The Declining Labor Market Prospects of Less-Educated Men

Online Appendix

Ariel J. Binder and John Bound*

Date: January 25, 2019

* *Ariel Binder is a PhD candidate in Economics and Pre-Doctoral Trainee at the Population Studies Center, University of Michigan, Ann Arbor, Michigan. John Bound is the George E. Johnson Collegiate Professor of Economics and a Research Professor at the Population Studies Center, University of Michigan, Ann Arbor, Michigan. Their email addresses are <ajbinder@umich.edu> and <jbound@umich.edu>, respectively.*

Data Processing Information

We constructed original output for the main text using data from the March Supplement to the Current Population Survey, U.S. Census and American Community Survey Public Use Microdata, and Survey of Income and Program Participation Data linked to Social Security Administration Earnings Records (SIPP-SSA). Below is additional information on how this output was constructed.

Construction of Main Samples

The main samples, used in the analyses of March CPS and U.S. Census Bureau data, were constructed according to the following specifications: we considered all civilian males aged 25-54 with non-imputed age, sex, race, or education information. When measuring labor-force participation and wages in the CPS, we further excluded individuals with imputed current labor-force status and individuals with imputed hours worked per week or weeks worked last year. When computing wages, we experimented with further dropping individuals with imputed wage income. However, this had virtually no impact on calculated wage statistics. Thus, to preserve consistency with the other analyses, we retained individuals with imputed wage income when constructing and analyzing wages. We considered 3 main samples: all men, non-Hispanic whites, and non-Hispanic blacks.

Table 1 of the main text is based on SIPP-SSA data. We used a slightly different, though highly comparable, main sample in these analyses. See Table 1 notes for details.

Construction of Hourly Wages in March CPS Data

This involved several straightforward steps. First, we adjusted observed wage incomes for top-coding. Before the 1995 survey, wage incomes were top-coded at a common value. We replaced these cases with the top-code multiplied by 1.5. From 1996-2010, wage incomes above a top-code threshold were replaced with means of incomes above the top-code, conditional on certain observed characteristics. After 2010, wage incomes above the top-code threshold (different for each state) were systematically swapped with other reported values within a bounded interval. We elected not to implement any top-coding adjustments post-1995.

Second, we used the Personal Consumption Expenditures Deflator to convert nominal values into 2017 dollars. Third, we computed annual hours worked. After the 1976 survey, this simply involved multiplying weeks worked by usual hours worked per week. Before 1976, weeks worked information is available only in the form of intervals, and usual hours worked per week is not available. However, hours worked last week is available. Thus, before 1976, we imputed weeks worked using demographic information (race, age, education) in conjunction with the observed weeks worked bin. We imputed usual hours worked per week using demographic information in conjunction with the observed weeks worked bin and hours worked last week. We used 1976-1981 data to condition the imputation regressions.

Finally, we divided real annual earnings by annual hours worked to compute real hourly wages. We trimmed wage outliers with calculated wages below $2.50 or above $175 from the sample. In Figure 1 of the main text, we compute the average wage in a given year by applying the exponential function to the average log wage. In Figure 2, we compute the average wage in year y relative to 1973 by applying the exponential function to the difference in average log wages between year y and 1973. Hence the series can be interpreted as geometric averages.

Re-Weighting to Hold the Age Distribution Constant Throughout Time

Throughout the main text we often consider 3 age groups: 25-34, 35-44, 45-54. However, in some cases we construct time series statistics based on the entire 25-54 age range. When we do this, we apply a re-weighting procedure to hold the age distribution constant throughout time.

The procedure works as follows. Suppose we are considering the time period between year y_0 and year y_1. We divide the prime-age population into 6 age groups: 25-29, 30-34, …, 50-54. Denote these as age groups 1 through 6. We compute the share of the population observed between y_0 and y_1 belonging to each of the age groups: these become weights w_1 through w_6. To construct an age-adjusted time series for the concept *C* for the entire prime-age population, we compute *C* within each age group and each year (using individual sampling weights within each age group and year to ensure national representation). Then we apply the weights to the individual age group measures. Thus, for a given year *y*,

$$C_y = \sum_{i=1}^{6} w_i \times C_{yi}$$

where C_{yi} is the measure of *C* for age group *i* in year *y*.

Construction of Yearly Employment Measures from SIPP-SSA Data

Table 1 is based data from the SIPP Synthetic data product produced by the U.S. Census Bureau. See Benedetto, Stinson, and Abowd (2013) for extensive information on data construction. The SIPP data record individuals' labor market activities at the monthly level, for periods of 24 months or more; the SSA data record individuals' annual earnings histories over a long horizon.

The bottom panel of Table 1 uses a yearly measure of labor-force attachment based on SSA earnings records. The SIPP-SSA data contains 4 sources of earnings variables: total non-deferred earnings from FICA-covered jobs; total deferred earnings from FICA-covered jobs; total non-deferred earnings from jobs not covered by the FICA tax; and total deferred earnings from jobs not covered by the FICA tax. We summed all 4 sources of administrative earnings together to come up with a measure of total yearly earnings. Next, we computed yearly labor-force attachment measures based on whether total earnings for the year were above a certain minimum threshold. Following Coglianese (2018), we used a threshold of one-half of the federal minimum wage times 40 hours per week times 13 weeks per year.

Additional Information Regarding Household Income Tabulations

As discussed in the main text, we use the years 1992-2017 for this table, as this is the range of years for which the March CPS fully distinguishes between all relevant sources of income.[1] We exclude households with imputed sources of income. A substantial share of households in our sample (around 29%) contain a member who did not respond to the business income question. Thus, excluding these households resulted in a substantial change in the sample. We verified that our tabulations were not sensitive to the exclusion of these households.

For ease of exposition and to conserve space, Table 2 only distinguishes between the man's own disability-related benefits and "other unearned income." Indeed, as the table reports,

[1] We exclude 2004, as food stamps information is not available for this year.

disability benefits appear substantially more important than these men's other sources of unearned income. Further inspection revealed that unemployment insurance benefits were by far the largest source of other unearned income, accounting for a majority of total unearned income across most demographic groups, especially for whites. Various public assistance programs (bundled together in the CPS as "welfare") also accounted for non-trivial sources of other unearned income, especially for blacks. Retirement benefits and veteran's benefits were also non-trivial for men aged 45-54.

The table also does not distinguish among household members who are not the man's parents or spouse. Further analysis revealed that among whites aged 35-44 (45-54), own children accounted for around one-third (one-half) of other household members' earnings. For blacks aged 45-54, own children accounted for 25-30 percent of other household members' earnings. Unmarried partners accounted for roughly 20-25 (15) percent of other household members' earnings for whites (blacks) aged 25-44. Across most demographic groups, especially for blacks, unmarried partners and own children could not account for a majority of other household members' earnings. We did not delve further into this but suspect that siblings' earnings may be relatively important for blacks. The remainder comprises a mix of other relatives' and non-relatives' earnings.

Finally, note that Table 2 does not distinguish between a man who receives most of his income from one source and a man who receives a non-trivial share of his income from multiple sources. Appendix Table A3 records *major*, rather than *maximal*, sources of income. Households in which no source of income accounts for the majority of total income are classified as having multiple minority sources of income. According to the table, relatively small but non-trivial shares of men across all demographic groups depend heavily on multiple sources of income.

Decomposition Details

Table 5 of the main text and Table A4 of this appendix report the results of within/between decomposition analyses of changes in the labor-force participation rate over a given time period. Here we provide details on the execution of these analyses. Suppose we are interested in how much of the LFP rate change between two years—y_0 and y_1—is due to changes in the LFP rate *within* a given set of statuses (e.g. married and unmarried), and how much is due to changes *between* the two statuses (e.g. a shrinking size of the married group and growing size of the unmarried group). Formally, we write

$$\begin{aligned}\Delta LFP &= LFP_1 - LFP_0 \\ &= p_{m1}LFP_{m1} + p_{u1}LFP_{u1} - (p_{m0}LFP_{m0} + p_{u0}LFP_{u0})\end{aligned}$$

where p_{st} represents the proportion of the sample with marital status *s* (married or unmarried) at time *t*; and LFP_{st} represents the LFP rate of individuals with marital status *s* at time *t*.

To implement the decomposition, we re-express the above equation as

$$\begin{aligned}&(p_{m1} - p_{m0})\overline{LFP}_m + (p_{u1} - p_{u0})\overline{LFP}_u \\ &+\ p_{u1}(LFP_{u1} - \overline{LFP}_u) +\ p_{u0}(\overline{LFP}_u - LFP_{u0}) \\ &+\ p_{m1}(LFP_{m1} - \overline{LFP}_m) +\ p_{m0}(\overline{LFP}_m - LFP_{m0})\end{aligned}$$

where the overline denotes the average of *LFP* between the two time periods. In this decomposition, the first term describes the portion of the overall change that can be attributed to

movements of the population *between* marital statuses. For example, if married individuals work more than single individuals and there is a decline in the marriage rate between the two time points, the between term will be negative. The second and third terms describe the portion of the overall change that can be attributed to changes in the LFP rate *within* unmarried and married statuses. If married men and unmarried both experience declines in labor-force attachment between the two time points, these terms will also be negative.

The general decomposition formula, in the case of an arbitrary number *N* of statuses, is

$$\sum_{s=1}^{N}(p_{s1}-p_{s0})\overline{LFP_s} + \sum_{s=1}^{N}\{\, p_{s1}(LFP_{s1}-\overline{LFP_s}) + \, p_{s0}(\overline{LFP_s}-LFP_{s0})\,\}$$

where the first term is the "between status" term and each term *s* of the summation in the second line is the "within status *s*" term.

Additional Information Regarding Disability Insurance

A Brief History of the Social Security Disability Insurance program

The Social Security Disability Insurance program (DI) was enacted in 1956 and originally targeted individuals above the age of 50. In 1960, individuals under 50 were made eligible for the program. Subsequently, eligibility standards liberalized and benefit levels increased, with after-tax wage replacement rates reaching 60 percent by the mid-1970s. With these increases in availability and generosity, participation in the DI program grew rapidly during the 1960s and 1970s. By 1980, no less than 2 percent of the working-age population was enrolled and in receipt of benefits (Bound and Waidmann, 1992).

Concern grew during the 1970s that many DI beneficiaries might not actually be eligible under the law. The Social Security Administration first responded to this situation by refining the regulations guiding the decision to award DI. The consequences were dramatic: award rates fell from 48.8 to 33.3 percent between 1975 and 1980. In 1980, Congress passed legislation to further tighten administrative control over the DI distribution process. The number of new awards accordingly dropped from .40 to .29 percent of all insured workers between 1980 and 1982. At the same time, there was a five-fold increase in the number of terminations: in two years' time, 25 percent of beneficiaries had their cases reviewed, and more than 40 percent of reviewed cases were terminated

These stricter practices led to questions about due process. Many who had their benefits terminated during this period won reinstatement on appeal, and concern grew that many of those who did not appeal their terminations were, in fact, eligible for benefits. Widespread criticism led Congress to further change the law in 1984. These amendments had a profound effect on the standards used to evaluate DI eligibility. First, the burden of proof was shifted onto the Social Security Administration to demonstrate that the health of beneficiaries under review had improved sufficiently to allow them to return to work. Second, a moratorium was imposed on reevaluations of the most troublesome cases—those that involved mental impairments or pain—until more appropriate guidelines could be developed. Third, benefits were continued for those whose terminations were under appeal. Fourth, source evidence

(evidence provided by the claimant's own physician) was required to be considered prior to the results of an SSA consultative examination. Fifth, consideration had to be given to the combined effects of all an individual's impairments, regardless of whether any single impairment was severe enough to qualify the individual for benefits. Finally, and perhaps most importantly, the Social Security Administration substantially revised its treatment of mental illness, reducing the weight given to diagnostic factors and emphasizing the ability of an individual to function in work or work-like settings.

Eligibility criteria further liberalized in 1988 and then again in 1991 when the Social Security Administration issued new rulings on pain that gave controlling weight to source evidence when such opinions were supported by medical evidence and were not inconsistent with other evidence in the case record. In addition, court opinions throughout the 1980s and early 1990s tended to reinforce the increasing weight placed on source evidence (Social Security Advisory Board 2001). Accordingly, new awards grew dramatically for men during the late 1980s and early 1990s. Since then, conditional on age and the local unemployment rate, they have remained stable (Liebman, 2015).

Appendix Figure A5 tracks the fraction of prime-age men receiving DI by age group. While the fraction of men receiving disability insurance was rising, the proportion of men out of the labor force was also rising—especially older men. The coincidence of these two trends seems to suggest a causal connection in which the availability of generous disability benefits induced older men to leave the labor force to qualify for benefits (Parsons, 1980). The movement of men in relatively poor health out of the labor force and onto disability rolls—a phenomenon Bound and Waidmann (1992) referred to as the earlier accommodation of health limitations—can account for a significant fraction of the drop in the workforce attachment of older prime aged men between 1960 and the late 1980s. It is difficult, however, to gauge the extent to which this phenomenon can be causally attributed to the growth in the availability of disability insurance programs as opposed to other forces (e.g., a drop in the demand for older, less-skilled workers in poor health). See the main text for further analysis and discussion.

Other Disability Insurance Programs

Along with DI, the federal government runs two other programs targeted at the disabled: the Supplementary Security Income (SSI) program and the Veterans Disability benefit program. SSI benefits men who have had a very weak attachment to the workforce (Bound, Burkhauser and Nichols, 2003), so it is unlikely to have any large effect on labor force participation rates. Veterans Disability Compensation (DC) benefits are limited to veterans who can link their disability to the service. Access to such benefits was dramatically increased when the VA decided in 2001 to cover diabetes for Vietnam era veterans who had served in theater. Census estimates show that roughly 30 percent of men aged 45-54 in 2000 were Vietnam era veterans. Autor et al. (2016) estimate that roughly 18 percent of Vietnam era veterans were receiving DC benefits by 2014 and that this reduced the labor-force participation of this group by 18 percentage points. This suggests an effect on the overall population of 45-54 year old men of less than 1 percentage point (0.3 times 0.18 times 0.18). These calculations lead us to conclude the DC benefits have not contributed in a major way to drop in prime-age male labor-force participation.

Investigation of Changing Skill Composition of Less-Educated Population

As mentioned in the main text, when analyzing secular change in labor market outcomes conditional on educational attainment, it is important to consider the possibility that the underlying skill composition of the less-educated population has changed over time. This is especially relevant when considering the high-school-dropout and high-school-degree-only populations, which have shrunk in size over time relative to the college-educated population.

To address this issue, we use the dataset of Deming (2017), which contains a variety of cognitive and non-cognitive skill measures derived from National Longitudinal Surveys of Youth data. Importantly, such measures are consistently defined across all survey waves and exist in both the NLSY79 and NLSY97, allowing for comparison across time. We consider three composite skill measures: cognitive, non-cognitive, and social. All skill measures are consistently defined across survey waves and normalized to have mean 0 and standard deviation 1 across the entire population of adult respondents. The cognitive measure is the Armed Force Qualification Test score, adjusted for maximum comparability across respondents and survey waves by Altonji, Bharadwaj and Lange (2012). The non-cognitive measure is a normalized average of the Rotter Locus of Control and Rosenberg Self-Esteem Scale, constructed by Deming (2017) and also used by Heckman, Stixrud and Urzua (2006). The social measure is a normalized average of measures self-reported sociability and elicited conscientiousness. See pages 1616 and 1618 of Deming (2017) for more detail.

Table A5 considers how average skill levels have changed over time within demographic groups and how these changes may have contributed to secular change in labor market outcomes. We consider a sample of men aged 25-33 to maximize overlap in age range across survey waves. We consider two cohort groups: the 1959-65 cohorts (taken from NLSY79 data) and the 1980-84 cohorts (taken from NLSY97). The table contains two panels: one for high school dropouts and one for high school graduates (but with no further education). Within each education group, the top sub-panel reports average skill levels by race and cohort. The numbers reported in the bottom sub-panel answer the question: "if we fixed average skill levels in the 1980-84 cohort to those of the 1959-65 cohort, by how much would we expect average labor market outcomes of the 1980-84 cohort to change?" These numbers are calculated via standard decomposition analysis. For each race group in the 1980-84 sample, we regress the labor market outcome of interest on the vector of skills, with controls for education-by-age interactions. We then interact the vector of estimated skill coefficients with a vector of -1*change in average skill levels between the 1959-64 and 1980-84 cohorts. That is, we estimate the regression

$$y_{ir} = \alpha_{ir} + \beta_1 cog_{ir} + \beta_2 noncog_{ir} + \beta_3 social_{ir} + error_{ir}$$

among respondents *i* in the 1980-84 cohorts of race *r* (whether the intercept term contains a constant and education-by-age effects). With the estimated coefficients, we compute

$$predictedChange_{er} = \widehat{\beta_1}(\overline{cog}_{er}^{59-65} - \overline{cog}_{er}^{80-84}) + \widehat{\beta_2}(\overline{noncog}_{er}^{59-65} - \overline{noncog}_{er}^{80-84})$$

$$+\widehat{\beta_3}(\overline{social}_{er}^{59-65} - \overline{social}_{er}^{80-84})$$

for each education-by-race group (where an overline denotes an average for the given education by race by cohort group). We repeat this procedure for log wages and for employment status.

According to the table, average cognitive and non-cognitive skill levels appear to have *increased* between the two cohorts for dropouts and for blacks. Social skills have decreased between cohorts across all demographic groups. The regression decomposition analyses find that had average skills been fixed at 1959-65 cohort levels, wages and employment would have *fallen further*, albeit modestly, between the two cohort groups than they did in reality. Average skill levels have declined slightly for white high school graduates, but not in a quantitatively important manner for wage and employment trends.

Though these results may appear surprising given secular changes in high school and college completion rates, they are relatively consistent with the work of Altonji, Bharadwaj and Lange (2012) documenting population improvements in skill levels between the NLSY79 and 97 cohorts, especially for minority groups. One caveat is that we do not account for other factors plausibly related to labor market outcomes in adulthood, such as childhood family income and family structure. These variables plausibly determine measured skill levels but may also impact labor market skills in unobserved ways. Regardless, our analysis fails to find evidence that the no-college population of men has become increasingly negatively selected on labor market skills since the 1980s.

References

Altonji, Joseph G., Prashant Bharadwaj, and Fabian Lange. 2012. "Changes in the Characteristics of American Youth: Implications for Adult Outcomes." *Journal of Labor Economics* 30 (4): 783-828.

Benedetto, Gary, Martha Stinson, and John M. Abowd. 2013. "The Creation and Use of the SIPP Synthetic Beta." United States Census Bureau. http://ecommons.cornell.edu/handle/1813/43924.

Bound, John, Austin Nichols, and Richard V Burkhauser. 2003. "Tracking the Household Income of SSDI and SSI Applicants." In *Worker Well-Being and Public Policy*, 22:113–58. Research in Labor Economics 22. Emerald Group Publishing Limited. https://doi.org/10.1016/S0147-9121(03)22004-5.

Bound, John, and Timothy Waidmann. 1992. "Disability Transfers, Self-Reported Health, and the Labor Force Attachment of Older Men: Evidence from the Historical Record." *The Quarterly Journal of Economics* 107 (4): 1393–1419. https://doi.org/10.2307/2118393.

Coglianese, John. 2018. "The Rise of In-and-Outs: Declining Labor Force Participation of Prime Age Men." Harvard University. https://scholar.harvard.edu/files/coglianese/files/coglianese_2017_in-and-outs.pdf

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132 (4): 1593-1640.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3): 411-482.

Liebman, Jeffrey B. 2015. "Understanding the Increase in Disability Insurance Benefit Receipt in the United States." *Journal of Economic Perspectives* 29 (2): 123–50. https://doi.org/10.1257/jep.29.2.123.

Parsons, Donald O. 1980. "The Decline in Male Labor Force Participation." *Journal of Political Economy* 88 (1): 117–34. https://doi.org/10.1086/260850.

Appendix Tables and Figures

Table A1. The Changing Demographic Composition of the Workforce, 1960-2016 *(shares)*

Education	Age	Group	1960	1970	1980	1990	2000	2010	2016
Dropouts	25-34	Native men	0.71	0.65	0.54	0.48	0.33	0.28	0.31
		Immigrant men	0.03	0.04	0.09	0.17	0.34	0.40	0.36
		Women	0.26	0.31	0.36	0.35	0.33	0.33	0.33
	35-44	Native men	0.67	0.63	0.54	0.44	0.36	0.23	0.22
		Immigrant men	0.03	0.04	0.07	0.15	0.26	0.40	0.42
		Women	0.30	0.33	0.39	0.41	0.38	0.37	0.36
	45-54	Native men	0.64	0.62	0.58	0.48	0.37	0.30	0.24
		Immigrant men	0.06	0.04	0.05	0.10	0.22	0.31	0.39
		Women	0.30	0.34	0.36	0.42	0.40	0.39	0.38
HS Grads	25-34	Native men	0.63	0.61	0.52	0.53	0.49	0.49	0.51
		Immigrant men	0.01	0.02	0.02	0.04	0.07	0.11	0.10
		Women	0.36	0.38	0.46	0.44	0.44	0.41	0.40
	35-44	Native men	0.60	0.55	0.51	0.47	0.48	0.46	0.47
		Immigrant men	0.02	0.02	0.02	0.03	0.05	0.10	0.12
		Women	0.38	0.43	0.47	0.50	0.47	0.44	0.41
	45-54	Native men	0.56	0.54	0.50	0.47	0.44	0.46	0.46
		Immigrant men	0.04	0.02	0.02	0.03	0.04	0.06	0.09
		Women	0.40	0.44	0.48	0.51	0.52	0.47	0.45
Some College	25-34	Native men	0.69	0.65	0.55	0.46	0.44	0.43	0.44
		Immigrant men	0.03	0.03	0.03	0.04	0.06	0.06	0.06
		Women	0.29	0.32	0.42	0.50	0.50	0.51	0.50
	35-44	Native men	0.65	0.62	0.55	0.49	0.43	0.42	0.42
		Immigrant men	0.03	0.03	0.03	0.04	0.05	0.07	0.07
		Women	0.32	0.34	0.42	0.48	0.51	0.51	0.50
	45-54	Native men	0.57	0.60	0.54	0.49	0.47	0.41	0.41
		Immigrant men	0.04	0.03	0.03	0.04	0.04	0.06	0.07
		Women	0.39	0.37	0.42	0.48	0.48	0.53	0.52
Completed College	25-34	Native men	0.73	0.61	0.55	0.47	0.43	0.40	0.41
		Immigrant men	0.02	0.03	0.03	0.05	0.06	0.07	0.07
		Women	0.25	0.37	0.42	0.49	0.51	0.53	0.52
	35-44	Native men	0.71	0.71	0.60	0.53	0.45	0.42	0.40
		Immigrant men	0.03	0.03	0.05	0.05	0.07	0.09	0.09
		Women	0.25	0.26	0.35	0.42	0.48	0.49	0.51
	45-54	Native men	0.58	0.67	0.65	0.55	0.50	0.43	0.42
		Immigrant men	0.04	0.03	0.04	0.06	0.06	0.08	0.08
		Women	0.38	0.30	0.31	0.40	0.44	0.49	0.50
Advanced Degree	25-34	Native men	0.79	0.71	0.57	0.46	0.36	0.30	0.31
		Immigrant men	0.05	0.06	0.05	0.10	0.13	0.11	0.11
		Women	0.16	0.23	0.38	0.44	0.51	0.59	0.58
	35-44	Native men	0.76	0.74	0.64	0.52	0.43	0.36	0.32
		Immigrant men	0.05	0.07	0.08	0.08	0.13	0.13	0.13
		Women	0.19	0.20	0.29	0.41	0.44	0.51	0.55
	45-54	Native men	0.65	0.68	0.66	0.57	0.47	0.41	0.37
		Immigrant men	0.06	0.06	0.06	0.08	0.08	0.11	0.13
		Women	0.29	0.26	0.28	0.35	0.45	0.48	0.50

Source: Authors' calculations based on U.S. Census (1960-2000) and American Community Survey (2010-2016) public use samples. We define the workforce for a given year as everyone who was employed > 13 weeks.

Table A2. Education Status Decomposition of Changes in the Labor-Force Participation Rate Among Males Aged 25-54

(percentage point changes in the LFP rate between 1967 and 2015)

Sample	Total Change	Between	Within				
			HS dropout	HS grad	Some coll	Coll degree	Adv degree
All Men	-7.73	2.65	-4.10	-4.14	-1.51	-0.51	-0.13
Whites	-7.07	4.74	-5.89	-3.89	-1.43	-0.48	-0.11
Blacks	-12.75	8.72	-12.78	-6.12	-2.00	-0.50	-0.08

Source: Author's calculations based on March Supplement to the Current Population Survey. See first section of this Appendix for detail on how the within/between decomposition was executed. LFP rates were measured in 5-year windows around the beginning and endpoints: thus 1967 refers to 1965-69; 2015 refers to 2013-17.

Table A3. Additional Household Income Characteristics of Men with Low Labor-Force Attachment by Race, Education and Age, 1992-2017

Panel A. High School Dropouts

	Whites			Blacks		
	25-34	35-44	45-54	25-34	35-44	45-54
Major Source of Income (%)						
Own earnings	2	2	2	1	1	1
Own disability-related benefits	11	20	29	8	16	26
Earnings OR unearned income from:						
parents	29	20	10	36	20	13
spouse	14	17	18	4	11	11
other HH members	22	17	18	28	26	22
HH food stamps income	3	3	2	3	3	3
Other source	2	4	4	2	3	4
Multiple sources	11	12	12	12	13	12
None (living on < $4 per day)	6	5	5	6	7	8

Panel B. High School Graduates

	Whites			Blacks		
	25-34	35-44	45-54	25-34	35-44	45-54
Major Source of Income (%)						
Own earnings	2	3	2	2	2	2
Own disability-related benefits	8	17	23	7	13	22
Earnings OR unearned income from:						
parents	33	19	10	36	22	10
spouse	13	19	21	7	15	16
other HH members	23	17	17	25	21	21
HH food stamps income	2	2	2	2	3	3
Other source	4	5	8	2	4	6
Multiple sources	10	11	11	12	10	10
None (living on < $4 per day)	5	7	6	7	10	10

Source: Authors' calculations based on the March Supplement to the Current Population Survey. Sample consists of all households in which at least one prime-age man with "low labor-force attachment" resides, defined as a man who worked no more than 13 weeks in the reference year. Households with imputed sources of income are excluded. Disability-related benefits are not fully identifiable until 1988; food stamps benefits are not identifiable until 1992; as a result, we consider the years 1992-2017. The numbers record the frequency with which each source of earnings accounts for the majority of total household income. Households in which no single income source accounts for a majority of total income are classified in a separate category. Extremely poor households subsisting on less than $4 per day (with a square-root equivalence scale employed to adjust for household size), are classified as having no maximal source of income. See main text for further detail.

Table A4. Household Structure Decompositions of Changes in the Labor-Force Participation Rate Among Males with 0-10 Years of Potential Experience
(percentage point changes in the LFP rate between 1997 and 2015)

Ethnicity	Education	Total Change	Between	Within		
				w/ Parent	Unmarried	Married
All Men	Dropouts	-15.6	-1.1	-12.8	-1.4	-0.3
	HS grads	-5.9	-1.0	-3.6	-0.7	-0.6
	Some college	-0.6	-0.9	-0.8	1.0	0.2
Whites	Dropouts	-19.6	-1.2	-16.2	-1.3	-0.8
	HS grads	-6.1	-0.7	-3.8	-0.9	-0.7
	Some college	-0.6	-0.6	-0.6	0.4	0.1
Blacks	Dropouts	-18.3	-0.1	-13.5	-4.2	-0.5
	HS grads	-6.1	-1.2	-2.8	-1.2	-0.8
	Some college	0.3	-1.2	-0.3	1.8	0.0

Source: Authors' calculations based on the March Supplement to the Current Population Survey. See first section of this Appendix for detail on how the within/between decomposition was executed. LFP rates were measured in 5-year windows around the beginning and endpoints: thus 1997 refers to 1995-99; 2015 refers to 2013-17.

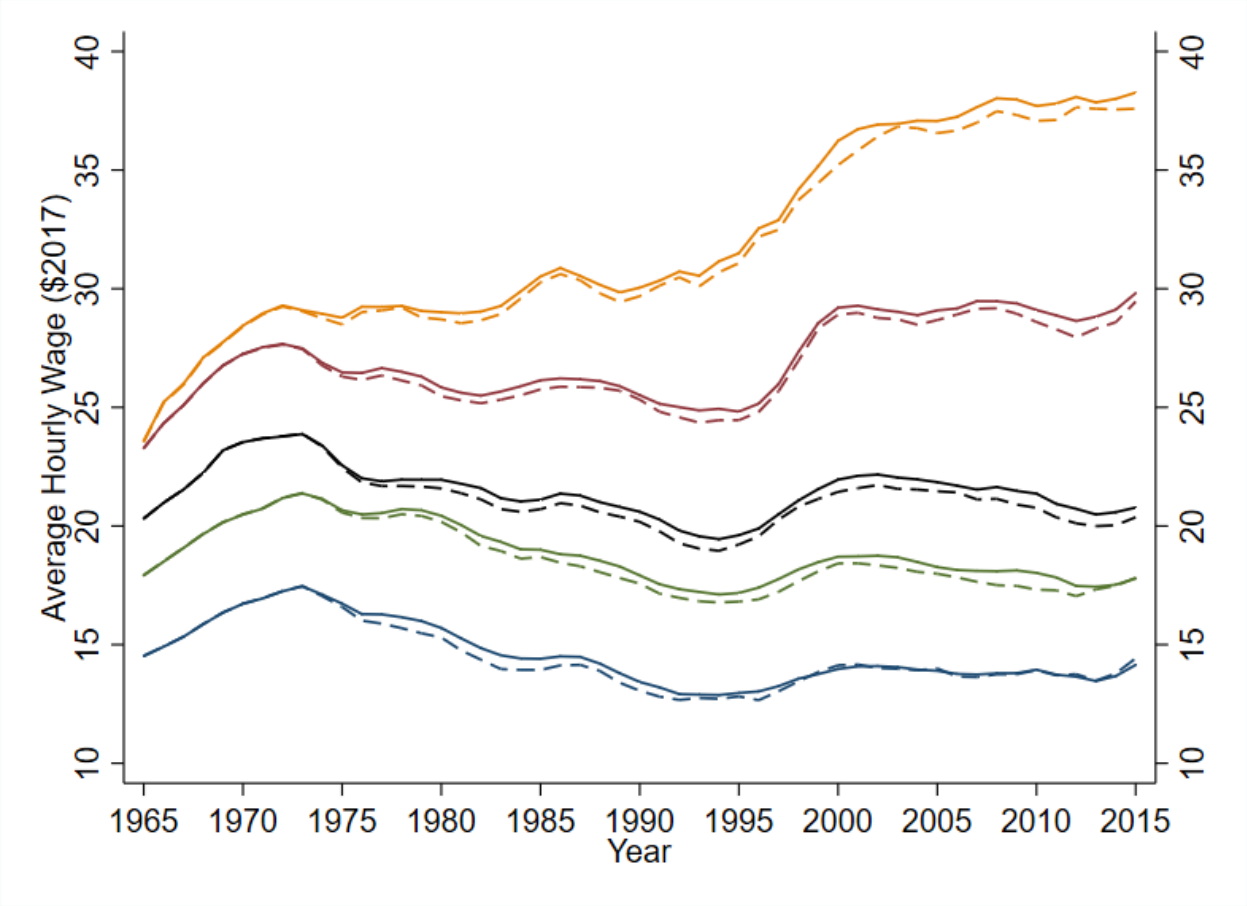
Table A5. Assessment of Changing Skill Composition of Less-Educated Male Populations over Time: Evidence from the NLSY79 and 97

	Whites		Blacks	
	1959-65 cohorts (NLSY79)	1980-84 cohorts (NLSY97)	1959-65 cohorts (NLSY79)	1980-84 cohorts (NLSY97)
	Panel A. High School Dropouts			
skill type	Average normalized skill levels			
cognitive	-0.76	-0.19	-1.39	-1.10
non-cognitive	-0.38	-0.31	-0.51	-0.05
social	-0.11	-0.14	-0.26	-0.33
labor mkt outcome	Predicted change if average skills were fixed at 1959-65 cohort levels			
avg(ln(wage))	--	-0.03	--	-0.02
full-time employment rate	--	-0.02	--	-0.03
	Panel B. High School Graduates			
skill type	Average normalized skill levels			
cognitive	0.08	0.04	-0.97	-0.60
non-cognitive	-0.08	-0.13	-0.14	-0.08
social	0.03	-0.12	0.06	-0.25
labor mkt outcome	Predicted change if average skills were fixed at 1959-65 cohort levels			
avg(ln(wage))	--	0.01	--	-0.02
full-time employment rate	--	0.01	--	-0.02

Source: Authors' calculations based on NLSY79 and 97 data taken from the dataset used in Deming (2017). All skill measures are consistently defined across survey waves and normalized to have mean 0 and standard deviation 1 across the entire population of adult respondents. The cognitive measure is the Armed Force Qualification Test score, adjusted for maximum comparability across respondents and survey waves by Altonji, Bharadwaj and Lange (2012). The non-cognitive measure is a normalized average of the Rotter Locus of Control and Rosenberg Self-Esteem Scale, constructed by Deming (2017) and also used by Heckman, Stixrud and Urzua (2006). The social measure is a normalized average of measures self-reported sociability and elicited conscientiousness. See pages 1616 and 1618 of Deming (2017) for more detail.

This table considers men aged 25-33, to maximize overlap in age range across survey waves. Within each education group, the top sub-panel reports average skill levels by race and cohort. The numbers reported in the bottom sub-panel answer the question: "if we fixed average skill levels in the 1980-84 cohort to those of the 1959-65 cohort, by how much would we expect average labor market outcomes of the 1980-84 cohort to change?" These numbers are calculated via standard decomposition analysis: for each race group in the 1980-84 sample, we regress the labor market outcome of interest on the vector of skills and include controls for education-by-age interactions. We then interact the vector of estimated skill coefficients with a vector of -1*change in average skill levels between the 1959-64 and 1980-84 cohorts. See pages 7-8 of this appendix for further detail.

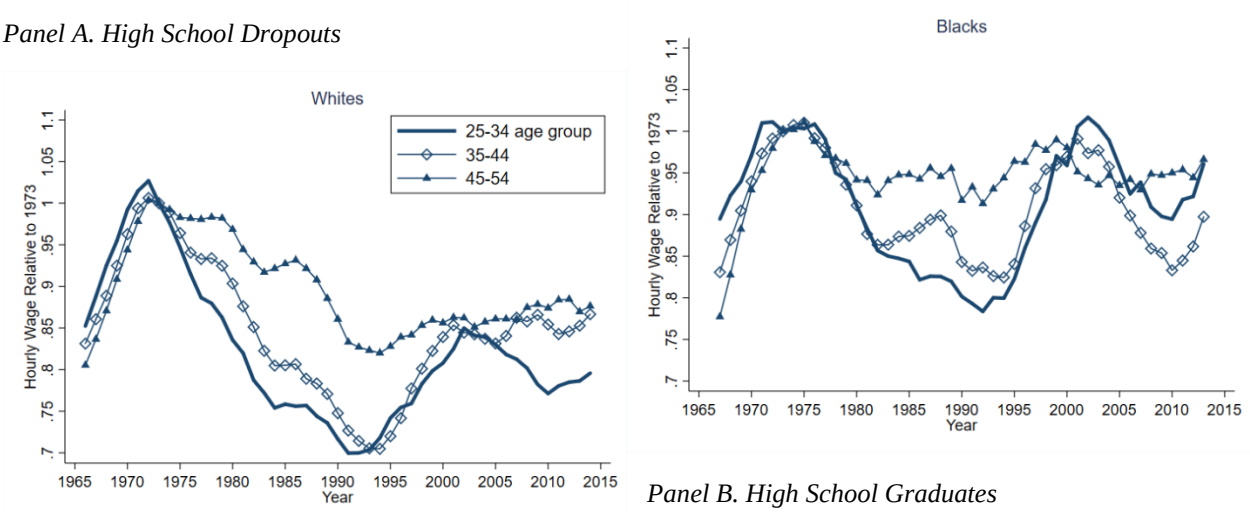
Figure A1. Real Hourly Earnings by Education Status, Comparison of Original Series to those which Adjust for Non-Workers, 1965-2016



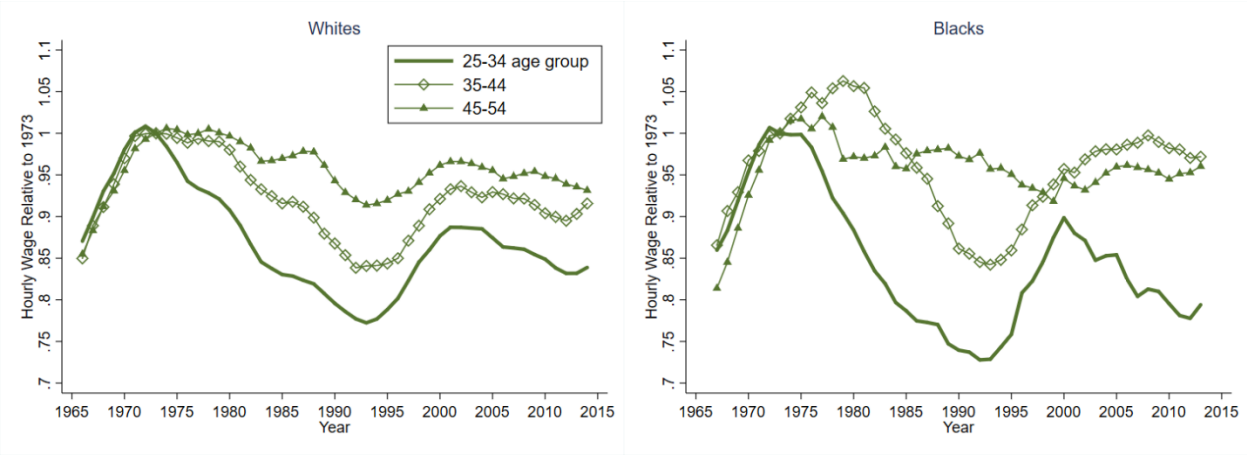
Source: Authors' calculations based on March CPS data. Graph is constructed in the same way as Figure 1 of the main text, except that we add dotted lines to represent geometric average hourly earnings for the entire population of prime-age men: i.e. including non-workers. Following Juhn, Murphy and Topel (1991), we impute hourly earnings for full-year non-workers based on the observed wages of comparable men who worked <= 13 weeks last year. See the above text of this appendix for further detail.

Figure A2. Male Real Hourly Earnings Relative to 1973 by Education, Race and Age, 1965-2016

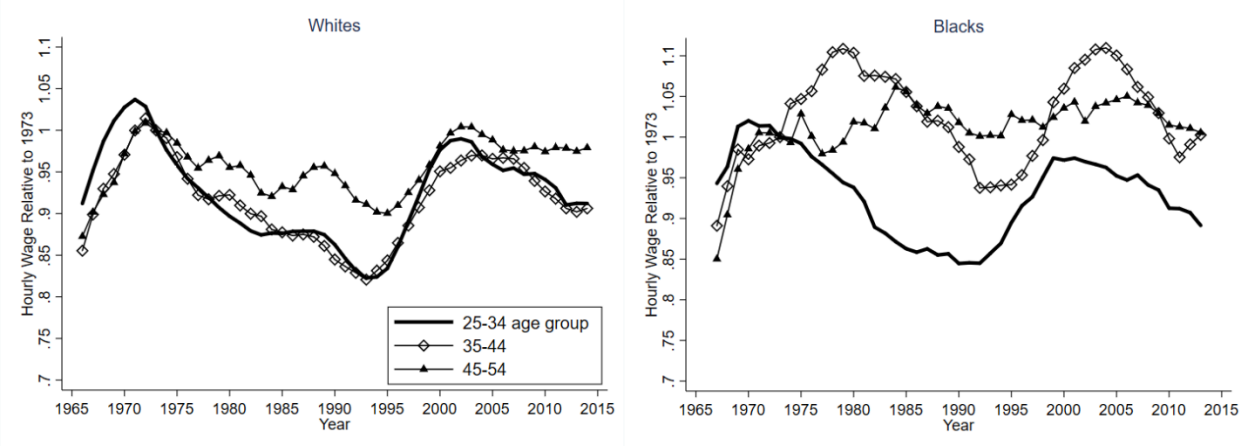
Panel A. High School Dropouts



Panel B. High School Graduates

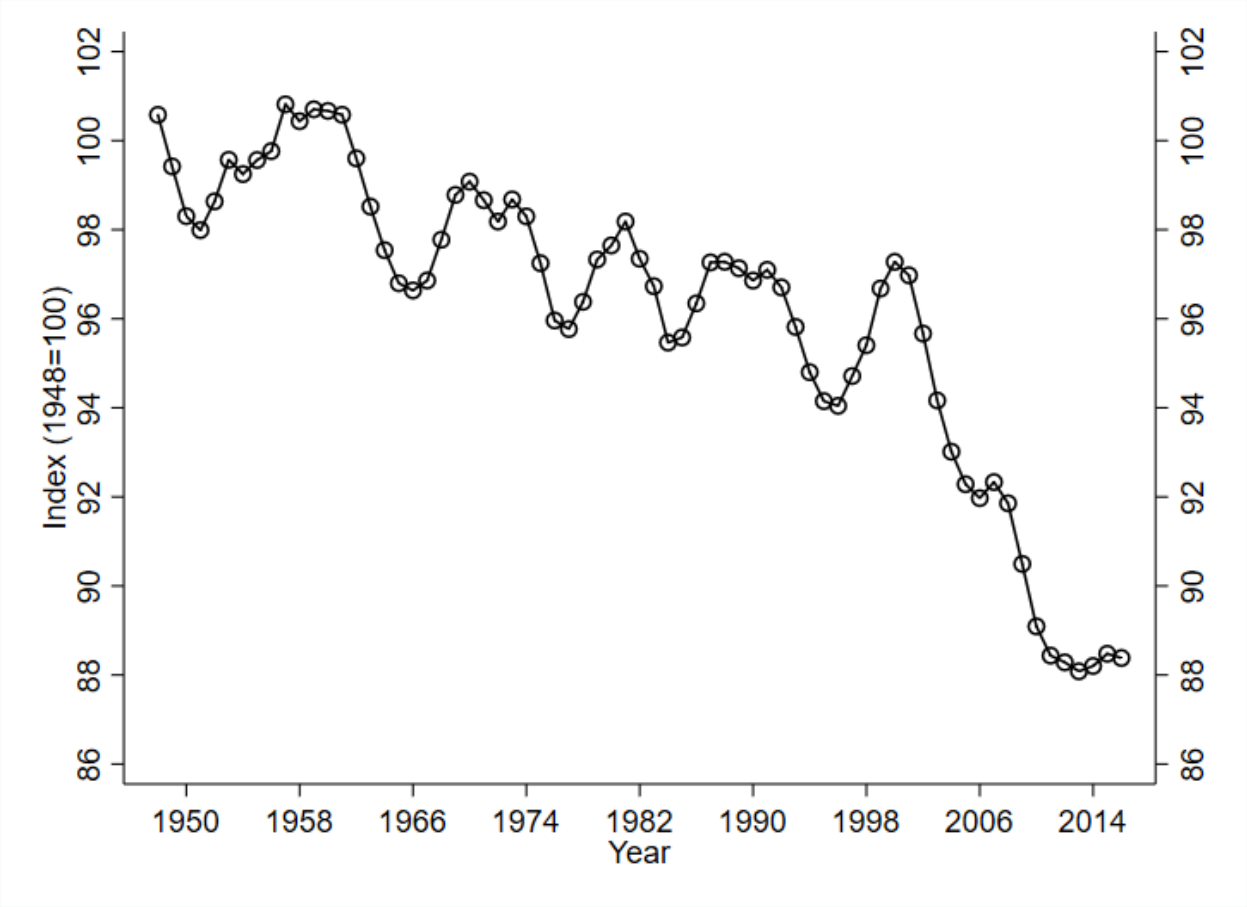


Panel C. Some College Completed



Source: Authors' calculations based on the March Supplement to the Current Population Survey. Graphs display 5-(7-) year centered moving averages for whites (blacks).

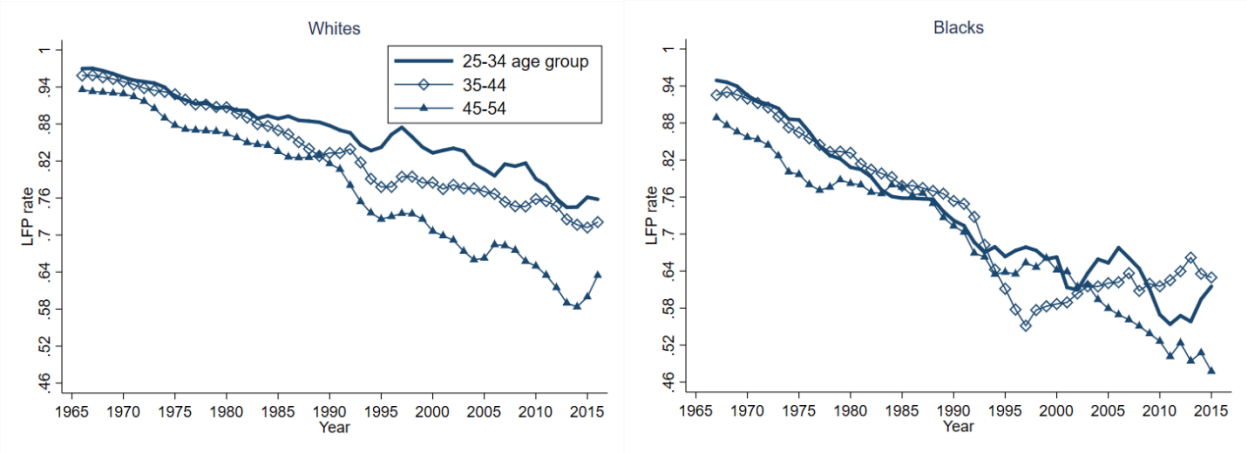
Figure A3. The Falling Labor Share, Non-Farm Business Sector, 1948-2016
(*index)*



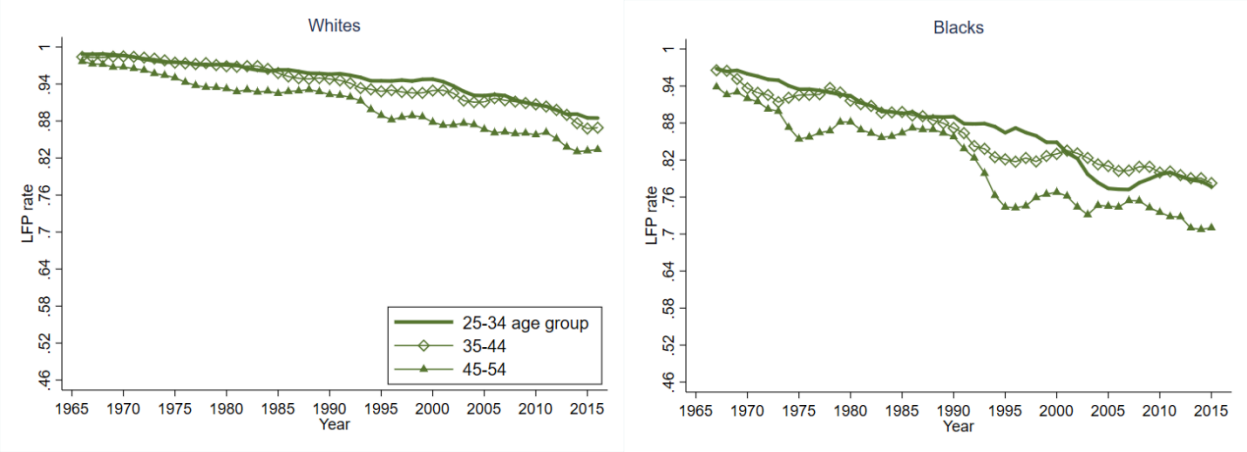
Source: Bureau of Labor Statistics. Graph presents 3-year centered moving average.

Figure A4. Male Labor-Force Participation Rates by Education, Race and Age, 1965-2016

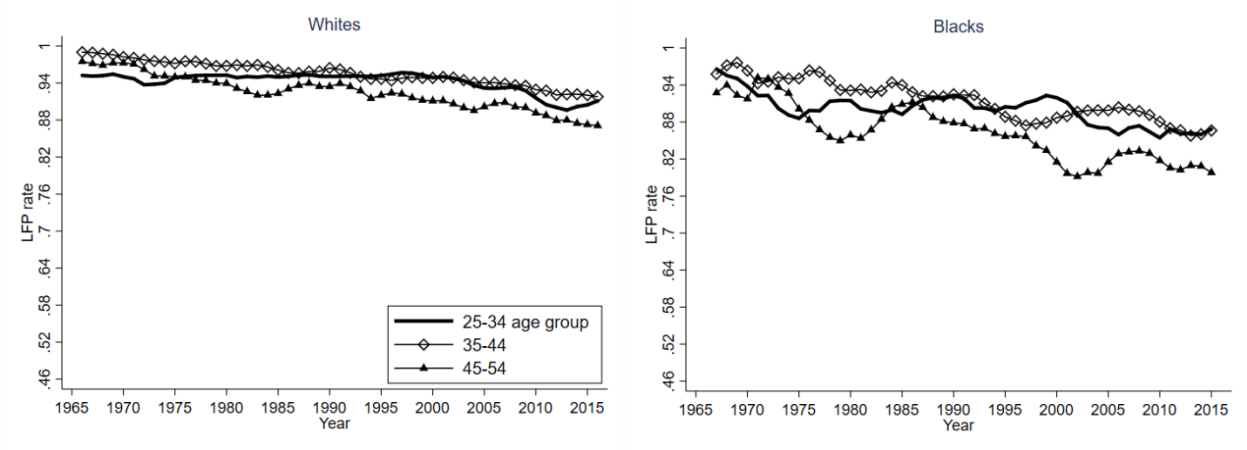
Panel A. High School Dropouts



Panel B. High School Graduates

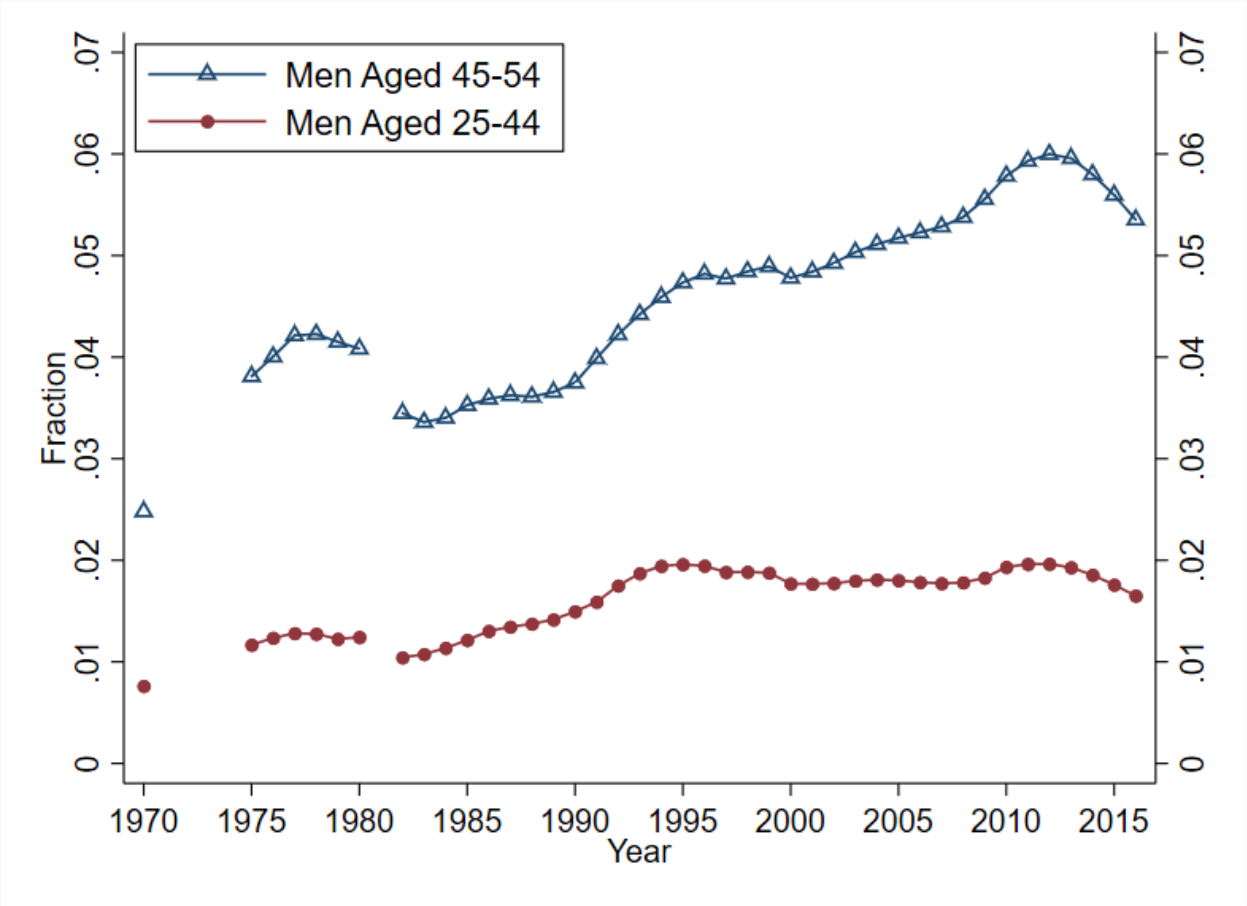


Panel C. Some College Completed



Source: Authors' calculations based on the March Supplement to the Current Population Survey. Graphs present 3-year centered moving averages for whites and 5-year centered moving averages for blacks.

Figure A5. Male Participation Rates in the Social Security Disability Insurance Program



Source: Social Security Administration