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Pulled Out or Pushed Out? Declining Male Labor Force Participation

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Abstract

The fraction of men working in the United States has declined consistently since the 1950s. This has contributed to slower labor force growth and resulted in considerable gaps between labor force participation in the U.S. and its industrialized peers. In this paper we examine the drivers of this trend, focusing specifically on prime-age men (aged 25–54). We compare non-participation rates across four generations – the Silent Generation, Baby Boomers, Generation X, and Millennials – and decompose generational gaps into "push" and "pull" factors that are intended to be descriptive, rather than causal, by design. We define pull factors as those that draw men out of the labor force such as schooling or caretaking. Push factors are those that limit labor market opportunities, such as skills mismatch or disability. Our findings suggest that both pull and push factors are important with the most notable being skills mismatch, caretaking responsibilities, and prolonged continuing education.

Keywords: labor force participation, prime-age men, cohort analysis

JEL codes: J11, J16, J21, J82

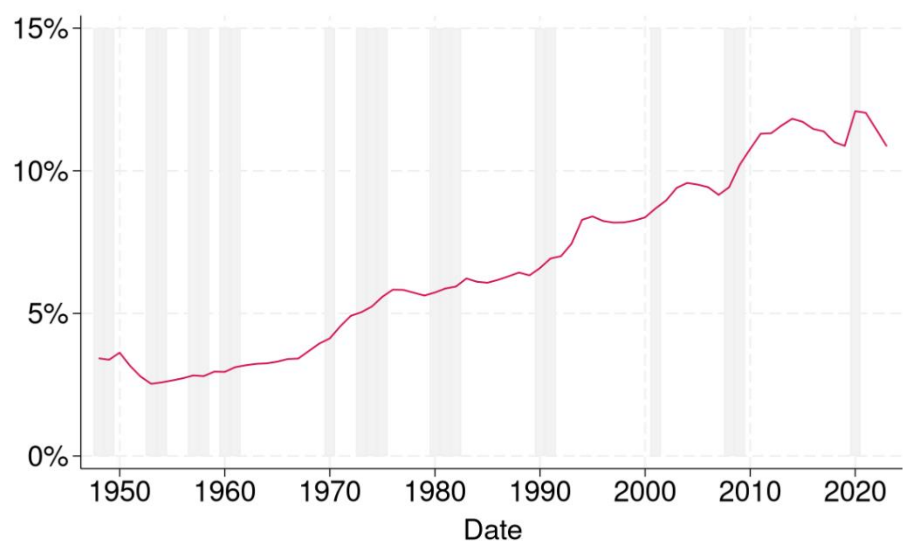
The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of San Francisco or the Board of Governors of the Federal Reserve System.

Introduction

In 1960, 1 in 35 men between the ages of 25 and 54 were on the sidelines of the labor force. By 2023, that number rose to 1 in 9. This has significant implications for the economy because prime-age men make up over one third of the work force, so forces affecting labor force participation for prime-age men will have an outsized impact on the economy as a whole. In the short run, missing workers increase labor market tightness, and in the long run this shortfall has a negative consequence for the growth of the U.S. economy. If prime-age men in the present day participated in the labor force at the same rate as their counterparts in 1960, there would have been around 5.0 million more prime-age men in the labor force in 2023. By way of comparison, the average gap between the number of job vacancies and the unemployed in 2023 was 3.3 million workers. Based purely on numbers, the amount of "missing" prime-age men would be more than enough to fill this vacancy gap.

The rise in the male labor force non-participation rate is also a critical national issue, both for the well-being of individuals, families, and communities and for the economy's ability to grow. Employment, and more broadly labor force attachment, is one of the primary ways that individuals gain human capital and increase their earnings and earnings potential. The labor force attachment of prime-age individuals (those between the ages of 25 and 54) is of particular importance because these are core years for generating labor income and workforce experience. The non-participation rate for prime-age men has been steadily increasing since the 1950s (Figure 1). In the 1950s, on average just 2.9% of prime-age men were non-participants (not working and not looking for work). By 2023, this fraction had risen to 10.9%, more than three times as high. Notably, this pattern of increased labor force non-participation is more prominent for groups of prime-age men that tend to have less favorable economic outcomes, such as black men and men without a college degree.

Figure 1. Labor force non-participation rate for prime-age men

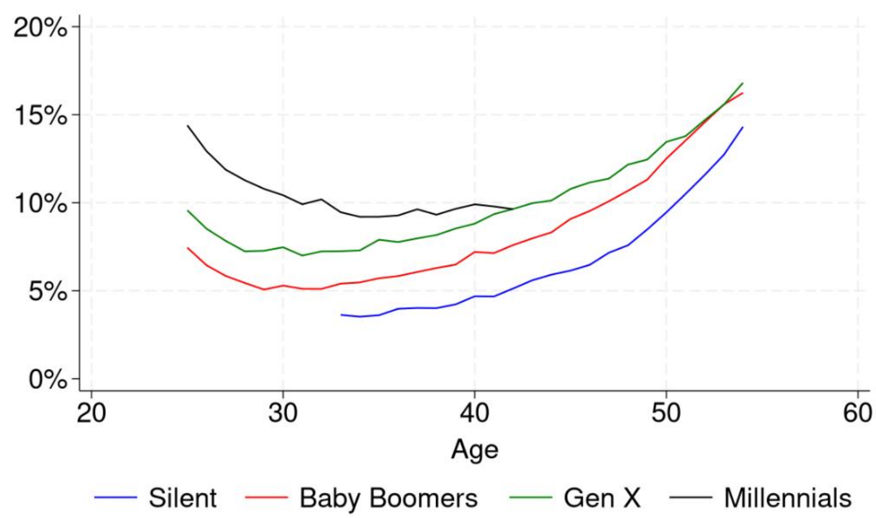


Note: Gray shading indicates NBER recession dates.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

In this paper we consider key drivers of this long-term increase in non-participation. Studying why men no longer participate will help understand whether non-participation trends will continue, slow, or reverse. This topic has a robust body of existing work. Past researchers have noted the role of industry structure, partially due to increased import competition from China (Autor, Dorn, and Hanson 2013), robotization (Acemoglu and Restrepo 2017), skills mismatch (Valletta and Barlow 2018, Council of Economic Advisors 2016), health concerns and disability (Binder and Bound 2019, Krueger 2017), improved leisure technology (Aguiar, Bils, Charles and Hurst 2021), a rise in temporary spells of non-participation (Coglianese 2018), as well as population aging (Van Zandweghe 2012, Abraham and Kearney 2020).[1] Our work adds to this literature in two dimensions: first, we focus on generational comparisons, which naturally side-steps explanations based on age structure and is studied less often in the existing literature, and second, we focus on a range of composite drivers or factors to explain the rise in non-participation.

Our analysis focuses on four generations – the Silent Generation (born 1928 – 1945), Baby Boomers (born 1946 – 1964), Generation X (born 1965 – 1980), and Millennials (born 1981 – 1996). Figure 2 plots non-participation rates for prime-age men over the life cycle for these four generations. The life cycle curves demonstrate that, for the most part, non-participation rates have been rising in each successive generation at each age, which is particularly evident for Millennial men in their late 20's and early 30's.

Figure 2. Life cycle non-participation rate for prime-age men by generation



Source: Current Population Survey and authors' calculations.

[1] If "gig" work is under-measured or under-reported in common surveys such as the CPS (meaning that "gig" workers get incorrectly classified as 'non-participants' rather than as 'employed'), a rise in "gig" work (Abraham et al. 2021) could make the measured labor force participation rate lower than the true participation rate. This would contribute upward pressure to the non-participation rate, but the presence of this kind of mis-classification is difficult to measure. Moreover, rising "gig" work is likely relevant only towards the end of our sample, but non-participation has been rising throughout.

Figure 2 also shows that younger men across earlier generations tend to have somewhat higher non-participation rates that decline until about age 30 and then increase for the rest of their lifespans. Millennial men, on the other hand, start with much higher non-participation rates in their late 20's that rapidly decrease and reach a minimum later in life, around the mid-30's, increasing only slightly after that. Comparing life cycle dynamics across generations suggests that the trends in rising non-participation rates reflect a phenomenon that is unlikely to naturally wane as time passes, though non-participation rates for older Millennials show some progress. With that in mind, the goal of this paper is to study the drivers of generational gaps in non-participation rates and to understand why life cycle non-participation dynamics of Millennial men look different from the dynamics of earlier generations.

To accomplish this, we consider a number of factors, synthesizing them into those that draw individuals out of the labor force by choice (such as delaying entry into the labor force due to schooling, training, or shifting caretaking responsibilities[2]; *pull factors*) and factors that push or leave individuals out of the labor force (such as skills mismatch, a lack of available jobs, or having a disability; *push factors*). We use "push" and "pull" as descriptive groupings to frame our analysis, not as labels that imply causality in either direction. Our approach allows us to distinguish gaps that policymakers might want to close from those that reflect personal choices or circumstances that are unlikely to be targets of policy intervention.

We formalize the evidence for our push and pull factors with regression models that estimate how each factor relates to labor force non-participation patterns conditional on age, demographics, and macroeconomic conditions. The analysis is based on over 45 years (1976-2023) of microdata from the U.S. Current Population Survey (CPS). As Figure 2 shows, non-participation has a clear life cycle pattern and has shifted up systematically across generations. While the literature has focused on explaining unconditional time-series patterns, our generational analysis allows us to see how the effects of each push and pull factor change over time across the age distribution.

When we explain generational gaps in non-participation with push and pull factors, we find that all the push and pull factors we consider have some role in changing non-participation rates. Notably, a substantial portion of the larger gap for younger Millennials relative to earlier generations is explained by prolonged continuing education (a pull factor). Skills mismatch (a push factor) and caretaking (a pull factor) also play an important role at all ages.

An implication of our findings is that there is not one easy solution to bolster prime-age male labor force participation. While the solutions still elude us, the impacts are clear. Families left more vulnerable to economic decline, a rising share of prime-age workers on publicly provided benefits, and slower labor force and potential output growth for the nation. Understanding the phenomenon and the extent to which the outcomes we observe reflect incentives that pull individuals out of the labor force or constraints that push them and keep them out remains important work.

[2] We classify caretaking as a pull factor because for prime-age men in particular, being out of the labor force for reasons related to caretaking may be likely to reflect a lifestyle choice, given prevailing social norms over the sample we study. We recognize that this characterization is not applicable to every case and that there is some ambiguity in whether caretaking is a push or pull factor.

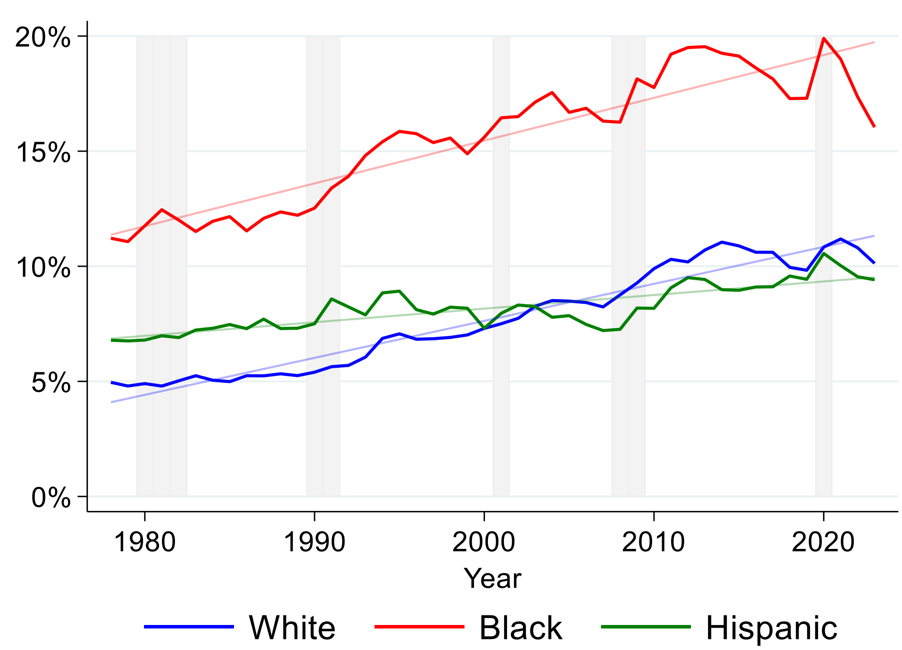
Basic trends in non-participation rates

Labor force status in the U.S. is measured in a monthly survey of individuals from about 60,000 households (the CPS) by the U.S. Bureau of Labor Statistics (BLS). The BLS releases the underlying monthly data, which are available at the individual level and include information about individuals' labor market status and demographic characteristics. We use the monthly microdata from 1976 on in our calculations and analysis (with some exceptions due to the availability of specific variables, as noted when relevant). Our analysis focuses on male respondents who were prime-age at the time of their interview.

The broad rise in non-participation seen in Figure 1 holds across groups of prime-age men, such as race and ethnicity and age group (Council of Economic Advisors 2016); however, research suggests that labor force participation rates across race, education levels, and age groups often evolve differently with a wide range of reasons affecting the behavior of each group (Pérez-Arce and Prados 2020). This variation in non-participation rates by demographic groups is relevant for our subsequent analysis.

Figure 3 demonstrates increasing non-participation rates across white, Black, and Hispanic prime-age men. From the late 1970's until 2023, rates for Black men rose from about 11% to about 16%, for Hispanic men from about 7% to 9%, and for white men from about 5% to 10%. Rates for Black prime-age men are the highest overall and increased at a somewhat faster pace than the rates for white and Hispanic men. Hispanic males experienced the slowest pace of increase in non-participation rates, and as a result, their non-participation rate fell below that for whites starting in the early 2000's.

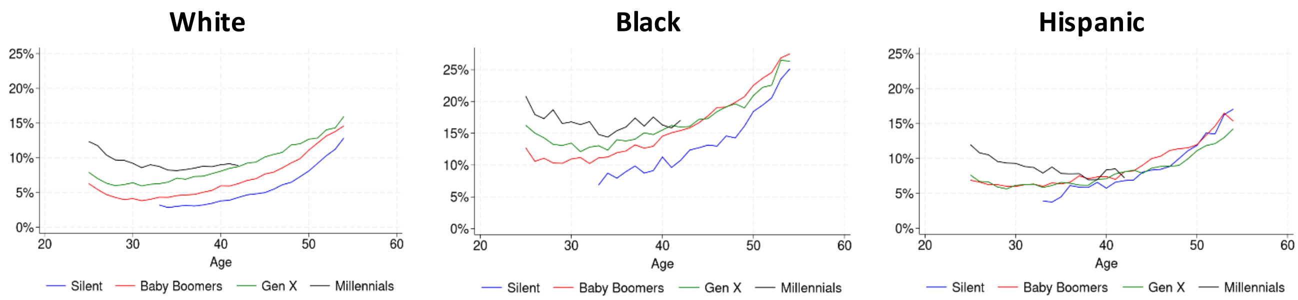
Figure 3. Labor force non-participation rate for prime-age men by race and ethnicity



Note: Linear trend lines shown in lighter shade. Gray shading indicates NBER recession dates.
Source: Current Population Survey and authors' calculations.

While labor force non-participation tends to increase during recessions and slowly and partially recover during expansions, demographic groups have a different degree of reaction to the business cycle. Hispanic and Black men are more sensitive to business cycles. Non-participation rates of these groups react more strongly to economic ups and downs than do rates for white men, as seen by the higher volatility of the green and, especially, red lines around their trends in Figure 3. This mirrors well-documented findings that Black individuals have higher and more cyclical unemployment rates than individuals of other races and ethnicities, though there has been some improvement over the past decades (Cajner et al. 2017, Duzhak 2021). Given the upward trend in non-participation, rates generally do not return to their pre-recession values during subsequent recoveries (the exception being after the COVID 19 pandemic and recession); however, the long recovery from the 2007-2009 recession significantly lowered non-participation rates to below or close to overall trends for most groups. We observe a similar fall in non-participation rates after the pandemic-induced recession. During that time, non-participation rates for Black men decreased to a level not seen since 2007, and rates for other groups fell as well. These cyclical patterns have motivated a number of studies to examine whether the decline in the labor force participation rate is cyclical or structural. Findings suggest a mix of both, and there does not seem to be a strong consensus (Congressional Budget Office 2014, Aaronson et al. 2012, Van Zandweghe 2012).

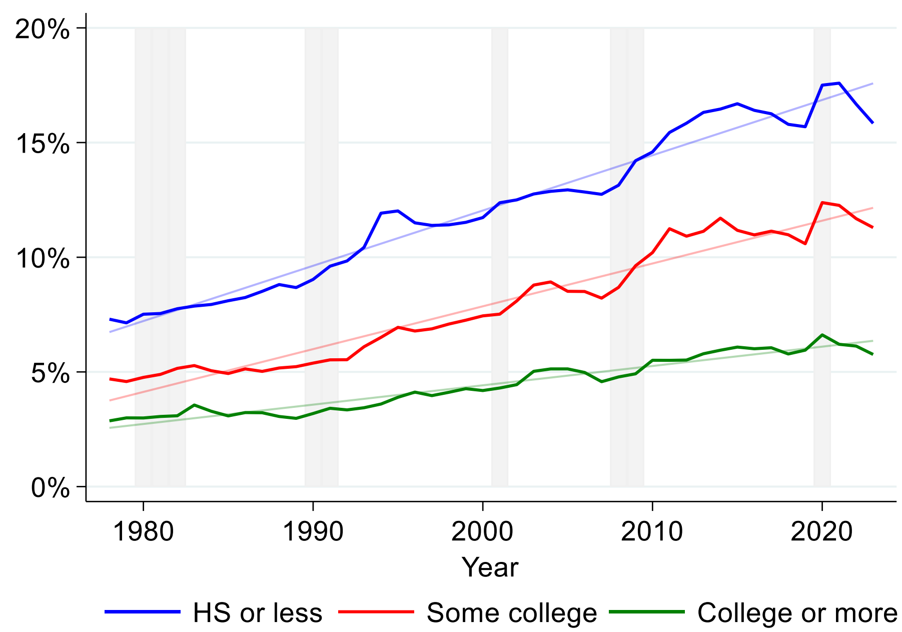
Figure 4. Life cycle non-participation rate for prime-age men by generation and race/ethnicity



Source: Current Population Survey and authors' calculations.

While life cycle patterns in non-participation rates vary by demographic group, we continue to see systematic generational gaps in these life cycle patterns across groups. This indicates that demographics alone cannot explain why non-participation has risen across generations and also underscores the idea that the simple passage of time is unlikely to bring down non-participation rates. Figure 4 is analogous to Figure 2 but shows trends for Black, white, and Hispanic prime-age men across generations. As we saw in the time series in Figure 3, non-participation rates are higher for Black individuals. Non-participation rates for Hispanic men show less pronounced changes between generations, except for young Millennials, whose non-participation rates across the life cycle look much like those for white Millennials. These less pronounced generational differences in Hispanic non-participation rates are likely driven by the changing demographic composition of the U.S. labor force. Foreign-born Hispanic men have one of the highest labor force participation rates, as many come to the U.S. to find jobs to support their families abroad. After the 1965 Immigration and Nationality Act, the flow of immigrants from Latin America increased significantly. If in 1960 the share of the Hispanic population born in Latin America was 0.5%, by 2019 this number increased to 6.5% (Hanson et al. 2023). This flow of foreign-born Hispanic men likely helped hold down non-participation rates for this group, at least through Generation X.

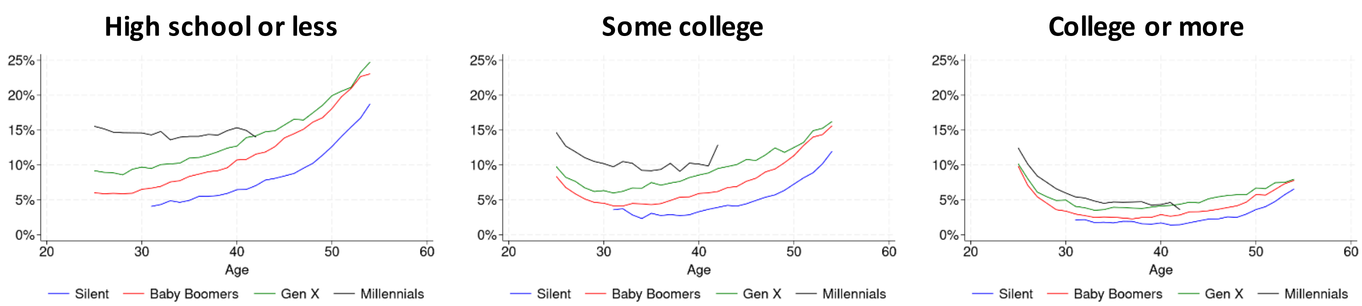
Figure 5. Non-participation rate for prime-age men by education



Note: Linear trend lines shown in lighter shade. Gray shading indicates NBER recession dates
Source: Current Population Survey and authors' calculations.

Non-participation rates also vary by educational attainment, with college graduates typically having the lowest rates. Those with no post-secondary education experienced a faster rise in non-participation, seen in the steeper slope for that education category in Figure 5. In fact, non-participation rates for men with at most a high school degree increased at more than twice the speed of those with at least a college degree, reaching about 16% by the end of our sample as opposed to 6% for college graduates. The gap in non-participation rates between the most and least educated has widened as a result. The figure also shows that the non-participation rate for individuals with at least a college degree increases the least during recessions (in percentage points), indicating that the rate for this group is the least sensitive to business cycle fluctuations. Though non-participation growth rates and levels are higher for those with less education, we also know that the fraction of individuals with a college degree is higher in younger generations. As these younger generations age and make up more of the prime-age population, that may put downward pressure on non-participation rates overall. Figure 6 supports the idea of lower non-participation rates for men with more years of education by comparing non-participation rates over the life cycle by educational attainment. The non-participation "curves" look very different for each education group. For men with post-secondary degrees, non-participation rates are highest at younger ages (i.e., 25–30), lowest around the late 30's, and then increase as men start reaching the age for retirement. Men with the fewest years of education have non-participation rates that remain flat or slightly upward sloping at younger ages. Rates then rise steadily with age, reaching a much higher level at older ages, although rates for high school educated Millennial men have remained largely flat. The patterns for men with some college education are a mix of what we see for the high school or less group and the college or more group. Though the shapes and levels of these life cycle trends differ by educational attainment, we still see rising non-participation across generations in each group.

Figure 6. Life cycle non-participation rate for prime-age men by generation and education



Source: Current Population Survey and authors' calculations.

The same conclusion holds when we compare prime-age men in other groups as well. For example, non-participation rates for rural populations of prime-age men for all generations reach a higher level at older ages than rates in urban populations, but generational participation gaps persist across both groups (Figure A5).[3] The time series and corresponding generational patterns shown above broadly suggest that demographics help us interpret the overall rise in non-participation we see but are not the only force behind the generational shifts.

Drivers of rising non-participation rates

Methods

The rise in male labor force non-participation in the U.S. is a much studied but still puzzling phenomenon. Research has pointed to various potential drivers that contribute to the overall trend, but none of them alone can explain the persistence of the trend over time (Krause and Sawhill 2017, Binder and Bound 2019, and Abraham and Kearney 2020 make related points). Rather than focus on any one factor, we consider a number of factors that push and pull individuals out of the labor force. To put the patterns above together, we formalize our study of prime-age men's non-participation with a regression framework that allows us to account for generational differences, demographics, and age effects. With this method, we can both control for population shifts in demographic, push, and pull factors across generations as well as compare how non-participation's sensitivity to these factors differs within and across generations.

We rely on individual-level regressions using the microdata from the CPS that control for a set of key demographic factors that our summary figures above suggest may explain variation in non-participation

[3] The Appendix contains time series figures of demographic breakdowns by residence (urban and rural) and marital status, as well as figures showing generational lifecycle non-participation rates.

rates. Our core model estimates the relationship between age and labor force non-participation for prime-age men in each generation separately. The structure of our specification is:

$$NILF_{ist} = \beta_1 \boldsymbol{A}_{it} + \beta_2 \boldsymbol{X}_{it} + \beta_3 UR_t + \gamma_s + \epsilon_{ist} \qquad (1)$$

where *NILF* is a 0/1 indicator for being out of the labor force, $\boldsymbol{A}$ is a full set of age indicators (with coefficient vector β_1), $\boldsymbol{X}$ is a set of demographic characteristics (indicators for race/ethnicity, educational attainment, marital status, urban/rural residence, and state-specific female labor force participation rates), and γ_s are state fixed effects. The subscripts *i*, *s*, and *t* index the individual, state, and time (in months).

Because we want to focus on factors not relating to the business cycle, we control for market conditions with the national unemployment rate (*UR*).[4] The regressions and all summary figures are weighted using the standard monthly weights in the CPS microdata and standard errors are clustered by birth year. With this specification, the coefficients tell us how much a change in a given explanatory variable is expected to change the probability of being out of the labor force (where a coefficient of 0.01 is a 1 percentage point increase in the probability of non-participation).

Baseline specification results

Table 1 shows selected coefficients. The results in the table corroborate the patterns in the figures above. Relative to white prime-age males, the probability of being out of the labor force is higher for Black men and men who are not white, Black, or Hispanic (the 'other' group). Notably, the relationships between race/ethnicity and non-participation are mostly getting weaker for each subsequent generation with Hispanic men being an exception. Non-participation rates are lower for those with some college and lower still for those with a college degree or more relative to men with a high school degree or less. Unmarried men have higher non-participation rates than do married men, and men living in rural areas are more likely to be out of the labor force than urban residents. Female labor force participation is negatively correlated with prime-age men's non-participation (positively correlated with prime-age men's participation) for all generations but the Silent Generation, reflecting that after about 2000, non-participation rates for men and women started to trend in a similar way. Finally, as we saw earlier, non-participation rates do move with the business cycle: the coefficient on the national unemployment rate is generally positive and significant.

[4] Some research indicates that prevailing economic conditions at the time of graduation have a sustained effect on earnings (Kahn 2010, Schwandt and von Wachter 2019), and could plausibly also affect labor force participation decisions. We do not include these conditions as a control since our ability to observe an individual's labor force entry decision is limited.

Table 1. Predictors of being out of the labor force: regression coefficients related to demographics

	Silent (born 1928–1945) (ages in sample: 31–54)	Baby Boomers (born 1946–1964) (ages in sample: 25–54)	Gen X (born 1965–1980) (ages in sample: 25–54)	Millennials (born 1981–1996) (ages in sample: 25–42)
Education				
Some college	-0.039***	-0.038***	-0.039***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.002)
College or more	-0.065***	-0.066***	-0.072***	-0.076***
	(0.001)	(0.001)	(0.001)	(0.001)
Race/Ethnicity				
Black	0.054***	0.062***	0.051***	0.049***
	(0.001)	(0.001)	(0.002)	(0.003)
Hispanic	0.018***	0.002	-0.028***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.002)
Other	0.045***	0.041***	0.027***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)
Not married	0.102***	0.091***	0.080***	0.071***
	(0.003)	(0.001)	(0.001)	(0.001)
Rural	0.019***	0.012***	0.019***	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)
U.S. unemployment rate	-0.161***	0.046*	0.126***	0.112**
	(0.043)	(0.022)	(0.014)	(0.038)
Female LFPR	0.070**	-0.035**	-0.230***	-0.247***
	(0.025)	(0.015)	(0.026)	(0.041)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	2098091	6528638	3916857	1459902
R-squared	0.060	0.063	0.048	0.036

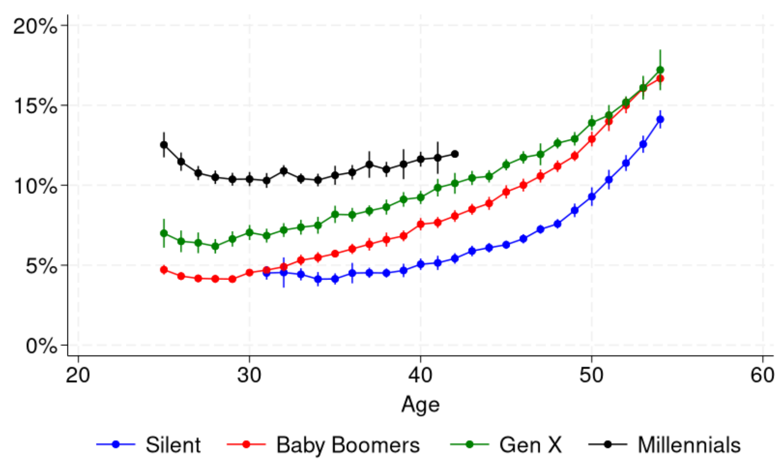
(cont.)

(cont.)

	Silent	Baby Boomers	Gen X	Millennials
Frac. some college	0.186	0.253	0.252	0.263
Frac. college or more	0.250	0.288	0.319	0.349
Frac. Black	0.100	0.110	0.119	0.133
Frac. Hispanic	0.060	0.092	0.174	0.194
Frac. other race	0.028	0.047	0.085	0.108
Frac. not married	0.196	0.324	0.406	0.594
Frac. Rural	0.263	0.198	0.139	0.112
Avg. U.S. unemployment rate	0.069	0.061	0.058	0.055
Avg. female LFPR	0.544	0.577	0.582	0.572

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Constant term, age and state fixed effects not shown. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey and author's calculations.

Figure 7. Life cycle non-participation rate for prime-age men by generation, regression adjusted for demographics



Note: Age effects shown (with 95% confidence intervals) are adjusted average predictions from specifications in Table 1.
Source: Current Population Survey and authors' calculations.

Using the estimation results from Table 1, Figure 7 plots regression-adjusted non-participation rates (and their 95% confidence intervals) at each age for each generation.[5] Even after controlling for demographic

[5] Coefficients on the age dummy variables are affected by the set of omitted categories in the models. Since we are interested in adjusted non-participation rates at each age rather than the marginal effect at each age, we plot

characteristics, we find that non-participation rates are systematically higher across the age distribution in each subsequent generation. Moreover, the non-participation rate gaps between each generation with the demographic controls are quite similar to the gaps obtained by taking simple means in Figure 2. In both figures, we see that life cycle dynamics differ for Millennials. In earlier generations, non-participation rates decline slightly through about age 30 and then increase with age. For Millennials, non-participation rates start out notably higher than rates for same-aged men in other generations and decline at a faster pace. After reaching a minimum at a slightly older age than in prior generations, non-participation rates for Millennials slowly increase. At the same time, there are a few notable differences between the raw and regression-adjusted results. First, regression-adjusted curves start at lower non-participation rates. Second, the regression-adjusted rates for men in their 20's do not decline as much as the simple means in Figure 2. As a result, the adjusted curves are flatter for younger men, particularly from the Millennial generation. This reflects the impact of demographic factors on non-participation rates, particularly those factors that are more prevalent at younger ages. Additionally, for Millennials, adjusted rates reach a minimum much sooner (around age 30) than when using simple means (around age 35). This keeps regression-adjusted rates for Millennials above those of the prior generation, unlike the convergence seen in the unadjusted means in Figure 2.

Forces that push and pull prime-age men out of the labor force

The finding that non-participation rate gaps are similar with and without demographic controls is consistent with the notion that demographic changes cannot explain all of the persistent rise in non-participation rates. As there is still a sizable portion of the generational differences that cannot be explained by demographic and regional factors, we are still left with the question: what keeps prime-age men out of the labor force?

We explore two potential classes of factors that could help explain rising non-participation across generations: 1) not participating or delaying labor market entry due to the draw of other opportunities or obligations (pull factors), and 2) leaving (or not entering) the labor force due to the lack of opportunities (push factors). The main factors we consider are delayed entry due to continuing education, caretaking (pull factors), having a disability, and skills mismatch or lack of available jobs (push factors).[6]

To do this, we consider each push and pull factor in turn, augmenting Equation (1) with variables that proxy for the particular push or pull factor ($\boldsymbol{F_{ist}}$):

$$NILF_{ist} = \beta_1 A_{it} + \beta_2 \boldsymbol{X}_{it} + \beta_3 UR_t + \gamma_s + \beta_4 \boldsymbol{F_{ist}} + \epsilon_{ist} \qquad (2)$$

Pull factor: additional years of schooling

Prime-age men may be drawn out of the labor force or delay entry to pursue additional education. Lower labor force participation in younger generations due to schooling is not necessarily a bad outcome because

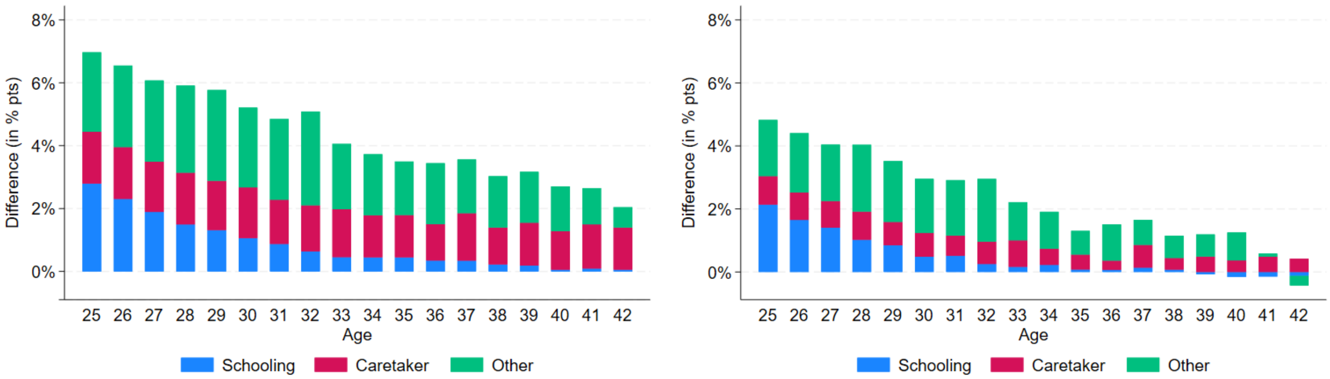
adjusted average age effects. For a given age, a, this is calculated as the average model-predicted non-participation rate assuming (counterfactually) that everyone were age a.

[6] The length of the sample varies by individual push and pull factors. For consistency and as a robustness check, Appendix Table A1 presents results with all controls and factors together, thereby using a common set of years and age ranges for all factors. The key comparisons are qualitatively similar in these results.

those who complete more years of school will probably re-join the labor force later and will likely have better long-term outcomes (e.g. Card 1999, Valletta 2019).

Figure 8. Generational difference in life cycle non-participation rate by reason for non-participation

A. Millennial and Baby Boomer prime-age men **B. Millennial and Generation X prime-age men**



Note: Figure based on respondent-given reasons for not being in the labor force at the time of the survey interview. Source: Current Population Survey and authors' calculations.

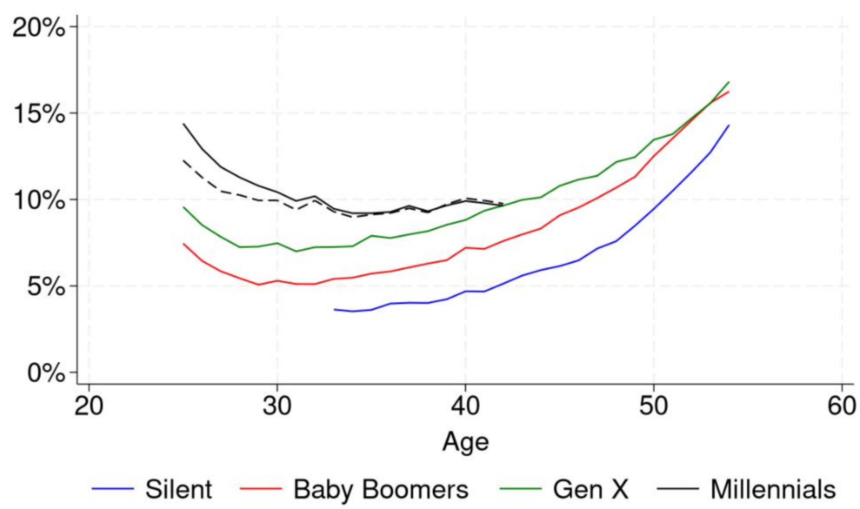
Educational attainment beyond high school (e.g., college and vocational and technical training) has increased over time. Figure 8 illustrates how this is reflected in higher temporary absence from the labor force due to schooling. Examining the difference between Millennials' and Baby Boomers' non-participation rates shows that education explains a large portion of the gap at younger ages, a pattern common across most racial/ethnic groups. This gap shrinks at older ages, reaching near zero at around age 40.

We see this pattern of initially large and then shrinking generational differences in non-participation due to schooling for all education groups. This suggests that the pattern is not only due to more men attending college, but also due to increased attendance of technical programs, two-year colleges, and graduate schools. In fact, for 25–30 year old men who indicated being out of the labor force due to schooling, across all years in our sample, between 11% and 21% had a high school degree or less at the time of survey, 35%–45% had some college, and 34%–49% had a bachelor's degree or more. To corroborate this analytically, we run a version of Equation (1) with "non-participation due to schooling" as the dependent variable (results available upon request). We find that having some college education and having a bachelor's degree or more both increase the probability of being out of the labor force due to schooling, relative to having a high school degree or less. The impact of post-secondary education is significant across all generations and the coefficients increase with each generation, suggesting that this pull factor has become a stronger force over time. Thus, as a larger share of the population pursues additional education, being out of the labor force due to schooling will likely continue to drive up the non-participation rate for younger men in subsequent generations. As a matter of fact, the National Student Clearinghouse Research

Center reported that 2024 enrollment numbers were notably higher for both college and certificate programs, particularly for students aged 21 and up.[7]

Prolonged education explains some of the atypical shape of the life cycle non-participation rate profile for Millennial men (seen in Figure 2 and described above). To explain the difference, we perform a counterfactual exercise where we calculate what would have happened if Millennial men were out of the labor force due to schooling at the same rate as men in Generation X of the same age. Figure 9 shows the counterfactual as a black dotted line. It demonstrates that in the absence of their higher rate of non-participation due to schooling, Millennials' non-participation profile would look more like the parallel upward shift seen between previous generations. Furthermore, these men will likely join the labor force at higher rates than their counterparts with less education because labor force participation rises with educational attainment. This helps explain why non-participation rates for Millennials have risen less with age and have bridged the gap to Generation X.

Figure 9. Life cycle non-participation rate for prime-age men by generation with a counterfactual for Millennial men



Note: The counterfactual assumes Millennial men are out of the labor force due to schooling at the same rate as men from Generation X of the same age.
Source: Current Population Survey and authors' calculations.

However, even after accounting for schooling, younger generations of prime-age men have higher non-participation rates than earlier generations do, so this pull factor cannot explain the full difference in generational gaps. Therefore, other reasons must still contribute to the gap in non-participation, as we can see in the sizable persistent gaps attributable to caretaking and the catch-all 'other' reasons (Figure 8). As Millennials have stayed in school longer than men in previous generations have, they may also delay other

[7] See https://nscresearchcenter.org/current-term-enrollment-estimates/.

milestones of adulthood, such as marriage and having children. In the next section, we will discuss how this social phenomenon has impacted male labor force participation rates.

Pull factor: caretaking and family obligations

An increasing share of prime-age men cite caretaking the main reason for being out of the labor force. At the same time, the share of prime-age women out of the labor force to take care of family members decreased from around 91% in the late 1970s to 61% in 2023. An aging population and shifts in childcare responsibilities may have increased the number of prime-age men caring for their children and other relatives, putting upward pressure on non-participation rates relative to earlier generations. Accordingly, we find that the fraction of men not participating due to caretaking is higher in each generation, with roughly parallel upward shifts from one generation to the next.

To understand what might be driving these patterns at an individual level, we examine how factors that capture the need and the capacity to be a caregiver interact with labor force non-participation. These factors are whether there are children in the household and if so, of what ages, and whether any other household member is employed.[8] The former captures the need for caretaking, and the latter captures the capacity of prime-age men to leave the labor force to be caretakers. We add these as separate categorical variables (main effects) and as interactions to our baseline specification. For the presence of children, we use four categories: 1) no children present (the omitted category), 2) one or more children aged 0-5 present, 3) one or more children aged 6-17 present, and 4) one or more children in both age groups present. For the employment of other household members, we have two categories, defined from the perspective of the prime-age man: 1) no other household members are employed[9] (the omitted category), and 2) at least one other household member is employed. This variable is a proxy for the employment status and earnings capacity of a prime-age man's partner, and thus also a proxy for household income or wealth. These concepts, along with the female labor force participation rate, are important controls given generational lifecycle changes in the entry of women into the labor force (Goldin and Mitchell 2017) and the effects this may have on the prevalence of dual earner households, including those in which women earn higher wages than male partners (Hotchkiss et al. 2017), and changes in childcare needs.

For this analysis, we use data back to 1982, as this is the first year in which we can reliably identify the ages of a household's children. We additionally restrict the sample to prime-age men age 42 and younger, which is the age of the oldest Millennial in our sample. This makes the samples of men used in each generation's regression more comparable, which is important because of strong life cycle patterns in marriage and non-linearities in household composition.[10] For example, younger and older prime-age men are less likely to have young children at home than men in the middle of the prime-age range.

[8] We focus on caregiving for young children because identifying households in which prime-age men face eldercare obligations is more difficult. For example, older relatives requiring care may live in a different household.

[9] "no other household members are employed" does not imply that the prime-age man in question is employed. He may be employed, unemployed, or out of the labor force.

[10] Note that using data starting in 1982 means that the age range for the Silent Generation is 37–42. Though this age range is less comparable to the age range in the other generations, results for the Silent Generation still provide a useful comparison.

Table 2. Predictors of being out of the labor force: regression coefficients related to caretaking needs and capacity

	Silent	Baby Boomers	Gen X	Millennials
Not married	0.057***	0.060***	0.045***	0.047***
	(0.004)	(0.002)	(0.001)	(0.001)
Has child(ren) 0-5 only	-0.017*	-0.023***	-0.059***	-0.084***
	(0.008)	(0.002)	(0.003)	(0.003)
Has child(ren) 6-17 only	-0.020**	-0.016***	-0.047***	-0.049***
	(0.007)	(0.003)	(0.003)	(0.005)
Has child(ren) 0-5 & 6-17	-0.021**	-0.020***	-0.065***	-0.087***
	(0.008)	(0.003)	(0.004)	(0.003)
Other HH member employed	-0.024**	-0.027***	-0.045***	-0.057***
	(0.006)	(0.002)	(0.001)	(0.002)
Has child(ren) 0-5 only X Other HH member employed	0.011	0.017***	0.044***	0.065***
	(0.008)	(0.002)	(0.002)	(0.003)
Has child(ren) 6-17 only X Other HH member employed	0.005	0.002	0.028***	0.051***
	(0.008)	(0.003)	(0.002)	(0.003)
Has child(ren) 0-5 & 6-17 X Other HH member employed	0.009	0.010***	0.048***	0.073***
	(0.008)	(0.003)	(0.003)	(0.002)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	196098	3470644	2830738	1459902
R^2	0.045	0.045	0.041	0.043
Frac. not married	0.211	0.343	0.435	0.592
Frac. with kids 0-5 only	0.059	0.165	0.179	0.164
Frac. with kids 6-17 only	0.510	0.265	0.205	0.126
Frac. with kids both age grps.	0.142	0.167	0.160	0.117
Frac. with other employed	0.613	0.617	0.636	0.662

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Constant term, age and state fixed effects, and demographic and macroeconomic controls (see Table 1) not shown. Samples in all generations are restricted to prime-age men age 42 and younger. Regressions are based on data from 1982 forward. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey and authors' calculations.

The results are in Table 2. Unmarried prime-age men are more likely to be out of the labor force than married prime-age men. This echoes our baseline results (Table 1), though here the relationship between being unmarried and non-participation is weaker for all generations. This likely reflects the correlation between marriage and having children and that prime-age men with children are more likely to be in the labor force (discussed further below).[11] The pattern that unmarried prime-age men are more likely to be out of the labor force than married prime-age men has been documented in prior work, such as Rothstein (2019), Binder and Bound (2019), and Lafortune et al. (2024), who document participation rate gaps across various groups. Results from Blandin, Jones, and Yang (2023) suggest that this may result from marriage itself encouraging employment (and thus labor force participation) rather than from assortative matching or the selection of which prime-age men marry and which do not. (Binder and Bound 2019 make a similar point.) Our results do not take a stand on the direction of causality, we merely note the association with non-participation and how the strength of this association has changed across generations. While the increase in non-participation associated with being unmarried is somewhat smaller in later generations (4.5 and 4.7 percentage points for Generation X and Millennials compared to 5.7 and 6.0 for the Silent Generation and Baby Boomers), men in younger generations are getting married later and at lower rates conditional on age (bottom panel of Table 2), which contributes to higher non-participation in younger generations.

Prime-age men in households with children are less likely to be out of the labor force than prime-age men in households with no children (as seen in prior work, for example Rothstein 2019). The forces drawing prime-age men with children into the labor force are larger in later generations, as seen by the general rise in coefficient magnitudes across generations. This would lower labor force non-participation in earlier generations; however, men in younger generations tend to have kids later in life. As a result, these younger generations of men are generally less likely than men in older generations to have kids, conditional on age (bottom panel of Table 2). Since having kids is associated with lower rates of non-participation, Millennials' lower likelihood of having children will tend to raise their non-participation rates relative to earlier generations.

As with the presence of children, living in a household in which another member is employed is associated with lower non-participation rates for prime-age men. This relationship is stronger in each subsequent generation. Millennial men living with a working household member are 5.7 percentage points less likely to be out of the labor force compared to men in households with no other earners, whereas the comparable value for Baby Boomer men is 2.7. Further, Millennial men are more likely than men in older generations to be in a household in which there is another earner (bottom panel of Table 2), which could be a combination of more young men living with family (consistent with findings in Binder and Bound 2019 and Rothstein 2019) and a cultural shift towards dual-earner couples. In this case, both the change in population characteristics and in the non-participation rate's sensitivity to the presence of other household earners put downward pressure on non-participation rates for Millennials.

When both the need and capacity to leave the labor force to be a caretaker are present, our results support the idea that caretaking pulls prime-age men out of the labor force. The coefficients on the interaction terms are positive, indicating that the tendency for prime-age men who have kids to be in the labor force is notably weaker for men who live with an employed household member (who is very likely a working partner). There is some evidence that this pull factor is stronger when children are younger, as the coefficients on the interaction terms are larger for households in which the oldest child is at most five.

[11] Another difference between Tables 1 and 2 is that Table 2 includes only men up to age 42 for all generations to match the age range available for Millennials. This age range restriction is only a partial reason for the reduction in the coefficients on 'not married' between Tables 1 and 2.

We also find that the magnitudes of the interaction term coefficients are notably larger for later generations, suggesting that the caretaking pull factor has strengthened. This is consistent with Fry (2023), who shows that there has been a slight increase from 1989 to 2021 in the fraction of men who are stay-at-home dads (defined as men aged 18 to 69 who are not working and who have children at home). Still, prime-age men in later generations are notably less likely to have kids in the first place, which would counteract some of the upward pressure in non-participation rates from the rise in the interaction term coefficients.

One possible reason that non-participation rates of men with kids fall less when men also have a working partner is limited generosity of policies related to childcare. We can test for suggestive evidence of this narrative by running a similar analysis with a sample of Canadian prime-age men, since childcare is relatively less expensive in Canada than in the U.S. (OECD 2024), and Canadian parental leave and childcare access policies are more generous than in the U.S. (Morrissey 2017). Using data from the Canadian Labour Force Survey (LFS, the Canadian analog of the CPS in the U.S.), we find that, unlike in the U.S., the interaction term coefficients are negative (for all generations except for the Silent Generation). This means that the relationship between having kids and the likelihood of non-participation tilts away from non-participation for men with an employed partner (Appendix Table A2).[12] This pattern is consistent with relatively more supportive childcare policies in Canada bolstering labor force attachment. Moreover, this relationship becomes notably stronger for younger generations, which may reflect more recent increases in the generosity of some parental leave and childcare policies in Canada. For example, maternal and parental leave policies were expanded substantially in the mid-1980s and 1990s (Baker and Milligan 2008) and Quebec introduced low-cost early education and childcare starting in the late 1990s. Researchers have found that these policies improved labor market attachment and outcomes, though the existing research focuses on women and mothers (Baker and Milligan 2008, Morrissey 2017). While Canada differs from the U.S. in more than just access to childcare, this is consistent, though merely suggestive, that the better childcare options in Canada allow these Canadian men to remain in the labor force.

Overall, caretaking as a pull factor should be interpreted within the context of women's rising labor force attachment across generations. As more women (including those who are married, have children, or both) have entered the workforce, that could in theory substitute for the employment and labor income of their male partners. Our results and those of others suggest that on net, this is unlikely (Juhn and Potter 2006, Council of Economic Advisors 2016 are examples). We find, as others have, that male labor force participation decisions are positively related to the prevailing female labor force participation rate (Table 1) and at an individual level, that men with another employed household member are more, not less, likely to be in the labor force. Our results on the pull factor created by caretaking needs and capacity add nuance to the findings that women's participation is not substituting for men's. Our results are saying that this overall pattern is tempered somewhat, though not fully, for cases in which men face both the need and capacity to be a caretaker.

[12] See the note in Appendix Table A2 for sample and variable details. In particular, 'having an employed partner' is technically 'the prime-age male respondent lives in a household with a household head and/or partner of that household head who is employed.'

Push factor: disability

Disability can create barriers to labor force participation or push prime-age men out of the labor force. It is the most common reason prime-age men are out of the labor force (Appendix Figure A1). In 2023, 38% of non-participating prime-age men listed disability as the main reason.

The link between disability and weaker labor market outcomes is well-documented. For example, Bengali et al. (2021) show that individuals with disabilities are much less likely to be employed than those without disabilities and have substantially lower earnings (based on data from 2009-2020). Focusing specifically on prime-age men, Kreuger (2017) finds that prime-age men who are not in the labor force are much more likely to have a disability than prime-age men who are in the labor force (34% of non-participants compared to 3-6% for the employed and unemployed) and are more likely to report being in poor health.[13] In addition, individuals who are not working due to having a disability are less likely to re-join the labor force, therefore permanently increasing non-participation of men in this group (e.g. Autor and Duggan 2003, Burkhauser, Daly, and Ziebarth 2016); however, there is some evidence that at least on the margin, strong labor markets can improve employment and earnings outcomes for those with disabilities. Bengali et al. (2021) and Ne'eman and Maestas (2023) find that at the end of the recovery from the 2007-2009 recession and during the recovery from the 2020 recession (both examples of strong labor markets when labor demand barriers arguably eased), labor market outcomes for individuals with disabilities improved.[14] Together, these findings are consistent with the idea that individuals with disabilities face barriers to labor market participation due to physical and cognitive conditions that restrict the ability to work (the labor supply side) and to labor demand constraints, both forces that push prime-age men out of the labor force.

Our evidence suggests that disability is a notable push factor (see Figure 8; disability is the majority of the 'other' category). Starting in 1994, disability is included as a separately coded reason that respondents can give for being out of the labor force. Since this level of detail has been available, disability has been the most-frequently given reason for non-participation among prime-age men, ranging from 46% in 1994 to 38% in 2023 (Appendix Figure A1). Moreover, supplementary calculations from the CPS Annual Social and Economic Supplement (ASEC) also indicate that having a disability can be a strong factor pushing men out of the labor force. In 2023, about 45% of non-participating prime-age men reported having a disability in the prior year, and almost 70% of prime-age men who indicated having a disability in the prior year were out of the labor force when surveyed.[15]

Comparing this push factor across generations, Figure 10 shows the predicted probability of being out of the labor force due to disability as the primary reason by age and generation, after adjusting for demographics. Comparing generations, the patterns are quite similar, as this probability increases notably

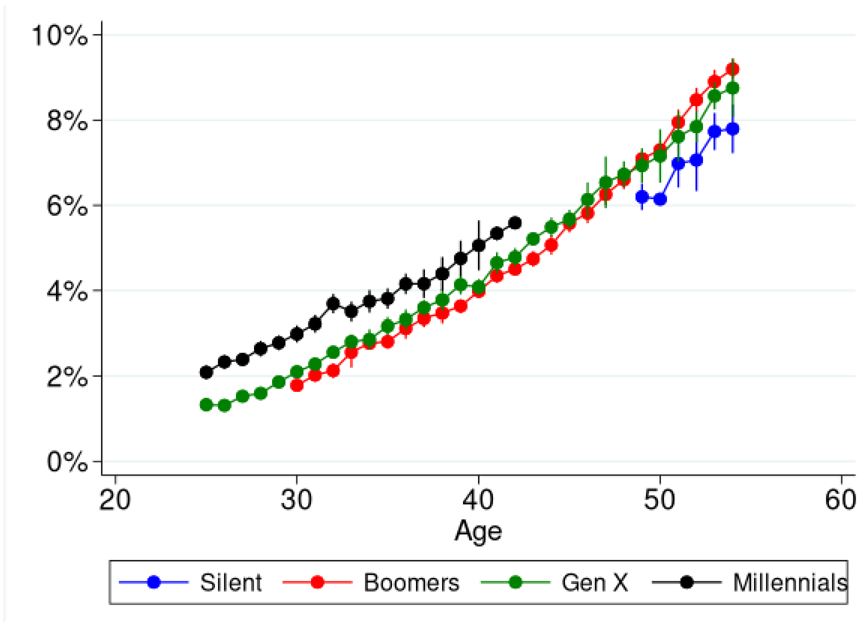
[13] Related to health more broadly, Butcher and Park (2008) study the relationship between obesity, which has increased over time and which may create conditions that limit an individual's ability to do work, and non-employment over time. Their findings suggest that the rise in obesity can explain some of the rise in non-employment.

[14] The labor force participation rate for individuals with a disability rose in the years following the 2020 recession, from 21% in 2020 to over 24% in 2023 (BLS). Rising participation of this group contributes to the overall recent increase in participation and could matter going forward if the trend continues.

[15] This measure of disability comes from a question asking about work-limiting disabilities that was introduced in the 1988 ASEC survey. There are well-documented limitations of this measure (see Bengali et al. 2021, for example), but using it is still instructive for our purposes.

with age. The figure also shows that Millennial men are more likely than their counterparts in earlier generations to identify being out of the labor force due to disability.[16] Despite this pattern, we hesitate to make strong claims about the extent to which disability prevalence may have driven changes in non-participation across generations. Disability is difficult to measure in the CPS, and other CPS measures of disability prevalence, such as from the CPS ASEC, show a less systematic increase in age-specific disability prevalence across generations (though prevalence for Millennials is generally above that for men in Generation X, Appendix Figure A8). Further, in supplementary regressions with CPS ASEC data the (strong positive) relationship between having a disability and being out of the labor force is quite similar for Baby Boomers and Millennials and actually a bit weaker than the relationship for Generation X (Appendix Table A3).[17]

Figure 10. Percent of prime-age men out of the labor force due to disability over the life cycle by generation, regression adjusted for demographics



Note: Regressions run as in Table 1, but as a logit specification with a different dependent variable. The dependent variable is an indicator that the respondent gave disability as the primary reason for non-participation. Regressions are based on data from 1994 forward. Age effects shown (with 95% confidence intervals) are adjusted average predictions.
Source: Current Population Survey and authors' calculations.

[16] This trend is also seen in the raw data, though the percent of older Millennials out of the labor force due to disability is similar to that for men in Generation X of the same age (Appendix Figure A7).
[17] This coefficient comparison is based on regressions that restrict ages in all generations to the age range available for Millennials (25–42). Using all prime-age men from prior generations, we find that the relationship between having a disability and non-participation is weaker for Millennials than it is for all prior generations (not shown).

Disability as a push factor interacts closely with participation in disability insurance programs.[18] At the margin, disability insurance availability and generosity can add to the strength of the push factor by lowering the cost of leaving the labor force. We examine the relationship between disability insurance generosity and labor force non-participation to assess whether this one component of labor force participation decisions that is related to disability can help explain generational trends in non-participation.

A robust literature has explored the connection between higher disability insurance use and lower labor force participation (for example Autor and Duggan 2003; for a recent review, see Abraham and Kearney 2020). Several papers have used natural experiments and plausibly random variation to argue that enrollment in disability insurance programs causally lowers labor force participation (Maestas, Mullen, and Strand 2013, French and Song 2014, Autor et al. 2016).

To explore this relationship across generations, we return to our basic CPS monthly data and add the ratio of disability insurance payments to earnings to our baseline specification in Equation (2) to proxy for disability insurance generosity. Specifically, for disability insurance payments, we use the average monthly Social Security Disability Insurance (SSDI) payment awarded to new male awardees of this program.[19] For earnings, we use median earnings of male full-time wage and salary workers from the BLS.[20] Though there are weaknesses with this ratio as an approximation of disability insurance generosity, it will capture major changes in how disability insurance payments compare to the outside option. (For example, a ratio based on aggregate earnings and payments will necessarily miss individual-level variation in both. Moreover, to the extent that median earnings exceed the value of the outside option for marginal disability insurance recipients, that would understate the true degree of disability insurance generosity.) Furthermore, using the measure of the proportion of people who are awarded or currently receive disability insurance as a proxy for disability insurance generosity yields similar results.

We find that for most generations, prime-age men facing a more generous disability insurance option are more likely to be out of the labor force (Table 3). Furthermore, the impact of disability insurance generosity increases for each generation up to Millennial men. Results suggest that for prime-age men in the Baby Boomer generation, an increase of 2 percentage points (roughly one standard deviation) in the award amount as a percent of earnings is associated with a 0.7 percentage point increase in the probability of being out of the labor force. For men in Generation X, the impact increases to 0.8 percentage points. In addition to more generous SSDI potentially increasing the value of being out of the labor force, the SSDI program experienced notable growth in the mid-1980s through the 1990s, years that mostly affected Baby Boomers and men in Generation X. This could contribute to the stronger positive relationship between SSDI generosity and non-participation for these generations of men, particularly since receipt of SSDI tends to be an absorbing state. For the Millennial generation, however, the relationship is negative and insignificant, meaning that more generous disability insurance does not have a strong association

[18] Note that listing disability as a reason for not participating in the labor force does not necessarily mean that the individual is receiving disability insurance.

[19] Award amounts for SSDI are provided by the Social Security Administration and are available monthly for our full sample. There is also the Supplemental Security Insurance (SSI) program for low-income disabled individuals, but due to data availability, we focus on data from the SSDI program.

[20] The BLS reports median weekly earnings, which we scale up to a monthly amount by multiplying by 52/12. Earnings are only reported at a quarterly frequency, so we make a simple approximation and use the quarterly value for each month in the quarter.

with non-participation.[21] Binder and Bound (2019) find that rising disability insurance program use explains relatively little of the rise in non-participation of younger prime-age men, so our findings for Millennials could be driven by the Millennial sample being younger (at most age 42) and the fact that SSDI recipiency is quite low for those age 42 and younger (Center on Budget and Policy Priorities, 2025); however, when we restrict the sample to those 42 and younger for all generations (the oldest Millennials in our sample are 42), we observe a similar sign flip for Millennials.

Additionally, the disability insurance award amount as a fraction of earnings has been falling over a time when many Millennial males were in the prime-age range (though this fraction is still higher than for earlier generations, bottom panel of Table 3 and Appendix Figure A9). The ratio of new disability insurance recipients to the population has also fallen substantially over a similar period (Appendix Figure A10). So, Millennial prime-age men may be less likely to think about disability insurance as a feasible option, at least on the margin. This is consistent with Abel and Deitz (2024) who study labor force detachment (those who have been non-participants for at least one year) and find that recent improvements are driven by declines in detachment due to illness and disability. They posit that the strong recovery from the 2007–2009 recession improved the outside option of working (from more labor market opportunities and higher wages), making disability insurance relatively less attractive. Since the change in the replacement rate itself and the change in non-participation's responsiveness to the replacement rate move in opposite directions during the 2000's, disability insurance may have little explanatory power for the overall increase in non-participation rates for Millennials but may be more relevant for earlier generations.

Table 3. Predictors of being out of the labor force: regression coefficients related to disability insurance generosity

	Silent	Baby Boomers	Gen X	Millennials
SSDI award replacement rate (frac.)	0.348***	0.356***	0.422***	-0.227*
	(0.056)	(0.026)	(0.054)	(0.107)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1855050	6382171	3916857	1459902
R^2	0.061	0.063	0.048	0.036
Avg. SSDI award replacement rate (frac.)	0.304	0.325	0.346	0.351

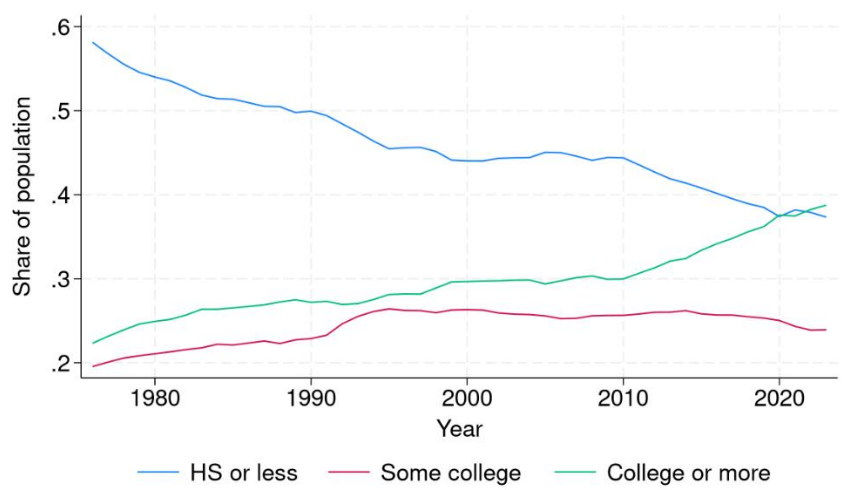
Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Constant term, age and state fixed effects, and demographic and macroeconomic controls (see Table 1) not shown. See text for description of the SSDI award rate variable. Regressions are based on data from 1979 forward. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey, Social Security Administration, U.S. Bureau of Labor Statistics, and authors' calculations.

[21] When we use the ASEC sample, which allows us to identify individuals with disabilities directly, we find that more generous disability insurance is associated with a higher likelihood of non-participation for all generations and that those with disabilities have a stronger response to changes in disability insurance generosity than those without disabilities (Appendix Table A4).

Push factor: skills mismatch

Even though skills necessary to perform the job vary across industries and occupations, one of the determinant factors for these skills is educational attainment. Some jobs, primarily in manufacturing, construction, and mining, mainly use manual labor and do not require a post-secondary degree. Others, such as jobs in professional and health services, primarily employ college graduates and those with professional degrees. Past work has highlighted falling demand for less-skilled workers as a reason for increases in the non-participation rate (Valletta and Barlow 2018, Tuzemen 2019, Juhn and Potter 2006), attributing the decline in demand in part to import competition and technology advancements (Acemoglu and Restrepo 2017, Abraham and Kearney 2020). The resulting decline in wages associated with this falling demand could provide further disincentive for labor force participation for prime-age men whose skills have become less sought after (Council of Economic Advisors 2016). Lower real wages for younger generations and therefore lower expectations for the wage growth over their life cycle discourage some men from actively seeking employment (Hotchkiss 2024). Both demand for and supply of skills have changed over the past five decades. Educational attainment, representing supply of skills, has shifted towards more educated workers, as seen in Figure 11. The share of most and least educated males converged to a similar value in 2020, and in 2022, for the first time, the number of college-educated prime-age men exceeded the number with at most a high school degree.

Figure 11. Share of education groups out of prime-age male population



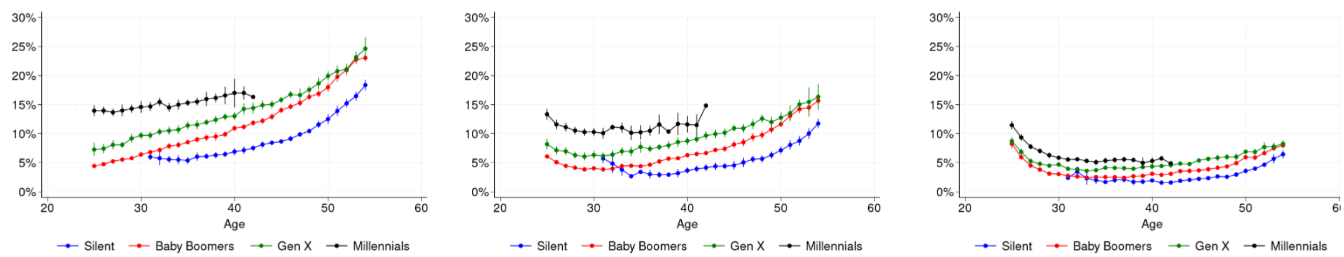
Source: Current Population Survey and authors' calculations.

We use three groups of educational attainment to approximate skill: individuals who have at most a high school degree, those with some college education, and individuals who have at least an undergraduate degree. Prime-age men with less education are more likely to face challenges in the labor market and thus are more likely to stay out of or leave the labor market. We use this group as a proxy for individuals facing labor market barriers related to skills mismatch.

Figure 12 presents generational non-participation rates by educational attainment that control for demographics and economic conditions as in Table 1. We continue to find that non-participation rates, for all educational attainment groups, are systematically higher across the age distribution for more recent generations. However, non-participation rates of low-skilled men with at most a high school degree rise steadily with age, whereas rates of men with at least a bachelor's degree fall until individuals reach their early 30's and then slowly increase. This initial decline is in part due to young men transitioning into the labor market after receiving additional education.

Figure 12. Life cycle non-participation rate for prime-age men by generation, regression adjusted for demographics

High school or less **Some college** **College or more**

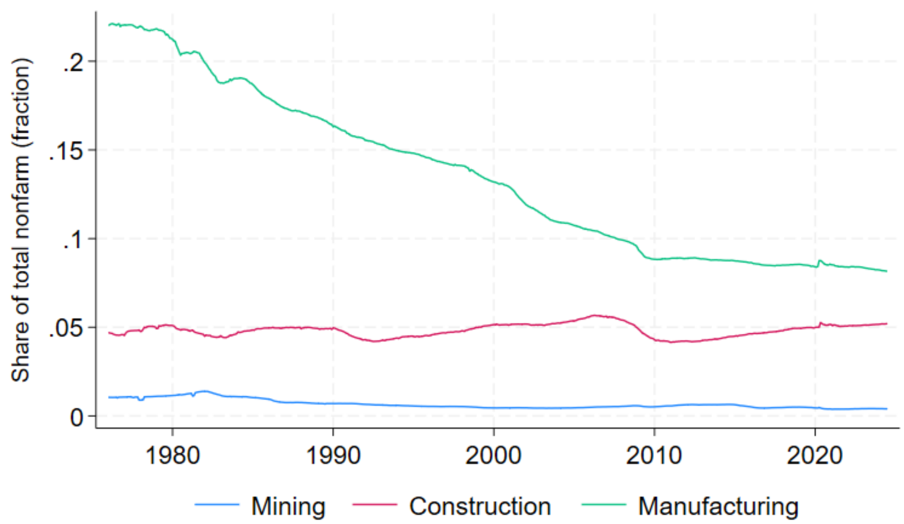


Note: Regressions run separately for each education group but are otherwise as in Table 1. Age effects shown (with 95% confidence intervals) are adjusted average predictions.
Source: Current Population Survey and authors' calculations.

Additionally, Figure 12 demonstrates that the biggest generational gaps exist among prime-age men with no college degree, particularly for those with high school education or less. For this group the gap in non-participation rates between Millennials and Baby Boomers at age 25 is 9.4 percentage points, whereas the gap for individuals with at least a college degree is 3.2 percentage points. By age 40, the Millennial-to-Boomer gap shrinks to 6 percentage points for the lowest education group, and to 2.3 percentage points for the highest education group. Therefore, a large portion of the generational non-participation gap comes from lower skilled workers. These results support the idea that low-skilled men face more difficulties participating in the work force than high-skilled men do, and that this difficulty has increased for each generation. Furthermore, some men might get discouraged from supplying their labor due to low wages. For low skilled workers the market wage is often times close to the minimum wage. In real terms minimum wages have been declining, therefore getting closer to lower skilled workers' reservation wage. That makes their decision to participate in the labor market even more sensitive to widening of the minimum wage gap. At the same time, to get a better understanding of the skill mismatch, we also examine the demand for various skills by looking at changing industry composition.

Demand for goods-producing jobs has decreased, as the employment share in these industries has substantially declined. Prior work links these changes in industry structure and falling demand for jobs that prime-age men traditionally hold to lower labor force participation (Valletta and Barlow 2018). The changing landscape of goods-producing employment is well-demonstrated in Figure 13, with a steady decline in the share of manufacturing jobs that stabilizes after the Great Recession. This has an important implication for the job prospects of prime-age men, since goods-producing industries such as manufacturing, mining, and construction have a high concentration of male workers. For instance, in 2022, the share of male workers in these industries was close to 80%. Manufacturing and mining, due to their historically high unionization levels, usually provide relatively higher salaries for low-skilled workers. Falling employment in these industries may discourage some lower-skilled workers from searching for jobs all together. Autor et al. (2025) show that many manufacturing workers who lost their job did not transition into the services sector. Rather, it was new workers who took new service-sector jobs in these communities, thus leaving former manufacturing workers vulnerable to the skills mismatch produced by changing industries composition.

Figure 13: Employment share in goods-producing industries



Source: U.S. Bureau of Labor Statistics and authors' calculations.

To capture the impact of changes in the share of jobs in goods producing industries on workers at different skill levels, we include the share of employment in mining, construction, and manufacturing industries ("Goods employment share") at the state and month level and interact this share with educational attainment. We also include the difference between the mean and the minimum hourly wage (deflated to $2022 using headline PCE) at the state and quarter level, and its interaction with educational attainment, to account for earnings inequality resulting from shifts in the demand and supply of low-skill workers. Interacting the factors with the level of education expands Equation (2) and gives us Equation (3) below.

$$NILF_{ist} = \beta_1 A_{it} + \beta_2 \boldsymbol{X}_{it} + \beta_3 UR_t + \gamma_s + \beta_4 \boldsymbol{F_{ist}} + \beta_5 \boldsymbol{F}_{st} * Educ_{it} + \epsilon_{ist} \qquad (3)$$

The vector $\boldsymbol{F}_{st}$ includes factors related to skill mismatch for state s at time t.

Table 4. Predictors of being out of the labor force: regression coefficients related to skill mismatch

	Baby Boomers	Gen X	Millennials
Some college	-0.02*** (0.007)	-0.004 (0.007)	-0.016* (0.009)
College or more	-0.027*** (0.007)	-0.019** (0.007)	-0.033*** (0.008)
Goods employment share	-0.321*** (0.041)	-0.350*** (0.026)	-0.540*** (0.135)
Some college X Goods empl. share	-0.049** (0.023)	-0.074*** (0.024)	-0.134** (0.050)
College or more X Goods empl. share	-0.042* (0.022)	-0.0003 (0.023)	-0.018 (0.035)
Min. wage gap	0.0016*** (0.000)	0.0023*** (0.000)	0.0021*** (0.000)
Some college X Min. wage gap	-0.0025*** (0.000)	-0.002*** (0.000)	-0.0002 (0.000)
College or more X Min. wage gap	-0.0059*** (0.000)	-0.0041*** (0.000)	-0.0023*** (0.000)
Age FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	4406027	3916857	1459902
R-squared	0.068	0.049	0.037
Frac. some college	0.256	0.252	0.263
Frac. college or more	0.294	0.319	0.349
Avg. min. wage gap ($2022)	7.964	12.70	17.56
Avg goods empl. share (frac.)	0.180	0.155	0.139

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Constant term, age and state fixed effects, and demographic and macroeconomic controls (see Table 1) not shown. Regressions are based on data starting in 1990. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey, U.S. Bureau of Labor Statistics (employment shares, wages), Department of Labor (minimum wages), and authors' calculations.

Table 4 displays the regression coefficients for three generations. These regressions omit the Silent Generation due to the shorter sample necessitated by variable availability limitations (data on employment shares at the state level are only available starting in 1990). The first two rows examine the role of men's skills acquired through education across the generations. Estimation results indicate that men with higher skills (approximated by those with more education) are less likely to be out of the labor force, as we saw in our earlier results. Larger magnitudes of regression coefficients suggest the increasing importance of education.[22] The growing impact is well seen for Millennials, whose regression coefficients are notably larger in magnitude than those for Generation X, capturing both declines in the share of less educated men, as well as changing demands for skilled workers.

The impact of labor demand shifting away from goods-producing jobs is particularly evident in the estimates of the goods employment share and its interaction with education. Estimated coefficients show that a decreasing share of employment in these sectors consistently increases the probability of prime-age men being out of the labor force across generations.[23] The effect is even bigger for Millennial men and those with less education. College educated men do not show any significant additional sensitivity to changes in the goods employment share, likely due to their lower exposure to these types of jobs.[24] A larger participation penalty for less educated Millennial men when the employment share of goods-producing jobs falls might stem from a bigger exposure of these workers to large employment losses in construction and manufacturing industries following the Great Recession. These job losses were concentrated among workers with less education and, in some cases such as construction, employment levels for workers with less education never recovered to their pre-recession levels.

Other types of low-skilled workers that might be affected are those that seek employment of minimum wage jobs. Our results show that an increase in the gap between minimum and average real wages in the state of residence increases the probability of being out of the labor force. Not surprisingly, this effect mostly affects workers with lower education, as evident in the sign of the interaction coefficients. Furthermore, this effect for the lowest education group is stronger for younger generations. For example, for Baby Boomers, a ten dollar increase in the minimum wage gap is predicted to increase labor force non-participation of prime-age men with lower skills by 1.6 percentage points and to decrease the probability of high skilled non-participation by 4.3 percentage points. For Millennial prime-age men, these probabilities change to an increase of 2.1 percentage points and a decrease of 0.2 percentage points respectively. These numbers also suggest that high-skilled workers with more education from earlier generations were shielded more from the effects of lower minimum wages than Millennial college educated prime-age men. The fact that less skilled workers are less likely to be in the labor force if their state's minimum wage falls relative to the average wage supports the hypothesis that lack of skills, as measured by education, can push prime-age men out of the labor force, as they get discouraged by lower pay or as the local labor market demand shifts towards relatively more skilled workers.

[22] The mostly larger coefficients for the Baby Boomer generation are likely due to the somewhat older sample for this group.

[23] Another way to capture workers skill mismatch is to use the non-cognitive, routine occupation employment share instead of the goods employment share (as in Valletta 2019: occupations in construction and extraction; installation, maintenance, and repair; production; and transportation and material moving). Doing so yields qualitatively similar results, although the main effect of the occupational share for Millennials is close to that for Generation X.

[24] We also test for differential experience of men from the rust belt and find that these men are more likely to be out of the labor force and their non-participation is more sensitive to changes in industry composition than for men from the other parts of the U.S.

Discussion

Throughout the paper, we analyzed how non-participation gaps across generations can be explained by various factors that push and pull prime-age men out of the labor force. As part of this discussion, we referenced how both changes in population characteristics (the mean of each factor) and changes in the sensitivity of non-participation to each factor (the regression coefficients) could affect overall non-participation across generations. In this section, we make this decomposition explicit, comparing the magnitudes of generational non-participation differences due to changes in means and changes in coefficients for each push and pull factor. That way we can gain a better understanding of where policy can have the greatest impact.

The regression results from Tables 2–4 show how characteristics related to push and pull factors influence non-participation rates for individuals within a generation. To make comparisons across generations, we use a decomposition similar to that used in Daly, Hobijn, and Pedtke (2020) (based on methods from Blinder 1973 and Oaxaca 1973). This method breaks down the difference in non-participation rates between two generations (G1 and G2) into a component due to the differences in observed characteristics (often called the "explained component" in the literature), a component due to differences in the relationships between non-participation and the explanatory variables (often called the "unexplained component" in the literature), and the interaction between changes in both characteristics and coefficients:

$$\overline{\boldsymbol{NILF}}_{G1} - \overline{\boldsymbol{NILF}}_{G2} = \hat{\beta}_{G2} * (\overline{\boldsymbol{X}}_{G1} - \overline{\boldsymbol{X}}_{G2}) + \overline{\boldsymbol{X}}_{G2} * \left(\hat{\beta}_{G1} - \hat{\beta}_{G2}\right) + (\overline{\boldsymbol{X}}_{G1} - \overline{\boldsymbol{X}}_{G2}) * \left(\hat{\beta}_{G1} - \hat{\beta}_{G2}\right)$$

$$= \hat{\beta}_{G2} * \Delta\overline{\boldsymbol{X}} + \overline{\boldsymbol{X}}_{G2} * \Delta\hat{\beta} + \Delta\overline{\boldsymbol{X}}\Delta\hat{\beta}$$

$$= explained\ by\ means + explained\ by\ coefficients + interaction$$

The three components can be further broken down into differences due to groups of explanatory variables. To implement this decomposition, we run a variant of Equation (2) that includes all of the measures from the individual regressions in Tables 2–4 above. Due to restrictions imposed by the availability of the employment share variables, we compare Millennials (G1) to Generation X (G2), as we have observations for a comparable set of ages for these groups (age 25–42).

The results of this decomposition are in Table 5.[25] The top panel shows the total average non-participation rate gap between Millennials and Generation X, 2.9 percentage points. About 80% of that 2.9 percentage point gap is explained by our regression model and is attributable to differences in observable population characteristics, holding the coefficients fixed. Differences in the coefficients are estimated to have a negative effect. As a result, Millennials would have had a *lower* non-participation rate than men in Generation X by about 0.3 percentage points (about 11%). The interaction between changes in population characteristics and changes in coefficients compound to account for about 30% of the gap. Panel B breaks down these contributions within each type (means, coefficients, and interactions). To simplify the table, we group explanatory variables into demographics (age, marital status, race, and urban/rural residence), skills (educational attainment, the goods employment share, its interaction with educational attainment,

[25] In this specification that puts all push and pull factor variables into the same regression, the coefficients on the controls and push and pull factor variables are quite similar to those in the regressions run with each set of push and pull factors separately. One notable exception is the coefficient on the SSDI replacement rate. In the combined regression, the point estimates shrink in magnitude and are not statistically significant. See Appendix Table A1.

the real minimum wage gap, and its interaction with educational attainment), caretaking (the presence of children, other household earners, and their interaction), disability insurance generosity, and other controls (state dummies, the national unemployment rate, the female labor force participation rate, and the constant term).

Table 5. Blinder-Oaxaca decomposition of non-participation rate gap between Millennial and Generation X prime-age men

Panel A. Overall non-participation rate decomposition

Category	**Contributions**	**% of Total**
Millennials	0.109***	
	(0.003)	
Gen X	0.080***	
	(0.002)	
Difference	0.029***	
	(0.003)	
Endowments	0.023***	80.4
	(0.004)	
Coefficients	-0.003	-10.6
	(0.005)	
Interaction	0.009*	30.2
	(0.005)	

Panel B. Decomposition components

	Endowments (means)		Coefficients		Interaction	
	Contributions	% of Total	Contributions	% of Total	Contributions	% of Total
Demographics	0.007***	23.7	-0.016***	-55.6	0.003***	11.5
	(0.001)		(0.003)		(0.001)	
Skills	0.012***	41.3	-0.077***	-269.9	0.007	23.7
	(0.003)		(0.026)		(0.005)	
Caretaking	0.003***	10.5	-0.008***	-26.7	-0.001	-2.7
	(0.001)		(0.003)		(0.001)	
Disability insurance	0.000	0.4	-0.045	-158.0	-0.001	-3.0
	(0.000)		(0.041)		(0.001)	
Controls	0.001***	4.6	0.143***	500.0	0.000	0.6
	(0.000)		(0.048)		(0.001)	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Samples in all generations are restricted to prime-age men age 42 and younger. Regressions are based on data from 1990 forward. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year.
Source: Current Population Survey, U.S. Bureau of Labor Statistics, Department of Labor, Social Security Administration, and authors' calculations.

The left-most columns of panel B show how much of the non-participation rate gap differences in each generation's population characteristics can explain. The results indicate changes in skills and caretaking variable means contributed the most to explaining the intergenerational gap in prime-age men's non-participation rates. The contribution of the variables related to skills largely stems from the rise in non-participation associated with the decline in the share of manufacturing jobs as well as the increase in the real minimum wage gap, both of which capture a rise in the potential for skills mismatch. For caretaking, Millennial men are less likely to have children than their counterparts in the prior generation, increasing non-participation rates and dominating the countervailing decline in non-participation associated with Millennials being more likely to live in a household with another earner. Changes in demographic characteristics generally increased non-participation rates, contributing about 24% to explained changes. Finally, changes in the average generosity of disability insurance made only a small (and statistically insignificant) contribution to explaining the non-participation gap.

The next two columns show the contribution of each factor due to changes in the coefficients on, or non-participation's sensitivity to, the push and pull factors. While the overall contribution of changes in sensitivities is relatively small (about -11%), contributions of disaggregated groups of factors can be quite large. The constant term, which captures differences between the two generations not accounted for in the model, is included in the 'controls' grouping. Changes attributable to the constant term dominate, and its sign means that differences not accounted for in the model increase non-participation rates for Millennials. From the perspective of our model, the difference driven by the constant term is essentially a residual, or a generational fixed effect. Secular trends in prime-age male non-participation that are not directly tied to the push and pull factors we consider may be part of the explanation.[26] While determining the exact nature of the unexplained difference remains for future work, the non-participation rate's sensitivity to the push and pull factors we study (skills, disability insurance, and caretaking) nonetheless collectively counteracts these unaccounted differences, meaning that changes in sensitivities for Millennials tend to lower non-participation rates. For example, skill mismatch characteristics such as a stronger inverse relationship between non-participation rates and the goods employment share suggests lower non-participation rates for Millennial prime-age men. This, however, is assuming goods employment shares were the same as in Generation X, while in fact, the shares have declined substantially.

The last two columns show how the interaction of changes in observable means together with changes in sensitivities contributed to the intergenerational nonparticipation gap. Two contributions stand out in terms of their magnitudes – interactions related to demographics and interactions related to skills mismatch. For example, marriage rates (included in the demographics category) are lower for Millennials, which tends to increase non-participation since men who are not married are more likely to be out of the labor force. Moreover, since the relationship between not being married and non-participation strengthened a bit in the Millennial generation (Appendix Table A1), these two changes compound and result in a positive contribution from the interaction term for demographics. In the skills mismatch category, part of the positive contribution is the result of a lower share of goods employment interacting with a stronger negative coefficient for the same category.

These findings allow us to think about gaps that policy might be able to address and those that are less likely to be affected by policy changes. For example, policy may have less influence on those who are ill or have a disability. Though disability insurance generosity is (in theory) easy to change with policy levers, our findings suggest that changes in generosity have minimal impacts on non-participation rate gaps. On the other hand, skills mismatch is a push factor that has natural ties to policy and could notably affect non-participation. Since we find that having some college education (such as a two-year degree or technical training) or more affords a substantial boost to labor force participation, increasing educational and training options could improve labor force participation.

Our results show that rising non-participation is an issue stemming from both push and pull factors, so research and solutions cannot focus on just one or the other. Our work helps us understand where the participation gaps are and what factors to target to make the biggest changes.

The rise in non-participation matters for output growth over the business cycle and for structural growth going forward because rising non-participation will further restrict the pool of workers who are supporting a growing number of aging individuals. In the end, rising non-participation is not driven exclusively by any one factor, either within a generation or between generations. Push and pull factors will always coexist but vary in how much they respond to policy and in how prominent they are in each generation. Thus,

[26] The breakdown in Figure 8 of generational changes in respondent-provided reasons for non-participation provides some hints. For example, averaging across ages 25–41 in the figure, the category 'disability, illness, and other reasons' accounts for 55% of the difference in non-participation between Millennials and Generation X. (At age 42, the difference in the non-participation rate between Millennials and Generation X is essentially zero, which distorts the average share accounted for by the combined 'other' category.) These reasons are not directly included in our model and thus could be picked up in the 'controls' category in Table 5. That said, our results in the section on disability and disability insurance caution against heavily attributing the contributions from the 'controls' category to disability alone. Other possibilities include a rise in the prevalence of temporary non-participation spells (Coglianese 2018) and changes in culture, globalization, and automation that are difficult to measure directly.

effective policy and research should be cognizant that each factors' relative importance will fluctuate over time.

References

Aaronson, Daniel, Jonathan Davis, and Luojia Hu (2012) "Explaining the Decline in the U.S. Labor Force Participation Rate," Federal Reserve Bank of Chicago, *Chicago Fed Letter* 296.

Aaronson, Stephanie, Bruce Fallick, Andrew Figura, and Jonathan F. Pingle (2006) "The Recent Decline in the Labor Force Participation Rate and Its Implications for Potential Labor Supply," *Brookings Papers on Economic Activity* 37 (Spring): 69-134.

Abel, Jaison R. and Richard Deitz (2024) "The Long-Term Rise of Labor Market Detachment: Evidence from Local Labor Markets," *FRB of New York Staff Report* 1138.

Abraham, Katharine, John Haltiwanger, Kristin Sandusky, and James Spletzer (2021) "Measuring the gig economy: Current knowledge and open issues," In *Measuring and Accounting for Innovation in the 21st Century*, 257–98. University Of Chicago Press.

Abraham, Katharine G. and Melissa S. Kearney (2020) "Explaining the Decline in the US Employment-to-Population Ratio: A Review of the Evidence," *Journal of Economic Literature*, 58 (3): 585-643.

Acemoglu, Daron and Pascual Restrepo (2020) "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy* 128 (6): 2188-2244.

Aguiar, Mark, Mark Bils, Kerwin Kofi Charles, and Erik Hurst (2021) "Leisure Luxuries and the Labor Supply of Young Men," *Journal of Political Economy* 129 (2): 337-382.

Autor, David H., David Dorn, and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review* 103 (6): 2121–68.

Autor, David, David Dorn, Gordon H. Hanson, Maggie R. Jones, and Bradley Setzler (2025) "Places versus People: The Ins and Outs of Labor Market Adjustment to Globalization," *National Bureau of Economic Research Working Paper*.

Autor, David H. and Mark G. Duggan (2003) "The rise in the disability rolls and the decline in unemployment," *The Quarterly Journal of Economics* 118 (1): 157-206.

Autor, David H., Mark G. Duggan, Kyle Greenberg, and David S. Lyle (2016) "The impact of disability benefits on labor supply: Evidence from the VA's disability compensation program," *American Economic Journal: Applied Economics* 8 (3): 31-68.

Baker, Michael and Kevin Milligan (2008) "How does job-protected maternity leave affect mothers' employment?" *Journal of Labor Economics* 26 (4): 655-691.

Bengali, Leila, Mary C. Daly, Olivia Lofton, and Robert G. Valletta (2019) "The economic status of people with disabilities and their families since the Great Recession," *The ANNALS of the American Academy of Political and Social Science* 695 (1): 123-142.

Binder, Ariel J. and John Bound (2019) "The Declining labor Market Prospects of Less-Educated Men," *Journal of Economic Perspectives* 33(2): 163-90.

Blandin, Adam, John Bailey Jones, and Fang Yang (2023) "Marriage and Work among Prime-Age Men," *Federal Reserve Bank of Richmond Working Paper Series* 23-02.

Blinder, Alan S (1973) "Wage discrimination: reduced form and structural estimates." *Journal of Human Resources*: 436-455.

Burkhauser, Richard V., and Mary C. Daly (2011) "The declining work and welfare of people with disabilities: What went wrong and a strategy for change," AEI Press.

Burkhauser, Richard V., Mary C. Daly, and Nicolas R. Ziebarth (2016) "Protecting Working-Age People with Disabilities: Experiences of Four Industrialized Nations," *Journal for Labour Market Research* 49: 367–386.

Butcher, Kristin F. and Kyung H. Park (2008) "Obesity, Disability, and the Labor Force" *Federal Reserve Bank of Chicago Economic Perspectives* Q1-2008.

Cajner, Tomaz, Tyler Radler, David Ratner, and Ivan Vidangos (2017) "Racial Gaps in Labor Market Outcomes in the Last Four Decades and Over the Business Cycle," *FEDS Working Paper* 2017-71.

Center on Budget and Policy Priorities (2025) "Chart Book: Social Security Disability Insurance," (https://www.cbpp.org/research/social-security/social-security-disability-insurance-0).

Coglianese, John (2018) "The rise of in-and-outs: Declining labor force participation of prime age men," In *Society of Labor Economics Annual Meeting, Toronto* May (5): 5-4.

Congressional Budget Office (2014) "The Slow Recovery of the Labor Market."

Council of Economic Advisors (2016) "The Long-Term Decline in Prime-Age Male Labor Force Participation."

Daly, Mary C., Bart Hobijn, and Joseph H. Pedtke (2020) "Labor market dynamics and black–white earnings gaps," *Economics Letters* 186: 108807.

Duzhak, Evgeniya (2021) "How Do Business Cycles Affect Worker Groups Differently?" *FRBSF Economic Letter*, Federal Reserve Bank of San Francisco 2021 (25).

French, Eric, and Jae Song (2014) "The effect of disability insurance receipt on labor supply," *American Economic Journal: Economic Policy* 6 (2): 291-337.

Fry, Richard (2023) "Almost 1 in 5 stay-at-home parents in the U.S. are dads," Pew Research Center, August 3.

Goldin, Claudia and Joshua Mitchell (2017) "The new life cycle of women's employment: Disappearing humps, sagging middles, expanding tops," *Journal of Economic Perspectives* 31 (1): 161-182.

Hanson, Gordon, Pia Orrenius, and Madeline Zavodny (2023) "US Immigration from Latin America in Historical Perspective," *Journal of Economic Perspectives* 37 (1): 199–222.

Hotchkiss, Julie L. (2024) "Generations of Discontent: Labor Force Participation and Wages," *Federal Reserve Bank of Atlanta Policy Hub* 2024-9.

Hotchkiss, Julie L., Robert E. Moore, Fernando Rios-Avila, and Melissa R. Trussell (2017) "A tale of two decades: Relative intra-family earning capacity and changes in family welfare over time," *Review of Economics of the Household* 15: 707-737.

Juhn, Chinhui and Simon Potter (2006) "Changes in Labor Force Participation in the United States," *Journal of Economic* Perspectives 20(3): 27-46.

Kahn, Lisa B. (2010) "The long-term labor market consequences of graduating from college in a bad economy" *Labour Economics* 17 (2): 303-316.

Krause, Eleanor and Isabel Sawhill (2017) "What we know and don't know about declining labor force participation: a review," *Center on Children and Families, Brookings Institution*, Washington, DC.

Krueger, Alan B. (2017) "Where Have All of the Workers Gone? An Inquiry into the Decline of the Labor Force Participation Rate," *Brookings Papers on Economic Activity*: 1–59.

Lafortune, Julien, Sarah Bohn, Marisol Cuellar Mejia, Jenny Duan, Hans Johnson, and Shannon McConville (2024) "Labor Force Participation in California: Trends, Gaps, and Policy Considerations," *Public Policy Institute of California*.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand (2013) "Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt," *American Economic Review* 103 (5): 1797-1829.

Morrissey, Taryn (2017) "Child care and parent labor force participation: a review of the research literature," *Review Economics of the Household* 15: 1–24.

Ne'eman, Ari, and Nicole Maestas (2023) "How has COVID-19 impacted disability employment?" *Disability and Health Journal* 16 (2): 101429.

Oaxaca, Ronald (1973) "Male-female wage differentials in urban labor markets," *International Economic Review*: 693-709.

OECD (2024) "Net childcare costs (indicator)," doi: 10.1787/e328a9ee-en (Accessed on 24 May 2024).

Pérez-Arce, Francisco and María J. Prados (2020) "The Decline in the U.S. Labor Force Participation Rate: A Literature Review," *USC CESR-Schaeffer Working Paper Series*: 2020-005.

Rothstein, Donna (2019) "Men who do not work during their prime years: What do the National Longitudinal Surveys of Youth data reveal?" U.S. Bureau of Labor Statistics, *Beyond the Numbers* 8 (11).

Schwandt, Hannes, and Till Von Wachter (2019) "Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets," *Journal of Labor Economics* 37 (S1): S161-S198.

Tuzemen, Didem (2019) "Disappearing Routine Occupations and Declining Prime-Age Labor Force Participation," *KCFed Research Working Papers*: 19-03.

Valletta, Robert G. (2019) "Recent Flattening in the Higher Education Wage Premium: Polarization, Skill Downgrading, or Both?" In *Education, Skills, and Technical Change: Implications for Future U.S. GDP Growth*, eds. Charles Hulten and Valerie Ramey, NBER-CRIW conference volume 313-3. Chicago: University of Chicago Press.

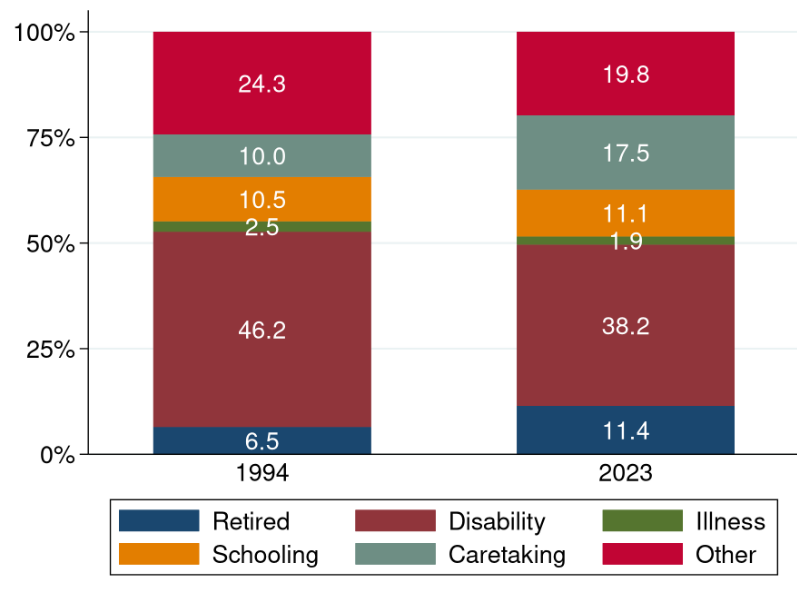
Valletta, Robert G. and Nathaniel Barlow (2018) "The Prime-Age Workforce and Labor Market Polarization," *FRBSF Economic Letter* 2018-21.

Van Zandweghe, Willem (2012) "Interpreting the Recent Decline in Labor Force Participation," *Federal Reserve Bank of Kansas City Economic Review* Q1: 5–34.

Appendix

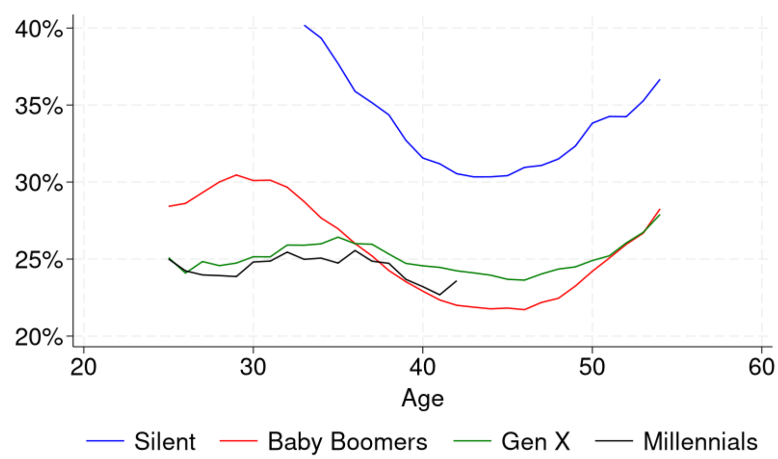
Additional figures

Appendix Figure A1. Reasons for non-participation as share of total male non-participants



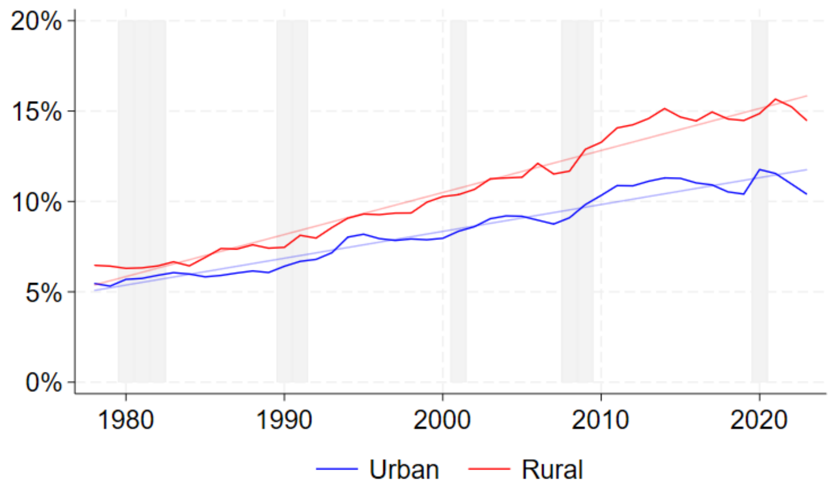
Source: Current Population Survey and authors' calculations.

Appendix Figure A2. Life cycle non-participation rate for prime-age women by generation



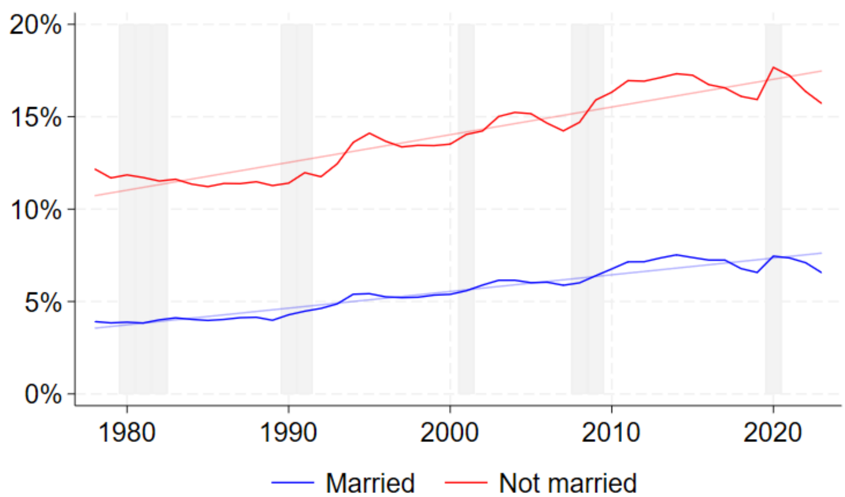
Source: Current Population Survey and authors' calculations.

Appendix Figure A3. Non-participation rate for prime-age men by urban/rural status



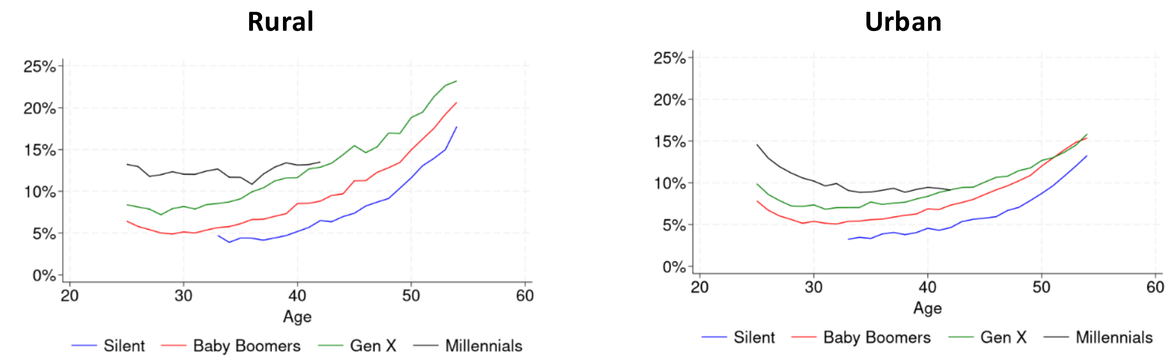
Note: Linear trend lines shown in lighter shade. Gray shading indicates NBER recession dates.
Source: Current Population Survey and authors' calculations.

Appendix Figure A4. Non-participation rate for prime-age men by marital status



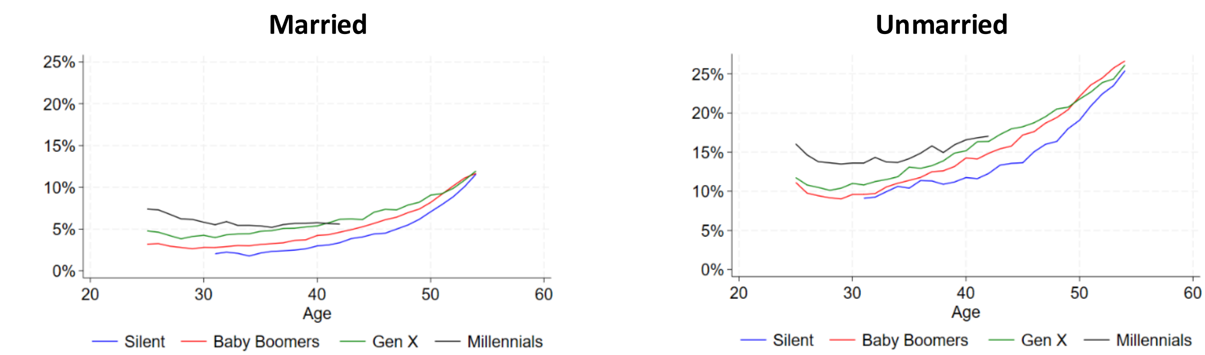
Note: Linear trend lines shown in lighter shade. Gray shading indicates NBER recession dates.
Source: Current Population Survey and authors' calculations.

Figure A5. Life cycle non-participation rate for prime-age men by geographic location



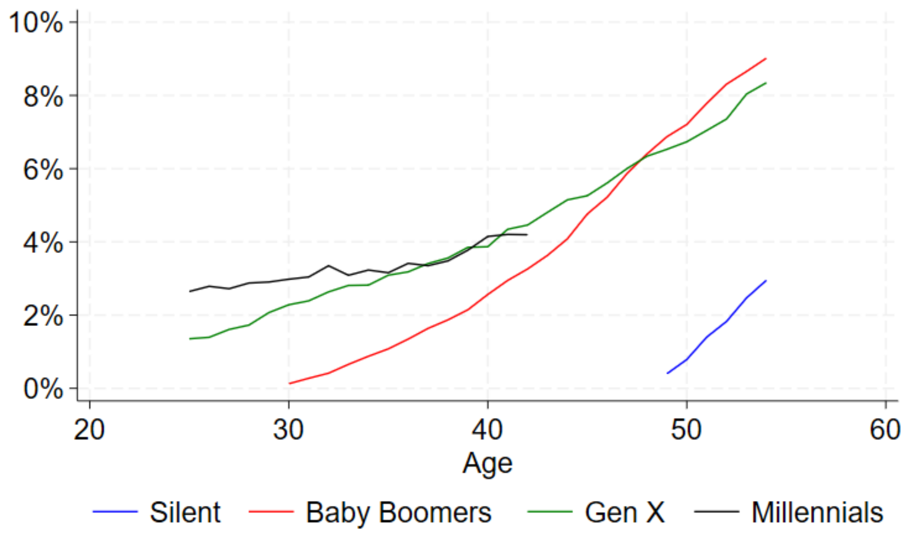
Source: Current Population Survey and authors' calculations.

Figure A6. Life cycle non-participation rate for prime-age men by marital status



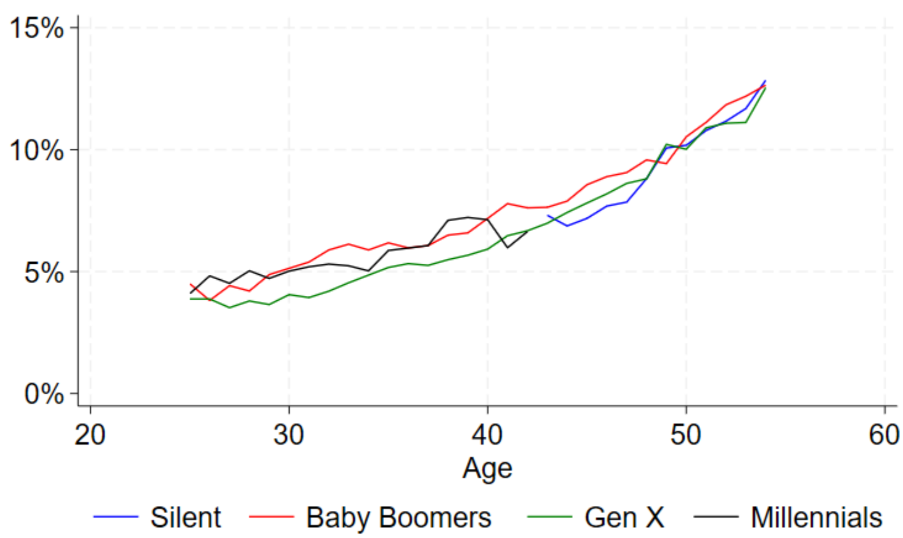
Source: Current Population Survey and authors' calculations.

Appendix Figure A7. Percent of prime-age men out of the labor force due to disability over the life cycle by generation



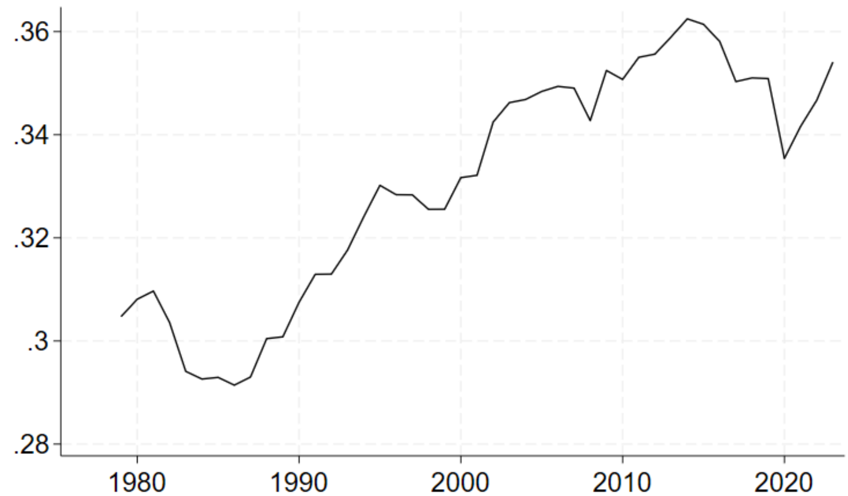
Note: Figure shows the percent of respondents who were not in the labor force and listed disability as the primary reason for non-participation. Figure is based on data from 1994 forward.
Source: Current Population Survey and authors' calculations.

Appendix Figure A8. Percent of prime-age men with a disability over the life cycle by generation



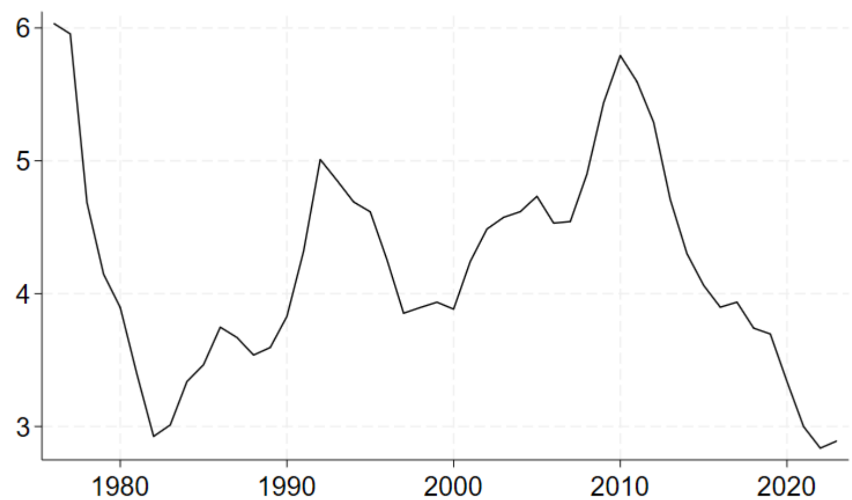
Note: Disability is measured using a question asking about work-limiting disabilities that was introduced in the 1988 CPS ASEC survey.
Source: Current Population Survey ASEC sample and authors' calculations.

Appendix Figure A9. Social Security Disability Insurance (SSDI) award replacement rate (fraction)



Note: For disability insurance payments, we use the average monthly SSDI payment awarded to new male awardees. For earnings, we use median earnings of male full-time wage and salary workers from the BLS. See text for details.
Source: U.S. Bureau of Labor Statistics, Social Security Administration, and authors' calculations.

Appendix Figure A10. Social Security Disability Insurance (SSDI) new male awards per 1000 men aged 16–64



Source: U.S. Bureau of Labor Statistics, Social Security Administration, and authors' calculations.

Additional tables

Appendix Table A1. Predictors of being out of the labor force: all controls and factors

	Gen X	Millennials
Some college	0.003	-0.020**
	(0.009)	(0.009)
College or more	-0.008	-0.046***
	(0.007)	(0.007)
Min. wage gap	0.003***	0.002***
	(0.001)	(0.000)
Some college X Min. wage gap	-0.002***	-0.000
	(0.000)	(0.000)
College or more X Min. wage gap	-0.004***	-0.002***
	(0.000)	(0.000)
Goods share	-0.254***	-0.611***
	(0.043)	(0.133)
Some college X Goods empl. share	-0.105***	-0.131**
	(0.033)	(0.051)
College or more X Goods empl. share	-0.043*	0.003
	(0.021)	(0.034)
Black	0.052***	0.047***
	(0.001)	(0.003)
Hispanic	-0.020***	-0.027***
	(0.003)	(0.002)
Other	0.034***	0.028***
	(0.003)	(0.002)
Not married	0.045***	0.047***
	(0.001)	(0.001)
Rural	0.015***	0.014***
	(0.001)	(0.002)
U.S. unemployment rate	0.029	0.165***
	(0.026)	(0.035)
Female LFPR	-0.113***	-0.168***
	(0.017)	(0.028)

(cont.)

(cont.)

	Gen X	Millennials
Has child(ren) 0-5 only	-0.058***	-0.083***
	(0.003)	(0.003)
Has child(ren) 6-17 only	-0.046***	-0.049***
	(0.003)	(0.005)
Has child(ren) 0-5 & 6-17	-0.064***	-0.086***
	(0.004)	(0.004)
Other HH member employed	-0.045***	-0.057***
	(0.001)	(0.002)
Has child(ren) 0-5 only X Other HH member employed	0.044***	0.065***
	(0.002)	(0.003)
Has child(ren) 6-17 only X Other HH member employed	0.028***	0.051***
	(0.002)	(0.003)
Has child(ren) 0-5 & 6-17 X Other HH member employed	0.048***	0.073***
	(0.003)	(0.002)
SSDI award replacement rate (frac.)	0.017	-0.114
	(0.068)	(0.089)
Age FE	Yes	Yes
State FE	Yes	Yes
Observations	2830738	1459902
R^2	0.042	0.043
Frac. some college	0.256	0.263
Frac. college or more	0.304	0.349
Frac. Black	0.118	0.133
Frac. Hispanic	0.178	0.194
Frac. other race	0.082	0.108
Frac. rural	0.143	0.112
Avg. national unemployment rate	0.059	0.055
Avg. female LFPR	0.588	0.572
Frac. not married	0.435	0.592
Frac. with kids 0-5 only	0.179	0.164
Frac. with kids 6-17 only	0.205	0.126
Frac. with kids both age grps.	0.160	0.117
Frac. with other employed	0.636	0.662
Avg. SSDI award replacement rate (frac.)	0.344	0.351
Avg. min. wage gap ($2022)	10.522	17.558
Avg. goods empl. share (frac.)	0.162	0.139

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Constant term, age and state fixed effects not shown. Samples in all generations are restricted to prime-age men age 42 and younger. Regressions are based on data from 1990 on. The regressions are weighted using the standard monthly weights in the CPS microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey, U.S. Bureau of Labor Statistics, Department of Labor, Social Security Administration, and authors' calculations.

Appendix Table A2. Predictors of being out of the labor force for Canadian prime-age men: regression coefficients related to caretaking needs and capacity

	Silent	Baby Boomers	Gen X	Millennials
Not married	0.054***	0.059***	0.065***	0.091***
	(0.006)	(0.001)	(0.002)	(0.003)
Youngest child(ren) 0-5	-0.049***	-0.010***	0.012***	0.044***
	(0.005)	(0.003)	(0.002)	(0.003)
Youngest child(ren) 6-17	-0.046***	-0.008***	0.000	0.029***
	(0.006)	(0.003)	(0.002)	(0.009)
Other household head/partner employed	-0.054***	-0.015***	-0.005	0.036***
	(0.005)	(0.003)	(0.003)	(0.003)
Youngest child(ren) 0-5 X Other household head/partner employed	0.041***	-0.012**	-0.042***	-0.078***
	(0.006)	(0.005)	(0.003)	(0.004)
Youngest child(ren) 6-17 X Other household head/partner employed	0.032***	-0.025***	-0.036***	-0.063***
	(0.005)	(0.004)	(0.003)	(0.006)
Age FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	372427	4259636	3045941	1470956
R^2	0.051	0.035	0.029	0.028
Frac. NILF	0.053	0.068	0.078	0.089
Frac. not married	0.163	0.279	0.359	0.482
Frac. w/ youngest kids 0-5	0.166	0.286	0.275	0.222
Frac. w/ youngest kids 6-17	0.540	0.265	0.174	0.056
Frac. w/ spouse employed	0.505	0.500	0.504	0.462

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions use the microdata from the Canadian Labour Force Survey (LFS). Demographic and macroeconomic controls (an indicator for having at least a college degree, national unemployment rate, female LFPR) as well as a constant term are not shown. Age fixed effects are in 5-year age groupings due to data limitations in the LFS. Samples in all generations are restricted to prime-age men age 42 and younger. Regressions are based on data from 1982 forward for comparability with regressions using the U.S. CPS. The regressions are weighted using the LFS monthly survey weights and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table. Relative to the CPS, we do not have urban/ rural residential status, we can only create a two-level education variable (less than a college degree or at least a college degree), we do not have information about race, we only know ages of the youngest children, and we only have information on the employment status of household heads/partners with which the respondent lives (so 'other employed' is most accurately 'respondent lives in a household in which the household head and/or partner is employed'). Versions of the U.S. regressions with variable and sample definitions altered from those in the main text to be as similar as possible to Canadian variable definitions (available upon request) yield similar cross-country comparisons.
Source: Labour Force Survey and authors' calculations.

Appendix Table A3. Predictors of being out of the labor force: coefficients related to disability

	Baby Boomers	Gen X	Millennials
Some College	-0.022***	-0.017***	-0.018***
	(0.001)	(0.001)	(0.002)
College or more	-0.022***	-0.026***	-0.043***
	(0.002)	(0.002)	(0.002)
Black	0.057***	0.050***	0.049***
	(0.003)	(0.003)	(0.004)
Hispanic	0.015***	-0.005*	-0.014***
	(0.002)	(0.003)	(0.003)
Other	0.047***	0.036***	0.034***
	(0.004)	(0.002)	(0.004)
Not married	0.049***	0.047***	0.053***
	(0.001)	(0.001)	(0.002)
Rural	0.006***	0.006***	0.008*
	(0.002)	(0.002)	(0.004)
U.S. unemployment rate	-0.001**	0.001**	0.002***
	(0.001)	(0.000)	(0.000)
SSDI award replacement	0.549***	0.629***	-0.003
	(0.060)	(0.071)	(0.177)
Female LFPR	-0.106**	-0.120***	-0.098
	(0.040)	(0.032)	(0.056)
Has disability	0.541***	0.611***	0.548***
	(0.007)	(0.006)	(0.010)
Age FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	228005	353637	182476
R^2	0.303	0.253	0.183
Avg. SSDI award replacement rate (frac.)	0.319	0.345	0.352
Frac. with disability	0.063	0.048	0.052

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Constant term, age and state fixed effects not shown. See text for description of the SSDI award rate variable. Samples in all generations are restricted to prime-age men age 42 and younger. Regressions are based on data from 1988 forward using CPS ASEC data. The regressions are weighted using the standard ASEC weights in the CPS ASEC microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.
Source: Current Population Survey ASEC, Social Security Administration, U.S. Bureau of Labor Statistics, and authors' calculations.

Appendix Table A4. Predictors of being out of the labor force: regression coefficients related to disability insurance generosity

Panel A. Individuals without disabilities

	Silent	Baby Boomers	Gen X	Millennials
Some College	-0.008**	-0.016***	-0.014***	-0.006***
	(0.004)	(0.001)	(0.001)	(0.002)
College or more	-0.020***	-0.025***	-0.027***	-0.032***
	(0.003)	(0.001)	(0.001)	(0.002)
Black	0.033***	0.041***	0.040***	0.041***
	(0.005)	(0.001)	(0.003)	(0.004)
Hispanic	0.007*	0.007***	-0.009***	-0.011***
	(0.004)	(0.002)	(0.002)	(0.003)
Other	0.019***	0.032***	0.030***	0.034***
	(0.006)	(0.002)	(0.002)	(0.003)
Not married	0.042***	0.045***	0.047***	0.049***
	(0.006)	(0.001)	(0.001)	(0.001)
Rural	0.009*	0.001	0.006***	0.006
	(0.005)	(0.001)	(0.001)	(0.004)
U.S. unemployment rate	-0.003	0.001	0.001**	0.001
	(0.002)	(0.000)	(0.000)	(0.001)
SSDI award replacement rate (frac.)	0.332	0.364***	0.370***	-0.136
	(0.235)	(0.030)	(0.074)	(0.180)
Female LFPR	-0.040	-0.079***	-0.165***	-0.117**
	(0.066)	(0.013)	(0.018)	(0.053)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	52018	476298	468271	173815
R^2	0.020	0.027	0.022	0.025
Avg. SSDI award replacement rate (frac.)	0.313	0.331	0.347	0.352

Panel B. Individuals with disabilities

	Silent	Baby Boomers	Gen X	Millennials
Some College	-0.119***	-0.104***	-0.113***	-0.168***
	(0.016)	(0.007)	(0.008)	(0.014)
College or more	-0.238***	-0.235***	-0.233***	-0.336***
	(0.015)	(0.011)	(0.015)	(0.021)
Black	0.097***	0.113***	0.088***	0.135***
	(0.021)	(0.009)	(0.009)	(0.020)
Hispanic	0.104***	0.072***	0.024*	-0.026
	(0.026)	(0.013)	(0.013)	(0.018)
Other	0.042	0.037***	0.022	0.005
	(0.036)	(0.011)	(0.019)	(0.027)
Not married	0.112***	0.101***	0.114***	0.133***
	(0.015)	(0.004)	(0.010)	(0.021)
Rural	0.038**	0.047***	0.043***	0.040**
	(0.014)	(0.009)	(0.010)	(0.015)
U.S. unemployment rate	-0.014*	-0.003	0.007***	0.014***
	(0.007)	(0.002)	(0.002)	(0.003)
SSDI award replacement rate (frac.)	3.306***	2.414***	1.750***	2.222***
	(1.018)	(0.200)	(0.404)	(0.731)
Female LFPR	-0.581	-0.054	-0.317*	0.052
	(0.558)	(0.170)	(0.156)	(0.265)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	5734	39175	26698	8661
R^2	0.112	0.115	0.098	0.130
Avg. SSDI award replacement rate (frac.)	0.314	0.335	0.349	0.352

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Constant term, age and state fixed effects not shown. See text for description of the SSDI award rate variable. Regressions are based on data from 1988 forward using CPS ASEC data. The regressions are weighted using the standard ASEC weights in the CPS ASEC microdata and standard errors (in parentheses) are clustered by birth year. Means of key controls shown at the bottom of the table.

Source: Current Population Survey ASEC, Social Security Administration, U.S. Bureau of Labor Statistics, and authors' calculations.