Accounting for gender and race labor market gaps during the life cycle: a search and matching approach

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Abstract

We investigate the underlying sources of gender and race differences in labor market outcomes over the life-cycle using a canonical version of Mortensen and Pissarides (1994, MP henceforth). The model exhibits learning-by-doing so that non-employment spells are particularly costly for human capital accumulation. We use the model to reverse engineer life-cycle human capital stocks and matching technologies, for each gender and race pair, needed to exactly match the stylized life-cycle patterns of wages and job finding rates for the unemployed and the non-participants. We find that search frictions play a central role in shaping life-cycle profiles. While wage profiles properly describe the human capital of workers in frictionless models, wage and human profiles differ significantly in the presence of frictions. Wages peak at around age 50-55 but human capital keep increasing until retirement in the MP model. Moreover, while wage differentials among race and gender first widen and then compress during the life-cycle, human capital always widen. Our exercise also indicates large differences in matching technologies, or hiring costs, by race and gender favoring males and particularly unfavorable for the old and Asian females. However, the significant differences in wages and job finding rates between groups, for given experience and education levels, are mainly arising from the differences in future labor market attachment. These results suggest that there exists significant statistical discrimination in the labor market with frictions against all female groups and black males, arising from their weaker labor market attachment, while the possible taste-based discrimination seems to play only a minor role.

1 Introduction

There are significant differences in wage, employment, and labor market outcomes between genders and races, and these differences have persisted in the U.S. after a rapid convergence in 1960s (Altonji & Blank 1999). It is typically hard to explain these differences using observable data on individual characteristics, like age, education level, state of residence, and marital status, especially when looking at the differences between blacks and whites (Cajner et. al. 2017). Overall, the literature explaining all the labor market outcomes jointly is fairly narrow. This implies that it is likely important to study the differences jointly using a more structural approach which accommodates variation in the labor market behavior between different groups. In this paper, we take a structural approach with an attempt to explain various labor market outcomes for different genders and races/ethnicities (non-Hispanic Whites, Blacks, Hispanics, and Asians) by building a life-cycle version of MP search and matching model in which human capital accumulates through learning-by-doing. The key idea of the paper is to perform a theory-based accounting exercise in which we seek to understand the data from the point of view of the model. In other words, we take as granted that the model provides a good description of the data and, under this assumption, use the model to reverse engineer the underlying parameters needed to exactly replicate the data. This exercise is informative to the extent that it builds upon a canonical model of the labor market, the MP model, and a commonly used learning-by-doing formulation.

The model parameters, that we are specifically interested in studying, are the returns to experience, the matching productivity, which is defined as in the standard Cobb-Douglas matching function, and the search efficiency of nonparticipants. We also calibrate the baseline productivities for each gender-race pair, separately for skilled (college-degree) and unskilled (no college-degree). Calibration of these parameters allows us to describe the possible differences in the labor market, captured by these parameters, which are not observable in the data. This helps us to understand better the observable differences in the labor market data between groups. Our estimates on returns to experience also allows us to back out the human capital for each studied group over the life cycle, which allows us to make predictions about human capital accumulation over the life cycle.

Our model deviates from the standard MP (1994) framework through the following main ways, based on an earlier work of Isojarvi (2019). First, we allow workers to be nonparticipating in addition to employment and unemployment. This feature allows us to consider the significant differences in participation rates between different genders and races. Nonparticipants are allowed to search for jobs in the model to match the observed flows from nonparticipation to employment, but unemployed and nonparticipating workers differ by their search intensities. We introduce the life-cycle aspects to the model by assuming that workers retire deterministically at a certain age, which means that the match between a retiring worker and a firm breaks with certainty. This feature allows us to study the labor market outcomes over the life cycle, but also lets us to take into an account that firms care about the length of the match in a market with frictions. We also allow for human capital accumulation through learning-by-doing: whenever workers are employed, their work experience increases in a deterministic manner leading to a higher amount of human capital. Non-employed workers' experience stays constant, which means that non-working periods are costly for workers through lost human capital growth. This is where the significant differences in labor market attachment matter most for the wage growth: the groups that are more likely to move out of labor force are affected through lost human capital causing stagnation in their wage growth. Firms also care about the labor market attachment of their workers – as posting a vacancy is costly for a firm, the higher likelihood of a match break has a negative effect on the number of vacancies a firm is willing to open and the wages the firm is willing to pay.

We calibrate the model parameters to exactly match the employment, unemployment, participation, and wage growth patterns over the life cycle. We use the U.S. data from CPS, where we directly observe wages and labor market stocks for each group we are studying. However, in the model calibration, we are using the flow probabilities between different labor market states, which are flows from employment to unemployment (EU), unemployment to employment (UE), employment to nonparticipation (EN), nonparticipation to employment (NE), unemployment to nonparticipation (UN), and nonparticipation to unemployment (NU) for each of these groups. We estimate monthly, age-specific transition probabilities for each group from CPS data following the method in Choi et. al. (2014). The key idea in the calibration strategy is to fully control the possible, and likely large differences in these labor market flows as they are closely connected not only to different employment and participation outcomes, but also the wage growth patterns. By controlling for the employment outcomes, we can study the other possible gender and race differences in the labor market. For each group, we calibrate age-specific returns to experience, which then determines the shape of the human capital function for each group, using the observed wages in the data. We also calibrate the productivity of the matching function, and the search intensity for nonparticipants for each group and for every age using the estimated job finding rates for an unemployed (UE) and a nonparticipant (NE). The calibration of these parameters reveal possible underlying differences in the labor market that are not easily observed in the data.

Our results show that a finite life-cycle search and matching model with wage bargaining generates an increasing human capital stock over the life cycle so that the model can match the observed wage growth patterns in the data. In our model, the rising path for human capital over the life cycle captures the impacts of finite working lives (horizon effect) and wage negotiation between workers and firms in a labor market with frictions. As in Cheron, Hairault, and Langot (2007, 2013), the horizon effect arises from the fact that firms operating in a labor market with search frictions are reluctant to hire older workers, as older workers' employment span is shorter and firms' need to cover the costs of hiring the worker. The similar effect plays a role in our model: the growth in the human capital causes wages of the younger workers to grow, since the horizon effect is not yet strong enough. However, when workers approach to retirement, the horizon effect starts to dominate. This finding gives a structure on a shape for a life-cycle human capital stock – human capital does not depreciate for older workers, but keeps growing until the retirement. Moreover, while wage differentials among race and gender first widen and then compress during the life-cycle, human capital always widen. As a result, the MP model predicts very different returns to experience than what is suggested by Mincer regressions on wages. In addition, we find significant gender differences in the wage-to-human-capital ratios. Our exercise shows that firms are extracting a greater fraction of female worker's human capital compared to male workers, and this difference is especially strong for workers in their prime working ages. We also find that there are significant differences in matching technologies across groups. Matching productivities are especially high for males and younger workers while particularly unfavorable for the old and Asian females.

We then conduct our accounting exercise. We decompose gaps in wages, in employment, unemployment, and participation, and in labor market tightnesses and job finding probabilities (compared to white males) using the age-, gender-, and race-specific variation in exogenous flows estimated in the data (EU, EN, UN, NU), and in the calibrated parameters. First, we find that even though the calibrated matching producitivities vary significantly between groups over the life cycle, this variation cannot explain the majority of the wage and other gaps in the labor market. As differences in matching productivities can capture taste-based discrimination in the labor market, we find that taste-based discrimination does not seem to be very strong in the labor market. However, we find strong evidence on statistical discrimination arising from the group differences in labor market attachment. We find that the differences in flows from employment to nonparticipation can explain, on average, about one-third of the wage gap over the life-cycle for female groups and black males. When looking at the importance of the flow EN for each experience level, we find that EN is especially important in explaining the wage gaps for lower experience levels (ie. younger ages) for females, while the differences in returns to experience start to explain an increasing share of the wage gap for the higher levels of experience. For black males, EN stays important during the whole life cycle. Similarly, EN can explain significant fraction of the differences in job finding rates for each level of experience, indicating that there are large statistical discrimination in both wages and hiring against females and black males, arising from their weaker attachment to labor market (ie. higher EN). For other male groups, the differences in labor market outcomes can largely be explained by the differences in returns to experience and in baseline productivities. For females, higher EN can largely be explained by their higher likelihood of taking breaks because of family, but the significantly higher EN for black males compared to any other male group remains a puzzle.

There are earlier papers that study human capital and wage growth in search frameworks. The literature usually study the role of human capital investment (either general or firm-specific) versus on-the-job search on the wage growth. Flinn et. al. (2017) study how firms and workers choose to invest in general and firm-specific human capital in a partial and general equilibrium search model, and how much can wage growth of the workers be explained by investment in human capital versus searching for new, more productive employment opportunities. They link their results with Mincer equation and find decreasing returns to investment in both types of human capital. Burdett et. al. (2011) also build a search model with general human capital accumulation and on-the-job search to investigate the role of each of these channels in human capital growth in the steady state, but in their model, general human capital accumulates through learning-by-doing. They also connect their results with Mincer equation to see if their model generates reasonable connection with Mincer literature. However, they assume constant returns to experience, which differs with typical decreasing returns in experience in Mincer equations. Bagger et. al. (2014) build a model along the same lines as Burdett et. al. (2014), but allow for an employee and an employer heterogeneity and productivity shocks, and they estimate the life cycle wage growth patterns. Our paper also assumes human capital accumulation through learning-by-doing, but the main difference in our framework is that we also require our model to generate realistic employment, unemployment and nonparticipation outcomes over the life cycle, in addition to wage outcomes. These other labor market outcomes are tightly linked with the wage outcomes through human capital accumulation and through the wage bargaining between a worker and a firm. We also study quantitatively how well our framework can explain race and gender differences in all these labor market outcomes.

This paper also combines the literature on wage gaps with the growing literature on transition flows and their importance on unemployment and participation rates of workers (Choi et.al 2014, Elsby et. al. 2015, Kroft et. al. 2016, Menzio, Telyukova, and Visschers 2016) by studying how much gender and race differences in flow probabilities can explain differences in wage growth patterns and other labor market outcomes. This paper also relates to the literature on finite life-cycle search models (Cheron, Hairault, and Langot 2013, Esteban-Pretel and Fujimoto 2014, Fujimoto 2013, Hahn 2009, Hairault, Cheron, and Langot 2007) by studying wage growth and the gender and race wage gaps in a finite life-cycle environment with human capital growth due to experience. Finally, our paper contributes to the literature studying gender and race differences in wages and other labor market outcomes (see Altonji & Blank 1999, Blau & Kahn 2017 for literature reviews.)

2 Data

We use the basic monthly data between years 1998 and 2018 from the CPS for the U.S. workers. We calculate mean, cross-sectional life-cycle wage growth patterns, as well as employment, unemployment, and nonparticipation patterns for both gender and for different races (non-Hispanic Whites, African-Americans, and Asians). We then estimate age-specific, life-cycle monthly transition probabilities between employment, unemployment and nonparticipation separately for each of these groups following the method in Choi et. al. (2014). The estimated flows between different labor market states are flow probabilities from employment to unemployment (EU), unemployment to employment (UE), employment to nonparticipation (EN), nonparticipation to employment (NE), unemployment to nonparticipation (UN), and nonparticipation to unemployment (NU) for each of these groups. We first describe the life cycle wages and job finding probabilities for unemployed and nonparticipants, as those are used as a target in our model calibration. We then describe other labor market flow that are used in the calibration.

We first plot mean, cross-sectional wages betweeen ages 25 and 65 for each gender-race pairs, and we observe the following patterns. For each gender-race pair, life-cycle wage growth shows the well-known pattern: wages grow rapidly for young workers, the wage growth then flattens, and starts to decrease later in the career. Both the wages of Asian males and females have slightly different patterns in the CPS data compared to other groups, as their wages peak earlier, around age 40, and start to decrease after that. The within-group wage gaps are fairly small for young workers, but as the wage growth rates differ between groups, the wage gaps increase over the life cycle. Within race, males have higher wage growth rates compared to females, and Asians have the highest wage growth rate among each gender, following by whites and blacks. Interestingly, mean Asian males and females have the highest wage growth rates early in life, along with white males, which possible arises because of the higher schooling level of an average Asian. The high wage growth rate for Asian females may also results from their higher labor market attachment, especially when comparing to other female groups. Overall, wage gaps start small, increase over the life cycle, but compress at the end of the working life.

We next describe the group differences in labor market outcomes by looking at the job finding probabilities for different groups.This graph consists annual job finding probabilities for unemployed estimated from the CPS data. Overall, men tend to have higher job finding rates compared to females, especially during the prime working years, but older black males' job finding rates are closer to female groups than other male groups. White males seem to have the highest job finding rates over the whole life cycle compared to any other group, and Asian males have very similar job finding probabilities compared to white males during the prime working years between ages 30 and 50 after a slower start. All females' job finding rates follow similar patterns and levels, white females having the highest job finding rates over the whole working life. The greatest difference between males' and females' job finding rates for each race occurs between ages 25 and 45: while males' job finding rates are at their highest for every group, females' job finding rates slightly decrease. We also plot the job finding probabilities for nonparticipants, and very similar patterns are observed. A notable difference is that Asian males are having the highest job finding probabilities for nonparticipants during the life cycle, except for workers under 32. Also, nonparticipating Asian females are significantly more likely to find jobs after age 45 when comparing to other female groups. In general, job finding probabilities for unemployed are overall higher for all groups when comparing to job finding probabilities for nonparticipants, which demonstrates that these two groups should be treated separately.

Wage growth patterns for males and females with different education levels have been ploted separatetly. No-college groups represent workers with high-school education or lower, while college groups have obtained at least some college education. Not surprisingly, workers with college education have higher wage growth rates compared to no-college workers, and males' wages grow faster than females' wages for both education groups. For workers with college education, the wage growth rates for both genders are very similar until age 30, when females' wage growth starts to slow down. This is likely related to the fact that females are starting to take breaks in their careers because of children. Similar patterns are observed for unskilled workers, but the wage growth of unskilled females is already much slower than unshilled males at 25.

Job finding probabilities for unemployed and nonparticipants whites with different education levels are aslo in the picture. Somewhat surprising results is that males are almost always having higher job finding rates despite of their education level compared to females. Male workers with no college education are more likely to move from unemployment or nonparticipation to employment compared to female workers with college education. It is possible that female workers are not searching as efficiently for jobs, especially when they are nonparticipating, which could explain the lower job finding rates. The other explanation is that firms are not willing to hire female workers, especially during the prime child-rearing ages.

We also plot the annual job destruction rates in the case when a worker moves from employment to unemployment. Blacks are drastically more likely to move from employment to unemployment compared to other races, and the difference is especially large for younger workers. This can likely explain blacks' lower wage growth rate that is observed in the graph for wages. In general, male workers in each race are more likely to move from employment to unemployment. However, this result reverse when one looks at the job destruction rate to nonparticipation, as females are more likely to move from employment to nonparticipation, especially during the prime working years. Also, black males are notably more likely to move to nonparticipation compared to other male groups. From the graph of job destruction, it confimrs that the jobs for highly educated males and females are less likely to be destroyed. Finally, the flow probabilities from unemployment to nonparticipation show that females are more likely to move from unemployment to nonparticipation, and this holds for during almost the whole life cycle for all races and education levels. To conclude, females are more likely to move to nonparticipation over the life cycle compared to males, and blacks have considerably higher job destruction rates compared to other races.

3 The Model

3.1 Preliminaries

Workers. Workers seek to maximize their expected present value of consumption. Workers are risk neutral and discount the future according to the discount factor $\beta \in (0,1)$. A mass 1 of workers of type i enters the labor market each period. Subscript i refers to the gender (female, male), race and/or ethnicity (non-Hispanic White, African-American, Hispanic or Asian), and educational level (skilled, unskilled). For example, i could refer to an unskilled black male. Time is discrete and age is denoted by a where $a \in [\underline{a}, \bar{a}]$. Workers go through a deterministic life-cycle, entering the labor market at age $\underline{a}$, retiring at age a_R, and dying at age $\bar{a}$ where $\bar{a} > a_R$. Workers at any point in time are either employed, $\overline{E}$, unemployed, $\overline{U}$, or nonparticipants, $\overline{N}$. Let $s \in \left\{\overline{E}, \overline{U}, \overline{N}\right\}$ denote the employment status of a worker.

Workers of a particular type i are ex-ante identical but become heterogenous over time due to labor market shocks. In particular, workers of a given status, type and age could differ in their levels of experience, e, where $e \in [0, a]$. Denote $m_i^s(e,a)$ the mass of workers of a particular status, type, experience and age. The initial mass distribution, $m_i^s(0,\underline{a})$ for all s and i, is given. Workers transition into unemployment and nonparticipation at the exogenous rates $\pi_{EU}^i(a)$, $\pi_{EU}^i(a)$, $\pi_{UN}^i(a)$, and $\pi_{NU}^i(a)$, and into employment at the endogenous rates $\pi_{NE}^i(e,a)$ and $\pi_{UE}^i(e,a)$. The notation $\pi_{ss'}^i(e,a)$ refers to the one-period transition probability from status s to status s' for a worker of type i.[1] Let $w_i(e,a)$ denote the wage, and consumption, of an employed worker of type i, experience e and age a, while $c_i^U(e,a)$, $c_i^N(e,a)$ and $c_i^R(e,a_R)$ denote the corresponding consumption of an unemployed, a nonparticipant and a retired worker respectively.

Human capital: Human capital is of the general type. There is no firm specific human capital. We assume that a worker's human capital, $h_i(e,a)$, depends on his type, i, labor market experience, e, and age, a. Experience in the beginning of the career is set to be 0, each period of employment increases experience by one unit, $e_{a+1} = e_a + 1$, and each non-working period keeps experience constant, $e_{a+1} = e_a$. We assume the following functional form for $h_i(e,a)$:

$$h_i(e,a) = y_i e^{r_i(a)e},$$

where y_i is a scale parameter associated to group i while $r_i(a)$ is an age and group specific return to experience. Differences in baseline productivity, y_i, and returns to experience, $r_i(a)$, across types capture differences in entering levels of human capital but also differences in occupations and industries. Our formulation assumes that post-schooling human capital formation is of the learning by doing type as in Barlevy (2008), Yamaguchi (2010) or Bagger et. al. (2014). A more complicated formulation, for example of the Ben-Porath form, is possible but Heckman et. al. (2002) argue that it is difficult to distinguish between learning-by-doing and on-the-job training based on the evidence.

Firms: There is a continuum of infinitely lived firms who seek to maximize their expected present value of profits net of hiring costs. Firms are risk neutral and discount the future at the same rate as workers do. Labor markets are assumed to be perfectly segmented. A firm can post vacancies in a specific labor market identified by a type-age-experience-status of the worker. Firms can freely enter in any of the segmented labor markets. Firms post vacancies for long term positions at a cost of $\kappa_i(e,a)$ per-vacancy. The cost can depend on workers' type, experience and age. Jobs are destroyed exogenously at the rates $\pi_{EU}^i + \pi_{EN}^i$. A match produces $h_i(e,a)$ unit of output per-period while gross, per-period profits are $h_i(e,a) - w_i(e,a)$.

Matching technology: A worker and a firm with a vacant position are randomly matched according to the matching technology $M_i(u_i^s(e,a), v_i^s(e,a); a)$, where $u_i^s(e,a)$ and $v_i^s(e,a)$ are the masses of workers and firms searching in particular labor market as identified by the worker's status, type, experience and age. We assume that all unemployed and nonpartipant workers search for a job while employed workers do not search. Thus,

$$\begin{aligned} u_i^U(e,a) &= m_i^U(e,a), \\ u_i^N(e,a) &= m_i^N(e,a), \text{ and} \\ u_i^E(e,a) &= 0. \end{aligned} \tag{1}$$

We assume that the matching technology adopts the standard Cobb-Douglas form $M_i(u,v;a,s) = A_i(s,a)u^{\alpha}v^{(1-\alpha)}$ where $A_i(a,s)$ represents the efficiency of the matching technology and it is allowed to depend on workers' type, age and labor status. Differences in matching efficiency across types reflect search frictions associated to particular labor markets. Once a match is formed, the output of the match is distributed according to a Nash bargaining solution in which the worker's bargaining power is ϕ_i.

[1] Due to data limitations, the exogenous transition probabilities are assumed to depend only on age but not on experience.

Let $\theta_i^s(e,a) \equiv \frac{v_i^s(e,a)}{u_i^s(e,a)}$ denotes the tightness of a particular labor market, the relative aboundance of vacancies per job seeker. A firm's probability of filling a vacancy is given by $q_i^s(e,a) = M_i(u,v;a,s)/v = A_i(a,s)\left(\theta_i^s(e,a)\right)^{-\alpha}$, and a nonemployed worker's probability of finding a job as $f_i^s(e,a) = M_i(u,v)/u = A_i(a,s)\left(\theta_i^s(e,a)\right)^{1-\alpha}$. These expressions make clear that finding rates are exclusive functions of job tightness rates and the efficiency of the matching function.

3.2 Recursive formulation

3.2.1 A firm' problem

Let $\bar{V}$ be the (maximum) value of a firm with no worker and $J_i(e,a)$ be the value of a firm with a worker of type i, experience e and age a. Then

$$J_i(e,a) = \left\{ \begin{array}{c} h_i(e,a) - w_i(e,a) + \beta\left[\left(\pi_{EU}^i(a) + \pi_{EN}^i(a)\right)\bar{V} + \left(1 - \pi_{EU}^i(a) - \pi_{EN}^i(a)\right) J_i(e+1,a+1)\right] \\ \text{if } \underline{a} \leq a < a_R - 1, \\ h_i(e,a) - w_i(e,a) + \beta\bar{V} \text{ if } a = a_R - 1 \end{array} \right\}$$

The first part of this expression states that the value of a firm with a worker is the flow of gross profits plus the discount value of posting a new vacancy, $\bar{V}$, if the match is destroyed, which occurs with a probability $\pi_{EU}^i(a) + \pi_{EN}^i(a)$, plus the discounted value of remaining in the match, $J_i(e+1,a+1)$, which occurs with a probability $1 - \pi_{EU}^i(a) - \pi_{EN}^i(a)$. The second part states that a firm with a worker who is about to retire will become a firm with no workers in the following period.

The value of a firm posting a vacancy for a type$-i$ worker of age a and experience e is:

$$V_i^s(e,a) = \max\left\{-\kappa_i(e,a) + \beta\left[q_i^s(e,a) J_i(e,a+1) + (1 - q_i^s(e,a))\bar{V}\right], 0\right\}.$$

The maximum value of posting a vacancy in any labor market is then given by:

$$\bar{V} = \underset{e,a,s,i}{max}\{V_i^s(e,a), 0\}.$$

Free entry of firms into any labor market guarantees that the values of unfilled vacancies must all be equal to zero: $V_i^s(e,a) = 0$ for any all e, a, i and s. As a result $\bar{V} = 0$ as well. Firms are thus indifferent about which type of worker to hire and in what segmented market to operate as long as the free entry condition holds.

The firm's problem simplifies as follows:

$$J_i(e,a) = \left\{ \begin{array}{c} h_i(e,a) - w_i(e,a) + \beta\left(1 - \pi_{EU}^i(a) - \pi_{EN}^i(a)\right) J_i(e+1,a+1) \\ \text{for } \underline{a} \leq a < a_R - 1, \\ h_i(e,a) - w_i(e,a) \text{ for } a = a_R - 1 \end{array} \right\}, \tag{2}$$

$$\kappa_i(e,a) = \beta q_i^U(e,a) J_i(e,a+1) = \beta f_i^U(e,a)\,\theta_i^U(e,a)^{-1} J_i(e,a+1) \text{ for } \underline{a} \leq a < a_R - 1. \tag{3}$$

$$\kappa_i(e,a) = \beta q_i^N(e,a) J_i(e,a+1) = \beta f_i^N(e,a)\,\theta_i^N(e,a)^{-1} J_i(e,a+1) \text{ for } \underline{a} \leq a < a_R - 1.. \tag{4}$$

The last two equations state that the expected present value of filling a vacancy must be just enough to recover the costs of posting the vacancy. As a result, and as long as posting costs are independent of worker's status, job filling rates must be the same for unemployed and nonparticipant workers, $q_i^U(e,a) = q_i^N(e,a) = q_i(e,a)$. Since $q_i(e,a) = A_i(a,s)\left(\theta_i^s(e,a)\right)^{-\alpha}$ it follows that $\theta_i^s(e,a) = \left[\frac{A_i(a,s)}{q_i(e,a)}\right]^{1/\alpha}$ for all (e,a) meaning that tightness rates differ across status. Moreover,

$$f_i^s(e,a) = A_i(a,s)\left(\theta_i^s(e,a)\right)^{1-\alpha} = A_i(a,s)^{1/\alpha}\left(q_i(e,a)\right)^{(\alpha-1)\alpha} \tag{5}$$

also depend on s.

3.2.2 A worker's problem

Consider now the (maximum) expected value of earnings of an employed worker, E, an unemployed worker, U, a nonparticipant worker, N, and a retired worker, R. In particular, the expected utility of a newly retiree satisfies:

$$R_i\left(e, a_R\right) = \sum_{i=a_R}^{\overline{a}} \beta^{i-a_R} c_i^R\left(e, a_R\right) = \frac{1-\beta^{\overline{a}-a_R-1}}{1-\beta} c_i^R\left(e, a_R\right). \tag{6}$$

The corresponding value functions E, U and N can then be written recursively as:

$$E_i(e,a) = \left\{ \begin{array}{c} w_i(e,a) + \beta \left[\begin{array}{c} \pi_i^{EU}(a)U(e+1,a+1) + \pi_i^{EN}(a)N(e+1,a+1) \\ +(1-\pi_i^{EU}(a) - \pi_i^{EN}(a))E^U(e+1,a+1) \end{array} \right] \\ \text{if } \underline{a} \leq a < a_R - 1 \\ w_i(e,a) + \beta R_i\left(e+1, a_R\right) \text{ if } a = a_R - 1 \end{array} \right\}, \tag{7}$$

$$U_i(e,a) = \left\{ \begin{array}{c} c_i^U\left(e,a\right) + \beta \left[\begin{array}{c} f_i^U(e,a)E(e,a+1) + \pi_i^{UN}(a)N(e,a+1) \\ +(1-f_i^U(e,a) - \pi_i^{UN}(a))U(e,a+1) \end{array} \right] \\ \text{if } \underline{a} \leq a < a_R - 1 \\ c_i^U(e,a) + \beta R_i\left(e, a_R\right) \text{ if } a = a_R - 1 \end{array} \right\}, \tag{8}$$

$$N_i(e,a) = \left\{ \begin{array}{c} c_i^N\left(e,a\right) + \beta \left[\begin{array}{c} f_i^N(e,a)E(e,a+1) + \pi_i^{NU}(a)U(e,a+1) \\ +(1-\pi_i^{NU}(a) - f_i^N(e,a))N(e,a+1) \end{array} \right] \\ \text{if } \underline{a} \leq a < a_R - 1 \\ c_i^N(e,a) + \beta R_i\left(e, a_R\right) \text{ if } a = a_R - 1 \end{array} \right\}. \tag{9}$$

The interpretation of these functionals is intuitive. At the beginning of each period, an unemployed worker consumes $c_i^U\left(e,a\right)$ during unemployment. Next period, he may find a job with probability $f_i^U(e,a)$ in which case he moves to the employment state. He may also move to nonparticipation with age- and type-dependent probability $\pi_i^{UN}(a)$, and otherwise he will stay unemployed. Similarly, a nonparticipating worker consumes $c_i^N\left(e,a\right)$ this period, finds a job with a probability $f_i^N(e,a)$ or moves to unemployment with probability $\pi_i^{NU}(a)$ next period, and otherwise stays nonparticipating. A match can be destroyed in two ways: with a probability $\pi_i^{EU}(a)$, a worker becomes unemployed. If this does not occur, a match may break because the worker moves to nonparticipation with a probability $\pi_i^{EN}(a)$. If the match is not broken, the worker will continue producing with probability $[1-\pi_i^{EU}(a)-\pi_i^{EN}(a)]$ and stays in the employment state.

3.2.3 Nash bargaining

The wages in the model are negotiated through Nash bargaining. Firms and workers share the match surplus $S_i(e,a) = E_i(e,a) - U_i(e,a) + J_i(e,a)$, given the bargaining weights ϕ_i for the worker and $1-\phi_i$ for the firm, in the following way:

$$\underset{E_i - U_i, J_i}{max} (E_i(e,a) - U_i(e,a))^{\phi_i} J_i(e,a)^{(1-\phi_i)} \text{ subject to } S_i(e,a) = E_i(e,a) - U_i(e,a) + J_i(e,a).$$

The solutions for each labor market satisfy:

$$J_i(e,a) = \Theta_i(E_i(e,a) - U_i(e,a)) \text{ where } \Theta_i = \frac{1-\phi_i}{\phi_i}. \tag{10}$$

3.3 Aggregate restrictions

Given an initial distribution of workers at age $\underline{a}$, $m_i^s(0,\underline{a})$ for all s and i, and job finding rates $f_i^s(e,a)$ for all a, s and i, the subsequent distribution of workers $m_i^s(e,\underline{a})$ can be calculated assuming a law of large numbers. The mass of individuals with no experience at any age $a \in [\underline{a}, a_R - 2]$ satisfies:

$$\begin{aligned} m_i^U(0,a+1) &= (1-\pi_i^{UN}(a) - f_i^U(0,a)) \times m_i^U(0,a) + \pi_i^{NU}(a) \times m_i^N(0,a), \\ m_i^N(0,a+1) &= (1-\pi_i^{NU}(a) - f_i^N(0,a)) \times m_i^N(0,a) + \pi_i^{UN}(a) \times m_i^U(0,a), \\ m_i^E(0,a+1) &= f_i^U(0,a) \times m_i^U(0,a) + f_i^N(0,a) \times m_i^N(0,a); \end{aligned}$$

Moreover, the mass of individuals with experience $e \in [1,a]$ at any age $a \in [\underline{a}, a_R - 2]$ satisfies:

$$\begin{aligned} m_i^U(e,a+1) &= (1-\pi_i^{UN}(a) - f_i^U(e,a)) \times m_i^U(e,a) + \pi_i^{NU}(a) \times m_i^N(e,a) \\ &\quad +\pi_i^{EU}(a) \times m_i^E(e-1,a), \\ m_i^N(e,a+1) &= (1-\pi_i^{NU}(a) - f_i^N(e,a)) \times m_i^N(e,a) + \pi_i^{UN}(a) \times m_i^U(e,a) \\ &\quad +\pi_i^{EN}(a) \times m_i^E(e-1,a) \\ m_i^E(e,a+1) &= (1-\pi_i^{EU}(a) - \pi_i^{EN}(a)) \times m_i^E(e-1,a) + f_i^U(e,a) \times m_i^U(e,a) \\ &\quad +f_i^N(e,a) \times m_i^N(e,a). \end{aligned}$$

3.4 Solution concept (to be written)

- Exogenous variables: $c_i^U(e,a), c_i^N(e,a), c_i^R(e,a), r_i(a), y_i, \phi_i, \beta,\ A_i(a), \kappa_i(e,a)$,
- Endogenous variables: J,E,U,N,$w_i(e,a)$,$\theta_i(e,a), f_i(e,a), q_i(e,a), m_i^s(e,a)$.

4 Solution

We now characterize the solution for wages, tightness rates and job finding rates. The solution uses backward induction. Closed form solutions for the last period of work can be obtained and then used to find solutions for the previous periods.

4.1 Solution for $a = a_R - 1$

Using (2), (7) and (8), the Nash Bargaining solution (10) for $a = a_R$ simplifies to:

$$h_i(e,a_R-1) - w_i(e,a_R-1) = \Theta_i\left[w_i(e,a_R-1) - c_i^U(e,a_R-1) + \beta\Delta R_i(e+1,a_R)\right].$$

where $\Delta R_i(e+1,a_R) = R_i(e+1,a_R) - R_i(e,a_R)$ is the increase in retirement funds due to an extra year of experience at the moment of retirement. This equation provides a solution for the last period wages as:

$$w_i(e,a_R-1) = \frac{h_i(e,a_R-1) + \Theta_i\left[c_i^U(e,a_R-1) - \beta\Delta R_i(e+1,a_R)\right]}{1+\Theta_i}. \tag{11}$$

According to this expression, wages are a weighted average between the worker's human capital and the level of consumption if unemployed net of gains in retirement funds. If the worker has all the bargaining power, the case $\Theta_i = 0$, wage equals human capital. On the other extreme, if the firm holds all the power, the case $\Theta_i = \infty$, then wages equal consumption of the unemployed minus any gains in retirement funds.

The solution for the terminal value of the firm, $J_i(e, a_R - 1)$, is then given by

$$J_i(e, a_R - 1) = (1 - \phi_i) \left[h_i(e, a_R - 1) + \beta \Delta R_i(e + 1, a_R) - c_i^U(e, a_R - 1)\right]. \tag{12}$$

The terminal value of the firm is proportional to a measure of output plus added retirement funds minus unemployed consumption. An implicit restriction for firms to operate, and for workers to work, is that $h_i(e, a_R - 1) + \Delta R_i(e, a_R) \geq c_i^U(e, a_R - 1)$ meaning that the match produces a surplus. We assume that $h_i(e, a) \geq c_i^U(e, a)$ for all (e, a) and that $\Delta R_i(e, a_R) \geq 0$ meaning that experience increase pensions. If these conditions are met, then it follows from (11) that $h_i(e, a_R) \geq w_i^U(e, a_R)$.

The terminal value of the firm can be used to determine the terminal job tightness ratio, according to (3), as:

$$\theta_i^s(e, a_R - 2) = \frac{v_i^s(e, a_R - 2)}{u_i^s(e, a_R - 2)} = \left[\frac{\beta A_i(a, s)}{\kappa_i(e, a_R - 2)} (1 - \phi_i) \left[h_i(e, a_R - 1) + \beta \Delta R_i(e + 1, a_R) - c_i^U(e, a_R - 1)\right]\right]^{1/\alpha}. \tag{13}$$

This result shows that vacancies are more abundant for those workers with higher human capital or lower outside consumption or in more efficient labor markets characterized by high A and/or low κ. The model predicts, for example, that more experienced workers and immigrants with lower outside options would benefit from more vacancy posting. Finally, the terminal job finding rate can be solved as

$$f_i^s(e, a_R - 2) = A_i(a_R - 2, s) \left(\theta_i^s(e, a_R - 2)\right)^{1-\alpha}.$$

Job finding rates are higher in markets with higher tightness rates and more efficient matching technologies.

4.2 Solution for $a < a_R - 1$

The solutions for ealier periods can be expressed in terms of the following workers' surpluses:

$$\begin{aligned} S_{EU}(e, a) &= E(e, a) - U(e, a);\ S_{EN}(e, a) = E(e, a) - N(e, a); \\ S_{NU}(e, a) &= N(e, a) - U(e, a);\ S_{UN}(e, a) = U(e, a) - N(e, a); \\ \Delta U(e, a) &= U(e, a) - U(e - 1, a);\ \Delta N(e, a) = (N(e, a) - N(e - 1, a)). \end{aligned} \tag{14}$$

The following proposition provides a partial characterization of the solution for wages, tightness rates and job finding rates.

Proposition The solutions for $S_{EU}^i(e, a)$, $w_i(e, a)$, $\theta_i^s(e, a)$ and $f_i^s(e, a)$ satisfy, for $0 \leq a < a_R - 1$:

$$w_i(e, a) = \frac{h_i(e, a) + \Theta_i c_i^U(e, a) + \beta \Theta_i W_i(e + 1, a + 1)}{1 + \Theta_i}, \tag{15}$$

$$\theta_i^s(e, a) = \left[\frac{\beta A_i(a, s) \Theta_i S_{EU}^i(e, a + 1)}{\kappa_i(e, a)}\right]^{\frac{1}{\alpha}}, \tag{16}$$

$$f_i^s(e, a) = A_i(a, s) \left(\theta_i^s(e, a)\right)^{1-\alpha}. \tag{17}$$

where

$$\begin{aligned} W_i(e + 1, a + 1) &= f_i^U(e, a) S_{EU}^i(e, a + 1) - \Delta U^i(e + 1, a + 1) + \pi_i^{UN}(a) S_{NU}^i(e, a + 1) \\ &\quad + \pi_i^{EN}(a) \left[S_{EN}^i(e + 1, a + 1) - S_{EU}^i(e + 1, a + 1)\right]. \end{aligned}$$

Proof. See Appendix.

The expression for wages, equation (15), is a generalization of (11). The term $\beta W_i(e+1,a+1)$ collects all future "net" losses of remaining employed. If $W_i(e+1,a+1) > 0$ then wages increase to compensate for those losses, while wages falls if $W_i(e+1,a+1) < 0$. In particular, a higher job finding probability, f_i, increases wages since $S^i_{EU}(e,a+1) > 0$. Intuitively, the higher the chances of finding a new job the higher the losses associated to remaining in the current job. Furthermore, if $\Theta_i = 0$ then wages equal human capital while if $\Theta_i = \infty$ wages equals $c_i^U(e,a) + \beta W_i(e+1,a+1)$.

To gain some further intuition about the determination of wages, consider the case $a = a_R - 2$. First, using the solutions already obtained for $a = a_R - 1$, the following results can be found:

$$\begin{aligned}
S_{EU}(e,a_R-1) &= w_i(e,a_R-1) - c_i^U(e,a_R-1) + \beta\Delta R_i(e+1,a_R),\\
S^i_{EN}(e,a_R-1) &= w_i(e,a_R-1) - c_i^N(e,a_R-1) + \beta\Delta R_i(e+1,a_R),\\
S^i_{NU}(e,a_R-1) &= c_i^N(e,a_R-1) - c_i^U(e,a_R-1),\\
\Delta U^i(e+1,a_R-1) &= c_i^U(e+1,a_R-1) - c_i^U(e,a_R-1) + \beta\Delta R_i(e+1,a_R).
\end{aligned}$$

Furthermore, suppose $c_i^U(e,a_R-1) = c_i^N(e,a_R-1)$, $c_i^U(e,a_R-1) = c_i^U(e+1,a_R-1)$ for all e, and $\Delta R_i(e+1,a_R) = 0$. In that case

$$\begin{aligned}
S_{EU}(e,a_R-1) &= w_i(e,a_R-1) - c_i^U(e,a_R-1),\\
S^i_{EN}(e,a_R-1) &= w_i(e,a_R-1) - c_i^N(e,a_R-1),\\
S^i_{NU}(e,a_R-1) &= 0,\ \Delta U^i(e+1,a_R-1) = 0, \text{ and}\\
W_i(e+1,a+1) &= f_i^U(e,a) S^i_{EU}(e,a+1).
\end{aligned}$$

Plugging these results into (15), it follows that:

$$w_i(e,a_R-2) = \frac{h_i(e,a_R-2) + \Theta_i c_i^U(e,a_R-2) + \beta\Theta_i f_i^U(e,a_R-2)\left(w_i(e,a_R-1) - c_i^U(e,a_R-1)\right)}{1+\Theta_i}.$$

This expression illustrates the determination of wages, and in particular the role of the job finding rate. A higher job finding rate increases wages. Again, if $\Theta = 0$ then $w_i(e,a_R-2) = h_i(e,a_R-2)$ while if $\Theta = \infty$ then

$$w_i(e,a_R-2) = c_i^U(e,a_R-2) + \beta f_i^U(e,a_R-2)\left(w_i(e,a_R-1) - c_i^U(e,a_R-1)\right).$$

5 Calibration strategy

The calibration is the key exercise of the paper. The spirit of that of a theory based accounting exercise in which we seek to understand the data from the point of view of the model. In other words, we take as granted that the model provides a good description of the data and, under this assumption, use the model to reverse engineering the underlying parameters needed to exactly replicate the data. This exercise is informative to the extent that it builds upon a canonical model of the labor market, the Mortensen-Pissarides model, and a commonly used learning by doing formulation.

We set the model period to be a year and we concentrate on workers between ages 25 and 64. The discount rate is set to be $\beta = 0.9615$, which implies that the real interest rate equals 4 percent annually. We assume that at age 25 the initial mass one of workers is divided between employment, unemployment, and nonparticipation states in the way that it is observed in the CPS data.

The estimates on flow probabilities from in to and out from employment, unemployment, and nonparticipation for males and females are estimated from age-specific, life-cycle monthly transition probabilities for U.S. workers using CPS data. We estimate transition probabilities from employment to unemployment, $\pi^i_{EU}(a)$, employment to nonparticipation, $\pi^i_{EN}(a)$, unemployment to nonparticipation, $\pi^i_{UN}(a)$, nonparticipation to unemployment, $\pi^i_{NU}(a)$, and unemployment and nonparticipation to employment, $\pi^i_{UE}(a)$ and $\pi^i_{NE}(a)$. As the time period is set to be a year instead of a month, we calculate age- and gender-dependent, annual transition probability matrix, Λ^i_Q, using Markov transition matrix as follows:

$$\Lambda^i_Q = (\Lambda^i_M)^{12} \; where \; \Lambda^i_M = \begin{pmatrix} [1-\pi^i_{EU}(a)-\pi^i_{EN}(a)] & \pi^i_{EU}(a) & \pi^i_{EN}(a) \\ \pi^i_{UE}(a) & [1-\pi^i_{UE}(a)-\pi^i_{UN}(a)] & \pi^i_{UN}(a) \\ \pi^i_{NE}(a) & \pi^i_{NU}(a) & [1-\pi^i_{NE}(a)-\pi^i_{NU}(a)] \end{pmatrix}.$$

The key stylied facts that we require the model to replicate are the life-cycle wage profiles and life-cycle finding rate profiles reported in Figures 1 to 3. The parameters allowing this match are the human capital functions, $h_i(e,a)$, and the matching productivity parameters $A_i(e,a)$ and $s_i(e,a)$. We assume the following functional form for $h_i(e,a)$:

$$h_i(e,a) = y_i e^{r_i(a)e},$$

where y_i is a scale parameter associated to group i while $r_i(a)$ is an age and group specific return to experience. The calibration of $h_i(e,a)$, and in particular of $r_i(a)$, is based on equations (11) and (15). These equations provide a direct connection between wages and human capital at each age, and therefore between average wages, which we observe, and average unobservable human capital.

Parameters $A_i(a,s)$ is calibrated using (3) and (4) which could be written, using (5) as:

$$A_i(a,s) = \frac{\pi^i_{Us}(e,a)^{\alpha}\kappa(a)^{1-\alpha}}{(\beta J(e,a+1))^{1-\alpha}} = \frac{\left[A_i(a,s)\times\theta^s_i(e,a)^{1-\alpha}\right]^{\alpha}\kappa(a)^{1-\alpha}}{(\beta J(e,a+1))^{1-\alpha}}, \tag{18}$$

where $\pi^i_{US}(e,a) = f^s_i(e,a)$ is the observed job finding rate. This equation provides a connection between the average job finding rate, $\pi^i_{EU}(a)$, which is observed, and parameter $A_i(a,s)$. We assume $\kappa(a) = 1$. This is because the model implies that it is only the join term $A_i(a,s)/\kappa(a)^{1-\alpha}$ what affects the job finding rates. The interpretation for our calibrated job market productivity parameters, $A_i(a,s)$, is really relative to job-posting costs. Thus, a higher calibrated productivity could also reflect lower cost of posting vancancies.

We adopt the following simple formulation for parameters $c^U_i(e,a)$, $c^N_i(e,a)$ and $z_i(e,a)$:

$$\begin{aligned} c^U_i(e,a) &= \gamma^U_i \cdot h_i(e,a), \\ c^N_i(e,a) &= \gamma^N_i \cdot h_i(e,a), \text{ and} \\ z_i(e,a) &= \gamma_i \cdot h_i(e,a). \end{aligned}$$

According to this formulation, consumption while unemployed or nonparticipant is proportional to the human capital of the worker. We set $\gamma^U_i = 0.2$, $\gamma^N_i = 0.25$ and $\gamma_i = 0.3$ and carry out robustness checks. We assume that the bargaining power of the worker, ϕ, as well as the elasticity of the matching function, α, equals to 0.5, assuming that the Hosios' condition holds. [2]

[2]Our simulations indicate that the results we report are generally robust to the exact choices of these parameters. We are still in the process of better pinning down their exact values.

6 Calibration results

6.1 Human capital accumulation over the life cycle

Figure 9 shows the calibrated average human capital by race over the life cycle for both genders. We first look at the human capital growth patterns for blacks, whites, and hispanics, as they behave in a similar way. Human capital increases fairly steadily for each of these groups. Human capital for white and hispanic females stagnates between ages 30 and 50, likely because of their lower labor market participation, but does not significantly decrease. The counterintuitive finding is that human capital at the end of the working life does not closely follow the shape of wages observed in Figure 1. In fact, while human capital keeps rising, the wages start to decrease. These rising paths for human capital over the life cycle are likely to capture the impacts of finite working lives (horizon effect) and wage negotiation between workers and firms in a labor market with frictions.

Human capital growth for average Asian females and males show quite different patterns compared to other groups: their human capital increases significantly faster until age 35, and starts to decrease after that, until it starts to grow again for older workers. Asians' human capital growth follows somewhat closely their wage growth shown in Figure 1, which shows that Asians' wages also start to decrease fairly early compared to other groups. It is also interesting to look at the relationship between wage and human capital growth for Asian females and males – while both genders' wage growth is very similar until age 27, Asian females' human capital grows much faster. Thus, there is a gender difference between wages-to-human-capital ratio for Asians. This pattern is confirmed for other groups in Figure 8. Figure 8 plots the difference between a worker's human capital and wages over the life cycle, and this difference represents the fraction of a worker's human capital that is obtained by a firm through wage bargaining. We see that the difference is larger for females during majority of the life cycle, and especially large between ages 25 and 35. This is an important finding as it seems to support the idea that female and male workers are treated differently in the labor market. This difference for blacks starts to close much earlier, around age 45, compared to Asians and white, for whom the gap starts to close only around age 60. Figures 7b and 8b show similar results for whites with different education. While white females' human capital grows at a similar rate compared to males early in life, their wages grow less compared to white males, and firms are extracting a higher fraction females' human capital. These results hold for both education groups, but the differences are higher for highly educated workers.

These results may be related to the differences in labor market attachment between different groups. As white and Asian females are more likely to leave the labor market compared to males, this increases the cost of hiring female workers, and firms need to extract a bigger fraction of females' human capital to cover the cost. This cost is even higher for highly-educated workers. As the labor market attachment differences between black females and males are much smaller, this story supports the different observation for blacks.

6.2 Returns to experience

Figure 9 plots returns to experience agains experience and age. The returns to experience are first decreasing with experience after 5 years of experience, but interestingly, the returns to experience are not decreasing monotonically, but start to slightly increase around age 50. This result is very different from standard estimates from Mincer-type equation, where the returns to experience are increasing concavely (see, for example Rubinstein & Weiss 2006). Return to experience for young Asian and white females are notably higher compared to any other groups, but these differences diminish between ages 30 and 35. After that, both white males and females have highest returns to experience, followed by black and Asians. Figures 9b and 10b show, not surprisingly, that the returns to experience are higher for groups with higher education.

6.3 Matching productivity

We will next describe how the calibrated matching productivity for each group in every age differs over the life cycle. Figure 11a shows matching productivities for each race and gender. Overall, the variation in matching productivities is much higher for younger workers, and the variation significantly decreases for workers older than 45. The matching productivities are decreasing drastically for older workers, showing that the labor market is getting less favorable for them. All male groups tend to have higher matching productivities, especially during the prime working ages from 25 to 45, compared to female groups, and for every group, the matching productivity follows the shape of the corresponding job finding probability.

An interesting thing to notice is that even though the matching productivities for blacks and whites are quite close to each other over the life cycle, the difference in their job finding probabilities is much greater. Given the matching function used in the model, this implies that the labor market is less tight for black males meaning that firms post relatively less vacancies for black males. The matching productivity seems to also be significantly lower for Asian females.

The variation in the matching productivities between groups capture the variation in the job finding rates observed in the data, that the model otherwise cannot explain given the observable differences between groups. For example, as there are significant group differences in transition probabilities from employment to unemployment, and these differences affect firms' willingness to hire certain groups, the variation in these transition probabilities should be captured by the differences in the number of vacancies firms are opening for each groups, and thus, labor market tightnesses. Matching productivities can be, thus, interpreted to capture the residual differences in the job finding rates that cannot be explained by the firms' and workers' behavior in the model.

6.4 Search effort of nonparticipants

Figure 12a shows the results for race-gender pairs. First thing to observe is that the search effort for all groups at age 20 are calibrated to be greater than one, meaning that the young nonparticipants are searching harder compared to unemployed 20-year-olds. The other explanation may be related to schooling – a significant fraction of 20-year-olds are still at school, and their higher effort compared to unemployed may just reflect that they are graduating and finding jobs easier than 20-year-old unemployed. The common trend in nonparticipants search effort for blacks and whites is the decrease in effort with age. The trend is quite different for Asians, especially Asian nonparticipating males: their search effort exceeds the search effort of unemployed Asian males between ages 28 and 50, and starts to decrease after that. Also, even though Asian nonparticipating females' search effort during the prime child-bearing ages follows quite closely to the one of white females, their search effort does not decrease after that as rapidly.

While the search effort for Asian and white males and females differ significantly until ages between 45 and 50, females' searching less efficiently, and converges after that, the search effort for black males and females evolve hand-in-hand pretty much over the whole life cycle. This could be explained the higher fraction of single-mothers among blacks, which implies that a black female is often the only breadwinner in the family. This leads to their higher search effort and labor market participation.

Figure 12b shows the calibrated search effort for nonparticipating college and non-college educated whites. The search effort for college educated males exceeds the effort by non-college educated males after age 28, and the difference arises with age. The model predicts that highly educated females have higher search effort compared to lower educated females, except between ages 30 and 40. This is an interesting finding since one might think that college-educated females should always be searching with higher efficiency. The search effort between females and males for both education groups show very similar patterns. The search effort of females is much lower before age 45, and the difference is highest around age 30. However, the search effort converges for non-college educated around age 43, and for college educated around 10 years later.

6.5 Labor market tightness

Figures 13a to 14b show how the labor market tightnesses variate for different groups in different labor market states (unemployment and nonparticipation). The higher the labor market tightness, the more vacancies there are available in the labor market per a worker searching for a job. First of all, our model predicts that the tightness is drastically higher for white and Asian males, while the tightness for black males if closer to the ones of white and Asian females. These results suggest that it is more valuable for firms to open vacancies for white and Asian males, which implies the higher tightness for these groups. Higher job market tightness, all else equal, translates to higher job finding probability for these groups. Black females have the lowest labor market tightness over the whole life cycle for both labor market states. Labor market tightness is also higher for highly educated groups within gender.

7 Decomposition of the labor market gaps

In this section, we decompose the gaps in the labor market outcomes for each group studied. We study the relative importance of each exogenous variable in creating those gaps. Exogenous labor market flows (π_{EN}, π_{EU}, π_{UN}, π_{NU}) are estimated using the CPS data. The rest of the variables are separately calibrated for each group within our model, and those variables are the baseline productivity, y, returns to experience, $r(a)$, matching productivity, A, and search effort of nonparticipants, μ. The groups studied are also allowed to differ at the age of 25 with respect to how they are distributed between different labor market states (employment, unemployment, and nonparticipation). However, we do not specifically concentrate on this exogenous variation since the impact of this variation is very small in creating the gaps.

The specific labor market gaps of our interest are the following. We study both wage and employment, unemployment, and nonparticipation gaps simultaneously. Our model also endogenously solves for the labor market tightnesses for each specific group, as well as the job finding rates, so we also study the gaps in those labor market variables. The wage gap is presented as a gap in dollars-per-hour earned. The other gaps are presented in percentage points, except the gaps in labor market tighnesses are just the differences in the measure of labor market tightness, which is the vacancy-to-job-seeker ratio.

We calculate the relative importance of each exogenous variable in creating the studied labor market gaps by equalizing each exogenous variable one-by-one with the corresponding variable of the baseline group. We separately study the importance of every variable for the gaps in every experience level, as well the average impact of each variable on the mean gap over all experience levels. We decompose the labor market gaps separately for both genders, all races/ethnicities and education levels. We use white males as a baseline group for each group, given the education level. For example, white, college-educated (skilled) males serve as a baseline group for the other college-educated groups. Similarly, white males without college-education (unskilled) serve as a baseline group for other groups without college-education.

Figures 17–33 show the counterfactual results for each subgroup and for each level of experience. Figures 17–23 present the average results for both gender, each race, and for average education level. Figures 24–33 show similar results but separately for different levels of schooling. That last set of figures exclude Asian males and females because of lack of sufficient data. Tables 2–7 show the average gaps over the experience levels for each group. In general, we find that there are significant wage and other labor market gaps between the baseline groups and other groups, given labor market experience level.

As we are studying the labor market gaps while controlling for experience, education, and the baseline productivity levels of a worker in the model, we interpret the remaining gaps in wages, job market tightnesses, and job finding rates as inefficiencies in the labor market, which could arise from statistical discrimination based on age, gender, and race. For example, if firms are less likely to open vacancies for females workers as they are, on average, more likely to leave the firm earlier, this can be interpreted as a statistical discrimination as firms' are making decisions based on a job applicants gender.

7.1 Wage gaps

We first concentrate on explaining the wage gap decomposition. The wage gaps are presented as a dollar difference in hourly wages for each experience level. The majority of the wage gap of each group can be explained by three variables: the differences in baseline productivities, y, returns to experience, $r(a)$, and transition probabilities from employment to nonparticipation, π_{EN}. As the baseline productivity and returns to experience are directly related to the human capital function of each group, it is natural that the wage differences are closely related to differences in those variables. Somewhat surprisingly, π_{EN}, can explain a significant fraction of the wage gaps for a given experience level, and the importance of π_{EN} is especially noticeable for all female groups and black males. This variable captures differences in behavior between groups over the life cycle. As we are looking at the whole life-cycle of workers in our model, and the model takes into an account these differences in behavior over the life-cycle, we can study the impact of these behavioral differences on wages.

The distinct baseline productivities can be interpreted as differences in group averages regarding to sectors and occupations where an average worker works and school majors that a worker has chosen, which are typically observable characteristics of a worker but are not taken into an account in our model. The importance of y varies between different genders, races, and education levels. The group differences in y can explain, on average, about 60 percent of the wage gap over the experience levels between white and hispanic males, and the productivity differences are especially important for unskilled workers. The importance of y is not as drastic when explaining the wage gaps of skilled white and hispanic females compared to skilled white males, but it seems to matter more for unskilled. One explanation can be that unskilled female workers are more likely to work in service sector with, on average, lower total factor productivity, while unskilled white males are more likely to work in manufacturing with higher average productivity. For black females, the y is fairly important for both skilled and unskilled groups, explaining about 30 percent of the total wage gap, while for black males, the y is only important for skilled black males. Finally, the baseline productivity for both male and female Asians is higher compared to white males, and those differences have a significant impact on the wage differences between Asians and white males. On average, our decomposition shows that Asians earn about \$1.95 per hour more compared to white males, given the experience level, because of their higher baseline productivity (Table 7).

The role of returns to experience in explaining the wage gaps varies significantly between groups. For females, on average, returns to experience start to play more important role for higher experience levels, explaining an increasing fraction of the wage gap. One interpretation for this results is that women do not choose or not get selected to the positions with the highest returns to experience. This could be because females choose to have positions with more flexibility but lower wages, or because females do not get promoted to the best positions. Skilled white females seem to actually have higher returns to experience compared to skilled white males for the first ten years of experience, which might reflect that white skilled females are advancing in their careers faster compared to skilled white males. However, this result could also reflect the fact that there may be less statistical discrimination against females in the labor market based on their higher likelihood of leaving employment, than our model predicts, which could also explain this result. A similar pattern, but at a smaller scale, is observed for skilled hispanic females, but not for skilled black females. For skilled black females, the importance of returns to experience is higher earlier in the career compared to other female groups, and the importance starts to decrease after that. For unskilled females, the patterns are fairly similar.

For Asian males and females, returns to experience can explain a significant fraction of the wage gaps. This occurs as Asians' wage growth later in life is drastically slower compared to white males, while both Asian males and females start with a high level of wages. To imitate the wage growth patterns for Asians observed in the data, given the high starting wages, the returns to experience for Asians has to be significantly smaller compared to white males, increasing the significance of returns to experience in explaining the wage gap. For average wage gaps for male groups, returns to experience are not very important in explaining black-white gap, but are quite important for hispanic-white gaps. For skilled black males, returns to experience are fairly important for the first 20 years of experience, but at the higher experience levels, the importance disappears. On average, the differences in returns to experience explain about 46 cents of the average total 2.63 dollar-per-hour gap between skilled black and white males (Table 3). For skilled hispanic males, returns to experience differences are fairly stable for every experience level, increasing somewhat for the last ten years of experience. Returns to experience cannot explain an important share of wage gap between unskilled black and white males, while the opposite is true for unskilled hispanics: having the same returns to experience as unskilled white males would decrease the average, total wage gap of 1.97 dollars by 74 cents (Table 5).

The gender differences in transition probabilities from employment to nonparticipation explain a significant fraction of wage gaps between female groups and white males, and that variable is especially important for lower experience level (i.e. younger ages). The standard explanation is straightforward: as females are more likely to move from employment to nonparticipation, they gain less experience and earn less. However, as we compute the wage gap while controlling for experience level, we interpret the impact of π_{EN} as a possible statistical discrimination in the labor market against women arising from the differences in labor market attachment during the career. Statistical discrimination arises in the model from firms' optimization problem: as females, on average, are more likely to leave the firm compared to white males, and hiring a worker is costly in a labor market with frictions, firms are not willing to pay females the same wage as to comparable white males. The importance of π_{EN} in explaining the wage gap is especially higher for skilled females compared to unskilled females, which is consistent with the earlier findings that career breaks are more costly for workers in occupations that are more analytic in nature, and likely to require more formal schooling (Adda et.al. 2017). Our decomposition shows that the average hourly wage gap of 1.99 dollars between skilled white females and males would decrease by 1.38 dollars if females had the same transition flows than males. Smaller, but still important effects can be found for skilled black and hispanic females - the total wage gaps for those groups would decrease by 1.1 dollars for blacks and 1.34 dollars for hispanics (Tables 4 and 6).

Interestingly, the similar force seems to play role for black males, but not for hispanic or Asian males. The differences in π_{EN} between black and white males can explain on average about 30 percent of the wage gap between skilled black and white males, while 58 percent of the wage gap between unskilled. Again, as these impacts can be interpreted as statistical discrimination, these results show that a significant amount the black-white wage gap can be accounted to a form of discrimination, arising from the differences in the labor market attachment. However, it is not clear why black males, in particular, are more likely to move from employment to nonparticipation compared to all other male groups.

The other exogenous variables have significantly smaller explanatory power on wage gaps. The exogenous labor market flows between unemployment and nonparticipation have zero or close-to-zero impacts on wage gaps, which is not surprising since both unemployed and nonparticipating workers are not gaining labor market experience. The differences in the transition from employment to unemployment, π_{EU}, can explain a small fraction of the wage gaps between blacks and hispanic males compared to white males. The search effort of nonparticipants, μ, was identified by comparing the job finding rates between unemployed and nonparticipants - s measures the difference in the job finding rates that cannot be accounted for any other difference in observable variables in the model. The search effort differences are not the main drivers of the wage gap, but the decomposition results suggest that white and Asian females are less likely to look for jobs during the prime child-rearing ages when nonparticipating, while other groups seem to be searching slightly more actively compared to baseline groups.

Finally, we look at how much distinct matching productivities measured by A can explain the observed wage gaps. Even though our calibration results (Figure 10) imply that there is a significant variation between group-specific As, those differences are not the main drivers of the wage gaps. The way to interpret A is to consider it as an inverse of a matching friction in the model. In our calibration, we identify A/κ, by normalizing κ to one. The differences in A can thus capture differences in both productivities in the matching technology and differences in the vacancy costs (κ), which could also be interpreted as inefficiencies in the labor market that cannot be explained by the observed differences between groups. When the productivity of matches, A, decreases (or κ increases), there are more frictions in the labor market, and matches are less likely to occur. The opposite is true for high A and low κ. One explanation for different matching frictions can be taste-based discrimination, which cannot be explained by any observed differences between groups, but other interpretation for A are also possible. The results show that matching frictions play a small negative role mainly for white and Asian females during the first twenty years of experience, and for unskilled black males over the whole life cycle. Hispanic males seem to benefit from smaller labor matching frictions compared to white males and any other group, and the matching frictions are especially low for unskilled hispanic males. Even though matching friction differences exist, they seem not to be the main driver of wage gaps. This implies that, according to our model, the taste-based discrimination in the market cannot explain a significant fraction of the wage gaps.

7.2 Employment, unemployment, participation, and nonparticipation gaps

We next move on explaining the decomposition of the gaps in employment, unemployment, and participation. We are looking at employment and unemployment masses, defined as a number of employed or unemployed people in each group over the whole population in each group, instead of employment and unemployment rates. We think that these measures make it easier to compare the outcomes of groups with very different labor market participation rates. The main finding is that the differences in transition rates between different labor market states explain a large part of the variation in the employment and unemployment outcomes between groups.

The possible gaps in employment, participation, and, thus, nonparticipation can largely be accounted to the differences in transitions from employment to nonparticipation, π_{EN}. As the employment and participation gaps compared to white males are especially large for all female groups and black males, those gaps would be largely eliminated if these groups experienced similar flows than white males. The remaining employment and participation gaps for these groups are quite evenly explained by differences in other exogenous variables. The employment and participation gaps are very small for hispanic males, and even negative for Asian males, and π_{EN} can only explain a fraction of the gap for hispanic males later in their careers. For these groups, their high employment and participation masses are largely arising from the smaller matching frictions and higher search effort of nonparticipants. For example, even if hispanic males are more likely to move out of employment compared to their white counterparts, this negative impact is largely eliminated as they are finding new jobs more easily.

Unemployment gaps - the positive gap showing a smaller unemployment mass for a comparison group and vice versa - are more evenly explained by different exogenous variables. White and Asian females have lower unemployment masses compared to white males, and these outcomes can largely be explained by females' smaller likelihood of moving from employment or nonparticipation to unemployment. Thus, these female groups are more likely to be nonparticipating rather than unemployed. Black females have a higher unemployment mass when they have of 20 years or less of experience, but their unemployment gap turns positive after that. The negative gap earlier in their careers is largely explained because their higher likelihood of losing a job and moving from employment to unemployment. The difference compared to the baseline group is especially large for workers with less experience, but the difference is decreasing with experience. This is true for both skilled and unskilled black females. Similar, and even stronger, patterns are true for black males, whose unemployment is higher for every experience levels compared to white males, and the difference is especially large when looking workers with less experience. The higher unemployment of hispanic males can also largely be explained by differences in π_{EU}, but the importance of this transition rate stays stable for every experience level, except for low-experience, unskilled hispanic males. Also, higher matching productivity of hispanic males compensate for their higher job losing rate.

While the transition from unemployment to nonparticipation, π_{UN}, is not strongly explaining any other gaps in the labor market, it significantly lowers the unemployment for all female groups and for black males. As females are more likely to move to nonparticipation rather than stay unemployed, their unemployment is not as high. A similar pattern is observed especially for unskilled black males - in fact, if unskilled black males had the same π_{UN} compared to unskilled white males, their mean unemployment mass would be about 1 percentage point higher. As the unemployment of unskilled black males is already the highest among all groups, their unemployment numbers would look even worse had they stayed participating. Other exogenous variables seem to be play a different role for different groups in explaining unemployment gaps, but the magnitude of their importance is fairly small.

To conclude, females and black males behave very differently compared to white, hispanic, and Asian males, as they are more likely to move to nonparticipation from both employment and unemployment. These differences can explain the majority of the gaps in employment, participation, and unemployment. A puzzle is why black males behave very differently from other male groups. Higher flows from unemployment to nonparticipation may arise from drastically higher incarceration rates of black males, but it is not clear whether employed black males are more likely to be incarcerated compared to other male groups.

7.3 Labor market tightness and job finding rate gaps

Our model predicts significant differences in labor market tightnesses and job finding rates for different groups. A gap in the labor market tightness shows the difference in vacancy-to-job-seeker ratios. For example, if the labor market tightness is smaller for the comparison group compared to the baseline group, that implies that firms post relatively less vacancies per every person looking for a job in the submarket of the comparison group. A gap in the job finding rates shows the difference in the probability of finding a job withing a given time period. We look separately the labor market tightnesses and job finding rates for unemployed and nonparticipants.

The gaps in labor market tightnesses for all female groups and black males can largely be explained because of the differences in π_{EN}. As these groups are less attached to the labor force and employment, firms are less willing to hire them at every experience level. This shows that there likely is a significant amount of statistical discrimination in hiring, and the statistical discrimination arises largely from the differences in labor market attachment. The differences in baseline productivities and returns to experience can also account for the differences in labor market tightnesses. As those variables impact the profits of a firm, they will have a direct impact on how many vacancies firms will open. Differences in human capital variables explain almost all the differences in labor market tightnesses when comparing white males to hispanic and Asian males. Other exogenous variables, mainly the differences in π_{EU} and matching friction, A, can explain a small part of the gaps for some groups, but vast majority of the gaps are arising from the differences in human capital function variables or transitions from employment to nonparticipation.

As job finding rates are defined as $A\theta^{1-\alpha}$, where θ is the labor market tightness, it is natural that the differences in A are relatively more important in explaining the differences in job finding rates for many groups. However, we still see that π_{EN} dominates as an explanation for the job finding rate gaps through the labor market tightness, θ, for females and black males. These results, along with the findings that a higher π_{EN} has a significant impact on a worker's wages, show that differences in labor market attachment first-order impacts on all labor market outcomes, starting from the probability of finding a job.

7.4 Robustness checks

To be completed

8 Conclusions

To be completed

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A Proof of proposition 1

Using the definitions of surpluses given in (14), equations (2), (3) and (10) can be written as,

$$\Theta_i S^i_{EU}(e,a) = h_i(e,a) - w_i(e,a) + \beta(1-\pi_i^{EU}(a) - \pi_i^{EN}(a))\Theta_i S_{EU}(e+1,a+1), \tag{19}$$

$$\kappa_i(e,a) = \beta A_i(a,s)\,\theta_i^s(e,a)^{-\alpha}\,\Theta_i S^i_{EU}(e,a+1), \tag{20}$$

while equations (7) and (8) read:

$$E_i(e,a) = w_i(e,a) + \beta\left[E_i(e+1,a+1) - \pi_i^{EU}(a)S^i_{EU}(e+1,a+1) - \pi_i^{EN}(a)S^i_{EN}(e+1,a+1)\right]; \tag{21}$$

$$\begin{aligned} U_i(e,a) &= c_i^U(e,a) + \beta\left[U_i(e,a+1) + f_i^U(e,a)S^i_{EU}(e,a+1) + \pi_i^{UN}(a)S^i_{NU}(e,a+1)\right] \\ &= c_i^U(e,a) + \beta\left[\begin{array}{c} U_i(e+1,a+1) - \Delta U_i(e+1,a+1) + f_i^U(e,a)S_{EU}(e,a+1) \\ +\pi_i^{UN}(a)S_{NU}(e,a+1)\end{array}\right]; \end{aligned}$$

Substracting the second equation from the first one:

$$\begin{aligned} S^i_{EU}(e,a) &= w_i(e,a) - c_i^U(e,a) + \\ &\quad \beta\left[\begin{array}{c} S^i_{EU}(e+1,a+1) + \Delta U_i(e+1,a+1) - f_i^U(e,a)S^i_{EU}(e,a+1) \\ -\pi_i^{EU}(a)S^i_{EU}(e+1,a+1) - \pi_i^{EN}(a)S^i_{EN}(e+1,a+1) - \pi_i^{UN}(a)S^i_{NU}(e,a+1)\end{array}\right] \end{aligned}$$

or

$$S_{EU}(e,a) = w_i(e,a) - c_i^U(e,a) + \beta E\left[\widetilde{S}^i_{EU}(e,a+1)\right] \tag{22}$$

where $E\left[\widetilde{S}^i_{EU}(e,a+1)\right]$ is the expected surplus at age $a+1$ of an employed worker in state $(e,a+1)$. It is defined as:

$$E\left[\widetilde{S}^i_{EU}(e,a+1)\right] = \left[\begin{array}{c} \left(1-\pi_i^{EU}(a)\right)S^i_{EU}(e+1,a+1) - \pi_i^{EN}(a)S^i_{EN}(e+1,a+1) - \pi_i^{UN}(a)S^i_{NU}(e,a+1) \\ -f_i^U(e,a)S^i_{EU}(e,a+1) + \Delta U^i(e+1,a+1)\end{array}\right]$$

Similarly, rewrite (9) as:

$$\begin{aligned} N_i(e,a) &= c_i^N(e,a) + \beta\left[N_i(e,a+1) + f_i^N(e,a)S^i_{EN}(e,a+1) + \pi_i^{NU}(a)S^i_{UN}(e,a+1)\right] \\ &= c_i^N(e,a) + \beta\left[N_i(e+1,a+1) - \Delta N_i(e+1,a+1) + f_i^N(e,a)S^i_{EN}(e,a+1) - \pi_i^{NU}(a)S^i_{NU}(e,a+1)\right]. \end{aligned}$$

Substracting this equation from (21):

$$\begin{aligned} S^i_{EN}(e,a) &= w_i(e,a) - c_i^N(e,a) + \\ &\quad \beta\left[\begin{array}{c} S^i_{EN}(e+1,a+1) + \Delta N_i(e+1,a+1) - f_i^N(e,a)S^i_{EN}(e,a+1) \\ -\pi_i^{EU}(a)S^i_{EU}(e+1,a+1) - \pi_i^{EN}(a)S^i_{EN}(e+1,a+1) + \pi_i^{NU}(a)S^i_{NU}(e,a+1)\end{array}\right] \end{aligned}$$

or

$$S^i_{EN}(e,a) = w_i(e,a) - c_i^N(e,a) + \beta E\left[\widetilde{S}^i_{EN}(e,a+1)\right] \tag{23}$$

where

$$E\left[\widetilde{S}^i_{EN}(e,a+1)\right] = \left[\begin{array}{c} \left(1-\pi_i^{EU}(a)\right)S^i_{EN}(e+1,a+1) - f_i^N(e,a)S^i_{EN}(e,a+1) \\ -\pi_i^{EU}(a)S^i_{EU}(e+1,a+1) + \pi_i^{NU}(a)S^i_{NU}(e,a+1) + \Delta N_i(e+1,a+1)\end{array}\right]$$

is the expected value of the future surplus, at $a+1$, of an employed worker with state $(e, a+1)$.

Equations (2), (19), (20), (22) and (23) form a system of five equations in four unknowns: that can be solved for each (i, e, a) state given future values of those same variables: $\left\{J_i(e,a), S_{EU}(e,a), \theta_i^s(e,a), w_i(e,a), S_{EN}^i(e,a)\right\}_{(i,e,a)}$. Equation (20) can be used to directly solve for $\theta_i(e,a)$ as a function of $J_i(e, a+1)$. To solve for $w_i^U(e,a)$, use (19) and (22) to obtain:

$$\begin{aligned} & \Theta_i\left[w_i(e,a) - c_i^U(e,a) + \beta E\left[\widetilde{S}_{EU}^i(e,a+1)\right]\right] \\ = \; & h_i(e,a) - w_i(e,a) + \beta\left[(1-\pi_i^{EU}(a) - \pi_i^{EN}(a))\Theta_i S_{EU}(e+1,a+1)\right]. \end{aligned}$$

Solving for $w_i(e,a)$ gives

$$w_i(e,a) = \frac{h_i(e,a) + \Theta_i c_i^U(e,a) + \beta\Theta_i W_i(e+1,a+1)}{1+\Theta_i}.$$

where $W_i(e+1,a+1) = (1-\pi_i^{EU}(a) - \pi_i^{EN}(a))S_{EU}(e+1,a+1) - E\left[\widetilde{S}_{EU}^i(e,a+1)\right]$. Notice that

$$\begin{aligned} & W_i(e+1,a+1) \\ = \; & (1-\pi_i^{EU}(a) - \pi_i^{EN}(a))S_{EU}^i(e+1,a+1) - E\left[\widetilde{S}_{EU}^i(e,a+1)\right] \\ = \; & (1-\pi_i^{EU}(a) - \pi_i^{EN}(a))S_{EU}^i(e+1,a+1) - \left(1-\pi_i^{EU}(a)\right)S_{EU}^i(e+1,a+1) + \pi_i^{EN}(a)S_{EN}^i(e+1,a+1) \\ & +\pi_i^{UN}(a)S_{NU}^i(e,a+1) + f_i^U(e,a)S_{EU}^i(e,a+1) - \Delta U^i(e+1,a+1) \end{aligned}$$

or

$$\begin{aligned} W_i(e+1,a+1) \; = \; & \pi_i^{EN}(a)\left[S_{EN}^i(e+1,a+1) - S_{EU}^i(e+1,a+1)\right] + \pi_i^{UN}(a)S_{NU}^i(e,a+1) \\ & +f_i^U(e,a)S_{EU}^i(e,a+1) - \Delta U^i(e+1,a+1). \end{aligned}$$

B Details of the calibration

In this section we rewrite the model in a way that emphasizes how parameters are calibrated. The idea is to take the future as given (since the model is solved backwards) and focus on the connection between data at state (i, e, a) and parameters at that stage. For example, the model predicts $w_i(e,a)$ is function of parameters. The question is what should be the value of those parameters so that the wage predicted by the model is exactly equal to the data.

Let's write the model, for $a < a_R$, in the following form (functions $\Omega_j(i,a,e)$ can be considered as known in this formulation as explained below):

$$J(e,a) = h_i(e,a) - w_i(e,a) + \Omega_1(i,a,e);$$

$$\kappa(e,a) = \beta A_i(a,U) \times \theta^U(e,a)^{-\alpha} J(e,a+1);$$

$$\kappa(e,a) = \beta s(a) A_i(a,N) \times \theta^N(e,a)^{-\alpha} J(e,a+1);$$

$$E(e,a) = w_i(e,a) + \Omega_3(i,a,e);$$

$$U(e,a) = c_i^U(e,a) + \Omega_5(i,a,e) A_i(a,U)\theta^U(e,a)^{1-\alpha} + \Omega_6(i,a,e);$$

$$N(e,a) = c_i^N(e,a) + \Omega_7(i,a,e) A_i(a,s)\theta^N(e,a)^{1-\alpha}) + \Omega_8(i,a,e);$$

$$J(e,a)) = \Theta_i(e,a)\left(E^U(e,a) - U(e,a)\right);$$

where

$$\Omega_1(i,a,e) = \beta\left[(1-\pi_i^{EU}(a)-\pi_i^{EN}(a))\times J(e+1,a+1)\right],$$

$$\Omega_3(i,a,e) = \beta\left[\begin{array}{c} E(e+1,a+1)-\pi_i^{EU}(a)\left(E^U(e+1,a+1)-U(e+1,a+1)\right) \\ -\pi_i^{EN}(a)\left(E(e+1,a+1)-N(e+1,a+1)\right) \end{array}\right]$$

$$\Omega_5(i,a,e) = \beta\left(E(e,a+1)-U(e,a+1)\right)$$

$$\Omega_6(i,a,e) = \beta\left[U(e,a+1)+\pi_i^{UN}(a)\left(N(e,a+1)-U(e,a+1)\right)\right]$$

$$\Omega_7(i,a,e) = \beta\left(E(e,a+1)-N(e,a+1)\right)$$

$$\Omega_8(i,a,e) = \beta\left[N(e,a+1)+\pi_i^{NU}(a)\left(U(e,a+1)-N(e,a+1)\right)\right]$$

We now simplify the equations above eliminating J's and levels of E and N leaving only surpluses $S^U(e,a) = (E(e,a)-U(e,a))$ and $S^N(e,a) = E(e,a)-N(e,a)$:

$$\Theta_i^U(e,a)\,S^U(e,a) = h_i(e,a)-w_i^U(e,a)+\Omega_1(i,a,e)$$

$$\Theta_i^N(e,a)\,S^N(e,a) = h_i(e,a)-w_i^N(e,a)+\Omega_2(i,a,e)\,;$$

$$\kappa(e,a) = \beta A_i(a,U)\times\theta^U(e,a)^{-\alpha}J(e,a+1);$$

$$\kappa(e,a) = \beta A_i(a,N)\times\theta^N(e,a)^{-\alpha}J(e,a+1);$$

$$S^U(e,a) = w_i^U(e,a)-c_i^U(e,a)-\Omega_5(i,a,e)\,A_i(e,a)\,\theta^U(e,a)^{1-\alpha}+\Omega_9(i,a,e)\,;$$

$$S^N(e,a) = w_i^N(e,a)-c_i^N(e,a)-\Omega_7(i,a,e)\,s(a)A(e,a)\,\theta^N(e,a)^{1-\alpha}+\Omega_{10}(i,a,e)\,;$$

where

$$\begin{aligned}
\Omega_9(i,a,e) &= \Omega_3(i,a,e)-\Omega_6(i,a,e) \\
&= \beta\left[\begin{array}{c} E^U(e+1,a+1)-\pi_i^{EU}(a)\left(E^U(e+1,a+1)-U(e+1,a+1)\right) \\ -\pi_i^{EN}(a)\left(E^U(e+1,a+1)-N(e+1,a+1)\right) \end{array}\right] \\
&\quad -\beta\left[U(e,a+1)+\pi_i^{UN}(a)\left(N(e,a+1)-U(e,a+1)\right)\right] \\
&= \beta\left[E^U(e+1,a+1)-\pi_i^{EU}(a)S_{EU}^U(e+1,a+1)-\pi_i^{EN}(a)S_{EN}^U(e+1,a+1)\right] \\
&\quad -\beta\left[U(e,a+1)-\pi_i^{UN}(a)S_{UN}(e,a+1)\right] \\
&= \beta\left[\begin{array}{c} E^U(e+1,a+1)-U(e,a+1)-\pi_i^{EU}(a)S_{EU}^U(e+1,a+1) \\ -\pi_i^{EN}(a)S_{EN}^U(e+1,a+1)+\pi_i^{UN}(a)S_{UN}(e,a+1) \end{array}\right]
\end{aligned}$$

and $\Omega_{10}(i,a,e) = \Omega_4(i,a,e)-\Omega_8(i,a,e)$. The unknowns in this system of 6 equations are $S^U(e,a), S^N(e,a), w_i^U(e,a), w_i^N(e,a)$

Simplifying further, getting rid of surpluses:

$$\begin{aligned}
&\Theta_i^U(e,a)\left[w_i^U(e,a)-c_i^U(e,a)-\Omega_5(i,a,e)\,A_i(e,a)\,\theta^U(e,a)^{1-\alpha}+\Omega_9(i,a,e)\right] \\
=\;& h_i(e,a)-w_i^U(e,a)+\Omega_1(i,a,e)
\end{aligned}$$

$$\begin{aligned}
&\Theta_i^N(e,a)\left[w_i^N(e,a)-c_i^N(e,a)-\Omega_7(i,a,e)\,s(a)A(e,a)\,\theta^N(e,a)^{1-\alpha}+\Omega_{10}(i,a,e)\right] \\
=\;& h_i(e,a)-w_i^N(e,a)+\Omega_2(i,a,e)\,;
\end{aligned}$$

$$\kappa\left(e,a\right)=\beta A_i\left(e,a\right)\times\theta^U\left(e,a\right)^{-\alpha}J^U(e,a+1);$$
$$\kappa\left(e,a\right)=\beta s(a)A_i\left(e,a\right)\times\theta^N\left(e,a\right)^{-\alpha}J^N(e,a+1);$$

Here is a way to write the system in a way that is suitable for calibration. The following way to write the system is useful when if the targets of the model are wages and job finding rates. Define $f\left(i,e,a,U\right)=A_i\left(e,a\right)\theta^U\left(e,a\right)^{1-\alpha}$ and $f\left(i,e,a,N\right)=s(a)A_i\left(e,a\right)\theta^N\left(e,a\right)^{1-\alpha}$ be the job finding rates. Then write the system as:

$$\Theta_i^U\left(e,a\right)\left[w_i^U(e,a)-c_i^U\left(e,a\right)-\Omega_5\left(i,a,e\right)f\left(i,e,a,U\right)+\Omega_9\left(i,a,e\right)\right]=h_i\left(e,a\right)-w_i^U(e,a)+\Omega_1\left(i,a,e\right)$$
$$\Theta_i^N\left(e,a\right)\left[w_i^N(e,a)-c_i^N\left(e,a\right)-\Omega_7\left(i,a,e\right)f\left(i,e,a,N\right)+\Omega_{10}\left(i,a,e\right)\right]=h_i\left(e,a\right)-w_i^N(e,a)+\Omega_2\left(i,a,e\right);$$
$$\theta^U\left(e,a\right)=\beta f\left(i,e,a,U\right)J^U(e,a+1)/\kappa\left(e,a\right);$$
$$\theta^N\left(e,a\right)=\beta f\left(i,e,a,N\right)J^N(e,a+1)/\kappa\left(e,a\right);$$

Wages can be solved from the first two equations as:

$$w_i(e,a)=\frac{1}{1+\Theta_i}\left[h_i\left(e,a\right)+\Omega_1\left(i,a,e\right)+\Theta_i^U\left(e,a\right)\left(c_i^U\left(e,a\right)+\Omega_5\left(i,a,e\right)f\left(i,e,a,U\right)-\Omega_9\left(i,a,e\right)\right)\right] \tag{24}$$

Now, from the last two equations, for $\theta^U\left(e,a\right)$ and $\theta^N\left(e,a\right)$, and the definition of job finding rates one finds the following two parametric restrictions:

$$f\left(i,e,a,U\right)^{\alpha}=A_i\left(a,s\right)\left(\beta J^U(e,a+1)/\kappa\left(e,a\right)\right)^{1-\alpha} \tag{25}$$

$$f\left(i,e,a,N\right)^{\alpha}=A_i\left(a,s\right)\left(\beta J^N(e,a+1)/\kappa\left(e,a\right)\right)^{1-\alpha} \tag{26}$$

The last three equations are general and key for the calibration exercise. They can be used to match observations of wages and job finding rates into parameters. The equations for wages are valid for $a<a_R$. There are no additional equations for job finding rates for $a=a_R$. Job finding rates are zero from there on.

C Identification and calibration strategy

The following identification strategy uses only average wages and average job finding rates, at each age, to calibrate parameters. The calibration of the key parametes $A_i\left(a,s\right)$, $r_i\left(a\right)$ and y_i will come from a iteration process that start with an initial guess of an initial guess.

Assume that $m_i^s(e,a)$ is known. This is not the case in general. The algorithm below works on updating $m_i^s(e,a)$ starting at at initial guess. Define average wages, average finding rates, average human capital, average outside consumption, and average bargaining power as:

$$w_i(a)=\frac{\sum_e m_i^E\left(e,a\right)w_i(e,a)}{\sum_e m_i^{E_U}\left(e,a_R\right)} \tag{27}$$

$$h_i(a)=\frac{\sum_e m_i^E\left(e,a\right)h_i(e,a)}{\sum_e m_i^E\left(e,a_R\right)} \tag{28}$$

$$c_i(a)=\frac{\sum_e m_i^E\left(e,a\right)c_i^U(e,a)}{\sum_e m_i^E\left(e,a_R\right)} \tag{29}$$

$$f\left(i,a,U\right)=\frac{\sum_e m_i^U\left(e,a\right)f\left(i,e,a,U\right)}{\sum_e m_i^U\left(e,a\right)};\;f\left(i,a,N\right)=\frac{\sum_e m_i^N\left(e,a\right)f\left(i,e,a,N\right)}{\sum_e m_i^N\left(e,a\right)};$$

C.1 Calibration for $a = a_R - 1$

Let's start backwards, from $a_R - 1$, to describe the calibration methodology. According to (27), (11) and (**??**) average wage at age $a_R - 1$ satisfies

$$\begin{aligned} w_i(a_R - 1) &= \frac{\sum_e m_i^E(e, a_R - 1)\, w_i(e, a_R - 1)}{\sum_e m_i^E(e, a_R - 1)} \\ &= \frac{\sum_e m_i^E(e, a_R - 1)\, \frac{1}{1+\Theta_i}\left[h_i(e, a_R - 1) + \Theta_i(a)\, c_i^U(e, a_R - 1)\right]}{\sum_e m_i^E(e, a_R - 1)} \\ &= \frac{1}{1+\Theta_i}\left(h_i(a_R - 1) + \Theta_i c_i(a_R - 1)\right) \end{aligned}$$

Given data for $w_i(a_R - 1)$ this expression could be used to solve for $h_i(a)$ as:

$$h_i(a_R - 1) = w_i(a_R - 1)(1 + \Theta_i) - \Theta_i c_i(a_R - 1) \tag{30}$$

One can then use these calibrated parameter values to calculate wages (not just average wages) according to (11):

$$w_i(e, a_R - 1) = \frac{1}{1+\Theta_i}\left[h_i(e, a_R - 1) + \Theta_i c_i^U(e, a_R - 1)\right],$$

These wages can then be plugged into (2), (7), and (8) to find $J(e, a_R - 1)$, $E_i(e, a_R - 1)$, and $U_i(e, a_R - 1)$.

C.2 Calibration for $a < a_R - 1$.

Given value functions for $age = a + 1$ (in particular starting with $age = a + 1 = a_R - 1$, these values can then be used to calculate the parameters values $\Omega_j(i, a, e)$ for $j = [1, .., 9]$ using the definitions of $\Omega_j(i, a, e)$ given above. Also, define:

$$\Omega_j^E(i, a) = \sum_e m_i^E(e, a)\, \Omega_j(i, a, e) \text{ and } \Omega_j^E(i, a) = \sum_e m_i^E(e, a)\, \Omega_j(i, a, e).$$

Given the values of $J^U(e, a+1)$, averages job finding rates for $age = a$ can be found using (18) and (26). In particular, using (18):

$$f(i, a, U) = A_i(a)^{\frac{1}{\alpha}} \frac{\sum_e m_i^U(e, a)\left(\beta J^U(e, a+1)/\kappa(e, a)\right)^{\frac{1-\alpha}{\alpha}}}{\sum_e m_i^U(e, a)}$$

or

$$A_i(a, U) = \left[\frac{f(i, a, U)\sum_e m_i^U(e, a)}{\sum_e m_i^U(e, a)\left(\beta J^U(e, a+1)/\kappa(e, a)\right)^{\frac{1-\alpha}{\alpha}}}\right]^{\alpha}$$

Similarly,

$$A_i(a, N) = \left[\frac{f(i, a, N)\sum_e m_i^N(e, a)}{\sum_e m_i^N(e, a)\left(\beta J^N(e, a+1)/\kappa(e, a)\right)^{\frac{1-\alpha}{\alpha}}}\right]^{\alpha}.$$

These two expressions provide the calibrated values of $A_i(a, U)$ and $A(a, N)$. These formulas are not only correct for a_R but are also correct for all a. Given these parametric values then one can calculate job finding rates for all e, not just on average, $f(i, e, a_{R-1}, U)$ and $f(i, e, a_{R-1}, N)$ using (18) and (26).

Next, define

$$\overline{\Omega}_5^U(i,a) = \sum_e m_i^E(e,a)\,\Omega_5(i,a,e)\,f(i,e,a,U) \text{ and}$$

$$\overline{\Omega}_7^N(i,a) = \sum_e m_i^E(e,a)\,\Omega_7(i,a,e)\,f(i,e,a,N).$$

Notice that $\overline{\Omega}_5^U(i,a)$ is different from $\Omega_5(i,a)$. Similarly for $\overline{\Omega}_7^N(i,a)$ and $\Omega_7(i,a)$ .According to (24), average wages satisfy:

$$\begin{aligned} w_i(a) &= \frac{1}{1+\Theta_i}\sum_e m_i^E(e,a)\left[\begin{array}{c} h_i(e,a)+\Omega_1(i,a,e)+ \\ \Theta_i^U(a)\left(c_i^U+\Omega_5(i,a,e)\,f(i,e,a,U)-\Omega_9(i,a,e)\right) \end{array}\right] \\ &= \frac{1}{1+\Theta_i}\left[h_i(a)+\Omega_1^E(i,a)+\Theta_i\left(c_i^U+\overline{\Omega}_5^U(i,a)-\Omega_9^U(i,a)\right)\right] \end{aligned}$$

Given data for $w_i(a_R)$ this expression could be used to solve for $h_i^E(a)$ as:

$$h_i(a) = w_i(a)(1+\Theta_i)-\Omega_1^E(i,a)-\Theta_i\left(c_i^U+\overline{\Omega}_5^U(i,a)-\Omega_9^U(i,a)\right). \tag{31}$$

One can then use these calibrated parameter values to calculate wages (not just average wages) according to (15):

$$w_i(e,a_R-1) = \frac{1}{1+\Theta_i}\left[h_i(e,a_R-1)+\Theta_i c_i^U(e,a_R-1)\right],$$

These wages can then be plugged into (2), (7), and (8) to find $J_i(e,a)$, $E_i(e,a)$, and $U_i(e,a)$.

[to be completed].

Figure 1: Labor Market Outcomes by Race, Gender and Ethnicity

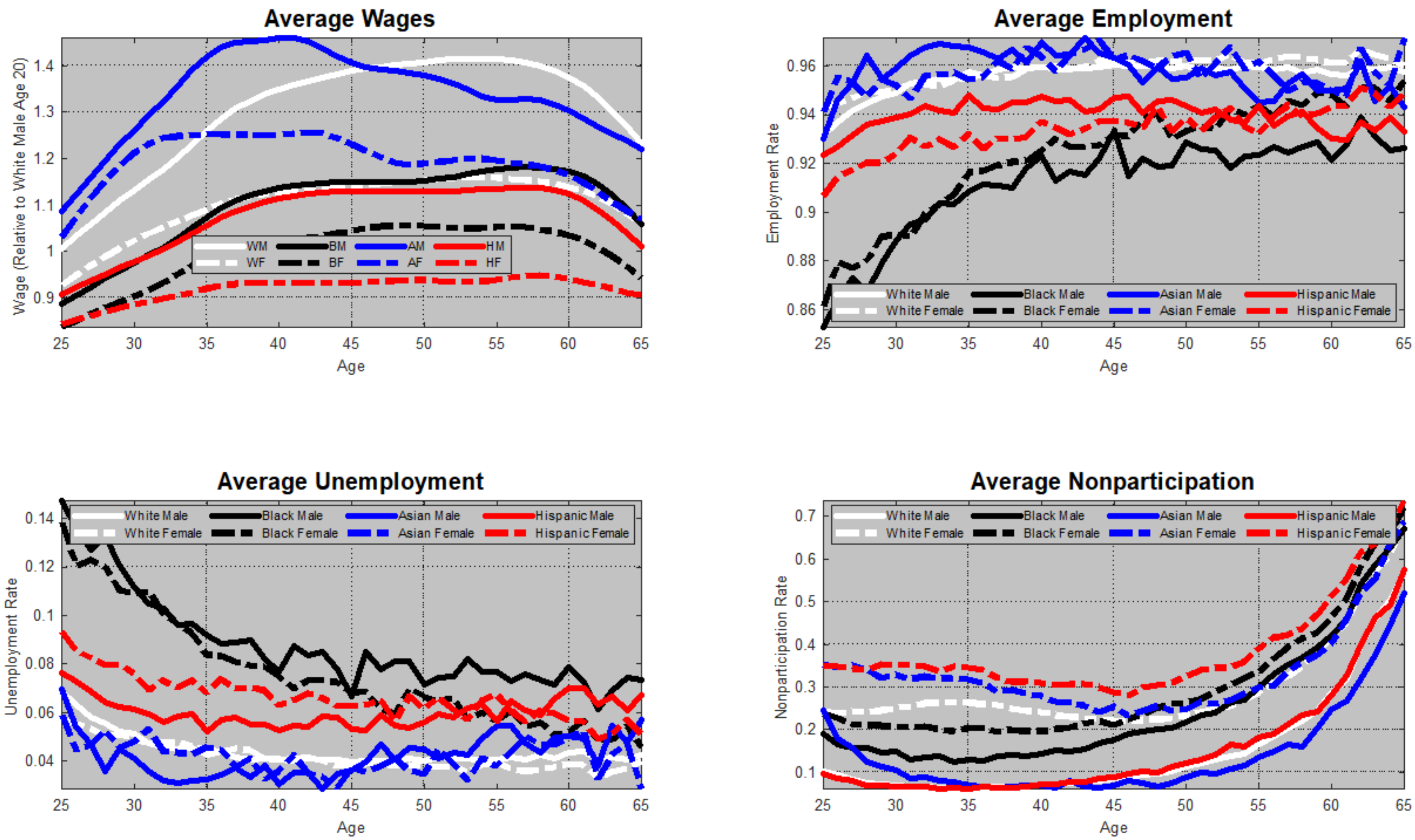

Figure 2: Job Finding and Destruction Rates by Race, Gender and Ethnicity

Figure 3: Wages by Education, Race, Gender and Ethnicity

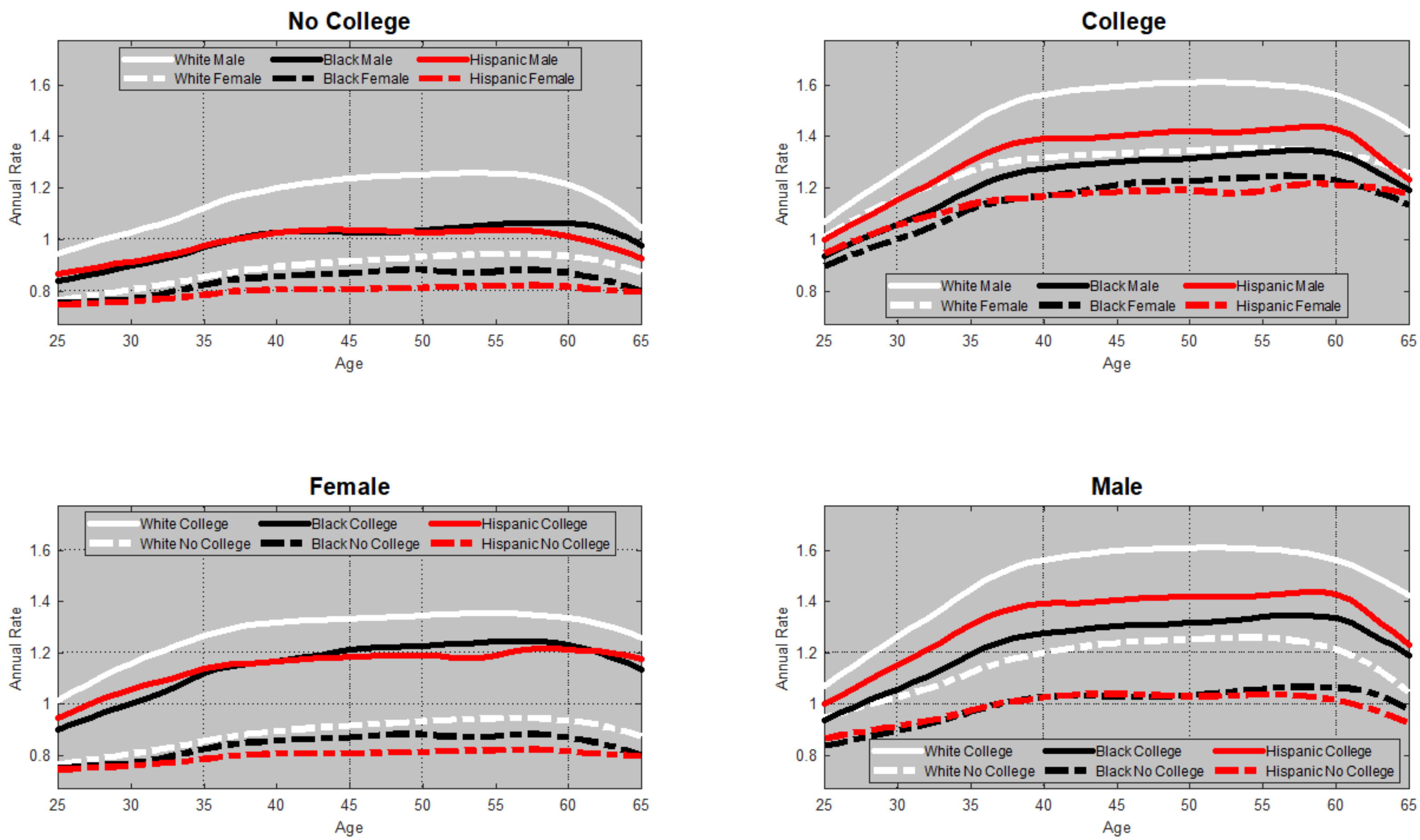

Figure 4: Job Finding Rates Unemployed

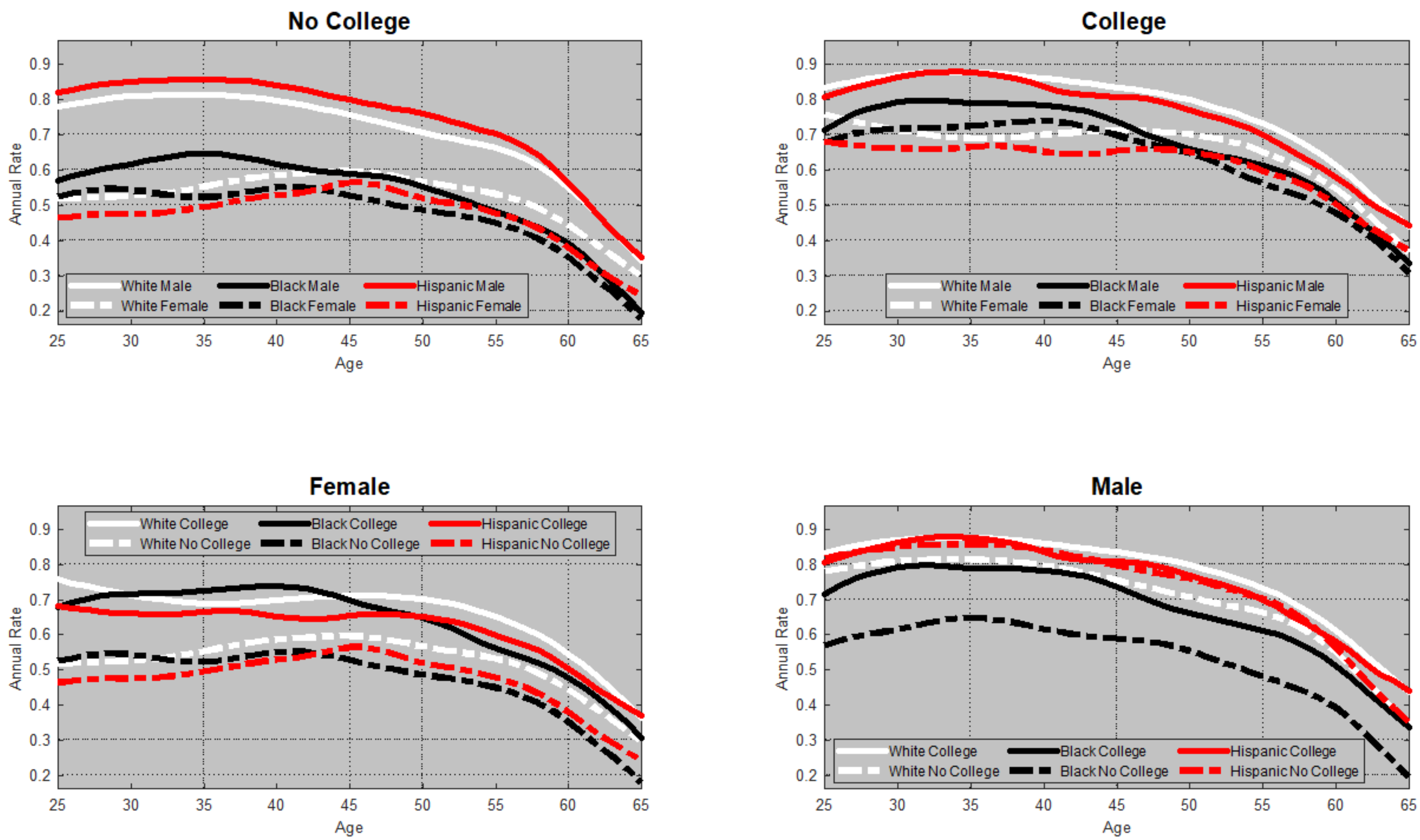

Figure 5: Job Finding Rates Nonparticipants

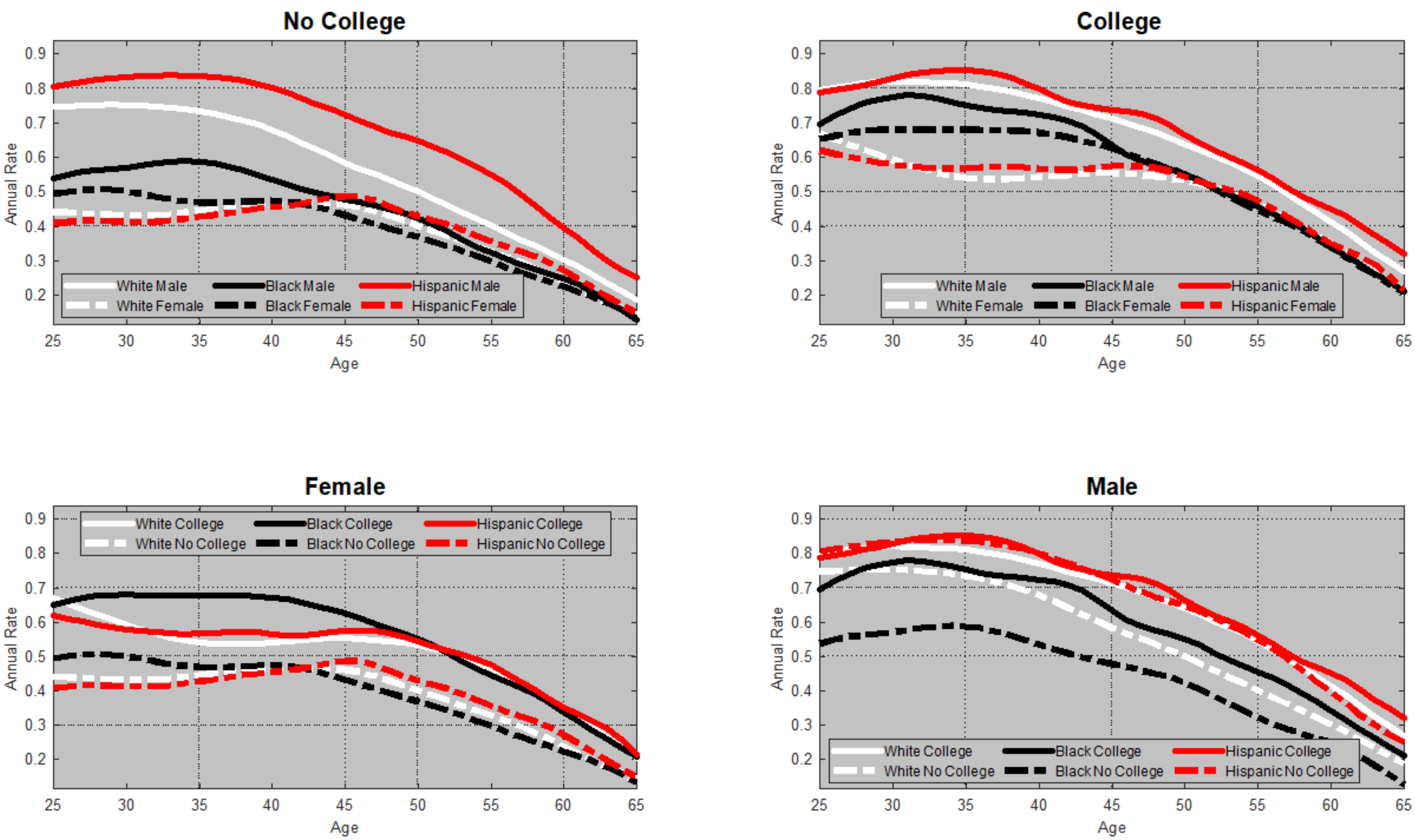

Figure 6: Job Destruction Rate to Unemployment

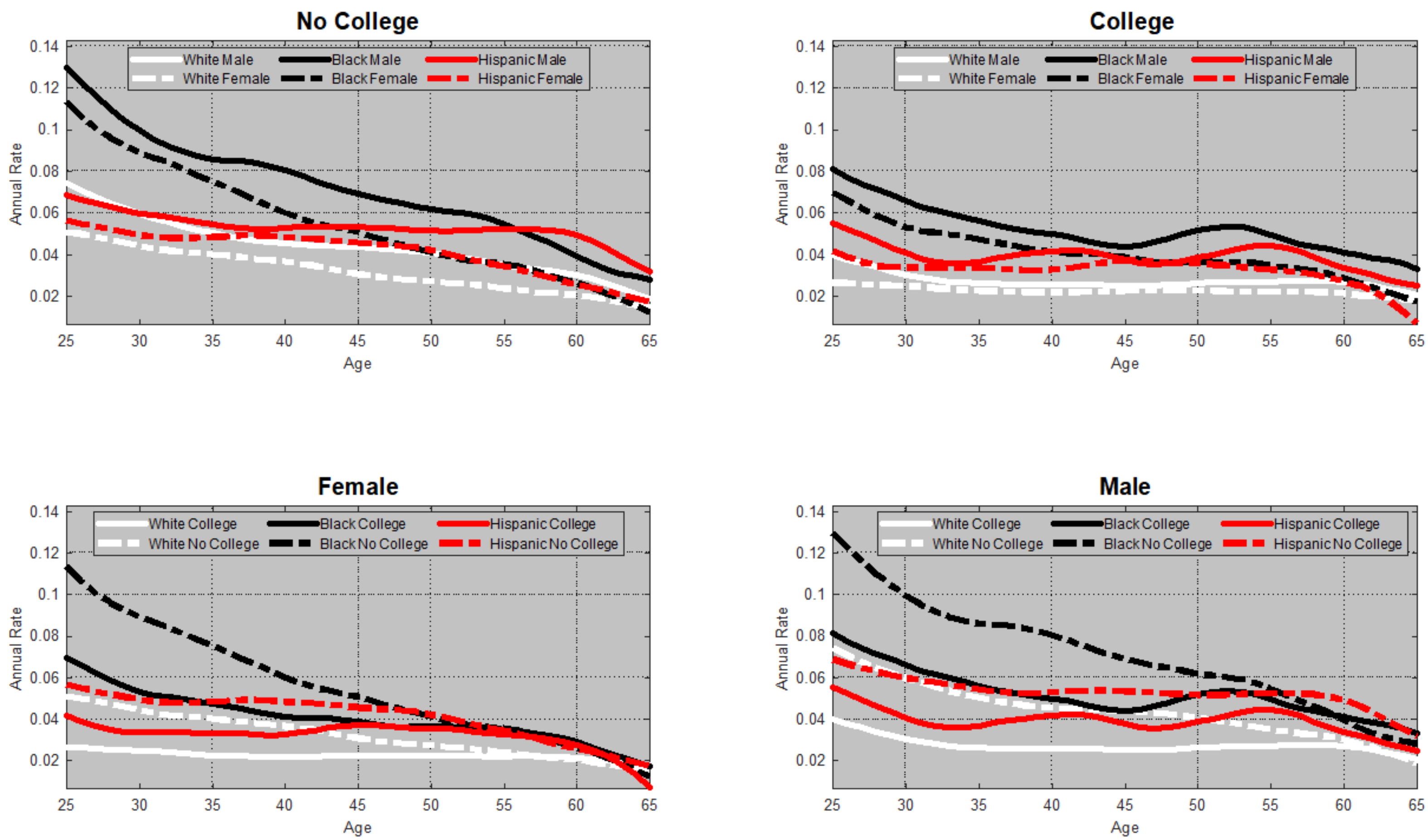

Figure 7: Job Destruction Rate to Nonparticipation

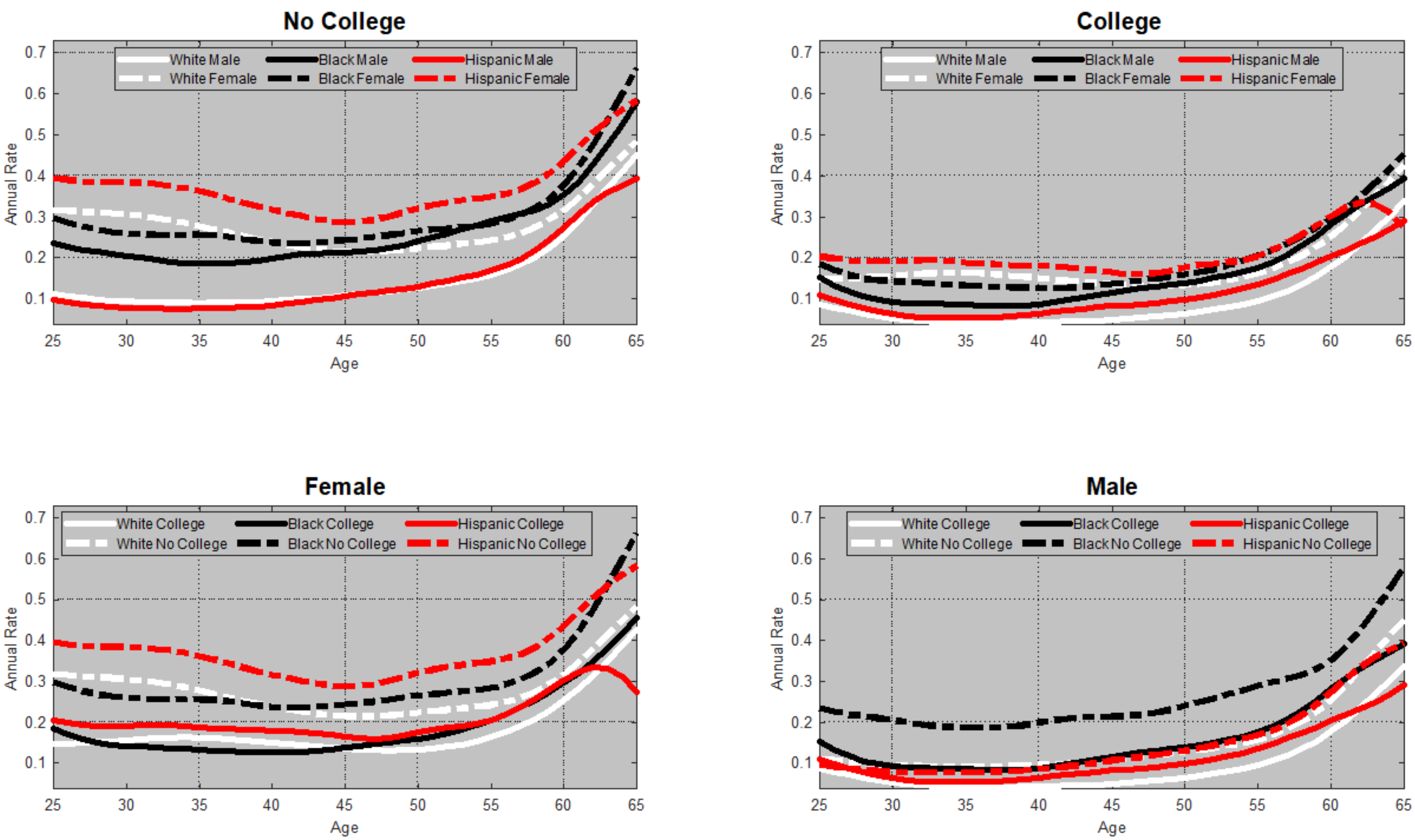

Figure 8: Transition to Nonparticipation from Unemployment

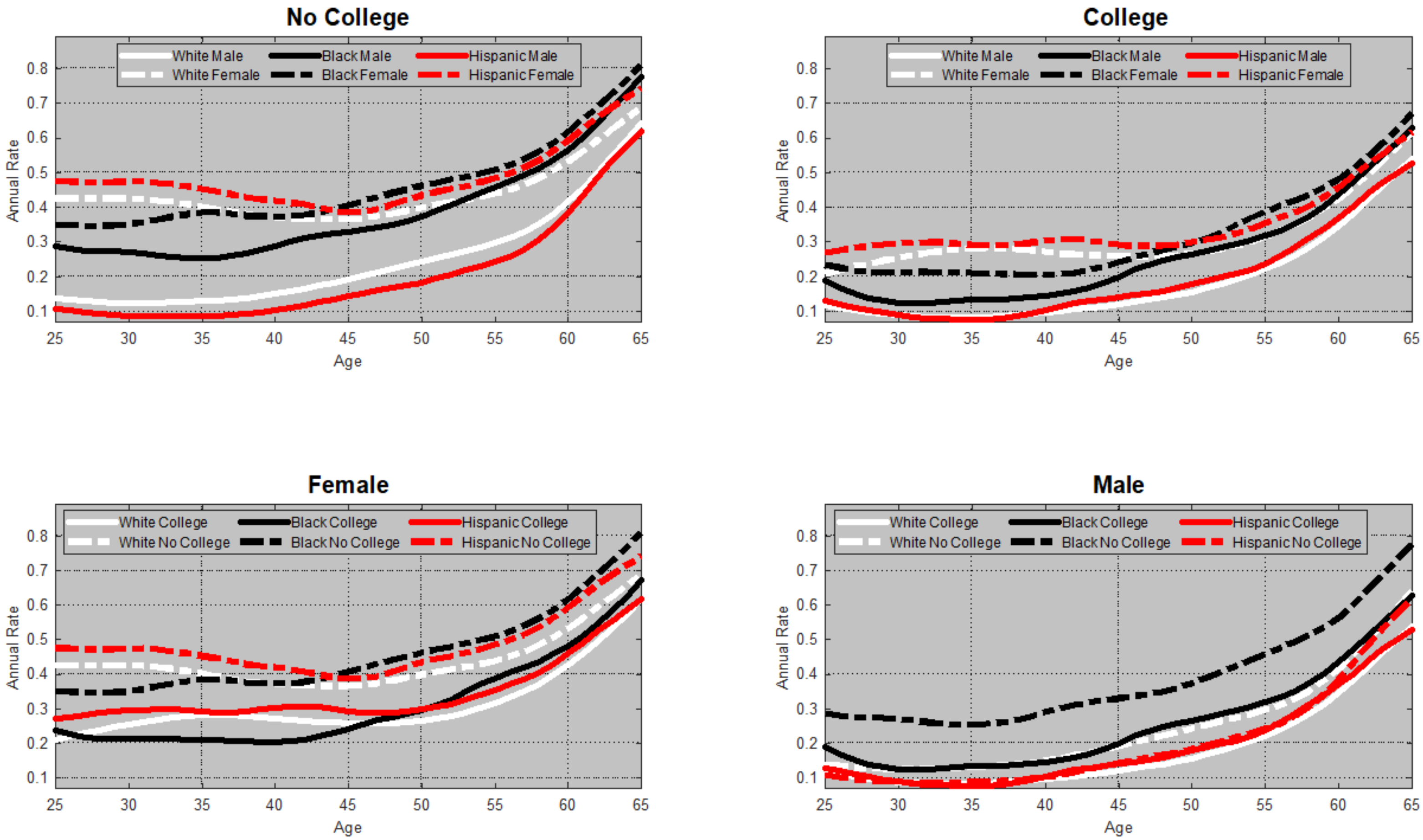

Figure 9: Human Capital, Returns to Experience and Profits by Race, Gender and Ethnicity

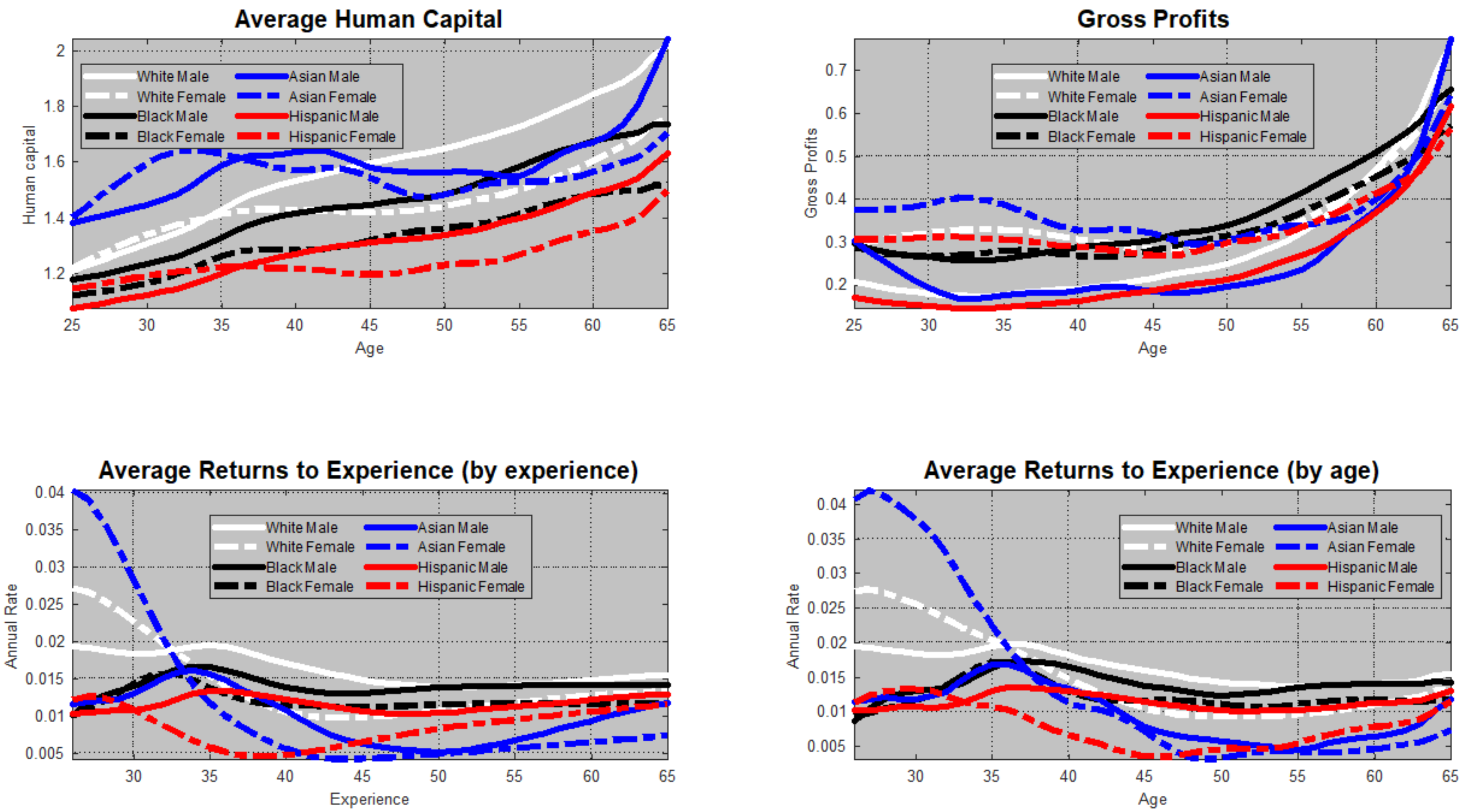

Figure 10: Matching Productivity and Job Market Tightness by Race, Gender and Ethnicity

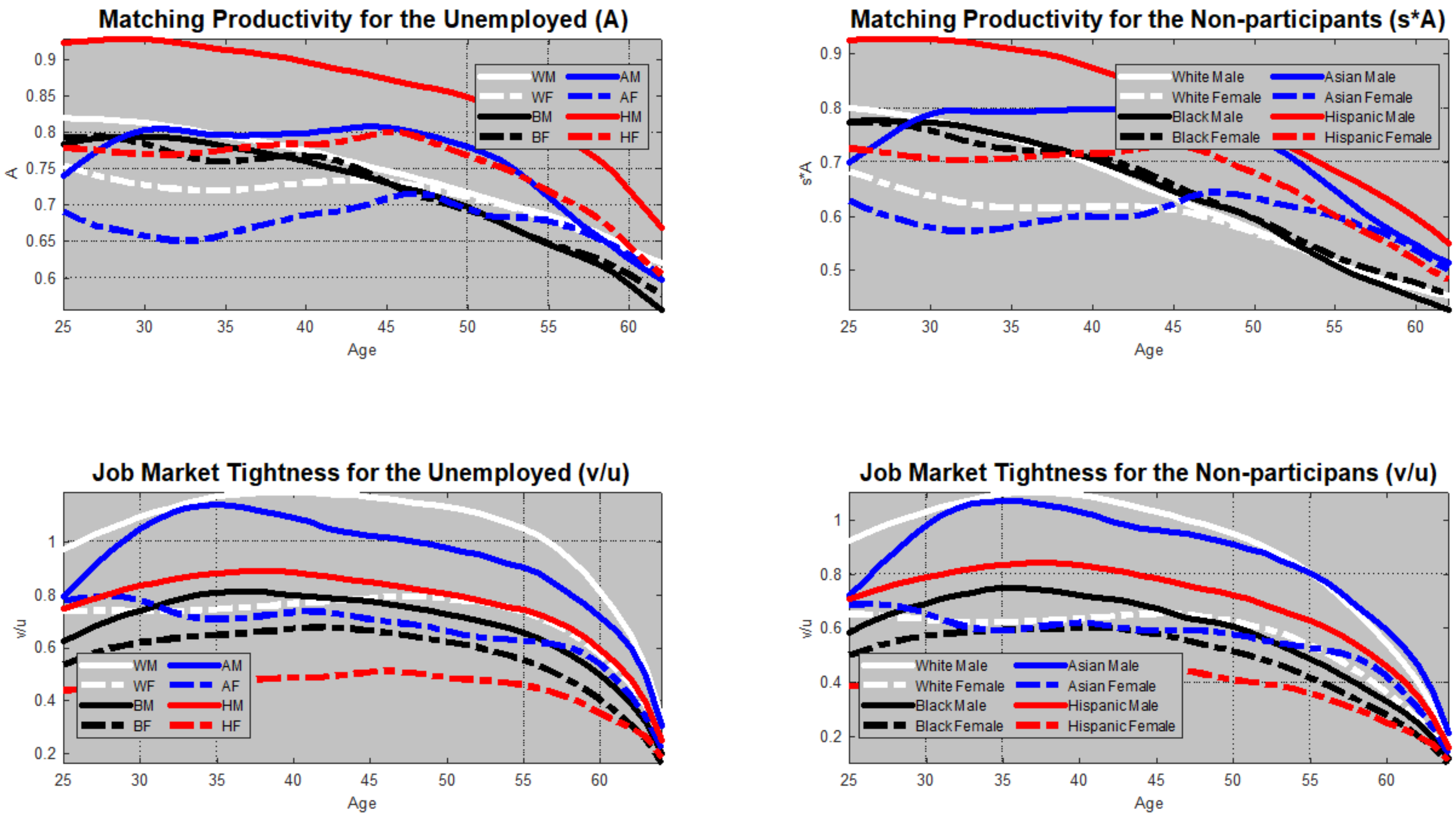

Figure 11: Average Human Capital by Education, Gender, Race and Ethnicity

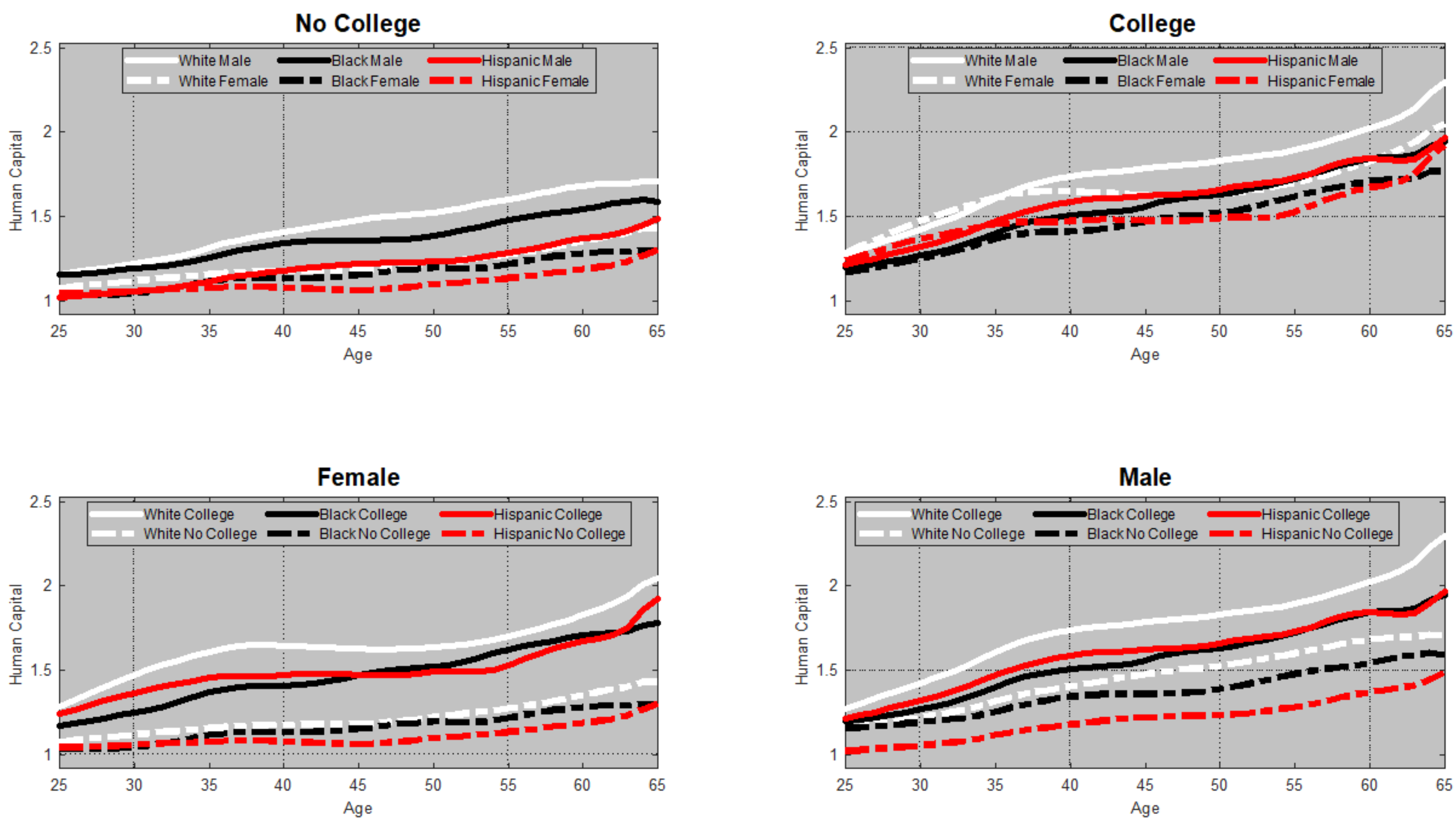

Figure 12: Gross Profits by Education, Gender, Race and Ethnicity

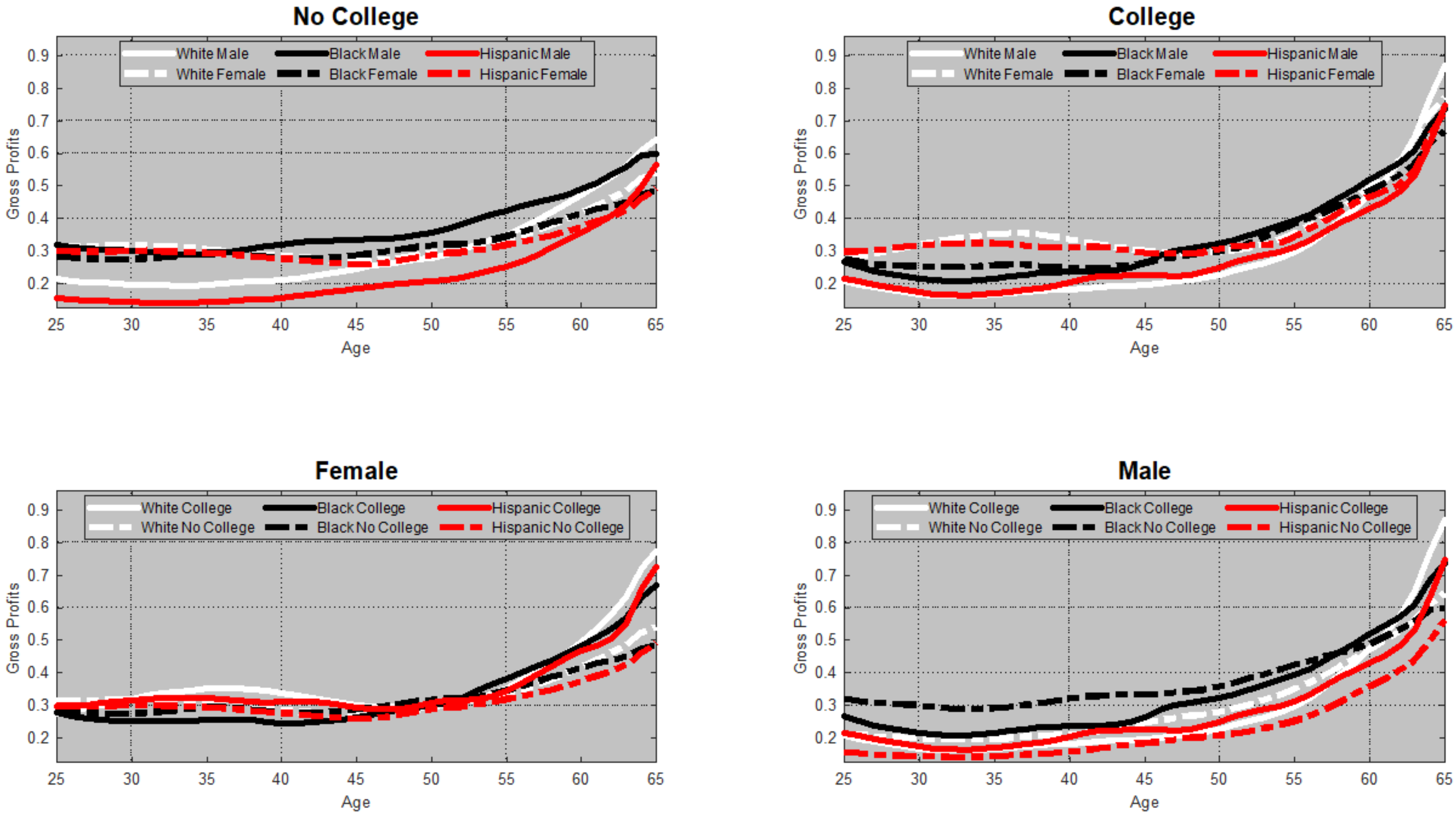

Figure 13: Returns to Experience by Education, Gender, Race and Ethnicity

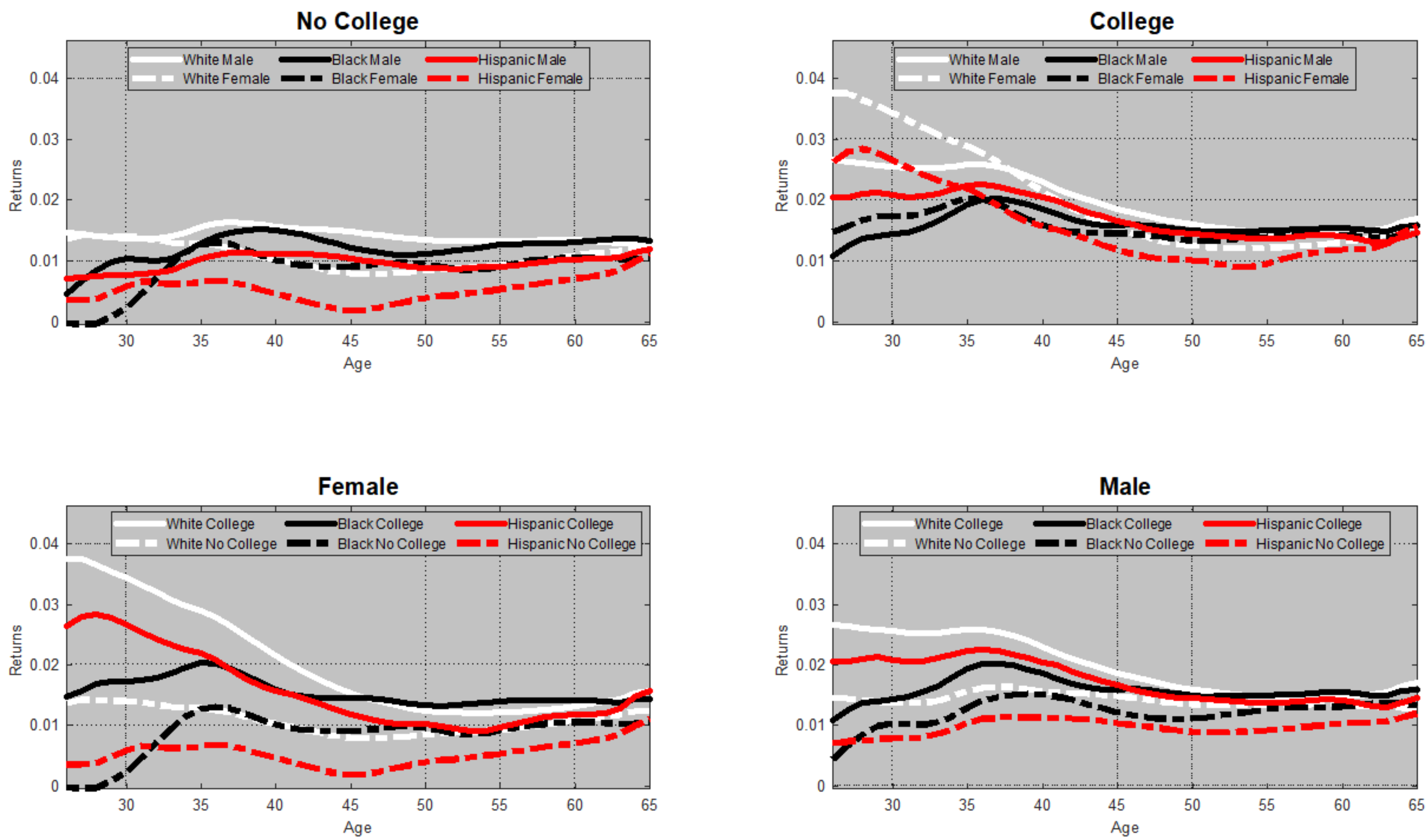

Figure 14: Matching Productivity (A) by Education, Gender, Race and Ethnicity

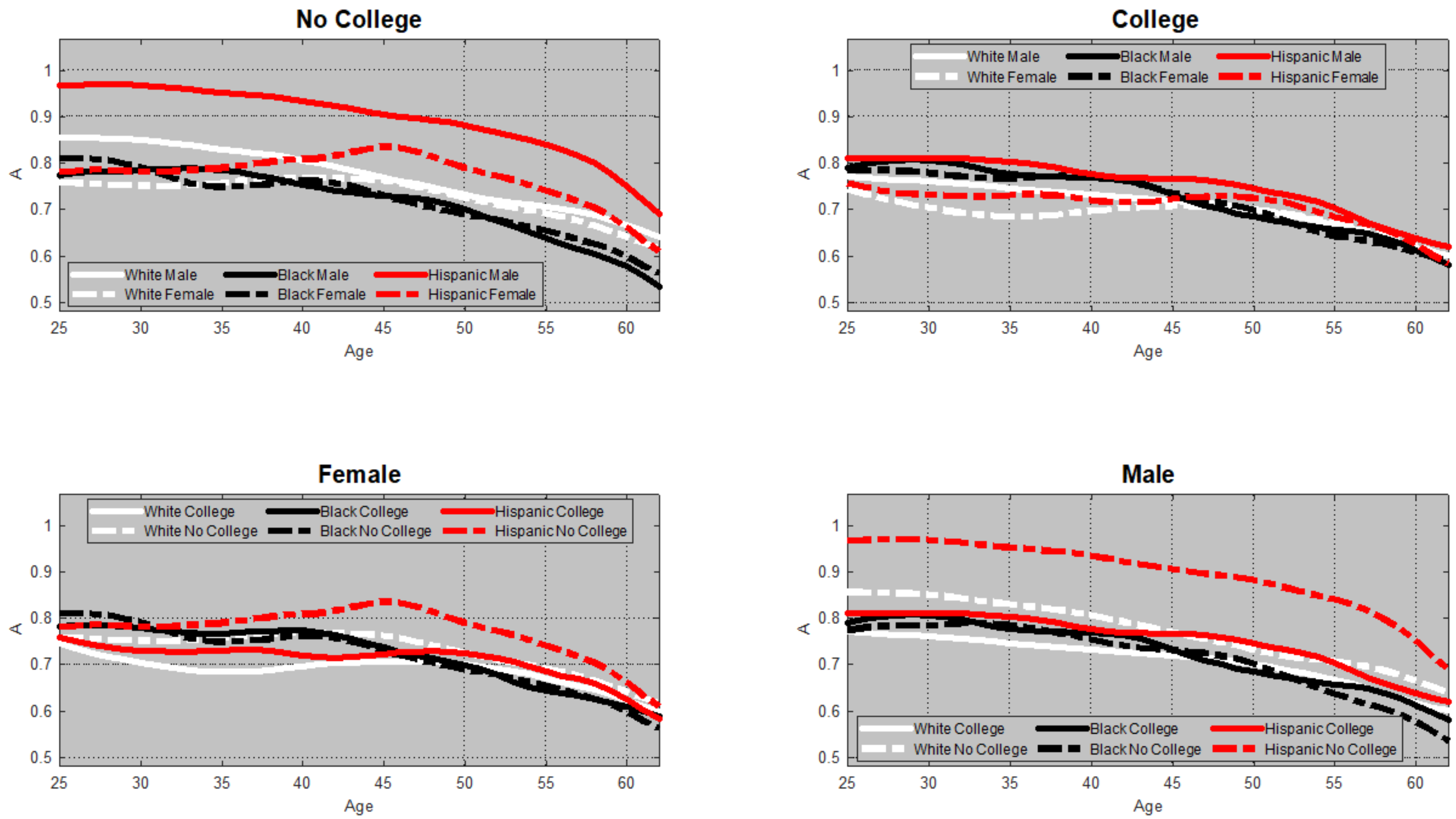

Figure 15: Job Market Tightness (v/u) for the Unemployed

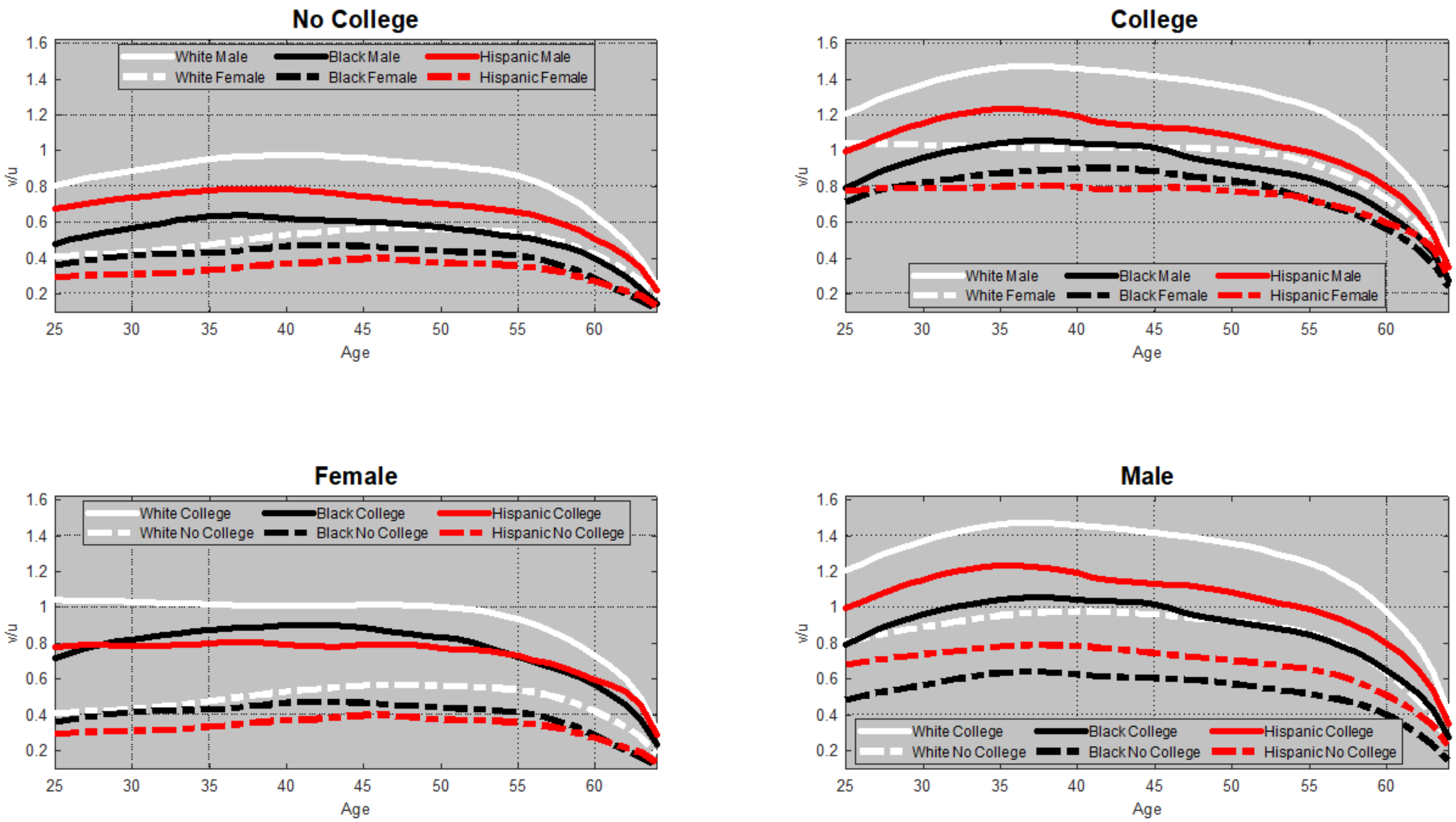

Figure 16: Job Market Tightness (v/u) for Non-participants

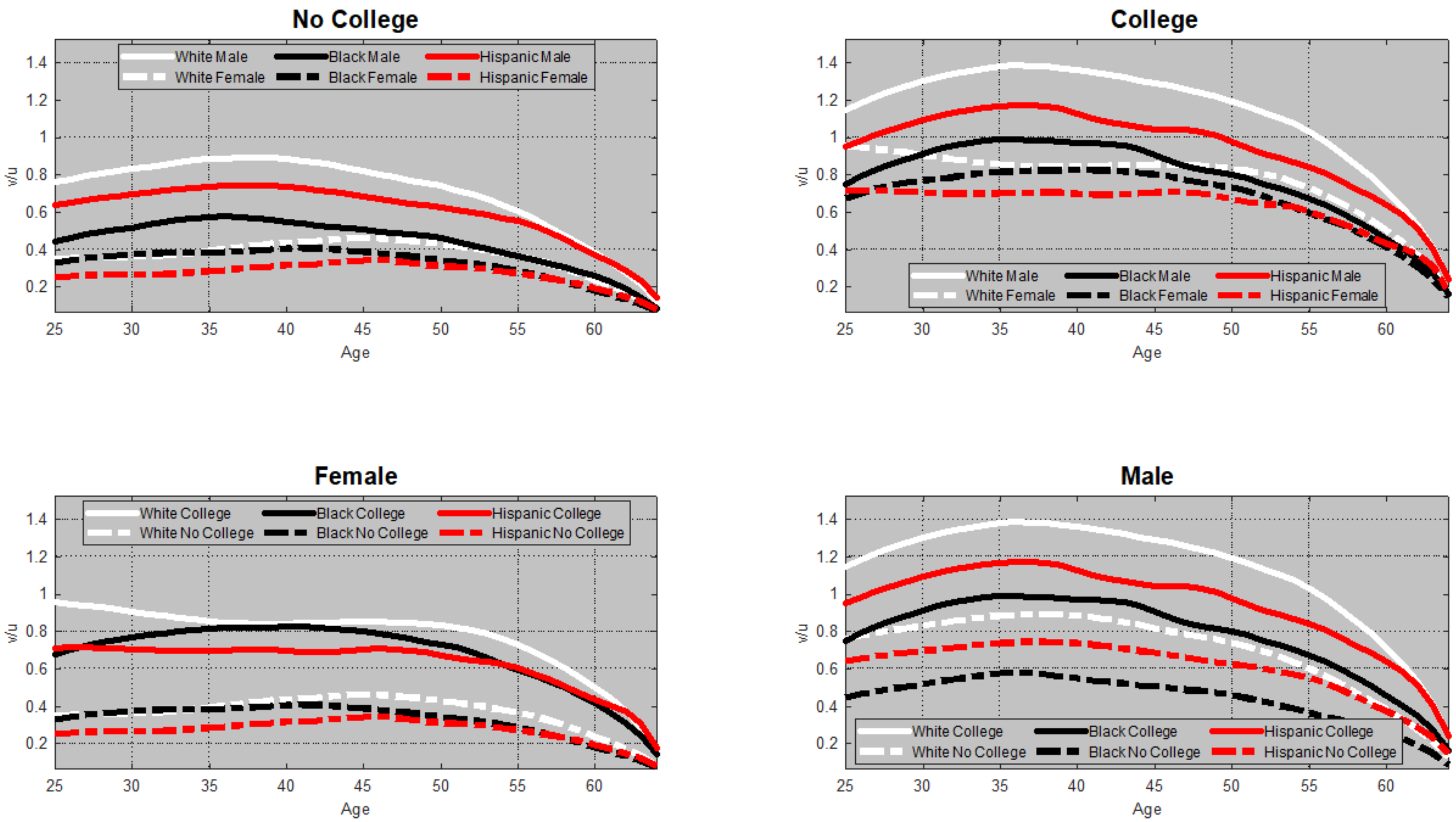

Figure 17: Counterfactual White Females (compared to White Males)

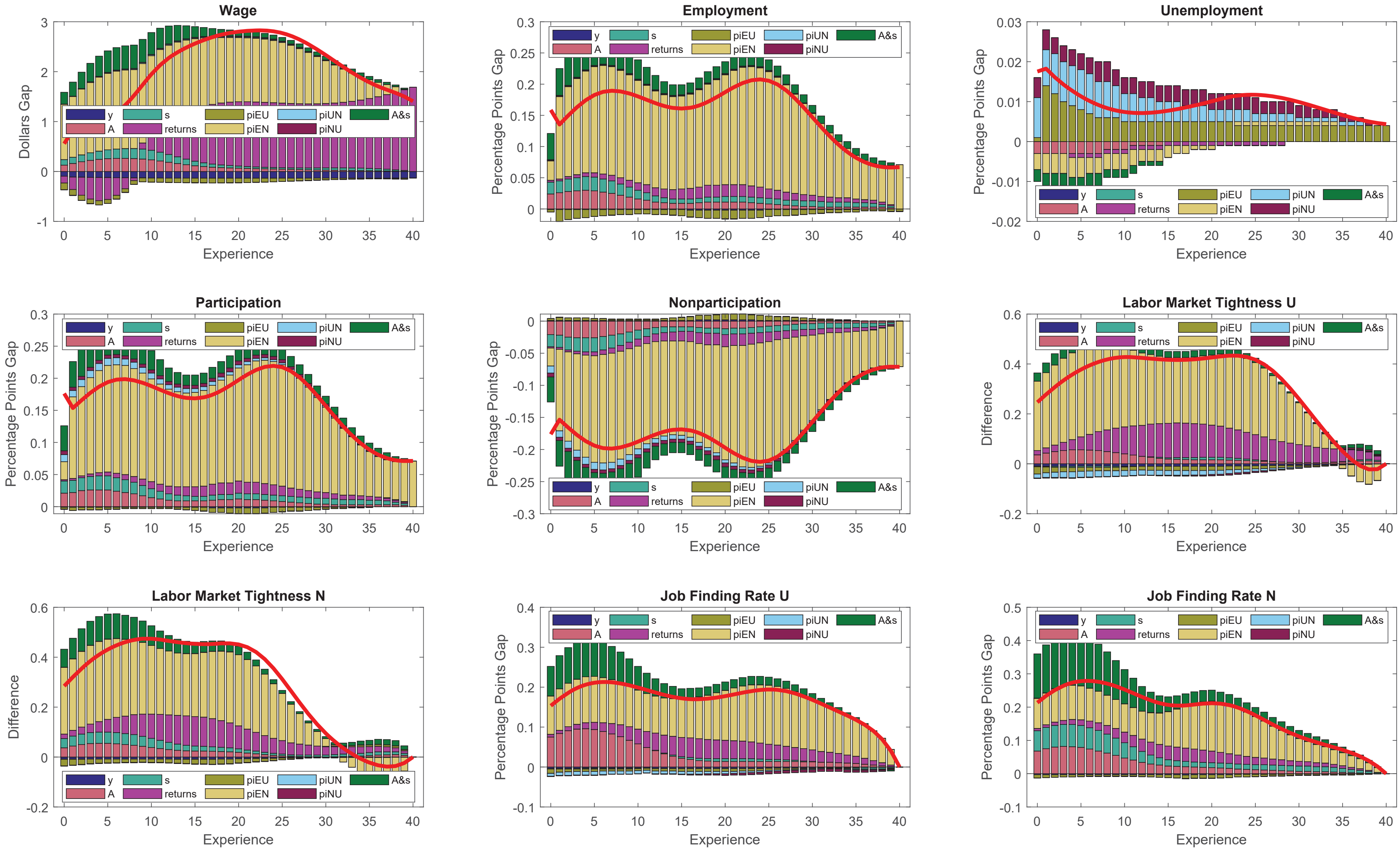

Figure 18: Counterfactual Black Males (compared to White Males)

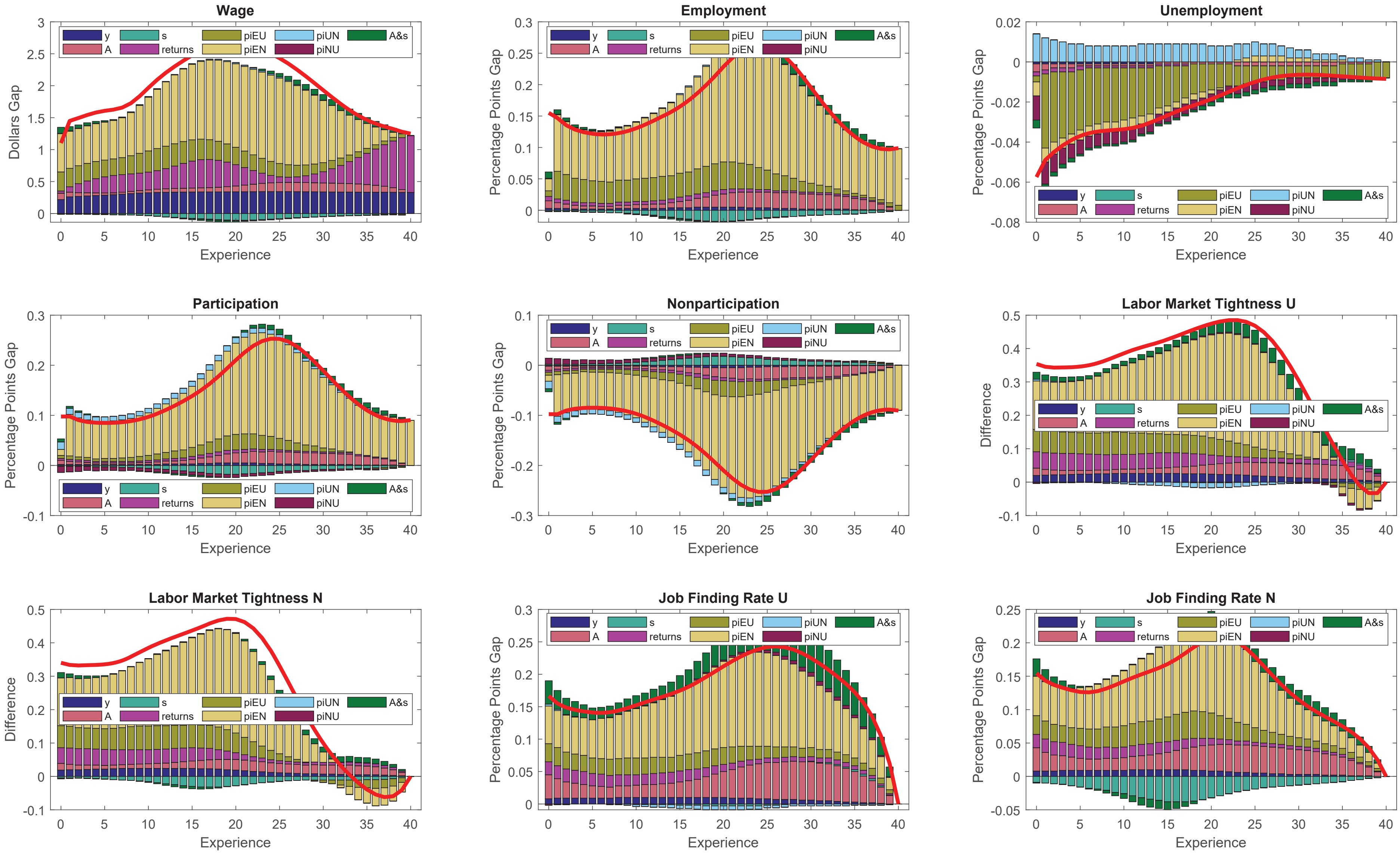

Figure 19: Counterfactual Black Females (compared to White Males)

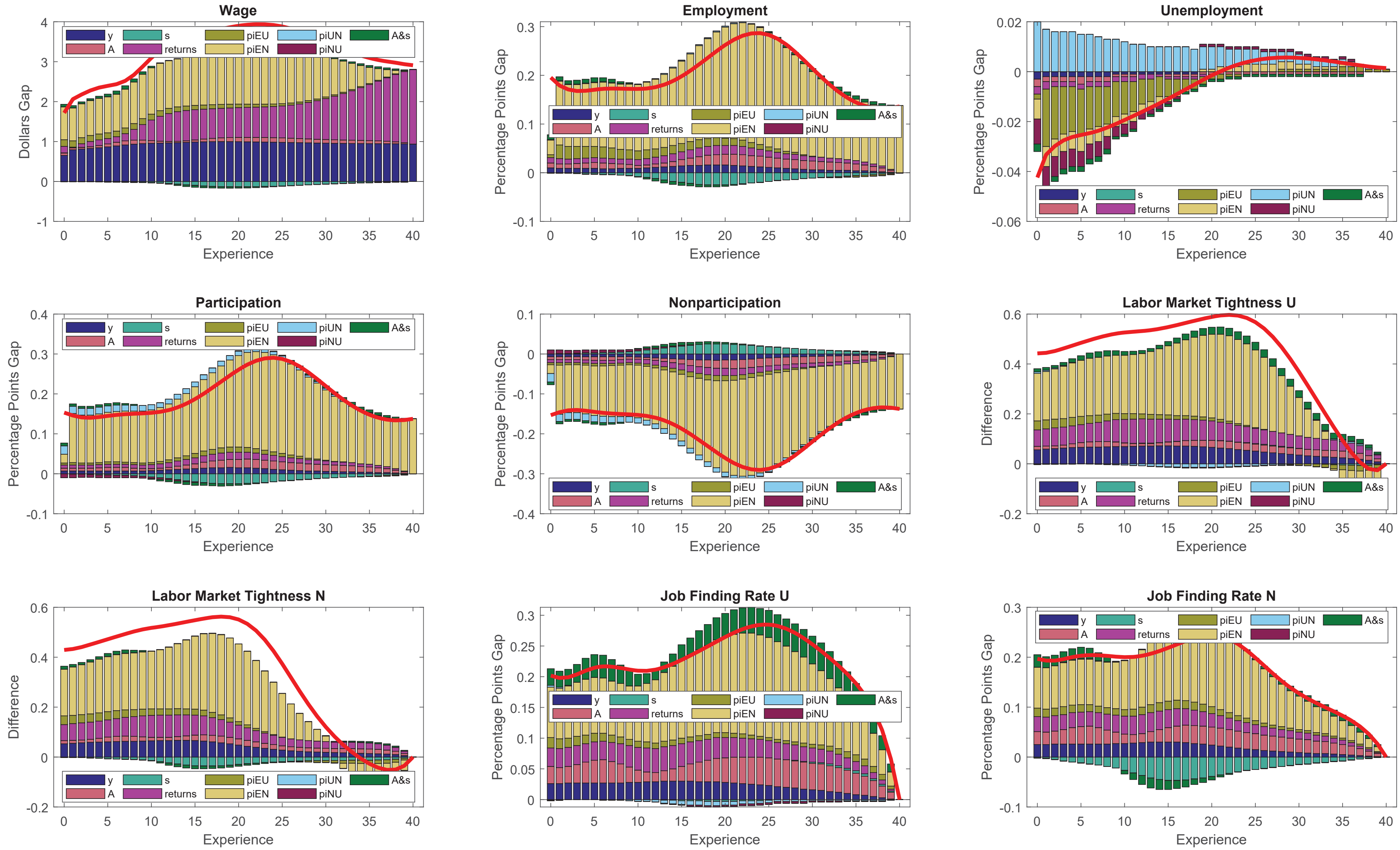

Figure 20: Counterfactual Asian Males (compared to White Males)

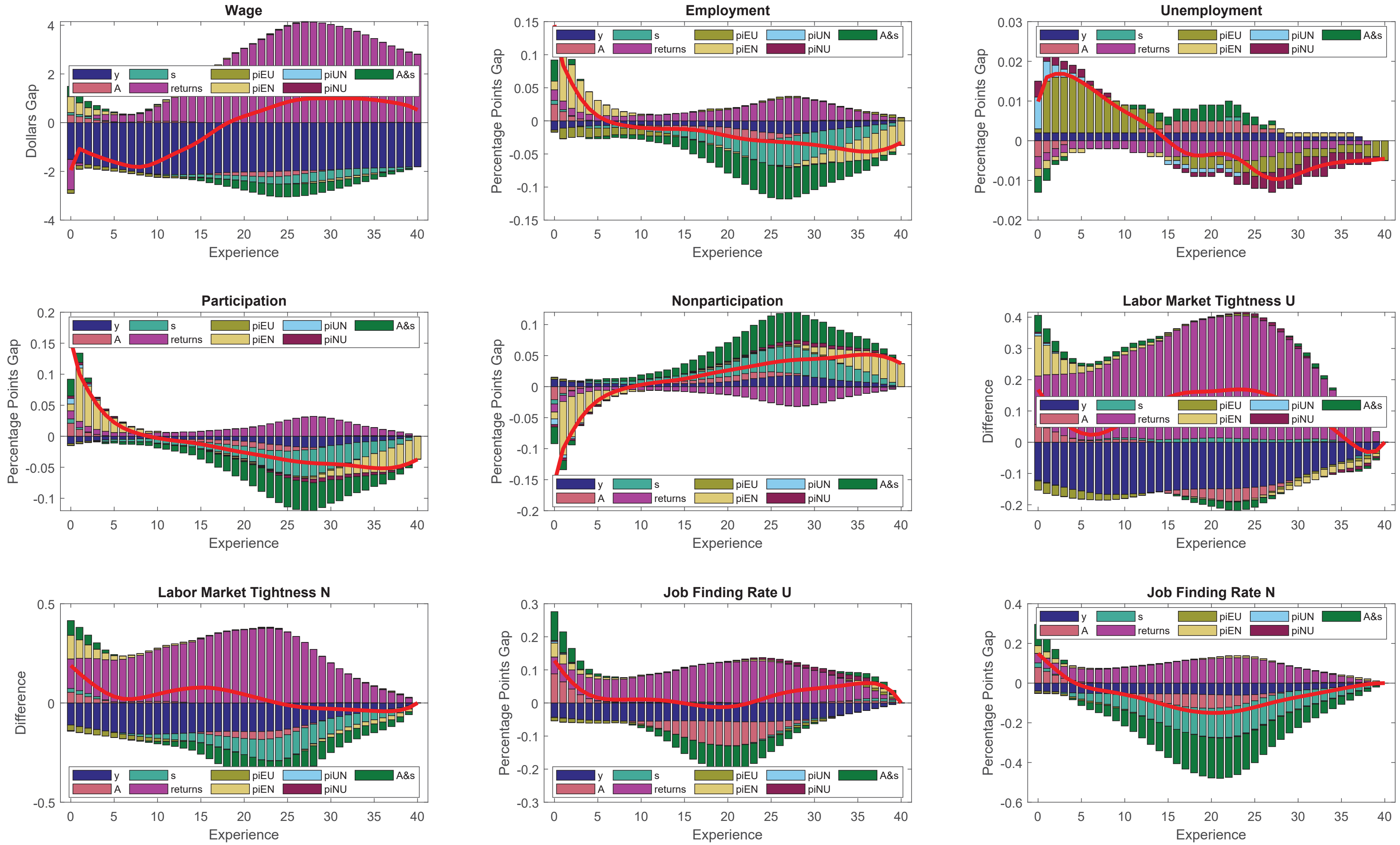

Figure 21: Counterfactual Asian Females (compared to White Males)

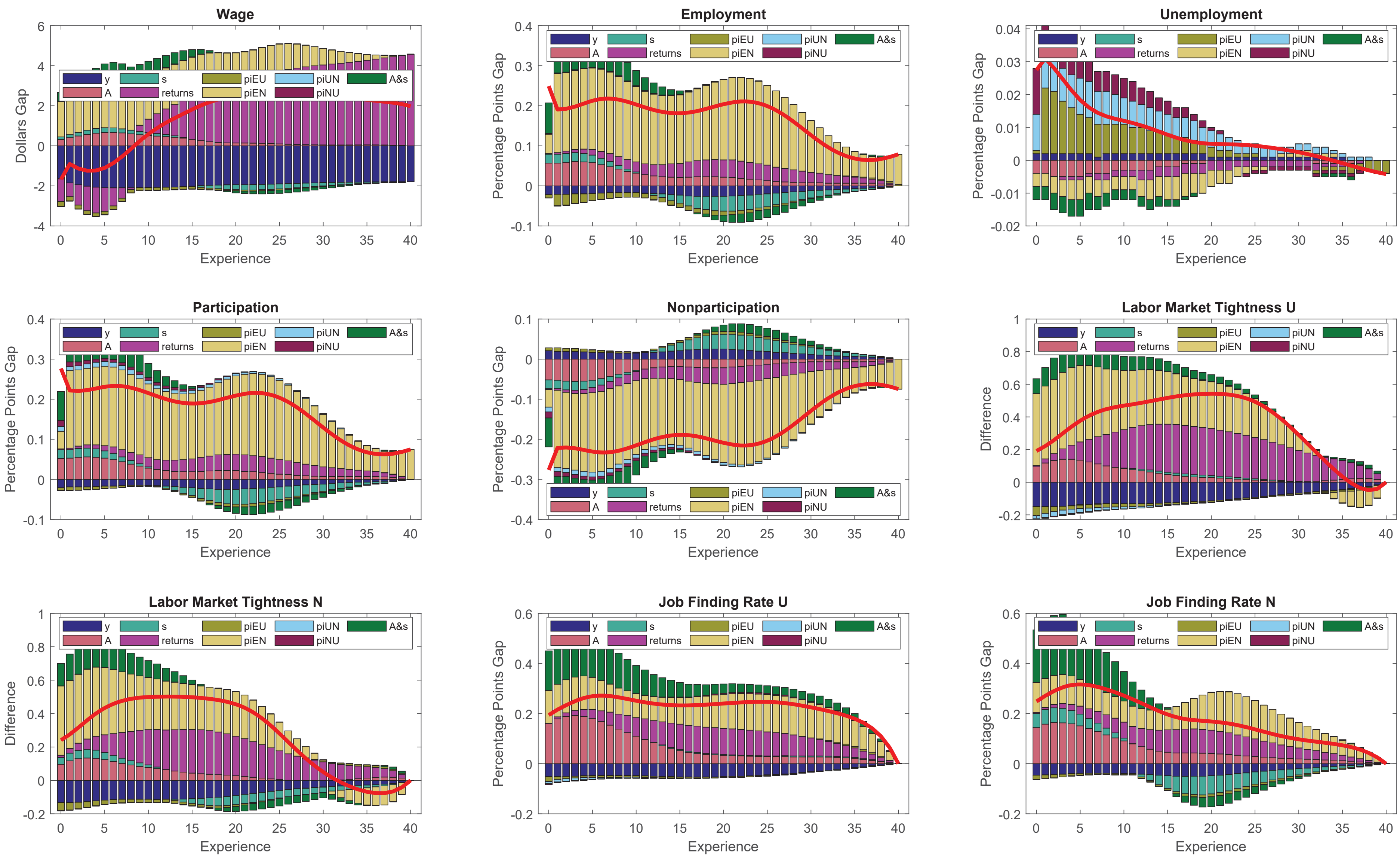

Figure 22: Counterfactual Hispanic Males (compared to White Males)

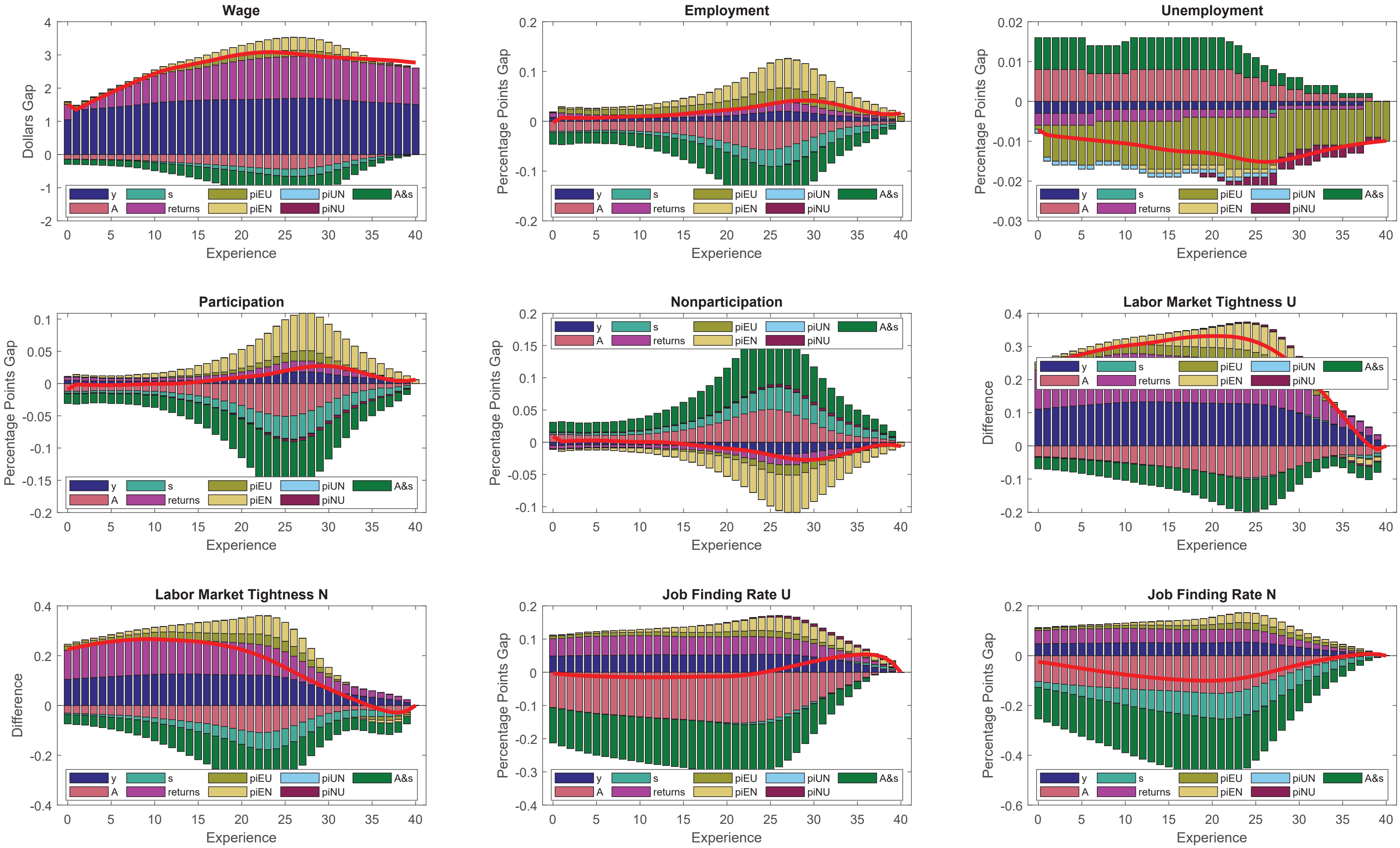

Figure 23: Counterfactual Hispanic Females (compared to White Males)

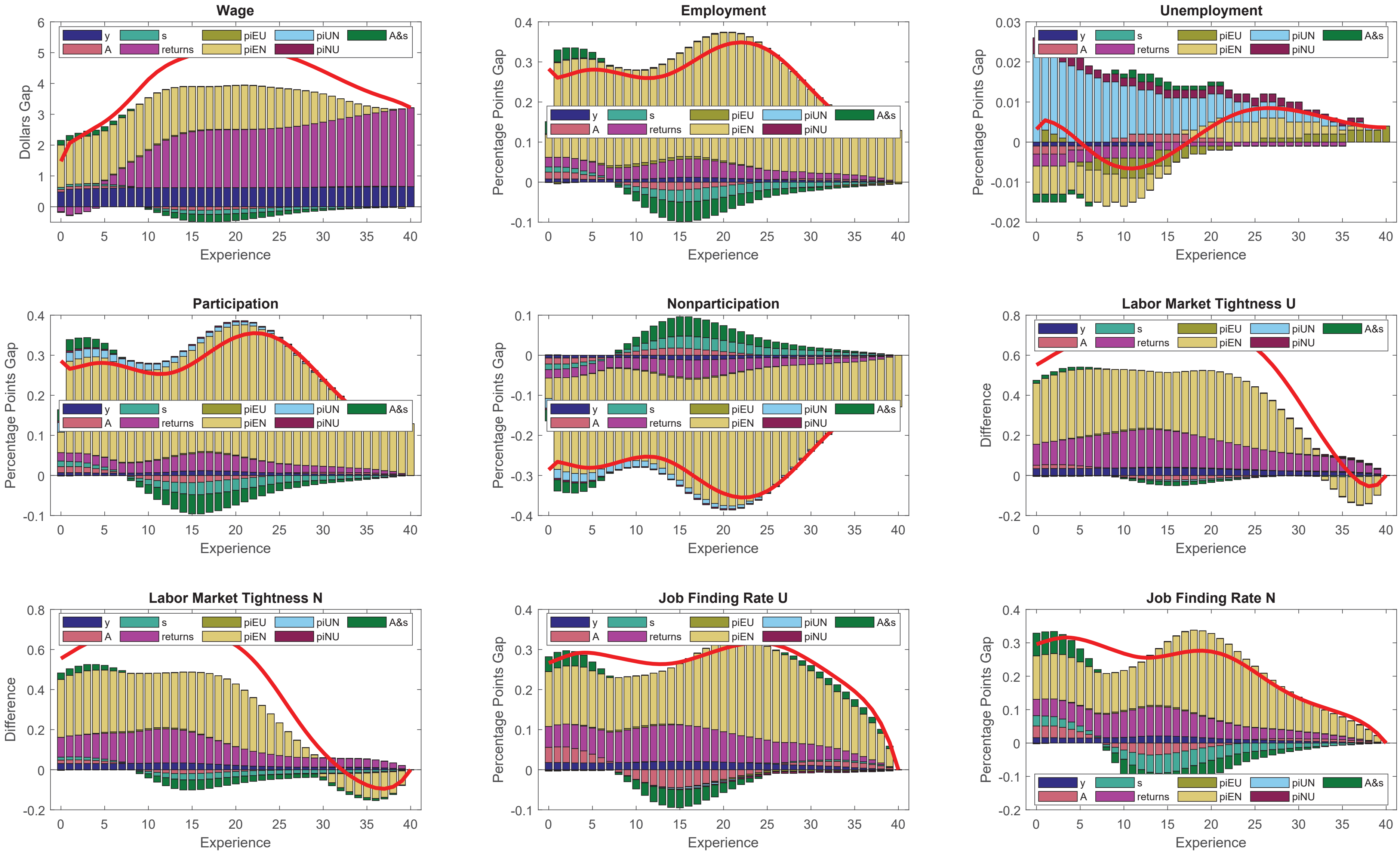

Figure 24: Counterfactual Skilled White Females (compared to Skilled White Males)

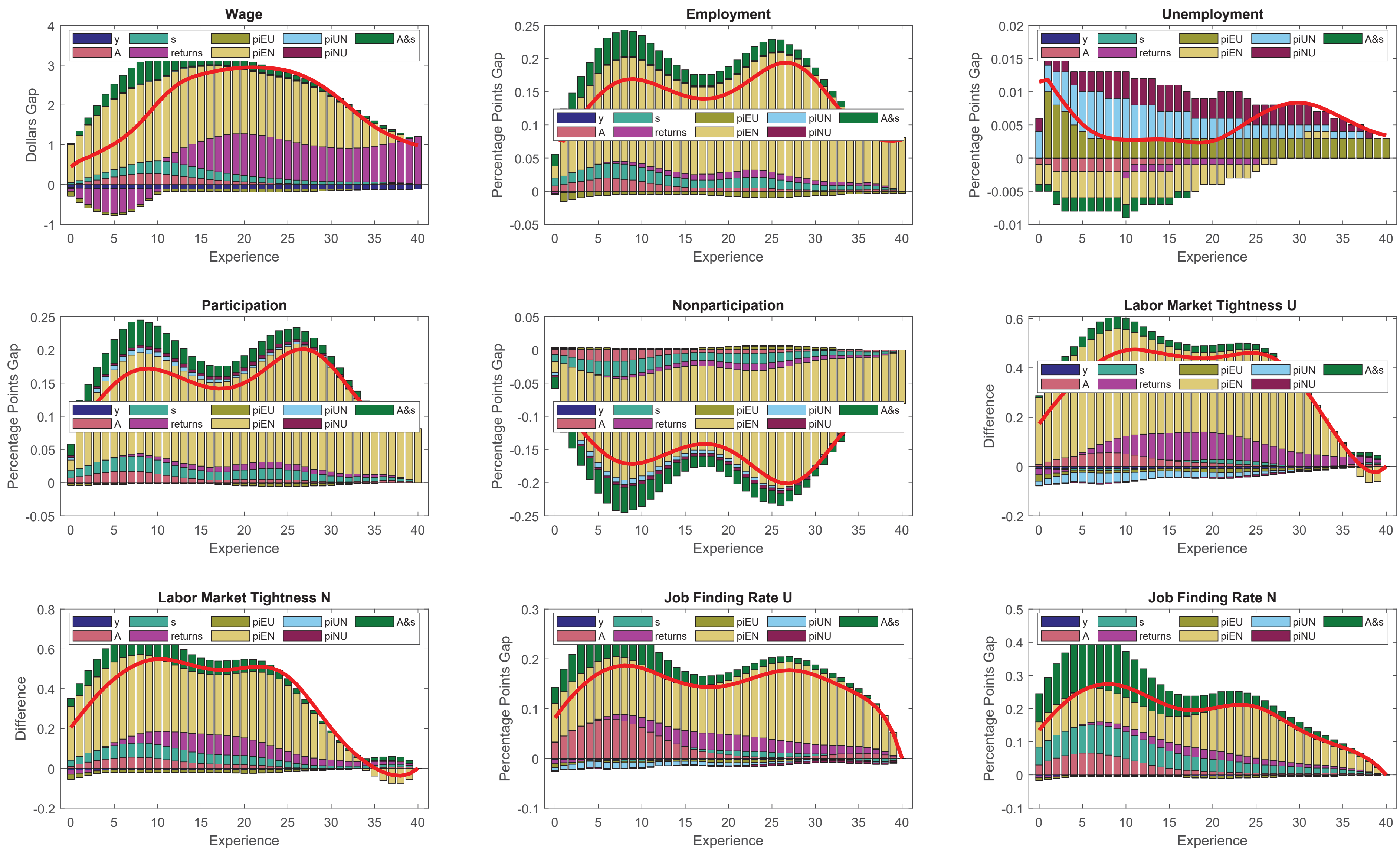

Figure 25: Counterfactual Unskilled White Females (compared to Unskilled White Males)

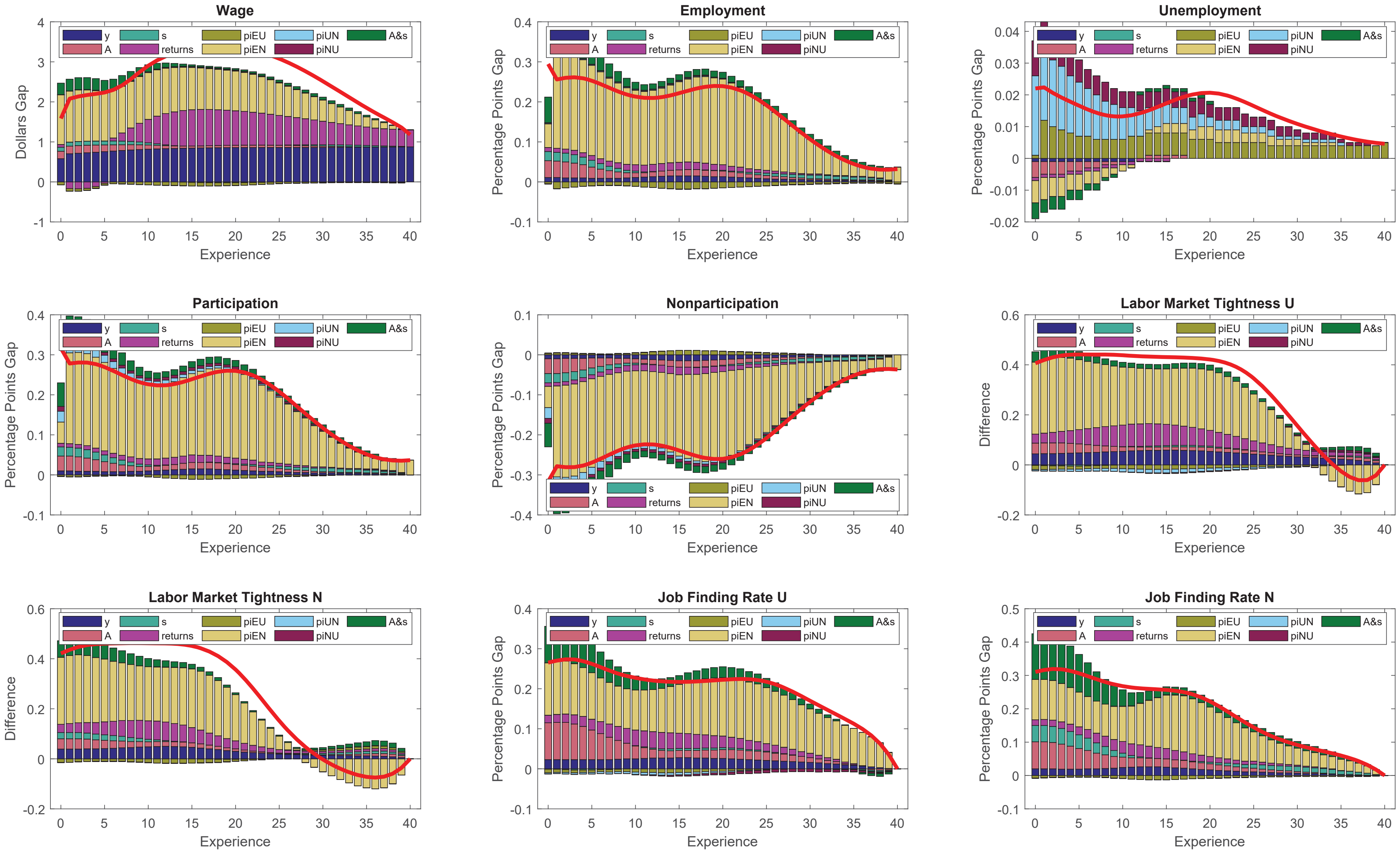

Figure 26: Counterfactual Skilled Black Males (compared to Skilled White Males)

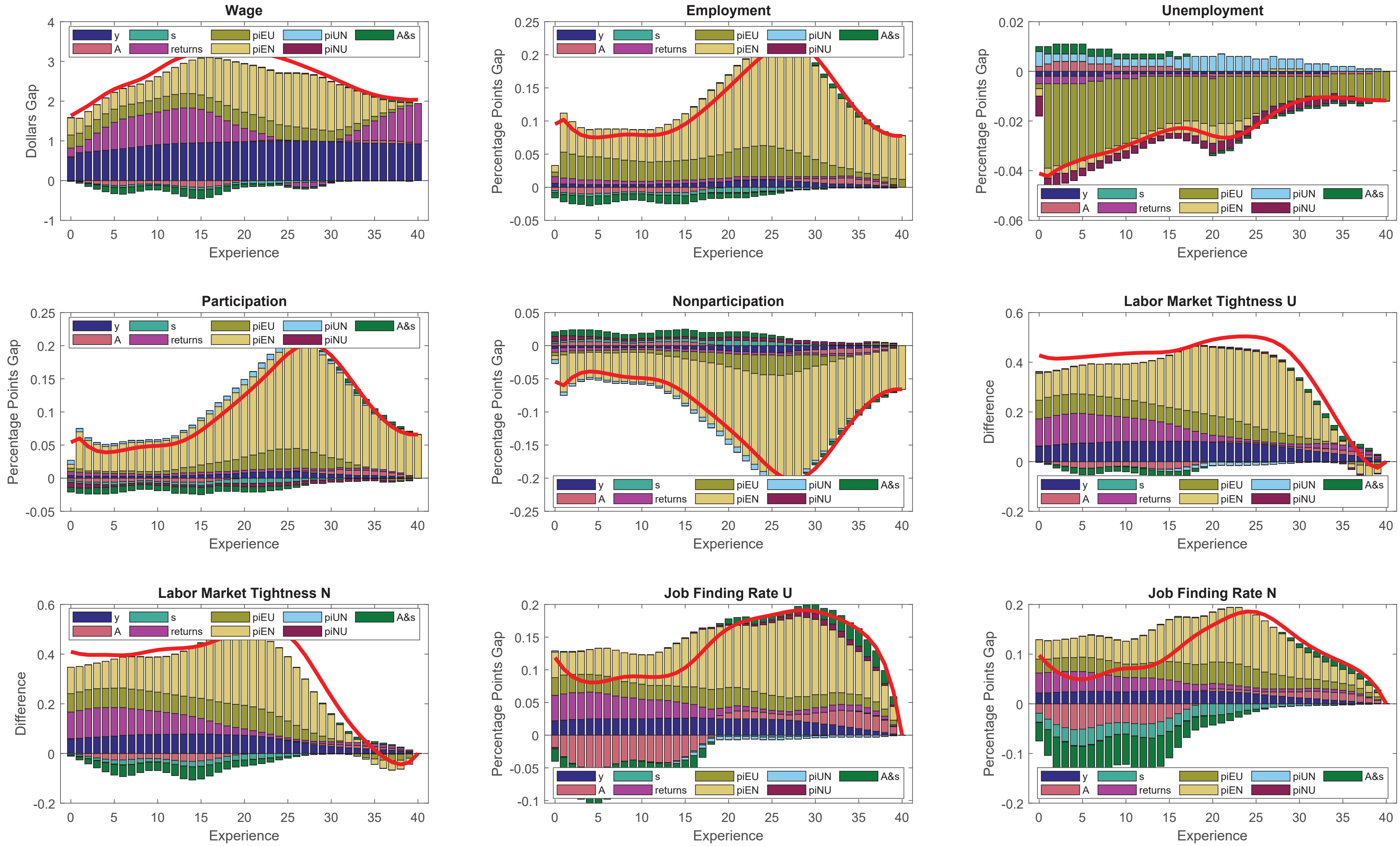

Figure 27: Counterfactual Unskilled Black Males (compared to Unskilled White Males)

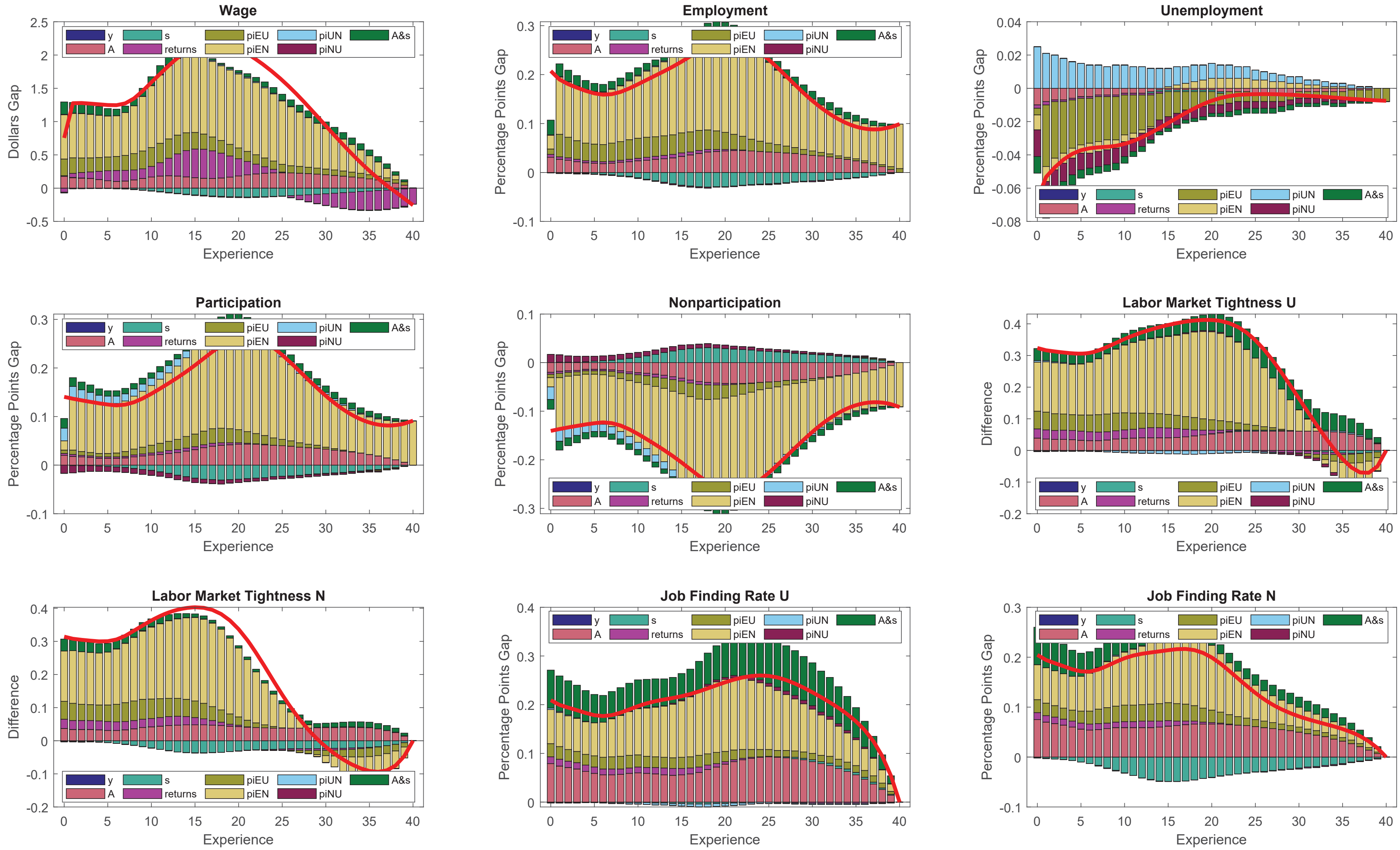

Figure 28: Counterfactual Skilled Black Females (compared to Skilled White Males)

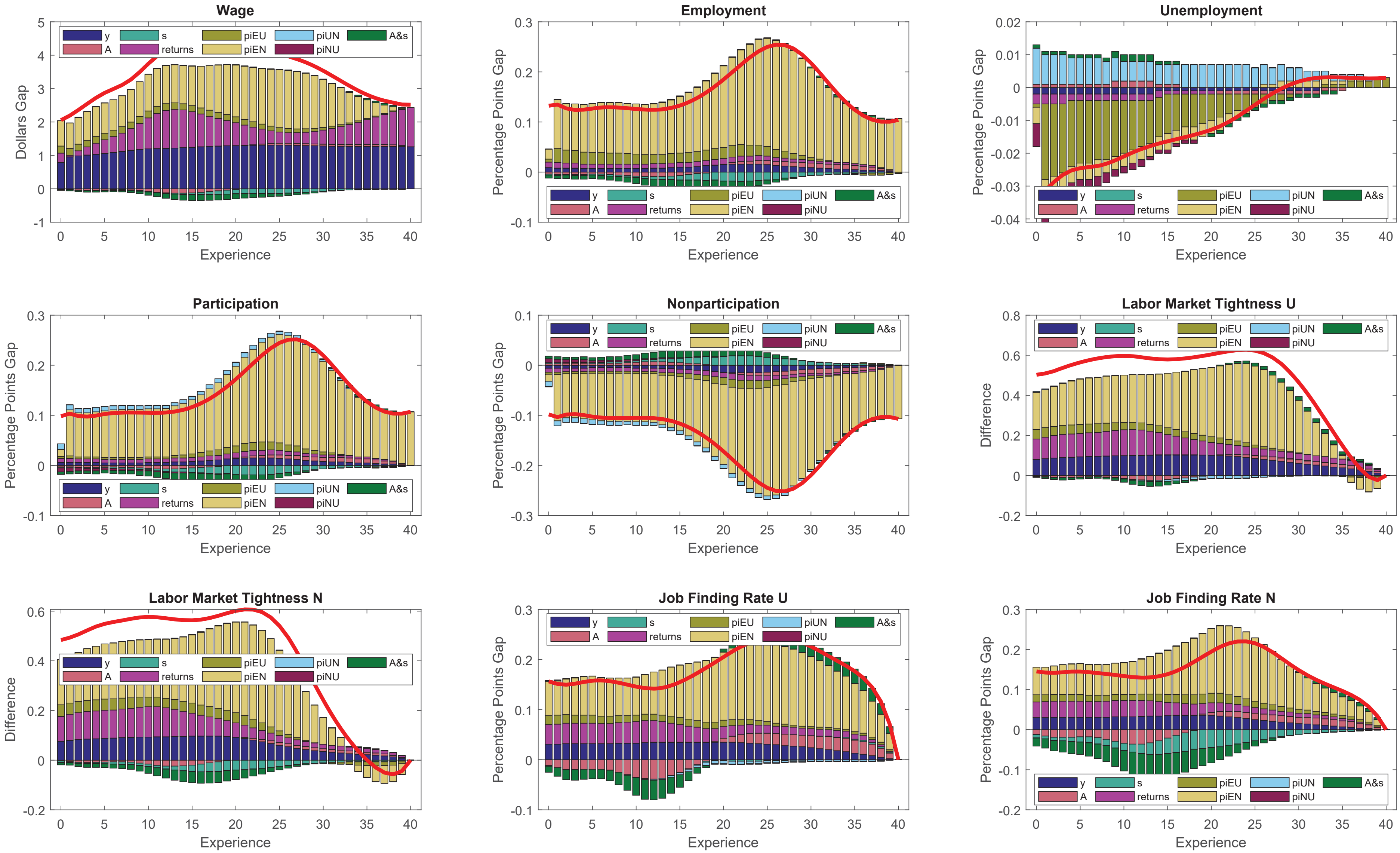

Figure 29: Counterfactual Unskilled Black Females (compared to Unskilled White Males)

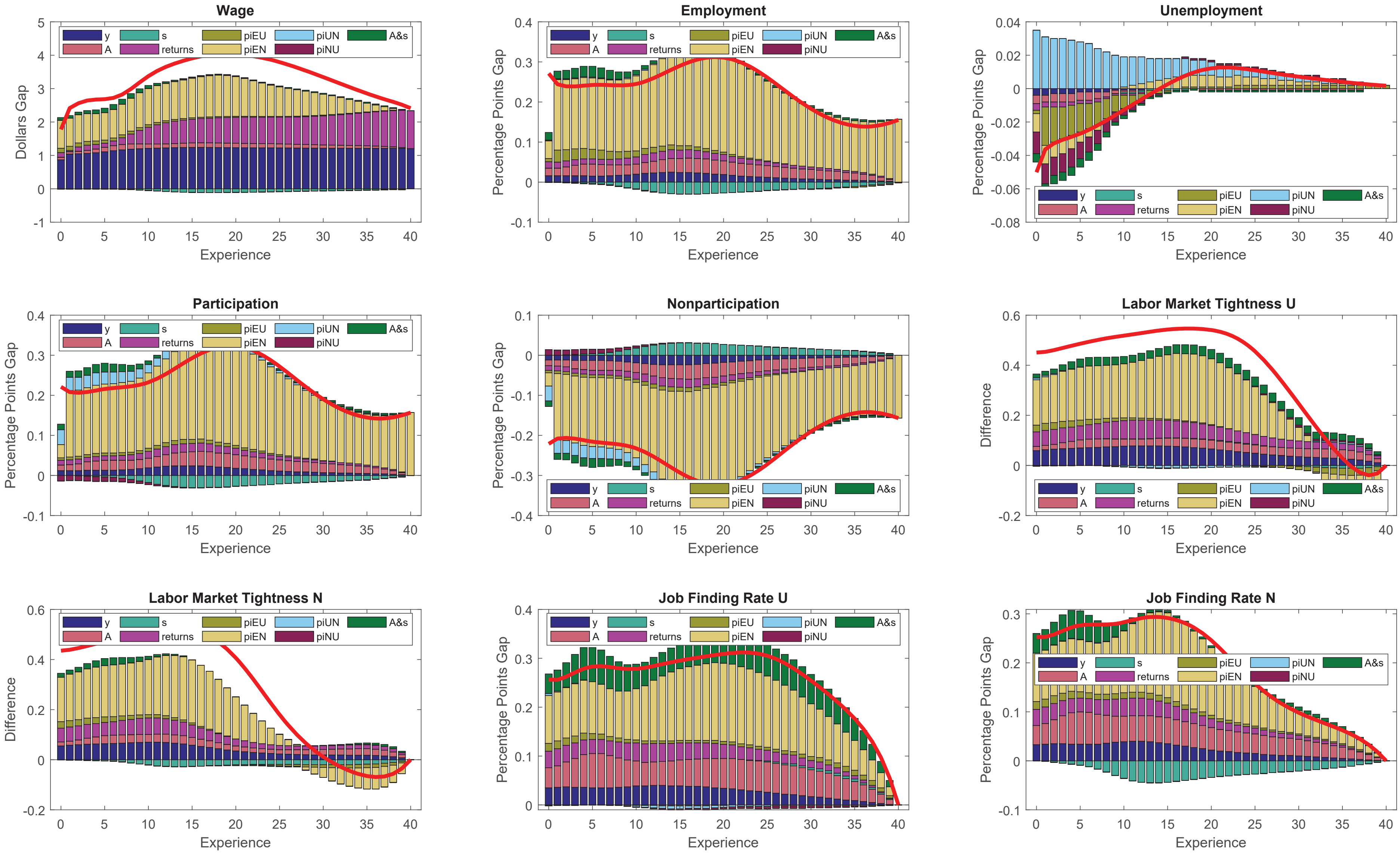

Figure 30: Counterfactual Skilled Hispanic Males (compared to Skilled White Males)

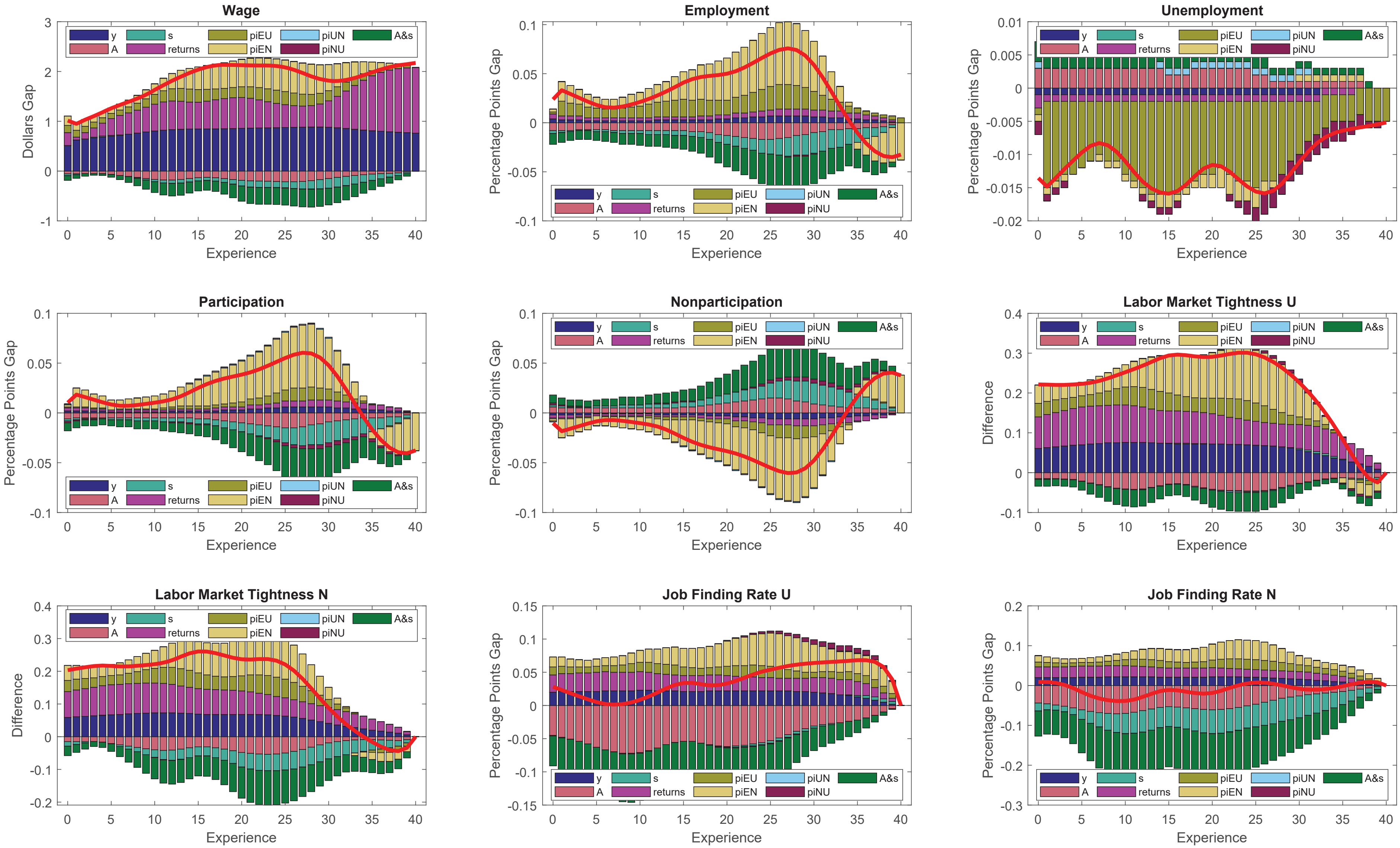

Figure 31: Counterfactual Unskilled Hispanic Males (compared to Unskilled White Males)

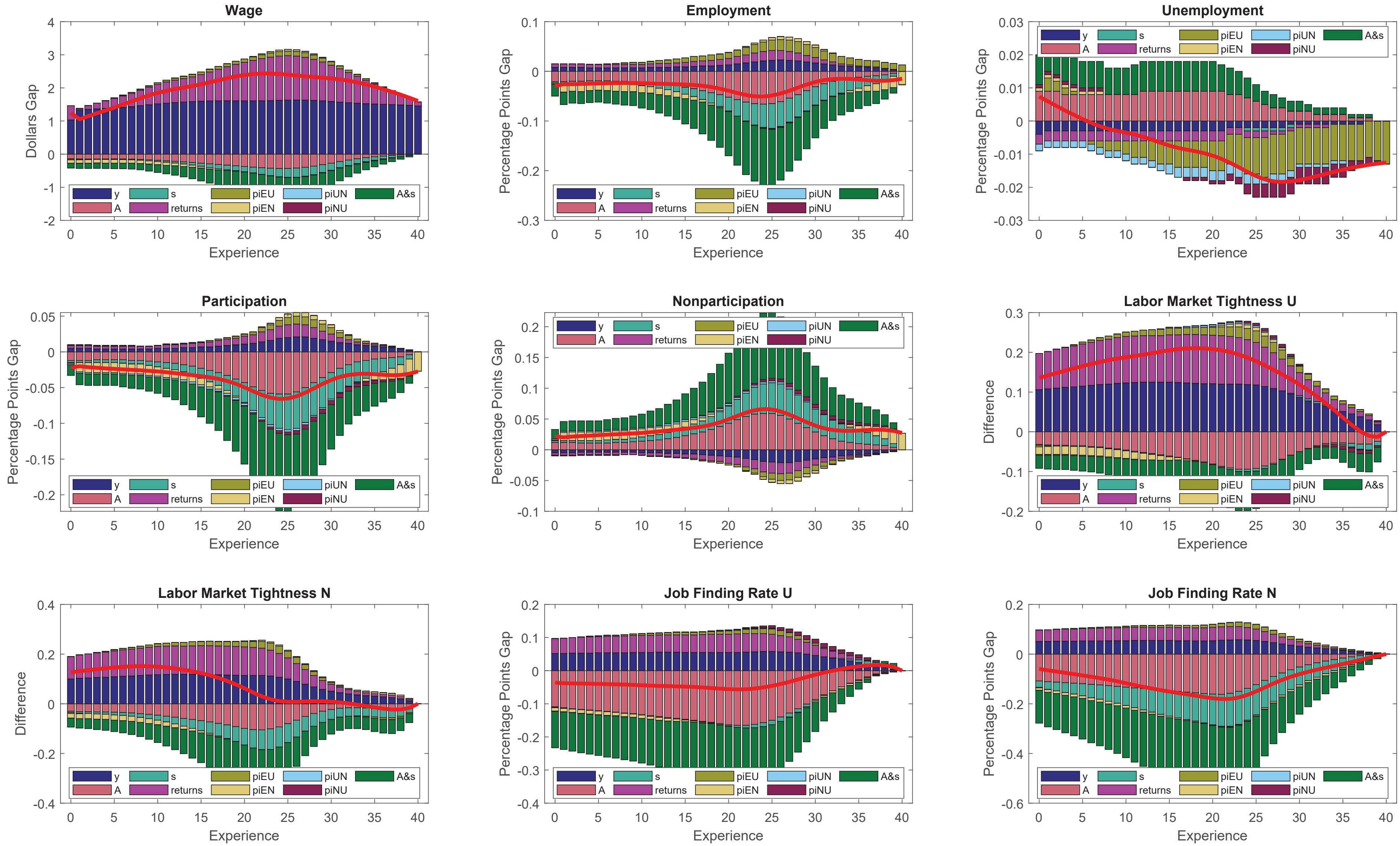

Figure 32: Counterfactual Skilled Hispanic Females (compared to Skilled White Males)

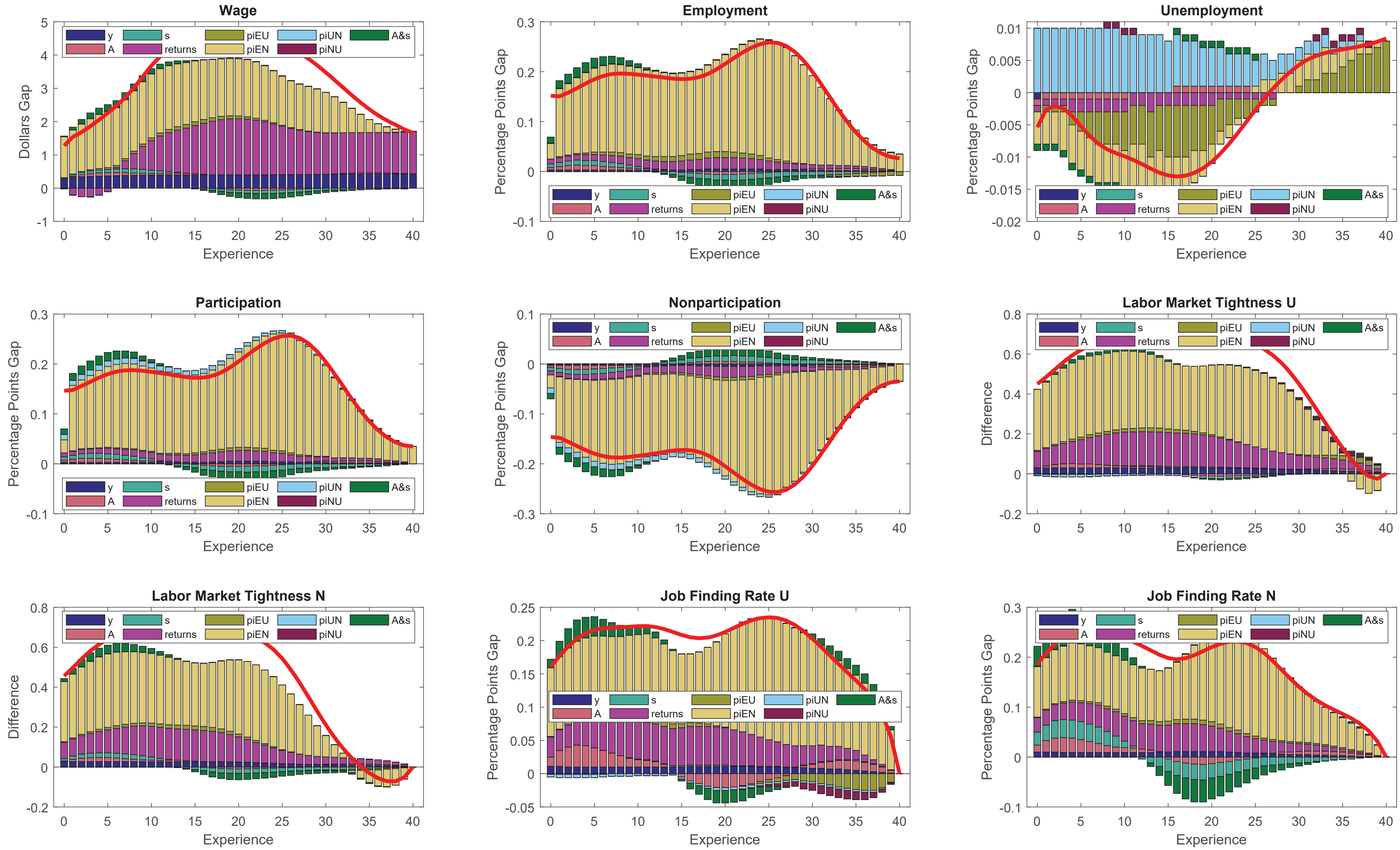

Figure 33: Counterfactual Unskilled Hispanic Females (compared to Unskilled White Males)

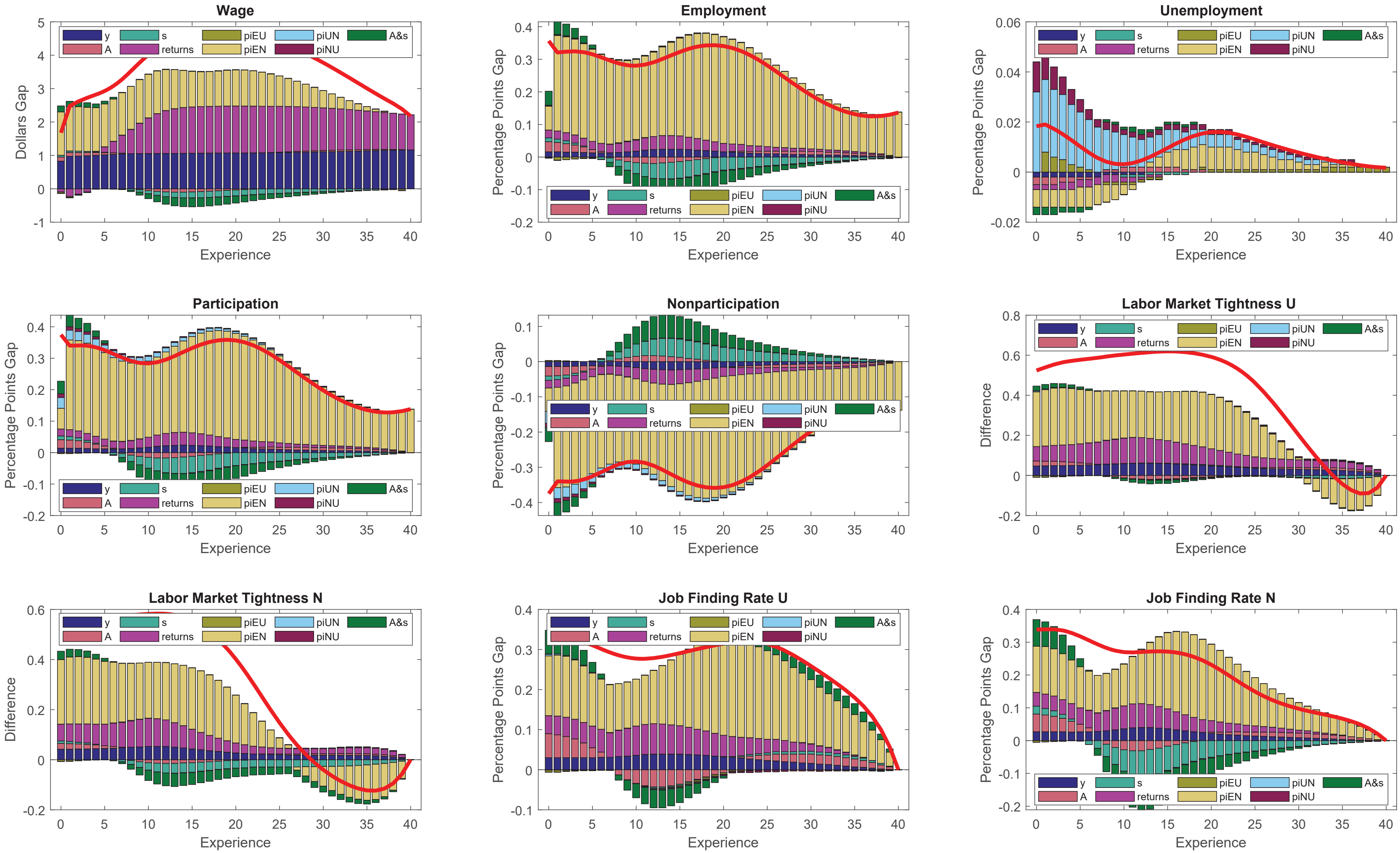

Table 1: Mean labor market statistic over the life cycle

Groups	Wage (dollars/hr)	Employment (%)	Unemployment (%)	Participation (%)	Nonparticipation (%)	θ_U (v/u)	θ_N (v/n)	π_{UE} (%)	π_{NE} (%)
All									
White Male	14.419	0.777	0.035	0.812	0.188	1.019	0.871	0.671	0.516
White Female	12.395	0.622	0.025	0.647	0.353	0.712	0.582	0.505	0.339
Black Male	12.456	0.61	0.056	0.666	0.334	0.695	0.602	0.495	0.38
Black Female	11.196	0.578	0.043	0.62	0.38	0.602	0.53	0.453	0.345
Asian Male	14.58	0.791	0.034	0.825	0.175	0.926	0.846	0.645	0.575
Asian Female	12.967	0.611	0.027	0.637	0.363	0.675	0.592	0.452	0.342
Hispanic Male	11.803	0.757	0.047	0.803	0.197	0.775	0.707	0.665	0.571
Hispanic Female	10.378	0.52	0.032	0.553	0.447	0.508	0.46	0.414	0.303
Skilled									
Skilled White Male	16.446	0.83	0.029	0.859	0.141	1.247	1.096	0.714	0.582
Skilled White Female	14.451	0.69	0.024	0.714	0.286	0.914	0.753	0.568	0.404
Skilled Black Male	13.815	0.705	0.052	0.757	0.243	0.875	0.768	0.584	0.479
Skilled Black Female	12.999	0.671	0.04	0.711	0.289	0.776	0.688	0.539	0.438
Skilled Hispanic Male	14.639	0.799	0.04	0.84	0.16	1.03	0.933	0.677	0.591
Skilled Hispanic Female	13.131	0.656	0.032	0.688	0.312	0.739	0.648	0.523	0.4
Unskilled									
Unskilled White Male	12.789	0.705	0.042	0.747	0.253	0.836	0.701	0.62	0.452
Unskilled White Female	10.2	0.528	0.027	0.555	0.445	0.539	0.451	0.424	0.263
Unskilled Black Male	11.516	0.524	0.06	0.584	0.416	0.578	0.506	0.421	0.308
Unskilled Black Female	9.518	0.472	0.045	0.516	0.484	0.461	0.421	0.366	0.26
Unskilled Hispanic Male	10.819	0.733	0.051	0.783	0.217	0.693	0.634	0.65	0.555
Unskilled Hispanic Female	9.116	0.444	0.032	0.476	0.524	0.433	0.411	0.356	0.255

Table 2: Decomposition of the labor market gaps: White female - White male

White female, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	2.024	0.155	0.01	-0.165	0.308	0.289	0.166	0.177
Explained gap	1.966	0.166	0.009	-0.174	0.292	0.258	0.154	0.159
Baseline productivity, y	-0.129	-0.001	0	0.001	-0.008	-0.006	-0.003	-0.002
Matching productivity, A/κ	0.104	0.012	-0.001	-0.011	0.023	0.021	0.033	0.029
Search effort, μ	0.086	0.011	0	-0.011	0.002	0.021	0.001	0.028
Returns to experience	0.857	0.011	-0.001	-0.01	0.081	0.059	0.029	0.021
Transition from E to U, π_{EU}	-0.066	-0.009	0.005	0.004	-0.012	-0.009	-0.005	-0.006
Transition from E to N, π_{EN}	1.096	0.14	-0.001	-0.138	0.22	0.173	0.107	0.089
Transition from U to N, π_{UN}	0.011	0.001	0.004	-0.005	-0.013	0	-0.005	0
Transition from N to U, π_{NU}	0.007	0.001	0.003	-0.004	-0.001	-0.001	-0.003	0
Combined A/κ and μ	0.193	0.022	-0.001	-0.022	0.024	0.043	0.035	0.06

White female, college - White male, college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.994	0.14	0.005	-0.145	0.334	0.342	0.146	0.178
Explained gap	2.005	0.15	0.006	-0.157	0.333	0.329	0.143	0.164
Baseline productivity, y	-0.109	-0.001	0	0.001	-0.007	-0.006	-0.002	-0.002
Matching productivity, A/κ	0.09	0.007	-0.001	-0.007	0.019	0.02	0.026	0.023
Search effort, μ	0.147	0.013	0	-0.013	0.003	0.038	0.002	0.042
Returns to experience	0.529	0.005	0	-0.005	0.057	0.044	0.017	0.013
Transition from E to U, π_{EU}	-0.053	-0.006	0.003	0.002	-0.01	-0.009	-0.003	-0.004
Transition from E to N, π_{EN}	1.382	0.13	-0.002	-0.128	0.292	0.242	0.111	0.092
Transition from U to N, π_{UN}	0.011	0.001	0.003	-0.004	-0.018	0.001	-0.006	0
Transition from N to U, π_{NU}	0.008	0.001	0.003	-0.003	-0.003	-0.001	-0.002	0
Combined A/κ and μ	0.237	0.02	-0.001	-0.019	0.022	0.057	0.028	0.068

White female, no college - White male, no college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	2.588	0.177	0.014	-0.191	0.297	0.25	0.196	0.189
Explained gap	2.25	0.181	0.015	-0.196	0.247	0.19	0.174	0.158
Baseline productivity, y	0.828	0.009	0	-0.008	0.042	0.029	0.02	0.014
Matching productivity, A/κ	0.072	0.013	-0.001	-0.013	0.017	0.015	0.029	0.025
Search effort, μ	0.031	0.007	0	-0.007	0.001	0.008	0.001	0.015
Returns to experience	0.526	0.01	0	-0.009	0.048	0.033	0.022	0.016
Transition from E to U, π_{EU}	-0.049	-0.01	0.006	0.004	-0.01	-0.005	-0.004	-0.006
Transition from E to N, π_{EN}	0.829	0.15	0	-0.15	0.155	0.11	0.112	0.094
Transition from U to N, π_{UN}	0.008	0.001	0.006	-0.008	-0.007	0	-0.003	0
Transition from N to U, π_{NU}	0.005	0.001	0.004	-0.005	0.001	0	-0.003	0
Combined A/κ and μ	0.107	0.021	-0.001	-0.02	0.019	0.023	0.03	0.042

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.

Table 3: Decomposition of the labor market gaps: Black male - White male

Black male, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.963	0.167	-0.021	-0.145	0.324	0.268	0.176	0.136
Explained gap	1.749	0.162	-0.017	-0.146	0.281	0.222	0.161	0.125
Baseline productivity, y	0.324	0.003	0	-0.002	0.019	0.015	0.007	0.006
Matching productivity, A/κ	0.085	0.014	-0.001	-0.013	0.026	0.021	0.035	0.028
Search effort of nonparticipants, μ	-0.048	-0.008	0	0.008	-0.001	-0.015	0	-0.019
Returns to experience	0.315	0.004	-0.001	-0.004	0.03	0.025	0.012	0.011
Transition from E to U, π_{EU}	0.222	0.028	-0.016	-0.012	0.037	0.035	0.02	0.024
Transition from E to N, π_{EN}	0.848	0.121	-0.002	-0.12	0.174	0.14	0.088	0.075
Transition from U to N, π_{UN}	0.005	0.001	0.007	-0.008	-0.004	0.001	-0.003	0
Transition from N to U, π_{NU}	-0.002	-0.001	-0.004	0.005	0	0	0.002	0
Combined A/κ and μ	0.036	0.006	-0.002	-0.004	0.025	0.006	0.035	0.007

Black male, college - White male, college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	2.63	0.125	-0.023	-0.102	0.372	0.327	0.13	0.102
Explained gap	2.375	0.123	-0.02	-0.1	0.318	0.272	0.122	0.097
Baseline productivity, y	0.914	0.006	-0.001	-0.005	0.062	0.053	0.021	0.018
Matching productivity, A/κ	-0.035	-0.001	0.001	0.001	-0.005	-0.007	-0.009	-0.011
Search effort of nonparticipants, μ	-0.035	-0.004	0	0.004	-0.001	-0.012	-0.001	-0.017
Returns to experience	0.46	0.005	-0.001	-0.004	0.052	0.048	0.018	0.018
Transition from E to U, π_{EU}	0.293	0.029	-0.018	-0.011	0.051	0.052	0.022	0.028
Transition from E to N, π_{EN}	0.776	0.088	-0.002	-0.085	0.162	0.138	0.07	0.061
Transition from U to N, π_{UN}	0.004	0	0.004	-0.004	-0.004	0	-0.002	0
Transition from N to U, π_{NU}	-0.002	0	-0.003	0.004	0.001	0	0.003	0
Combined A/κ and μ	-0.07	-0.005	0.001	0.004	-0.006	-0.019	-0.01	-0.028

Black male, no college - White male, no college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.272	0.181	-0.018	-0.162	0.258	0.195	0.199	0.143
Explained gap	1.049	0.171	-0.013	-0.159	0.221	0.159	0.182	0.13
Baseline productivity, y	0.002	0	0	0	0	0	0	0
Matching productivity, A/κ	0.158	0.029	-0.003	-0.027	0.045	0.038	0.065	0.053
Search effort of nonparticipants, μ	-0.064	-0.015	0	0.015	-0.001	-0.02	0	-0.024
Returns to experience	0.05	0.002	0	-0.002	0.012	0.01	0.006	0.005
Transition from E to U, π_{EU}	0.162	0.025	-0.013	-0.012	0.023	0.021	0.019	0.02
Transition from E to N, π_{EN}	0.739	0.13	0	-0.13	0.146	0.11	0.091	0.076
Transition from U to N, π_{UN}	0.004	0.001	0.009	-0.01	-0.003	0	-0.002	0
Transition from N to U, π_{NU}	-0.002	-0.001	-0.006	0.007	-0.001	0	0.003	0
Combined A/κ and μ	0.088	0.014	-0.003	-0.011	0.044	0.016	0.066	0.024

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.

Table 4: Decomposition of the labor market gaps: Black female - White male

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Black female, all - White male, all								
Total gap	3.223	0.199	-0.008	-0.191	0.418	0.341	0.218	0.171
Explained gap	2.841	0.198	-0.004	-0.194	0.335	0.26	0.195	0.152
Baseline productivity, y	0.94	0.009	-0.001	-0.008	0.051	0.041	0.022	0.018
Matching productivity, A/κ	0.076	0.014	-0.001	-0.013	0.021	0.017	0.032	0.026
Search effort of nonparticipants, μ	-0.059	-0.011	0	0.011	0	-0.016	0	-0.021
Returns to experience	0.794	0.011	-0.001	-0.01	0.065	0.051	0.027	0.023
Transition from E to U, π_{EU}	0.086	0.011	-0.006	-0.006	0.01	0.011	0.009	0.01
Transition from E to N, π_{EN}	1.001	0.163	-0.001	-0.161	0.193	0.156	0.109	0.096
Transition from U to N, π_{UN}	0.003	0.001	0.008	-0.009	-0.004	0	-0.003	0
Transition from N to U, π_{NU}	0	0	-0.002	0.002	-0.001	0	-0.001	0
Combined A/κ and μ	0.016	0.002	-0.001	-0.001	0.02	0	0.032	0.004
Black female, college - White male, college								
Total gap	3.446	0.159	-0.011	-0.147	0.472	0.408	0.175	0.143
Explained gap	3.024	0.158	-0.007	-0.149	0.389	0.324	0.162	0.133
Baseline productivity, y	1.214	0.009	-0.001	-0.008	0.077	0.065	0.027	0.024
Matching productivity, A/κ	-0.009	0.001	0	-0.001	0	-0.001	0	-0.003
Search effort of nonparticipants, μ	-0.055	-0.007	0	0.007	0	-0.016	0	-0.02
Returns to experience	0.648	0.008	-0.001	-0.007	0.07	0.062	0.025	0.023
Transition from E to U, π_{EU}	0.139	0.014	-0.008	-0.006	0.022	0.023	0.01	0.015
Transition from E to N, π_{EN}	1.085	0.132	-0.002	-0.129	0.224	0.191	0.103	0.094
Transition from U to N, π_{UN}	0.002	0.001	0.006	-0.006	-0.004	0	-0.003	0
Transition from N to U, π_{NU}	0	0	-0.001	0.001	0	0	0	0
Combined A/κ and μ	-0.064	-0.007	0	0.006	0	-0.017	-0.001	-0.023
Black female, no college - White male, no college								
Total gap	3.27	0.233	-0.003	-0.23	0.374	0.28	0.254	0.192
Explained gap	2.764	0.226	0.004	-0.231	0.278	0.189	0.217	0.16
Baseline productivity, y	1.191	0.014	-0.001	-0.013	0.054	0.04	0.027	0.022
Matching productivity, A/κ	0.107	0.025	-0.002	-0.024	0.03	0.024	0.051	0.041
Search effort of nonparticipants, μ	-0.056	-0.016	0	0.016	-0.001	-0.016	0.001	-0.023
Returns to experience	0.673	0.012	-0.001	-0.011	0.048	0.034	0.024	0.019
Transition from E to U, π_{EU}	0.047	0.008	-0.003	-0.005	0.001	0.003	0.008	0.008
Transition from E to N, π_{EN}	0.8	0.182	0.001	-0.183	0.146	0.104	0.11	0.093
Transition from U to N, π_{UN}	0.002	0.001	0.012	-0.013	-0.002	0	-0.002	0
Transition from N to U, π_{NU}	0	0	-0.002	0.002	0.002	0	-0.002	0
Combined A/κ and μ	0.046	0.009	-0.002	-0.007	0.029	0.006	0.052	0.015

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.

Table 5: Decomposition of the labor market gaps: Hispanic male - White male

Hispanic male, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	2.616	0.02	-0.012	-0.008	0.244	0.164	0.006	-0.055
Explained gap	2.472	0.016	-0.01	-0.005	0.214	0.155	0.015	-0.045
Baseline productivity, y	1.567	0.01	-0.002	-0.008	0.106	0.093	0.045	0.041
Matching productivity, A/κ	-0.236	-0.027	0.006	0.021	-0.054	-0.052	-0.106	-0.098
Search effort of nonparticipants, μ	-0.098	-0.015	0	0.015	-0.002	-0.032	-0.002	-0.061
Returns to experience	0.952	0.01	-0.002	-0.008	0.109	0.098	0.045	0.042
Transition from E to U, π_{EU}	0.121	0.015	-0.01	-0.005	0.022	0.02	0.011	0.015
Transition from E to N, π_{EN}	0.166	0.023	0	-0.022	0.032	0.028	0.02	0.016
Transition from U to N, π_{UN}	0	0	-0.001	0.001	0	0	0	0
Transition from N to U, π_{NU}	0	0	-0.001	0.001	0.001	0	0.002	0
Combined A/κ and μ	-0.334	-0.042	0.006	0.037	-0.056	-0.085	-0.107	-0.15

Hispanic male, college - White male, college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.806	0.03	-0.011	-0.019	0.218	0.163	0.037	-0.009
Explained gap	1.717	0.027	-0.012	-0.016	0.194	0.148	0.035	-0.009
Baseline productivity, y	0.804	0.004	-0.001	-0.003	0.06	0.054	0.019	0.017
Matching productivity, A/κ	-0.125	-0.009	0.002	0.007	-0.029	-0.028	-0.047	-0.044
Search effort of nonparticipants, μ	-0.083	-0.009	0	0.009	0	-0.029	-0.001	-0.042
Returns to experience	0.608	0.004	-0.001	-0.004	0.07	0.064	0.022	0.021
Transition from E to U, π_{EU}	0.175	0.014	-0.01	-0.004	0.029	0.031	0.012	0.015
Transition from E to N, π_{EN}	0.337	0.023	-0.001	-0.022	0.064	0.056	0.028	0.024
Transition from U to N, π_{UN}	0.001	0	0	0	-0.001	0	0	0
Transition from N to U, π_{NU}	0	0	-0.001	0.001	0.001	0	0.002	0
Combined A/κ and μ	-0.208	-0.018	0.002	0.016	-0.029	-0.058	-0.047	-0.083

Hispanic male, no college - White male, no college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.97	-0.028	-0.009	0.037	0.143	0.067	-0.031	-0.103
Explained gap	1.953	-0.027	-0.009	0.036	0.138	0.083	-0.022	-0.092
Baseline productivity, y	1.522	0.011	-0.002	-0.009	0.099	0.086	0.046	0.043
Matching productivity, A/κ	-0.226	-0.03	0.006	0.024	-0.052	-0.049	-0.109	-0.1
Search effort of nonparticipants, μ	-0.112	-0.02	0	0.02	-0.003	-0.036	-0.002	-0.073
Returns to experience	0.743	0.009	-0.002	-0.007	0.086	0.077	0.039	0.037
Transition from E to U, π_{EU}	0.062	0.01	-0.007	-0.003	0.013	0.01	0.005	0.008
Transition from E to N, π_{EN}	-0.034	-0.007	0	0.007	-0.006	-0.005	-0.005	-0.007
Transition from U to N, π_{UN}	-0.001	0	-0.002	0.002	0.001	0	0	0
Transition from N to U, π_{NU}	-0.001	0	-0.002	0.002	0	0	0.004	0
Combined A/κ and μ	-0.336	-0.052	0.006	0.046	-0.055	-0.085	-0.11	-0.162

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.

Table 6: Decomposition of the labor market gaps: Hispanic female - White male

Hispanic female, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	4.041	0.256	0.002	-0.259	0.511	0.411	0.257	0.213
Explained gap	3.277	0.251	0.007	-0.259	0.359	0.266	0.22	0.179
Baseline productivity, y	0.618	0.007	0	-0.006	0.028	0.021	0.014	0.012
Matching productivity, A/κ	-0.009	-0.002	0	0.001	-0.003	-0.001	-0.003	-0.001
Search effort of nonparticipants, μ	-0.05	-0.011	0	0.011	0	-0.013	0.001	-0.017
Returns to experience	1.555	0.025	-0.002	-0.024	0.12	0.092	0.057	0.046
Transition from E to U, π_{EU}	0.012	0.001	0	-0.001	0.003	0.001	-0.001	0.002
Transition from E to N, π_{EN}	1.149	0.23	-0.001	-0.229	0.212	0.166	0.156	0.137
Transition from U to N, π_{UN}	0.002	0.001	0.008	-0.009	-0.002	0	-0.002	0
Transition from N to U, π_{NU}	0	0	0.002	-0.002	0.001	0	-0.002	0
Combined A/κ and μ	-0.057	-0.013	0	0.013	-0.003	-0.014	-0.002	-0.016

Hispanic female, college - White male, college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	3.314	0.174	-0.003	-0.17	0.509	0.448	0.191	0.182
Explained gap	2.829	0.174	0.001	-0.174	0.425	0.352	0.17	0.161
Baseline productivity, y	0.397	0.003	0	-0.003	0.024	0.019	0.009	0.007
Matching productivity, A/κ	0.016	0.002	0	-0.001	0.004	0.004	0.005	0.005
Search effort of nonparticipants, μ	-0.009	-0.003	0	0.003	0.001	-0.004	0.001	-0.003
Returns to experience	1.034	0.013	-0.001	-0.012	0.109	0.09	0.038	0.032
Transition from E to U, π_{EU}	0.045	0.004	-0.002	-0.002	0.011	0.007	-0.004	0.005
Transition from E to N, π_{EN}	1.34	0.154	-0.002	-0.152	0.279	0.235	0.127	0.115
Transition from U to N, π_{UN}	0.006	0.001	0.006	-0.007	-0.006	0.001	-0.003	0
Transition from N to U, π_{NU}	0	0	0	0	0.003	0	-0.003	0
Combined A/κ and μ	0.007	-0.001	0	0.001	0.005	0	0.006	0.003

Hispanic female, no college - White male, no college

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	3.672	0.261	0.009	-0.27	0.403	0.29	0.264	0.197
Explained gap	2.873	0.252	0.012	-0.264	0.259	0.17	0.223	0.162
Baseline productivity, y	1.073	0.013	-0.001	-0.012	0.042	0.031	0.025	0.02
Matching productivity, A/κ	0.006	0.003	0	-0.003	0.002	0.002	0.005	0.006
Search effort of nonparticipants, μ	-0.083	-0.021	0	0.021	-0.003	-0.021	0.002	-0.029
Returns to experience	1.019	0.021	-0.001	-0.02	0.072	0.053	0.041	0.033
Transition from E to U, π_{EU}	-0.004	-0.002	0.001	0.001	-0.002	0	-0.001	-0.001
Transition from E to N, π_{EN}	0.862	0.237	0.001	-0.238	0.146	0.105	0.153	0.133
Transition from U to N, π_{UN}	0	0.001	0.009	-0.01	0	0	0	0
Transition from N to U, π_{NU}	0	0	0.003	-0.003	0.002	0	-0.002	0
Combined A/κ and μ	-0.074	-0.018	0	0.018	-0.001	-0.019	0.007	-0.021

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.

Table 7: Decomposition of the labor market gaps: Asian male and female - White male

Asian male, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	-0.161	-0.014	0	0.013	0.094	0.025	0.026	-0.059
Explained gap	0.155	-0.016	0.001	0.016	0.133	0.07	0.03	-0.053
Baseline productivity, y	-1.947	-0.01	0.002	0.008	-0.126	-0.113	-0.046	-0.043
Matching productivity, A/κ	-0.013	-0.002	0.001	0.001	-0.004	-0.003	-0.014	-0.013
Search effort of nonparticipants, μ	-0.148	-0.017	0	0.017	0.005	-0.047	0	-0.077
Returns to experience	2.248	0.016	-0.003	-0.013	0.258	0.233	0.082	0.077
Transition from E to U, π_{EU}	-0.036	-0.002	0.002	0.001	-0.008	-0.006	-0.002	-0.004
Transition from E to N, π_{EN}	0.051	-0.001	0	0.001	0.006	0.006	0.006	0.007
Transition from U to N, π_{UN}	0	0	0	0	0.001	0	0	0
Transition from N to U, π_{NU}	0	0	-0.001	0.001	0.001	0	0.004	0
Combined A/κ and μ	-0.162	-0.019	0.001	0.018	0.002	-0.05	-0.013	-0.086

Asian female, all - White male, all

Exogenous variables	Wage (dollars/hr)	Employment (% pts)	Unemployment (% pts)	Nonparticipation (% pts)	θ_U (v/u)	θ_N (v/n)	π_{UE} (% pts)	π_{NE} (% pts)
Total gap	1.452	0.166	0.008	-0.174	0.344	0.279	0.219	0.174
Explained gap	1.875	0.171	0.006	-0.177	0.354	0.276	0.206	0.157
Baseline productivity, y	-1.93	-0.017	0.001	0.016	-0.099	-0.079	-0.04	-0.032
Matching productivity, A/κ	0.254	0.024	-0.002	-0.022	0.049	0.044	0.068	0.059
Search effort of nonparticipants, μ	-0.035	-0.01	0	0.01	0.004	-0.011	0.002	-0.014
Returns to experience	2.281	0.025	-0.002	-0.023	0.184	0.145	0.064	0.051
Transition from E to U, π_{EU}	-0.089	-0.008	0.004	0.004	-0.013	-0.01	-0.003	-0.007
Transition from E to N, π_{EN}	1.385	0.156	-0.003	-0.153	0.236	0.187	0.116	0.1
Transition from U to N, π_{UN}	0.005	0.001	0.005	-0.006	-0.007	0	-0.003	0
Transition from N to U, π_{NU}	0.004	0	0.003	-0.003	0	0	0.002	0
Combined A/κ and μ	0.228	0.015	-0.002	-0.013	0.053	0.035	0.071	0.049

Notes: Average counterfactuals over the life cycle. Wage gaps are shown in dollars, and employment, unemployment, nonparticipation and transition gaps in percentage points. The gaps in labor market tightnesses show the gap in the vacancy/job-seeker -ratios. Total gap -row shows the average gap observed in the model, while Explained gap -row sums up the individual impact of each exogenous variable.