

Employment Inequality:

Why Do the Low-Skilled Work Less Now?

Erin L. Wolcott *

Middlebury College

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Abstract

Low-skilled prime-age men are less likely to be employed than high-skilled prime-age men, and the differential has increased since the 1970s. This paper investigates why. I build a labor search model encompassing three explanations: (1) factors increasing the value of leisure, such as welfare or recreational gaming/computer technology, reduced the supply of lower skilled workers; (2) automation and trade reduced the demand for lower skilled workers; and (3) factors affecting job search, such as online job posting boards, reduced search frictions for higher skilled workers. I augment the model with heterogeneous workers and occupational choice and calibrate it to match a novel empirical finding: diverging labor market tightness by skill. The empirical finding along with data on wages and worker flows enables me to separately identify effects of all three mechanisms. I find a shift in the demand away from lower skilled workers is the leading cause. A shift in the supply of lower skilled workers cannot explain diverging employment rates and search frictions actually reduced the divergence. In other words, search frictions for higher skilled workers increased, and had that not been the case, employment inequality today would be worse.

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1 Introduction

Low-skilled prime-age men are less likely to be employed today than high-skilled prime-age men. This gap emerged 50 years ago and has been growing ever since. Figure 1 plots employment-population ratios of two educational groups: prime-age men with a high school degree or less in red (which I will refer to as low-skilled) and prime-age men with one year of college or more in blue (which I will refer to as high-skilled).¹ In 1950 both groups had an employment rate of approximately 90 percent. In the subsequent decades employment rates of both groups declined, while the spread increased.

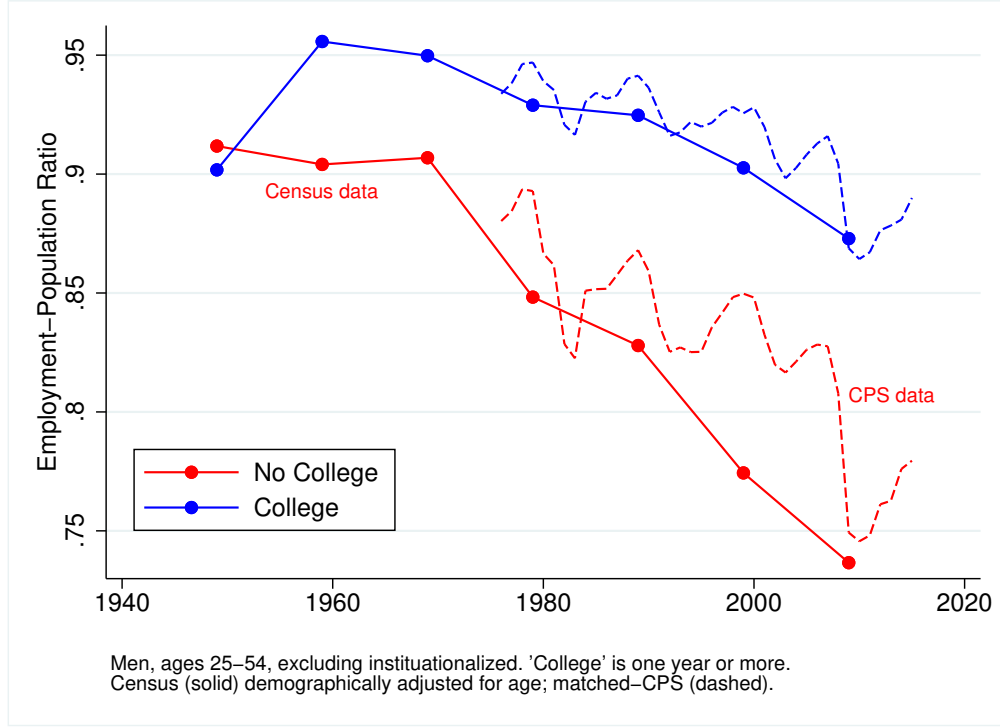
Why do the low-skilled work less now? There are a lot of incomplete or unpersuasive answers. I attempt to remedy the incompleteness by running a horse race between three leading candidates: (1) factors increasing the value of leisure, such as welfare or recreational gaming/computer technology, reduced the supply of lower skilled workers; (2) automation and trade reduced the demand for lower skilled workers; and (3) factors affecting job search, such as online job posting boards, reduced search frictions for higher skilled workers.² Identification comes from building and calibrating a labor search model and matching it to a novel empirical finding about labor market tightness.

Depending on which mechanism widens the employment gap, policy implications will differ. If declining health, more people on disability insurance, or life-like computer and video game graphics reduced low-skilled reservation wages relative to offer wages, appropriate policy responses may include restructuring healthcare and social security; although, in the case of increased leisure enjoyment it is not clear policy should respond. If robots and outsourcing

¹I focus on men because their labor force participation decisions have been more straightforward over this period. Appendix A shows gap emerged for women and other subgroups.

²Cortes, Jaimovich, and Siu (2016) and the Council of Economic Advisors' 2016 Economic Report of the President find demographic changes cannot account for the decline in low-skilled employment or labor force participation. The CEA report also rules out a working spouse or other household member as an explanation because the share of prime-age men out of the labor force with a working household member is small and has declined over time. I exclude composition changes and other household income as possible channels.

Figure 1: Widening Employment Gap³



reduced low-skilled offer wages relative to reservation wages, training programs or policies promoting demand for low-skilled workers could help. Lastly, if growing popularity of online job posting boards differentially reduced search frictions for the high-skilled, policies lessening information or geographical frictions for the low-skilled could be the optimal response. The goal of this paper is to uncover why employment rates have diverged so we can better understand the appropriate policy response.

The paper has three contributions. The first contribution is documenting an empirical finding about labor market tightness. Labor market tightness is the ratio of job openings to

³Data from the matched CPS and Census in Figure 1 differ for two reasons. First, I demographically adjust Census data for age to show the divergence is not driven by changes in composition. I overlay unadjusted CPS data because this is the data I use to calibrate my model. Second—and this is where most of the discrepancy between the solid and dashed lines comes from—there is severe selection bias. Men who can be followed for four consecutive months in the matched CPS are systematically different from the men interviewed once in the Census, and this is particularly true for non-college men without. The difference between these two sources is striking and warrants further research, although measurement issues in the CPS is hardly a new topic. For example, see Peracchi and Welch (1994), Moscarini and Thomsson (2007), Kambourov and Manovskii (2013).

job seekers. I find tightness between high- and low-skilled labor markets has diverged since the 1970s (see Figure 3 in Section 2). This data is vital for estimation because by calibrating the model to match it, I separately identify the importance of search frictions from the other channels. I combine several data sources to construct measures of labor market tightness for two peaks of the business cycle: 1979 and 2007. I find the low-skilled labor market was slightly tighter than the high-skilled market in 1979, while the high-skilled labor market was substantially tighter than the low-skilled market in 2007. Put differently, there is more slack in the low-skilled labor market today than there was several decades ago.

The second contribution is theoretical. I build a search and matching model in the spirit of Diamond (1982), Mortensen (1982), and Pissarides (1985) (DMP henceforth) to quantify the reasons why low-skilled employment rates have declined. In DMP models, job openings and job seekers simultaneously exist. This is a realistic feature of the labor market—the unemployment rate is always positive and labor market tightness is never infinite—yet most macro models gloss over this fact. DMP models get closer to reality by including a friction between firms searching for employees and workers searching for jobs. I augment the standard model by assuming workers have heterogeneous ability and choose to search for jobs requiring either low-skilled or high-skilled tasks, where ability is only relevant in jobs requiring high-skilled tasks. Heterogeneity in worker ability and occupational choice are important additions because selection is part of the employment inequality story: as more men attend college, the ability composition of the college and non-college job market changes.⁴ Ability here can also be interpreted as some other permanent characteristic acting as a barrier to college, such as family wealth or access to student loans. I also augment the model to include a channel for demand-side effects of automation and trade. The model in this paper is flexible enough to allow for three broad channels to influence differential employment trends, and for agents to respond accordingly.

⁴In the 1970s approximately 40 percent of prime-age men had some college experience, while in the 2000s the majority had some college experience.

The final contribution is quantitative. I calibrate two steady states to understand how a supply shift, demand shift, and search frictions impacted employment rates in the 1970s and 2000s. I find a demand shift is the main driver, while a supply shift had little effect and search frictions actually reduced employment inequality since the 1970s. I do this by first targeting job finding rates and labor market tightness to identify dispersion in matching efficiency parameters (i.e. search frictions) across low- and high-skilled jobs. Since the high-skilled market became tighter over this period while relative job finding rates remained constant, this implies that the high-skilled market today is less efficient at matching job seekers with job openings. Then, I target wages and labor market tightness to identify how changes in the parameters representing the value of leisure (i.e. a supply shift) differ from changes in the parameters representing automation and trade (i.e. a demand shift). The demand shift ends up beating out the supply shift because the wage gap widened substantially over this period. If low-skilled men were home playing video games because sophisticated computer graphics made it that much more enjoyable (or because welfare payments increased or their health exogenously decreased) their wages would have increased, not decreased. Lastly, I take job separations directly from the data.⁵ Because the model focuses on the worker side and does not micro-found job separations, the quantitative results should be interpreted as a lower bound for the role of demand. To the extent automation and trade operate through the job separation margin, in addition to the job finding margin, it is plausible that demand shifting away from low-skilled workers and towards high-skilled workers is even more important for explaining rising employment inequality than what the baseline results imply.

This paper provides a unified framework to quantify how multiple channels contribute to employment inequality. In contrast, previous papers have focused on a single mechanism. For example, several papers postulate an increase in low-skilled workers' value of leisure is an

⁵As is common in the search literature, this model abstracts from firm creation and focuses on the worker side. It details the choice a worker makes about whether to work, but does not microfound the choice a firm makes about whether to operate. As such, the three channels of interest (supply shift, demand shift, and search frictions) operate through the worker side and job finding rates, while job separation rates are taken as exogenous.

important driver of differential employment trends. Aguiar and Hurst (2007, 2008) examine time-use data and find in 1985 nonemployed men with 12 years of education or less had 1.3 more hours of leisure than men with more education, after adjusting for demographics.⁶ In the 2000s this difference increased to a striking 9.7 hours. Aguiar and Hurst (2008) postulate that, “The results documented in this paper suggest heterogeneity in the relative value of market goods and free time...may be a fruitful framework to understand income inequality.” One caveat with this hypothesis is less educated workers may have more leisure because they *cannot find work*, not because they *prefer not to work*, and this descriptive approach does not necessarily distinguish between the two. In contrast, Aguiar, Bils, Charles, and Hurst (2017) take a more structural approach focusing on younger men, ages 21 to 30, and find about half of their decline in hours worked since 2004 was from gaming/recreational computer use.⁷ Barnichon and Figura (2015a) attempt to isolate the labor supply shift channel by looking at the share of nonparticipants who answered “yes” to wanting work. They find the share of work-wanting individuals declined in the late 1990s, most severely for prime-age females. Another reason opportunity costs of labor may have changed over this period regards health. Case and Deaton (2017) and Krueger (2016) highlight the role of health issues as barriers to work, particularly among the less educated. My approach differs from these papers, as I calibrate a structural model to quantify the importance of non-market activity relative to other channels in accounting for the growing employment rate gap.

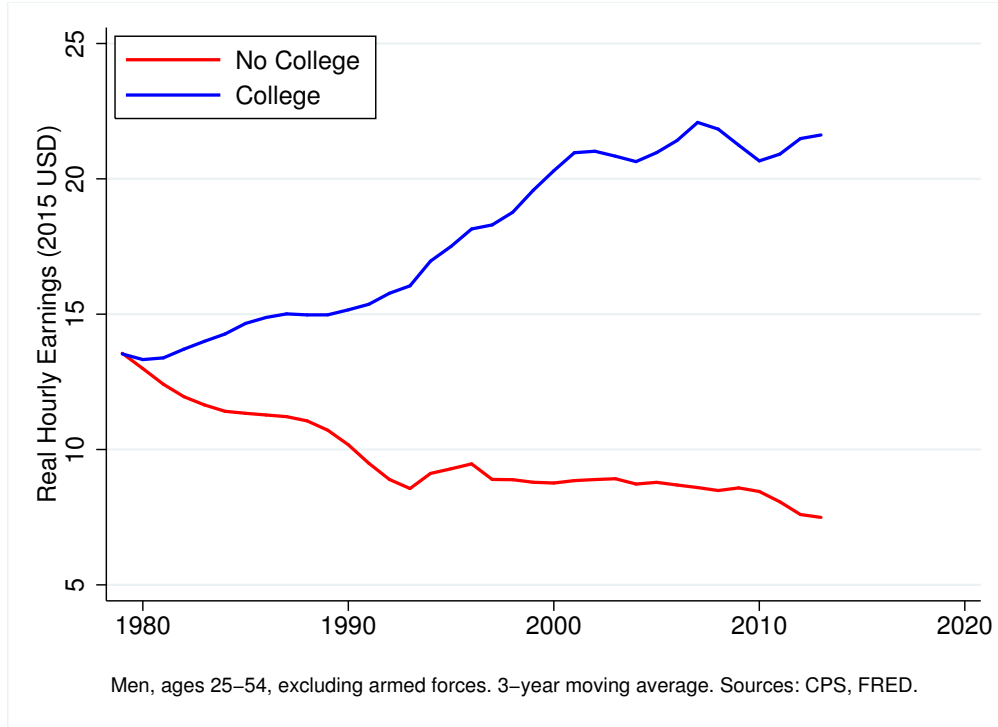
Other studies focus on understanding how a demand shift has differentially impacted

⁶Aguiar and Hurst (2008) define leisure as activity excluding non-market work, child care, home production, medical care, and religious/civic duties.

⁷Aguiar, Bils, Charles, and Hurst (2017) exclude full-time students so the vast majority of this population has less than a bachelors’ degree.

⁸To compare between-group wage dispersion, I calculate real hourly earnings in the March CPS by dividing pre-tax wage and salary income by the number of weeks worked and the usual number of hours worked in a given week from the preceding calendar year (see Lemieux (2006) for a discussion). I exclude respondents who had no wage or salary income, who did not work a single week, or who usually worked zero hours per week last year. Although, an imperfect measure due to recall bias, this approach provides a rough estimate of hourly earnings. I scale this measure by the Consumer Price Index to convert to real hourly earnings. I test robustness to excluding respondents who worked less than 50 weeks per year and less than 35 hours per week under the presumption recall bias may be stronger among part-time workers with more flexible schedules. Nevertheless, the trend in real hourly earnings is robust to these changes.

Figure 2: Widening Wage Gap⁸



employment rates using wage data. For example, Autor, Katz, and Krueger (1998) find despite the threefold increase in the employment share of college graduates from 1950 to 1996 demand for college workers must have increased substantially in order to reconcile the widening wage gap. Figure 2 illustrates the severity of the wage gap by plotting real hourly earnings for college and non-college workers. Other papers have similarly point out that growing wage inequality is more consistent with a demand-side explanation than a supply-side one (see Katz (2000) for a review). The two leading candidates behind a demand shift are automation of low-skilled jobs (Autor (2014), Acemoglu and Restrepo (2017)) and competition of low-skilled labor from abroad (Autor, Dorn, and Hanson (2013, 2015); Pierce and Schott (2016)).

Finally, there is a sizable literature studying matching efficiency, which is an important labor market friction (Lipsey (1966), Abraham and Wachter (1987), Blanchard and Diamond (1989)). More recently the focus has been on explaining the decline in matching

efficiency during and after the Great Recession (Barnichon, Elsby, Hobijn, and Sahin (2012); Davis, Faberman, and Haltiwanger (2013); Şahin, Song, Topa, and Violante (2014); Hall and Schulhofer-Wohl (2015); Herz and Van Rens (2015); Barnichon and Figura (2015b); Hornstein and Kudlyak (2016)). I look over a longer period and ask how relative matching efficiency across skill groups has evolved. *A priori* it is not clear whether changes in relative matching efficiency enlarge or narrow the employment rate gap. If high-skilled workers are more likely to use online job posting boards and this new technology minimizes search frictions, the employment rate gap would widen.⁹ However, online job search is not a panacea. In fact, Bayer et al. (2008) and Brown et al. (2016) find referred candidates have better job prospects, and less educated workers are more likely to use these informal hiring channels. Together this suggests online search technology may accentuate search frictions, and the highly educated are disproportionately affected because they use this technology more. Aside from online job search, other things have changed in the labor market. Moscarini (2001) points out that increasing specialization and diversification makes it more difficult to assign the right person to the right job. If increased specialization is primarily a high-skilled phenomenon, this could have decreased high-skilled matching efficiency and closed the employment rate gap. I find the latter explanations more likely: search frictions increased for college workers and decreased for non-college workers between 1979 and 2007.

2 Empirical Findings

This section documents a novel empirical finding: the market for low-skilled labor has more slack than the market for high-skilled labor today, which was not the case in the late 1970s. By calibrating the model to match this empirical finding, I can distinguish how three potential mechanisms influence employment inequality.

⁹Faberman and Kudlyak (2016) find the share of job seekers with a bachelor’s degree or more on Snagajob (an online job posting board) is nearly twice as large as the share of unemployed workers with a Bachelor’s degree or more in the CPS.

2.1 Labor Market Tightness Definition

The standard definition of labor market tightness, which I denote θ_j^u , uses unemployment in the denominator:

$$\theta_j^u \equiv \frac{V_j}{U_j},$$

where the numerator is the number of job vacancies and the denominator is the number of unemployed individuals. In this context, tightness is disaggregated by skill where $j \in \{L, H\}$. Specifically, V_L is the number of vacancies for low-skilled, non-college positions and U_L is the number of unemployed prime-age men without college experience. Similarly, V_H is the number of vacancies for high-skilled, college positions and U_H is the number of unemployed prime-age men with college experience. The intuition is as follows. If θ_j^u is large, there are many vacancies for every unemployed worker. If θ_j^u is small, there are relatively few vacancies for every unemployed worker. Thus, we expect job finding rates to generally increase with labor market tightness.

For simplification purposes, agents in my model can only have one of two labor market statuses: employed or nonemployed. In other words, I group unemployed men with men who are out of the labor force. While unemployment and nonparticipation are distinct labor market statuses over the business cycle, Elsby and Shapiro (2012) and Juhn, Murphy, and Topel (1991, 2002) argue the boundary is blurred over the long-run. At low frequencies, unemployed men resemble nonparticipants because they have relatively long spells of joblessness and minimal employment opportunities. Moreover, the number of nonparticipants who transition to employment is greater than the number of unemployed who transition to employment in a given month (Fallick and Fleischman (2004), Hornstein, Kudlyak, and Lange (2014)). For these reasons the baseline measure of labor market tightness in this paper, which I denote θ_j^n , uses nonemployment in the denominator, although I test robustness to the more standard unemployment measure. I restrict attention to men, ages 25-54,

because men’s labor force participation decisions have been historically less complex than women’s. Specifically, the baseline nonemployment measure defines labor market tightness as:

$$\theta_j^n \equiv \frac{V_j}{U_j + NLF_j},$$

for $j \in \{L, H\}$, where NLF_L is the number of prime-age men not in the labor force with no college experience and NLF_H is the number of prime-age men not in the labor force with college experience.

Lastly, I calculate the tightness gap, which is a useful statistic illustrating how relative tightness between high- and low-skilled labor markets has evolved:

$$\text{Tightness Gap}^m \equiv 100 \times \frac{\theta_H^m - \theta_L^m}{\theta_L^m},$$

where $m \in \{u, n\}$ is the type of tightness measure used to construct the gap, namely the unemployment measure or nonemployment measure.

2.2 Data

I use three datasets to create measures of market tightness by skill for the 1970s and 2000s: (1) the BLS 1979 job openings pilot program, (2) data constructed by Hobijn (2012), and (3) the Integrated Public Use Microdata Survey (IPUMS-CPS).

BLS Pilot Program. In order to classify job openings as high-skilled or low-skilled, I use data disaggregated by occupation. Occupations group jobs based on the task or skill content of their employees, which unlike industries group jobs based on the product category of their output. Thus, occupations are a better dimension along which to divide vacancies into high- and low-skilled. Unfortunately, U.S. vacancy data by occupation is difficult to

come by due to its costly collection procedure.¹⁰ To my knowledge, the only comprehensive national vacancy datasets disaggregated by occupation are The Conference Board’s Help-Wanted Online (HWOL) and Hobijn (2012)’s constructed series, both of which start in the second quarter of 2005. Fortunately, in 1979 the BLS conducted a pilot study to analyze the feasibility of collecting detailed vacancy data. The pilot surveyed 465 establishments for six consecutive quarters throughout four states: Florida, Massachusetts, Texas, and Utah.¹¹ Occupational detail was collected for 19 occupations, which are based on the 1977 Standard Occupation Classification (SOC) system. Appendix B lists these occupations. I convert occupational codes to the 1970 Census system using an archived crosswalk published by the National Crosswalk Service Center.¹² This conversion allows me to merge vacancy data with employment data from the CPS.

Hobijn (2012) Data. Hobijn (2012) uses state establishment surveys covering about 10 percent of U.S. payrolls and the labor force to construct nationally representative series of job openings by occupation. Thirteen states have conducted job vacancy surveys at least once over the period 2005 to 2013. Hobijn (2012) merges this data with vacancies by industry from the job openings and Labor Turnover Survey (JOLTS) and data on employment shares from the CPS to construct his series. Data is the monthly average over the second quarter of each year and lists occupations by 2010 2-digit SOC codes. Appendix B lists these occupations. I convert occupational codes to the 2000 Census system using a crosswalk published by the National Crosswalk Service Center.¹³ This conversion allows me to merge vacancy data with employment data from the CPS.

CPS Micro Data. Individual-level data on employment status and college attainment is

¹⁰Unlike industries where vacancies from a single firm have the same classification, occupations require firms to list openings by occupation when filling out a job openings survey.

¹¹ Plunkert (1981) publishes a subset of this data, which includes 1979Q1-1979Q3 for Florida, Massachusetts, and Texas, and 1979Q1-1979Q2 for Utah. According to the BLS, records of the remaining data no longer exist.

¹²<http://www.xwalkcenter.org/index.php/classifications/crosswalks>

¹³<http://www.workforceinfodb.org/ftp/download/xwalks>

from the Integrated Public Use Microdata Series, version 4.0 (Flood et al. (2015)). Monthly observations for a nationally representative sample of the U.S. population start in 1976. I classify individuals who have completed at least one year of college as high-skilled, and the remaining individuals as low-skilled.

In order to construct tightness ratios by two broad categories of skill, I need to classify vacancies as either high- or low-skilled to coincide with nonemployed workers who are designated high- and low-skilled. I do this by defining z as the share of individuals with at least one year of college who are employed in a given occupation. I then choose a cutoff z^* to define high-skilled vacancies. For example, let occupations where more than sixty percent ($z^* = 0.6$) of the workforce has one year or more of college experience be classified as high-skilled jobs. I check robustness to various cutoffs. Figure 4 plots tightness gaps where cutoff z^* ranges from 50 to 80 percent. For the baseline cutoff $z^* = 0.6$, Appendix B lists which occupations in the 1979 BLS pilot and Hobijn (2012) data are categorized as high- and low-skilled.

2.3 Labor Market Tightness Measure

Figure 3 plots the monthly average of job openings (red) and number of nonemployed prime-age men (blue) by low- and high-skilled in 1979 and 2007. Vacancies are categorized as high-skilled if more than 60 percent of employees in an occupation have at least one-year of college ($z^* = 0.6$). Nonemployed men are split into two categories: unemployed (dark blue) and out of the labor force (light blue). The vertical axis is the number of nonemployed workers or vacancies in thousands. Magnitudes differ drastically across the two panels because in 1979 data is only available for four states, while in 2007 data is only available for the entire U.S. The nonemployment measures of labor market tightness, as reported in Table 1, are simply the red bars divided by the total blue bars. The unemployment measures in

Table 1: Tightness Ratios

Measure	Year	Data Sources	θ_H	θ_L	Gap
Nonemployment	1979	BLS, CPS	0.44	0.73	-40%
Nonemployment	2007	Hobijn (2012), CPS	1.03	0.37	177%
Unemployment	1979	BLS, CPS	1.22	2.71	-55%
Unemployment	2007	Hobijn (2012), CPS	3.68	1.56	136%

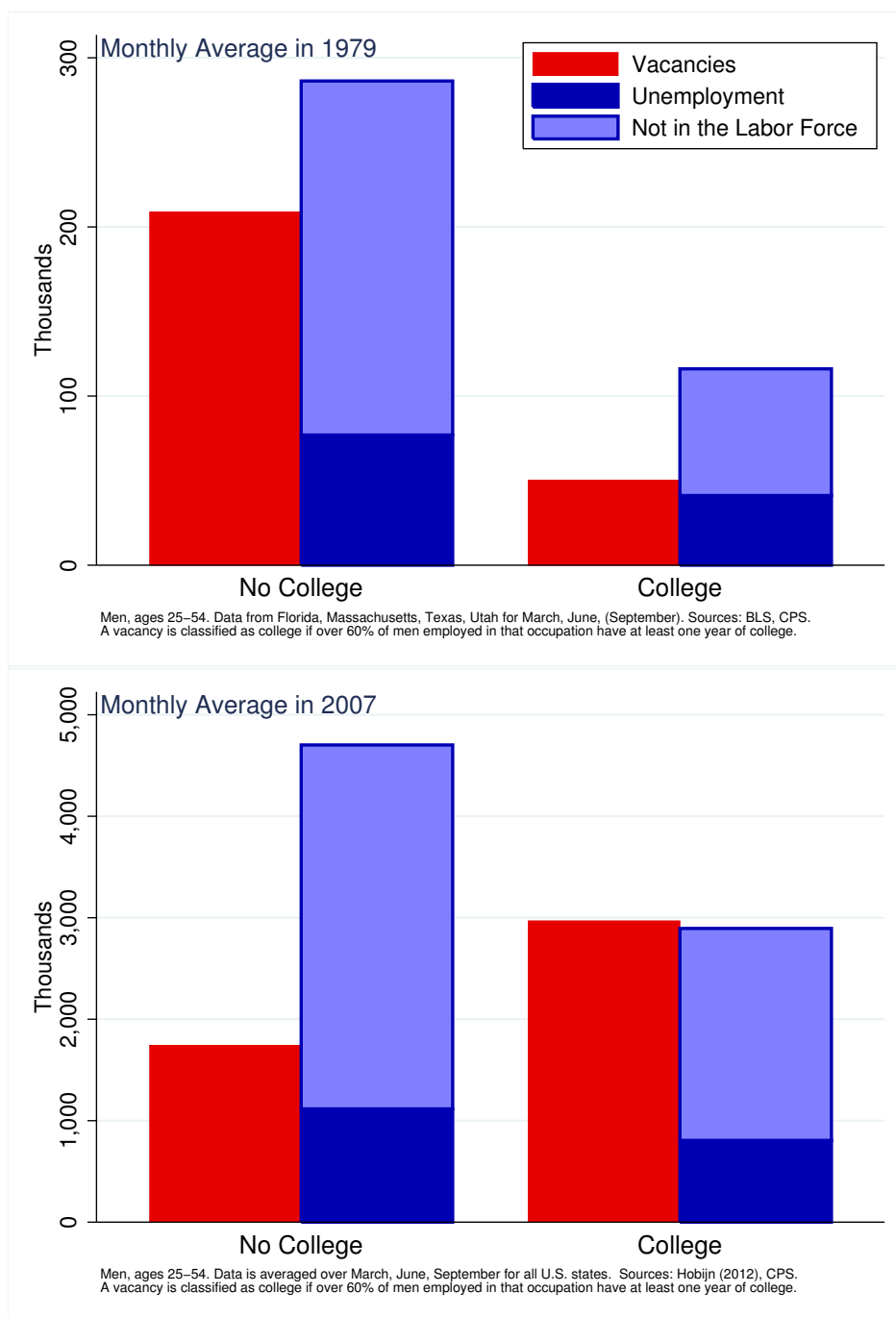
Men, ages 25-54. Reported tightness is the monthly average over March, June, September in 1979 and March, April, May in 2007. Utah in 1979 is the exception; tightness is only averaged over March and June. Data from 1979 only includes Florida, Massachusetts, Texas, and Utah.

Table 1 are the red bars divided by the dark blue bars.

Turning to the top panel of Figure 3, in 1979 the number of nonemployed men exceeds the number of vacancies in both markets. However, the non-college market is tighter—there are 0.73 vacancies for every nonemployed non-college male, while there are only 0.44 vacancies for every nonemployed college male. Turning to the bottom panel, in 2007 the number of college vacancies almost equals the number of nonemployed college males. Moreover, the college market is much tighter than the non-college market—there is approximately one vacancy for every nonemployed college male, and only 0.37 vacancies for every nonemployed non-college male. From the perspective of firms, in 1979 the non-college market was tighter, but in 2007 the college market was tighter. Table 1 calculates the tightness gaps. In 1979 the market for college workers had 40% more *slack* than that for non-college workers, but in 2007 the market for college workers was 177% *tighter*. In recent decades firms have wanted to hire college-educated workers, but there are relatively few college-educated prime-age men available.

These same patterns of relative tightness hold if we use the unemployment measure of labor market tightness. Restricting attention to the dark blue bars in Figure 3, we see

Figure 3: Differential Market Tightness

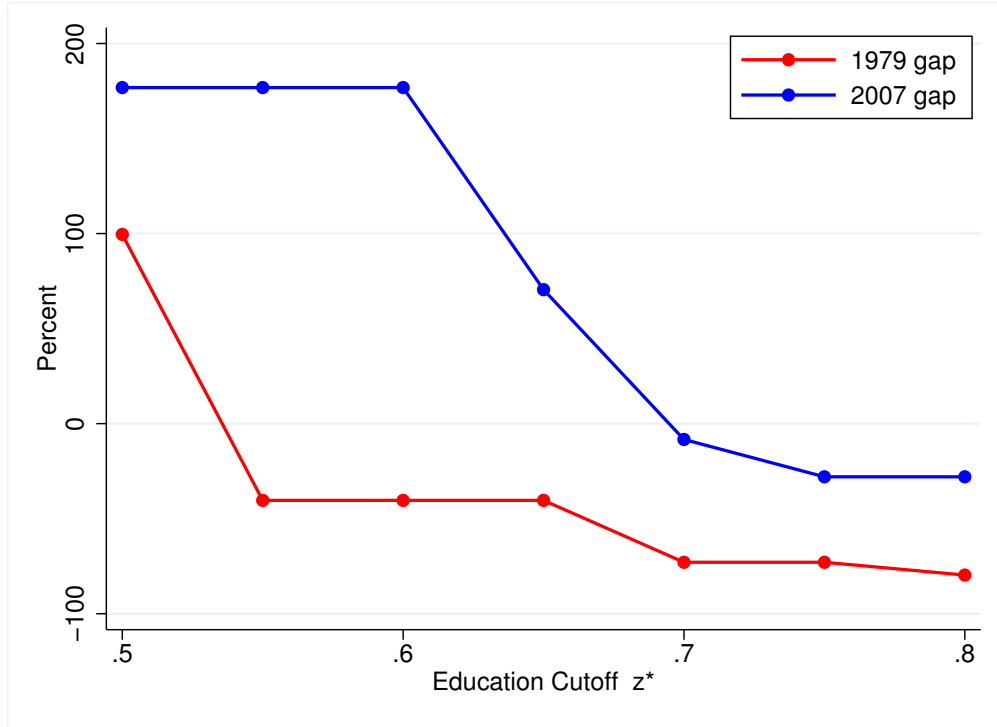


the low-skilled labor market was tighter in 1979 and the high-skilled market was tighter in 2007. This is because changes in tightness were primarily being driven by changes in vacancy postings, not the number of job seekers. The potential concern in using a measure of tightness with nonemployment in the denominator regards being able to separately identify matching efficiency from workers' value of leisure. If nonemployed individuals on average search less intensely than unemployed individuals because they have a higher reservation wage, the non-standard measure would attribute value of leisure to market slack. In practice, this is not a concern because relative tightness is comparable across the two measures. The tightness gap using unemployed men in 1979 was -55% and in 2007 was 136%, which is comparable to -40% and 177%, respectively. I use the nonemployment measure in this analysis because it drastically simplifies the model.

Appendix E checks robustness to using *unemployed* men and *women* in the denominator of the market tightness measure and shows the tightness gap is similar to baseline. If women's participation in the labor force is skewed towards the college job market as Cortes and Jaimovich (2016) suggest, this may drive college vacancy creation and overestimate the baseline tightness gap. I am able to rule out this potential bias because tightness gaps using unemployed men and women are similar to both measures reported in Table 1. Additionally, Appendix K shows estimates of matching efficiency are robust to this alternative measure.

Since we only observe labor market tightness for four states, the 1979 tightness gap may not be nationally representative even though the BLS strategically choose a diverse set of states. Appendix C lists the tightness gap separately for each state. The tightness gap remains negative for this diverse set of states, suggesting the negative gap in 1979 was not a product of state idiosyncrasies. Another concern is that data for three months of one year may not accurately reflect the tightness gap for an entire decade. This is a limitation of the data, however, Appendix D shows the tightness gap remained above 100 percent throughout the 2000s despite the large business cycle (the Great Recession). This suggests the tightness

Figure 4: Tightness Gap by Educational Cutoff



gap is at least twofold larger today than it was in the 1970s, regardless of cyclical fluctuations.

One last concern is the magnitudes in Figure 3 are a function of the criterion classifying vacancies as either college or non-college. Figure 4 illustrates the percent gap between high-skilled, college market tightness (θ_H^n) and low-skilled, non-college market tightness (θ_L^n) of varying education cutoffs. The horizontal axis lists cutoffs for the share of college employment defining a high-skilled vacancy. The vertical axis is the tightness gap between high- and low-skilled jobs. Red plots the tightness gap in 1979 and blue plots the tightness gap in 2007. The tightness gap in 2007 always exceeds that in 1979, regardless of how a high-skilled vacancy is defined. Note, Figure 4 plots tightness gaps using the nonemployment measure of labor market tightness. Appendix E plots tightness gaps using the unemployment measure including women, which looks remarkably similar to Figure 4.

Overall, this section finds differential market tightness, disfavoring low-skilled workers is a pervasive and robust labor market phenomenon. This type of inequality, i.e. varying labor

market conditions across skill types, did not exist in the late 1970s, but today is ubiquitous.

3 Model

The goal of this section is to build a tractable model of the labor market capturing the conditions workers face when choosing an employment status and occupation. For simplicity, the model includes only two labor force statuses: employment (e) and nonemployment (n); and two types of occupations: low-skilled (L) and high-skilled (H). The low-skilled group represents jobs requiring workers with a high school degree or less, who perform routine and/or non-cognitive tasks. The high-skilled group represents jobs requiring workers with a college education, who perform analytical and cognitive tasks.

To capture the empirical observation that job openings and job seekers simultaneously exist, I build a DMP model, where a friction in the labor market prevents openings and job seekers from perfectly matching up. I augment the standard model with heterogeneous worker ability and two types of occupations workers endogenously self-select into. I complicate the model with these additions because empirically the composition of workers searching for low- and high-skilled jobs has changed over time. Appendix F illustrates in the 1980s the low- and high-skilled markets were both composed of lower ability workers than in the 2000s. As such, I allow workers in my model to choose an occupation based on their ability and the economic environment. Occupational choice has important implications for employment rates because higher ability workers are generally more productive and therefore more likely to be employed. If higher ability workers are more likely to choose one occupation over another, this impacts differential employment rates. As in the data, my model predicts both

markets were made up of lower ability workers in the latter period.¹⁴ The model is similar to Moscarini (2001) by combining self-selection in the tradition of Roy (1951) with a labor search model. It departs from Moscarini (2001) because workers here are heterogenous along one dimension, not two, and firms always perfectly observe a worker's type.

3.1 Environment

Time is discrete and indexed by $t \in \{0, 1, 2, \dots, \infty\}$.

Workers. Workers are heterogeneous in their ability. I consider an economy populated by M types of workers, indexed by $x \in \{x_1 < x_2 < \dots < x_M\}$. Ability is permanent and perfectly observable to employers and is a discrete approximation of log-normal.¹⁵ I ex-ante sort workers into submarkets based on their ability. Therefore, the aggregate labor market is organized in M submarkets indexed by worker type x . In each submarket there is a measure $M(x)$ of infinitely lived workers of type x (with $\sum_x M(x) = 1$) who are either employed $e(x) \in [0, 1]$ or nonemployed $n(x) \in [0, 1]$. The aggregate labor force is then $\sum_x (e(x) + n(x))M(x) = 1$. Each worker is endowed with one unit of labor. For simplicity, on-the-job search is ruled out. Lastly, workers have risk-neutral preferences and discount future payoffs at rate $\beta \in (0, 1)$.

Firms. The economy is also populated by an infinite mass of identical and infinitely lived employers who either produce output $y(x)$, or post job vacancies $v(x)$ aimed at a specific worker type x . Employers have risk-neutral preferences and also discount the future by β . Following Menzio and Shi (2010) I assume directed search such that firms target a specific

¹⁴Beaudry, Green, and Sand (2016) and Abel, Deitz, and Su (2014) find since the early 2000s college workers are underemployed, meaning workers with a college degree work jobs not necessarily requiring a college degree. This raises concerns about college no longer being a good proxy for high-skilled labor. However, Abel and Deitz (2014) find there are still substantial positive returns to a bachelor's degree and associate's degree. This is especially true when comparing today to the 1970s.

¹⁵When calibrating the model in Section 4, I focus on ability deciles such that there are $M = 10$ types of ability levels in the economy.

submarket x to post a vacancy and only post in one submarket at a time.

Production Technology. There are two types of production technologies in the economy. Technology used at low-skilled (L) occupations, where output is not a function of worker ability. Think of a conveyor belt in an assembly line, which arguably complements all manufacturing workers in the same way, regardless of their underlying ability (assuming workers show up for work). The other type of technology is used at high-skilled (H) occupations, where output is a function of worker ability. Think of a computer, which complements high ability workers well, and low ability workers to potentially a lesser degree. Put differently, a worker's ability x is irrelevant when matched with a low-skilled job and operative when matched with a high-skilled job. The occupation-specific production function per worker is:

$$y_{jt}(x) = \begin{cases} A_L & \text{if } j = L \\ A_H x & \text{if } j = H \end{cases}$$

Here, labor-augmenting technology for low-skilled jobs equals A_L regardless of underlying ability, while labor-augmenting technology for high-skilled jobs, A_H , interacts with ability x . Changes in A_L and A_H represent shifts in demand, such as automation and competition from abroad. For instance, a decrease in A_L resembles machines and trade replacing low-skilled workers, while an increase in A_H resembles computers and communication technology increasing high-skilled workers' productivity.¹⁶

Matching Technology. Markets are frictional. In each submarket x , there exists two constant returns to scale matching technology, one for each occupation type $j \in \{L, H\}$:

$$m_{jt}(n_t(x), v_t(x)) = \phi_j n_t(x)^\alpha v_t(x)^{1-\alpha}, \quad (1)$$

where $\alpha \in (0, 1)$ and ϕ_j is matching efficiency. Changes in ϕ_j represent shifts in search

¹⁶The production function is similar to that in Gaetani and Doepke (2016), except in their model, college is a fixed characteristics instead of a choice variable.

frictions. Let $\theta_t(x) = \frac{v_t(x)}{n_t(x)}$ denote market tightness in submarket x at time t . The job finding rate is then $f_j(n_t(x), v_t(x)) = \frac{m_{jt}(x)}{n_t(x)} = \phi_j \theta_t(x)^{1-\alpha}$, which I denote $f_{jt}(\theta)$ from now on to save on notation. Similarly, the job filling rate $q_j(n_t(x), v_{jt}(x)) = \frac{m_{jt}(x)}{v_t(x)} = \phi_j \theta_t(x)^{-\alpha}$, which I denote $q_{jt}(\theta)$.

Timing. Employers post job vacancies and nonemployed workers search for jobs, given relative matching efficiencies, job separations, values of leisure, and productivities next period $\{\phi_{jt+1}, \delta_{jt+t}, b_{jt+1}, A_{jt+1}\}$. Nonemployed workers meet firms at time t and if profitable produce output at $t + 1$.

3.2 Equilibrium

Firm's Problem. Let $V_{jt}(x)$ be the value to a firm of posting a vacancy for a worker of ability x and a job that uses either high- or low-skilled technology $j \in \{L, H\}$ at time t . Note if the vacancy is for a low-skilled occupation $j = L$, ability is irrelevant.

$$V_{jt}(x) = -\kappa + \beta \left[q_{jt}(\theta) J_{jt+1}(x) \right], \quad (2)$$

where κ is the cost of posting a vacancy.¹⁷ $J_{jt+1}(x)$ is a firm's surplus next period from matching with a worker using technology j . The value of posting a vacancy is a function of the type of technology because firm surplus depends on technology. Firm surplus this period equals:

$$J_{jt}(x) = y_{jt}(x) - \omega_{jt}(x) + \beta \left[(1 - \delta_j) J_{jt+1}(x) \right], \quad (3)$$

where $\omega_{jt}(x)$ is the endogenously determined wage paid to a worker with ability x using technology j . The occupation-specific parameter δ_j is the exogenous separation rate. Here,

¹⁷In the baseline specification κ is constant across occupations, but Appendix L tests robustness to $\kappa_H > \kappa_L$.

all workers in their respective occupational categories separate from their job at rate δ_j .¹⁸

Worker's Problem. On the worker side, the value being matched with a job is the discounted value of retaining that match or entering the nonemployment pool next period,

$$W_{jt}(x) = \omega_{jt}(x) + \beta \left[(1 - \delta_j)W_{jt+1}(x) + \delta_j N_{jt+1}(x) \right]. \quad (4)$$

The value of being nonemployed $N_{jt}(x)$ is defined by the following condition:

$$N_{jt}(x) = \max \left[N_{Lt}^c(x), N_{Ht}^c(x) \right], \quad (5)$$

where $N_{Lt}^c(x)$ represents the continuation value of nonemployment when a worker chooses to search for low-skilled work (i.e. jobs where their ability does not matter) and $N_{Ht}^c(x)$ represents the continuation value of nonemployment when a worker chooses to search for high-skilled work (i.e. jobs where output and therefore wages depend on ability). The recursive formulation for the continuation value of nonemployment, when an individual searches for $j \in \{L, H\}$ type work follows:

$$N_{jt}^c(x) = b_j + \beta \left[f_{jt}(\theta)W_{jt+1}(x) + (1 - f_{jt}(\theta))N_{jt+1}(x) \right], \quad (6)$$

where b_j is the value of leisure, which varies between low- and high-skilled occupations.¹⁹ Changes in b_j represent shifts in labor supply. When an agent chooses to search in the low-skilled market, think of that worker as forgoing college. When an agent chooses to search in the high-skilled market, think of that worker as attending college so that she can search for college jobs. Dynamically, agents can switch from a high- to low- skill job. Empirically,

¹⁸See Fujita and Ramey (2013) for an assessment of the various approaches to modeling the separation rate. For the purposes of this model, I assume an exogenous separation rate.

¹⁹Appendix M checks robustness to an alternative specification where high-skilled value of leisure is a function of ability, namely $b_H x$. For computational purposes I keep low-skilled value of leisure fixed at b_L . In this alternative setup, the ratio of b_H to b_L increases more, relative to the baseline, in order to match the data. This is because lower values of x dampen overall leisure in the high-skilled, but not the low-skilled.

workers cannot switch from having some college experience to no college experience. Section 5 calibrates the model to match two steady states: 1979 and 2007, such that agents do not switch occupations in a given steady state. Agents who do switch occupations between 1979 and 2007 should be thought of as different people with the same ability level.

Nash Bargaining. Workers and firms in each market negotiate a contract dividing match surplus according to the Nash bargaining solution, where $\pi \in (0, 1)$ is the worker's bargaining weight.²⁰ Total match surplus is calculated by adding up firm value $J_{jt}(x)$ and worker value $W_{jt}(x)$ minus values of the outside options $V_{jt}(x)$ and $N_{jt}(x)$. Let $S_{jt}(x) = \max\{J_{jt}(x) + W_{jt}(x) - V_{jt}(x) - N_{jt}(x), 0\}$ denote total match surplus in submarket x using technology j . Workers receive $\pi S_{jt}(x)$ from a match and firms receive $(1 - \pi)S_{jt}(x)$.²¹ The worker and firm will agree to continue the match if $S_{jt}(x) > 0$, otherwise they will separate, in which case $S_{jt}(x) = 0$.

Free Entry. To close the model I assume an infinite number of firms are free to enter each submarket and post vacancies, thereby pushing down the value of posting a vacancy to zero. The free entry condition implies $V_{jt}(x) = 0, \forall j, t, x$.²²

3.3 Steady State

The following subsection derives four expressions summarizing the steady-state equilibrium, namely the job creation curve, wages, nonemployment, and a condition representing how agents choose whether to search for a low- or high-skilled occupation. To simplify notation, let any variable $Z_t = Z_{t+1} = Z$ for the remainder of this subsection.

²⁰In the baseline specification π is constant across occupations, but Appendix L tests robustness to $\pi_H > \pi_L$.

²¹Nash bargaining provides additional expressions representing worker and firm value of a match, such that we can set $W_{jt}(x) - N_{jt}(x) = \pi S_{jt}(x)$ and $J_{jt}(x) = (1 - \pi)S_{jt}(x)$.

²²For the baseline calibration, I impose the Hosios condition in each submarket ($\alpha = \pi$), such that the equilibrium is optimal (i.e. the Panner's solution equals the market equilibrium).

Job Creation Curve. In steady state, combining equation (2), equation (3), and the free entry condition yields:

$$y_j(x) - \omega_j(x) - \frac{\kappa(\beta^{-1} + \delta_j - 1)}{q_j(\theta)} = 0. \quad (7)$$

The DMP literature refers to this expression as the job creation curve. If the firm had no hiring cost, κ would be zero and equation (7) would be the standard marginal productivity condition where marginal product equals wage. In DMP models, nonzero vacancy posting costs cut into total surplus and under Nash bargaining that cut translates into lower wages.

Steady State Wages. Under Nash bargaining and free entry, equations (1)-(6) endogenously determine wages:

$$\omega_j(x) = (1 - \pi)b_j + \pi(y_j(x) + \kappa\theta). \quad (8)$$

See Appendix G for a derivation. Workers are rewarded for helping firms save on hiring costs. Workers also enjoy a share of output and a fraction of the outside option. Wages are increasing in market tightness, and for high-skilled jobs, wages are increasing in ability and labor-augmenting technology.

Steady State Nonemployment. The rate at which employed workers enter the nonemployment pool is governed by δ_j . The flow of workers moving from employment to nonemployment in each submarket and period is then $\delta_j(1 - n_j(x))$. Conversely, the rate at which nonemployed workers find jobs is governed by $f_j(\theta)$. The flow of workers moving from nonemployment to employment in each submarket and period is then $f_j(\theta)n_j(x)$. In steady state the flow into employment (nonemployment) must equal the flow out of employment

(nonemployment). Therefore, $\delta_j(1 - n_j(x)) = f_j(\theta)n_j(x)$ which reduces to:

$$n_j(x) = \frac{\delta_j}{\delta_j + \phi_j \theta^{1-\alpha}}. \quad (9)$$

In steady state the number of nonemployed people within a given ability level is a function of the exogenous separation rate, matching efficiency, and tightness ratio. The upcoming proposition illustrates market tightness θ is generally a function of labor-augmenting technology and ability. Therefore, employment rates vary not only over occupations, but also over ability x .

Choosing a High- or Low-Skilled Occupation. When in the nonemployment pool, workers endogenously choose which type of occupation they want to search for. They make this decision by maximizing over the future discounted value of both options. In steady state, this decision (i.e. equation (9)) becomes the following after substituting in equation (4):

$$\max_j N_j(x) = \max_j \left[\frac{b_j(\beta^{-1} + \delta_j - 1) + f_j(\theta)\omega_j(\theta)}{(1 - \beta)(\beta^{-1} - 1 + f_j(\theta) + \delta_j)} \right]. \quad (10)$$

Equations (7), (8), (9) and (10) determine the steady-state equilibrium. Let $x_\xi \in \{x_1 < x_2 < \dots < x_M\}$ be the highest ability (or cutoff) worker either employed or searching for work in a low-skilled occupation.

Balanced Growth. This economy does not necessarily follow a balanced growth path. In other words, technology may differentially affect workers and their employment statuses. The following proposition specifies a condition sufficient for balanced growth.

Proposition. *If vacancy posting costs κ and the value of leisure b_j are directly proportional to output, then tightness θ is constant across ability x and labor-augmenting technology A_j .*

Proof. Steady state tightness θ solves:

$$y_j(A_j, x) = \theta^\alpha \kappa \left(\frac{\beta^{-1} + \delta_j - 1}{\phi_j(1 - \pi)} \right) + \theta \kappa \left(\frac{\pi}{1 - \pi} \right) + b_j \cdot f \quad (11)$$

Suppose $\kappa = \tilde{\kappa}y_j$ and $b_j = \tilde{b}_jy_j$ then equation (1) is not a function of x or A_j . □

Equation (11) is instrumental to understanding how automation and trade generates different employment outcomes across ability levels. Suppose vacancy posting costs and the value of leisure are both directly proportional to output. In other words, replace wherever there is a κ with $\tilde{\kappa}y_j$, and a b_j with $\tilde{b}_jy_j$ in equation (11). The economic interpretations of these changes is that it is more costly for firms to post vacancies for jobs with higher output potential, and leisure is valued more by workers with higher output potential. Imposing both assumptions implies a balanced growth path, meaning equation (11) is no longer a function of output—because y_j can be divided out—and therefore market tightness is no longer a function of ability or labor-augmenting technology. With this setup, it would be impossible for automation and trade to affect tightness and therefore the employment gap. Thus, the model in this paper assumes non-balanced growth.

That said, the assumption for balanced growth is not entirely unfounded. Productive jobs may require more effort to find the right worker-job match relative to less productive jobs. Unemployment benefits—which are one component of the value of leisure—in the U.S. are between 40 and 50 percent of previous pay.²³ However, it is unlikely *both* parameters—vacancy posting costs and value of leisure—are *directly* proportional to output. As long as at least one is not directly proportional, then market tightness is a function of output, and the employment gap will co-move with technological change and competition from abroad. In the baseline model, for simplicity, I assume neither vacancy posting costs or the value of leisure depend on output.

²³<http://workforcesecurity.doleta.gov/unemploy/docs/repl.FY13.txt>.

4 Calibration

I consider three possible mechanisms contributing to the evolving employment gap, namely, a supply shift, a demand shift, and search frictions. How the parameters—representing these three mechanisms—change across low- and high-skilled workers determines relative employment outcomes. I compare the 1970s to the 2000s by calibrating two steady states, one representing the 1979 business cycle peak, and the other representing the 2007 peak. There are three stages to the estimation procedure. First, I recover matching efficiency (the key search friction parameter) in both markets and time periods using the matching function. Second, I jointly determine value of leisure (the key supply shift parameter) and labor-augmenting technology (the key demand shift parameter) using the job creation curve and wage equation. Third, I recover the mean and standard deviation of ability levels in this economy by targeting the share of workers in the high-skilled market in 1979 and 2007.

4.1 Matching Efficiency

Matching technology, summarized by equation (1) depends on four parameters: the job finding rate f , tightness θ , matching elasticity α , and matching efficiency ϕ . I have estimates for three of these four parameters, which allows me to recover matching efficiency.

Section 2 provides estimates of tightness in the low- and high-skilled market. I take an estimate of elasticity α from the literature. Rewriting equation (1) depicts an expression for matching efficiency:

$$\phi_j = \frac{f_j(\theta(x))}{\theta(x)^{1-\alpha}}. \quad (12)$$

From the proposition in Section 3.3, we know market tightness is generally a function of individual ability x . Since we do not have estimates of market tightness and job finding

rates by ability in the data, I aggregate over individuals within a given occupation category j for the empirical analogue of equation (12).²⁴ Specifically, matching efficiency estimates are calculated as:

$$\hat{\phi}_j = \frac{\hat{f}_j}{\hat{\theta}_j^{1-\alpha}}, \quad (13)$$

where $\hat{f}_j$ is the empirical job finding rate and $\hat{\theta}_j$ is the empirical market tightness measure for men without college experience $j = L$ and men with at least some college experience $j = H$. I do this separately for 1979 and 2007 to recover the following set of parameters: $\{\hat{\phi}_{L,1979}, \hat{\phi}_{H,1979}, \hat{\phi}_{L,2007}, \hat{\phi}_{H,2007}\}$.

4.2 Disentangling Supply and Demand

It is a bit more involved to identify changes in the value of leisure, the supply shift parameter, from changes in labor-augmenting technology, the demand shift parameter. Equations (7) and (8) provide two equations to do this. For each period and occupation, there are two equations (a job creation curve and wage equation) and two unknown parameters (value of leisure and labor-augmenting technology.) The estimation procedure relies on simulated method of moments (SMM). For 1979, I choose an initial $\{b_L, b_H, A_L, A_H\}$ and solve for tightness and wages using the job creation curve and wage equation. For 2007, I choose an initial $\{b_L, b_H, A_L, A_H\}$ and likewise solve for tightness and wages. I then compare the model's generated parameters with the empirical market tightness and wage data. I minimize the squared difference to back out the true values of leisure and technology. One complication is the model produces a tightness and wage for each ability level in the high-skilled labor market, rather than an aggregate, as in the low-skilled market. Before comparing the model's tightness and wage parameters with the data, I must average over ability within the

²⁴Given the functional form of the production function, tightness is only a function of ability in the high-skilled market. Since output does not vary by ability in the low-skilled market, neither does labor market tightness.

high-skilled market $j = H$. Specifically, I minimize the following expressions:

$$w_{T\theta} \left(\hat{\theta}_{HT} - \frac{1}{M} \sum_{x_\xi}^{x_M} \theta_{HT}(x) \right)^2, \quad (14)$$

$$w_{T\omega} \left(\hat{\omega}_{HT} - \frac{1}{M} \sum_{x_\xi}^{x_M} \omega_{HT}(x) \right)^2, \quad (15)$$

where $\hat{\theta}_{HT}$ and $\hat{\omega}_{HT}$ are the empirical tightness ratio and real wage of the high-skilled market in year $T \in \{1979, 2007\}$. Additionally, $w_{T\theta}$ and $w_{T\omega}$ are the weights associated with each component.²⁵

4.3 Ability Parameters

The final set of parameters to recover are the mean μ_x and standard deviation σ_x of ability. I do this by targeting the share of men with college experience. The assumption here is men who attended at least one year of college search for high-skilled, college jobs and men with less than one year of college search for low-skilled, non-college jobs. In 1979, 43 percent of prime-age men had at least one year of college, while in 2007, 56 percent had at least one year of college. Appendix H plots the time series of college share with reference lines at 1979 and 2007. Matching these moments allows me to recover μ_x and σ_x .

5 Results

Table 2 lists the parameter estimates for 1979 and 2007, where $z^* = 0.6$.²⁶ The first third of the table take values from the literature. I calibrate the model to match monthly obser-

²⁵I weight each component by its percent difference such that larger values of tightness or wages are not automatically given more importance.

²⁶Appendix J shows counterfactuals where $z^* = 0.5$ and $z^* = 0.65$.

vations and accordingly set the discount rate β to 0.9967. The elasticity parameter $\alpha = 0.62$ is from Veracierto (2011), which is estimated for a matching function where nonparticipants are grouped with the unemployed. Worker bargaining power follows the Hosios (1990) condition, equaling the elasticity parameter $\pi = \alpha$, such that the allocation of labor is efficient. It is plausible high-skilled bargaining power is greater than that of the low-skilled; Appendix L tests robustness to $\pi_H > \pi_L$. There is a wide range of values for vacancy posting costs in the literature. Cairo and Cajner (2013) find the ratio of average recruiting costs to average wages in a given month hovers around 0.1 regardless of education, while Gavazza, Mongey, and Violante (2016) find it is closer to 0.9. I split the difference and use 0.5.²⁷

The second third of the table takes estimates from the data. Using matched CPS data from Nekarda (2009), I compute separation and job finding rates for men in the low- and high-skilled labor market. Appendix I plots these data by college and non-college, with reference lines at 1979 and 2007. Separation rates (employment to nonemployment) are taken directly from the data while matching efficiencies are recovered by targeting job finding rates (nonemployment to employment), as described in Section 4. I find matching efficiency increased for low-skilled workers and decreased for high-skilled workers from the 1970s to 2000s. In 1979 the high-skilled market was more efficient at linking job openings with job seekers, while in 2007 the low-skilled market was more efficient. This fact also holds when using unemployed men and women rather than nonemployed men. Appendix K lists matching efficiency estimates for a tightness measure with unemployed men and women in the denominator and job finding rates using U-E flows for men and woman.

The last third of the table lists parameters disciplined by the job creation curve (7) and wage equation (8). Low- and high-skilled value of leisure both decreased between 1979 and 2007, yet high-skilled value of leisure decreased by more, which is consistent with higher paid workers having higher reservation wages. Regardless of the parameterization, low-skilled

²⁷Appendix L tests robustness to high-skilled vacancy posting costs being greater than low-skilled posting costs, $\kappa_H > \kappa_L$.

Table 2: Parameter Estimates for 1979 and 2007 Steady States

Parameter	Explanation	Value	Source
β	discount factor	0.9967	monthly rate
$\alpha_{j,t}$	matching elasticity	0.62	Veracierto (2011)
$\pi_{j,t}$	bargaining weight	0.62	Hosios condition
$\kappa_{j,t}$	vacancy posting cost	0.5	share of 1979 offer wages
$\delta_{L,79}$	separation rate	0.0223	CPS
$\delta_{L,07}$	separation rate	0.0326	CPS
$\delta_{H,79}$	separation rate	0.0121	CPS
$\delta_{H,07}$	separation rate	0.0162	CPS
$\phi_{L,79}$	matching efficiency	0.1892	CPS job finding rate = 0.1679
$\phi_{L,07}$	matching efficiency	0.2116	CPS job finding rate = 0.1451
$\phi_{H,79}$	matching efficiency	0.2710	CPS job finding rate = 0.1975
$\phi_{H,07}$	matching efficiency	0.1593	CPS job finding rate = 0.1608
$b_{L,79}$	value of leisure	0.30	calibrated
$b_{L,07}$	value of leisure	0.26	calibrated
$b_{H,79}$	value of leisure	0.63	calibrated
$b_{H,07}$	value of leisure	0.57	calibrated
$A_{L,79}$	technology	1.05	calibrated
$A_{L,07}$	technology	0.69	calibrated
$A_{H,79}$	technology	0.66	calibrated
$A_{H,07}$	technology	1.11	calibrated
μ_x	mean ability	0.35	calibrated
σ_x	standard deviation of ability	0.15	calibrated

Table 3: Targeted Moments

Moment	Explanation	Year	Model	Data	Model Gap	Data Gap
$\theta_{L,79}$	L tightness	1979	0.73	0.73		
$\bar{\theta}_{H,79}$	H tightness	1979	0.43	0.44	-40%	-40%
$\theta_{L,07}$	L tightness	2007	0.37	0.37		
$\bar{\theta}_{H,07}$	H tightness	2007	1.05	1.03	184%	177%
$\omega_{L,79}$	L wages (normalized)	1979	0.99	1.00		
$\bar{\omega}_{H,79}$	H wages	1979	1.00	1.00	2%	0%
$\omega_{L,07}$	L wages	2007	0.64	0.63		
$\bar{\omega}_{H,07}$	H wages	2007	1.53	1.60	138%	154%
$\frac{100 \times (M - \xi)}{M}$	H share	1979	50%	43%		
$\frac{100 \times (M - \xi)}{M}$	H share	2007	90%	56%		

Table 4: Non-Targeted Moments

Moment	Explanation	Period	Model	Data	Model Gap	Data Gap
$e_{L,79}$	L employment rate	1979	88%	89%		
$\bar{e}_{H,79}$	H employment rate	1979	94%	95%	5.9 pp	5.4 pp
$e_{L,07}$	L employment rate	2007	82%	83%		
$\bar{e}_{H,07}$	H employment rate	2007	90%	92%	9.2 pp	8.8 pp
Difference					3.3 pp	3.4 pp

value of leisure always falls. This is because the drastic decline in low-skilled labor market tightness, as displayed in Table 3, was not matched by a comparable decline in real hourly earnings. Put differently, since the decline in job openings was not fully reflected in wages, the value of non-market activity for low-skilled workers must have increased, thereby encouraging firms to keep wages high to attract workers. Regarding the technology parameters, low-skilled productivity decreased between 1979 and 2007, while high-skilled productivity increased. This is consistent with technology and competition from abroad replacing low-skilled workers and complementing high-skilled workers. Lastly, the model recovers a mean and standard deviation of ability somewhat able to replicate the share of prime-age men who chose the high-skilled market.

Table 3 shows the model matches the targeted moments quite well. I target the levels of tightness and wages, but for illustration purposes also show how well the model matches the percent gaps between the high- and low-skilled. The model slightly overestimates high-skilled tightness in 2007, leading to a larger gap than what is observed in the data. The model also slightly overestimates the wage gap in 1979, however, it still hovers around zero, meaning average wages in the late 1970s were similar between high- and low-skilled occupations. The model underestimates the large wage gap that emerged in the 2000s, yet it still produces over a twofold increase. Lastly, the model replicates the fact that in the 1970s there were fewer men in the high-skilled market than there are today. The model somewhat matches the college share in 1979, but over predicts the share in 2007. Although including occupational choice is a realistic feature, in practice it does not significantly impact the calibration outcomes. Appendix N shows results of counterfactual exercises when this self-selection mechanism is turned off and results look similar to baseline.

Table 4 then compares the model’s generated employment rates with the data, which are technically non-targeted moments. The model directly targets job finding and separation rates. In the model, steady state employment is determined by setting job finding and

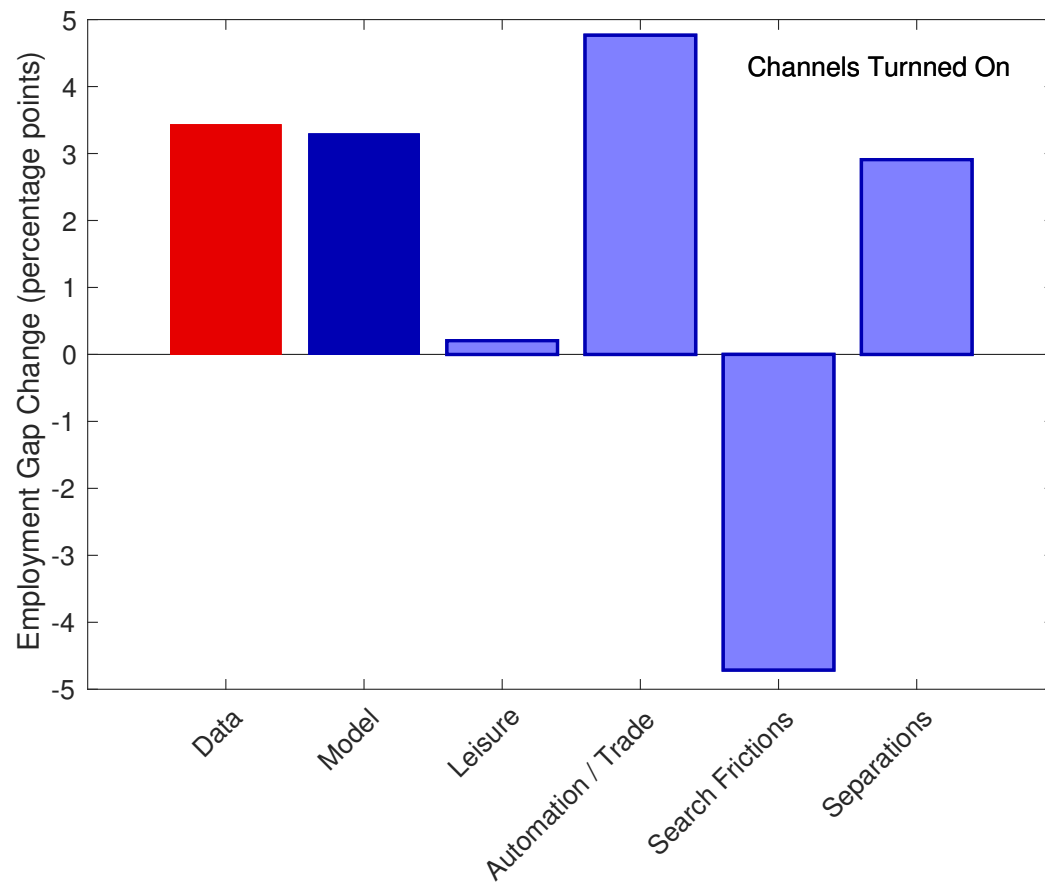
separation rates equal to each other. The model will match the data to the extent 1979 and 2007 are in fact steady states. The model captures both high- and low-skilled employment rates hovered around 90 percent in 1979 and the low-skilled employment rate fell to the low eighties by 2007. Overall, the model predicts the employment gap increased by 3.3 percentage points over this period, nearly matching the 3.4 percentage point rise we observe in the data.

Figure 5 illustrates results of counterfactual exercises. The vertical axis depicts how much the employment gap changed between 1979 to 2007, in percentage points. The red bar represents the data, with an employment gap increase of 3.4 percentage points as displayed in Table 4. The dark blue bar represents the model with all of its channels turned on. The subsequent light blue bars illustrate the change in the employment gap when each channel is turned on one at a time. In other words, if all but one parameter is fixed at its 1979 level and the remaining parameter evolves according to Table 2, what would happen to the employment rate gap?

Turning to the most leftward light blue bar, we see when value of leisure for both the low- and high-skilled changes according to its calibrated value and all other channels are turned off, the employment gap increases by only 0.2 percentage points from 1979 to 2007. In other words, a relative change in lower skilled workers' value of leisure barely widened the employment gap.²⁸ The direction is consistent with increases in government spending on disability insurance over this period, which Barnichon and Figura (2015a) and the Council of Economic Advisors' 2016 Economic Report of the President document and propose as possible evidence for an increase in low-skilled workers' value of non-work activity. However, Appendix J reveals this result is not robust to alternative specifications. When alternative education cutoffs for defining a vacancy are used, the value of leisure channel may narrow the employment rate gap, while qualitatively all other results are robust. Therefore, I conclude

²⁸In Table 2, low-skilled value of leisure decreased in absolute terms, but decreased by less than high-skilled value of leisure.

Figure 5: Counterfactuals



a supply shift has not robustly altered employment inequality since the 1970s.

The automation and trade channel, on the other hand, robustly increased employment inequality over this period. If labor-augmenting technology for both the low- and high-skilled changes according to its calibrated value and all other channels are turned off, the employment gap increases by nearly 5 percentage points. In other words, an increase in higher skilled labor productivity widened the employment gap and can account for all (and more) of the observed rise in employment inequality. This result is consistent with Autor et al. (1998) who find a demand-side explanation led to approximately a 3 to 4 percent annual increase in the wage gap from 1970 to 1996.

The second most rightward bar reveals if matching efficiency is the only channel turned on, the employment gap would be negative, meaning search frictions actually reduced employment inequality. In 1979, the high-skilled labor market was more efficient than the low-skilled labor market at matching job seekers with job openings, $\phi_{H,79} > \phi_{L,79}$. However, in 2007, the low-skilled market was more efficient at this process than the high-skilled, $\phi_{H,07} < \phi_{L,07}$. One possible explanation is lower skilled workers have been relatively more mobile. Molloy, Smith, and Wozniak (2014) find interstate migration decreased for all education levels between the 1980s and 2000s, but the decrease was monotonically larger for the more educated. Another explanation is high-skilled, college jobs became more specialized over this period, such that high-skilled jobs-seekers have more difficulty finding good matches. A third explanation is online job may actually reduce matching efficiency. Bayer et al. (2008) and Brown et al. (2016) find referred candidates have better job prospects, and less educated workers are more likely to use these informal hiring channels. Together this suggests online search technology may accentuate search frictions, and the highly educated are disproportionately affected because they use this technology more.

Lastly, if job separation rates were fixed at their 1979 levels, there would be minimal employment inequality. In other words, job separations which are exogenous in this setup

and come directly from the data can account for a large share of the growing employment rate gap. Workers may separate from employment for a host of reasons. In theory, low-skilled separation rates could have increased because of any of the three mechanisms discussed extensively in this paper (a supply shift, demand shift, or search frictions), or another reason all together. However, given parameters on the other side of the model (the job-finding side) point to such large declines in relative demand for low-skilled labor, a demand shift is a plausible candidate. One way to interpret the results is to view the contribution of automation and trade in Figure 5 as a lower bound. Reason being, if demand-side factors also generated diverging separation rates, then automation and trade would have played an even larger role in determining employment inequality.

An interesting thing to note is that on net, diverging employment rates were driven by diverging outflows rather than inflows. Appendix I illustrates this by showing the spread in separation rates between high- and low-skilled workers increased over this period, while the spread in job finding rates remained constant. Job finding rates in this setup are a function of matching efficiency and market tightness, where the latter is a function of value of leisure and labor-augmenting technology. Figure 5 shows matching efficiency narrowed the employment rate gap, while the value of leisure, and automation and trade widened the gap. On net, search frictions offset the substantial demand shift such that job finding rates did not contribute to rising employment inequality. Instead, all the bite came from separations.

6 Conclusion

In this paper I explore what mechanisms account for diverging employment rates. Employment rates of men who attended college and those who did not attend college began to differ in the 1960s, and have been diverging ever since. I calibrate an augmented DMP model to match two business cycle peaks, 1979 and 2007, and compare the recovered parameters.

This approach differs from previous work because I build a unified framework to quantify how multiple channels contribute to employment inequality, rather than a single mechanism. By calibrating my model to match data on wages, worker flows, and labor market tightness, I uncover the role a supply shift, demand shift, and search frictions play in driving employment inequality. I find a shift in the demand away from lower skilled workers is the leading cause. A shift in the supply cannot explain diverging employment rates and search frictions actually reduced the divergence. In other words, had search frictions not increased for higher skilled workers, employment inequality today would be worse than much worse. On net, this led to a three percentage point increase in the spread of college and non-college male employment rates between 1979 and 2007.

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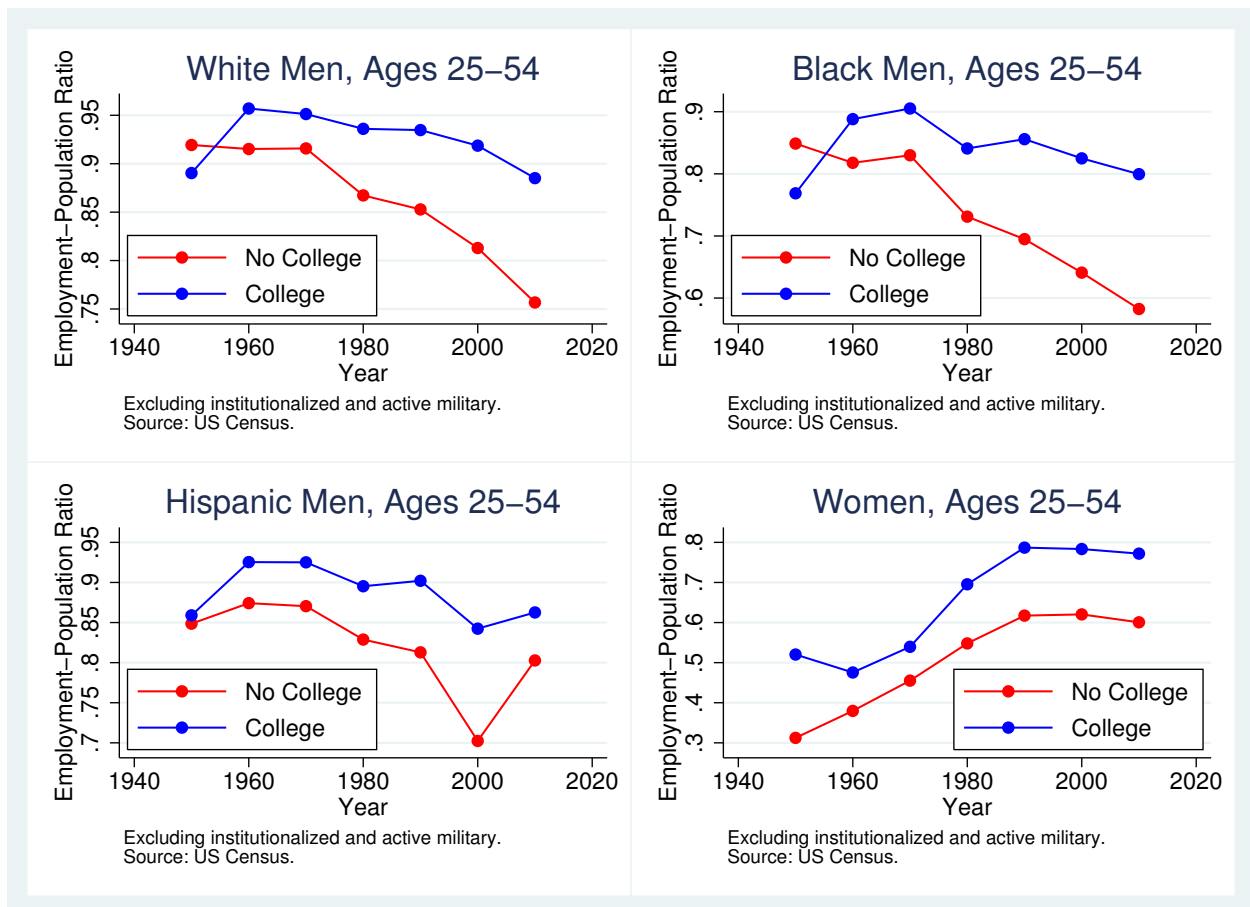
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A Appendix: Employment Inequality within Subgroups

Widening Employment Gap



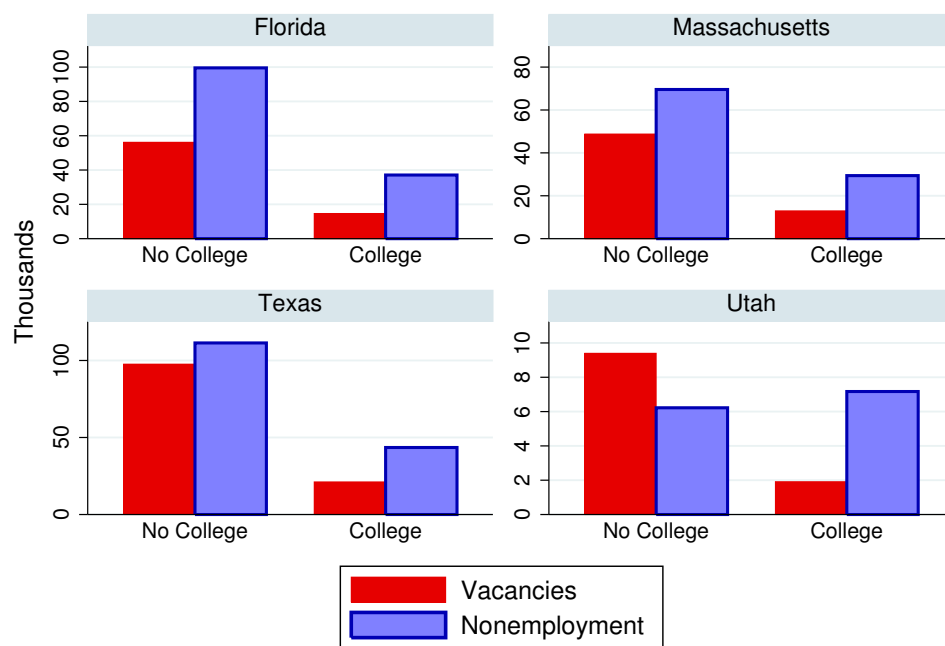
B Appendix: Baseline Vacancy Categorization, $z^* = 0.6$

BLS Pilot Vacancy Data
(2-digit 1977 SOC)

Hobijn (2012) Vacancy Data
(2-digit 2000 SOC)

High-Skilled Occupations	
Executive, Administrative & Managerial Engineers & Architects Natural Scientists & Mathematicians Social Scientists, Social Workers, Religious Workers & Lawyers Teachers, Librarians & Counselors Health Diagnosing & Treating Practitioners RNs, Pharmacists, Dietitians, Therapists & Physicians Assistants Writers, Entertainers, Artists & Athletes Health Technologists & Technicians Marketing & Sales	Management Business and Financial Operations Computer & Mathematical Science Architecture and Engineering Life, Physical & Social Science Community and Social Services Legal Education, Training & Library Arts, Design, Entertainment, Sports & Media Healthcare Practitioners & Technical Healthcare Support Protective Service Personal Care & Service Sales & Related Office & Administrative Support Installation, Maintenance & Repair
Low-Skilled Occupations	
Clerical Occupations Construction & Extractive Occupations Agricultural, Forestry, Fishers & Hunters Transportation & Material Moving Construction & Extraction Production Transportation & Material Moving	Food Production & Serving Related Building & Grounds Cleaning & Maintenance Farming, Fishing, and Forestry Mechanics & Repairs Production Work Occupations Material Handlers, Equipment Cleaners & Laborers

C Appendix: 1979 Tightness Gap by State



Tightness Gap

Florida	-30%
Massachusetts	-37%
Texas	-44%
Utah	-82%

D Appendix: 2000s Tightness Gap by Year

Hobijn (2012) and CPS Data

Year*	θ_H	θ_L	Percent Gap
2005	0.848	0.314	170
2006	0.898	0.395	128
2007	1.026	0.370	177
2008	0.805	0.266	203
2009	0.386	0.100	286
2010	0.466	0.127	268
2011	0.458	0.158	191
2012	0.579	0.204	184
2013	0.581	0.278	135

*Tightness is averaged over 3 months in the second quarter of the reference year.

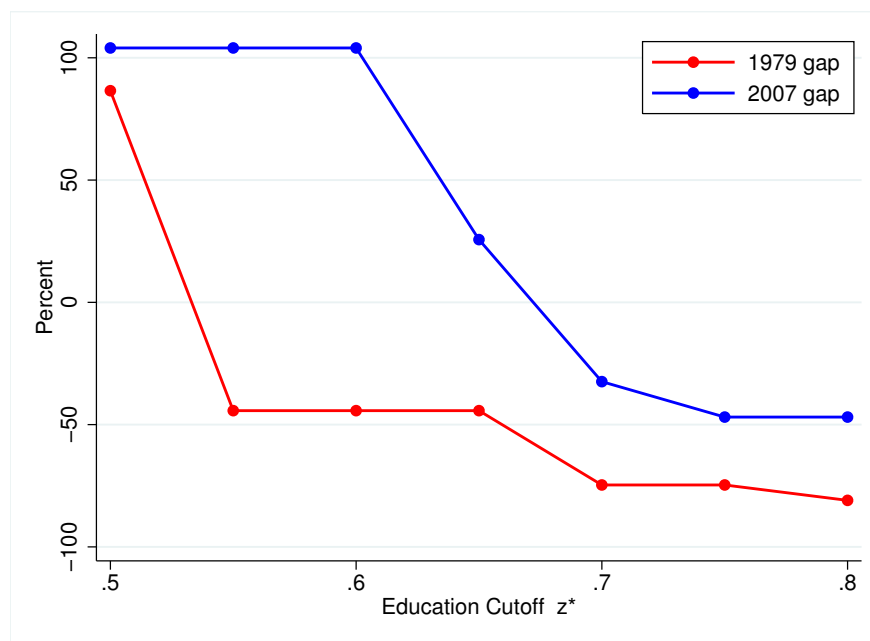
E Appendix: Tightness with Alt. Denominator

This appendix calculates labor market tightness using the number of prime-age men and women who are unemployed in the denominator. This is in contrast to the unemployment measure in Table 1, which uses only prime-age men. If vacancy creation is differentially affected by female labor force participation, tightness ratios in Table 1 may bias matching efficiency. However, since the tightness gap including unemployed women is similar to the baseline, I can rule out this type of biases. Moreover, in using this alternative measure we see the high-skilled market is substantially tighter than the low-skilled market for various education cutoffs z^* , as is the case with the baseline measure in Figure 4.

Tightness Ratios Including Women

Measure	Year	Data Sources	θ_H	θ_L	Percent Gap
Unemployment	1979	BLS, CPS	0.5891	1.0574	-44.3
Unemployment	2007	Hobijn (2012), CPS	1.7888	0.8768	104

Percent Gap by Education Cutoff: Unemployment Measure Including Women

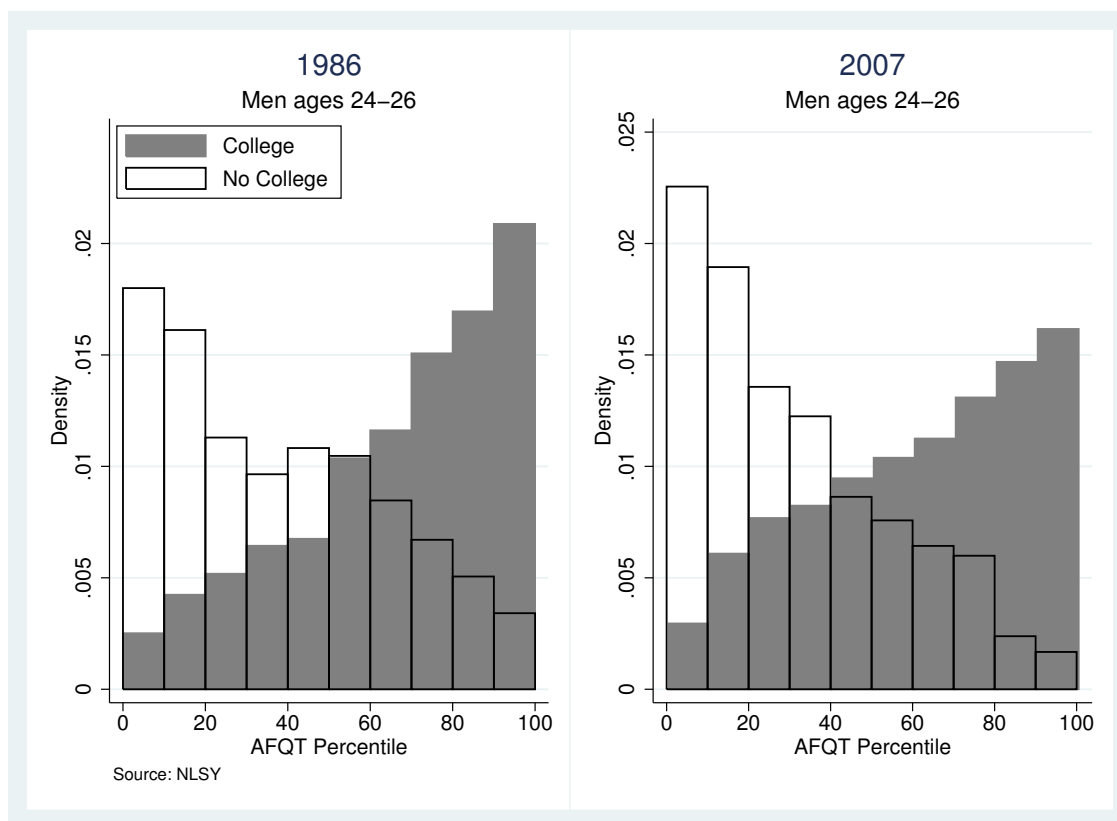


F Appendix: Ability Composition

The structural framework in this paper adds three ingredients to the standard DMP model. Two of the three ingredients are heterogeneous ability and occupational choice. This appendix illustrates the composition of low- and high-skilled workers has changed over the last few decades. Workers searching for college and non-college jobs in the 2000s are of lower ability than workers in the 1980s. Such ability sorting likely has implications for labor market conditions across the two groups and therefore is an important feature for the model to match. Cunha, Karahan, and Soares (2011) and Carneiro and Lee (2011) make a similar point about the importance of ability sorting and relate it to the college premium.

Specifically, I document the ability composition of men who attended college and men who did not attend college has changed over time. This is not to say particular individuals moved across categories, but rather particular ability levels have historically moved across categories. The population with some college experience in the 1980s was made up of people with certain permanent characteristics and today it is made up of people with different permanent characteristics.

Figure 6: Compositional Change of College and Non-College



To illustrate this I use two cohorts of the National Longitudinal Survey of Youth (NLSY). Respondents from the 1979 cohort were ages 14 to 22 during the first year of the survey and respondents from the 1997 cohort were ages 12 to 16 during the first year of the survey. Within the first two years of each survey’s inception both cohorts were administered the Ability Services Vocational Aptitude Battery (ASVAB). The ASVAB consists of a battery of 10 tests intended to measure developed abilities and help predict future academic and occupational success in the military.²⁹ The NLSY reports a composite score derived from select sections of the battery used to approximate an unofficial Armed Forces Qualifications Test score (AFQT) for each youth. The AFQT includes the following four sections of the ASVAB: arithmetic reasoning, world knowledge, paragraph comprehension, and numerical operations.³⁰ Furthermore, the NLSY’s AFQT-3 variable re-norms scores, controlling for age, so that scores from the 1979 and 1997 cohorts are comparable. Percentile of AFQT scores are reported on the horizontal axis of Figure 6.

The left panel of Figure 6 plots a subset of the 1979 cohort in 1986. The right panel plots a subset of the 1997 cohort in 2007. Years are chosen so age groups and places in the business cycle are comparable across panels. Turning to the gray bars, in 1986, men in the 90th percentile of the AFQT distribution (the most rightward gray bar) made up 21 percent of the college population, while in 2007 the 90th percentile made up only 16 percent. Moreover, men in the 60th percentile made up a larger share of the college population in 1986 than in 2007. Put differently, the college population consisted of lower-ability prime-age men in 2007.³¹

Turning to the clear bars, in 1987 the bottom 10 percent of the ability distribution (the most leftward clear bar) made up 18 percent of the non-college population, while in 2007 it made up 23 percent. Moreover, the bottom 40 percent made up a larger share of the non-college population in 2007 than in 1986. In other words, the non-college population consisted of lower-ability prime-age men in 2007.³²

To summarize, the ability composition of the college and non-college labor market has changed.³³ In the model, workers endogenously choose whether to search for college or non-college jobs based on their underlying ability. The model is able to match the fact that median worker ability in both markets fell over the last few decades.

²⁹<http://official-asvab.com>

³⁰<https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores/page/0/0/#asvab>

³¹The two-sample Kolmogorov-Smirnov test rejects the null hypothesis at the one percent level that college respondents in both years come from the same AFQT distribution.

³²The two-sample Kolmogorov-Smirnov test rejects the null hypothesis at the one percent level that non-college respondents in 198 and 2008 come from the same AFQT distribution.

³³ Archibald, Feldman, and McHenry (2015) find despite college attendance rates rising, student quality at 4-year institutions has remained unchanged over the last few decades, while student quality at 2-year institutions has declined. The authors attribute unchanging student quality at 4-year institutions to better sorting; student characteristics other than grades and test scores, such as race and parents’ education, have become less predictive. This trend is not the same at 2-year institutions and for students with at least one year of college or more (as shown above).

G Appendix: Derivation of Equilibrium Wages

This derivation is adapted from that in Chapter 1 of Pissarides (2000). Time here is discrete rather than continuous.

Under Nash bargaining and free entry, if a worker matches he gets a share of the surplus $\pi S_{jt}^c(x) = \pi (J_{jt}(x) + W_{jt}(x) - N_{jt}(x))$. Since the worker gives up the value of nonemployment to receive the value of a match, this implies the difference must equal his share of the match surplus:

$$W_{jt}(x) - N_{jt}(x) = \pi (J_{jt}(x) + W_{jt}(x) - N_{jt}(x)). \quad (16)$$

To solve for the equilibrium wage, we will first solve for wages in terms of nonemployment. Substituting in equations (3) and (4) into equation (16) yields:

$$\omega_{jt}(x) = \pi y_{jt}(x) + (1 - \pi) (N_{jt}(x) - \beta \delta N_{jt+1}(x)) + \beta (1 - \delta) [\pi J_{jt+1}(x) - (1 - \pi) W_{jt+1}(x)]. \quad (17)$$

Rewriting equation (16) as $-(1 - \pi) N_{jt+1}(x) = \pi J_{t+1}(x) - (1 - \pi) W_{jt+1}(x)$ and substituting it into equation (17) gives:

$$\omega_{jt}(x) = \pi y_{jt}(x) + (1 - \pi) (N_{jt}(x) - \beta N_{jt+1}(x)). \quad (18)$$

Next, I solve for the equilibrium path of nonemployment so I can plug it into equation (16) and solve for wages just as a function of parameters. Taking equation (6) and repeatedly substituting in (16) and the equilibrium condition for jobs (3) results in:

$$N_{jt}(x) - \beta N_{jt+1}(x) = b_j + \frac{\pi \kappa f_{jt}(\theta)}{q_{jt}(\theta)} [1 + \pi + \pi^2 + \pi^3 + \dots]. \quad (19)$$

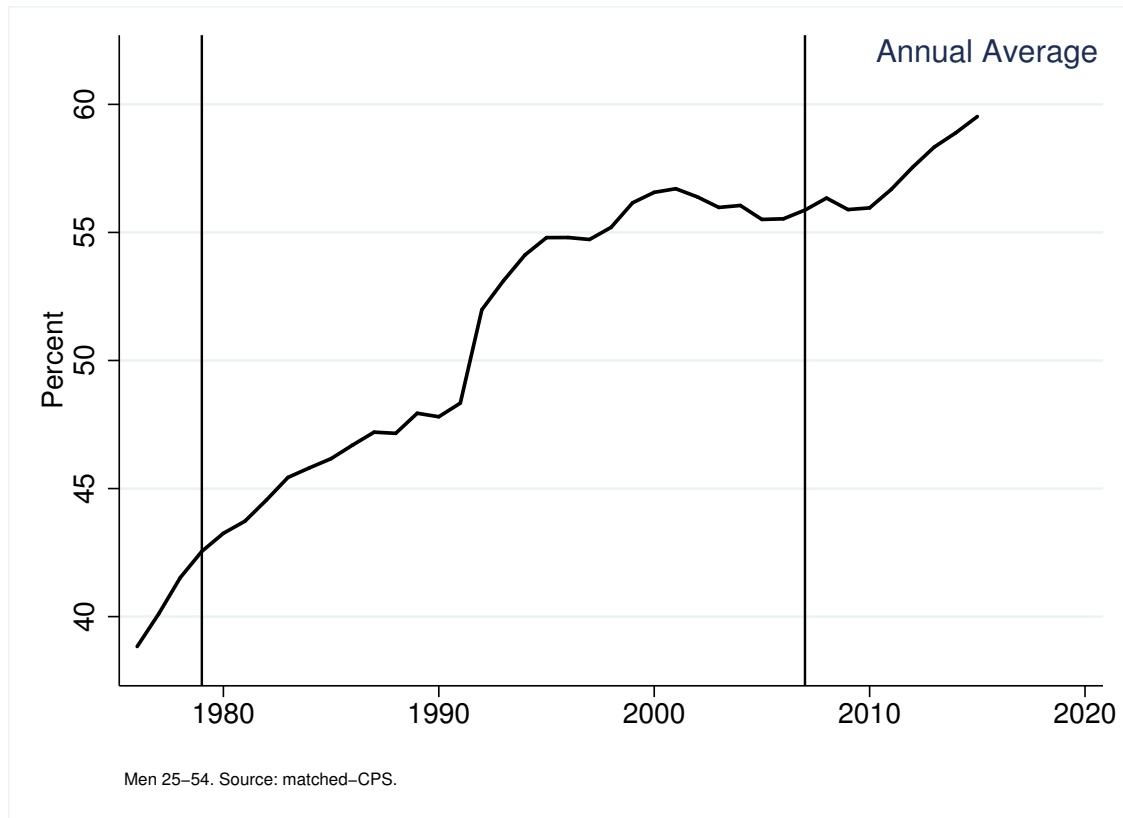
Inserting functional forms for the job finding and filling rates as well as the expression of the sum of an infinite geometric series yields:

$$N_{jt}(x) - \beta N_{jt+1}(x) = b_j + \left(\frac{\pi \kappa}{1 - \pi} \right) \theta. \quad (20)$$

An equation for the equilibrium wage results for combining equations (18) and (20)

$$\omega_{jt} = (1 - \pi) b_j + \pi (y_{jt}(x) + \kappa \theta). \quad (21)$$

H Appendix: Time Series of College Share



I Appendix: Time Series of Worker Flows

Figure 7: Job Finding Rates: $U+NLF \rightarrow E$

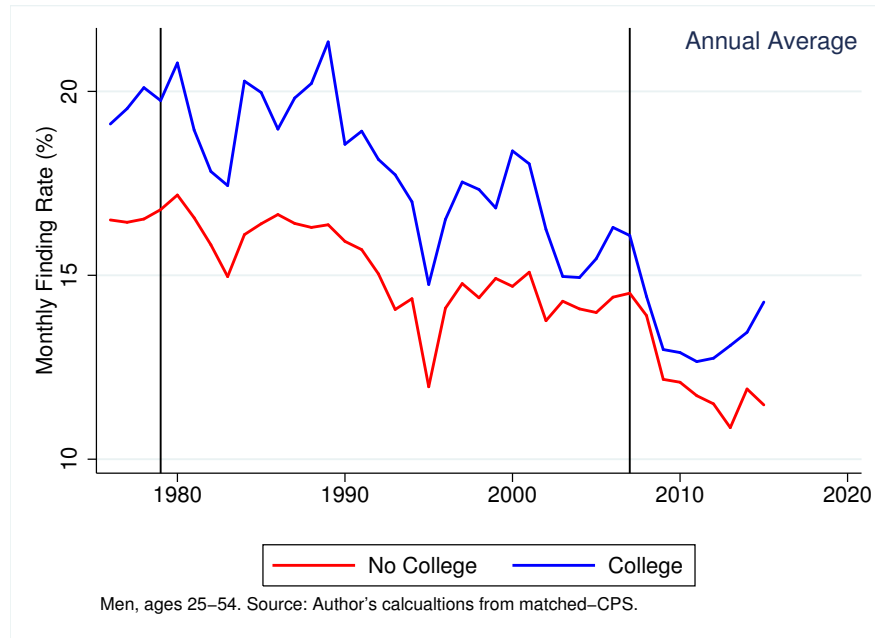
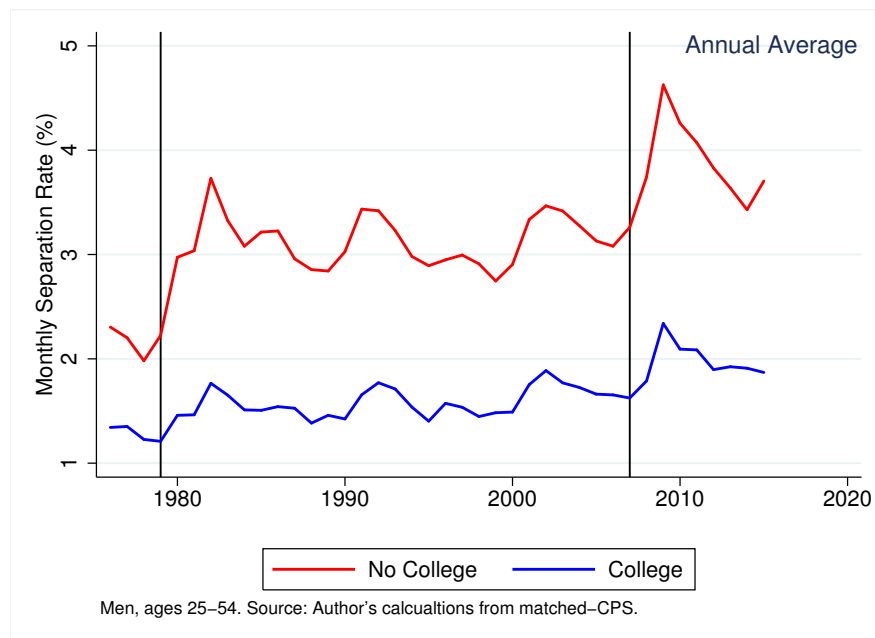
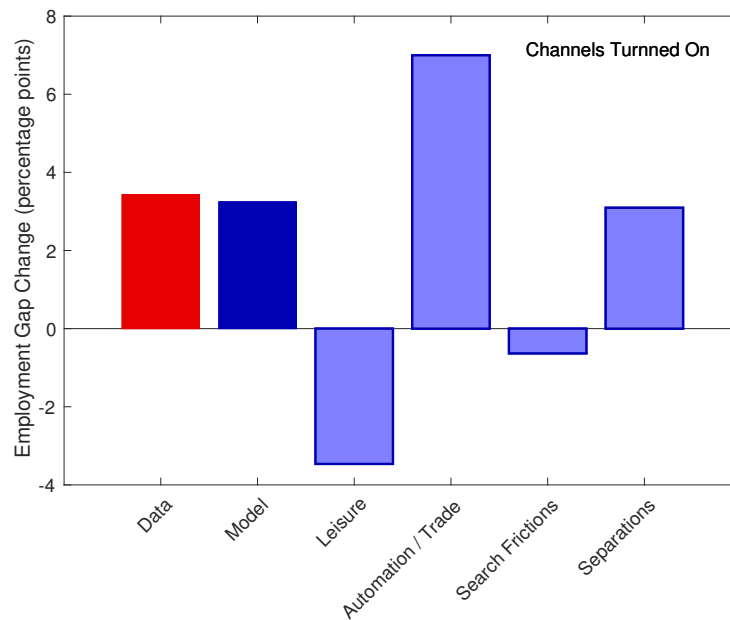


Figure 8: Separation Rates: $E \rightarrow U+NLF$

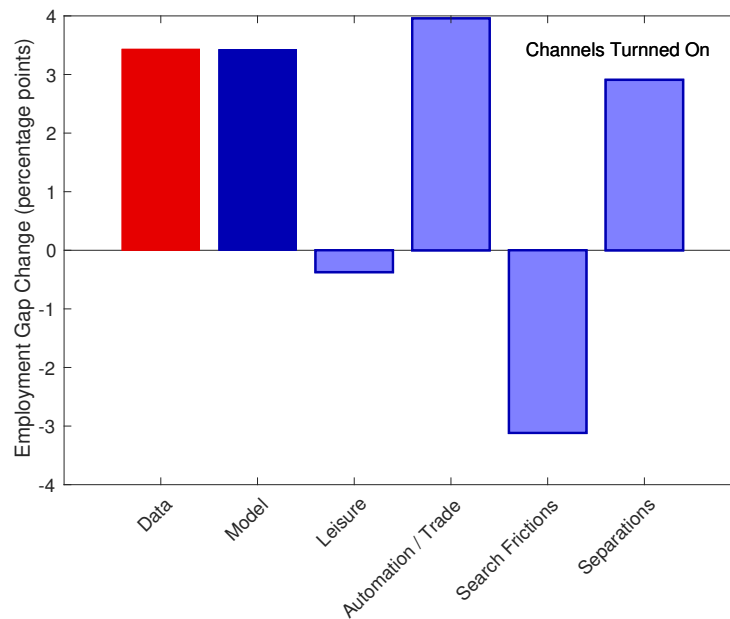


J Appendix: Counterfactuals with Alternative Education Cutoff z^*

Education Cutoff $z^* = 0.5$



Education Cutoff $z^* = 0.65$

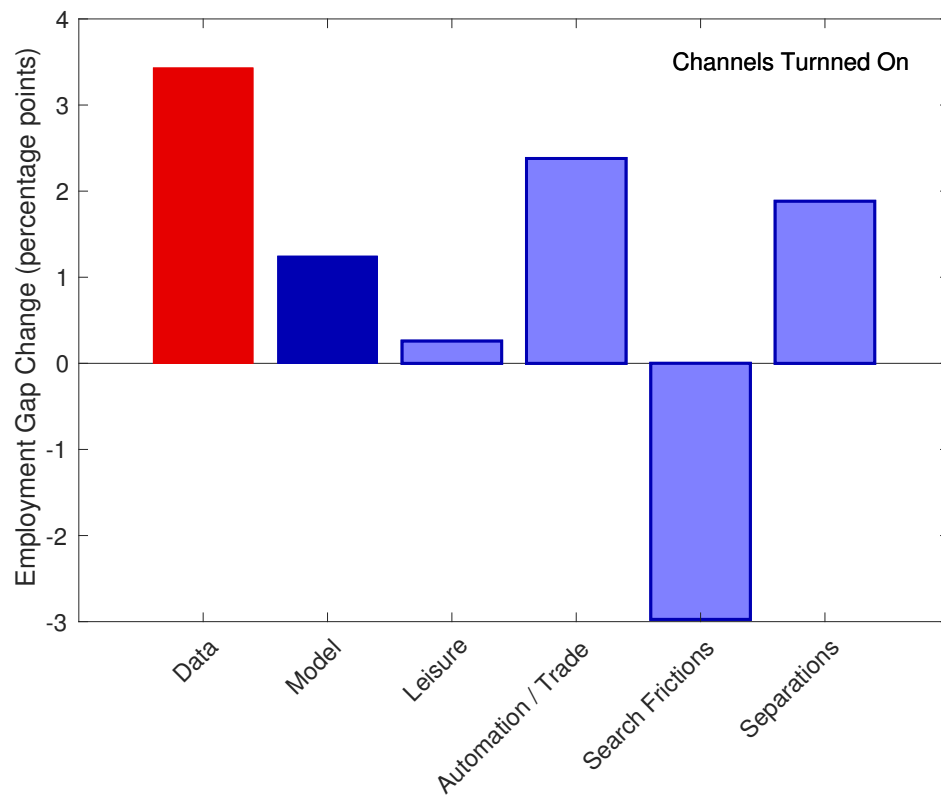


K Appendix: Counterfactuals with Alternative Matching Efficiency

Estimates of Matching Efficiency for Unemployed Men and Women

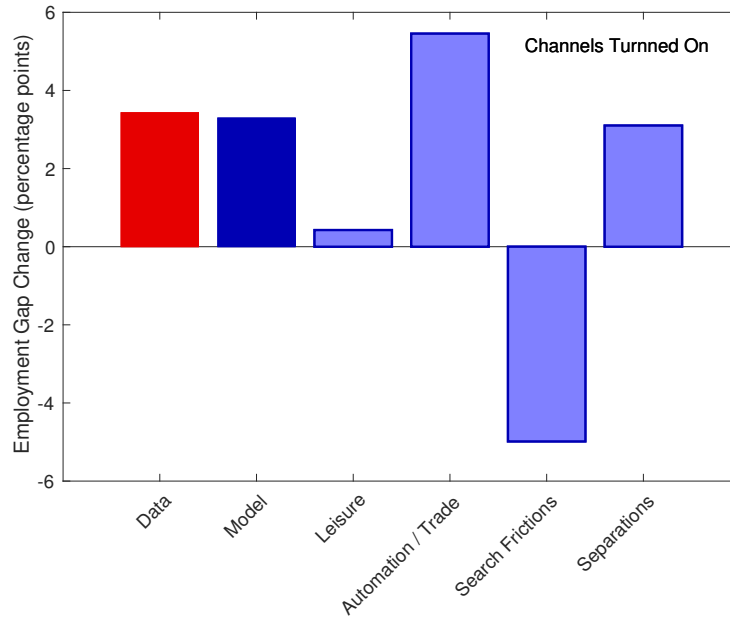
$\phi_{L,79}$	matching efficiency	0.2674	CPS job finding rate = 0.2732
$\phi_{L,07}$	matching efficiency	0.2952	CPS job finding rate = 0.2808
$\phi_{H,79}$	matching efficiency	0.3602	CPS job finding rate = 0.2946
$\phi_{H,07}$	matching efficiency	0.2214	CPS job finding rate = 0.2762

Counterfactuals with Matching Efficiency for Unemployed Men and Women

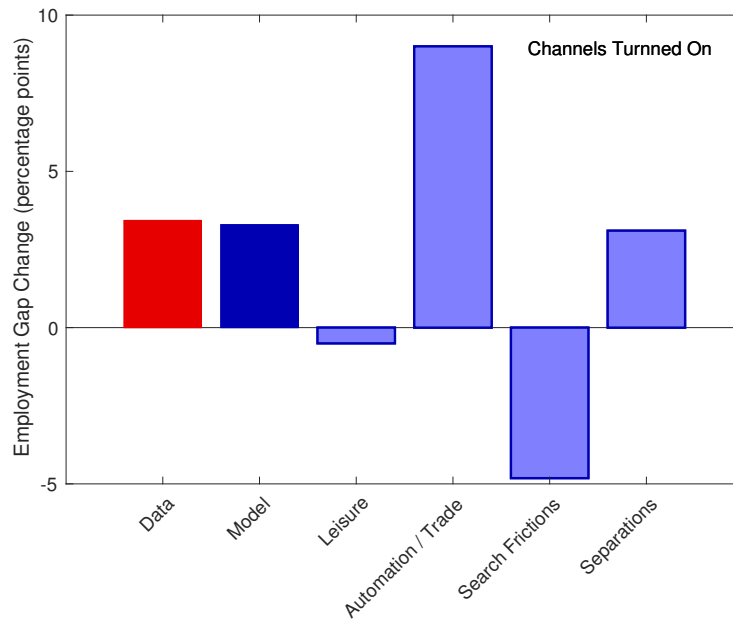


L Appendix: Counterfactuals with Alternative Parameterization

Counterfactuals with Bargaining Power $\pi_L = 0.52$ and $\pi_H = 0.72$



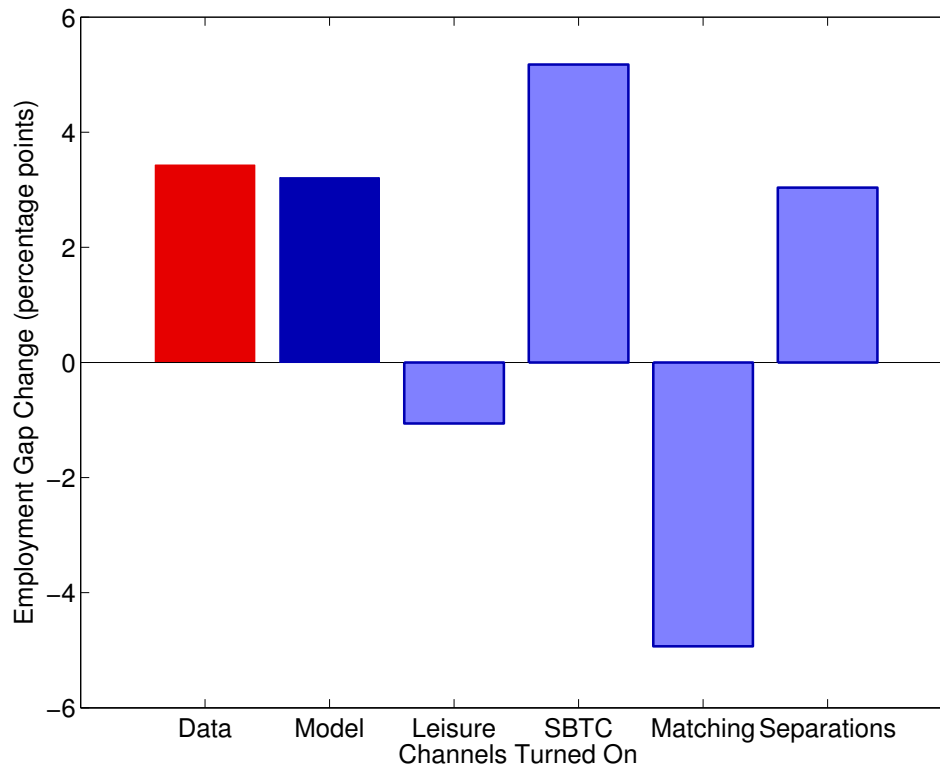
Counterfactuals with Vacancy Posting Costs $\kappa_L = 0.3$ and $\kappa_H = 0.7$



M Appendix: Counterfactuals with High-Skilled Value of Leisure as a Function of Ability

In this specification, high-skilled value of leisure is directly proportional to ability (i.e. $b_H x$), which is in contrast to the baseline where leisure does not depend on ability (i.e. b_H). For computational purposes, low-skilled value of leisure is kept at b_L .

High-Skilled Value of Leisure Proportional to Ability



N Appendix: Counterfactuals Turning Off Occupational Choice

In this specification the share of workers in the high-skilled market is fixed at 50 percent, meaning the top half of the ability distribution is in the high-skilled market and bottom half is in the low-skilled market. The mean and standard deviation of ability is kept at the baseline values.

College Share Fixed at 50 Percent

