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by

Remy Levin
University of Connecticut

Daniela Vidart
University of Connecticut

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365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

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'Nobody Wants to Work Anymore': Lifetime Wage Experiences and the Decline of Male LFP in the United States*

Remy Levin
University of Connecticut

Daniela Vidart
University of Connecticut

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Abstract

Male labor force participation (MLFP) has declined sharply over the past 50 years in the United States. We show that a key driver of this decline is changes in mens' beliefs about the returns to work, shaped by their lifetime experiences of aggregate male wages. Using PSID data tracking individual labor histories linked to state-level real male wage time series, we find that prime-age MLFP increases with the average male wage in a man's state of birth over his lifetime, even after controlling for current labor market conditions and a host of fixed effects and covariates. A one standard deviation increase in the average experienced aggregate lifetime hourly wage—corresponding to $0.33 and comparable to the difference in 2000 between being born in 1970 in Louisiana and Texas—raises the probability of labor force participation by 10 percentage points. These effects persist for men who migrate and are stronger when restricting to same-race wages. Our findings suggest that lifetime wage experiences shape long-term beliefs about work, generating lasting spillovers from labor demand to labor supply.

Keywords: Male labor force participation, experience effects

JEL Codes: E24, J22, J24, D83

*Email: remy.levin@uconn.edu, and daniela.vidart@uconn.edu. We would like to thank Jason Fletcher and Carolyn Moehling for helpful comments. We are also grateful for the insightful comments of participants at the Mountain West Economic History Conference.

Male labor force participation (MLFP) has declined significantly in the United States over the last 50 years. In 1970, 95% of prime-aged men (ages 25–54) participated in the labor force. By 2015, this number had fallen to 88%. This decline is primarily driven by cohort-level differences: younger cohorts are less likely than their older counterparts to participate in the labor force at all ages. For example, 97% of men born between 1941 and 1945 participated in the labor force at age 35, while only 90% of men born between 1976 and 1980 did so.

A large body of work in economics has sought to explain the causes of this decline, but so far with limited success, as illustrated by two recent reviews of the literature. Binder and Bound (2019) study the roles that changes in labor demand, rising access to disability insurance, and mass incarceration have played in the decline in MLFP since the 1970's, and conclude that these factors cannot adequately explain the observed trends.[1] Abraham and Kearney (2020) conduct a comprehensive review of the evidence on the decline of the employment-to-population ratio in the United States from 1999 to 2018.[2] According to their quantitative analysis, less than 50% of the decline over this period is explained by the contributing factors studied in the literature.[3]

In this paper, we propose a new channel driving the long-run decline in MLFP in the United States: changes in men's experienced aggregate lifetime wages have shaped their beliefs about the returns to work, influencing their labor supply decisions. We provide empirical evidence for this channel by showing that lifetime experiences of average male wages—defined as the wages observed for other men in their environment throughout their lives—are positively correlated with men's likelihood of participating in the labor market, even after accounting

[1] Binder and Bound (2019) instead propose that the long-run decline in MLFP is due to changes in family structure and the marriage market that have affected male labor supply incentives.

[2] The employment-to-population ratio (EPOP) is a closely-related but distinct statistic from labor force participation (LFP). Generally, LFP is calculated as the number of individuals currently working, only temporarily laid off, or unemployed and searching for work, divided by the total civilian, non-institutionalized population. EPOP is usually calculated as the ratio of individuals currently employed to total population, though sometimes the denominator used is the civilian, non-institutionalized population. EPOP tends to exhibit more volatility and cyclicality than LFP, particularly over short and medium time horizons, but the two statistics closely track each other over the longer-run.

[3] In particular, Abraham and Kearney (2020) attribute 35% of the decline in EPOP over the 1999-2018 period to changes in labor demand due to automation and increased import competition from China, and an additional 10% to increases in the generosity of disability benefits, higher minimum wages, and increased rates of incarceration. They argue that several proposed factors have negligible effects, including the expansion of SNAP, increases in the EITC, the passage of the ACA, expanded immigration, and lack of family leave. They also conclude that several proposed explanations in the literature might have effects, but that the magnitude of these is still unclear given the available evidence. These factors include the lack of child care, changes in leisure options, changes in social norms, increased use of opioids, the rise in occupational licensing, and increases in institutional frictions and mismatch.

for current labor market conditions and a wide battery of fixed effects and controls.

We are not the first to suggest that labor market conditions, and in particular declining wages, are closely linked to the decline in MLFP in the United States. This connection was first recognized in the early 1990s (Juhn (1992)), and the positive relationship between contemporaneous male wages and employment is central to demand-side explanations of MLFP decline, such as those driven by trade competition and automation (Autor et al. (2013), Autor et al. (2015), Acemoglu and Restrepo (2020)). Where our analysis differs from previous work is in the purported *mechanism* and *timescale* of this relationship. We argue that wage declines can produce long-run spillovers to labor supply, even when initially driven by short-term declines in labor demand. These lagged supply effects arise because individuals form beliefs about the returns to work based on their personal experiences, which develop over the long run and persistently shape their labor market entry and exit decisions. Empirically, this channel generates meaningful between-cohort differences in MLFP consistent with those observed in the data. It also does a better job of accounting for certain aggregate trends, such as the continued decline in US MLFP during the 1990s and early 2000s, which coincided with sharp increases in average male wages over the same period, and is thus less consistent with demand-side explanations.

In our analysis we estimate the effects of aggregate lifetime wage experiences on labor force decisions using a regression with individual, year, and state-of-birth-by-year fixed effects, leveraging two data sources. First, we use the Panel Study of Income Dynamics (PSID) to obtain the labor force participation histories of different individuals over time. Second, we construct a time series of real male hourly wages in each state for 1961–2019 using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). We assign these state-level wages to PSID subjects based on their state of birth.[4] Aggregate lifetime wage experiences are calculated as the mean of this time series from birth to each PSID survey wave for each subject.

This empirical approach provides several identification advantages. First, the *aggregate* lifetime wage experiences—approximated using state-wide wages—are exogenous to individuals, as they are general equilibrium objects unaffected by individual labor market situations. Sec-

[4]We use state-of-birth wages to capture work conditions during an individual's formative years and to address migration-induced sorting, where individuals with higher work propensities may move to states with better opportunities. In addition, and given that one key way through which work conditions in the state of birth may affect labor decisions is by encouraging migration to states with better work opportunities, in Section 3.3.1 we provide additional results exploring the scope of migration in driving our results.

ond, by relying on state-of-birth wages, we mitigate concerns about endogenous migration and labor sorting, since individuals do not choose their birth state. Third, our analysis exploits both cross-sectional (state) and cohort variation, allowing us to disentangle the effects of lifetime wage experiences from broader cohort and state trends in male labor force participation. Fourth, the inclusion of individual fixed effects ensures that time-invariant unobserved individual heterogeneity does not drive our results. Finally, year and state-of-birth-by-year fixed effects account for *current* labor market conditions, isolating the role of lifetime wage experiences from present-day events.

We find that a \$0.33 increase in the average experienced aggregate lifetime hourly wage of men, corresponding to one standard deviation, raises their probability of labor force participation by 10 percentage points. To illustrate, this \$0.33 increase is equivalent to comparing, in 2000, a man born in 1970 in Louisiana, to a man born in 1970 in Texas. This positive effect is also prevalent when using employment or lifetime labor force participation as alternative outcome variables; and is robust to the inclusion of a battery of demographic, income, and asset controls, as well as accounting for potential endogenous migration.

We then provide two pieces of evidence suggesting that individuals' beliefs about the returns to work play a key role in linking male labor force participation decisions to experienced aggregate lifetime wages. First, when considering the role of migration, we find that the lifetime wage environment in an individual's state of birth continues to influence his labor force participation choices even after he migrates, including those who moved at a young age. This underscores the importance of beliefs about the returns to work in driving our results, as individuals carry their lived experiences and subjective beliefs with them, while the objective returns to work are determined by the new state's labor market conditions. Second, when considering the role of race, we find that the effect of lifetime wage experiences on labor force participation is about two times stronger for Black men than for White men, and that men's participation decisions are particularly influenced by the wage experiences of others who share their racial identity. This further supports the role of beliefs, as individuals may place greater weight on the experiences of those who resemble them.

Related literature

This paper combines insights from two separate bodies of literature: work on the supply-side drivers of the decline in MLFP in the US, and work on long-run experience effects on economic beliefs and preferences. Research on the supply-side drivers of MLFP decline has primarily focused on factors affecting the non-work component of the labor-leisure tradeoff,

such as the generosity of safety net programs (Maestas et al. (2013), East (2018), Duggan et al. (2019)), the price and quality of leisure goods like video games (Aguiar et al. (2021)), and opioid use (Aliprantis et al. (2023)). We contribute to this literature by introducing a new, complementary channel affecting the work component of this tradeoff: the long-run formation of beliefs about wages. More broadly, this paper challenges the dichotomy between demand-side and supply-side explanations of declining male LFP in this literature, by demonstrating that short-run demand-side factors affecting male wages can spill over into long-run supply-side drivers of labor market outcomes.

The experience effects literature has examined how macroeconomic fluctuations shape risk-taking and investment decisions (Malmendier et al. (2017), Malmendier and Steiny (2016), Levin and Vidart (2025))), beliefs about inflation (Malmendier and Nagel (2016)), and consumption patterns (Malmendier and Shen (2021)). We contribute to this literature by providing evidence that experience effects also shape beliefs and preferences in labor supply decisions. To our knowledge, this is the first paper in the literature that demonstrates that experience effects are operating in the domain of labor decisions, as opposed to consumption or investment decisions.

This paper is also related to an extensive literature in economics on gender differences in labor force participation in the United States and other developed countries (Goldin (1990), Attanasio et al. (2008), Olivetti and Petrongolo (2016)). This literature, which has been primarily focused on explaining rates of female LFP, has highlighted the key roles of expectations (Goldin et al. (2006), Fernández (2013)) and local, gender-peer comparisons (Fogli and Veldkamp (2011), Olivetti et al. (2020)) in driving the decisions of women to enter and remain in the labor force. We contribute to this literature by providing evidence that these channels play an important role in the labor market decisions of men as well. Our findings provide a link between this literature and emerging work in the economics and sociology of gender on the 'boy crisis', or the multi-front decline in the prospects of men over the last few decades (Warren Farrell and Gray (2018), Reeves (2022)).

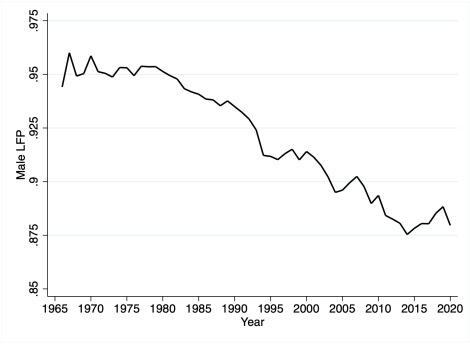
The rest of the paper is organized as follows. Section 1 provides a brief history of MLFP in the United States from 1970 to 2020, with a discussion of the importance of cohort-level differences and wages that motivates our approach. In Section 2, we describe the data, outline our empirical methodology, and discuss identification. Section 3 presents the main empirical findings, robustness tests, and an exploration of the mechanisms driving these results. Section 4 concludes.

1 Context and motivation: Decline of male LFP and the role of lifetime experiences

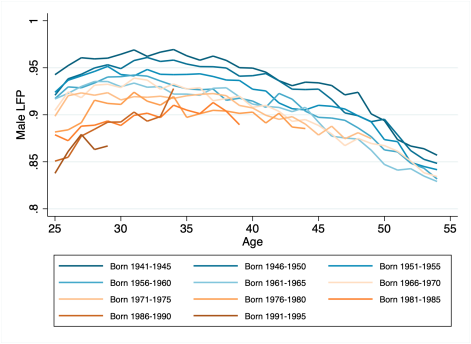
MLFP has declined significantly in the United States over the past 50 years. Panel (a) of Figure 1.1 illustrates this trend for prime-aged men, while panel (b) shows that much of the decline stems from younger cohorts, with reduced participation evident across all ages.

Figure 1.1: Male LFP in the United States

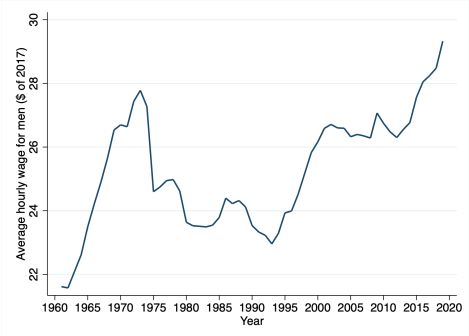
(a) Male LFP over time (men ages 25–54)



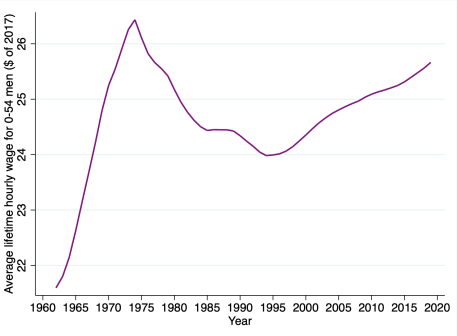
(b) Male LFP across cohorts (men ages 25–54)



(c) Average wages for men



(d) Average lifetime wage experiences over time (men ages 0–54 and born in 1961–1995+)



Notes: Panel (a) presents the male labor force participation rate for men ages 25–54 in the United States in 1966–2019. Panel (b) presents the male labor force participation rate of cohorts born between 1941 and 1995 at ages 25–54. Panel (c) presents the national average real male wage (in dollars of 2017) in 1961–2019. Panel (d) presents the mean national lifetime average real wage (in dollars of 2017) perceived since birth for men born in 1961–1995 and aged 0–54 in 1961–2019. Data for panels (a) and (b) comes from the CPS ASEC in 1966–2019, while data for panels (c) and (d) comes from the CPS ASEC in 1962–2020 and leverages hourly wage information from all men who report it in each given year. These wages are winsorized at the 1–99 level to reduce measurement error.

This paper connects the decline in MLFP to changes in experienced wages. We argue that lifetime wage experiences—defined as the wages observed by men in their surrounding en-

vironment—shape beliefs about the returns to work, thereby influencing labor market participation. Panel (c) shows a sharp decline in average real hourly male wages from 1970 to 1995, which coincides with the childhood and teenage years of the younger cohorts depicted in panel (b). This indicates that men born between 1970 and 1995 observed significantly lower average wages during their formative years compared to those born in the 1960s, aligning with the sharper LFP declines observed for post-1970 cohorts in panel (b).

Panel (c) also suggests that these cohort-level declines in MLFP cannot be fully explained by contemporaneous yearly wage changes. For instance, while real average male wages grew in the late 1990s, LFP continued to decline sharply for cohorts coming of age during this period, as also noted by Binder and Bound (2019). Our hypothesis is that the wage declines of the 1980s, combined with wage stagnation from 2000 to 2015, shaped men's lifetime wage experiences, altering their beliefs about the returns to work and contributing to long-term LFP declines. This hypothesis is supported by panel (d), which plots the mean lifetime average yearly wage experienced by men born in 1961–1995 and aged 0–54 at different years. This figure indicates that men born in the 1960s experienced substantially higher average wages during their youth compared to later cohorts. For example, at age 24 in 1975, men born in 1961 observed an average real hourly wage of nearly $26.50, while for men born in 1971 this figure was $24 at age 24 in 1995. The plot also shows that, despite recent wage gains, average lifetime real wages today remain below 1970 levels.

2 Data and methodology

In this section, we describe the data and methodology used to estimate the effects of lifetime wage experiences on labor force participation decisions.

2.1 Panel survey data

Our survey data comes from the Panel Study of Income Dynamics (PSID), a large longitudinal household survey that began in 1968 with a nationally representative sample of over 18,000 individuals from 5,000 families across the United States. Data on these individuals and their descendants has been collected continuously—annually until 1997 and biannually thereafter. This data allows us to track the labor force participation histories of different individuals over time.

2.1.1 Labor force variables

We construct three measures of labor force participation. The first measure, "Labor Force Participation (LFP)," follows the standard definition: it equals one if an individual is currently working, temporarily laid off, or unemployed and actively seeking work, and zero otherwise. This is our preferred measure as it comprehensively reflects labor supply by capturing both employed individuals and those looking for jobs. The second measure, "Ever Labor Force Participation (Ever LFP)," captures lifetime labor force patterns and equals one if an individual has ever participated in the labor force based on the LFP definition above, and zero otherwise. The third measure, "Employed," equals one if an individual is currently employed and zero otherwise.

2.1.2 Sample

For our analysis, we focus on native-born prime-age men (ages 25–54) observed in various PSID waves. Since we aim to observe lifetime wage histories from birth, and given that the wage data begins in 1961 (see Section 2.2 for details), we focus on men born between 1961 and 1994, using data from PSID waves conducted from 1986 to 2019. This results in a sample of 4,308 individuals, observed an average of 3.74 times, resulting in 27,917 person-year observations.[5] We provide summary statistics for our sample by decade in Table A.1.[6]

2.2 Lifetime wage data

We use wage data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) from 1962 to 2020 to construct measures of aggregate lifetime wage experiences, which serve as the primary independent variables in our analysis. Since ASEC is conducted in March and collects information on wage income, weeks worked, and usual hours worked per week for the previous year, we construct realized hourly wage variables for 1961–2019.[7]

[5] In Figure A.1, we further depict the temporal distribution of the sample by plotting a histogram of the number of years elapsed between the first and last PSID measurement of every individual in the sample.

[6] Our results are weighted using the longitudinal weights provided by the PSID, excluding individuals whose longitudinal weights are set to zero. According to the PSID, these are "nonsample" persons who are neither original residents of a 1968 PSID sample family nor their descendants. Examples of "nonsample" persons include new spouses or other family members. Given the substantial data loss from excluding these individuals, Table B.5 presents our main results using an unweighted regression, which shows similar patterns.

[7] For 1961–1975, weeks worked and usual hours per week are imputed using the mid-point of the respective brackets.

For our analysis, we first construct real hourly wages, deflated using the national CPI,[8] for each person with available wage income, weeks worked, and hours worked data. To mitigate the effects of measurement error, we winsorize the real wage measures at the 1st and 99th percentiles. We then compute the average hourly wage reported by men in each state for each survey year, weighted using the provided yearly survey weights.

We then use this state-level wage time series to construct measures of aggregate lifetime wage experiences. Specifically, we assign each individual in our primary PSID sample a wage time series based on their state and year of birth.[9] For each individual, this time series includes the average real male wage in their state of birth from the year they were born until the survey year. Using this time series, we calculate the lifetime average real male wage ($W_{i,t}$) from birth to the year of measurement.[10] For example, to calculate the lifetime experienced wage for a man born in Iowa in 1981 and observed in the PSID in 2010, we use the average real male wage time series for Iowa from 1981 to 2010 and compute the average.

Formally, let $w_{i,s}$ represent the average real male wage in the state of birth of person i in year s, and let b_i be their birth year. For year of measurement t, the lifetime average real male wage $W_{i,t}$ is calculated as:

$$W_{i,t} = \frac{1}{t - b_i + 1} \sum_{s=b_i}^{t} w_{i,s}.$$

Panel (a) of Figure 2.1 shows the average real male wage time series for each state and the nation as a whole. These series display substantial variation both across states and over time, as evidenced by the marked differences between two states, Connecticut and Mississippi. Panel (b) further showcases this variation by plotting a histogram of the lifetime average real male wage ($W_{i,t}$) for the main sample.

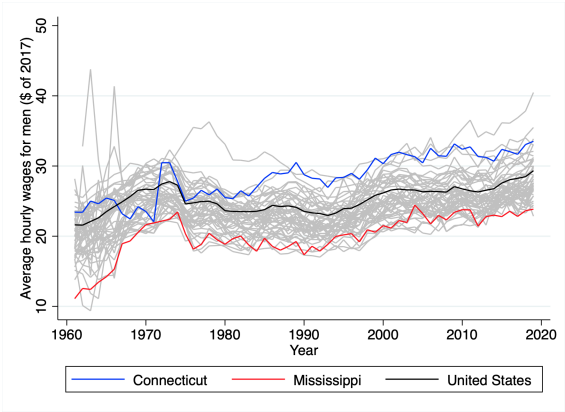
[8] To account for regional cost of living differences, Appendix B.2 tests the robustness of our results using state-level inflation measures from Hazell et al. (2022). The results are similar but use fewer observations, as the data only covers 1966–2017, limiting our sample to individuals born between 1966 and 1992, observed in 1991–2017.

[9] We use wages from each subject's state of birth to capture the work conditions present during their formative years and to control for migration-induced sorting, which could lead individuals with a higher propensity to work to move to states with better opportunities. In Section 3.3.1, we provide additional results exploring migration's role in our findings. Since the state of birth is often unavailable for non-household heads, it is imputed as the state where the individual lived when first surveyed, if they were aged 10 or younger.

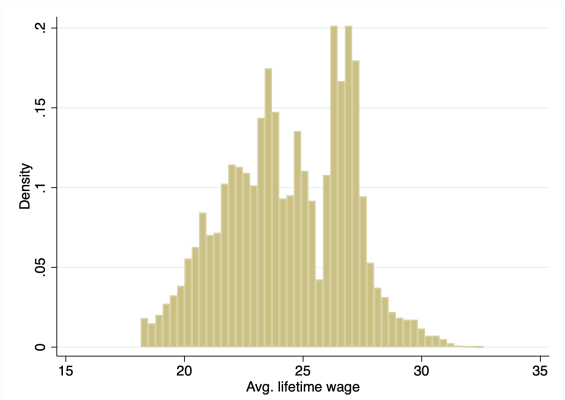
[10] An alternative approach, rather than calculating this lifetime average, would involve regressing labor force participation on the average male wage observed in each year of an individual's life. However, this approach would likely be underpowered due to the large number of parameters required (Malmendier and Nagel (2011)).

Figure 2.1: Variation in yearly and lifetime wages

(a) Average real male wage time series across states



(b) Histogram of the lifetime average real male wage



Notes: Panel (a) presents the average real male wage in 1961–2019 across all 50 states and nationally (in dollars of 2017). Panel (b) presents the histogram of the lifetime average real male wage ($W_{i,t}$) for the main sample. Data for panel (a) comes from the CPS ASEC in 1962–2020, and leverages hourly wage information from all men who report it in each given year and state. Individuals' wages are winsorized at the 1–99 level to reduce measurement error. Wages are weighted using the yearly weights provided in the survey. Data for panel (b) uses this CPS ASEC data for native-born men of ages 25–54 in the PSID waves conducted in 1986–2019. This histogram is unweighted for ease of interpretation.

2.3 Empirical specification

Our baseline empirical specification follows:

$$L_{i,t} = \alpha + \beta W_{i,t} + \alpha_i + \alpha_t + \alpha_{s,t} + \epsilon_{i,t}, \tag{1}$$

where $L_{i,t}$ represents each of our labor force participation variables for individual i at time t, and $W_{i,t}$ is the lifetime average real male wage. The regression includes individual fixed effects (α_i), year fixed effects (α_t), and state-by-year fixed effects ($\alpha_{s,t}$), where state s is the birth state of individual i. Standard errors ($\epsilon_{i,t}$) are clustered at the state-of-birth by year and birth-year level, which is the level of treatment in our analysis.[11]

In what follows, given the inclusion of individual fixed effects, we rescale the lifetime average real male wage, $W_{i,t}$, using its within standard deviation, which captures variability within individuals over time.

[11] To account for potential serial correlation in lifetime wage histories for individuals from the same state and adjacent birth years, Appendix B.4 tests robustness using progressively more conservative clustering levels, including state-of-birth by year and 5- and 10-year birth-year bins, state-by-year, and state of birth. Results remain highly significant in all cases.

2.4 Identification

The aim of our empirical analysis is to estimate the causal effects of aggregate lifetime wage experiences on men's labor force participation. The ideal experiment would involve assigning random, independent aggregate wage paths since birth to each man and evaluating how these paths influence labor force decisions in adulthood. While this ideal experiment is infeasible, our setup provides some key similarities to this design, offering several advantages for identifying the effects of lifetime wage experiences.

First, the *aggregate* lifetime wage experiences, approximated using state-level wages in our analysis, are exogenous to individuals since they represent general equilibrium outcomes and are not influenced by individual situations. Second, using wage experiences from the state of birth helps control for endogenous migration and labor sorting, as individuals do not choose their birth state. Third, our analysis exploits both cross-sectional (state) and cohort variation, allowing us to disentangle the effects of lifetime wage experiences from broader cohort and state trends. Fourth, individual fixed effects in our model control for time-invariant unobserved individual heterogeneity. Finally, year and state-of-birth-by-year fixed effects account for *current* labor market conditions, isolating the role of lifetime wage experiences from present-day events.

3 Results

3.1 Main results

We present the main results of Equation (1) in Table 3.1. In column 1, we find that a one standard deviation increase in the average experienced aggregate lifetime hourly wage, corresponding to \$0.33, raises men's probability of labor force participation by 10 percentage points. To illustrate, this \$0.33 increase is equivalent to comparing, in 2000, a man born in 1970 in Louisiana, and a man born in 1970 in Texas. Columns 2 and 3 indicate that this positive effect also applies to having ever participated in the labor force and to being employed.

In Figure B.1, we present binned scatterplots of these results,[12] showing that the positive relationship between labor force participation and average lifetime wage is approximately linear across both high and low wage experience environments.

[12] Specifically, we plot the relationship between the residuals of each labor force variable and the average lifetime wage variable after controlling for individual, year, and state-of-birth-by-year fixed effects as in Equation (1).

Table 3.1: Main results

VARIABLES	(1) LFP	(2) Ever LFP	(3) Employed
Avg. lifetime wage	0.10***	0.02***	0.11***
	(0.02)	(0.00)	(0.02)
Constant	-6.28***	-0.51*	-7.04***
	(1.24)	(0.30)	(1.53)
Observations	25,719	27,221	25,719
R-squared	0.49	0.78	0.47
Individual FE	Y	Y	Y
Year FE	Y	Y	Y
State of Birth x Year FE	Y	Y	Y

Notes: This specification corresponds to that of Equation (1). The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.2 Inclusion of controls and additional robustness

3.2.1 Inclusion of controls

Our main results are estimated without any socioeconomic controls, as many of these are endogenous to labor force decisions and could introduce post-treatment bias. However, we aim to determine whether the observed effects on labor force participation reflect changes in underlying beliefs about the returns to work or are simply driven by changes in personal economic circumstances. Furthermore, it is useful to test whether wage experiences specifically drive the observed effects, or if other experiences—such as changes in familial wealth due to bequests or emergencies—play a central role.

To this end, we provide evidence in Table B.1, where we progressively add controls to the preferred specification from column 1 of Table 3.1.[13] These controls include time-varying demographics (marital status, educational attainment, household size and household size squared), as well as household income and wealth.[14] Our results are highly robust to the inclusion of these covariates, suggesting that the effects we estimate are driven by lifetime wage experiences and reflect changes in attitudes towards work.

[13] Results for the other two labor force variables are available in Table B.2 and Table B.3, showing that these effects are also robust to the inclusion of controls.

[14] All monetary variables are inflation-adjusted using the national consumer price index.

3.2.2 Additional robustness

We assess the robustness of our main results to: (1) using regional inflation measures to deflate the wages in the CPS (Appendix B.2); (2) conducting an unweighted regression that includes "nonsample" persons in the PSID, substantially increasing the sample size (Appendix B.3); and (3) using progressively more conservative clustering levels, including state-of-birth by year, 5- and 10-year birth-year bins, and state of birth (Appendix B.4). The results remain consistent with the baseline across these specifications.

3.3 Mechanisms

We now provide two pieces of evidence highlighting the role of individuals' beliefs about the returns to work in driving the link between male labor force participation decisions and experienced aggregate lifetime wages documented previously. First, we examine the impact of migration. Second, we explore how the results vary by race, and when using lifetime wage experience measures based only on men of the same race as the individual.

3.3.1 Migration

We begin by examining the role of migration in driving our results. This is important for two reasons. First, labor conditions in the state of birth may influence labor decisions by encouraging migration to states with better work opportunities. Second, if the wage environment in an individual's state of birth continues to affect their labor force participation even after migrating to a different state, it further highlights the significance of beliefs.

To evaluate the importance of each of these mechanisms, we assess how our main results change when we: (1) exclude individuals who have ever migrated out of their state of birth; (2) include a comprehensive set of state-of-residence fixed effects (state, state by year, state by birth year, and state by birth year by year), which allows the effect of lifetime wage experiences to be estimated solely from movers; (3) consider individuals who migrated out of their state of birth only; and (4) consider individuals who migrated out of their state of birth when young (under the age of 18) only, which helps address concerns of endogenous migration as early-life migration decisions are likely made by subjects' parents. We present these results for the labor force participation outcome in Table 3.2.[15]

The first column replicates the main results presented in column 1 of Table 3.1. Column 2

[15] Results for the other two labor force variables are available in Table C.1 and Table C.2 and show similar patterns.

shows that the effect of lifetime wage experiences increases when we exclude individuals who have migrated out of their state of birth. This suggests that migration serves as a mechanism to escape low-wage environments: individuals move from low-wage states in search of better opportunities and are thus more likely to work in their new locations. As a result, migration attenuates the impact of the lifetime wage environment prevalent in individuals' state of birth on labor decisions.

Table 3.2: Role of migration

VARIABLES	(1) LFP	(2) LFP	(3) LFP	(4) LFP	(5) LFP
Avg. lifetime wage	0.10***	0.15***	0.12*	0.11***	0.11**
	(0.02)	(0.03)	(0.06)	(0.03)	(0.04)
Constant	-6.28***	-9.96***	-8.07*	-7.53***	-7.41**
	(1.24)	(2.25)	(4.64)	(1.97)	(3.28)
Observations	25,719	9,638	21,642	10,525	4,807
R-squared	0.49	0.56	0.73	0.51	0.59
Individual FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y
Drop movers		Y			
Keep only movers				All	Young
State of Residence FE			Y		
State of Residence x Year FE			Y		
State of Residence x Birth Year FE			Y		
State of Residence x Birth Year x Year			Y		

Notes: The first columns replicates Equation (1). The other four columns modify Equation (1) by: (1) excluding individuals who have ever migrated out of their state of birth; (2) adding a full set of state of residence fixed effects, namely state of residence, state of residence by year, state of residence by birth year, and state of residence by birth year by year; (3) considering individuals who migrated out of their state of birth only; and (4) considering individuals who migrated out of their state of birth when young (under the age of 18) only. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Columns 3, 4, and 5 show that the positive relationship between aggregate lifetime wage experiences and male labor force participation persists even when identified solely from movers. This holds regardless of whether current labor market conditions in their destination states are controlled for, and whether the move occurred when individuals were young and not fully in control of the decision. This further suggests a role for beliefs: even after relocating, individuals who grew up in states with lower average male wages participate in the labor force at lower rates than those from states with higher average wages.

3.3.2 Racial decomposition

We now examine the role of race in driving our results. Specifically, we examine how our previous results vary when considering black and white men separately, and when constructing lifetime wage experiences based on individuals of the same race.[16] This distinction is important, because individuals are likely to pay more attention to the wages of people who resemble them when forming their beliefs about the returns to work.

Table 3.3: Racial decomposition (for LFP outcome variable)

	(1)	(2)	(3)	(4)	(5)	(6)
	LFP	LFP	LFP	LFP	LFP	LFP
VARIABLES	White men	Black men	White men	Black men	White men	Black men
Avg. lifetime wage (all)	0.08***	0.18***				
	(0.02)	(0.04)				
Avg. lifetime wage (white)			0.06***		0.09***	0.13**
			(0.02)		(0.02)	(0.06)
Avg. lifetime wage (black)				0.24***	-0.04*	0.13*
				(0.05)	(0.02)	(0.07)
Constant	-5.15***	-12.84***	-3.74***	-13.28***	-3.35**	-16.65***
	(1.34)	(3.31)	(1.42)	(3.07)	(1.42)	(3.65)
Observations	15,763	9,285	16,290	8,970	16,290	8,970
R-squared	0.49	0.57	0.49	0.58	0.49	0.58
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but (1) limiting to white and black individuals, respectively; and (2) constructing lifetime wage experience measures using information from white and black men, respectively. The analyses encompass native-born white and black men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We present these results for the labor force participation outcome in Table 3.3.[17] Columns 1 and 2 replicate the main analysis from column 1 of Table 3.1, splitting the sample by race. The results suggest that the effect of average lifetime wages on labor force participation is positive for both black and white men, but over two times stronger for black men. Columns 3 and 4 show these results using lifetime wage measures based only on men of the same race

[16] We focus solely on black and white men in this analysis given that the CPS ASEC, where we build wage histories from, only considered these two racial categories in the 1960–1980 period. In addition, as the PSID does not provide race data for non-household heads, race is inferred from the household head with whom the individual lived when first surveyed, provided they were 10 years old or younger.

[17] Results for the other two labor force variables are available in Table C.3 and Table C.4 and show similar patterns.

as the respondent. For black men, labor force participation responds more strongly to black wages than to overall wages, while the opposite is true for white men.

In columns 5 and 6, we delve deeper by including both black and white lifetime wage experiences in each regression. The results indicate that, for white men, the positive link between lifetime wages and labor force participation is primarily driven by the wages of other white men, while the wages of black men have a small negative effect. This suggests that white men pay more attention to the wages of those who resemble them. For black men, however, both black and white wage trajectories have a positive and symmetrical effect, suggesting that black men form their beliefs more broadly. This is consistent with the fact that black men represent a smaller share of the male population and are thus more exposed to white male work experiences compared to their white counterparts.

4 Conclusions

In this paper, we contribute to the ongoing debate on the long-run decline in male labor force participation in the United States by identifying and analyzing a novel channel: the influence of aggregate lifetime wages on men's labor supply decisions. Our findings show that aggregate lifetime wages, serving as a proxy for men's perceived returns to work, are positively and significantly correlated with their participation in the labor force. This relationship persists even after controlling for current labor market conditions, as well as demographic, income, and wealth variables, indicating a robust link between long-term wage experiences and labor market engagement. Furthermore, by examining the role of migration and race, our study also underscores the role of individual beliefs in driving these. The observed cohort differences and the persistence of these effects across different labor market conditions emphasize the importance of considering long-term wage trends and perceptions in policy-making aimed at improving labor force participation.

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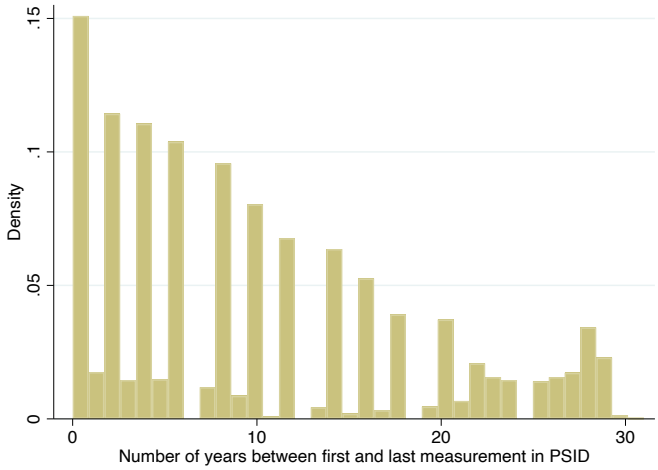
Supplemental Appendix

A Summary statistics

Figure A.1: Histogram of number of years elapsed between first and last measurement of sample individuals



Notes: This figure presents the histogram of the number of years elapsed between the first and last PSID measurement of native-born men of ages 25–54 in the PSID waves conducted in 1986–2019. This histogram is unweighted for ease of interpretation.

Table A.1: Summary statistics of sample

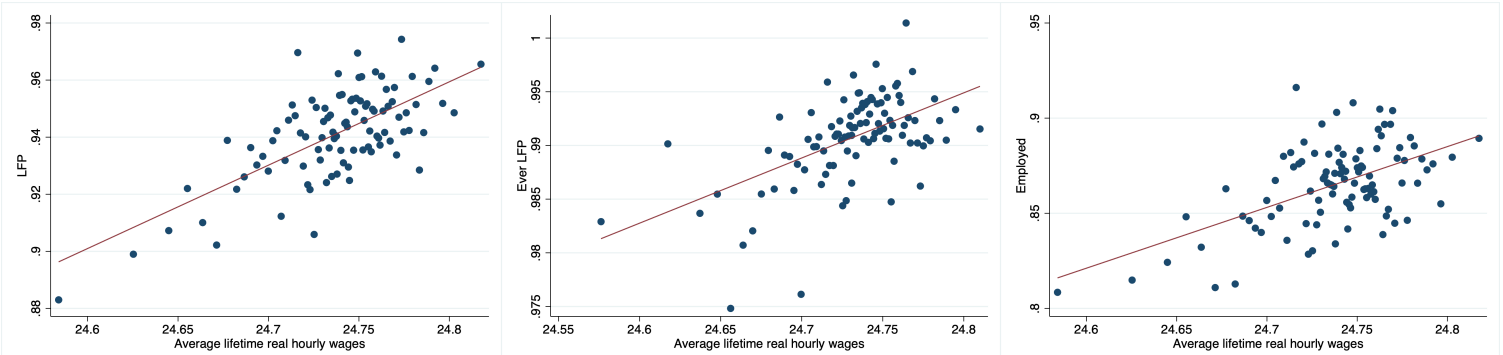
	(1) 1980s	(2)	(3) 1990s	(4)	(5) 2000s	(6)	(7) 2010s	(8)
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd
LFP	0.97	0.18	0.97	0.18	0.95	0.22	0.92	0.27
Employed	0.89	0.31	0.91	0.29	0.87	0.33	0.84	0.37
Ever LFP	0.99	0.12	0.99	0.11	0.99	0.089	0.99	0.093
Avg. lifetime wage	24.4	2.67	24.2	2.57	24.5	2.42	25.1	2.41
Age	25.8	0.89	29.1	3.08	34.1	6.01	37.8	8.27
Born in Northeast	0.26	0.44	0.24	0.43	0.20	0.40	0.20	0.40
Born in Midwest	0.33	0.47	0.31	0.46	0.31	0.46	0.29	0.45
Born in South	0.23	0.42	0.28	0.45	0.29	0.46	0.31	0.46
Born in West	0.17	0.38	0.17	0.38	0.19	0.39	0.20	0.40
White	0.87	0.34	0.86	0.35	0.85	0.35	0.82	0.38
Married	0.45	0.50	0.53	0.50	0.61	0.49	0.57	0.49
No. people in HH	2.50	1.44	2.65	1.43	2.88	1.53	2.81	1.54
Years of schooling	13.3	2.00	13.3	2.07	13.6	2.09	13.9	2.15
HH income (Dollars of 2017)	67,336	47,584	74,475	56,740	97,117	139,731	96,670	124,627
HH wealth (Dollars of 2017)	101,956	311,524	140,357	397,568	215,408	719,125	207,226	727,365
Observations	828	828	7038	7038	7574	7574	12477	12477

Notes: These summary statistics correspond to native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey.

B Robustness of main results

Figure B.1: Binned scatterplots of relationship between labor force variables and average aggregate lifetime wage

(a) LFP (b) Ever LFP (c) Employed



Notes: These figures present the average residual of each of the labor force variables, namely LFP, Ever LFP, and Employed, for different equal-sized bins of the residual of the (non-standardized) average lifetime wage variable, after controlling for individual, year, and state of birth by year fixed effects as in Equation (1). The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.1 Inclusion of controls

Table B.1: Inclusion of controls (for LFP outcome variable)

	(1)	(2)	(3)	(4)
VARIABLES	LFP	LFP	LFP	LFP
Avg. lifetime wage	0.10***	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-6.28***	-5.79***	-5.85***	-6.05***
	(1.24)	(1.28)	(1.28)	(1.37)
Observations	25,719	25,107	25,107	19,783
R-squared	0.49	0.50	0.50	0.54
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y
Demographics		Y	Y	Y
HH Income			Y	Y
HH Wealth				Y

Notes: This specification corresponds to that of Equation (1), but progressively includes the following control variables: marital status, educational attainment, household size, and household size squared; along with household income and wealth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.2: Inclusion of controls (for Ever LFP outcome variable)

VARIABLES	(1) Ever LFP	(2) Ever LFP	(3) Ever LFP	(4) Ever LFP
Avg. lifetime wage	0.02***	0.004*	0.004*	0.004*
	(0.00)	(0.00)	(0.002)	(0.002)
Constant	-0.51*	0.63***	0.64***	0.66***
	(0.30)	(0.18)	(0.18)	(0.19)
Observations	27,221	25,449	25,449	20,006
R-squared	0.78	0.86	0.86	0.88
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y
Demographics		Y	Y	Y
HH Income			Y	Y
HH Wealth				Y

Notes: This specification corresponds to that of Equation (1), but progressively includes the following control variables: marital status, educational attainment, household size, and household size squared; along with household income and wealth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.3: Inclusion of controls (for Employed outcome variable)

VARIABLES	(1) Employed	(2) Employed	(3) Employed	(4) Employed
Avg. lifetime wage	0.11***	0.10***	0.10***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-7.04***	-6.35***	-6.42***	-7.26***
	(1.53)	(1.58)	(1.58)	(1.69)
Observations	25,719	25,107	25,107	19,783
R-squared	0.47	0.48	0.48	0.51
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y
Demographics		Y	Y	Y
HH Income			Y	Y
HH Wealth				Y

Notes: This specification corresponds to that of Equation (1), but progressively includes the following control variables: marital status, educational attainment, household size, and household size squared; along with household income and wealth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.2 Adjusting wages using state-level CPI

In our main analysis, and in order to maximize the temporal and regional coverage of the sample, we construct subject lifetime wage experiences using the average real hourly wage in each year and state of the CPS deflated using the national CPI. However, given that the cost of living may differ across different states, we now consider the robustness of our main results to using regional inflation measures to deflate the wages in the CPS. We combine two sources of data for this purpose. The first source of data follows from the state-level inflation measures built by Hazell et al. (2022) from which we build CPI measures for the years 1977–2017 in 21 states,[18] and the years 1988–2017 in the rest. The second source of data corresponds to regional-level CPI measures built by the Bureau of Labor Statistics (BLS) since 1966.[19] We use this data to complement the state-level inflation information so that we can extend our sample further back.[20] Thus, the CPI time series used to deflate the wages observed yearly in each state is given by the corresponding regional CPI in 1966–1976 and the state-level CPI in 1977–2017 for 21 states, and the regional CPI in 1966–1987 and the state-level CPI in 1988–2017 for the rest.

Table B.4: Adjusting wages using state-level CPI

VARIABLES	(1) LFP	(2) Ever LFP	(3) Employed
Avg. lifetime wage	0.05***	0.01**	0.07***
	(0.02)	(0.00)	(0.02)
Constant	-2.72**	0.26	-4.38***
	(1.26)	(0.31)	(1.66)
Observations	15,702	16,718	15,702
R-squared	0.50	0.73	0.49
Individual FE	Y	Y	Y
Year FE	Y	Y	Y
State of Birth x Year FE	Y	Y	Y

Notes: This specification corresponds to that of Equation (1). The analyses encompass native-born prime-age men (ages 25–54) born in 1966–1992 observed in the PSID waves in 2002–2017. Results are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Given these data constraints, the analysis in this case focuses on native-born prime-age men

[18] The states with information starting in 1977 are Alaska, California, District of Columbia, Florida, Georgia, Hawaii, Illinois, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Jersey, New York, Ohio, Oregon, Pennsylvania, Tennessee, Texas, Washington, and Wisconsin.

[19] The regions considered in this data are Northeast, Midwest, South, and West.

[20] Both sources of data contain information for every quarter in each year. We use information from the fourth quarter in order to construct our yearly CPI measures.

(ages 25–54) born in 1966–1992 observed in the PSID waves in 1991–2017. We present the results of the main analysis using this alternate measure of subject lifetime wage experiences in Table B.4. The results are similar to baseline, but comprise significantly fewer observations and become slightly smaller.

B.3 Unweighted results

Table B.5: Unweighted results

VARIABLES	(1) LFP	(2) Ever LFP	(3) Employed
Avg. lifetime wage	0.08***	0.02***	0.11***
	(0.01)	(0.00)	(0.01)
Constant	-5.10***	-0.49**	-7.23***
	(0.78)	(0.24)	(1.05)
Observations	41,903	44,610	41,903
R-squared	0.50	0.78	0.49
Individual FE	Y	Y	Y
Year FE	Y	Y	Y
State of Birth x Year FE	Y	Y	Y

Notes: This specification corresponds to that of Equation (1). The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are unweighted. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.4 Alternate clustering

Table B.6: Alternate clustering (for LFP outcome variable)

VARIABLES	(1) LFP	(2) LFP	(3) LFP	(4) LFP
Avg. lifetime wage	0.10***	0.10***	0.10***	0.10***
	(0.02)	(0.01)	(0.02)	(0.02)
Constant	-6.28***	-6.28***	-6.28***	-6.28***
	(1.21)	(1.05)	(1.14)	(1.73)
Observations	25,719	25,719	25,719	25,719
R-squared	0.49	0.49	0.49	0.49
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but considers different levels of clustering for standard errors, namely (1) state-of-birth by year and 5-year birth-year bins; (2) state-of-birth by year and 10-year birth-year bins; (3) state-of-birth by year; and (4) state of birth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at each level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.7: Alternate clustering (for Ever LFP outcome variable)

VARIABLES	(1) Ever LFP	(2) Ever LFP	(3) Ever LFP	(4) Ever LFP
Avg. lifetime wage	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	-0.51	-0.51	-0.51	-0.51
	(0.31)	(0.33)	(0.32)	(0.46)
Observations	27,221	27,221	27,221	27,221
R-squared	0.78	0.78	0.78	0.78
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but considers different levels of clustering for standard errors, namely (1) state-of-birth by year and 5-year birth-year bins; (2) state-of-birth by year and 10-year birth-year bins; (3) state-of-birth by year; and (4) state of birth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at each level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.8: Alternate clustering (for Employed outcome variable)

VARIABLES	(1) Employed	(2) Employed	(3) Employed	(4) Employed
Avg. lifetime wage	0.11***	0.11***	0.11***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-7.04***	-7.04***	-7.04***	-7.04***
	(1.49)	(1.38)	(1.43)	(1.61)
Observations	25,719	25,719	25,719	25,719
R-squared	0.47	0.47	0.47	0.47
Individual FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but considers different levels of clustering for standard errors, namely (1) state-of-birth by year and 5-year birth-year bins; (2) state-of-birth by year and 10-year birth-year bins; (3) state-of-birth by year; and (4) state of birth. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at each level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Robustness of mechanisms

C.1 Migration

Table C.1: Role of migration (for Ever LFP outcome variable)

VARIABLES	(1) Ever LFP	(2) Ever LFP	(3) Ever LFP	(4) Ever LFP	(5) Ever LFP
Avg. lifetime wage	0.02***	0.01**	-0.01	0.01***	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Constant	-0.51*	-0.12	1.44	0.11	0.80*
	(0.30)	(0.54)	(1.10)	(0.31)	(0.45)
Observations	27,221	10,260	23,238	10,959	5,047
R-squared	0.78	0.85	0.90	0.83	0.82
Individual FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y
Drop movers		Y			
Keep only movers				All	Young
State of Residence FE			Y		
State of Residence x Year FE			Y		
State of Residence x Birth Year FE			Y		
State of Residence x Birth Year x Year			Y		

Notes: This specification corresponds to that of Equation (1), but (1) excluding individuals who have ever migrated out of their state of birth; and (2) adding a full set of state of residence fixed effects, namely state of residence, state of residence by year, and state of residence by birth year. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Role of migration (for Employed outcome variable)

VARIABLES	(1) Employed	(2) Employed	(3) Employed	(4) Employed	(5) Employed
Avg. lifetime wage	0.11***	0.14***	0.09	0.12***	0.11**
	(0.02)	(0.04)	(0.09)	(0.03)	(0.05)
Constant	-7.04***	-9.33***	-5.95	-8.32***	-7.42**
	(1.53)	(2.86)	(6.78)	(2.40)	(3.58)
Observations	25,719	9,638	21,642	10,525	4,807
R-squared	0.47	0.53	0.71	0.50	0.55
Individual FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y
Drop movers		Y			
Keep only movers				All	Young
State of Residence FE			Y		
State of Residence x Year FE			Y		
State of Residence x Birth Year FE			Y		
State of Residence x Birth Year x Year			Y		

Notes: This specification corresponds to that of Equation (1), but (1) excluding individuals who have ever migrated out of their state of birth; and (2) adding a full set of state of residence fixed effects, namely state of residence, state of residence by year, and state of residence by birth year. The analyses encompass native-born men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.2 Racial decomposition

Table C.3: Racial decomposition (for Ever LFP outcome variable)

VARIABLES	(1) Ever LFP White men	(2) Ever LFP Black men	(3) Ever LFP White men	(4) Ever LFP Black men	(5) Ever LFP White men	(6) Ever LFP Black men
Avg. lifetime wage (all)	0.01***	0.02***				
	(0.00)	(0.01)				
Avg. lifetime wage (white)			0.01***		0.01***	0.01
			(0.00)		(0.00)	(0.01)
Avg. lifetime wage (black)				0.01**	-0.00	0.01
				(0.01)	(0.00)	(0.01)
Constant	0.01	-0.44	-0.03	0.22	-0.01	0.06
	(0.28)	(0.44)	(0.30)	(0.37)	(0.30)	(0.43)
Observations	16,229	10,300	16,826	9,940	16,826	9,940
R-squared	0.79	0.83	0.78	0.85	0.78	0.85
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but (1) limiting to white and black individuals, respectively; and (2) constructing lifetime wage experience measures using information from white and black men, respectively. The analyses encompass native-born white and black men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.4: Racial decomposition (for Employed outcome variable)

VARIABLES	(1) Employed White men	(2) Employed Black men	(3) Employed White men	(4) Employed Black men	(5) Employed White men	(6) Employed Black men
Avg. lifetime wage (all)	0.10***	0.22***				
	(0.02)	(0.06)				
Avg. lifetime wage (white)			0.08***		0.08***	0.16*
			(0.02)		(0.03)	(0.09)
Avg. lifetime wage (black)				0.23***	-0.00	0.09
				(0.07)	(0.03)	(0.11)
Constant	-6.56***	-15.96***	-5.20***	-12.38***	-5.16***	-16.41***
	(1.63)	(4.32)	(1.75)	(4.31)	(1.77)	(5.04)
Observations	15,763	9,285	16,290	8,970	16,290	8,970
R-squared	0.46	0.55	0.46	0.55	0.46	0.55
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State of Birth x Year FE	Y	Y	Y	Y	Y	Y

Notes: This specification corresponds to that of Equation (1), but (1) limiting to white and black individuals, respectively; and (2) constructing lifetime wage experience measures using information from white and black men, respectively. The analyses encompass native-born white and black men of ages 25–54 in the PSID waves conducted in 1986–2019, and are weighted using the longitudinal weights provided in the survey. Standard errors clustered at the birth-year by state-of-birth and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.