}N_{x-1} + {}^{a}N_x} \right] \left(1 - {}^{\bullet}p_x^{d}\right)$$

Note that the data in equations (1) and (2) are averaged across ages x and x-1. Following Krueger (2004):

> Life table calculations focus on persons at exact age x. The mortality data as published are computed for exact ages x—they represent the probability of survival from one exact age to the next age. However, since the population activity data are based on surveyed age reported in single-digit values only, age in that data has an expected value of x + ½. Therefore, when we compute the transition probabilities, we need to re-center the survey data across the range of x ± ½ by combining two ages from survey data. (p. 335)

The final two transition probabilities can be calculated from the following identities which restrict the sum of the probabilities of transitioning from one state at age x to any of the possible alternative states at age x+1 to be equal to one:

$$(3) \qquad {}^{a}p_x^{i} = 1 - {}^{a}p_x^{a} - {}^{\bullet}p_x^{d}$$

$$(4) \qquad {}^{i}p_x^{a} = 1 - {}^{i}p_x^{i} - {}^{\bullet}p_x^{d}$$

Equation (3) is the probability of going from active at age x to inactive at age x+1. Equation (4) is the probability of going from inactive at age x to active at age x+1.

VI. Comparing Transition Probabilities

We begin by comparing transition probabilities for all males in 1980-1985 to those in 2005-2010. Following recent CPS-based worklife studies, we choose to average transition probabilities across five-year periods.[16] This avoids biases potentially caused by short term economic fluctuations and improves the precision of our estimates. Further we follow recent studies by smoothing estimated transition probabilities over contiguous ages.[17] We choose a centered moving average of five years as a compromise between the variance stabilizing effect of long moving averages and the bias induced by averaging over ages where transition probabilities change sharply.

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[16]See, for example, Krueger (2004) or Skoog, et al. (2011).
[17]See, for example, Millimet, et al., (2003, p. 87) and their reference to Schoen and Woodrow (1980).

Figure 1 compares the probability of remaining active, ${}^{a}p_{x}^{a}$, by age, for males across the two periods. For men below the age of 60, the probability of remaining active has fallen by from one to two percentage points. In contrast, the probability of remaining active has risen substantially for men over the age of 60, by from four to eight percentage points. These differences can be shown to be statistically significant.[18] Although not shown in the figure, the ${}^{a}p_{x}^{i}$ for both periods are reflections of the ${}^{a}p_{x}^{a}$. The newer period has a relatively higher ${}^{a}p_{x}^{i}$ through about age 60, and then it falls relative to the earlier period.

Male transition probabilities were also examined by education: specifically, men with less than a high school degree, men with a high school degree, and men with a bachelor's degree.[19] For all three groups, the newer period has a relatively lower ${}^{a}p_{x}^{a}$ (and a relatively higher ${}^{a}p_{x}^{i}$) through about age 60. However, the magnitude of the difference between the 1980-1985 group and the 2005-2010 group gets smaller as education increases. For non-high school-educated men, the difference between groups is pronounced; for college graduates, the difference is almost non-existent. For men across all educations, beyond age 60, the relationship between ${}^{a}p_{x}^{a}$ for the 1980-1985 group and the 2005-2010 group is less clear. At some ages ${}^{a}p_{x}^{a}$ is higher for the 2005-2012 group. At other ages it is higher for the 1980-1985 group.

Figure 2 compares the probabilities of remaining inactive, ${}^{i}p_{x}^{i}$, for all men in 1980-1985 and in 2005-2010. The probability of remaining inactive has increased under the age of 60 but is little changed for men over the age of 60. The same generally holds when the data are disaggregated by education. However, there is much more variation in the data when disaggregated by education.

Female transition probabilities by age and period are summarized in Figures 3 and 4. Figure 3 shows female transition probabilities ${}^{a}p_{x}^{a}$ by age for the 1980-1985 period and for the 2005-2010 period. Women in the newer period have a relatively higher ${}^{a}p_{x}^{a}$ at almost all ages than their counterparts in the earlier period. The relatively higher ${}^{a}p_{x}^{a}$ for women in the 2005-2010 period is driven by women with college educations. For college-educated women of almost any age, the 2005-2010 period has a higher ${}^{a}p_{x}^{a}$ than the 1980-1985 period. For women with no degree, however, the opposite holds. The ${}^{a}p_{x}^{a}$ at almost any age in the 2005-2010 period is significantly below the ${}^{a}p_{x}^{a}$ for their age counterpart in the earlier period.

[18]Tables with significance levels are available on request from the authors.

[19]The breakdown by education in all tables excludes individuals in other education categories such as holding a GED, some college or with advanced/professional degrees.

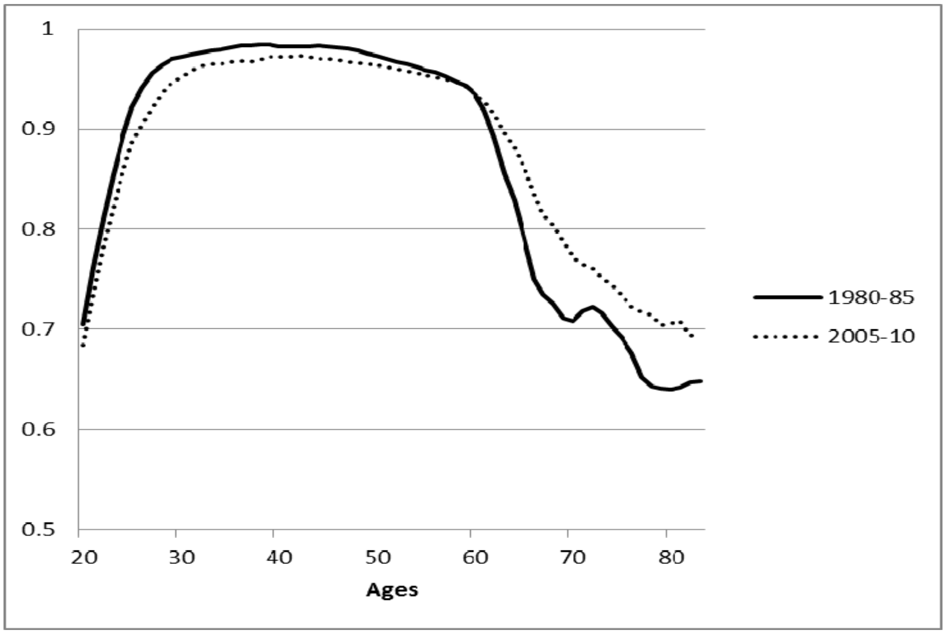

Figure 1. Male Probability of Remaining Active (${}^{a}p_{x}^{a}$):
Comparing 1980-1985 and 2005-2010 Samples

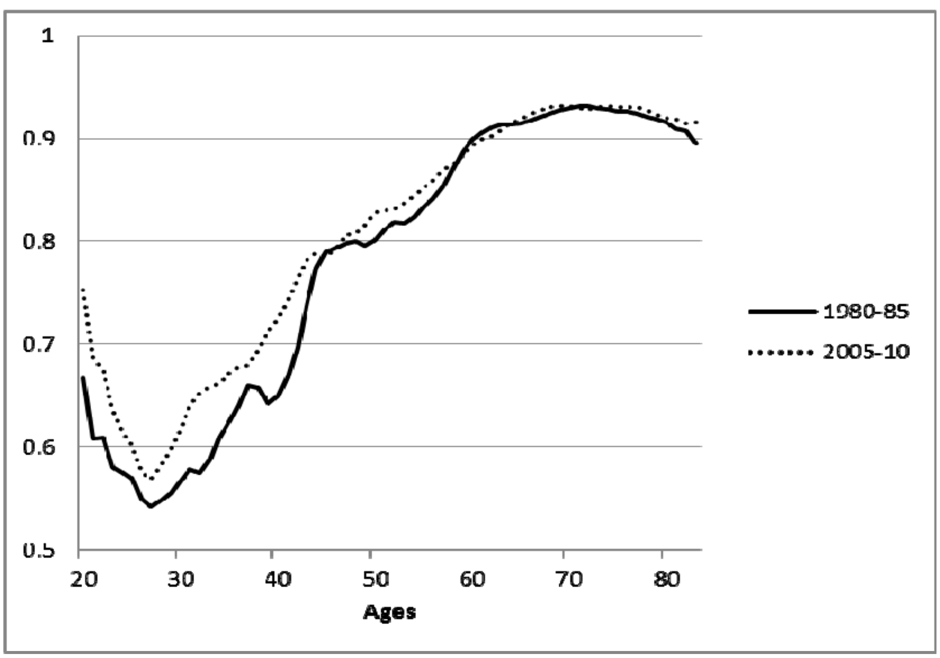

Figure 2. Male Probability of Remaining Inactive (${}^{i}p_{x}^{i}$):
Comparing 1980-1985 and 2005-2010 Samples

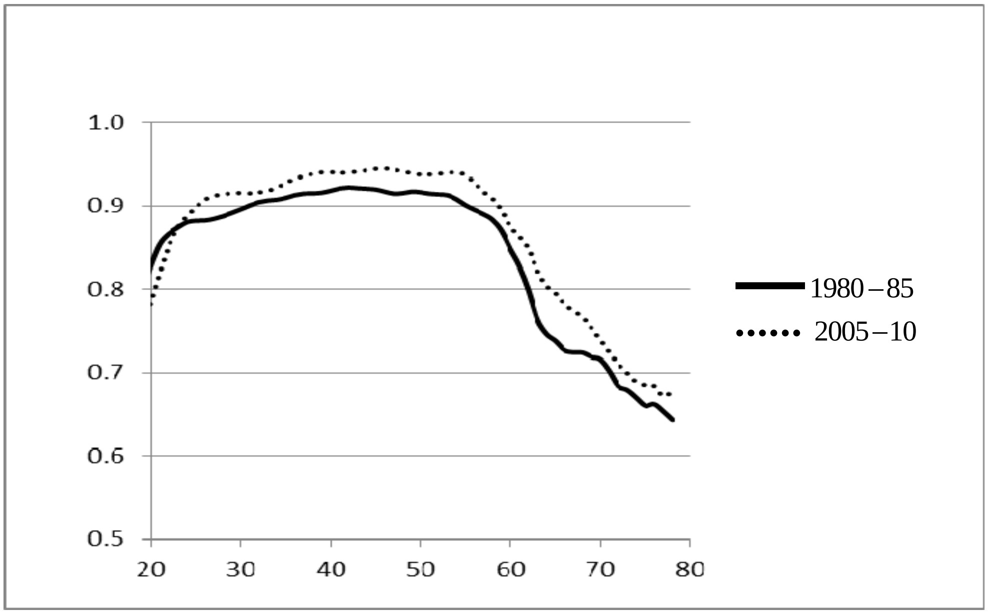

Figure 3. Female Probability of Remaining Active (${}^{a}p_{x}^{a}$):
Comparing 1980-1985 Sample and 2006-2010 Sample

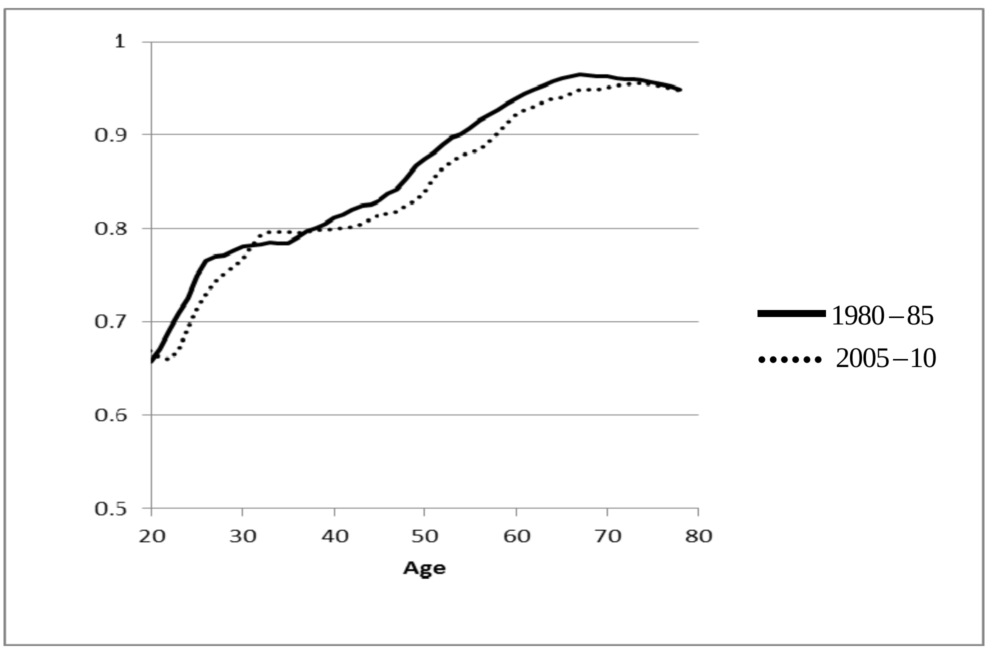

Figure 4. Female Annual Transition Probabilities (${}^{i}p_{x}^{i}$):
Comparing 1980-1985 Sample and 2005-2010 Sample

Figure 4 shows female transition probabilities ${}^{i}p_{x}^{i}$ by age for the 1980-1985 period and for the 2005-2010 period. Women in the earlier group who were inactive at almost any age have a higher probability of remaining inactive than their counterparts in the latter group. Results are no more revealing when disaggregated by education.

As a whole, the results show that young men in 2005-2010 are less likely to remain active than they were in the first half of the 1980s. Once they become inactive, young men in the newer period are more likely to remain inactive and less likely to become active than their earlier period, age-equivalent counterparts. For men of older ages, nearly the opposite holds. Older men in the newer period are more likely to remain active than their earlier period, age-equivalent counterparts. However, once they become inactive, they are just as likely as their earlier period, age-equivalent counterparts, to remain so. Women at almost every age in the newer period are more likely to either become or remain active than their age-equivalent counterparts in the earlier period.

These results are interesting when compared to evolving labor market participation rates. Toossi (2012) shows measured participation rates for the years 1990 to 2010 and estimated rates through 2020. For men, participation rates have declined from 1990 to 2010 and are projected to continue to decline modestly. Among 16- to 24-year-olds, participation drops from 71.8% in 1990 to 50.6% in 2020. Men ages 25 to 54 have a 5.3 percentage point drop in participation. In contrast, men 55 and older show an increase in participation rates from 39.4% in 1990 to 47.3% in 2020.[20] Older men in newer periods are increasingly more likely to participate in the labor force than their age-equivalent counterparts in earlier periods. This is reflected in the higher probabilities of remaining active at older ages exhibited by the newer period of men, as shown in Figure 1.

Toossi's (2012) results for women show that their overall participation peaked around 2000 and by 2020 is projected to be slightly below year 1990 levels. Women ages 25 to 54 had a modest increase in participation from 1990 to 2010 (about 1.2 percentage points) and are projecting a 0.6 percentage point decrease in participation by 2020. Women ages 55 and older steadily increase their participation rates from 22.9% in 1990 to 39.3% in 2020. Women 65 and older have an increase in participation from 8.6% in 1990 to 19.2% in 2020. The participation rate of women 75 and older almost triples over those 30 years. It would be interesting to see a breakdown of participation by education by women. Women's increased participation rates are consistent with our transition probability findings.

VII. Impacts on Worklives

The time series on transition probabilities allows estimating both period and cohort worklives. Period worklives take a snapshot of transition probabilities across all ages at one period in time and assume the same period transition probabilities hold as a person ages. This is the standard approach in the

[20]Men 65 and older have an increase in participation rates from 16.3% in 1990 to 26.7% in 2020. The participation rate of men 75 and older nearly doubles over those 30 years.

literature. Cohort worklives re-estimate age-specific transition probabilities each year as a person ages. The previous section showed that period transition probabilities may evolve over time. Given this evolution, two interesting questions arise: do period worklives evolve over time as well, and would following a cohort using a cohort worklife produce significantly different worklife estimates than worklives estimated from period tables at the beginning of the time series? We can answer both.

Skoog, et al. (2011) develop a method for estimating expected worklives from transition probabilities. They let $p_{YA}(x,m,y)$ measure the probability that "a person in state m at age x will accumulate y additional years in the labor force." (p. 172) The whole series of $p_{YA}(x,m,y)$ can be estimated using a set of global, boundary and recursive conditions carefully described in their paper. Then, the expected worklife of someone in state m at age x can be estimated as:

$$E(YA_{x,m}) = \sum_{y} y \cdot p_{YA}(x,m,y) = {}^{m}e_{x}^{a}. \tag{5}$$

Because the worklife calculation is a highly nonlinear function of the underlying estimated transition probabilities, we use a bootstrap method to assess the statistical properties of our estimators. We generate bootstrap samples by taking the number of active and inactive individuals at each age, N_{x-1}^{a} and N_{x-1}^{i}, and the estimated transition probabilities as our population. We then generate samples consisting of N_{x-1}^{a} draws from a Bernoulli with probability of success (becoming active) equal to our estimated ${}^{a}p_{x}^{a}$ value and N_{x-1}^{i} draws from a Bernoulli distribution with probability of success ${}^{i}p_{x}^{a}$. This experiment yields a new set of values for ${}^{a}N_{x}^{a}$ and ${}^{i}N_{x}^{a}$. We then use these generated values to construct the transition probabilities as described by equations (1) through (4). The estimates are smoothed with a centered moving average over five ages and then calculate the worklife implied by equation (5). We repeat this process 10,000 times to create a sampling distribution for our worklife estimates. The standard errors reported are the standard deviation of this sampling distribution.[21]

Results of the comparison of male worklives for the 1980-1985 and the 2005-2010 periods are shown in Table 2A.[22] Expected worklives and standard deviations are shown for men starting in either the active or inactive state at selected ages. At all ages, men in the 2005-2010 period have longer worklives than their age-equivalent counterparts in the 1980-1985 period. The differences are statistically significant beyond age 35 (45) for initially active (inac-

[21]Note that in this bootstrap procedure we used the raw, unweighted sample size for the number of active and inactive individuals rather than the weighted values used in estimating the probabilities. Also, we took the mortality probabilities as given rather than estimated.

[22]Appendix Table A1 shows comparative worklives for men and women of various ages from this study and from other studies performed over the 1980-2010 period.

tive) men.[23] The difference is less than two months for 25-year-olds, whether they are currently active or inactive. The differences expand with age, reaching just over one year for men in their fifties, and then slowly contracts to 2-6 months for 70-year-olds. As a whole, Table 2A indicates that not much has changed for men's worklives over the 30-year period. Worklives may have gotten a little longer, but only by a few months.

Table 2A
Comparison of Male Worklives by Age 1980-1985 and 2005-2010

	ALL MALES							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	33.8	0.12	32.1	0.15	33.9	0.15	32.2	0.18
30	29.4	0.12	27.4	0.18	29.7	0.15	27.4	0.21
35	24.9	0.12	22.4	0.23	25.4**	0.14	22.5	0.24
40	20.4	0.12	16.7	0.32	21.2**	0.14	17.3	0.25
45	16.1	0.11	11.8	0.31	17.1**	0.13	12.7*	0.24
50	12.0	0.10	7.5	0.25	13.3**	0.12	8.5**	0.21
55	8.3	0.09	3.6	0.15	9.8**	0.11	4.8**	0.16
60	5.0	0.08	1.8	0.08	6.6**	0.11	2.5**	0.10
65	3.4	0.09	0.9	0.05	4.5**	0.11	1.3**	0.07
70	2.9	0.10	0.4	0.03	3.4**	0.12	0.6**	0.05

Note: In Table 2A, comparisons are made between worklife expectancy for initial Actives in 1980-85 and worklife expectancy for initial Actives in 2005-10. Similarly, comparisons are made between worklife expectancy for initial Inactives in 1980-85 and worklife expectancy for initial Inactives in 2005-10. The shading only indicates the bigger of any of the two numbers being compared. Asterisks indicate statistical significance of differences in any pairs of worklife expectancies; * and ** denote that the difference between 2005-2010 and 1980-1985 period estimates is statistically significant at the five and one percent level respectively. We chose to put the asterisks next to the bigger of the two worklife expectancies being compared. For example, a 35-year-old active male in 1980-1985 has a worklife of 24.9 years. A 35-year-old active male in 2005-2010 has a worklife of 25.4 years. Using the associated bootstrap standard deviations, we test the null hypothesis that the difference between the worklife expectancies—0.5 in this case—is not significantly different from zero. In this case, we reject that hypothesis at the 1% level. The foregoing also applies to Tables 2B, 3A, and 3B.

Table 2B compares 1980-1985 and 2005-2010 period worklives for men by education. The results yield richness in variation that is unobservable from aggregate results. Younger men in the 1980-1985 period without a high school diploma have a longer worklife than their 2005-2010 period age and education equivalent counterparts. This holds whether they start in the active or inactive states. For men in their twenties, for example, the difference can be almost four years. Once men reach their mid-fifties, the data switch and men in the 2005-2010 period have slightly longer worklives. However, the difference is less than one year for any age beyond 55. The differences are statistically significant for all but the oldest men.

[23]Statistical significance is based on the standard statistic for the difference in two means, assuming independent samples.

Table 2B
Comparison of Male Worklives by Age and Education 1980-1985 and 2005-2010

	LESS THAN HIGH SCHOOL							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	32.4**	0.17	30.7**	0.23	28.6	0.12	26.8	0.23
30	28.1**	0.17	25.5**	0.30	24.8	0.12	22.0	0.27
35	23.7**	0.16	20.9**	0.33	21.1	0.12	17.8	0.27
40	19.4**	0.15	15.3**	0.38	17.4	0.12	13.4	0.27
45	15.2**	0.14	11.0**	0.36	14.0	0.11	9.2	0.24
50	11.2**	0.12	6.6*	0.28	10.8	0.10	5.9	0.19
55	7.7	0.10	3.2	0.16	8.2**	0.09	3.7*	0.13
60	4.6	0.09	1.5	0.08	5.3**	0.08	2.0**	0.09
65	3.1	0.09	0.8	0.05	3.8**	0.09	1.0**	0.06
70	2.6	0.11	0.4	0.03	2.7	0.10	0.4	0.04
	HIGH SCHOOL							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	33.2	0.93	31.9	0.97	32.5	0.22	30.5	0.23
30	28.8	0.93	27.0	1.19	28.5	0.21	25.7	0.22
35	24.3	0.92	20.4	1.99	24.4	0.20	21.3	0.22
40	20.2	0.87	14.0	1.91	20.3	0.19	16.7	0.21
45	16.1	0.86	10.3	1.46	16.4	0.18	12.2	0.21
50	12.0	0.81	7.2	2.08	12.7	0.18	8.1	0.20
55	8.1	0.78	2.3	0.91	9.3	0.16	4.5*	0.17
60	5.0	0.79	1.1	0.57	6.2	0.15	2.5*	0.13
65	5.0	0.75	0.6	0.43	4.3	0.14	1.4	0.11
70	3.1	0.79	0.0	0.07	3.3	0.14	0.6**	0.08
	BACHELOR'S DEGREE							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	36.6	0.38	35.0	0.48	36.5	0.25	35.1	0.26
30	32.1	0.38	30.4	0.52	32.0	0.25	30.8	0.25
35	27.5	0.38	26.2	0.48	27.4	0.25	25.6	0.26
40	22.9	0.39	21.4**	0.49	22.7	0.25	19.8	0.26
45	18.4	0.38	15.2	1.00	18.4	0.25	14.8	0.27
50	14.2	0.37	8.4	1.21	14.1	0.25	8.6	0.29
55	10.0	0.37	5.3	0.75	10.4	0.24	5.5	0.25
60	6.4	0.37	3.3	0.44	7.1	0.23	2.9	0.22
65	4.6	0.40	1.5	0.29	4.6	0.23	1.5	0.20
70	4.0	0.44	0.7	0.20	3.8	0.21	0.7	0.14

Note: See Table 2A note.

Regardless of initial workforce status, men with a high school diploma who are under 35 have slightly longer worklives in the 1980-1985 period than their age and education equivalent counterparts in the 2005-2010 period. Beyond age 35, the direction of the difference changes, with men in the 2005-2010 period having slightly longer worklives. For men who are initially active, the difference amounts to, at most, just over one year. None of these differences are statistically significant. For men with a high school diploma who start *inactive*, the magnitude of the difference can be larger at any age, reaching at most, 2.7 years. The level of statistical significance varies by age.

For men with a college diploma, whether initially active or inactive, there is almost no difference in worklives between the two periods. At some ages, men in the 1980-1985 period have a longer worklife. At other ages, the reverse is true. There seems to be no particular pattern to the relative worklives. The differences across periods are generally small—less than two months and are statistically insignificant in almost all cases.

Taken together, Tables 2A and 2B suggest that men with limited formal education are becoming less active in the labor market during their prime working years. The lack of earnings (and perhaps concomitant ability to save) may explain why their worklives have become longer at older ages. In contrast, men with college degrees have seen no real changes in their worklives. As a whole, the relative stability of college-educated men combined with the gains for high school-educated men temper the results for men with little education. This may explain why male worklives aggregated across levels of education (in Table 2A) have not evolved substantially over the 30-year span.

Results for women are shown in Table 3A and 3B. Table 3A shows worklives for all women, regardless of education. Young women in the 2005-2010 period have worklives almost four years longer than their age equivalent counterparts in the 1980-1985 period. Women in their forties and fifties in the 2005-2010 period have worklives approximately two-to-three years longer than their age equivalent counterparts in the 1980-1985 period. While the absolute difference in worklives gets smaller as age increases, the relative difference expands, particularly for women starting in the inactive state. All of these differences are statistically significant.

Table 3A
Comparison of Female Worklives by Age 1980-1985 and 2005-2010

	ALL FEMALES							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	25.8	0.18	23.4	0.18	30.0**	0.17	27.7**	0.18
30	22.6	0.17	19.9	0.18	26.5**	0.16	23.6**	0.18
35	19.3	0.16	16.3	0.18	23.1**	0.15	19.8**	0.17
40	16.0	0.15	12.6	0.17	19.5**	0.14	15.9**	0.17
45	12.8	0.14	8.9	0.16	15.8**	0.13	11.9**	0.17
50	9.9	0.12	5.3	0.13	12.3**	0.12	7.8**	0.16
55	7.2	0.11	2.7	0.09	9.0**	0.11	4.4**	0.13
60	4.8	0.10	1.2	0.06	6.1**	0.11	2.1**	0.08
65	3.4	0.11	0.5	0.03	4.2**	0.11	1.0**	0.06
70	2.8	0.13	0.2	0.02	3.1**	0.12	0.4**	0.03

Note: See Table 2A note.

Table 3B
Comparison of Female Worklives by Age and Education 1980-1985 and 2005-2010

	LESS THAN HIGH SCHOOL							
	1980-1985 Period				2005-2010 Period			
	Active		Inactive		Active		Inactive	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	23.7**	0.22	21.4**	0.23	20.7	0.49	18.9	0.49
30	20.9**	0.21	18.3**	0.22	18.8	0.46	16.5	0.46
35	18.0**	0.20	14.9*	0.21	16.5	0.42	13.8	0.44
40	15.0**	0.18	11.5	0.20	13.7	0.39	10.7	0.41
45	12.1**	0.16	8.1	0.18	11.0	0.36	7.7	0.36
50	9.4*	0.14	4.9	0.14	8.7	0.32	5.2	0.31
55	6.9	0.12	2.6	0.10	6.7	0.28	3.2*	0.24
60	4.5	0.11	1.1	0.06	4.5	0.25	1.2	0.14
65	3.3	0.12	0.5	0.04	3.0	0.23	0.5	0.08
70	2.8	0.16	0.2	0.02	2.3	0.26	0.2	0.05
	HIGH SCHOOL							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	30.1	1.41	27.8	1.43	28.1	0.31	25.9	0.33
30	26.3	1.39	24.4	1.42	24.8	0.29	22.0	0.32
35	22.7	1.38	19.9	1.43	21.7	0.26	18.5	0.30
40	18.8	1.35	15.3	1.47	18.3	0.24	15.1	0.29
45	15.2	1.30	11.6	1.49	14.9	0.22	11.0	0.29
50	12.1	1.22	7.8	1.41	11.5	0.20	6.6	0.27
55	9.2	1.19	3.5	1.02	8.5	0.18	3.5	0.19
60	6.5	1.15	2.0	0.72	5.6	0.17	1.8	0.13
65	4.9	0.90	0.7	0.50	4.0	0.18	0.9	0.08
70	3.0	0.81	0.1	0.09	3.2	0.20	0.4**	0.05
	BACHELOR'S DEGREE							
	1980-1985 Period				**2005-2010 Period**			
	Active		**Inactive**		**Active**		**Inactive**	
Age	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**	**Worklife**	**Std Dev**
25	27.7	0.61	25.4	0.65	31.8**	0.40	29.5**	0.45
30	24.0	0.60	21.2	0.64	28.2**	0.39	25.2**	0.44
35	20.6	0.59	17.1	0.64	24.7**	0.37	21.3**	0.42
40	17.1	0.57	13.5	0.64	21.0**	0.36	17.5**	0.42
45	13.5	0.55	10.4	0.63	17.2**	0.35	13.6**	0.43
50	10.2	0.51	6.5	0.58	13.4**	0.34	9.4**	0.44
55	7.3	0.48	2.8	0.42	9.8**	0.33	5.5**	0.39
60	5.1	0.45	1.1	0.27	6.7**	0.33	3.0**	0.30
65	3.3	0.47	0.4	0.13	4.6*	0.34	1.6**	0.22
70	2.9	0.39	0.1	0.07	3.3	0.38	0.7**	0.14

Note: See Table 2A note.

Table 3B compares 1980-1985 and 2005-2010 period worklives for women by education. Women with no diploma or only a high school diploma generally have longer worklives in the 1980-1985 period than their age and education equivalent counterparts in the 2005-2010 period. While the difference in work-lives can be up to three years, it is generally in the range of one-to-two years, even for relatively young women. The exception is women over 50 with no diploma who were initially inactive. For them, worklives are slightly longer in the 2005-2010 period.

In contrast, women with college educations universally have longer worklives in the 2005-2010 period than their age equivalent counterparts in the 1980-1985 period. The difference starts at more than four years for relatively younger women and slowly decreases for relatively older women. Differences at every age are statistically significant. Over this 30-year span, college-educated women are remaining active longer and are more likely to remain active from year to year. This is driving up their worklives and the worklives for all women regardless of education.

It is interesting to compare the results for men to those of women. For men, those with higher educations have relatively stable worklives. The instability comes for less educated men. For women, there is less instability among the less educated, although young uneducated women have seen their worklives shorten. In contrast, educated women have universally seen significant increases in their worklives.

The time series nature of the transition probability data also allows comparison of period and cohort worklife estimates. The period and cohort tables provide an opportunity to test whether period worklives are valid representations of a person's worklife experience as they age. The cohort worklife starts with transition probabilities in 1980-1981 and follows individuals as they age. Consider, for example, someone who is 25 years old in 1980. The transition probability at age 25 comes from the 1980-1981 transition probability for a 25-year-old. The transition probability at age 26 comes from the 1981-1982 transition probability for a 26-year-old. This progresses through age 55 where the transition probability comes from the 2009-2010 transition probability for a 55-year-old. All transition probabilities for ages over 55 come from the 2009-2010 table. If transition probabilities are fairly stable over time, then period and cohort results should be similar. This would imply that the standard method of using period transitions to calculate worklives would produce results that mirror peoples' experiences as they age.

Cohort and period results for men are compared in Table 4. The left-hand set of columns shows 1980-1985 period worklives for selected ages. The right-hand set of columns shows 1980-2010 cohort worklives for the same ages. For men of all ages, without making distinctions by education, the cohort worklives are longer than the 1980-1985 period worklives. The difference, however, is typically less than one year for initially active men and no more than 1.8 years for initially inactive men.

Looking at educational differences, for young men with no diploma, the cohort worklives are two to three years shorter than the 1980-1985 period worklives. Men 40-to-50 years old with no diploma have cohort worklives just a few months longer than their 1980-1985 period age equivalent counterparts. Among men with high school diplomas, those who are initially active have period worklives anywhere from one-to-25 months longer than age equivalent cohort worklives. For high school-educated males beyond age 35, those who are initially inactive have cohort worklives approximately two or more years longer than period worklives for their age equivalent counterparts. Cohort worklives generally are longer among college-educated men, but typically by less than one year.

These results suggest that over this three-decade period, using period worklives would not have seriously biased worklife estimates for men. There are some differences, but the effects are generally less than one year.

Table 4
Comparison of Male Worklives by Age and Education Cohort versus 1980-1985 Period

Age	1980-1985 Period Active	1980-1985 Period Inactive	Cohort Active	Cohort Inactive
ALL MALES				
25	33.8	32.1	34.6	32.7
30	29.4	27.4	30.4	28.1
35	24.9	22.4	25.8	23.5
40	20.4	16.7	21.3	17.9
45	16.1	11.8	16.9	13.4
50	12.0	7.5	13.1	9.3
NO DIPLOMA				
25	32.4	30.7	30.0	27.7
30	28.1	25.5	26.0	22.9
35	23.7	20.9	22.2	19.8
40	19.4	15.3	19.6	16.0
45	15.2	11.0	14.7	11.4
50	11.2	6.6	11.8	8.0
HIGH SCHOOL DIPLOMA				
25	33.2	31.9	32.3	31.8
30	28.8	27.0	26.7	25.6
35	24.3	20.4	23.7	22.6
40	20.2	14.0	19.8	16.9
45	16.1	10.3	16.0	12.0
50	12.0	7.2	13.5	13.0
COLLEGE DIPLOMA				
25	36.6	35.0	36.9	35.0
30	32.1	30.4	32.9	30.1
35	27.5	26.2	28.5	25.3
40	22.9	21.4	23.1	22.2
45	18.4	15.2	18.8	17.9
50	14.2	8.4	16.2	9.0

Note: In Table 4, comparisons are made between 1980-1985 Period worklife expectancies and Cohort worklife expectancies. The shading indicates the larger of the two numbers being compared. As no bootstrap errors were developed, no statistical tests are performed. The same applies to Table 5.

Table 5
Comparison of Female Worklives by Age and Education Cohort versus
1980-1985 Period

Age	1980-1985 Period Active	1980-1985 Period Inactive	Cohort Active	Cohort Inactive
ALL FEMALES				
25	25.8	23.4	30.1	27.9
30	22.6	19.9	26.8	23.9
35	19.3	16.3	22.3	19.2
40	16.0	12.6	17.6	14.3
45	12.8	8.9	13.4	9.4
50	10.0	5.3	10.8	6.3
NO DIPLOMA				
25	23.7	21.4	23.2	21.0
30	20.9	18.3	21.4	18.6
35	18.0	14.9	17.7	14.7
40	15.0	11.5	14.8	11.7
45	12.1	8.1	11.9	7.9
50	9.4	4.9	9.6	5.1
HIGH SCHOOL DIPLOMA				
25	30.1	27.8	29.6	27.7
30	26.3	24.4	26.3	24.1
35	22.7	19.9	24.5	18.8
40	18.8	15.3	17.7	15.2
45	15.2	11.6	16.7	13.2
50	12.1	7.8	12.7	10.5
COLLEGE DIPLOMA				
25	27.7	25.4	32.9	31.4
30	24.0	21.2	28.7	25.5
35	20.6	17.1	24.6	21.2
40	17.1	13.5	20.0	17.1
45	13.5	10.4	16.3	12.6
50	10.2	6.5	10.5	7.1

Note: See Table 4 note.

Cohort and period results for women are compared in Table 5. For women as a whole, among those in their twenties, cohort worklives are more than four years longer than 1980-1985 period worklives. For women in their thirties, the difference is approximately three years. Even for women who are 50, the difference can be 10 months to one year. Although there are differences among all education groups, the results are mainly driven by differences for college-educated women. Among those with a college degree, cohort worklives can be up to 60 months longer than age equivalent period worklives. Women in their thirties and forties have cohort worklives two to three years longer than the age equivalent period worklives. Clearly women are having very different labor market experiences than men. For women, especially college-educated women, using period transition probabilities would have failed to reflect an evolving labor market and would have downwardly biased worklife results. [24]

VIII. Conclusion

Current Population Survey data from 1980 through 2010 are used to derive a panel of age-specific transition probabilities, measuring movements between active and inactive states in the labor market. Changes in these transition probabilities across periods can provide interesting information on how labor market activity is evolving. In addition, the transition probabilities can be used to estimate both period and cohort worklives in a first-order Markov model. This comparison may help indicate whether worklives based on static information can be of use.

To begin the analysis, period transition probabilities from the early 1980s are compared to those from the late 2000s. This comparison shows that men under age 60 in the newer period have lower probabilities of remaining active from year-to-year than their age-equivalent counterparts in the earlier period. They are generally also less likely to transition back into the labor market once they become inactive. However, once men reach age 60, the newer period has a higher probability of remaining active from year to year than their age-equivalent counterparts in the earlier period. Relatively younger men in the 2000s are either electing to or are being forced to leave the labor market with a higher probability than their counterparts from the early 1980s were doing in their younger working years. In contrast, relatively older men in the 2000s are less likely to become inactive than their counterparts from the early 1980s. These differences may be results of demographics and the weak economy of the last several years. Younger men in the newer period may be discouraged, making them more likely to leave and less likely to re-enter the labor market. Older men in the newer period may be less likely to leave the labor market given longer life expectancies, potentially lower earnings during the recession and the prospect of having to fund longer retirements.

For women, the labor market activity is very different. At almost any age, women in the newer period have higher probabilities of remaining active from year-to-year than their age-equivalent counterpart in the earlier period. Once inactive, they are less likely to remain out of the labor market than their peers from the older period. This suggests that something very different is driving women's labor market decisions. Even with the recession, newer periods of women are more active than the periods before them.[25]

Period transition probabilities from the early 1980s and the late 2000s can be used to estimate period worklife expectancies for these two periods. Despite the difference in age-specific transition probabilities between the two periods,

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[24]We do not present formal statistical tests for the differences between cohort and period worklives. Bootstrapping these test statistics would involve some extremely cumbersome calculations. We conjecture that the large differences found for female workers are statistically significant.

[25]Significant research has been done exploring women's activities in the labor market. These studies have identified several potential influences, including women's wages, spouses' wages, education, children and birth control. See, for example, Toossi (2006); Blau and Kahn (2006); Bishop, Heim, and Mihaly (2009); Mammen and Paxson (2000); Bloom, et al., (2007); Olivetti (2006); and Bailey, et al., (2012).

for men of most ages, there does not appear to be much of a difference in worklives across periods. At almost any age, active men in the early 1980s had worklives about the same as their age-equivalent peers in to late 2000s. This result becomes more interesting when education is considered. In the later 2000s, young men with limited educations are finding the labor market less attractive and have shorter worklives than their age equivalent peers from the 1980s. Older men with limited educations, however, are remaining longer. In contrast, for men with a college education, little has changed over the last 30 years.

Women have a different experience. Period worklives for women of all ages —whether initially active or inactive—are longer in the newer period than for their age-equivalent counterparts in the earlier period. The difference ranges from more than four years for women in their twenty's to just over one year for women in their sixties. These results are driven by the experience of college-educated women. Less educated women have generally had their worklives decrease between 1980 and 2010.

The longitudinal nature of the data allows comparison of period and cohort worklives. The former assume that transition probabilities estimated at a point in time are relevant as a person ages. The latter re-estimates transition probabilities as a person ages. For men, period worklives from the early 1980s are not that different from cohort worklives calculated using data from 1980 through 2010. While there are fluctuations in the underlying transition probabilities over that period, those fluctuations generally did not significantly alter expected worklives. The exception is for relatively uneducated young men, where cohort worklives are two to three years shorter than 1980-1985 period worklives. For women, differences between cohort and period worklives are most significant for college-educated women. Among those women holding a college degree, cohort worklives can be as much as six years longer than 1980-1985 period worklives.

Collectively, the results indicate different labor market activity for men and women over this three decade period. While men had some fluctuations in their transition probabilities between 1980 and 2010, the most consequential impact was for those with little education. The impact on college-educated men was minimal. One implication of this is that over these three decades at least, using ubiquitous period worklife estimates did not bias results for college-educated men. For women, however, a different story unfolds. College-educated women in more recent years are more likely to remain active than their age-equal counterparts in earlier years. These changing transition probabilities appear to extend worklives for women in more recent periods. Comparison of cohort and period worklife estimates suggest that over this three decade span, period estimates may significantly underestimate worklives for highly educated women. It remains to be seen whether these effects continue into the future.

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Appendix

Accessing and Manipulating IPUMS-CPS and NBER CPS Data

- Creating and Downloading an IPUMS-CPS Data Extract

  1. (First Time only) Register for an Account: Go to: http://cps.ipums.org/cps-action/users/login. Type into your email address and click "Submit." You will be taken to a registration page. Fill in your details and check your email. You should then be able to sign in.
  2. Go to this page again: http://cps.ipums.org/cps-action/users/login. This time, when you type your email address, it should have a box for your password.
  3. Select Data Variables for Analysis: Go to: http://cps.ipums.org/cps-action/variables/cohort. Choose the variables you wish to analyze by clicking their section and then placing a checkmark next to them. When done, choose the green "View Cart" button.
  4. Select sample years: Click, "Add more Samples." Click "Submit sample selections."
  5. Checking out: There should be a large green "Check out: Create Data Extract button." Press it. Choose "Rectangular", not "Hierarchical." Then click on "Continue to next step." Scroll down to confirm everything looks okay and choose "Submit extract." The software will show you a confirmation page and will tell you when your download is available.
  6. Downloading the Data Extract: You will receive an email alert when your extract is ready. Follow this link: http://cps.ipums.org/cps-action/extract_requests/download. The extracts are listed in reverse order, with the newest extraction at the top. From your extraction, you will need to download the file marked "data" (this file will be quite large), and the file marked 'SPS'. Note where you have downloaded these as you will need to provide them to the application we have created to identify and merge individual records. Also note that when downloading the SPS file, you may need to Right Click->Save (Link|Target) As...

- Downloading the NBER CPS data

  1. Please ensure that you use files from this page: http://www.nber.org/data/current-population-survey-data.html, specifically the ones whose URLs resemble: http://www.nber.org/cps/cpsmarXX.zip (There are a few years that have missing links. The *zips* exist, try manipulating the URL)

- Using the Program
  You'll need to construct a database first. Minimal commands necessary:

  - "*mysql* -u root –p"
  - "create database *cps*"
  - "grant all on *cps*.* to '*cps*' *@localhost* identified by '*cps*';

Appendix Table A1
Comparison of Period Worklives Across Studies

	Male - Initially Active			
Age	1980-1985 (1)	1992-1993 (2)	1997-1998 (3)	2005-2010 (1)
25	32.97	32.90	33.62	32.19
35	24.27	24.30	25.03	24.09
45	15.64	15.70	16.64	16.14
55	8.02	8.00	8.97	9.10
	Male - Initially Inactive			
Age	1980-1985 (1)	1992-1993 (2)	1997-1998 (3)	2005-2010 (1)
25	31.38	31.40	32.27	30.53
35	21.86	21.60	22.32	21.30
45	11.50	11.80	12.29	11.95
55	3.48	3.90	4.69	4.42
	Female - Initially Active			
Age	1980-1985 (1)	1992-1993 (2)	1997-1998 (3)	2005-2010 (1)
25	25.30	27.30	28.73	28.97
35	18.94	20.50	21.50	22.26
45	12.54	13.50	14.10	15.23
55	7.02	7.10	7.53	8.62
	Female - Initially Inactive			
Age	1980-1985 (1)	1992-1993 (2)	1997-1998 (3)	2005-2010 (1)
25	22.97	25.30	26.99	26.71
35	15.98	17.50	18.72	19.08
45	8.68	9.30	10.24	11.41
55	2.65	2.80	3.20	4.15

(1) This analysis
(2) Ciecka, et al., (1995)
(3) Skoog and Ciecka (2001b)