

# The Rise of US Earnings Inequality: Does the Cycle Drive the Trend?\*

Jonathan Heathcote

Fabrizio Perri

Giovanni L. Violante

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## Abstract

We document that declining hours worked are the primary driver of widening inequality in the bottom half of the male labor earnings distribution in the United States over the past 52 years. This decline in hours is heavily concentrated in recessions: hours and earnings at the bottom fall sharply in recessions and do not fully recover in subsequent expansions. Motivated by this evidence, we build a structural model to explore the possibility that recessions *cause* persistent increases in inequality; that is, that the cycle drives the trend. The model features skill-biased technical change, which implies a trend decline in low-skill wages relative to the value of non-market activities. With this adverse trend in the background, recessions imply a potential *double-whammy* for low skilled men. This group is disproportionately likely to experience unemployment, which further reduces skills and potential earnings via a scarring effect. As unemployed low skilled men give up job search, recessions generate surges in non-participation. Because non-participation is highly persistent, earnings inequality remains elevated long after the recession ends.

**JEL Codes:** E24, E32, J24, J64.

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\*Heathcote: Federal Reserve Bank of Minneapolis and CEPR, [heathcote@minneapolisfed.org](mailto:heathcote@minneapolisfed.org) ; Perri: Federal Reserve Bank of Minneapolis and CEPR, [fperri@umn.edu](mailto:fperri@umn.edu); Violante: Princeton University, CEPR, IFS, IZA and NBER, [violante@princeton.edu](mailto:violante@princeton.edu). We thank Lukas Mann and Hugo Lhuillier for outstanding research assistance. We are grateful to Ayşegül Şahin for very useful feedback on an early version of the paper and to many other seminar participants for comments. This paper was prepared for the conference that celebrated the 25th anniversary of *Frontiers of Business Cycle Research* (Tom Cooley, Editor).

# 1 Introduction

Earnings inequality has dramatically widened over the past half century in the United States (Heathcote et al., 2010). This phenomenon has mostly been interpreted as reflecting slow-moving secular trends and, in particular, the effects of technical change that has generally favored relatively high skill workers (Katz and Murphy, 1992; Murphy and Welch, 1992). The goal of this paper is to explore the hypothesis that cyclical fluctuations have had persistent effects on earnings inequality. We will argue that some of the observed increase in inequality over the past half century can be attributed to the recessions the US has experienced over this period.

The first part of the paper is purely empirical. We document changes in the cross-sectional distribution of earnings using Current Population Survey (CPS) data for prime-age men covering the period from 1968 to 2018. We establish two striking features of this data. First, while earnings dispersion has increased steadily at the top of the earnings distribution (as measured, for example, by the 90/50 percentile ratio), there is a strong cyclical component to the dynamics of earnings inequality at the bottom. In particular, earnings inequality in the left-tail of the distribution, as measured by the 50/20 percentile ratio, widens sharply during recessions and tends to decline gradually during subsequent recoveries. Thus, in a purely accounting sense, all the observed increase in left-tail earnings inequality since 1967 has occurred during recessions.

The second key finding from the CPS data arises when we decompose earnings into hourly wages and annual hours worked. Almost all men at the top of the earnings distribution work full time, and thus changes in relative wages entirely account for the dynamics of earnings inequality at the top. At the bottom of the earnings distribution, the pattern is quite different. Hours worked at the bottom tend to decline sharply in recessions and also have a clear downward trend over time. Thus, understanding the dynamics of hours worked at the bottom of the earnings distribution is crucial for understanding both the cyclical dynamics and the long run trends in earnings inequality at the bottom.

This empirical evidence suggests an intriguing possibility—namely, that some of the observed long run increase in inequality at the bottom of the earnings distribution reflects the cumulative impact of a series of recessions. Put differently, earnings inequality today might be lower had the U.S. somehow avoided the recessions of the past half century. An alternative interpretation, of course, is that slow moving structural or technological trends drive the long run increase, and booms and recessions have delivered only temporary deviations around an immutable long run trend.

The narrative we have in mind for why recessions may have a persistent impact on inequality is as follows. Recessions are a time when many workers, and especially low wage workers, become unemployed. This recessionary spike in unemployment naturally increases bottom tail earnings inequality, simply because men experiencing an unemployment spell tend to have low annual earnings. Of course, unemployment rates tend to decline during recoveries, so an extra ingredient is required if recessions are to increase inequality in a persistent fashion. The extra ingredient we have in mind is that workers who experience unemployment tend to lose skills relative to their counterparts who remain employed. Thus, periods of unemployment can have a persistent scarring effect, as documented, for example, by [Davis and Von Wachter \(2011\)](#). As a result, some low skill workers who experience unemployment might decide to stop participating. In this way, a temporary surge in unemployment can potentially translate into a persistent increase in non-participation.

The second part of this paper develops a quantitative structural model that we can use to explore this potential interaction between cycle and trend. The model features over-lapping generations of men who differ in labor market skills. The only choice model individuals make is whether to participate in the labor market, a choice that balances the potential value of higher future earnings against the cost of lost leisure. Individual wages reflect individual skills, which tend to increase while working (*learning by doing*) but depreciate while unemployed (*scarring*). Conditional on participating, individuals face idiosyncratic unemployment risk, where the probability of being unemployed is lower for those currently employed and for high skilled workers relative to low skilled ones.

The model features two sources of aggregate dynamics. The background “trend” force is a steady increase over time in the relative importance in production of higher skilled workers. This simple model of skill-biased technical change implies a widening skill premium in wages and also a steady increase over time in the share of low wage men who have small or negative net present values from labor market participation. On top of this, we generate “cycles” in the economy by introducing time variation in job finding probabilities such that the economy generates realistic cyclical variation in the unemployment rate. We calibrate the model to replicate observed growth in top tail earnings inequality over time and over the life-cycle. We discipline the size of the scarring effect from non-participation by asking the model to replicate estimates of persistent earnings declines from mass layoffs from [Davis and Von Wachter \(2011\)](#).

We first explore how well the calibrated model replicates the observed cyclical and long run dynamics for bottom tail earnings inequality – recall that the model is calibrated

to replicate inequality at the top. The model generates realistic dynamics for the earnings share of the bottom 20%, for the 50/20 percentile ratio for earnings, and for the share of prime-age men with zero earnings in a given year. The fact that a combination of exogenous unemployment risk and endogenous participation choices can account for most of the cyclical dynamics in earnings inequality suggests a relatively minor role for cyclical variation in the process for hourly wages.

Next, we use the model to run some counterfactuals. In particular, we are interested in simulating two counterfactual histories for the United States, one in which we hold the unemployment rate constant over the past 52 years (no cycles) and a second in which we use the baseline cyclical variation in unemployment probabilities but shut down background skill biased technical change.

The key finding from these simulations is that there is an important interaction between trend and cycle. In particular, the long run increase in the fraction of men with zero earnings is much larger in the baseline model – with both trend and cyclical drivers of inequality – than would be suggested by considering the two experiments in which one force or the other is switched off; the combined effect of the two drivers together is larger than the sum of the two parts taken separately.

Our interpretation for this finding is as follows. Absent cycles, skill-biased technical change disfavors low skilled men, making them susceptible to choosing non-participation. But as long as they remain mostly employed, declining skill prices are partly offset by the learning-by-doing effect, so that most men avoid negative earnings growth and choose to keep participating. However, if a recession hits, low skill unemployed men face a *double-whammy*: they lose skills while unemployed, and skill prices continue to move against them because of the adverse trend. At some point, in the presence of (i) job search costs, (ii) low job finding probabilities, and (iii) low and continually declining skills, it becomes optimal to give up search and transition to non-participation. Once low skill men have been out of work for long enough, re-entering the labor force is not optimal, even once job finding probabilities recover. Key model ingredients for this model mechanism to generate sizable recession-induced declines in participation are, first, that unemployment is concentrated among low skill workers, and second, that unemployment spells in recessions are long enough to imply substantial skill loss.

## 1.1 Related literature

Our paper connects various strands of the literature on macroeconomics and labor economics. The first literature we contribute to are the studies on the dynamics of earnings

inequality in the United States (see [Acemoglu, 2002](#); [Katz et al., 1999](#); [Hornstein et al., 2005](#); [Blau and Kahn, 2020](#), for surveys of stylized facts and theoretical models). This literature has focused mostly on long term trends for the earnings of full-time workers with strong labor force attachment (as, e.g., in the classic papers by [Katz and Murphy, 1992](#); [Juhn et al., 1993](#); [Murphy and Welch, 1992](#); [Autor et al., 2008](#)) and often on the dynamics of inequality at the very top ([Piketty and Saez, 2003](#)). In doing so, it has overlooked the cyclical pattern of inequality and how the rise in inequality at the bottom of the skill distribution (e.g., the 50/20 earnings ratio) is driven overwhelmingly by the decline in hours worked by low-skilled workers. Both observations are central to our analysis. We borrow one of the key tenets of this literature: the dominant driver of long-term trends in the widening of the wage distribution is skill-biased technical change.

Several authors, at least since [Juhn et al. \(1991\)](#), have studied the rise in non participation of prime-age men that started in the 1970s. These authors have analyzed both demand and supply factors (see [Binder and Bound, 2019](#); [Abraham and Kearney, 2020](#), for recent surveys). On the demand side, the shift in labor demand against low-educated workers reduced the return to working for these low-skill individuals ([Juhn, 1992](#); [Moffitt, 2012](#); [Charles et al., 2019](#)). On the supply side, the literature focused on three factors: the increased participation in disability insurance ([Chen and Van der Klaauw, 2008](#); [French and Song, 2014](#)), the rise in wages and participation of women ([Jones et al., 2015](#)), which might have led to a different time allocation within the household, and improvements in leisure technology ([Aguiar et al., 2017](#)). We find that our model can replicate the long-term rise in non-participation even though it abstracts from these supply side channels. That demand side forces —the ones we emphasize— have played an historically bigger role than supply side ones seems to be the emerging consensus.<sup>1</sup>

The literature on economic fluctuations has long recognized that the extensive margin is the dominant factor in cyclical fluctuations of total hours worked (see [Keane and Rogerson, 2015](#), for a survey) and hence earnings at the bottom of the income distribution. In our model, we focus exclusively on this margin and aim at reproducing aggregate movements across the three employment states (employment, unemployment, and non-participation) in both the short run and the long run. The cyclical patterns of flows into and out of participation have also been the object of attention of a number of search mod-

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<sup>1</sup>For example, the 2016 CEA report on the topic ([Council of Economic Advisors, 2016](#)) argues that rising female participation cannot be a first-order factor because fewer than one quarter of non-participating men have a working spouse, and that share has declined over the past 50 years. Similarly, the rise in receipt of disability insurance income has occurred alongside reductions in eligibility for other public programs, e.g. TANF after 1996. [Aguiar et al. \(2017\)](#) conclude that leisure luxuries are a powerful explanation for younger men, of ages 21 to 30, but are less relevant for prime-age men.

els, most recently the one by [Krusell et al. \(2017\)](#). Our model features a simple search structure with exogenous separation and job-finding rates. We improve upon standard search models by letting the transition rates into and out of employment depend on skills, as they do in the data.

At least since [Mincer \(1986\)](#), many authors have estimated earnings losses upon displacement. What is especially relevant for us is the empirical finding that earnings losses are strongly countercyclical ([Davis and Von Wachter, 2011](#)): losing one's job in a recession implies a recovery path for earnings that is significantly slower compared with when displacement occurs in an expansion. We discipline our model to be consistent with this fact and connect it to the rise in non-participation. When workers are laid off in a recession, they suffer a persistent decline in expected earnings. Combined with the underlying trend in technology, this force pushes those at the bottom of the skill distribution out of the labor force.

Finally, the idea that recessions can have permanent effects –both positive and negative– on the labor market has a long tradition in macroeconomics ([Caballero and Hammour, 1994](#); [Barlevy, 2002](#); [Comin and Gertler, 2006](#)). In particular, the mechanism we explore is consistent with the fact, documented by [Jaimovich and Siu \(2020\)](#), that over the past four decades much of the permanent decline in employment for particular occupations (routine jobs in the taxonomy of [Acemoglu and Autor, 2011](#)) occurred during recessions. While the model does not have an explicit notion of occupation, our mechanism leads to long-lasting effects of recessions on employment for laid-off workers close to the non-participation margin. [Yagan \(2019\)](#) offers convincing empirical evidence that in geographical areas where the labor market was most depressed during the Great Recession the employment to population ratio was still significantly lower seven years later, especially among low-skilled individuals.

The theme of this special issue is to celebrate and build upon the *Frontiers of Business Cycle Research* volume ([Cooley and Prescott, 1995](#)). The original spirit of the business cycles agenda, clearly stated in the first chapter of that book, was to integrate the study of growth and business cycles. In this paper, we extend the Cooley-Prescott research agenda to the analysis of inequality and argue that a framework that integrates growth and business cycles offers powerful insight into the dynamics of income inequality.

Over the last two decades, it has become apparent that technological progress, the engine of long-run growth, is skill-biased and a key driver of the long-run rise in US earnings inequality. At the same time, fluctuations in unemployment are a fundamental aspect of the business cycle, and unemployment is clearly central to inequality at the bottom of

the earnings distribution. This paper argues that in order to understand long-run trends in inequality at the bottom of the earnings distribution, it is important to understand how these trend and cycle forces interact to shape the dynamics of labor force participation. One implication of the contention that cycles have persistent effects on participation and inequality is that the welfare cost of business cycles is likely much larger than existing estimates that abstract from the interaction between trend and cycle.

The rest of the paper is organized as follows. Section 2 describes the key facts about the distribution of earnings and hours worked that we aim to explain. Section 3 outlines the model. Section 4 describes the model parameterization. Section 5 presents the results of the model simulations and counterfactuals. Section 6 concludes.

## 2 Data

In this section we document the empirical relationships between recessions, earnings inequality, and hours worked in the United States, over the period 1967-2018. Our sample of interest is all men between the ages of 25 and 55. We focus on prime-age men because we want to zero in on the connection between recessions and labor market participation.<sup>2</sup> Our main data source is the Annual Social and Economic (ASEC) Supplement of the Current Population Survey (henceforth CPS) administered in March of every year, as reported by IPUMS. Our definition of earnings is standard and includes wage and salary income plus business and farm income earned over the course of a year, deflated using the PCE deflator.<sup>3</sup>

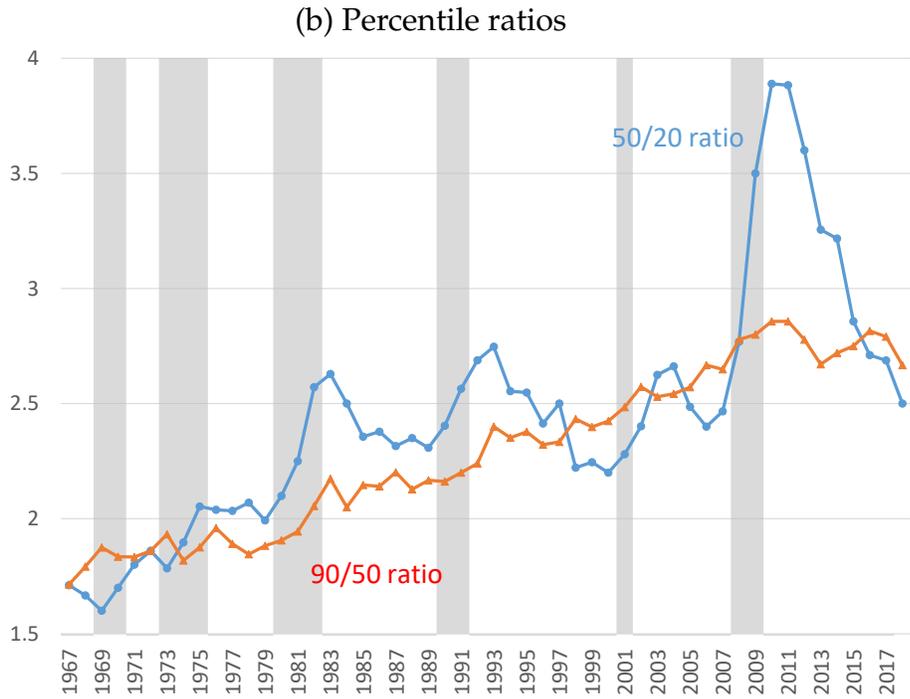
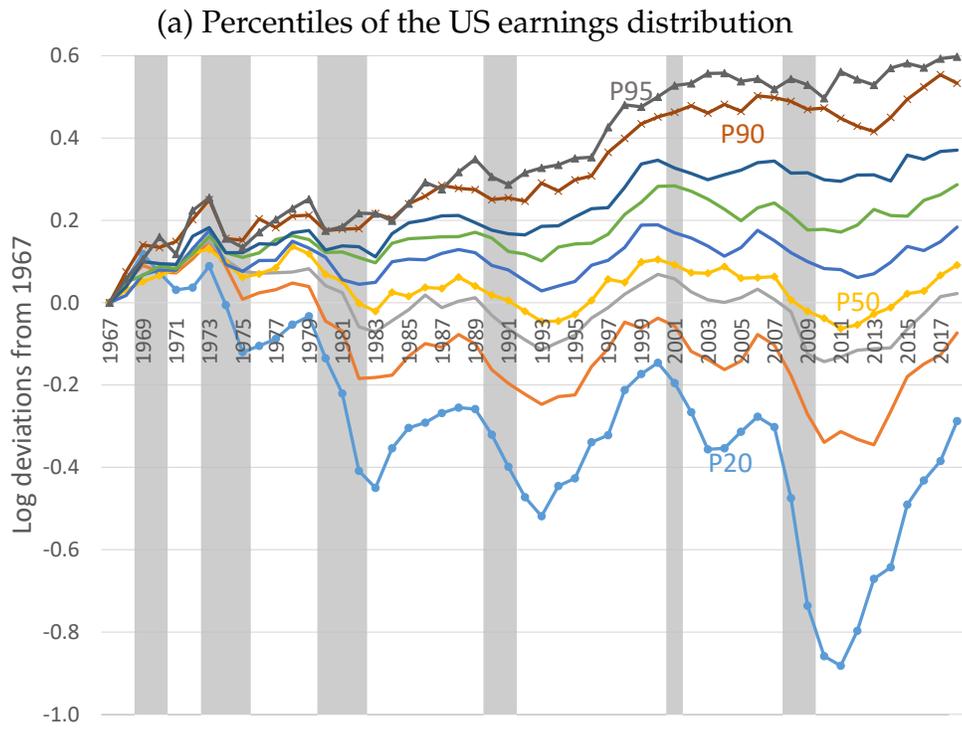
One feature of our sample worth emphasizing is that it comprises *all* prime-age men, including those with zero earnings. One obvious reason to keep the zeros is that we are interested in understanding the dynamics of non-participation. Another reason is that men with zero earnings are at the very bottom of the earnings distribution in the data, and retaining them is important if we want a comprehensive picture of earnings inequality. Put differently, dropping the zeros would make the earnings distribution appear less unequal than it really is. Worse, given that the number of zeros is rising over time, dropping the zeros will also make the increase in inequality over time appear milder than it really is.<sup>4</sup>

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<sup>2</sup>Other potentially important drivers of participation such as rising longevity and cultural change are likely to play a less central role for prime-age men than for women or older workers.

<sup>3</sup>See Appendix A for more details on data construction and sample selection.

<sup>4</sup>In contrast, as discussed in the Introduction, many empirical papers documenting the evolution of inequality have effectively ignored all the zeros, either because they have focused on inequality in hourly wages – which can only be measured for individuals with strictly positive hours and earnings – or because



Note: the shaded areas represent years which contain an NBER dated recession

Figure 1: The evolution of the US earnings distribution

Figure 1 illustrates the evolution of earnings inequality over the past 52 years. Better understanding this picture is our prime objective. Each line in panel (a) of the figure plots a given percentile of the earnings distribution, where the 1967 value of each percentile is normalized to 1. Thus, for example, a man at the 95th percentile of the 2018 male earnings distribution earned 0.6 log points (47%) more than a man at the 95th percentile of the 1967 distribution. The two lines in panel (b) show two percentile ratios that summarize inequality at the bottom (the 50/20 ratio) and inequality at the top (the 90/50 ratio).<sup>5</sup> In both panels, NBER recession dates are shaded in grey.

Both figures show a sizable increase in earnings inequality over time. In panel (a), the increase is manifested in the fanning out of the percentile lines, while in panel (b) it is captured by the increasing trend in both ratios. The main fact we want to highlight from these two figures is that the nature of the increase in inequality at the top and at the bottom is quite different. Inequality at the top (the 90/50) increases steadily (until 2010) and does not exhibit any particular cyclical pattern. Inequality at the bottom (the 50/20), in contrast, increases sharply in each recession, and in general this increase is partly retraced in subsequent expansions. The longer the expansion, the more inequality declines, and during the long 1990s expansion, inequality at the bottom declines to below its level in the late 1980s. Thus, increases in inequality are concentrated in recessions: the cumulative increase in the 50/20 ratio that happened during US recessions exceeds the overall increase in the same ratio over the entire 1968-2018 period.

Figure 1 establishes that the cyclical properties of earnings inequality are different at the bottom and at the top. In order to better understand the origin of this difference, Figure 2 decomposes annual earnings into weekly wages versus weeks worked. We do this by recording average earnings and average weeks worked for three slices of the earnings distribution: those between the 85th and 95th percentiles of the distribution (the top), those between the 45th and 55th (the middle), and those between the 0th and 20th percentiles (the bottom). For each group, wages are defined as average annual earnings divided by average annual weeks worked.<sup>6</sup>

Comparing panels (a) and (b) of Figure 2 shows that the stark increase in earnings inequality at the top is driven entirely by the differential growth in real wages at the top vis-a-vis the middle, with top wages increasing 70% and middle wages remaining

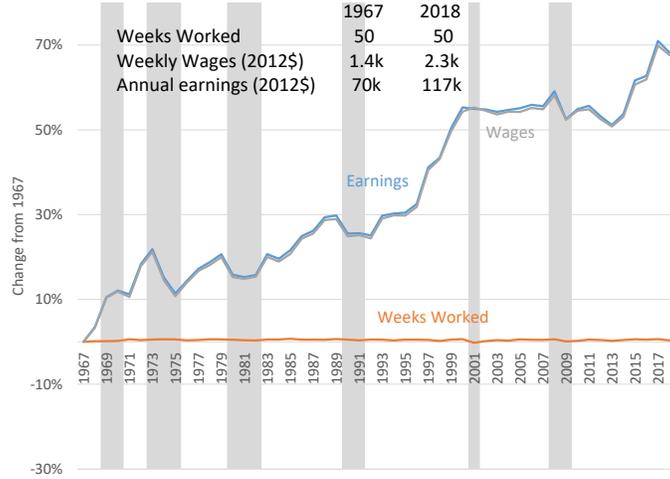
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they have focused on measures of inequality such as the variance of logs that are ill-defined when zeros are included in the sample.

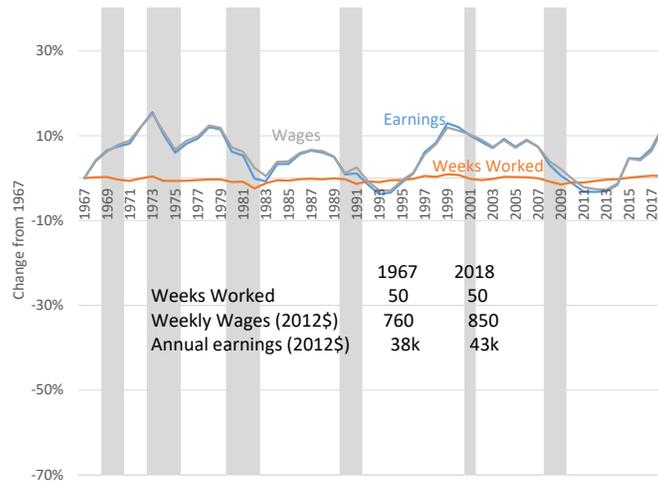
<sup>5</sup>We plot the 50/20 ratio, rather than the 50/10 ratio, because earnings at the 10th percentile are zero in some years, and thus the 50/10 ratio explodes.

<sup>6</sup>Blundell et al. (2018) apply an analogous decomposition to micro data on the earnings distribution for the US and the UK and arrive at similar conclusions.

(a) Top (85-95)



(b) Mid (45-55)



(c) Bottom (0-20)

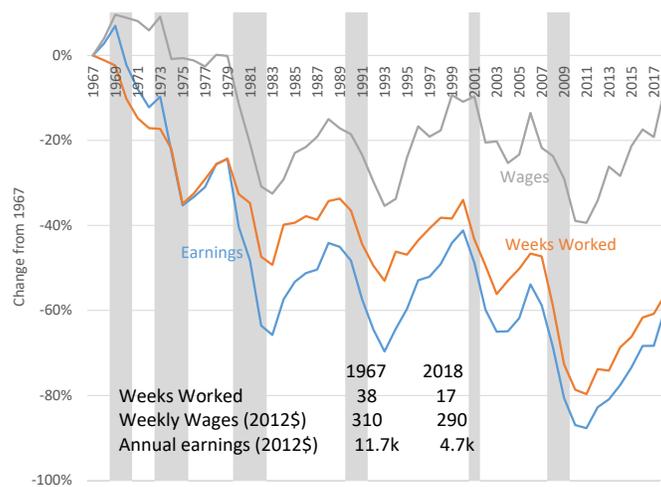


Figure 2: Wages, earnings and weeks worked in three slices of the earnings distribution

essentially flat over this 52 year period. Weeks worked at the top and in the middle are very stable over the entire period, at 50 weeks per year for both groups.

In contrast, comparing panels (b) and (c) shows that the long-run increase in inequality at the bottom of the distribution is determined mostly by a decline in weeks worked in the lower part of the distribution. Furthermore, both wages and weeks worked at the bottom are cyclical and fall in recessions. However, while wages at the bottom typically recover in expansions, the recovery in weeks worked is much weaker. As a result, over the course of our sample, wages at the bottom of the distribution decline by less than 10%, while weeks worked decline by 60%.<sup>7</sup>

What drives this patterns for weeks worked at the bottom of the earnings distribution? The fact that unemployment rises sharply in recessions and declines gradually in expansions obviously plays an important role in the cyclical pattern. At the same time, declining labor force participation accounts for the long run downward trend: there is no long term trend in the unemployment rate.

Figure 3 decomposes average weeks worked by men in the bottom 20 percent of the earnings distribution as the product of two terms: average weeks worked conditional on working a positive number of weeks, and the fraction of men who work a positive number of weeks. The figure shows that weeks worked conditional on working are highly cyclical, reflecting fluctuating unemployment, but have little long run trend. In contrast, the fraction of men working positive weeks accounts for almost all of the long run decline in weeks worked at the bottom of the distribution. The share of men with positive weeks exhibits slightly milder cyclical fluctuations than the average weeks worked series, but there is still a clear cyclical pattern, suggesting that recessions reduce labor force participation.

To recap, a large part of the increase in inequality at the bottom of the male earnings distribution in the United States over the past 52 years reflects declining weeks worked, which in turn is explained by an increase in the fraction of men not working at all.

Figure 4 illustrates the close connection between the rise in non-work and the rise in inequality at the bottom of the distribution. Each time a recession hits the economy, there is a surge in unemployment. This surge in unemployment reduces earnings at the lower percentiles of the earnings distribution and increases measured inequality at the bottom (i.e., the 50/20 percentile ratio), primarily because of a decline in earnings at the

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<sup>7</sup>Note that there is likely selection into non-work. If men with lower hourly wages are disproportionately likely to exhibit declines in weeks worked over the sample period, then the decline in latent offered hourly wages will be larger than the decline in measured wages. The same type of selection will be operative in the model.



Figure 3: Intensive and extensive margins of labor supply for the bottom 20% of the earnings distribution

20th percentile. Recessions also increase the number of men with zero weeks worked in a year, through some combination of higher non-participation and higher long-term unemployment. As the economy recovers following a recession, unemployment gradually declines, and lower unemployment means higher bottom tail earnings and thus a lower 50/20 percentile ratio. However, even though unemployment typically falls to its pre-recession level, the number of non-working men does not. This translates into a gradual ratcheting up in inequality over time. In particular, because non-work increases in a very persistent way in each recession, recoveries that take the unemployment rate back to its pre-recession level can still lead to long-lasting increases in the 50/20 earnings ratio. The only times during which the 50/20 ratio recovers after a recession are the two longest expansions in our sample period –the 1990s expansion and the post Great Recession expansion– during which the unemployment rate fell to extremely low levels.

Finally, note that the extent to which an increase in unemployment reduces earnings at the 20th percentile – thereby boosting the 50/20 ratio – depends on the pattern of selection into unemployment. Consider the following two stylized examples. If unemployment risk is perfectly inversely correlated with wages so that only the lowest wage workers become unemployed, then a rise in the unemployment rate will have no impact on earnings

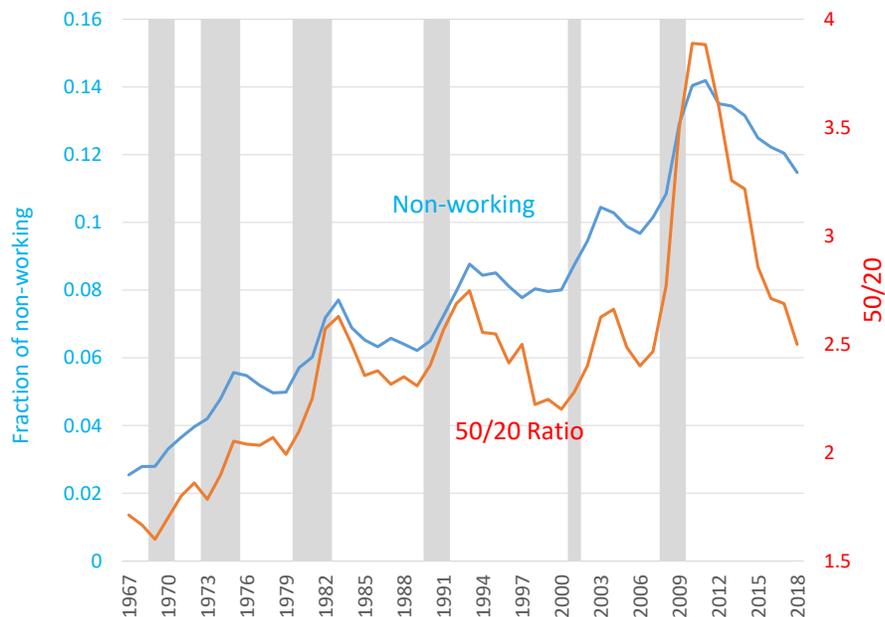


Figure 4: Non-work and inequality at the bottom

at the 20th percentile, as long as the unemployment rate remains below 20 percent. In contrast, if unemployment risk is only weakly correlated with wages, an increase in the unemployment rate will have a large effect on the 20th earnings percentile, since as unemployment pushes some high wage workers down below the 20th earnings percentile, lower-wage but employed workers must move up.<sup>8</sup> In our model, we will take care to have a realistic incidence of unemployment by wage, to generate a realistic pattern of selection into unemployment.

### 3 Model

We now describe a simple life-cycle overlapping generations model that delivers predictions for the joint dynamics of wages, participation, and unemployment. We will use this model to explore how much of the upward trend in non-work in the United States reflects a persistent impact of recessions on labor force participation.

<sup>8</sup>Consider the following stylized example. Suppose that the population distribution of latent wages is constant, and that in a recession, a random 10 percent of men become full year unemployed. Pre-recession, with zero unemployment, the 20th percentile of the earnings distribution corresponds to the 20th percentile of the latent wage distribution. In a recession, the 20th percentile of the earnings distribution will correspond to an employed worker at the 11th percentile of the wage distribution, implying a large recessionary decline in the 20th percentile for earnings.

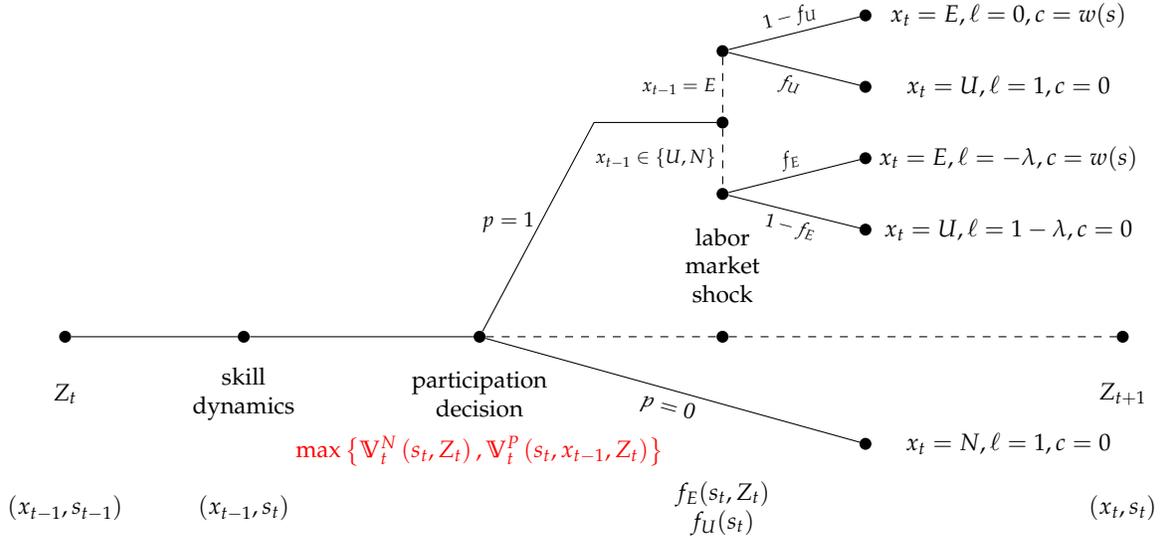


Figure 5: Timeline of individual decisions and shocks.

**Model overview:** Individual wages depend on skills, which reflect a combination of idiosyncratic luck and past labor market experience. There are three stages to each period of a man's life. First, he draws an idiosyncratic shock to his skills. Second, he chooses whether to participate in the labor market. Third, if he chooses to participate, he draws an idiosyncratic shock that determines whether he will be employed. Employment probabilities depend on an individual's lagged labor market status, individual skills, and the current aggregate cyclical state of the economy. Lagged labor market status is denoted  $x_{i,t-1} \in \{E, U, N\}$ , where  $E$  denotes employed,  $U$  denotes unemployed, and  $N$  denotes out of the labor force. The current cyclical state of the economy is denoted  $Z_t \in \{B, X, R, C\}$ , where  $B$  denotes boom,  $X$  denotes expansion,  $R$  denotes recession, and  $C$  denotes crisis. Figure 5 depicts the model's timeline.

**Demographics:** At each date  $t$ , a new cohort of working-age men enter the economy with age  $a = 0$ . These men live for  $A$  periods, and each cohort is of size  $1/A$ , so the total population size is one.

**Preferences:** Individuals seek to maximize expected lifetime utility, which for a man entering at date  $t$  is given by

$$\mathbb{E}_t \sum_{a=0}^{A-1} \beta^a u_i(c_{i,a,t+a}, \ell_{i,a,t+a}),$$

where  $c_{i,a,t}$  and  $\ell_{i,a,t}$  denote consumption and leisure for individual  $i$  at age  $a$  and date  $t$

and where  $\beta \in [0, 1]$  denotes the discount factor. We further assume that period utility is linear in its two arguments

$$u_i(c_{i,a,t}, \ell_{i,a,t}) = c_{i,a,t} + \exp(\phi_i) \ell_{i,a,t},$$

where  $\exp(\phi_i)$  denotes the preference for leisure relative to consumption.

Consumption and leisure depend on a man's idiosyncratic labor market status. In each state, consumption is equal to earnings, since we do not allow for saving or borrowing. Men who are employed work one unit of time and earn and consume their wage,  $c_i = w_i$ . Those who are unemployed or non-participating have zero earnings and consumption.

Leisure depends on an individual's past and new employment status. Those who choose non-participation enjoy  $\ell_i = 1$ , and so do those workers who are laid off and (by assumption) miss the opportunity to search in the current period. Searching reduces leisure by  $\lambda$  units, while working reduces leisure by 1 unit. Continuously employed workers do not need to search and enjoy  $\ell_i = 0$ . Newly employed workers who were previously unemployed or non-participating (and thus pay both the search and work costs) enjoy  $\ell_i = -\lambda$ . Jobseekers who do not find employment enjoy  $\ell_i = 1 - \lambda$ .

Note that in this model, participation choices trade off the value of additional consumption from potentially working against additional leisure from non-participation. The term  $\exp(\phi_i)$  captures the opportunity cost of work and can therefore be equivalently interpreted as capturing the value of leisure, or of home production, or of unemployment benefits and other government transfers to the non employed.

The idiosyncratic preference parameter  $\phi_i$  is common across all individuals belonging to the same cohort and is fixed over an individual's lifetime, but it potentially varies across cohorts. In particular,  $\phi_i = \mu_{\phi, t-a}$  where  $\mu_{\phi, t-a}$  is a cohort effect.

**Technology and Wages:** An individual's wage, should he choose to participate and find employment, reflects his idiosyncratic skills  $s_{it} \in \mathbb{R}$ . The price (wage) associated with a given skill level is determined in equilibrium via the following production technology:

$$Y_t = \int \exp(\sigma_t s) \cdot L_t(s) ds,$$

where  $L_t(s)$  denotes the measure of men with skill level  $s$  who are employed at date  $t$ . The production input weight  $\exp(\sigma_t s)$  defines the marginal (and average) product of workers of skill level  $s$  at date  $t$ . We assume labor markets are competitive, so the equilibrium

wage at date  $t$  for a worker with skill level  $s_{it}$  is given by

$$w_{it} = \exp(\sigma_t s_{it}).$$

The parameter  $\sigma_t$  determines the relative price of difference skill levels and thus the mapping from skill dispersion to equilibrium wage dispersion. In particular, note that

$$\log w_{it} = \sigma_t s_{it},$$

so  $\sigma_t$  can be interpreted as the return to skill in a Mincerian wage regression. We will allow  $\sigma_t$  to rise over time as a simple way to capture skill-biased technical change. For a given distribution for skills, growth in  $\sigma_t$  will imply rising wage inequality.

When men first enter the economy, they draw an initial skill value  $s_0$  from a standard normal distribution

$$s_0 \sim \mathcal{N}\left(\frac{\mu_{s,t}}{\sigma_t}, 1\right).$$

Note that this implies a distribution of log wages for labor market entrants with variance  $\sigma_t^2$ :

$$\sigma_t s_0 \sim \mathcal{N}\left(\mu_{s,t}, \sigma_t^2\right).$$

We assume that  $\sigma_t^2$  grows over time at a constant rate  $\gamma_\sigma$ :

$$\sigma_{t+1}^2 = \sigma_t^2 + \gamma_\sigma.$$

This growth in the return to skills is what we will label skill-biased technical change. We assume that men have perfect foresight over the future path for  $\sigma_t$  and thus can perfectly predict the future mapping from skills to wages. Note that growth in  $\sigma_t^2$  is a time effect.

In addition, we will assume that  $\mu_{s,t}$  grows across cohorts at a constant rate  $\gamma_s$ . The preference parameter  $\mu_{\phi,t}$  grows at a potentially different rate:<sup>9</sup>

$$\mu_{s,t+1} = \mu_{s,t} + \gamma_s,$$

$$\mu_{\phi,t+1} = \mu_{\phi,t} + \gamma_\phi.$$

**Skill Dynamics:** We assume that a man's skills evolve according to the following

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<sup>9</sup>In fact, we will focus on a "balanced-growth" specification in which  $\gamma_s = \gamma_\phi$ , so that the median wage for labor market entrants rises across successive cohorts at the same rate as the taste for leisure.

law of motion:

$$s_{i,a+1,t+1} = \rho s_{i,a,t} + (1 - \rho) \frac{\mu_{s,t-a}}{\sigma_{t-a}} + \mathbb{I}_{\{x_{i,a,t}=E\}} \cdot \delta^+ - \mathbb{I}_{\{x_{i,a,t} \neq E\}} \delta^- + \varepsilon_{i,a+1,t+1}, \quad (1)$$

with

$$\varepsilon_{i,a,t} \sim \mathcal{N}(0, v_\varepsilon).$$

Here,  $\rho \leq 1$  is a persistence parameter, and the term pre-multiplied by  $(1 - \rho)$  generates reversion toward the cohort-specific median initial skill level. The parameters  $\delta^+$  and  $\delta^-$  define the effect of employment on skill accumulation and the effect of non-employment on skill loss respectively. The  $\delta^+$  parameter captures learning by doing, while  $\delta^-$  captures a variety of possible channels through which periods of non-employment depress future wages: skill depreciation, loss of firm-specific human capital, and so on. Finally,  $\varepsilon$  is an *iid* shock that will be an additional source of individual earnings volatility, and one which will generate an upward-sloping age profile for wage dispersion.

**Unemployment Risk:** At the employment stage, the probability that a man who has chosen to participate is unemployed depends on his previous labor market status,  $x_{t-1}$ ; his skills,  $s_t$ ; and the cyclical state of the economy  $Z_t$ . In particular, men will be more likely to be unemployed at  $t$  if they were not working at  $t - 1$ , if they have relatively low skills, and if the economy is in a recession. Let  $y_t(s)$  denote potential earnings at date  $t$  for a man with skills  $s$  relative to average earnings of new labor market entrants at date  $t$ :

$$y_t(s) = \frac{\exp(\sigma_t s)}{\mathbb{E}[\exp(\sigma_t s_0)]} = \frac{\exp(\sigma_t s)}{\exp\left(\mu_{s,t} + \frac{\sigma_t^2}{2}\right)}.$$

We need to specify the job loss probability  $f_U$  for previously employed workers and the job finding probability  $f_E$  for previously unemployed or non-participating workers, both conditional on participating in the current period.<sup>10</sup> Shimer (2012) shows that three-quarters of fluctuations in the unemployment rate reflect fluctuations in the job finding rate. We therefore allow job finding probabilities to vary with the aggregate state  $Z$  but assume that job loss probabilities are invariant to  $Z$ . We use a flexible logistic-style function

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<sup>10</sup>We assume that previously unemployed and previously non-participating men who choose to participate and search in the current period have identical job finding probabilities, conditional on having the same value for individual skills  $s$  and the same aggregate state  $Z$ .

to capture how these probabilities vary with skills. In particular,

$$f_U(s_{it}) = \gamma_0 \left[ 1 - \left( 1 + \frac{\gamma_1}{y_t(s_{it})} \right)^{-\frac{1}{\gamma_2}} \right], \quad (2)$$

with  $\gamma_0, \gamma_1, \gamma_2 > 0$ . Note that as  $y_t(s_{it}) \rightarrow 0$ , the job loss probability converges to  $\gamma_0$ , while as  $y_t(s_{it}) \rightarrow \infty$ , the job loss probability converges to 0. Similarly, the job finding probabilities are given by

$$f_E(s_{it}, Z_t) = \eta_0(Z_t) \left( 1 + \frac{\eta_1}{y_t(s_{it})} \right)^{-\frac{1}{\eta_2}}, \quad (3)$$

with  $\eta_0(Z_t), \eta_1, \eta_2 > 0$  for all  $Z_t$ . As  $y_t(s_{it}) \rightarrow 0$ , the job finding probability converges to 0, while as  $y_t(s_{it}) \rightarrow \infty$  the job finding probability converges to  $\eta_0(Z_t)$ .

**Cyclical Fluctuations:** We assume that the aggregate exogenous state of the economy  $Z_t$  follows a first order Markov process with transition probabilities given by the matrix  $\Gamma_Z$ . The reason men care about the state  $Z_t$  is its impact on the job finding probability via  $\eta_0(Z_t)$ . Variation in this shifter is the only source of business cycles in the model.

**Participation:** We formulate the participation choice problem recursively. The individual state variables are age  $a$ , current period skills  $s_t$ , taste for leisure  $\phi$ , and previous labor market status  $x_{t-1} \in \{E, U, N\}$ . The aggregate state variables are time  $t$ , and cyclical state  $Z_t$ .

Let  $\mathbb{V}_t(a, \phi, s_t, x_{t-1}, Z_t)$  denote a man's expected remaining lifetime utility at date  $t$ . Similarly, let  $\mathbb{V}_t^N, \mathbb{V}_t^P$  denote the values associated with non-participation and participation. Because participation is a choice, the lifetime value for a man at the beginning of period  $t$ , after the new skill level  $s_t$  has realized, is

$$\mathbb{V}_t(a, \phi, s_t, x_{t-1}, Z_t) = \max \left\{ \mathbb{V}_t^N(a, \phi, s_t, Z_t), \mathbb{V}_t^P(a, \phi, s_t, x_{t-1}, Z_t) \right\},$$

where the max operator captures the idea that participation is chosen optimally. Let  $p_t(a, \phi, s_t, x_{t-1}, Z_t) \in \{0, 1\}$  denote the associated participation choice.

Note that the value of participating depends on lagged labor market status  $x_{t-1}$ , because this determines job finding probabilities (higher when previously employed) and whether search costs must be paid (only if previously non-employed). In contrast, the

value of non-participation is independent of  $x_{t-1}$ , since non-participants do not look for work.

The value of non-participation is

$$\begin{aligned}\mathbb{V}_t^N(a, \phi, s_t, Z_t) &= \exp(\phi) + \beta \mathbb{E}_t [\mathbb{V}_{t+1}(a+1, \phi, s_{t+1}, N, Z_{t+1})] \\ &\quad s.t. \\ s_{t+1} &= \rho s_t + (1-\rho) \frac{\mu_{s,t-a}}{\sigma_{t-a}} - \delta^- + \varepsilon_{t+1} \\ Z_{t+1} &= \Gamma_Z(Z_t)\end{aligned}$$

where the expectation is with respect to  $\varepsilon_{t+1}$  and  $Z_{t+1}$ .

The value of participation for men who were previously in state  $E, U$  and  $N$  respectively is

$$\begin{aligned}\mathbb{V}_t^P(a, \phi, s_t, E, Z_t) &= f_U(s_t) \mathbb{V}_t^U(a, \phi, s_t, Z_t) + [1 - f_U(s_t)] \mathbb{V}_t^E(a, \phi, s_t, Z_t), \\ \mathbb{V}_t^P(a, \phi, s_t, U, Z_t) &= -\lambda \exp(\phi) + [1 - f_E(s_t, Z_t)] \mathbb{V}_t^U(a, \phi, s_t, Z_t) + f_E(s_t, Z_t) \mathbb{V}_t^E(a, \phi, s_t, Z_t), \\ \mathbb{V}_t^P(a, \phi, s_t, N, Z_t) &= \mathbb{V}_t^P(a, \phi, s_t, U, Z_t),\end{aligned}$$

where  $\mathbb{V}_t^U$  and  $\mathbb{V}_t^E$  denote the values of unemployment and employment at date  $t$ , measured in both cases after search costs have been paid.

The values of unemployment and employment are respectively

$$\mathbb{V}_t^U(a, \phi, s_t, Z_t) = \mathbb{V}_t^N(a, \phi, s_t, Z_t)$$

and

$$\begin{aligned}\mathbb{V}_t^E(a, \phi, s_t, Z_t) &= \exp(\sigma_t s_t) + \beta \mathbb{E}_t [\mathbb{V}_{t+1}(a, \phi, s_{t+1}, E, Z_{t+1})] \\ &\quad s.t. \\ s_{t+1} &= \rho s_t + (1-\rho) \frac{\mu_{s,t-a}}{\sigma_{t-a}} + \delta^+ + \varepsilon_{t+1} \\ Z_{t+1} &= \Gamma_Z(Z_t).\end{aligned}$$

The values of being unemployed and of non-participation are identical, because after search costs have been paid, unemployment and non-participation deliver identical flow utility and have identical implications for skill dynamics and future job finding probabilities.

**Equilibrium:** An equilibrium is a set of value functions  $\mathbb{V}_t(a, \phi, s_t, x_{t-1}, Z_t)$  that

solve the individual problems defined above, with associated participation decision rules,  $p_t(a, \phi, s_t, x_{t-1}, Z_t)$ . Note that there are no endogenous equilibrium prices in the model: individual choices depend only on current and expected values for individual state variables and the exogenous aggregate state  $Z_t$ . This simplifies computation. However, each cohort solves a different problem, because of the time trend in skill price dispersion.

**Characterizing Optimal Participation:** In the last period of life, at age  $A - 1$

$$\begin{aligned}\mathbb{V}_t^E(A - 1, \phi, s_t, Z_t) &= \exp(\sigma_t s_t) \\ \mathbb{V}_t^N(A - 1, \phi, s_t, Z_t) &= \mathbb{V}_t^U(A - 1, \phi, s_t, Z_t) = \exp(\phi),\end{aligned}$$

and thus optimal participation choices are given by

$$\begin{aligned}p_t(A - 1, \phi, s_t, E, Z_t) &= 1 \quad \text{iff } \exp(\sigma_t s_t) - \exp(\phi) \geq 0 \\ p_t(A - 1, \phi, s_t, N/U, Z_t) &= 1 \quad \text{iff } -\lambda \exp(\phi) + f_E(s_t, Z_t) [\exp(\sigma_t s_t) - \exp(\phi)] \geq 0.\end{aligned}$$

Thus, in the last period of life, participation is optimal if and only if the job search cost (if previously non-employed) is smaller than the probability of finding a job times the value of earnings net of the value of lost leisure. Note immediately that, all else equal, participation is more likely for previously employed workers, who need not pay the search cost.

When men are myopic ( $\beta = 0$ ), then the above participation rule will apply at each age. However, when  $\beta > 0$ , participation choices become dynamic. The above condition is still a sufficient condition for participation to be optimal at any age  $a$ , but it is no longer necessary.<sup>11</sup> In particular, there are two reasons why men below the maximum age  $A - 1$  may decide to participate even if the current payoff expected net payoff is negative. First, working increases skills – thanks to the  $\delta^+$  learning-by-doing parameter – and continued participation may eventually turn negative static utility flows positive. Second, even absent the learning by doing and scarring mechanisms, skills have a stochastic component. Thus, even if the current flow payoff from work is negative, there is a chance that favorable shocks will turn this payoff positive again. By continuing to work when the current flow payoff is negative, men can avoid having to pay search costs in the event that positive future shocks make working more attractive.

Men in the model with relatively low initial skills  $s_0$  will choose non-participation

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<sup>11</sup>It is sufficient for participation because employment implies higher expected skills in the next period, which increase expected continuation values. Employment also raises continuation values by increasing job finding probabilities and reducing job loss probabilities.

right at labor market entry. Non-participation rates will typically rise with age for two reasons. First, persistent skill shocks coupled with heterogeneous employment histories will imply increasing within cohort skill dispersion, with more low skill men who optimally choose not to participate. Second, as men age, the dynamic incentives for participation, in terms of higher future skills and lower future job search costs, become weaker.

**Changing Returns to Skill:** How does growth in the return to skill affect wage growth and thereby the incentive to participate? Wage growth in the model is given by

$$\frac{w_{t+1}}{w_t} = \frac{\exp(\sigma_{t+1}s_{t+1})}{\exp(\sigma_t s_t)} = \frac{\exp\left((\sigma_t^2 + \gamma_\sigma)^{\frac{1}{2}}\left(\rho s_t + (1 - \rho)\frac{\mu_{s,t-a}}{\sigma_{t-a}} + \delta^{+/-} + \varepsilon_{t+1}\right)\right)}{\exp(\sigma_t s_t)}.$$

It follows that log wage growth is given by the following affine function of skills:

$$\log\left(\frac{w_{t+1}}{w_t}\right) = \left[\left(1 + \frac{\gamma_\sigma}{\sigma_t^2}\right)^{\frac{1}{2}} \rho - 1\right] \sigma_t s_t + \left(1 + \frac{\gamma_\sigma}{\sigma_t^2}\right)^{\frac{1}{2}} \sigma_t \left[(1 - \rho)\frac{\mu_{s,t-a}}{\sigma_{t-a}} + \delta^{+/-} + \varepsilon_{t+1}\right].$$

Consider first a specification without skill-biased technical change; that is,  $\gamma_\sigma = 0$ . In that case, as long as  $\rho < 1$ , higher skill men can expect relatively slow wage growth; this is the standard mean-reversion force. Introducing skill-biased technical change ( $\gamma_\sigma > 0$ ) tilts wage growth in favor of high skill men. For moderate rates of SBTC, the process for skills effectively becomes more persistent: increasing  $\gamma_\sigma$  is equivalent to increasing  $\rho$ . For a sufficiently fast rate of SBTC such that  $\frac{\gamma_\sigma}{\sigma_t^2} > \frac{1}{\rho^2} - 1$ , SBTC dominates the mean-reversion force operating through  $\rho$ , and higher skill men can actually expect faster wage growth than their low skill counterparts.

How does SBTC affect the model's predictions for non-participation? Because SBTC makes skills more persistent and even potentially generates divergent expected wage growth, it implies faster within cohort growth in wage dispersion. As a result, it implies more low wage workers at older ages and thus higher rates of non-participation. In addition, because it implies more workers who are close to indifferent between participating and not participating, SBTC implies a larger aggregate decline in participation in response to a recession that raises unemployment risk. In particular, in a recession, many low skill workers experience unemployment spells. If – thanks to SBTC – many of these workers are already close to their participation threshold, the loss of skills associated with an unemployment spell may incentivize them to stop searching for work. In this fashion,

a temporary surge in unemployment potentially can translate into a much more persistent surge in non-participation. We will shortly calibrate and simulate the model to quantify the magnitude of this effect.

Appendix C outlines the algorithm we use to compute the equilibrium of the model.

## 4 Parameterization

We set the model period to a month.

**Demographics and preferences** The number of periods in the labor market is  $A = 360$ , corresponding to the 25-54 age range of individuals we study in the data. We set  $\beta = 0.9$  on an annual basis. A relatively low discount factor is a simple way to capture the idea that future labor income should be heavily discounted because it is very risky and highly correlated with individual consumption.<sup>12</sup> Moreover, the experimental evidence in Epper et al. (2020) suggests that low-income and low-education individuals, who are most likely to be marginal for participation decisions, heavily discount the future.

We set the job search cost  $\lambda$  to 0.2, so that in terms of lost leisure searching for work is 20 percent as costly as working.

The initial value of the preference parameter  $\mu_{\phi,67}$  is set to target the average fraction of men with zero annual earnings over the 1967–2018 period. Recall that a higher value for  $\mu_{\phi,t}$  reduces participation, implying more annual zeros. Its growth rate  $\gamma_{\phi}$  is set equal to the growth rate of median log wages,  $\gamma_s$ .

**Skill dynamics** For the process for skills, we start by fixing  $\rho = 0.95^{1/12}$ , which is in the middle of empirical estimates for the annual persistence of idiosyncratic shocks to wages (Meghir and Pistaferri, 2011). We normalize  $\mu_{s,67}$  to zero, and set  $\gamma_s$  and  $\delta^+$  to replicate the average growth rate of male earnings over time and over the life-cycle, respectively. More specifically, we compute average annual earnings for each age-year cell in our CPS sample for working-age men, and we regress these observations on year and age. We then search for values for  $\gamma_s$  and  $\delta^+$  such that the same model regressions reproduce the estimated year and age slope coefficients.

We set  $\sigma_{67}^2$  to replicate average 50/20 percentile ratio for earnings over the sample period. The parameters  $\gamma_{\sigma}$  and  $v_{\varepsilon}$  control how wage dispersion rises over time and over the

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<sup>12</sup>In our model, agents are risk neutral, so this logic does not strictly apply. A more realistic setting, however, would introduce risk aversion and allow for inter-temporal borrowing and lending. In such a setting, Huggett and Kaplan (2016) show that risky future labor earnings are effectively discounted at a much higher rate than the risk-free interest rate.

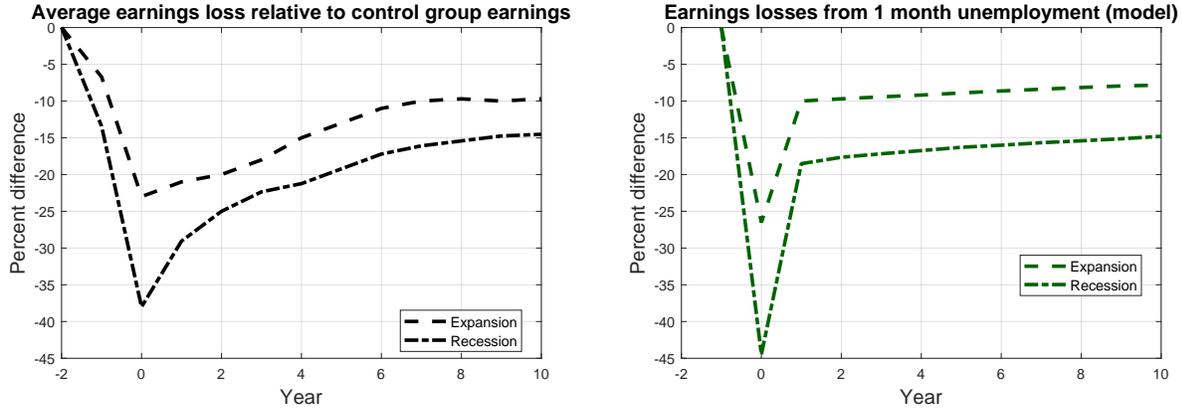


Figure 6: Left panel: Figure 4.c in [Davis and Von Wachter \(2011\)](#). Right panel: model counterpart. In the model, paths are generated by shocking a random group of employed workers with an unemployment shock and comparing dynamics for that group to a similar group that is not subject to the shock. We make this comparison when the economy is in an expansion ( $Z_t = X$ ) and when it is in a recession ( $Z_t = R$ ).

life-cycle. We estimate these parameters by focusing on replicating earnings inequality at the top of the earnings distribution, where men are typically working full time (recall that non-participation and unemployment are concentrated in the bottom tail of the earnings distribution). In particular, we compute the 90/50 percentile ratio for earnings for each age-year cell in our CPS data, regress these observations on year and age, and search for values for  $\gamma_\sigma$  and  $v_\varepsilon$  such that the model replicates the empirical slope coefficients.

Another important parameter is  $\delta^-$ , which determines the rate at which skills depreciate during non-employment. In the literature, a common approach to estimating this effect relies on the labor market experiences of men who have experienced mass layoffs. The hope is that the earnings losses of such men mostly reflect the pure effect of a spell of unemployment, rather than specific characteristics of workers that make them unusually susceptible to displacement. [Davis and Von Wachter \(2011\)](#) estimate that 10 years after an episode of unemployment that occurs in recessions, unemployed workers earn around 15 percent less than comparable workers who were not laid off. We set  $\delta^-$  so that, for a representative cross-section of 25-45 year old men in a model simulation, expected earnings 10 years after a mid-recession unemployment spell are 15 percent lower, on average, than for men who are employed in that month.

Figure 6 reproduces Figure 4.c in [Davis and Von Wachter \(2011\)](#) (left panel) and its model counterpart (right panel). That the earnings losses of displaced workers are much larger in recessions than in expansions, both in the short-run and in the long-run, is one of the key findings of [Davis and Von Wachter \(2011\)](#). The model is calibrated only to match the long-run value of average earnings losses in recessions but, as can be seen in

Parameter	Description	Value
$A$	maximum age (months)	360
$\beta$	discount factor	$0.90^{1/12}$
$\lambda$	search cost	0.2
$\mu_{\phi,67}$	mean of the value of log leisure	-0.999
$\mu_{s,67}$	initial level of median log wage	0
$\gamma_s = \gamma_\phi$	growth rate of log wage/leisure	0.000284
$\rho$	autoregressive parameter for log skills	$0.95^{1/12}$
$\delta^+$	rate of learning by doing	0.00491
$\delta^-$	earnings loss upon displacement	0.0647
$v_\varepsilon$	variance of skill shocks	0.00888
$\sigma_{67}^2$	initial variance of log wages	0.337
$\gamma_\sigma$	rate of skill-biased technical change	0.000379

Table 1: Summary of parameterization for demographics, preferences, skill dynamics and trend parameters. The model period is one month.

	Monthly $\Pr(Z_{t+1} Z_t)$			
	$B$	$X$	$R$	$C$
$B$	0.892	0.108	0.000	0.000
$X$	0.040	0.9292	0.0307	0.000
$R$	0.000	0.0653	0.915	0.020
$C$	0.000	0.000	0.062	0.937

Table 2: Transition matrix across the four aggregate states of the economy  $Z_t \in \{B, X, R, C\}$ . Each entry of the matrix is the monthly transition rate  $\Pr(Z_{t+1}|Z_t)$ . State  $Z_t$  is in the rows and  $Z_{t+1}$  is in the columns.

panel (b), also replicates this feature of the data. In addition, the model replicates the size of short-run earnings declines in both expansions and recessions. However, the earnings recovery is a little too fast in the model relative to the data. Note that in both model and data, the earnings differential between displaced and non-displaced workers reflects a mix of lower wages, thanks to skill depreciation, and lower hours, reflecting higher unemployment and non-participation rates.

Table 1 summarizes these parameters.

**Aggregate state** To estimate the transition matrix for the exogenous aggregate state  $Z$ , we classify the state of the economy in each month, based on the unemployment rate  $u_t$  for 25 to 54 year old men in the CPS from January 1948 to August 2019. In particular, we define  $Z_t = B$  if  $u_t < 3\%$ ,  $Z_t = X$  if  $u_t \in [3\%, 5\%)$ ,  $Z_t = R$  if  $u_t \in [5\%, 7\%)$ , and  $Z_t = C$  if  $u_t \geq 7\%$ . The implied monthly transition probabilities are in Table 2.

Job Losing	$f_U(s_{it}) = \gamma_0 \left[ 1 - \left( 1 + \frac{\gamma_1}{y_t(s_{it})} \right)^{-\frac{1}{\gamma_2}} \right]$
	$\gamma_0 = 0.481 \quad \hat{\gamma}_1 = 0.254 \quad \hat{\gamma}_2 = 12.97$
Job Finding	$f_E(s_{it}, Z_t) = \eta_0(Z_t) \left( 1 + \frac{\eta_1}{y_t(s_{it})} \right)^{-\frac{1}{\eta_2}}$
	$\hat{\eta}_1 = 0.0351 \quad \hat{\eta}_2 = 0.509$
Calibrated shifters	$\eta_0(B) = 0.564 \quad \eta_0(X) = 0.345 \quad \eta_0(R) = 0.227 \quad \eta_0(C) = 0.136$

Table 3: Parameters of the job losing and job finding probabilities. The  $\hat{\cdot}$  symbol denotes external estimates based on CPS data. The other parameter values are calibrated internally.

**Initial conditions** To simulate the economy going forward, we need to pin down the initial cross-sectional distribution across skills and labor market status in 1967. To construct a realistic cross-section for each age group, we trace each cohort back to its date of labor market entry and simulate its pre-1967 labor market history. For this pre-67 simulation, we assume the economy is in the expansion state until 1948 ( $Z_t = X$ ) and use the actual monthly unemployment rate from 1948 onward to identify the aggregate state  $Z_t$  from 1948 to 1967. We assume no skill-biased technical change before 1967 ( $\gamma_\sigma = 0$ ), while cross-cohort growth in preferences and median log wages occur at our baseline rate  $\gamma_s = \gamma_\phi$ . Agents have perfect foresight over the time paths for all structural parameters, and they form expectations over the distribution of future aggregate shocks using the transition probability matrix  $\Gamma_Z$ .

## 4.1 Estimation of job finding and job losing probability functions

There are two key features of the transition rates between employment and unemployment: their shape as a function of skills and their level as a function of the aggregate state.

### 4.1.1 Shape

To estimate how the job loss and job finding probabilities vary with the skill level  $s_{it}$ , we use the Basic Monthly Current Population Survey (CPS) from 1989 to 2019 merged with the Annual Social and Economic Supplement (ASEC). We pool all years together in order

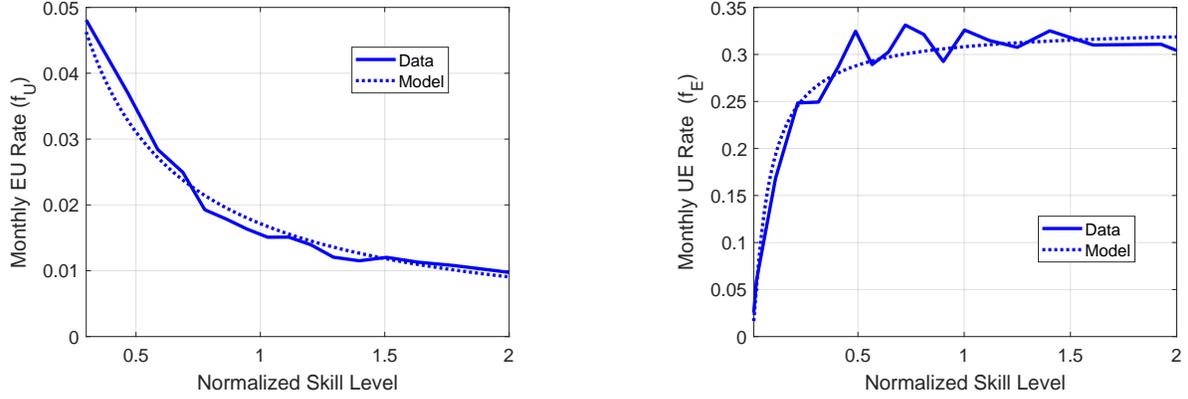


Figure 7: Left panel: job loss probability by skill level. Right panel: job finding probability by skill level. In both plots the average skill level of new entrants is normalized to 1.

to maximize the sample size. The implicit assumption is that the shape of the transition rates does not vary much with the state of the economy. In Appendix B, we describe in detail the sample construction and the estimation and show that this assumption holds in the data. The estimated parameter values are in Table 3.

Figure 7 plots the raw and fitted job losing and job finding probabilities. The probability of becoming unemployed is strongly declining in earnings (our proxy for skill): comparing a worker with relative skills of 2 and 1/2 (twice and half the skill level of the average new entrant in the economy), the job losing probability rises by a factor of three. On the other hand, the probability of finding a job is only mildly increasing in earnings over the same range. These findings are consistent with [Hobijn et al. \(2010\)](#): inflow rates into unemployment decrease with skills (measured as education level) a lot faster than do outflow rates.

#### 4.1.2 Level

The level shift parameters  $\gamma_0$  and  $\eta_0(Z_t)$  for  $Z_t \in \{B, X, R, C\}$  in the job losing and job finding probabilities  $f_U(s_{it})$  and  $f_E(s_{it}, Z_t)$  determine the level of unemployment in each aggregate state and the average duration of unemployment. We will set these five parameters to hit the following five targets. First, when we feed in the observed monthly sequence for the aggregate state from 1967 to 2018, we want the average unemployment rate in each of the four states to match its empirical counterpart. This requires  $\eta_0(B) > \eta_0(X) > \eta_0(R) > \eta_0(C)$ . Second, we set the job losing shift parameter  $\gamma_0$  to replicate the average share of the unemployed who are long-term unemployed, meaning

unemployed for at least six months. Intuitively, a smaller job losing rate necessitates a smaller job finding rate to replicate the same unemployment rate, and a smaller job finding rate implies longer expected unemployment duration. Generating a realistic share of long-term unemployment is important. If unemployment is very short-lived, unemployment shocks will not have much impact on participation choices. Conversely, when unemployment spells are expected to be long, men who become unemployed expect extended periods of skill depreciation coupled with unrewarded search costs, and thus unemployment is more likely to lead to exit from the labor force.<sup>13</sup>

## 5 Results

Our first exercise is to simulate our model economy for 624 months from January 1967 to December 2018. Cyclical changes in  $Z_t$  and trend growth in the skill bias parameter  $\sigma_t$  are the forces generating changes in measures of inequality over the course of this simulation. In each month  $t$ , we set the aggregate state  $Z_t$ , which determines the economy-wide job finding probability, to its empirical counterpart for that month. Recall that the skill-bias parameter  $\sigma_t$  rises over time in such a way that the variance of offered log wages for new labor market entrants grows at a constant rate  $\gamma_\sigma$ .

For each statistic of interest (for example, the 50/20 earnings ratio), we first plot the model-predicted time path against its empirical counterpart. We then conduct a set of decompositions to better understand what is driving the model-predicted path. In one experiment, we isolate the role of skill-biased technical change by assuming that from 1967 onward the economy is always in the expansion state,  $Z_t = X$ . In a second experiment, we isolate the role of cyclical fluctuations in unemployment by shutting down skill-biased technical change from 1967 onward, while retaining the observed history for  $Z_t$ . We also report the path in which we shut down both cycles and skill-biased technical change.<sup>14</sup>

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<sup>13</sup>Across the 52 year sample period, the monthly job losing and job finding rates in the CPS are slightly higher than those in the model. The reason is that we have scaled these rates down in the model in order to replicate the observed share of long term unemployment: absent that adjustment, the model would deliver much too little long term unemployment. One reason why the EU and UE rates are higher in the data is that there are always a lot of very short spells of employment and non-employment. Given the focus of our analysis, replicating also these high-frequency movements is outside the scope of our paper.

<sup>14</sup>In this counterfactual, there are still two sources of dynamics in the post 1967 period. First, before 1967, we always impose the actual observed path for  $Z_t$ . Thus, there are transitional dynamics in measures of inequality once we impose  $Z_t = X$  from 1967 onward. Second, we allow for growth in mean wages across cohorts in our our experiments. Thus, the model always implies growth in the levels of different earnings measures, even when measures of earnings inequality are stable.

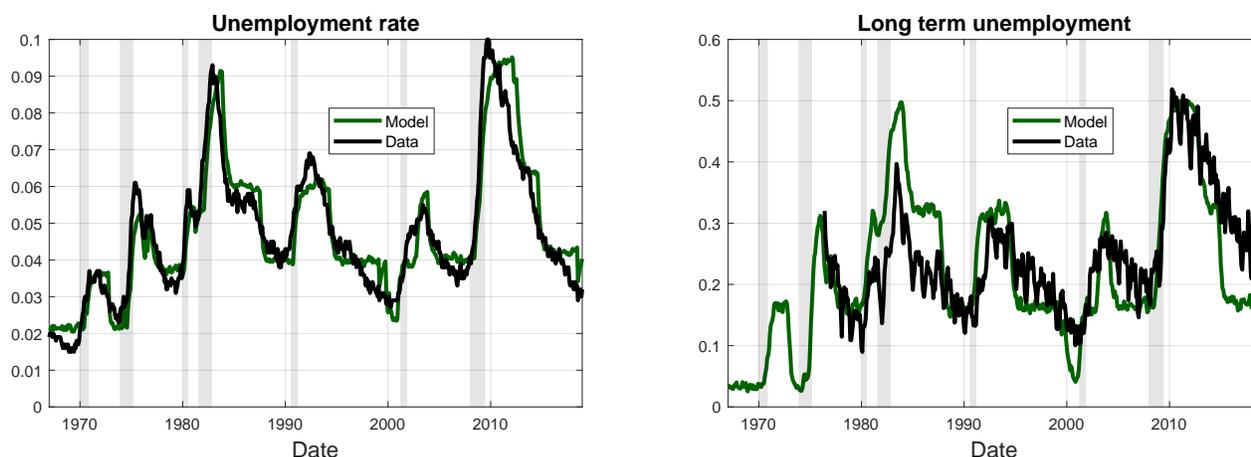


Figure 8: Left panel: Unemployment rate. Right panel: Share of prime-aged men unemployed for at least 6 months.

**Unemployment** The left panel of Figure 8 plots the model-implied path for the unemployment rate against the historical monthly series for prime-age men. Overall, our four-state process delivers a good approximation to the data. In the model, when the aggregate state  $Z_t$  changes – and with it, the job finding rate – the equilibrium unemployment rate quite quickly jumps to a new level. In the two crises in the data – the early 1980s and the Great Recession – the unemployment rate rises a little too slowly in the model, relative to the data. This indicates that in those two recessions, higher layoff rates in the early days of the recession likely played a role in generating rapid spikes in unemployment; recall that our calibration assumes a constant job losing rate.<sup>15</sup>

The right panel of Figure 8 plots the share of prime-age men who have been unemployed for at least six months. The average value for this statistic is matched by construction, but the model also broadly replicates its observed cyclical variation: the prevalence of long term unemployment rises in recessions, especially the two deepest recessions experienced by the US in the past half century.

**Share with zero earnings** We now turn to the model’s implications for the dynamics of earnings inequality at the bottom of the earnings distribution. The left panel of Figure 9 plots the share of men with zero annual earnings, model against data. The model broadly replicates the growth in this share over time. In both model and data, this trend pri-

<sup>15</sup>Figure D1 in Appendix D decomposes the paths of the unemployment rate and of long-term unemployment between trend and cycle and illustrates clearly that the trend plays no role whatsoever in their dynamics, neither directly nor through interaction with the cycle.

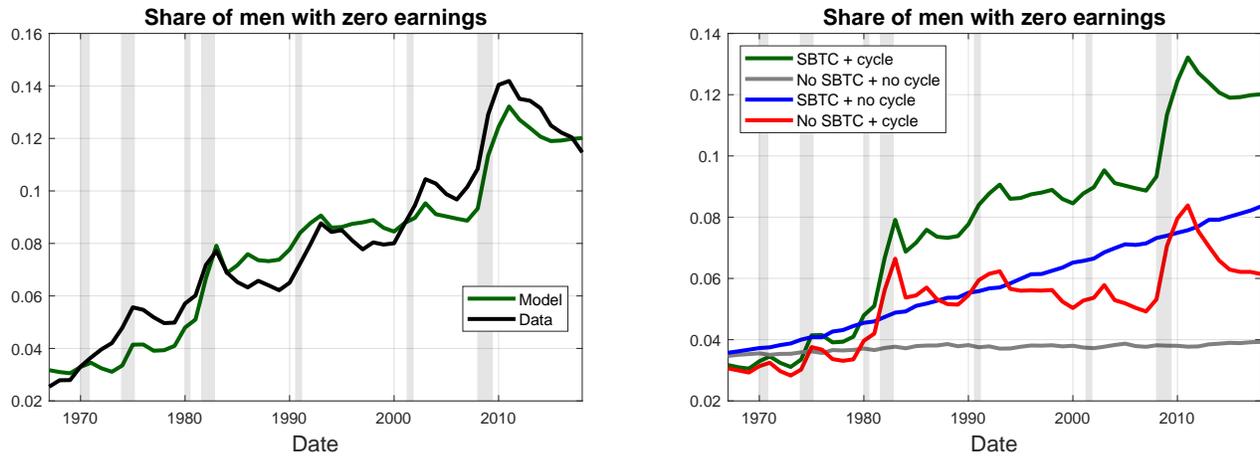


Figure 9: Left panel: Share of men with zero annual earnings (model and data). Right panel: Decomposition into cycle and SBTC. The line SBTC + cycle corresponds to the model line in the left panel. The other lines are counterfactuals.

marily reflects rising non-participation, rather than rising unemployment.<sup>16</sup> In the data, the number of annual zeros is clearly counter-cyclical, spiking in every recession. In the model, the number of zeros does peak notably in the two “crisis” recessions of the early 1980s and late 2000s. However, the cyclical bumps in annual zeros are smaller in other model recessions than in the data.

What drives the increase in the share of zeros in the model? The right panel of Figure 9 shows how the share of zeros evolves when either the cycle or skill-biased technical change are switched off (these counterfactuals are labeled “no cycle” and “no SBTC”). Clearly, skill-biased technical change by itself is the prime driver of rising non participation, accounting for 60 percent of the total increase. However, cyclical forces also play a role: the overall increase in zeros in the baseline model is four percentage points larger than in the counterfactual (SBTC + no cycle) in which the economy is kept in the expansion state from 1967 onward.

While much of this gap is accounted for by recessions alone (no SBTC + cycle), the decomposition also reveals an interaction between trend and cycle.<sup>17</sup> When the trend is switched off, recessions – especially the two big ones – increase the number of annual zeros, but the number of zeros tends to decline during subsequent expansions. In contrast, when the SBTC trend is switched on, recessions have more permanent effects on the share

<sup>16</sup>The unemployment rate is volatile, but there is no long run upward trend in unemployment. In any case, the share of the population unemployed for over 12 months (these are men with zero *annual* earnings) is never very large.

<sup>17</sup>The size of the interaction is the gap between the baseline (SBTC + cycle) and the sum of the two counterfactuals (SBTC + no cycle and No SBTC + cycle).

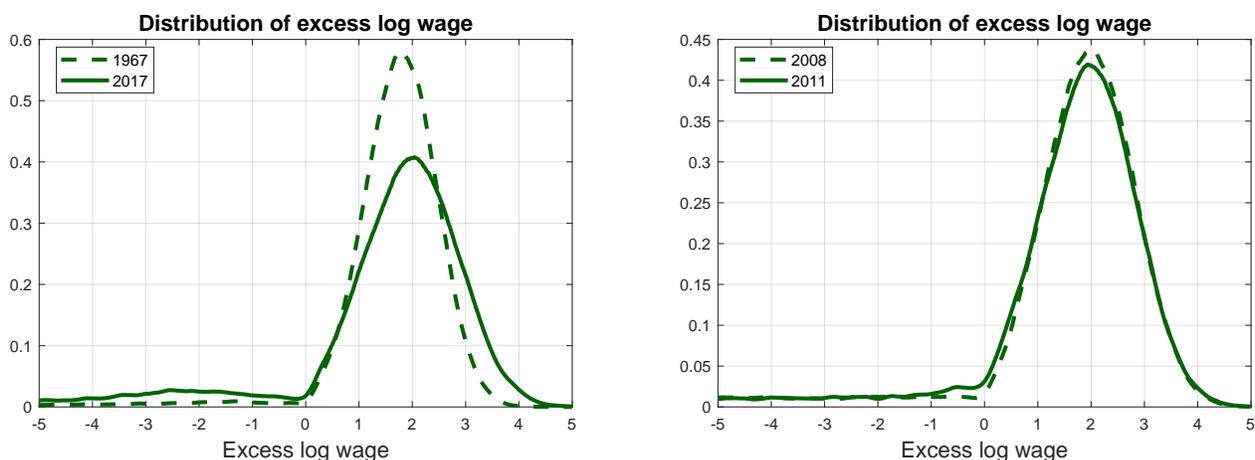


Figure 10: Left panel: Long-run changes in the model’s distribution of excess log-wage. Right panel: Changes in the model’s distribution of excess log-wage around the Great Recession.

of zero-earnings men. Thus, the trend and the cycle reinforce each other, in the sense that the increase in the zero earnings share when both forces are present is larger than the sum of the two effects separately. This is the “double-whammy” effect: there are low wage men who would keep participating if SBTC were the only threat to their earnings and who would similarly keep searching for work if unemployment were their only problem. But the two forces together mean that recessions impose persistent skill losses on lots of already marginal participants, leading to a permanent surge in non-participation.

**Participation choices** Figure 10 is designed to better understand participation choices and how participation interacts with the business cycle. We construct distributions of what we label the *excess wage*, the ratio between a man’s actual wage and the reservation wage at which he is indifferent between participating or not. An individual will choose to participate if and only if his excess wage is positive. Note that the reservation wage varies by age, time, and labor market status—all else equal, participation is more attractive for the employed, because they do not have to pay job search costs.

The left panel plots the log excess wage distribution for January 1967 and January 2017.<sup>18</sup> In 1967, the distribution is relatively compressed, and there is very little mass below zero, reflecting a participation rate close to 100 percent. Fifty years later, the distribution has changed in two ways. First, skill biased technical change has increased wage dispersion and thus spread out the distribution for the excess wage. Second, the distribution

<sup>18</sup>More precisely, we plot a kernel density estimate using an Epanechnikov kernel and a smoothing parameter of  $h = 0.2$ .

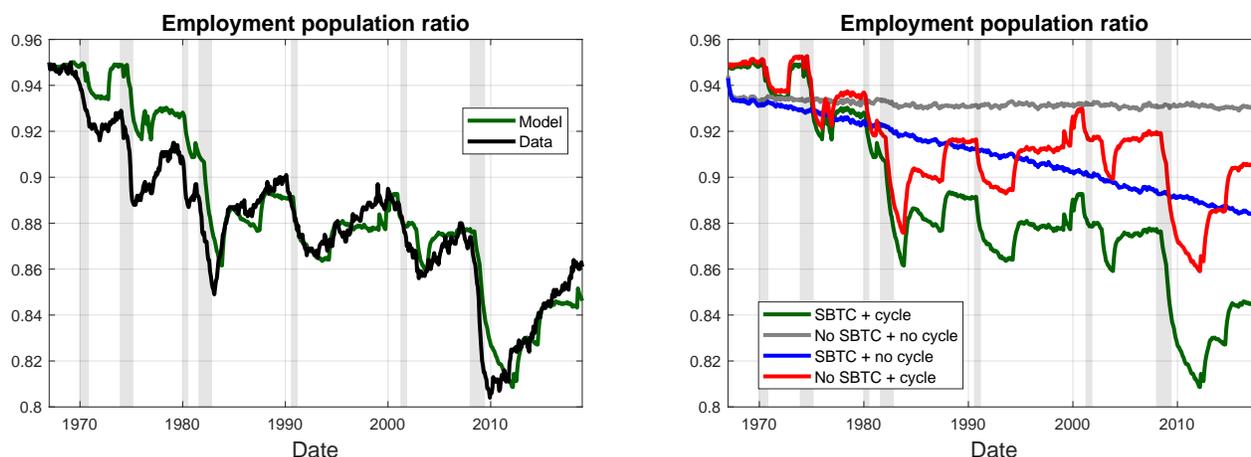


Figure 11: Left panel: Employment-population ratio (model and data). Right panel: Decomposition into cycle and SBTC.

now has a clear bi-modal shape. The bulk of the population is centered on a positive log excess wage; these men are all participants. Then, there is a second smaller mass centered on a negative excess wage; this is the group of non-participants. The two local modes arise because participation is an extremely persistent state in the model. Men who participate continuously acquire skills via the learning-by-doing parameter  $\delta^+$ , while those who drop out of the labor force and stay out continue to lose skills via the scarring effect  $\delta^-$ . Thus, the average wages of the two groups diverge over time, leading to the twin-peaked distribution in the figure.

A second point worth noting from the figure, another by-product of SBTC, is that the distribution in 2017 has a large mass of men with positive but small excess wages. Thus, there are more men who are close to indifferent about participation and who can be easily tipped into non-participation by an adverse skill shock or a spell of unemployment.

The right panel illustrates the impact of the Great Recession in this context. The two lines plotted here show the distribution of the excess log wage in January 2008 and January 2011, reflecting the situation before and after the surge in unemployment during the Great Recession. Overall, the two distributions are quite similar, but in 2011, there are more men with near-zero excess wages. These are men who have experienced unemployment, which has made them less keen to participate for two reasons. First, via the scarring effect, unemployment has reduced their skills, making work less attractive relative to leisure. Second, while unemployed, participation requires paying the job search cost. Given low job finding rates in the midst of a severe recession, men can expect to have to keep paying this cost for many months before they find a job.

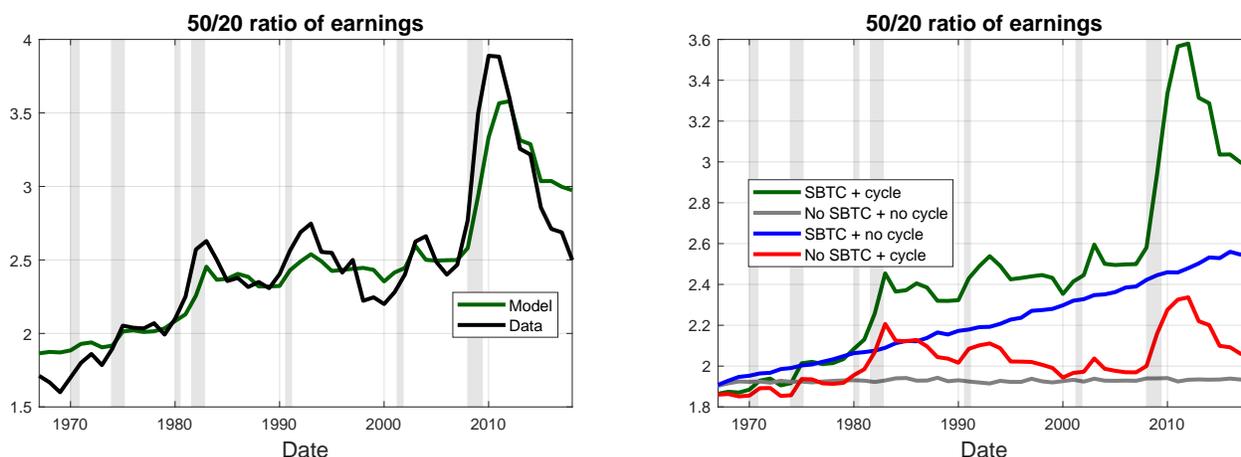


Figure 12: Left panel: 50-20 percentile earnings ratio (model and data). Right panel: Decomposition into cycle and SBTC.

**Employment-population ratio** The left panel of Figure 11 plots the employment-to-population ratio (the fraction of prime age men who are working in every month) in the model and in the data. The data are reminiscent of the patterns documented by [Jaimovich and Siu \(2020\)](#). The two series align closely. The downward trend in employment mostly reflects declining labor force participation over the past 52 years, while the cyclical fluctuations are the mirror image of the changes in the unemployment rate plotted in Figure 8. Note that in both model and data, the employment to population ratio swiftly declines in the 1970s and early 1980s, then falls much more slowly during the Great Moderation period, before falling sharply again in the Great Recession.

The right panel of Figure 11 decomposes the sources of this decline in male employment. The model attributes around two-thirds of the total decline to skill-biased technical change, but the rest is due to cyclical fluctuations and their interaction with the SBTC trend. Thus, we conclude that a significant portion of an important labor market trend is driven by the cycle.

**50/20 earnings ratio** The left panel of Figure 12 plots the dynamics of the 50/20 percentile ratio for annual earnings. The model matches the average value for this statistic by construction. The model also replicates observed trend growth in this measure of inequality, even though the speed of skill-biased technical change is calibrated to replicate growth in inequality at the top rather than at the bottom. The model generates some of the observed cyclical fluctuations in the 50/20 ratio, although the model ratio is less volatile than its empirical counterpart. The ratio goes up in recessions because the density of the

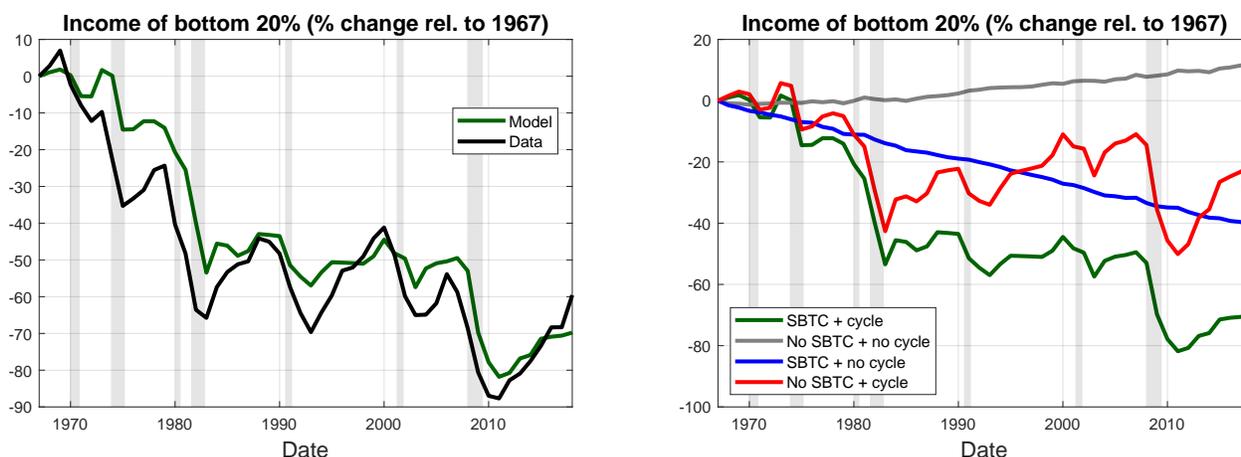


Figure 13: Left panel: Mean earnings of the bottom 20 percent of the earnings distribution (model and data). Right panel: Decomposition into cycle and SBTC.

bottom of the earnings distribution is more sensitive to unemployment than the top. In particular, in the midst of a recession, men around the 20th percentile of the earnings distribution are a mix of mid-wage men who have experienced part-year unemployment and very low wage men who have not.<sup>19</sup>

The right panel of Figure 12 plots the decomposition of 50/20 ratio. Skill-biased technical change is again the key driver of the upward trend: thanks to SBTC, long run wage growth is weaker at the 20<sup>th</sup> percentile of the skill distribution than at the 50<sup>th</sup>. And weaker wage growth at the 20th percentile has a second, indirect effect on earnings, via the fact that lower relative wages increase unemployment risk, given our skill-dependent job loss probability function.<sup>20</sup> What is the role of cyclical fluctuations in the path for the 50/20 ratio? Absent skill-biased technical change, the cycle does not contribute much: the 50/20 ratio increases in recessions and subsequently declines in expansions. A comparison of the bottom two lines of the figure indicates that the net effect over the entire sample period is very small. However, the interaction between trend and cycle is strong: when SBTC is operative in the background, a significant gap opens up between the lines with and without recessions. Downturns, and especially the early 1980s recession and the Great Recession, increase inequality more dramatically in the presence of background SBTC. And the amplified effects of these crises on inequality are not reversed during sub-

<sup>19</sup>Note that if a recession were so severe that over 20 percent of men were not working for a full year, the 50/20 ratio would explode to infinity.

<sup>20</sup>One might wonder why this does not translate into an upward trend in the unemployment rate (holding fixed the aggregate state  $Z_t$ ) in the model. The reason is that low wage men increasingly choose non-participation, which mechanically means they cannot be unemployed.

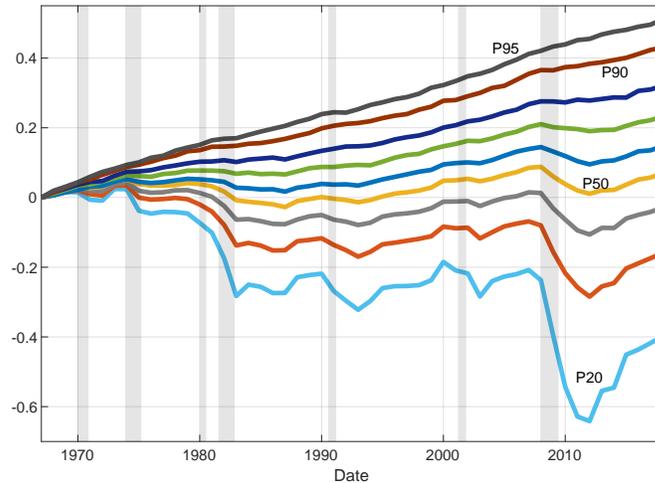


Figure 14: Percentiles of the earnings distribution from the model expressed in log-deviations from their 1967 value. This is the model equivalent of Figure 1.

sequent recoveries. This is another manifestation of the double whammy effect of SBTC and recessions on non-participation.

**Bottom 20 percent of earnings distribution** We next turn to look at total earnings of the bottom 20 percent. The left panel of Figure 13 plots the percentage change in this object relative to 1967, model against data. The model closely tracks the data series, with large declines in the early 80s recession and in the Great Recession. Turning to the decomposition in the right panel, note first that absent either SBTC or recessions, one would have expected modest *growth* in this statistic, reflecting growth in average wages across cohorts. Relative to this baseline, SBTC is the most important factor depressing average earnings at the bottom, but cycles play an almost equally important role. In particular, the two big recessions in the sample lead to large earnings declines at the bottom that are never fully retraced in subsequent expansions.

**Full earnings distribution** One of the key facts that motivated our analysis is the fan chart in Figure 1, which illustrates that earnings inequality is much more counter-cyclical at the bottom than at the top of the income distribution. Figure 14, which replicates the same fan chart from the model, shows this same qualitative pattern.

## 6 Conclusions

One of the central tenets of the research agenda outlined in *Frontiers of Business Cycle Research* is that macroeconomic phenomena are best analyzed through a framework that is consistent with the key features of both long-run growth and short-run business cycle fluctuations. We applied this insight to the study of the earnings distribution. We concluded that recessions, notwithstanding their temporary nature, have a long-lasting effect on inequality and non participation, when occurring against a backdrop of skill-biased technical change. The data show this phenomenon quite distinctly. The model we outlined captures this cycle-trend interaction by leveraging an important stylized fact: displaced individuals experience large and persistent earning losses which drive these workers closer to the non-participation margin. Skill-biased technical change further worsens the labor market opportunities of low-skilled men. The double whammy of long term unemployment coupled with falling low-skill wages causes many low-skilled individuals to exit the labor force during recessions. This interaction accounts for a non trivial share of the rise in non-participation for prime-age men over the past half century, and an important share of the rise in earnings inequality at the bottom of the income distribution. In both cases, the effects of cycles and trends together are notably larger than what can be explained by skill-biased technical change alone.

The modeling framework we have used is perhaps the simplest possible one for exploring how trend and cycle jointly determine the dynamics of inequality. Our trend is an exogenous linear path for the variance of log wages for labor market entrants. Our cycles are a four-state Markov process for the average job finding probability. We find it striking that such a simple framework does a very reasonable job of replicating the highly non-linear evolution of key measures of earnings inequality in the United States over the past half century. At the same time, the model could clearly be extended in various important directions. One notable shortcoming is that we chose a very reduced form model for the long-run rise in the value of non-work and simply assumed its growth rate equals the growth rate of aggregate productivity, a balanced growth restriction. However, over this period, the US witnessed numerous changes to policies that affect the participation decision (e.g., the minimum wage, the EITC, welfare benefits). Future work should isolate the role of these additional factors. Another worthwhile extension would be to introduce an explicit model of the household, and to consider joint labor participation choices. Other ways to make the model richer would be to add risk aversion and a savings margin, an intensive margin for labor supply, and heterogeneity in the taste for leisure.

Finally, we wrote this article in the midst of the COVID-19 recession. Real time numbers on UI claimants suggest that in the next few months, the number of jobless individuals will be unprecedented in US history. Through the lens of our model, a deep recession is likely to have long-lasting effects on the participation rates of low-skilled men and thus on earnings inequality. In ongoing work, we are applying our model to this episode.

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# APPENDIX

## A Sample and data for figures on earnings and weeks worked

The dataset used to construct figures 1, 2, 3, and 4 in the paper is the ASEC Supplement of the CPS, as reported by IPUMS. Our sample includes all years from 1968 to 2019 (which reports figures for the years 1967-2018). For each year, we select the sample of all men who are between the ages of 25 and 55. From this sample, we drop the following observations: men in the armed forces (they do not report weeks worked before 1989), men with a 0 ASEC weight, men who report 0 weeks worked during the year but positive earnings, men for whom information on weeks or earnings is missing. The two variables we use are total earnings last year and weeks worked last year. Total earnings include total pre-tax wage and salary income (variable INCWAGE), net pre-income-tax non-farm business and/or professional practice income (variable INCBUS) and net pre-income-tax earnings as a tenant farmer, sharecropper, or operator of his or her own farm (variable INCFARM). Whenever one of the variables included in earnings is top-coded, we set its value to the top-coding threshold. Weeks worked last year is an intervalled variable (the non intervalled variable is only available starting in 1976) and can take the values of 0, 6, 20, 33, 43, 48.5, 51. All statistics reported in the paper and in this appendix (except sample sizes) are computed using the ASEC person weights. Table 4 below reports the sample sizes and summary statistics for earnings (deflated using the Personal Consumption Expenditure Deflator, as reported by the BEA) and weeks worked.

## B Estimation of transition rates

To estimate how the job loss and job finding probabilities vary with the skill level  $s_{it}$ , we use the Basic Monthly Current Population Survey (CPS) from 1989 to 2019, merged with the Annual Social and Economic Supplement (ASEC).

The Basic Monthly CPS reports the employment status [EMPSTAT] of each individual interviewed. The ASEC asks each individual additional questions about past earnings and weeks worked in the CPS in March. We use the ASEC supplement because there is no measure of individual labor earnings in the Basic Monthly CPS. We keep in the sample those male individuals who appear in the ASEC and are of prime age (between 25 and

Year	Sample size	Mean Earnings (2012 \$)	Median Earnings (2012 \$)	Mean Weeks Worked
1967	25521	40742	37979	47.3
1970	24651	44216	40571	46.3
1975	23791	43192	40393	44.2
1980	33762	42586	40691	44.3
1985	31021	43600	38582	44.0
1990	32628	43711	38695	44.3
1995	27169	47357	36902	43.6
2000	46151	56312	42181	44.7
2005	42804	54145	40317	43.6
2010	41382	48822	36571	40.4
2015	35949	53909	38818	42.3
2018	34321	56610	41611	43.1

Table 4: Sample size and summary statistics for selected years

55 years old), a total of 2,146,305 workers.<sup>21</sup> We further drop all individuals who report positive weeks worked but no earnings and all entries that are assigned zero weight. This second step of sample selection leaves us with a sample of 2,007,067 entries, or 9,292 individuals per month on average.

We are interested in month-to-month changes in employment status, and therefore treat each observation as a pair of months,  $(m_t, m_{t+1})$ . We further clean the sample so as to keep only workers observed in at least two consecutive months. This leaves 1,393,609 observations, or 7,574 observations per month on average.

In the ASEC, we measure individuals' earnings from the annual pre-tax labor income measure available in the ASEC supplement [INCWAGE]. To obtain a proxy for skills, we compute weekly real earnings. We divide the reported nominal labor earnings by the Consumer Price Index (CPI-U) for that year, and then by the number of annual weeks worked [WKSWORK1]. Every individual in our sample is interviewed twice in the ASEC supplement, 12 months apart, in month (always March)  $t$  and  $t + 12$ . As a proxy for skills, we assign the weekly earnings estimated in month  $t$  to all the months before  $t$  in which the individual is present and the weekly earnings estimated in month  $t + 12$  to all the months between  $t$  and  $t + 12$  in which the individual is present. If the individual is interviewed in the months of April, May, and June after their second March survey

<sup>21</sup>Because of the rotating nature of the CPS, in which households are interviewed for four months, then left aside for eight months, and finally interviewed again for four months, this leaves many individuals in the Basic Monthly CPS out of our sample because they are not part of any ASEC supplement. More specifically, workers interviewed from July to November are not in our sample.

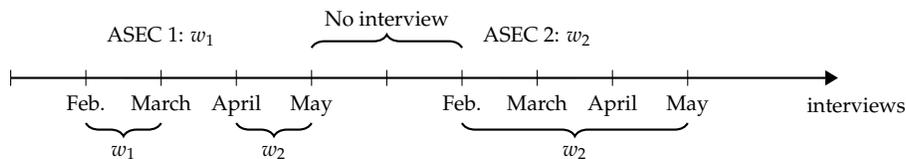


Figure B1: Graphical description of weekly earnings inference for individuals in our sample.

(i.e., months  $t + 13$ ,  $t + 14$ ,  $t + 15$ ), we assign the skill level computed from the second ASEC survey (in month  $t + 12$ ) to the individual in those months. Figure B1 graphically presents how the inference is implemented for a worker interviewed from February to May. If a worker reports zero annual earnings in one of the March Supplements, we use reported earnings from the other one and assign it to the worker in every month in which we observe him, as a proxy for his skills.<sup>22</sup> Finally, we express skills in relative terms, as the ratio of weekly individual earnings to the average weekly earnings of the 25 – 27 year old in each month.

We define the job loss probability in a given month as one minus the probability of remaining employed in month  $t + 1$ , as in equation (2). First, we keep in our sample all the individuals who are employed in  $t$ . We then compute, for each month, 20 quantiles of the relative skill distribution. Next, for quantile  $q$ , we compute the fraction of people in group  $q$  who are employed in both  $t$  and  $t + 1$ . We compute this fraction for each month and each quantile in our sample, and then take the average across the time series for each quantile. The job loss probability is one minus this fraction. Along the computation, we also measure the average skill in quantile  $q$ , first by computing the average relative earnings for each group  $q$  in each month in our sample, and then taking the average across the time series for each group.

The calculation of the job finding probability mirrors the one just described for the job loss. For quantile  $q$ , it is defined as the fraction of people in group  $q$  who are unemployed in  $t$  and employed in  $t + 1$ . We compute this fraction for each month and each quantile in our sample, and then take the average across the time series for each quantile. We measure the average skill in quantile  $q$  exactly as before.

At the estimation step, we use an equally weighted minimum quadratic distance estimator that minimizes the difference between the transition probabilities predicted by the statistical model and their empirical counterparts. The estimated parameter values are in

<sup>22</sup>This approach leaves a total of 79,950 individuals with zero weekly earnings, or 434 per month (because they report zero in both March Supplements). Of these, less than 9% are observations for (long-term) unemployed workers that we use in the estimation of transition rates.

	Boom (B)	Expansion (X)	Recession (R)	Crisis (C)
	Job Loss Prob. $f_u(Z_t) = 1 - \frac{\gamma_0(Z_t)}{\left[1 + \frac{\gamma_1(Z_t)}{y_t(s_{it})}\right]^{\frac{1}{\gamma_2(Z_t)}}}$			
$\hat{\gamma}_0$	1.000	1.000	1.000	1.000
$\hat{\gamma}_1$	0.141	0.256	0.246	0.394
$\hat{\gamma}_2$	9.354	13.547	11.840	14.644
	Job Finding Prob. $f_E(Z_t) = \frac{\eta_0(Z_t)}{\left[1 + \frac{\eta_1(Z_t)}{y_t(s_{it})}\right]^{\frac{1}{\eta_2(Z_t)}}}$			
$\hat{\eta}_0$	0.402	0.352	0.285	0.213
$\hat{\eta}_1$	0.009	0.026	0.113	0.000
$\hat{\eta}_2$	0.121	0.435	1.187	0.004

Table 5: Parameter estimates of the transition probabilities for each of the four aggregate states

Table 3 in the main text.

Figure 7 in the main text plots the raw and fitted job losing and job finding probabilities when pooling across all states. We have also estimated job losing and job finding functions allowing the estimated parameters to vary with the aggregate state,  $Z_t$ . We find that while the level of the job finding probability clearly varies in a pro-cyclical fashion with the aggregate state, the shapes of the job losing and job finding rates, as functions of the skill level, do not vary much with the cycle. Figure D2 shows the model’s fit when we allow parameters to vary by aggregate state. Table 5 reports parameter estimates for this case.

## C Computational algorithm

### C.1 Discretization

The model is computed by simulating the path of 200 individuals per cohort and using those simulated paths to calculate aggregate statistics. As each individual lives for 360 months, this means that in any given period, a total of 72,000 individuals are simulated.

The skill level is approximated on an equidistant grid with 240 points. The continuous process for skill is approximated by a Markov chain with grid points as states. The transition matrix for the resulting Markov chain is computed using the Tauchen method. This means that if  $P$  is the continuous probability measure on next period skills for a particular individual given his state, then the probability of transitioning into state  $s_i$  is equal

to  $P\left(\left[\frac{s_{i-1}+s_i}{2}, \frac{s_i+s_{i+1}}{2}\right]\right)$  for that individual.

## C.2 Policy computation

Since any individual is finitely lived, computation of the value function can be done by backward iteration from the last period of life and no convergence is required. For any cohort, we have their perfectly foreseeable time path for  $\sigma$  and the cohort's common value of  $\phi$ . We set to zero the value function for age  $A$  (the age at which the individual dies). Then, for any age  $a + 1$ , we derive the value function at age  $a$  as a function of the individual state (skill  $s$ , previous employment status  $x_-$ , aggregate state  $Z$ ). We also know the transition probabilities conditional on the state  $(s, x_-, Z)$  and the participation decision. Thus, given the participation decision, it is possible to calculate the value function at age  $a$  for any state  $(s, x_-, Z)$ .

The participation decision is equal to 1 if the value of participating is higher than the value of not participating. Given any combination  $(x_-, Z)$ , we can solve for the threshold skill required for participation by finding the two grid points of the grid for  $s$  between which the separation decision switches. This threshold  $s^*$  does not have to lie on the grid - it is obtained by linearly interpolating the excess value of participation and finding the point where this excess value crosses zero.

This procedure yields a participation threshold of skill for each  $(a, x_-, Z, t_0)$  (where  $t_0$  is the birth month of the cohort). Since the state space is quite large, we interpolate some of the cohort policies and compute only exact participation thresholds for cohorts every 7 years. More precisely, let  $f_{a,x_-,Z}(t_0)$  be the participation threshold for the cohort born in year  $t_0$ . We approximate the threshold  $f_{a,x_-,Z}(t'_0)$  for any cohort born at  $t'_0$  by linearly interpolating the thresholds computed for a set  $\mathcal{T}$  of periods which are each seven years apart.

This backward iteration ends the algorithm. Note that we don't need to solve for any equilibrium market clearing price; thus, even though the model features aggregate uncertainty, its solution does not require iteration over laws of motions for the aggregate states or for prices. The only aggregate state,  $Z_t$ , is exogenous and individuals know its law of motion.

The Julia code is available on the *Review of Economic Dynamics* website.

## D Additional figures

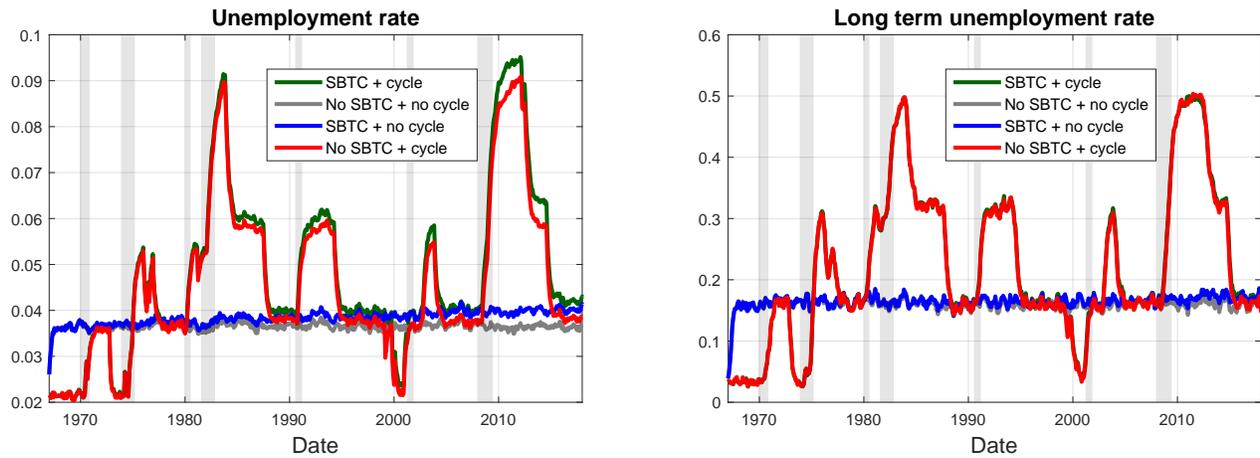


Figure D1: Left panel: decomposition of the unemployment rate into SBTC and cycle. Right panel: decomposition of long-term unemployment into SBTC and cycle.

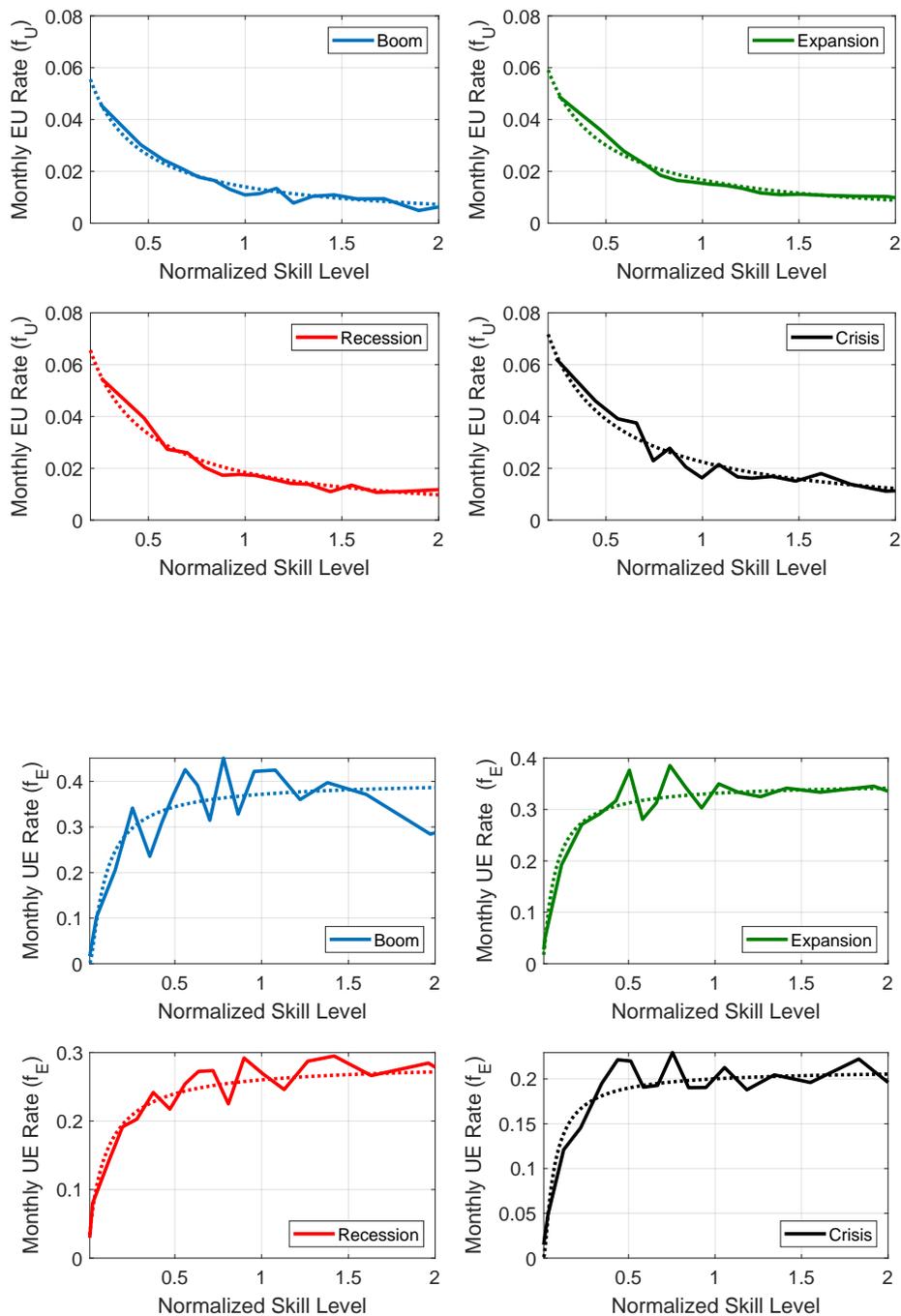


Figure D2: Top panel: job loss probability by skill level and by aggregate state of the economy. Bottom panel: job finding probability by skill level and by aggregate state of the economy. In both plots the average skill levels of the new entrants is normalized to 1.