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The Millennials' Transition from School-to-Work

by

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The Millennials' Transition from School-to-Work*

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March 30, 2020

Abstract

We present the first study of the high school-to-work transition for American Millennial males and females. Using data from the PSID Transition to Adulthood from 2005-2011, we estimate the Burdett and Mortensen (1998) model and study changes between Generation X and Millennials. We find convergence in racial differences in transition patterns across the generations and in gender earnings by the Great Recession. These patterns are driven by a large decline in search efficiencies for white males. Finally, we show the labor market deteriorated for high school graduates prior to, with a further decline during, the Great Recession.

Keywords: Millennials, school-to-work, search frictions, early career outcomes

*This paper was written in memory of George R. Neumann, who supervised both our dissertations and continued as a mentor and friend until his death. May he rest in peace. We thank Phuong Vu for her helpful research assistance.

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1 Introduction

The Millennials are often described as the unluckiest generation. Born between the early 1980s and the late 1990s, this generation is named for having come of age in the early 2000s, a decade of turmoil that started with the 9/11 attacks and ended with the Great Recession. Compared to previous generations the Millennials are the most educated, but also face the highest unemployment rates, highest educational debt load, lowest wage growth, and highest rates of living at home with their parents. For many, they are seen to have had difficulty in making the transition to adulthood including secure employment, marriage, and home ownership. Their poor early career labor market performance is often cited by the press as a reason.[1]

Among the components to labor market success, the school-to-work transition is unmistakably important.[2] The first school-to-work papers used the 1979 National Longitudinal Survey of Youth (NLSY-79) and search models to study the unemployment duration following high school graduation and subsequent wages and durations of first jobs.[3] These papers studied only males with a particular focus on explaining differences in the transition between black and white males. More recently, the school-to-work transition literature has explored the effects of graduating during different states of the business cycle and has found long-term negative effects of graduating during a recession.[4]

[1]For evidence and discussion of the Millennials, see Berridge (2014), Lusardi and Scheresberg (2015), BLS (2014) https://www.bls.gov/opub/mlr/2014/beyond-bls/millennials-after-the-great-recession.htm, and WSJ (2015) https://blogs.wsj.com/briefly/2015/11/25/5-facts-to-silence-your-smug-millennial-nephew-this-thanksgiving.

[2]Early labor market mobility, in particular, is thought to affect subsequence wage growth over one's life cycle. See, for example, Topel and Ward (1992).

[3]These included Wolpin (1987, 1992), Eckstein and Wolpin (1990, 1995) and Bowlus, Kiefer and Neumann (2001).

[4]Examples include Kahn (2010), Genda, Kondo and Ohta (2010), Oreopoulos, von Wachter and Heisz (2012), and Schwandt and von Wachter (2019).

In this paper, we revisit the school-to-work transition with a focus on Millennials. While much has been made of the labor market outcomes of the college-educated Millennials, little is known about those who graduate from high school but did not go on to college. Thus, we focus on the transition for Millennial high school graduates. Our school-to-work model is based on the canonical equilibrium job search framework of Burdett and Mortensen (1998), hereafter BM, and our estimation method is from Bowlus, Kiefer and Neumann (2001), hereafter BKN. We estimate the model for male and female Millennials providing the first gender-based comparisons of the school-to-work transition for the U.S. in addition to race-based comparisons. Going further, we explore how the school-to-work transition has changed over time. First, we assess the transitions and earnings outcomes of Millennials with reference to Generation X. In particular, we compare the experiences black and white male high school graduates across the two generations. Finally, in line with the more recent literature on business cycle effects, we examine within the Millennials the differences in the school-to-work transitions between those who graduated before the Great Recession and those who graduated during the Great Recession.

To conduct our analysis, we use education and employment history data from the Panel Study of Income Dynamics Transition to Adulthood (PSID-TA) file. We focus on youths who were between 14 and 21 in 2005 and follow them through 2011. As was true for the NLSY-79, the PSID-TA is uniquely suited to study the school-to-work transition, because it allows for the construction of completed education and employment histories.

One distinguishing feature of the PSID-TA is that is contains information on job search starting time. In particular, it documents whether and when job search started while respondents were still in school. This information is often missing in data sets used to study the school-to-work transition, which is problematic because a non-trivial fraction of students are often found to have started working before their graduation or imme-

diately upon graduation. Without record of their search period prior to accepting the job or prior to graduation even if they have not found a job by graduation, researchers face a classic initial condition problem.

With this information, we are able to explore its implications. In particular, we can test whether knowledge of this information changes the estimates regarding the arrival rates of job offers while unemployed as well as investigate the various solutions offered to solve the initial condition problem. Interestingly, we find evidence in support of the solution proposed by BKN to only use the unemployment spells following graduation for those who do not take up employment prior to or immediately after graduation rather than 'adjusting' the unemployment durations to handle the 0 duration spells and the time spent searching while in school.[5] In essence BKN used only the forward recurrence times. Under the assumption that the durations are distributed exponentially, the forward recurrence times (as well as the backward recurrence times) are also distributed exponentially with the same parameter.[6] Thus, BKN argued that the forward recurrence times would recover the underlying true parameter. Our test results concur. For black and white males and black females the exponential distribution is accepted and the exponential parameters recovered using the full duration data and the forward recurrence time only data are not statistically different. The only exception is white females for which the exponential distribution is rejected. Even so, the parameter

[5]The BKN approach is similar to Wolpin(1992) who started the labor market histories in the period after graduation implicitly ignoring the employment spells while in school and at the time of graduation. Eckstein and Wolpin (1990, 1995), Wolpin (1987) and van der Klaauw and van Vuuren (2010) are examples of papers that have assumed a period of search for all 0 length unemployment spells or that have augmented all unemployment spells with a fixed period of search during school. Our data indicate that there is a lot of heterogeneity in search periods during school such that assuming the same period for all would be quite inaccurate.

[6]This is due to the memoryless nature of the exponential distribution and is unique to that distribution. Duration models that contain duration dependence require knowledge of the full duration in order to estimate the underlying parameters of the distribution.

estimates for the full durations and the forward recurrence times are not statistically different for white females.

Based on the sample we construct, we document the school-to-work patterns for male and female high school graduates, separately for whites and blacks.[7] While the differences are not large, we find that females have shorter unemployment durations, longer job spells and a slightly higher chance of making a job-to-job transition following their first job spell. Despite more favorable transition patterns for females, mean monthly accepted earnings on the first job is higher for males. There are also very few differences for each sex group between blacks and whites indicating that for high school graduates racial differences have for the most part converged for the Millennials, at least in terms of the school-to-work transition.

Driven by the evidence that it takes time to find jobs after graduation and that the gender earnings gap persists despite favorable search processes for females relative to males, we adopt and estimate BM's general equilibrium search model. The model allows us to better understand and quantify the search frictions faced by graduates as they transition to work as well as how those frictions affect wages and wage dispersion through firms' wage posting decisions. It also gives a measure of the amount of monopsony power held by firms and how it may vary across groups or over time.

Our estimates show that females have higher job arrival rates while unemployed and a lower exogenous job destruction rate than males. White females also see higher job arrival rates while on the job than white males, while black females do not find jobs as quickly as black males while on the job. Normalizing the job offer arrival rates by the exogenous job destruction rate, however, both white and blacks females are more efficient than white and black males, respectively, in entering and moving up the wage ladder. Yet, mean earnings for females is less than males.

[7] In this way we follow BKN which is useful for comparison purposes.

We explore the male-female earnings gap by asking what would the outcomes have been for females if they had faced their search parameters but the firm productivity distribution of the males. Re-solving the equilibrium model, we find that the male-female earnings gap on first jobs would close in this case. This indicates that the gender earnings gap is due to productivity differences across males and females. This result is similar to Bowlus (1997), who found that 70-80% of the male-female earnings gap was due to productivity differences among new entrants to the labor market in the early 1980s.[8] One difference is that Bowlus (1997) focussed only on full-time jobs, while in this study we include part-time jobs with more than 20 hours/week. Given the females in our sample are much more likely to hold part-time jobs than the males, this may in part explain why productivity differences explain the male-female earnings gap.

Next, to determine how the labor market has changed over time, we compare the male Millennial results to the patterns found in BKN, who studied black and white male high school graduates using data from the NLSY-79. That data set covered those who were born in the early to mid 1960s and came of age in the late 1970s and early 1980s, the start of Generation X. We find that, compared to males from Generation X, Millennial males are far less likely to hold a job at graduation, take longer to find their first jobs, have shorter job durations, and are less likely to make a job-to-job transition following their first job and rather end up returning to unemployment. These differences indicate male Millennials faced greater search frictions and, hence, firms had more monopsony power during this period and were able to compress earnings as a result.

[8]Bowlus(1997) does not study the school-to-work transition but rather the transitions following the first full-time job with a focus on females leaving the labor market for child care reasons. In our data we find females are no longer exiting the labor force following the first job and, therefore, we do not focus on this issue. Rather we are interested in gender differences in the initial transition from school-to-work and are the first to focus on this transition for females.

Comparing the BM model estimates shows that the search frictions faced by male Millennials during their school-to-work transition were substantially higher than those found by BKN for Generation X males. In particular, both black and white male Millennials faced substantially lower arrival rates while unemployed. White males also saw their arrival rate of offers while employed fall significantly and their job destruction rate increase. In fact, unlike the case of Generation X where BKN found the white males outperformed the black males in every search dimension, we find that for the Millennials the labor market for white males has deteriorated so much more so than it has for black males that the white and black male high school graduates faced much more similar search parameters in the early mid 2000s. There are even some dimensions, e.g. on-the-job search, in which the black males now out perform the white males. Thus, over time racial differences in the school-to-work transition have converged. However, the convergence was not one that brought up the black male high school graduates to their white counterparts. Instead, both groups saw their labor markets deteriorate with the white male high school graduates converging down to their black counterparts.

Given the estimated firm productivity levels for the 2000s, we examine what the Millennial males' school-to-work transition would have looked like, i.e. how much better would it have been, if they had faced Generation X's lower search frictions. While both white and black males show higher earnings levels, this is particularly true for the white males. The higher earnings levels come from three sources: (1) increased reservation wages of the workers due to higher arrival rates of offers while unemployed, (2) decreased monopsony power of the firms as more competition due to higher arrival rates while employed and lower job destruction rates forces them to offer higher wages in the new equilibrium; and (3) higher earnings growth through on-the-job search because worker move up the job ladder faster due to higher offer rates while employed.

Finally, we study how the labor market for the Millennials changed within the generation by exploring the impact of the Great Recession on males and females.[9] We find that males and females who graduated during the Great Recession had substantially longer unemployment durations, shorter job durations, lower earnings and lower job-to-job transition rates than those who graduated before the Great Recession. The search estimates reveal that the relative position of females improved during the Great Recession even though it declined for both males and females. This is true even for the male-female earnings gap for first jobs after graduation, which completely closes. Thus, overall, we find a story of racial and gender convergence for Millennial high school graduates. Unfortunately it is convergence to a much lower earnings and search effectiveness level. As more data become available it will be interesting to see whether the school-to-work transition improved for future generations as the economy recovered from the Great Recession as well as whether the gaps reemerged.

The paper is organized as follows. Section 2 discusses the data and presents sample statistics for Millennial males and females. Section 3 briefly presents the BM model and the BKN estimation method. Section 4 presents the estimation results for Millennial males and females, while Section 5 explores the differences across Generation X and Millennials for males. The impact of the Great Recession on the school-to-work transitions of the Millennials is examined in Section 6. Section 7 concludes.

2 Data

As mentioned above, we use data from the PSID-TA to study the early labor market outcomes of the Millennials. In the PSID-TA, respondents are surveyed biannually to present. We use the years from 2005 to 2011.

[9]Here we combine blacks and whites and divide the sample only by sex. This allows us to have large enough sample sizes of those who graduated before the Great Recession and those who graduated during the Great Recession.

The PSID-TA file contains respondents' employment status, job history up to five jobs, non-employment status retrospectively on a monthly basis, income, and demographic information such as marital status, education attainment, and occupation. However, the file does not contain basic information such as age, sex, and race. To obtain this information, we link the sample to the 'individual files' of the PSID. Time is denominated in months in the PSID-TA files.

We restrict our sample to a fairly homogeneous group. We extract youths who were between 14 and 21 years old in 2005, and follow them through the 2011 interview. Further, we restrict our analysis to male and female high school graduates who are either black or white. In what follows, we describe how the sample was constructed and then provide sample characteristics.

2.1 Sample Construction

As a first step, we must determine the highest level of schooling attained in order to select those who have only attained a high school degree. Unfortunately, the 2005 and 2007 surveys do not contain information on the highest grade attained. Therefore, to assign the highest level of schooling completed for each respondent as well as the date of completion, we make use of the information recorded on the month and year of completing high school and the monthly enrollment status variable.

We exclude respondents who graduated before 2004, because there is no employment history recorded prior to 2004. We also exclude respondents whose education was ongoing through the 2011 interview or was followed by non-response in subsequent interviews such that an end date as well as a highest level could not be determined. Finally, we drop respondents who had missing or inconsistent information such that the highest schooling level and/or graduation month and year could not be assigned.

Next, we construct each respondent's employment history. The PSID-TA file collects respondent's unemployment and out of the labor force status each month retrospectively for 24 months in the 2007, 2009 and 2011 surveys and for 12 months in the 2005 survey. In addition, it collects job history information by asking respondents the start and stop months and years of the five most recent jobs held. While the five recorded jobs are in no particular chronological order, and can be missing from one interview to another, start and stop months and years were recorded for each job. Together with the 24-month retrospective non-employment record, the job spell data provide enough information to construct an initial unemployment spell following graduation, the length of the first job spell and its monthly earnings and the first transition following the first job spell.

2.2 Unemployment Durations

We follow BKN and others and do not distinguish between unemployment and out of the labor force.[10] We treat the unemployment duration as the elapsed time between the start of job search and the end of it when a 'real' job is found.[11] Here we define a 'real' job to be a job with at least 20 hours/week and a duration of at least 3 months.[12] If the 'real' job starts

[10]Separating unemployment from out of the labor force may add noise to the duration data as some respondents reported multiple unemployment spells and multiple transitions between unemployment and out of the labor force. In addition, as noted above, we find little need for a non-participation state for females unlike in Bowlus (1997).

[11]The term 'real' job was first used in this context by Wolpin (1987).

[12]Many labor studies, including BKN, use 35 or 30 hours/week as the minimum hours needed to be a 'real' job. However, in this sample, many respondents did not report hours worked or were not consistent in their reports. As a means to retain a reasonable number of school-to-work transitions, we lowered the limit to at least 20 hours per week. In particular, had we used 35+hours/week as our criterion, the sample would have contained respondents with higher unemployment durations (from about 12 to 20 months, on average, for both males and females). In addition, since many respondents never report having a 35+hour/week job, the majority of respondents who worked [20,35) hours would be right-censored (raising the overall censoring rate to over 0.50 for both sexes).

prior to graduation, we follow BKN and others and require it to last at least two months after graduation to rule out summer and temporary jobs. We also require that it be held less than 12 months prior to graduation. Further, we follow BKN and require respondents to find a 'real' job within three years of graduation.[13]

It is possible to only partially observe unemployment duration. This is the case if the start of job search is unknown (left-censoring) and/or the end of it is unknown (right-censoring). When the start of job search is unknown, there is a classic initial conditions problem. As we mentioned in the Introduction, the PSID-TA collected information on job search during school and so this problem is mitigated in our setting. We are able to use this information to construct the full unemployment duration prior to the first job. If the respondent has a 'real' job at graduation but does not report any search activity prior to the start of the job, then we exclude them from the sample.[14]

Since time spent searching in school is rarely recorded in surveys, we present in Figure 1 a histogram for the search durations prior to graduation or the backward recurrence times. Around 39 per cent of the male sample reported that they searched while in school. For females 20 per cent searched before graduation. Of males and females who did search prior to graduation, 80 per cent searched between one to five months.

[13]There are 8 males and 28 females who were unemployed longer than 36 months and removed from the sample. The higher number for females is due to a greater tendency for females to be out of the labor force following graduation, although the rate is much lower for the female Millennials than for past generations. We performed a sensitivity check and compared results for including these observations and excluding them and found the findings regarding the distributions of unemployment spells to be robust. We note that if we had increased the minimum hours requirement to 35, the number of respondents who searched for a job for three years or more would have increased to 67 cases for males and 101 cases for females. This highlights the importance of part-time work among the Millennials.

[14]This restriction excludes 21 males and 14 females. Here we take that stand that the behavior of those who secure jobs without searching is beyond the scope of the model. These may be individuals who took up jobs in family businesses or who took up jobs at work places they worked for in the past.

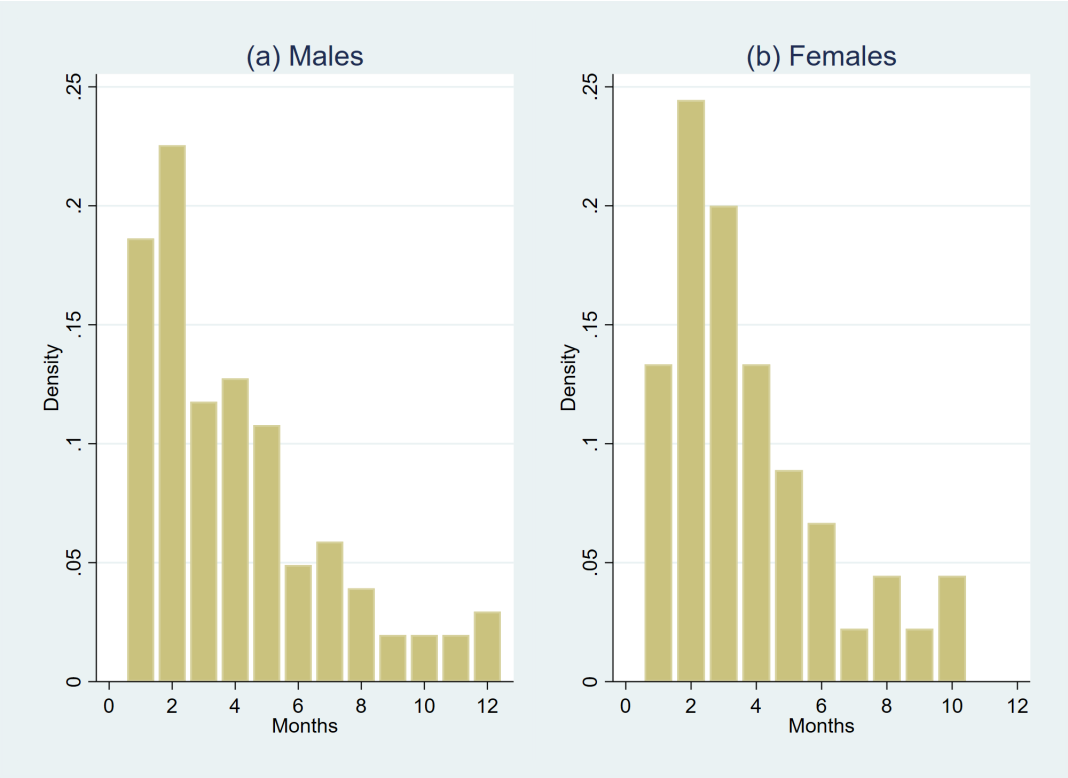

Figure 1: Search Durations Prior to Graduation

Given we have both the backward and the forward recurrence times, we test whether it is suitable to treat the unemployment durations as exponential such that, without information on backward recurrence times, the arrival rate parameter can be consistently estimated using only the forward recurrence times. We do so by testing whether the exponential parameters from using the full spell lengths are equal to the estimated parameters from the forward recurrence times only. We run the test separately for four groups: white males, black males, white females and black females. For all four groups, the estimated exponential parameters are found to not be statistically different across the two types of spells.[15]

[15]This result is likely not surprising given the vast majority of the respondents did not search prior to graduation. We anticipate that this result may not hold for graduates

This suggests that the method for handling the initial conditions problem as proposed by BKN to only use the forward recurrence times is likely more appropriate compared to other methods that add search time during school to the unemployment durations arbitrarily.[16] It also suggests that the search strategy for high school graduates during school is the same as that following graduation.

Right censoring occurs when unemployment spells are incomplete, i.e. a 'real' job is not found before another event happens that prevents the further collection of information. This can happen if the unemployment duration is still ongoing at the end of the last survey used or if the respondent leaves the sample early.[17] Right censoring also occurs when respondents accept a job, but the 'realness' of the job cannot be determined. This happens when hours are not recorded. Among all of the right-censored male observations, one-third is censored due to the survey's end or attrition and two-thirds are censored because hours were not reported.[18] In contrast, for females all of the right censored observations (N=16) are due to missing hours.

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of post-secondary programs where search during the last year of school may be more prevalent.

[16]Examples of the latter approach include Wolpin (1987), Eckstein and Wolpin (1990, 1995), and van den Klaauw and van Vuuren (2010). BKN show that this method can induce negative duration dependence in the unemployment durations even when such duration dependence is not present in the original forward recurrence spells.

[17]Some respondents moved in and out of the survey skipping interviews. This can be problematic because respondents may fail to accurately report periods of employment, and subsequent reports of being employed could refer to another job, with or without an intervening unemployment spell. In some cases, employment history information circumvents the problem. Where employment history offers no help, we right censor the observation at the last survey date prior to the skipped interviews.

[18]This composition (1/3, 2/3) and the overall censoring rate is similar to Wolpin (1987), who used a short panel from the NLSY. BKN reported much lower censoring rates when using a longer panel from the NLSY.

2.3 Job Duration

Job duration is the elapsed time between the start of a job and the end of it. Although we define a 'real' job as lasting at least 3 months, we have job spells that are shorter than this if they are right-censored. This occurs if the job is taken up fewer than three months prior to the final interview date.[19]

Similar to unemployment, job durations can be partially observed because of attrition or the end of the sample period. When spells are complete, we record whether the jobs ended in a job-to-job transition or a transition to unemployment. Job-to-job transitions are recorded if the respondent takes up another 'real' job within the same month their first 'real' job ended.[20] Jobs that do not end in a job-to-job transition are deemed to transition to unemployment. In the data this can be because the respondent either starts an unemployment spell or transitions to another job with fewer than 20 hours/week.

2.4 Earnings

For each job reported, earnings information is also available. In 2005, information on current and last year's earnings, time unit of pay, hours and weeks worked of each job was collected. Following 2005, this information was reported for the previous year and the year before that. For example, in 2007 respondents reported earnings information for 2006 and 2005. Thus, respondents who took up jobs in 2011 have no earnings information recorded for those jobs. We use additional data from the 2013 survey to circumvent this problem. Ideally, the 2013 survey should contain the entire history of earnings, hours, and weeks worked of the respondent

[19] In our sample, this occurs for 5 male and 12 female job spells.

[20] BKN use a two week window to determine job-to-job transitions. Unfortunately, the PSID-TA data are recorded in months. Here we use the same month to get as close to BKN as possible. Many more job-to-job transitions are recorded if we include 'real' jobs that started in the following month as well.

if the respondent held five or fewer jobs and if perfect recall occurred. We use this information to cross-check earnings across surveys to guard against misinformation using the record that was closest to the time when the employment occurred. In the PSID-TA the pay rates are categorized according to six time units: hourly, daily, weekly, biweekly, monthly, and annually. We standardize earnings into monthly rates to be consistent with the duration data. Earnings are in constant (2000) dollars. Respondents who were farmers or self-employed are removed from the sample as they were not salary workers.

Among respondents with non-missing earnings, some reported extreme pay rates. For example, one respondent reported an annual earnings of $20, while another reported $170,000. As in BKN, we handle the extreme earnings reports by cross-checking time and pay rate responses against upper and lower bounds (5th and 95th percentiles) collected from the Current Population Survey (CPS) for respondents of the same sex, age range and education level who worked 20 hours+/week in the same year when the job started.[21] Observations with earnings outside of the CPS wage bounds are treated as having earnings information that is missing.[22] We do not exclude the observations as in BKN in an effort to retain the number of observations contributing to the spell information. Out of all of the 'real' job spells for males, 21.37 per cent fell outside of the CPS wage bounds and 9.8 per cent were missing information such that earnings could not be calculated. For females, the percentages were 13.76 per cent and 8.72 per cent, respectively.

[21] See Appendix Table A1 for the bounds from the CPS.

[22] We also treat as missing 10 monthly earnings observations that are above $2300, five male observations and five female observations, and one female observation that is below $600. The BM model is known to have difficulties fitting earnings observations that are in the far right tail. We found the performance of the model, particularly for blacks, was improved substantially with the outliers above this cut off removed.

2.5 Sample Characteristics

Our final sample has 289 males respondents and 237 female respondents of which 206 males and 221 females have a non-censored unemployment duration and 138 males and 184 females have a valid earnings observation.[23] Table 1 shows sample statistics on durations and accepted earnings for black and white Millennial males and females.[24] Overall Table 1 shows surprisingly similar patterns across gender and race. All four groups have difficulty finding jobs prior to graduation with around 10 per cent of white and black females and 5 to 6 per cent of white and black males employed at the time of graduation. Average unemployment durations are relatively long for all four groups at around or just over a year. Despite showing similar average unemployment durations, actual unemployment durations are shorter for females than for males once censoring is taken into account, because the censoring rate is 3 to 6 times lower for females.[25] Thus, females are finding employment out of high school faster than males for both races.

Row 3 and 4 of Table 1 give the mean job durations and censoring rates. While mean job durations are similar between black and white males (0.31 months longer for white males), they are different for females with white females having 2.78 months longer mean job durations than black females. The racial pattern in the censoring rate for job durations is similar between

[23]In contrast, BKN had a sample size of 644 males with valid earnings observations and no right-censored unemployment durations. Our much lower sample size will hinder our ability to estimate the model for a variety of different groups. In particular, for small sample sizes the parameter estimates will not be estimated very precisely and the fit of the earnings distribution is likely to be poor.

[24]Here we report sample statistics for the earnings and spells that enter the likelihood function for estimation. This includes all of the unemployment durations. However, only the valid and non-missing earnings and the job durations and transitions that correspond to those earnings are included, as both the job durations and the transitions are functions of the earnings in the likelihood.

[25]The main reason for the lower censoring rate for females is that females' response rate is much higher. For example, they are more likely to answer the hours worked question and to give earnings responses that are within the CPS bounds. They are also less likely to attrit.

Table 1: Sample Statistics from Male and Female Millennial Estimation Samples

		Males		Females	
		Whites	Blacks	Whites	Blacks
1	Fraction of individuals employed at graduation	0.063	0.047	0.096	0.106
2	Mean unemployment duration (in months)	11.58	12.17	12.53	12.44
3	Fraction of censored spells among all unemployment spells	0.28	0.30	0.09	0.05
4	Mean job duration (in months)	17.99	17.68	19.72	16.94
5	Fraction of censored spells among all job spells	0.24	0.20	0.25	0.20
6	Fraction of completed job spells ending in a job-to-job transition	0.26	0.32	0.31	0.30
7	Mean monthly accepted earnings	1248.77	1237.76	1205.16	1180.08
8	Correlation between unemployment spells and accepted earnings	0.128	0.053	-0.109	0.027
9	Correlation between job spells and accepted earnings	0.100	0.110	-0.072	0.372

females and males with whites exhibiting a higher censoring rate (i.e. longer job durations) than blacks. Row 6 gives the job-to-job transition rates. These rates are similar across all of the groups except for white males who have a rate of 0.26 compared to around 0.30 for the others. Mean earnings on the first job are given in row 7. There is very little difference in mean earnings for black and white males. For white females, mean earnings is 2.1 per cent higher than for black females. The gender earnings gap is similar between blacks and whites at about 4 to 5 per cent.

The last two rows of Table 1 show the correlation between accepted earnings and the unemployment spells and job spells. The correlation between unemployment spells and accepted earnings is positive for all groups except white females. Further, the correlations for whites is much higher than those for blacks, more than double. The correlation between job spells and accepted earnings is positive for all four groups except white

females. In this case black females exhibit the highest correlation of all four groups by far.

In general, the sample statistics reveal more similarities than differences across the four groups. White females have a slightly higher mean unemployment duration than black females, but once they find a job, they tend to stay on the job longer and earn more. White and black males are more similar. Across the sexes, for whites, females have shorter mean unemployment and longer mean job durations taking censoring into account, and a higher probability of making a job-to-job transition than males. For blacks, females have shorter mean unemployment and job durations and a similar job-to-job transition probability compared to males. Despite slightly better labor market transition patterns, females from both races face lower earnings on their first job compared to males.

3 Model and Estimation Method

As noted in the Introduction, to study the school-to-work transition we use the BM equilibrium search model, which we briefly describe here. In the model time is continuous and lasts forever. There are two types of agents, workers and firms, exchanging labor services and wage compensation in the labor market. The measure of workers is 1, while the measure of firms is irrelevant due to an assumption of constant returns to scale in production.

3.1 Workers

Workers are identical to one another.[26] While unemployed, they receive a flow value of non-market time b. Conditional on a job offer that arrives at rate λ_0, workers sample a wage offer, w, from distribution $F(w)$ and decide whether or not to accept the job. They have a reservation wage r such that they are willing to accept a job when $w \geq r$. While employed, workers receive a flow payoff w. At rate δ the job dissolves exogenously. Workers also search on-the-job and receive job offers at rate λ_1. They accept a new job if it pays more than the current job, i.e. $w' > w$.[27] The rate that a job ends due to on-the-job search is thus $\lambda_1[1-F(w)]$. Define $\kappa_i \equiv \lambda_i/\delta$, where $i = 0, 1$. The κs are a measure of search efficiency indicating the number of offers expected during an employment spell. Letting the discount rate go to 1, a worker's reservation wage is given by

$$r = b + (\kappa_0 - \kappa_1) \int_r^\infty \frac{1 - F(w)}{1 + \kappa_1[1 - F(w)]} dw. \tag{1}$$

[26]The general approach has been to assume homogeneous workers and then make the samples as homogeneous as possible in terms of sex, race, schooling and years of experience as we have done. Bontemps et al. (1999) find that adding heterogeneity in the value of non-market time contributes very little to explaining the shape of the earnings distribution. Alternatively, one could add heterogeneity in the search parameters, but this complicates the solution to the equilibrium model and is unlikely to play an important role given the tests we ran did not reject the exponential distribution for most of the groups and if anything indicated positive not negative duration dependence.

[27]In this model, wage growth occurs via these job-to-job transitions, i.e. a job ladder. There is no on-the-job wage growth in the model. There is also very little on-the-job wage growth in our sample. This is likely because we are examining only first job spells for a short period during which the Great Recession onset.

3.2 Firms

Here we follow BKN and assume a discrete distribution of firm types.[28] There are $Q < \infty$ types of firms with productivity level $P_1 < ... < P_Q$. The fraction of firms having productivity P_j or less is $\gamma_j = \gamma(P_j)$. Each type of firm maximizes profits, $\pi_j(w)$, by posting a wage offer:

$$\pi_j(w) = \max_w (P_j - w) l(w), \tag{2}$$

where $l(w)$ is the measure of workers per firm paying a wage w.

3.3 Steady-State

In steady state, the flows of employed workers in and out at each wage must balance. The outflow from employment is given by the measure of employed workers with wage w, $G(w)(1-u)$, losing or leaving their jobs. Workers lose their job either exogenously at rate δ or leave their jobs endogenously at rate $\lambda_1[1-F(w)]$. The inflow is given by the measure of unemployed workers who get a job that offers wage w, $\lambda_0[F(w)-F(r)]u$. Equating the two flows and rearranging terms gives

$$G(w) = \frac{[F(w)-F(r)]}{1+\kappa_1[1-F(w)]} \frac{\kappa_0 u}{(1-u)}. \tag{3}$$

[28]It is well known that the equilibrium wage offer distribution with homogeneous firms has a convex shape that does not fit observed wage distributions. Adding firm heterogeneity, discrete or continuous, can dramatically improve the fit of the cumulative distribution function (cdf) as well as the probability distribution function (pdf) of wages. Often, however, continuous firm heterogeneity is rejected by the data in that a continuous distribution of productivity cannot be found that deliver the observed wage distribution given the search parameters and the equilibrium solution to the model. While the fit is not perfect, a discrete distribution can always be estimated. For this reason and to be comparable to BKN, we adopt the discrete distribution.

In equilibrium, firms that offer a wage less than r never attract any workers. Therefore, $F(r) = 0$. When $w = \infty$, equation (3) becomes

$$u = \frac{1}{1 + \kappa_0}. \tag{4}$$

Equation (4) is the steady state unemployment rate. Further, the measure of workers earning a wage w equals $g(w)(1-u)dw$, and the measure of firms offering a wage w equals $f(w)l(w; r, F)dw$. Simplifying, labor demand is given by

$$l(w; r, F) = \frac{g(w)dw}{f(w)dw}(1 - u) = \frac{\lambda_0 \delta(\delta + \lambda_1)}{(\delta + \lambda_0)\{\delta + \lambda_1[1 - F(w)]\}^2}. \tag{5}$$

3.4 Equilibrium

The equilibrium solution for the discrete heterogeneity version of the model is such that workers maximize utility given the wage offer distribution, firms maximize profits given the workers' reservation wage strategy, and profits are equalized across firms of the same type.

Mortensen (1990) shows the following properties hold in equilibrium: (1) the wage offer distribution has no mass points, (2) no firm offers a wage below r, i.e., $F(r) = 0$, and (3) firms with higher productivity values offer higher wages, i.e., $P_2 > P_1 \Rightarrow w_2 > w_1$. The latter property implies that the lowest wage offered by productivity type j, w_{Lj}, is equal to the highest wage offered by productivity type $j-1$, w_{Hj-1}. Mortensen (1990) then shows the equilibrium wage offer distribution is given by

$$F(w) = \phi_j(w), \ \forall w, \tag{6}$$

with ϕ_j defined by

$$\phi_j(w) \equiv \frac{1 + \kappa_1}{\kappa_1} \left[1 - \frac{1 + \kappa_1(1 - \gamma_{j-1})}{2\kappa_1} \sqrt{\frac{P_j - w}{P_j - w_{Hj-1}}} \right], \tag{7}$$

for $w_{Lj} < w \leq w_{Hj}$. The values for the wage cuts, w_{Lj} and w_{Hj}, can be solved for using the equilibrium properties and the fact that $F(w_{Hj}) = \gamma_j$. They are given by

$$\begin{aligned} w_{Hj} &= (1 - B_j)P_j - B_j w_{Hj-1}, \\ w_{Lj} &= w_{Hj-1}, \\ w_{L1} &= r, \end{aligned} \tag{8}$$

where $B = [(1+\kappa_1(1-\gamma_j))/(1+\kappa_1(1-\gamma_{j-1}))]^2$. Observe that $0 < B_j < 1$ for all j.

Note that kinks appear in the cdf at the wage cuts resulting in discontinuities in the pdf. This is the focus of the estimation strategy in the next section. The increasing density characteristic of the homogeneous case is now found along the support for each firm type, but with jumps at each wage cut. The addition of firm types allows for a better fit of the cdf of wages, but it is not obvious that the implied pdf will fit the data well.[29]

It is also interesting to note that the search parameters enter the wage offer distribution through κ_1, the number of offers expected over an employment spell. This ratio gives a measure of how much monopsony power the firm has over its workers, as the fewer offers workers receive, the more the firms can lower the wage offers away from the productivity values. Thus, differences across groups in κ_1 values may then be able to help explain observed earnings gaps.

3.5 Estimation Method

The model is quite parsimonious. It contains a small set of structural parameters including three arrival rates, the value of non-market time and the productivity distribution parameters. It is well known that λ_0

[29]BKN show that estimation of the search parameters (λ_0, λ_1 and δ) relies only on recovering the cdf well.

can be identified using unemployment duration spells and that job duration spells and job-to-job transition data can jointly identify λ_1 and δ. Accepted earnings data can then be used to uncover the productivity distribution parameters, although as shown below one must first deal with the discontinuities in the likelihood function for earnings.

Following BKN, the likelihood function can be built for labor market histories where youths entering the school-to-work transition experienced unemployment duration, D_1, received a wage on the first job, w, worked at that job for length D_2, and left the job either to another job ($C = 0$) or to unemployment ($C = 1$). Given the assumption of Poisson arrival rates, unemployment durations are exponential with intensity parameter λ_0. The marginal distribution of accepted wages is $f(w)$ given by

$$f(w) = \sum_{j=1}^{Q} \frac{1 + \kappa_1(1 - \gamma_{j-1})}{2\kappa_1} \sqrt{(P_j - w)(P_j - w_{Lj})} I(w_{Lj} < w \leq w_{Hj}), \tag{9}$$

where $I(x)$ is the indicator that the event x occurs. Conditional on the wage received, w, the density of job duration, $f(D_2|w)$, is also exponential with intensity parameter $\delta + \lambda_1[1 - F(w)]$, where $F(w)$ is given in equation (6). Finally the probability that a job ends by being lost, $\Pr(C = 1|w)$, is

$$\Pr(C = 1|w) = \frac{\delta}{\delta + \lambda_1[1 - F(w)]}. \tag{10}$$

The likelihood function (with complete spells) is then given by

$$\ell(\theta) = \lambda_0 \exp(-\lambda_0 D_1) f(w) \exp([-\delta + \lambda_1[1 - F(w)]]D_2) \delta^C (\lambda_1[1 - F(w)])^{1-C}, \tag{11}$$

where θ denotes the vector of parameters to be estimated including r, P_j and γ_j, $j = 1, ..., Q$, λ_0, λ_1, and δ.

We note that, from the equilibrium solution for the wage offer distribution, the productivity levels can be expressed as a function of the wage

cuts and the Bs. Rewriting equation (8) yields

$$P_j = \frac{w_{Hj} - B_j w_{Hj-1}}{1 - B_j}. \tag{12}$$

Equation (12) implies that if we know κ_1, r, w_{Hj}, and γ_j, $j = 1, ..., Q$, we can estimate the unobserved productivity levels, P_j. It turns out to be more straightforward to estimate the wage cuts and then calculate the productivity levels using equation (12) than it is to estimate the productivity levels directly. This is because the wage cuts are the points at which the discontinuities in the density function of wages occur and BKN show that the MLEs for these wage cuts must come from the set of observed wages. Thus, we proceed by substituting equation (12) into the likelihood function and estimating the wage cuts.

To estimate the model we follow the estimation procedure outlined in BKN. First, we use the lowest and highest earnings observed in data for the estimates of r and w_{HQ}. Then, for a given value of Q, the following two-stage optimization routine is repeated until the log-likelihood value converges. In the first stage, while fixing the arrival rate parameters, we maximize the log-likelihood function by sampling values from the earnings and using them for the estimates of $w_{H1}, ..., w_{HQ-1}$. In the second stage, while fixing the wage-cut levels, the log-likelihood function is maximized over the arrival rate parameters with a standard iterative optimization routine. Note that every time the objective function is evaluated at a new guess, the P_j's are calculated from the other parameters.

We conduct the above estimation for a series of Q values. The choice of Q in this framework is similar to choosing the points of support in the Heckman and Singer (1984) estimator of a mixing distribution. As of yet, there is no formal test for choosing the correct level of Q. We follow BKN and use the quasi-likelihood ratio test – $V = -2\triangle \log \ell < \chi^2_{05}$ – to choose Q where $\triangle \log \ell$ represents the difference associated with increasing Q by one. Since the likelihood function is nondecreasing in Q and the

Neyman-Pearson lemma applies, V is the right criterion function to use. However, what remains unknown is the distribution of V and, therefore, the appropriate critical values. BKN describe their experience using the 0.05 critical value of $\chi^2(1)$ with a small Monte Carlo study and based on those findings proceed with this criterion.

4 Millennial Estimation Results

We first report the benchmark estimation results for the Millennials. We follow BKN and estimate the model separately for blacks and whites. We also estimate the model separately by sex producing the first school-to-work estimates for black and white females in the US.

As noted above, we determine the number of firm types Q as in BKN. Their method yields $Q = 4$ for all four groups. Levels beyond four yielded no further improvements in the likelihood and productivity parameter estimates that were substantially higher at the top. In addition, the estimated search parameters were stable once the number of firm type was increased to this level.

The parameter estimates are presented in Tables 2 and 3. Columns 1 and 2 of Table 2 present the estimated values of the search parameters for white and black males, respectively, using the full equilibrium model. Columns 3 and 4 present the same for white and black females, respectively. Comparing estimates between the two male groups reveals that black males faced a lower arrival rate of offers while unemployed, but a higher rate when employed than white males. Black males also faced a slightly higher job destruction rate. However, the difference in the estimates across race are not statistically significantly different.[30] The values

[30]The relatively small sample sizes do contribute to higher standard errors making it difficult to discern differences across the samples. We do note that the likelihood ratio test of whether or not there is significant improvement in the likelihood if black and white males are estimated separately rejects combining the races in favor of separate estimation.

Table 2: Search Parameter Estimates for Male and Female Millennials

	Males		Females	
	Whites	Blacks	Whites	Blacks
λ_0	0.0627	0.0571	0.0728	0.0759
	(0.0054)	(0.0058)	(0.0056)	(0.0062)
λ_1	0.0243	0.0371	0.0269	0.0319
	(0.0067)	(0.0093)	(0.0063)	(0.0062)
δ	0.0306	0.0331	0.0288	0.0277
	(0.0050)	(0.0053)	(0.0044)	(0.0042)
Log-likelihood	-1254.75	-1020.91	-1240.25	-1532.42

Notes: Bootstrap standard errors are reported in parentheses.

of $\kappa_0 = \lambda_0/\delta$ and $\kappa_1 = \lambda_1/\delta$ for whites are 2.05 and 0.79 respectively, while for black males they are 1.73 and 1.12, respectively. The value of κ_1 being less than one for white males indicates that they received on average less than one outside offer during an employment spell. Comparatively black males faced slightly less search frictions receiving just over one outside offer, on average, during an employment spell. Relative to other studies, these values are low indicating a substantial degree of search frictions and, therefore, monopsony power held by firms.

For females, we find blacks faced slightly higher job arrival rates than whites when unemployed and employed and they faced lower job destruction rates, but again the differences are not significant.[31] Compared to males, females exhibited higher arrival rates while unemployed, similar arrival rates while employed, and lower job destruction rates.[32] From these patterns, it follows that the search efficiency levels are higher for black females than white females and for females in general compared to males. In particular, the estimated κ_0 and κ_1 for black females are 2.74 and 1.15, respectively. The values for white females are 2.53 and 0.93,

[31]As was noted for males, the likelihood ratio test rejects combining the races in favor of estimating them separately for females.

[32]The male-female parameter differences are not statistically significant except for the difference in the male λ_0 and the female λ_0 for blacks.

respectively. As noted, similar to males, black females had a higher κ_1, indicating they were more efficient than white females in moving up the wage ladder. Also, females had higher rates than males for both rates for each race indicating females were more efficient than males in entering and moving up the wage ladder. In particular, for whites, females exceed males by 23 per cent and 18 per cent, respectively, for κ_0 and κ_1. For blacks, females exceed males by 59 per cent and 3 per cent, respectively. In addition, similar to white males, the white females received less than one outside offer during an employment spell, while black females received only slightly more than one offer per spell as did black males. Again, these rates indicate a substantial degree of search frictions and monopsony power held by firms.

Table 3 shows the estimated support points of the wage offer distribution along with the productivity distribution estimates. White and black male parameter estimates are given in columns one and two, respectively, while white and black female parameter estimates are given in columns three and four, respectively. All four groups have reservation earnings levels, r, between \$600 and \$700 with white females exhibiting the highest reservation value. The average productivity level for white males is higher than for black males at 2584.59 vs 2153.34, respectively. For females, we also find that the average productivity level for whites is higher than for blacks at 2229.8 and 2069.4, respectively.[33] Finally, we note that the gender gap in the productivity levels is expected because in the model wages are governed by both the productivity and search parameters. Since females have similar or even more favourable search parameters but lower average earnings than males, their productivity levels must be less than males in order to reconcile the gender gap in earnings.

As a measure of model fit, Table 4 compares the sample statistics from Table 1 with the predicted moments from the model using the estimated

[33]The average productivity level is calculated by summing over the four firm types the product of the productivity level, P_j, and the fraction of firms of that type, $\gamma_j - \gamma_{j-1}$.

Table 3: Firm Parameter Estimates for Male and Female Millennials

	Males		Females	
	Whites	Blacks	Whites	Blacks
P_1	1854.30	1759.10	1366.04	1383.22
	(405.77)	(304.67)	(285.81)	(142.59)
P_2	2276.90	1993.10	2197.67	2066.91
	(395.63)	(307.77)	(416.02)	(295.56)
P_3	3444.30	3353.20	2834.20	2608.56
	(798.38)	(647.84)	(706.81)	(381.45)
P_4	5122.30	5027.80	4933.94	3410.85
	(1932.38)	(1669.24)	(1618.60)	(780.07)
γ_1	0.4211	0.4839	0.3614	0.4059
	(0.1703)	(0.2070)	(0.1551)	(0.1151)
γ_2	0.6974	0.8387	0.7952	0.7030
	(0.1300)	(0.1836)	(0.1935)	(0.1535)
γ_3	0.9211	0.9677	0.9036	0.8515
	(0.0756)	(0.0629)	(0.0787)	(0.1000)
γ_4	1.0000	1.0000	1.0000	1.0000
r	606.65	657.07	696.13	624.29
	(17.96)	(25.80)	(9.19)	(13.15)
w_{H1}	1028.40	1148.70	909.40	918.25
	(169.46)	(200.30)	(102.98)	(90.52)
w_{H2}	1375.70	1520.60	1479.69	1337.47
	(180.16)	(211.96)	(253.66)	(219.23)
w_{H3}	1925.90	1942.10	1699.88	1640.79
	(187.64)	(182.69)	(211.48)	(224.41)
w_{H4}	2292.11	2153.73	2211.17	2120.07
	(34.10)	(99.21)	(69.61)	(54.32)

Notes: Bootstrap standard errors are reported in parentheses.

parameters. As noted earlier, the predicted mean durations for both unemployment and job spells are higher than the means observed in the data, because the predicted means take into account the censoring rates in the data. The predicted accepted earnings averages match quite well for all four groups, as do the predicted transition rates to another job.

The longer predicted mean unemployment duration for black males stems from their lower arrival rate of job offers compared to white males, while white and black females have higher arrival rates yielding shorter mean unemployment durations. The shorter mean job duration for black males compared to the other three groups results from their higher arrival rate of job offers while employed as well as their slightly higher job destruction rate. While a higher job destruction rate slows the rate at which black males are moving up the wage ladder, a higher job-to-job transition rate quickens it. On net, as demonstrated by a higher κ_1, black males are more efficient than white males in moving up the wage ladder. However, black females are the most efficient of the four groups given their relatively high job arrival rate and lower job destruction rate.

In terms of the job-to-job transition rate, the fit is very good for all four groups except black females. A closer look at this case reveals that the estimation prefers a lower δ to fit the job duration data rather than a higher δ to fit the transition data.[34] The mean earnings are also quite close with the model predicting lower mean earnings in all four cases and the estimation results preserving the racial and gender gaps found in the data. Finally, in terms of the correlations, the model predicts no correlation between the unemployment spells and accepted earnings on the first job, which matches the black males and black females well. It predicts a positive correlation between job spells and accepted earnings as those with higher earnings are be more likely to reject outside offers and stay on their current job. This matches the correlations in the data for all four

[34]The likelihood function for black females appears to be quite flat in the region identifying δ. The estimates of λ_0 and λ_1 are fairly robust while the likelihood function changes only a small amount with changes in δ that provide a better fit to the job-to-job transitions but a worse fit to the job durations. Since the estimation method uses a search algorithm to search over the wage cut estimates, there is no guarantee that it returns the maximized log likelihood value. However, to determine whether this is a problem we ran the estimation starting at several different values for δ. For all starting values, the estimates we present were determined by the estimation routine to be the estimates with the highest log likelihood value.

Table 4: Sample Statistics Compared to Predicted Moments for Male and Female Millennials

		Males			
		Whites		Blacks	
		Observed	Predicted	Observed	Predicted
1	Mean unemployment duration (in months)	11.58	15.95	12.17	17.53
2	Mean job duration (in months)	17.99	24.23	17.68	20.54
3	Fraction of completed job spells ending in a job-to-job transition	0.26	0.26	0.32	0.33
4	Mean monthly accepted earnings	1248.77	1222.31	1237.76	1202.89
5	Correlation between unemployment spells and accepted earnings	0.128	0	0.053	0
6	Correlation between job spells and accepted earnings	0.100	0.170	0.110	0.220
		Females			
		Whites		Blacks	
		Observed	Predicted	Observed	Predicted
1	Mean unemployment duration (in months)	12.53	13.74	12.44	13.17
2	Mean job duration (in months)	19.72	24.45	16.94	24.62
3	Fraction of completed job spells ending in a job-to-job transition	0.31	0.29	0.30	0.34
4	Mean monthly accepted earnings	1205.16	1186.86	1180.08	1144.17
5	Correlation between unemployment spells and accepted earnings	-0.109	0	0.027	0
6	Correlation between job spells and accepted earnings	-0.072	0.183	0.372	0.190

groups except white females where the correlation in the data happens to be negative.

To further examine the fit of the earnings distributions, panels (a) and (b) of Figure 2 plot the observed and predicted cdfs for white and black males, respectively, while panels (c) and (d) plot the same for white and black females, respectively. All four panels show that the model can reproduce the cdfs very well. The observed and predicted pdfs for white and black males are shown in panels (a) and (b) of Figure 3, respectively, while panels (c) and (d) show the pdfs for white and black females, respectively. Here the fit, as expected, is not as good. The model fits the general

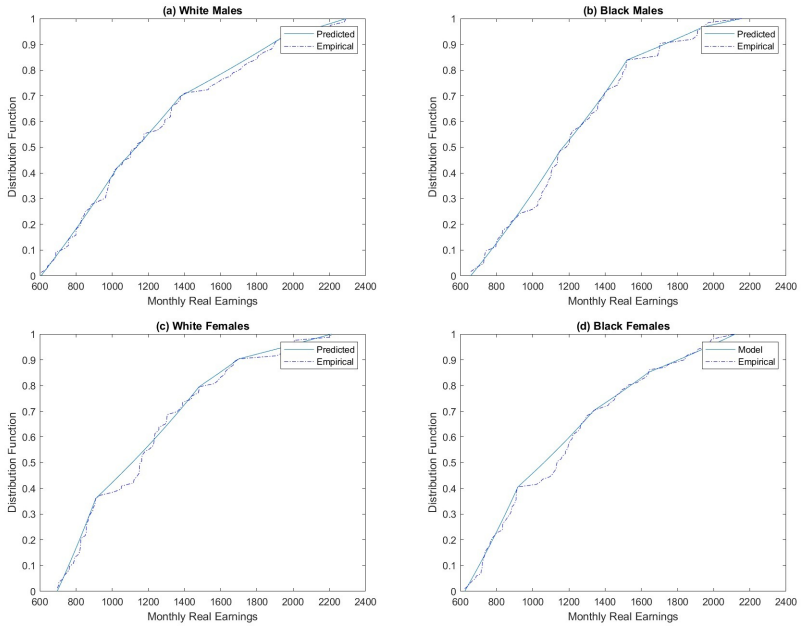

Figure 2: Comparison of Empirical and Predicted Cumulative Distribution Functions of Accepted Earnings

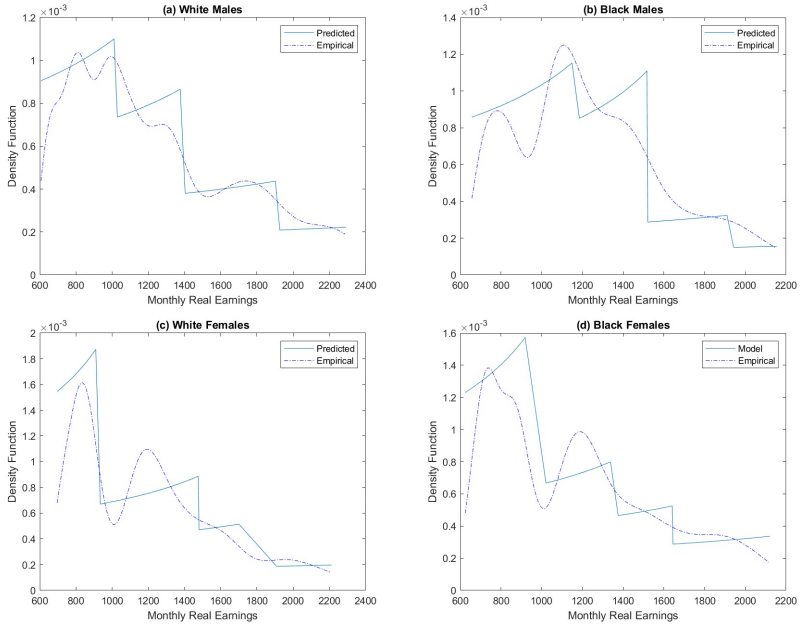

Figure 3: Comparison of Empirical and Predicted Probability Density Functions of Accepted Earnings

Table 5: Search Parameter Estimates for Male and Female Millennials using Empirical $F(w)$

	Males		Females	
	Whites	Blacks	Whites	Blacks
λ_0	0.0627	0.0571	0.0728	0.0759
	(0.0054)	(0.0060)	(0.0071)	(0.0071)
λ_1	0.0230	0.0342	0.0251	0.0296
	(0.0059)	(0.0083)	(0.0059)	(0.0059)
δ	0.0311	0.0339	0.0293	0.0282
	(0.0050)	(0.0057)	(0.0045)	(0.0037)
Log-likelihood	-709.14	-587.61	-662.73	-819.78

Notes: Asymptotic standard errors are reported in parentheses.

tendencies of the pdfs to decline, but the peaks due to the discontinuities do not always line up with humps in the empirical pdfs. To check how much distortion this causes in the search parameters, we re-estimate the search parameters using the empirical cdf as in Bontemps et al. (1999). This method essentially estimates a partial equilibrium job search model. Table 5 gives the search parameter estimates using the empirical cdfs and shows that the estimates are closely matched with the estimates from the BKN method using the general equilibrium model.

Finally, we ran two further diagnostics on the unemployment duration data. First, we ran the simple test of the exponential distribution by estimating a Weibull model on the unemployment duration data to test whether there is duration dependence. For males the exponential distribution was accepted for blacks at the 1 per cent level and for whites at the 5 per cent level. For white males, the Weibull parameter indicated positive duration dependence, if any, rather than the expected negative duration dependence. For females, the exponential distribution was accepted at the 5 per cent level for blacks, but was rejected for whites in favor of positive duration dependence.

Second, we examined the exponential distribution using only the forward recurrence times as in BKN and found that for all of the groups, except white females, the exponential distribution was accepted. The forward recurrence time unemployment durations for the white females exhibited positive duration dependence as with the full durations.[35] Given the similarity in the test results for the exponential distribution, we also tested whether the exponential parameters for the full durations and the forward recurrence time durations are statistically different. For all four cases, the parameter estimates are not statistically significantly different. Thus, the inference drawn from using the forward recurrence time durations is the same as that from using the full durations suggesting that the BKN solution for the initial condition problem is not inappropriate in this setting.

To explore the gender earnings gap further, we ask what would be the outcome for female Millennials if they faced their search parameters but the male Millennial productivity distribution. The results are given in Table 6. Here the predicted moments for the benchmark model use estimates from Tables 2 and 3 for females.[36] The predicted moments for the counterfactual simulations use the female search parameter estimates from Table 2 and the male productivity and γ parameter estimates from Table 3. In the counterfactual case, the model is resolved generating new reservation wages and wage cuts before predicting the moments.

Not surprisingly, Table 6 shows that the predictions regarding the spells and transitions change very little for both white and black females. This is because we did not change the search parameters. What changes

[35]We did examine whether this was due to the exclusion of those who searched more than 36 months in that this restriction could induce upward bias on the hazard at the end of the allowed duration period. This turns out not to be the case, as the positive duration dependence result remained when these longer spells are included. We do note that the exponential distribution cannot be rejected for the sample of unemployment durations for those who graduate during the Great Recession for white females. This sample is examined in Section 6.

[36]The predicted moments can be found in the lower panel of Table 4 as well.

Table 6: Predicted Moments: Benchmark Model and Counterfactual Simulations for Female Millennials

		Whites		Blacks	
		Benchmark	Counterfactual	Benchmark	Counterfactual
1	Mean unemployment duration (in months)	13.74	13.74	13.17	13.17
2	Mean job duration (in months)	24.45	24.72	24.62	23.53
3	Fraction of completed job spells ending in a job-to-job transition	0.29	0.29	0.34	0.34
4	Mean monthly accepted earnings	1186.86	1378.40	1144.17	1195.80

Notes: Predicted moments from the benchmark model use estimates from Tables 2 and 3 for females. Predicted moments for the counterfactual simulations use the female search parameter estimates from Table 2 and the male productivity and γ estimates from Table 3. In the counterfactual case, the model is resolved generating new reservation wages and wage cuts before predicting the moments.

are the mean accepted earnings. They increase substantially for both white and black females; eliminating the gender gap for black females and overtaking the male mean earnings for white females. This occurs not only because the males have a better productivity distribution, but also because in response females raise their reservation wage and with better search parameters face less monopsony power from the firms than the males leading to better offers. This result indicates that the main differences between the males and females that generate the earnings gaps are the differences in the productivity distributions.[37] Unlike Bowlus (1997), who found that 70 to 80 per cent of the gender gap in the mid- to late 1980s could be explained by productivity differences, we find that all of the gap can be explained by productivity differences for the Millennials.

5 Generation Gap

Given the above results indicate that the school-to-work experiences of blacks and whites is now be quite similar, it is interesting to compare the

[37]The counterfactual where females face their productivity distribution and the male search parameters actually leads to a lower mean accepted earnings value as reservation wages decline and monopsony power of the firms increases resulting in lower offers.

results in BKN for Generation X and our results for the Millennials for males.[38]

5.1 Sample Differences

Before we make the comparison, we review the differences between the two samples.[39] To start, the time period for the NLSY sample is 1979-92, which covers the recession in 1982. The time period for the PSID-TA sample is 2005-2011, which covers the Great Recession in 2007-2008. While we tried to construct our PSID-TA sample such that it mimicked the NLSY-79 BKN sample, there are several reasons why the two samples are still not directly comparable. First, the PSID-TA durations are likely over-estimated due to the monthly recording times. Spells that end at the beginning of the month have an entire extra month of duration added to the spell unlike with the weekly data of the NLSY-79. Second, as noted above, the job-to-job transitions recorded in the PSID-TA may understate the number of direct transitions between jobs, because they rule out transitions that occur at the end of the month with the new job starting at the beginning of the next month. Third, the definition of a 'real' job is different with jobs requiring fewer hours to be denoted as 'real' in the PSID-TA sample. This should have resulted in shorter unemployment durations for the PSID-TA sample, but in fact our mean unemployment durations for black and white males are longer. This suggests that, if we had invoked a stricter 'real' job definition like BKN, our average unemployment durations would have been even longer. Fourth, BKN do not include any time

[38]BKN only examined the school-to-work transition for males not females. Bowlus (1997) looked at male-female differences across first jobs but did not include the school-to-work transition period in the analysis. Interestingly, the parameters estimates for white female high school graduates in Bowlus (1997) are quite similar to the estimates for white female high school graduates presented here. This suggests that white females did not experience the deterioration of their labor market that we show in this section happened for white males.

[39]These differences are also documented in Appendix Table A2.

spent searching while in school because these durations are not recorded in the NLSY-79. Here we are able to include this search time and thus all of our spells have unemployed search information prior to the first job as well as potentially longer unemployment spells for those who do not find a 'real' job prior to graduation.[40] Finally, BKN deleted observations that contained missing hours and/or wages, while we retain both. For observations with missing hours and/or wages, we use the censored unemployment duration data only.

5.2 Comparison of Sample Statistics

Table 7 shows sample statistics on durations and accepted earnings from both samples. We convert BKN's time unit to monthly values by dividing duration data by 4 and by multiplying earnings data by 4, and adjust the real wage to 2000 dollars. The first row shows that youths from the NLSY-79 sample had a much easier time finding a job before or at graduation than those from the PSID-TA sample. With white and black Generation X graduates having 32 per cent and 22 per cent employed at graduation, respectively, while only 6.3 per cent and 4.7 per cent of white and black Millennials were employed at graduation, respectively.[41] This is the first sign that the Millennials faced a more difficult labor market than Generation X when they started their school-to-work transition.

[40]Because the search time prior to graduation is relatively short, the unemployment durations before jobs accepted while in school offset the potentially longer spells for those who do not secure employment while in school and, thus, the mean durations including forward and backward times (reported in Table 1) are not that different from the mean forward duration times. For white males, the mean of the full unemployment durations is 11.58 versus a mean of 11.32 for the forward recurrence times. Similarly for black males the means are 12.17 and 11.16, respectively.

[41]Our rate is not quite comparable to BKN's, because we excluded those who found jobs before graduation but did not search before finding them. This, however, is a small fraction of the sample. If they were included the fractions would still only be 0.133 for white males and 0.102 for black males.

Table 7: Sample Statistics from the NLSY-79 and PSID-TA Male Estimation Samples

		Generation X NLSY-79		Millennials PSID-TA	
		Whites	Blacks	Whites	Blacks
1	Fraction of individuals employed at graduation	0.32	0.22	0.063	0.047
2	Mean unemployment duration (in months)	9.27	11.26	11.58	12.17
3	Fraction of censored spells among all unemployment spells	0	0	0.28	0.30
4	Mean job duration (in months)	28.57	21.35	17.99	17.68
5	Fraction of censored spells among all job spells	0.09	0.10	0.24	0.20
6	Fraction of completed job spells ending in a job-to-job transition	0.45	0.29	0.26	0.32
7	Mean monthly accepted earnings	1590.82	1391.10	1248.77	1237.76
8	Correlation between unemployment spells and accepted wages	-0.056	-0.123	0.128	0.053
9	Correlation between job spells and accepted earnings	0.106	0.282	0.100	0.110

Notes: Source for Generation X: Table 3 in BKN converted to months.

While the PSID-TA sample shows that the white males non-employment duration increased about 2.3 months from the NLSY-79 sample, the increase is only 0.9 months for black males. As already noted above, the mean accepted earnings between black and white males are similar and lower in the PSID-TA sample. The average job duration between the two groups also became more similar, albeit much shorter, in the PSID-TA sample.[42] These results are again in contrast to BKN where substantial racial differences were found for earnings and job durations. The only

[42]This result may be related to the length of the sample periods in the two data sets. In the NLSY-79 sample, respondents were allowed to complete schooling within five years from 1979-84, while respondents in the PSID-TA sample also completed schooling within a five year period until 2010. However, the length of study in BKN is 14 years, whereas it is only 7 years in this study. Thus, for those graduating in 2009 or 2010, job duration is likely to be shorter or censored as the panel ends in 2011 with only few respondents' histories ending in the first quarter of 2012.

large difference across black and white males that we find is the job-to-job transition rate, and here black males out perform white males with a higher job-to-job transition rate. Again this contrasts with BKN where black males were found to perform substantially worse than white males on this dimension (0.45 for white males and 0.29 for black males).[43] The last two rows of Table 7 show the correlation between earnings and the two duration spells. Both correlations are positive for the PSID-TA sample, while for the NLSY-79 sample the correlation is negative between earnings and unemployment durations and positive between earnings and job durations.

5.3 Comparison of Estimates

Table 8 compares the male search parameter estimates for Generation X from the NLSY-79 sample and the Millennials from the PSID-TA sample.[44] For white males in the NLSY-79 sample, λ_0 is 72 per cent higher, λ_1 is 32 per cent higher, and δ is 43 per cent lower than those from the PSID-TA sample.[45] White males from Generation X found jobs much easier both while unemployed and employed, and were less likely to have their jobs destroyed than white male Millennials. Comparing the κ's, white males from Generation X were twice as efficient as the Millennial white males.

For black males in the NLSY-79 sample, λ_0 is 56 per cent higher and δ is 8 per cent lower than black males from the PSID-TA.[46] The higher arrival rate while unemployed for Generation X compared to the Millennials is consistent with those for white males, suggesting a deteriorating mar-

[43] As mentioned earlier, the PSID-TA sample faces the issue of aggregation bias because spells are recorded on a monthly basis. If we count transitions between time t and $t+1$ as job-to-job transitions, the job-to-job transition rates increase to about 40 per cent for both black and white males.

[44] Here we have reproduced the estimates for the male PSID-TA samples reported in Table 2, and have converted the parameter estimates reported in BKN's Table 4 to monthly rates in order to be comparable.

[45] The differences for λ_0 and δ are statistically significant, while that for λ_1 is not.

[46] Only the λ_0 difference is statistically significant.

Table 8: Comparison of Male Generation X and Millennial Search Parameter Estimates

	Generation X NLSY-79		Millennials PSID-TA	
	Whites	Blacks	Whites	Blacks
λ_0	0.1076	0.0892	0.0627	0.0571
	(0.0068)	(0.0072)	(0.0054)	(0.0058)
λ_1	0.0320	0.0320	0.0243	0.0371
	(0.0032)	(0.0064)	(0.0067)	(0.0093)
δ	0.0176	0.0304	0.0306	0.0331
	(0.0016)	(0.0044)	(0.0050)	(0.0053)

Notes: Bootstrap standard errors are reported in parentheses. Source for Generation X estimates: Table 4 in BKN (Q=4) converted to monthly rates.

ket for unemployed Millennial males relative to unemployed males from Generation X. However, λ_1 is 14 per cent lower for black males from Generation X than black male Millennials, indicating the labor market has improved along this dimension for black males. Overall in terms of search frictions, black males from Generation X are about 1.7 times more efficient than Millennial black males with respect to κ_0 and are similar with respect to κ_1.

These results indicate that the labor market has deteriorated for both male Millennial race groups, particularly for white males, making the school-to-work transition more difficult and less secure compared to those who graduated in the late 70s/early 80s. Unlike Generation X, the black-white differences have narrowed for the male Millennials with both groups declining but with white males declining far more than black males to achieve similar levels of search frictions.[47] Thus, over time racial differences in the school-to-work transition have converged not because black

[47]Both λ_0 and δ are statistically significantly different when comparing black and white males from Generation X. However, none of the parameters is statistically significantly different when comparing black and white male Millennials.

males caught up with white males. Rather, the labor market has deteriorated severely for white males to such an extent that their school-to-work transition appears to be similar to or even fallen behind that for black males.

One explanation for this pattern could be changes in selection patterns across the races in terms of educational degree completion. That is, white male high school graduates could have faced more negative selection than black males. However, statistics from the National Center for Education Statistics reveal that selection likely worked against black males more than white males.[48] In 1980, 89.1 per cent of white males age 25-29 had graduated from high school while only 74.7 per cent of black males age 25-29 had graduated. By 2005, those fractions had increased to 91.8 per cent and 86.6 per cent for white and black males, respectively. Further, in 1980, 26.8 per cent of white males age 25-29 had graduated with a BA degree or higher, and this figure increased to 30.7 per cent in 2005. Comparatively, the black BA plus rate was 10.5 per cent in 1980 and 14.2 per cent in 2005. Thus, black males faced a greater flow of high school dropouts into the high school graduate pool and a similar exit of BA graduates suggesting that the average quality of a black male high school graduate likely fell more over this period relative to a white male high school graduate. It is possible that anti-discrimination legislation is helping maintain the labor market outcomes of black high school graduates relative to white high school graduates, but in general the evidence appears to suggest declining labor market opportunities for white high school graduates relative to black high school graduates across the generations.

We next ask what would have happened to the male Millennials if they had faced the productivity distribution of the 2000s, but the arrival and job destruction rates of the 1980s. As we did for the Millennial females,

[48]Figures were taken from the National Center for Education Statistics' Digest of Education Statistics, 2018 Tables and Figures, Table 104.20. Percentage of persons 25 to 29 years old with selected levels of educational attainment, by race/ethnicity and sex: Selected years, 1920 through 2018.

in order to conduct this counterfactual experiment we resolve for the new equilibrium, including new reservation wages and a new wage offer distribution, given the productivity parameter estimates from the PSID-TA sample (Table 3), the arrival rate and job destruction rate estimates from the NLSY-79 sample (columns 1 and 2 of Table 5), and the equilibrium conditions of the model.

Table 9 gives the predicted moments from the benchmark model for the PSID-TA sample as well as the predicted moments from the counterfactual simulation. It shows that white Millennial males would have been better off in all dimensions, particularly in earnings, while black Millennial males would have been slightly better off. One reason the earnings increase a lot for white males is that the reservation wages increase a lot with the better search environment - to $1297 for white males compared to $946 for black males - as does the arrival rate of jobs while employed. Both of these factors reduce the monopsony power of the firms substantially and improve the wage offer distribution. In addition to a higher arrival rate of offers while employed, white males face a lower job destruction rate. Together these generate more competition for firms and force the firms to offer higher wages. The higher arrival rate of offers while employed also affects the supply side: white males will have more on-the-job search, allowing them to climb the wage ladder faster. The earnings improvement for blacks is not as great, because the improvement mainly comes from a higher job offer arrival rate while unemployed. Their job destruction rate does not improve as much, and the job offer arrival rate is actually lower.

6 The Great Recession

To get a sense of the impact of the Great Recession, hereafter GR, we re-partition the sample into those who graduated pre-GR and those who

Table 9: Predicted Moments: Benchmark Model and Counterfactual Simulations for Male Millennials

		Whites		Blacks	
		Benchmark	Counterfactual	Benchmark	Counterfactual
1	Mean unemployment duration (in months)	15.95	9.29	17.53	11.21
2	Mean job duration (in months)	24.23	32.73	20.54	22.10
3	Fraction of completed job spells ending in a job-to-job transition	0.26	0.43	0.33	0.32
4	Mean monthly accepted earnings	1222.31	1808.90	1202.89	1365.70

Notes: Predicted moments from the benchmark model use estimates from Tables 2 and 3 for males. Predicted moments for the counterfactual simulations use the Generation X search parameter estimates from Table 8 and the male Millennial productivity and γ estimates from Table 3. In the counterfactual case, the model is resolved generating new reservation wages and wage cuts before predicting the moments.

graduated during the GR for each gender.[49] In particular, we divide the sample into those who graduated in May 2006 or before (pre-GR) and those who graduated after May 2006 (GR).[50] Table 10 presents the sample statistics for these re-partitioned samples. Columns 1 and 2 of Table 10 show the statistics for males in the pre-GR and GR periods, respectively. We find that Millennial males who graduated prior to GR had substantially shorter unemployment durations, longer job durations, higher earnings and higher job-to-job transition rates than those who graduated

[49]The sample sizes are too small to subdivide into the four race-gender groups for the pre-GR and GR periods. We ran Kolmogrov-Smirnov's test for equality of the earnings distribution within each gender. The p-value for equality of the earnings distributions between blacks and whites is 0.622 and 0.427 for females and males, respectively. These p-values well exceed the 0.05 criterion, and so we accept the null of racial equality in the earnings distributions for each gender. Given the equality tests indicate no racial differences for the earnings distribution as well as similarity in the parameter estimates for blacks and whites from the PSID-TA data, we combine them for each gender to be able to do this GR analysis. We do continue to separate males and females for the analysis as equality tests reject equality of the male and female earnings distribution in the pre-GR sample at the 10 per cent level. The test does not reject equality for the GR sample.

[50]We use 2006 for two reasons. First, it appears that 2006 provides the greatest difference in labor market outcomes suggesting that the financial crisis, which is officially dated as starting in the autumn of 2007, affected those who graduated in spring 2007. Second, 2006 also allows us to have sufficient sample sizes in both periods, although we do face a substantial reduction in the number of wages reported for the post-2006 sample and this does affect the precision of our estimates.

during the GR. Interestingly, those who graduated during the GR were more likely to hold a job at graduation.[51] While better, the pre-GR Millennial male graduates still had poorer labor market outcomes than those of Generation X. Thus, the labor market had deteriorated prior to the early 2000s. That said, it is clear that the GR hit those who graduated in the midst of it very hard. The labor market outcomes of the GR male graduates were substantially worse. One interesting feature of the GR male graduate behavior is that the correlations appear quite different. Their correlation between unemployment spells and accepted earnings is now substantially different from zero and their correlation between job spells and accepted earnings is negative. This may suggest substantially different behavior during the GR as well as changing opportunities and is worthy of further exploration.[52]

Columns 3 and 4 of Table 10 show the female sample statistics for those who graduated pre-GR and GR, respectively. As with males we find that females who graduated during the GR were more likely to hold a job at graduation. While the pre-GR female graduates had 5 month longer job durations than females who graduate during the GR, there is almost no difference in average unemployment duration. Note, however, that almost all unemployed pre-GR female graduates found jobs as opposed to the 12 per cent censoring rate of GR female graduates. The higher rate for GR female graduates may not be solely affected by the GR, it could be a result of the short panel. Job-to-job transitions and mean earnings were also higher for pre-GR female graduates compared to GR

[51]This appears to be related to the exclusion of those who were employed at graduation, but said they did not search before securing the job. This outcome was much more prevalent before the GR than after resulting in what looks like an increase in the employment rate but is more likely a change in the composition of how graduates found jobs, where they had to rely on searching much more after the GR.

[52]Unfortunately, the number of valid and non-missing wage observations for the GR sample is very small at 55. This makes it difficult to say anything too definitive about earnings during the GR and these correlations nor does it allow us to further study these phenomena.

Table 10: Sample Statistics from Pre-GR and GR Estimation Samples

		Males		Females	
		Pre-GR	GR	Pre-GR	GR
1	Fraction of individuals employed at graduation	0.021	0.090	0.063	0.136
2	Mean unemployment duration (in months)	10.93	12.76	12.27	12.67
3	Fraction of censored spells among all unemployment spells	0.20	0.38	0.01	0.12
4	Mean job duration (in months)	18.61	16.88	20.95	15.85
5	Fraction of censored spells among all job spells	0.16	0.31	0.14	0.31
6	Fraction of completed job spells ending in a job-to-job transition	0.35	0.15	0.34	0.25
7	Mean monthly accepted earnings	1272.37	1192.99	1208.39	1171.17
8	Correlation between unemployment spells and accepted wages	0.03	0.25	0	-0.08
9	Correlation between job spells and accepted earnings	0.25	-0.16	0.24	0.14

female graduates. On the whole, the labor market outcomes of the GR female graduates were worse in terms of job related outcomes (duration, transition, wage) than for those who graduated pre-GR, but not so much in terms of unemployment. Correlation between unemployment spells and accepted earnings was almost zero regardless of the time of graduation, while that between employment spells and accepted earnings was higher for pre-GR female graduates by 0.1.

In terms of gender differences, pre-GR graduates had more differences in labor market outcomes than GR graduates in terms of unemployment duration, job duration, and mean accepted earnings. While GR male graduates had a positive correlation between unemployment spells and accepted earnings, the correlation for their female counterparts was negative and close to zero. The opposite pattern occurs for the correlation between employment spells and accepted earnings, where the correlation was negative for GR male graduates and positive for GR female gradu-

ates. Overall, it appears that the GR brought about further convergence between males and females.

Given the small number of earnings observations during the GR, the productivity distribution is difficult to estimate with any precision and the resulting productivity level estimates are quite large at the high end. Therefore, we report the arrival and destruction rate estimates using the empirical cdf of accepted earnings. These are reported in Table 11. As expected from the sample means, the arrival rate of job offers while unemployed, λ_0, is lower for the GR sample for both genders, as is the arrival rate for job offers while employed, λ_1.[53] Thus, it became substantially more difficult to secure job offers during the GR. Interestingly, the job destruction rate is the same pre-GR and GR for males, but it is slightly higher and closer to the male GR rate for females. This suggests that the issue for the high school graduate transition from school-to-work during the GR was related more to a lack of offers than more job loss for males, and both a lack of offers and more job loss for females. Despite the higher job loss rate for GR female graduates, the female rates are in general smaller than the male rates.

Finally, the values for κ_0 and κ_1 for pre-GR and GR male graduates are, respectively, $\kappa_0 = 2.28$ and $\kappa_1 = 1.26$, and $\kappa_0 = 1.52$ and $\kappa_1 = 0.33$. Those for females are $\kappa_0 = 3.00$ and $\kappa_1 = 1.14$ for pre-GR graduates and $\kappa_0 = 2.19$ and $\kappa_1 = 0.71$ for GR graduates. In general, the rates for females exceed males before and during the GR, indicating they were more efficient than males in entering and moving up the wage ladder. We note that Bowlus (1997) found the opposite with both κ_0 and κ_1 values higher for white males than white females. Thus, the deterioration of the white male labor market for high school graduates appears to have occurred relative to white females as well as black males. The value of κ_1 for the GR male graduates is very low suggesting a substantial increase in search

[53]These declines are statistically significant for males, but not for females. Across males and females, only λ_0 for the GR period is statistically significantly different.

Table 11: Search Parameter Estimates for Pre-GR and GR using Empirical $F(w)$

	Males		Females	
	Pre-GR	GR	Pre-GR	GR
λ_0	0.0733	0.0489	0.0808	0.0689
	(0.0068)	(0.0052)	(0.0077)	(0.0066)
λ_1	0.0406	0.0105	0.0308	0.0224
	(0.0078)	(0.0047)	(0.0057)	(0.0060)
δ	0.0322	0.0322	0.0269	0.0315
	(0.0046)	(0.0059)	(0.0035)	(0.0049)
Log-likelihood	-768.62	-518.01	-816.75	-662.79

Notes: Asymptotic standard errors are reported in parentheses.

frictions and monopsony power for the firms as well as a substantial loss of wage growth for these graduates through an inability to climb the job ladder.

As with black and white males, selection does not seem to be a candidate explanation as white females greatly outpaced white males in terms of the growth in the fraction with a BA degree or higher resulting in more adverse selection for them. Between 1980 to 2005, white females increased the fraction with a BA degree or higher from 23.2 per cent to 38.2 per cent, an increase of 15 percentage points compared to the white male increase of 4 percentage points.[54] Again anti-discrimination could be helping females maintain their labor market conditions, but the reason behind the deterioration of the white male labor market remains an open question. In addition, further studies are needed to see if the Millennials can recover from such a bad start as well as how the next generation's school-to-work transition goes during the GR recovery period.

[54]Similarly, black females increased from 12.4 per cent with a BA degree or higher in 1980 to 20.5 per cent in 2005. This increase of 8 percentage points is more than double the 3.7 percentage point increase of black males.

7 Conclusion

In this paper we have examined the job search and earnings outcomes of Millennials at the start of their careers. While much of the focus on Millennials has been directed at college graduates, we focus on high school graduates. We document standard labor market outcomes for the school-to-work transition during 2005-2011 and then estimate the BM general equilibrium search model to quantify the roles of various search frictions in determining these outcomes. We provide estimates for both black and white males and females. We also examine how the school-to-work transition has changed over time by comparing the Millennials to Generation X, and further explore the impact of the Great Recession on the Millennials.

In general our results show a convergence of labor market outcomes across race and gender. Compared to Generation X, the race gap has disappeared, and by the Great Recession much of the gender gap has disappeared as well. Unfortunately, this is not due to groups seeing improved labor market prospects. In contrast, our results show that the Millennials' labor market was significantly poorer than that faced by Generation X. In particular, it deteriorated quite a lot for white males such that their parameter estimates converged to or even became worse than those for black males. We show that this deterioration was present before the GR started and became even worse for those who graduated during the GR. We also show that, if the male Millennials had faced the search parameters of males from Generation X, they would have done much better, particularly white males. Thus, the poor labor market performance of the Millennials appears to have more to do with greater search frictions than a decline in productivity. In addition, we find that the initial gender gap for Millennials was primarily driven by productivity differences that were by and large eliminated during the Great Recession. Thus, by the time of the Great Recession we find that both the race and the gender earnings gaps have closed for first jobs.

It is clear from these results that more work needs to be done to understand the labor market forces at work affecting the Millennials, particularly those of white males. In regard to selection being a plausible explanation, a cursory examination of the education completion rates indicates no support as black males and females faced more adverse selection than white males for high school graduates. One avenue that may be worth exploring is to address the emergence of part-time work among the Millennials. As noted in our data description, our data set shows that, if we focused only on full-time jobs (35+hours/week), we would have had far fewer successful transitions to work in our sample and this would have lengthened the unemployment durations. To what extent this pattern is a result of the demand side or a result of the Millennials' labor supply choices remains an open question. With respect to the former, there may be fewer jobs are available because of robotics and technological improvements, jobs may have become so productive that fewer high school employees are needed to run the operation, or college graduates may be pushing high school graduates out of jobs (e.g. Acemoglu and Restrepo (forthcoming), Acemoglu and Autor (2010), Author et al. (2003), and Beaudry et al (2016)). With respect to the latter, a recent study by Aguiar et al. (2017) finds a reduction in work hours for low educated young males in the 2000s and suggests extra leisure through video-gaming can explain the phenomenon.

8 Appendix

Table A1: CPS Hourly Nominal Wage Bounds

		Less than HS		HS		Some College		College	
Year	Nominal Minimum Wage	5th	95th	5th	95th	5th	95th	5th	95th
				Males					
2005	5.15	5.00	12.00	5.00	13.00	4.00	13.00	6.00	16.00
2006	5.15	5.00	10.50	5.75	15.00	5.15	13.00	5.50	11.00
2007	5.85	5.15	11.00	6.00	18.00	5.50	17.00	6.13	22.00
2008	6.55	5.35	12.50	6.25	17.27	5.85	17.25	7.50	25.00
2009	7.25	6.00	13.00	6.65	18.00	3.50	19.00	8.00	30.00
2010	7.25	7.00	13.00	7.25	17.60	5.75	16.50	8.00	30.00
2011	7.25	7.00	14.25	7.25	18.00	7.25	18.00	8.00	31.00
				Females					
2005	5.15	5.00	10.00	3.00	11.00	2.83	13.00	3.12	13.08
2006	5.15	5.00	9.75	5.50	12.50	5.15	12.50	5.50	11.00
2007	5.85	5.15	9.25	5.00	14.00	5.15	17.00	6.38	20.00
2008	6.55	5.25	10.50	6.00	13.50	5.00	15.00	9.00	21.90
2009	7.25	6.00	10.50	6.50	15.00	3.13	17.00	8.00	32.50
2010	7.25	5.00	10.35	5.55	14.04	4.25	15.75	7.25	30.00
2011	7.25	7.00	11.00	6.00	16.92	5.00	16.37	8.00	30.19

The criteria for reported nominal earnings to be acceptable are:

1. If the pay unit is coded as hourly, earnings must fall within the bounds in Table A1 for a given year and education status;

2. If the pay unit is coded as daily, earnings must fall within the lower bound times 4 and the upper bound times 10;

3. If the pay unit is coded as weekly, earnings must fall within the lower bound times 20 and the upper bound times 50;

4. If the pay unit is coded as biweekly, earnings must fall within the bounds in condition 3 multiplied by 2;

5. If the pay unit is coded as monthly, earnings must fall within the bounds in condition 3 multiplied by 4.3; and

6. If the pay unit is coded as annually, earnings must fall within the bounds in condition 3 multiplied by 52.

Table A2: NLSY-79 And PSID-TA Sample Differences

	NLSY-79	PSID-TA
Survey period	1979-92	2005-11
Time Unit	weeks	months
Deflator	1990	2000
Full-time job definition	35hr+/wk	20hr+/wk
Left-censoring	forward recurrence time	backward and forward recurrence time
Missing hours	excluded	censored unemployment spell
Missing wages	excluded	retained
Job-to-job transitions	between t and t+2 weeks	within t month

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