Employment Inequality:
Why Do the Low-Skilled Work Less Now?

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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. I build a search model encompassing three explanations: (1) factors increasing the value of leisure, such as welfare and recreational gaming/computer technology, reduced the supply of low-skilled workers; (2) automation and trade reduced the demand for low-skilled workers; and (3) factors affecting job search, such as online job boards, reduced frictions for high-skilled workers. I find a supply shift had little effect, while a demand shift away from low-skilled workers was the leading cause, and search frictions actually reduced employment inequality.

1 Introduction

Low-skilled prime-age men are less likely to be employed today than high-skilled prime-age men. The 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. Using conservative estimates from the Current Population Survey (CPS), between 1980 and 2010 alone, employment rates diverged 5 percentage points.
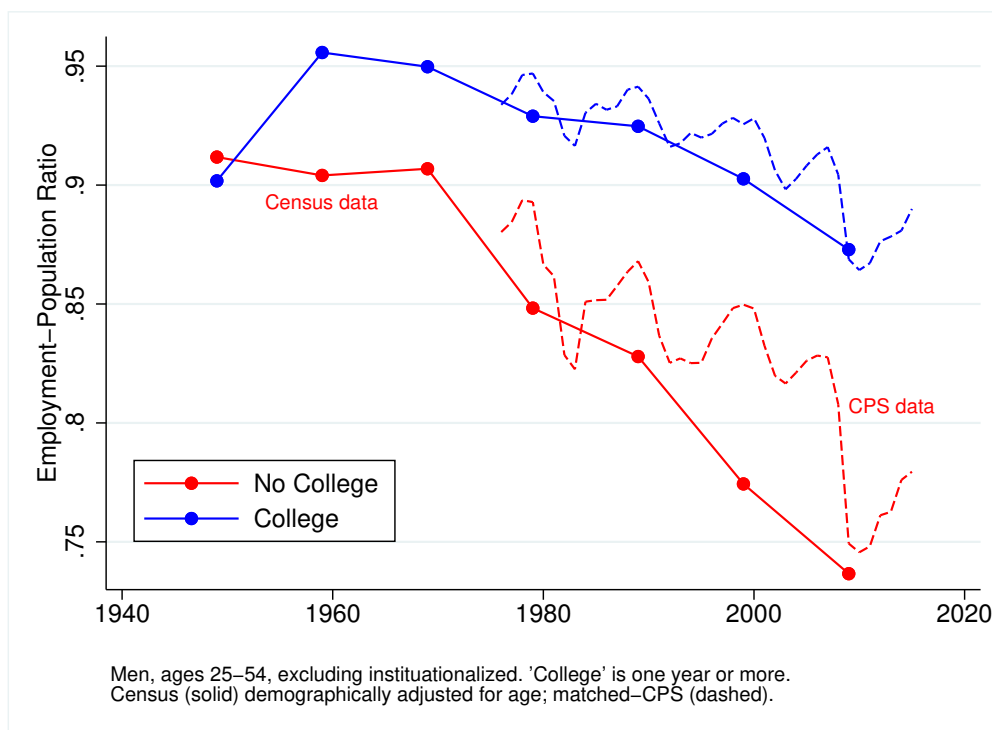
Why do the low-skilled work less now? There is no clear consensus. Two competing explanations include: (1) factors increasing the value of leisure, such as welfare and recreational gaming/computer technology, reduced the supply of low-skilled workers (Barnichon and Figura (2015a) and Aguiar et al. (2017)), and (2) automation and trade reduced the demand for low-skilled workers (Acemoglu and Restrepo (2017); Pierce and Schott (2016)). There is also a third explanation that has been overlooked: factors affecting job search, such as online job boards, may have reduced search frictions for high-skilled workers, and this third channel turns out to matter in a large and surprising way. To quantify the relative importance of all three channels, I build a unified framework.[2] Identification comes from calibrating the model and matching it to a novel empirical finding about labor market tightness.

Quantifying these mechanisms is important for policy. If the primary cause of employment inequality is declining health, one would expect more people on disability insurance and the policy response may be to restructure health benefits. Alternatively, if life-like computer and video game graphics reduced low-skilled reservation wages relative to offer wages, it is not clear policy should respond. If robots and outsourcing reduced low-skilled offer wages relative to reservation wages, training programs or policies promoting demand could help. Lastly, if growing popularity of online job boards only reduced search frictions for the high-

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[1]I focus on men because their labor force participation decisions have historically been less complex, but Appendix A shows the gap also emerged for women and other subgroups. I define 'college' as one year of college or more, but trends are similar if 'college' refers to college graduate.

[2]Cortes, Jaimovich, and Siu (2017) 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 cohabitant income as possible channels.

Figure 1: Widening Employment Gap[3]

Men, ages 25–54, excluding institutionalized. 'College' is one year or more.
Census (solid) demographically adjusted for age; matched–CPS (dashed).

skilled, policies lessening information or geographical frictions for the low-skilled could be optimal. The goal of this paper is to uncover why employment rates have diverged so we can better understand the appropriate response.

The paper has three contributions. First I document an empirical finding about labor market tightness, which is the ratio of job openings to job seekers. I combine several data sources to construct measures of labor market tightness for two peaks of the business cycle: 1979 and 2007. I find that 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 (see Figure 3 in Section 3). 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 design a model to replicate the growing share of low-skilled men who are not working at all (i.e. the extensive margin of the employ-

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[3]Data from the matched CPS, following Nekarda (2009), and from the one percent sample of the decennial Census, provided by IPUMS (www.ipus.org), differ for two reasons. First, I demographically adjust Census data for age to show the divergence is not driven by changes in composition. I do not adjust the CPS data because this is what I use to calibrate my model. Second—and this is where most of the discrepancy between the solid and dashed lines comes from—these are different surveys. According to the Census Bureau, the 2000 Census, in particular, underestimated employment levels for the less educated (see Palumbo et al. (2000) and Clark et al. (2003)).

ment decision). A search model in the spirit of Diamond (1982), Mortensen (1982), and Pissarides (1985) (DMP henceforth) is the ideal framework because, due to frictions in the search process, there is always a share of agents who don't work. Without friction, everyone would be employed in equilibrium and the model could not generate the observed decline in employment. I augment the standard DMP model by assuming workers (1) have heterogeneous ability and (2) choose whether or not to go to college based on their ability and the economic environment.[4] Heterogeneity in worker ability and college choice are important additions because selection is part of the employment inequality story: as more men attend college, the composition of worker ability in the college and non-college market changes, and this affects output and wages.[5] The model in this paper is flexible enough to allow for three broad channels (labor supply, labor demand, and search frictions) to influence differential employment trends, and for agents to optimize their college choice accordingly.

The final contribution is quantitative. I calibrate the model to match data on wages, worker flows, and the new documented fact about labor market tightness. I find that a shift in demand away from low-skilled workers is the leading cause, while a shift in supply had little effect, and search frictions actually reduced employment inequality. Given that both employment and wages of low-skilled workers fell since the 1970s (Figures 1 and 2), it is not surprising I find a shift in demand is the primary explanation. However, it is surprising that a shift in supply had no robust effect and that search frictions increased for high-skilled workers, offsetting some of the demand channel. The reason the supply-side has no bite is because real wages of low-skilled men fell from $14 to $8, while real wages of high-skilled men grew (see Figure 2). If low-skilled men were home playing video games because sophisticated computer graphics made leisure more enjoyable (or because health exogenously declined and welfare payments increased), their wages would not have fallen so drastically. The reason search frictions narrowed the employment rate gap is because the high-skilled market became tighter while relative job finding rates remained constant. In this setup, the only way for a tighter high-skilled labor market not to translate into higher job finding probabilities is if search frictions increased. One caveat is that the model—like most of the literature— focuses on job creation and does not micro-found job separations.[6] In other words, I can only identify a demand shift as it materializes through declining job finding rates, and not

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[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.

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

[6]Fujita and Ramey (2012) and Chassamboulli (2013), among others, endogenize job separations by assuming a stochastic process. When a negative shock hits a worker-firm pair, the worker separates from employment. Because adding this feature to the model does not help us understand the reasons workers separate from employment, I assume an exogenous separation rate, which I take directly from the data.

Figure 2: Widening Wage Gap[7]

Men, ages 25–54, excluding armed forces. 3–year moving average. Sources: CPS, FRED.
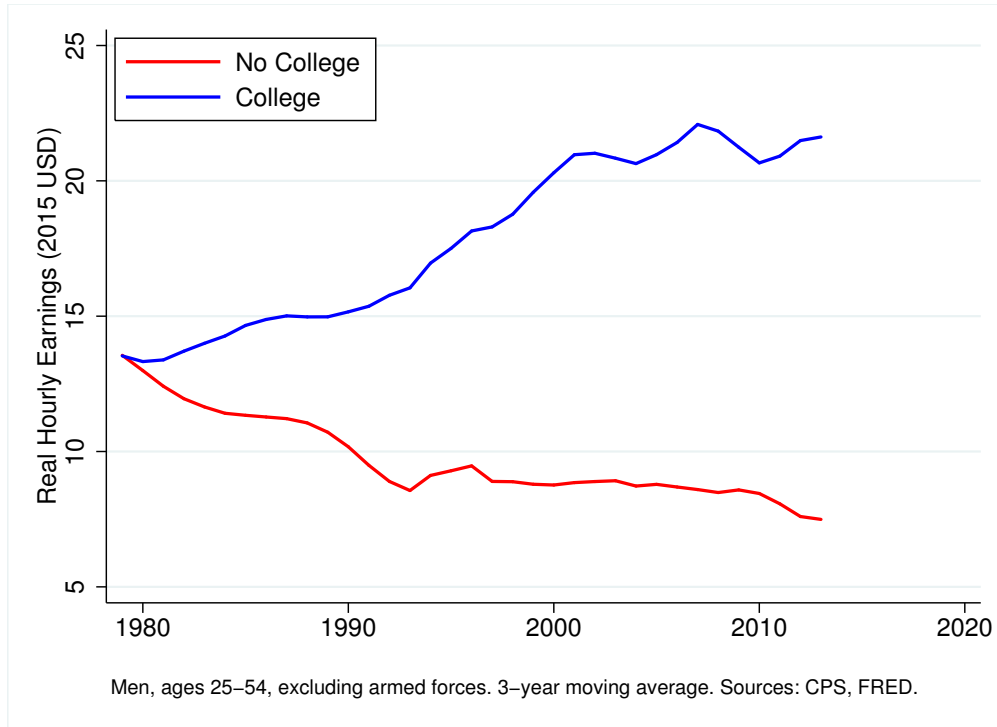
how it may affect job separations. The quantitative results should therefore be interpreted as a lower bound for the role of demand, because, to the extent things like automation and trade also operate through job separations, a demand shift is likely even more important for explaining employment inequality than what the baseline results imply.

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[7]To 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 that 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.

2 Related Research

This paper builds a unified framework to quantify the multiple channels that contribute to employment inequality. In contrast, previous papers have focused on a single mechanism.[8] For example, several papers postulate an increase in low-skilled workers' value of leisure is an important driver of differential employment trends. Aguiar and Hurst (2007, 2008) examine time-use data and find that 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.[9] In the 2000s this difference increased to a striking 9.7 hours. Aguiar and Hurst (2008) state 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 that 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 that nearly half of their decline in hours worked since 2004 was from gaming/recreational computer use.[10] 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 that 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 (2017) highlight the role of health issues, such as the opioid epidemic, 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.

This is far from the first paper to point out that growing wage inequality is more consistent with demand-side explanations (see Katz (2000) for a review). Autor, Katz, and Krueger (1998) find that 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

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[8]Two exceptions are Moffitt et al. (2012) and Abraham and Kearney (2018) who survey the literature on declining employment rates since 2000. In the first paper, Steven Davis writes in his comment, "I see a strong need for additional research to improve our understanding of the reasons for the worrisome declines in U.S. employment rates."

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

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

to reconcile the widening wage gap. However, to my knowledge this is the first paper to pit a demand-side explanation for rising employment inequality directly against a value of leisure story (which has recently gained traction). To this end, my work complements papers studying the details of a demand shift. For example, Frey and Osborne (2017) and Acemoglu and Restrepo (2017) focus on automation, while Autor, Dorn, and Hanson (2013, 2015); Acemoglu, Autor, Dorn, Hanson, and Price (2016); and Pierce and Schott (2016) examine competition from abroad.

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 Şahin (2012); Davis, Faberman, and Haltiwanger (2013); Şahin, Song, Topa, and Violante (2014); Barnichon and Figura (2015b); Hornstein and Kudlyak (2016); Hall and Schulhofer-Wohl (2018); Herz and Van Rens (2018)). 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 widen or narrow the employment rate gap. If high-skilled workers are more likely to use online job boards and this new technology minimizes search frictions, the employment rate gap would winden.[11] However, online job search is not a panacea. In fact, several papers find referred candidates have better job prospects, and Brown, Setren, and Topa (2016) find that less educated workers are more likely to use these informal hiring channels.[12] Together this suggests online search technology may accentuate search frictions, and the highly educated are disproportionally 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 these latter explanations more likely: search frictions increased for college workers and decreased for non-college workers between 1979 and 2007.

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[11]Faberman and Kudlyak (2016) find that 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.

[12]See Bayer, Ross, and Topa (2008); Dustmann, Glitz, Schönberg, and Brücker (2015); and Burks, Cowgill, Hoffman, and Housman (2015).

3 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. Although there are some limitations of this data, a host of robustness exercises confirm that labor market tightness by skill has differentially and drastically changed. By calibrating the model to match this empirical finding, I can distinguish how three potential mechanisms influence employment inequality.

3.1 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 low- and high-skilled occupations, $j \in \{L, H\}$. 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 robust-

ness 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 nonemployemnt 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.

3.2   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 and Perkowski (2016), and (3) the Integrated Public Use Microdata Series (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, while industries group jobs based on the product category of their output. This distinction makes occupations a better dimension along which to divide vacancies into low- and high-skilled. Unfortunately, U.S. vacancy data by occupation is difficult to come by due to its costly collection procedure.[13] To my knowledge, the only comprehensive national vacancy datasets disaggregated by occupation are the Help-Wanted Online (HWOL) database published by The Conference Board and the constructed series by Hobijn and Perkowski (2016), 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

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[13]Unlike 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.

states: Florida, Massachusetts, Texas, and Utah.[14] Data was collected for 19 occupations, which are based on the 1977 Standard Occupation Classification (SOC) system. Appendix B lists these occupations.[15]

Hobijn and Perkowski (2016) Data. These authors use state establishment surveys to construct a 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 and Perkowski (2016) merge these surveys with data on vacancies by industry from the job openings and Labor Turnover Survey (JOLTS), and data on employment shares from the CPS. They take the monthly average over the second quarter of each year and list 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.[16] 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 from the Integrated Public Use Microdata Series, version 4.0 (King et al. (2015)). Monthly observations for a nationally representative sample of the U.S. population start in 1976. Because I cannot observe the occupations of respondents who are out of the labor force, I define skill by education rather than occupation. 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 low- or high-skilled to coincide with nonemployed workers who are designated as either low- or high-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 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 and Perkowski (2016) data are categorized as low- and high-skilled.

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[14] 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.

[15] I convert occupational codes to the 1970 Census system using an archived crosswalk published by the National Crosswalk Service Center (http://www.xwalkcenter.org/index.php/classifications/crosswalks), which allows me to merge vacancy data with employment data from the CPS.

[16] http://www.workforceinfodb.org/ftp/download/xwalks

Because requirements changed over this period, some occupations whose college share was below the cutoff is now above. For instance, in 1979, 52 percent of workers in "Clerical Occupations" went to college, while in 2007, 61 percent of workers in "Office and Administrative Support" went to college. This is likely because the administrative tasks performed in 2007 required more skill, like computer and spreadsheet proficiency, so although it was considered a low-skilled occupation in 1979 it is now considered a high-skilled occupation. Another interpretation (which is inconsistent with the model) is that college is for signaling, not learning. If so, clerical/administrative occupations in both periods should be considered the same type of occupation. Appendix G.2 shows results are robust to this latter view.

3.3   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 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, while in 2007 the college market was tighter. Table 1 calculates the tightness gaps. In 1979 the market for college workers had 40 percent more *slack* than that for non-college workers (note the negative tightness gap). In 2007 the market for college workers was 177 percent *tighter*. Firms in recent decades have wanted to hire college-educated workers, but there are relatively few college-educated prime-age men available.
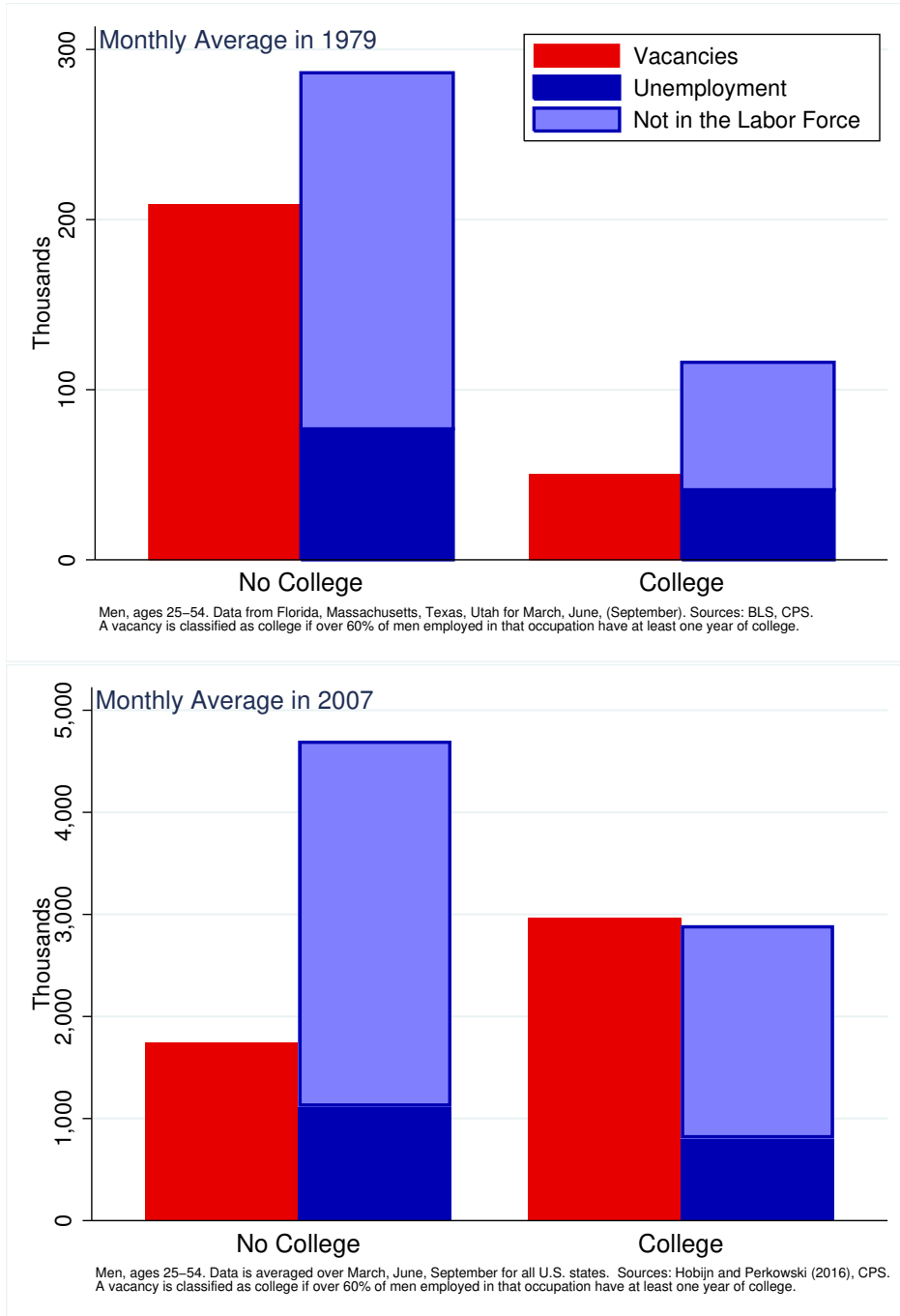
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Figure 3: Differential Market Tightness

Monthly Average in 1979

Legend:
- Vacancies
- Unemployment
- Not in the Labor Force

Men, ages 25–54. Data from Florida, Massachusetts, Texas, Utah for March, June, (September). Sources: BLS, CPS.
A vacancy is classified as college if over 60% of men employed in that occupation have at least one year of college.

Monthly Average in 2007

Men, ages 25–54. Data is averaged over March, June, September for all U.S. states. Sources: Hobijn and Perkowski (2016), CPS.
A vacancy is classified as college if over 60% of men employed in that occupation have at least one year of college.

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 et al. (2016), CPS	1.03	0.37	**177%**
Unemployment	1979	BLS, CPS	1.22	2.71	**-55%**
Unemployment	2007	Hobijn et al. (2016), 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.

The 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 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. A potential concern with using the unemployment measure 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 nonemployment tightness measure would attribute value of leisure to market slack. In practice, this is not a problem because relative tightness is comparable across the two measures: the unemployment measure gives a tightness gap of -55 percent in 1979 and 136 percent in 2007. I use the nonemployment measure because it drastically simplifies the model.

Since we only observe labor market tightness for four states, the 1979 tightness gap may not be nationally representative, despite the BLS strategically choosing a diverse set of states. Appendix E.1 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 E.2 shows the tightness gap remained above 100 percent throughout the 2000s despite the large business cycle swing (i.e. the Great Recession). This suggests the tightness gap is at least threefold larger today regardless of cyclical fluctuations.

Figure 4: Tightness Gap by Educational Cutoff
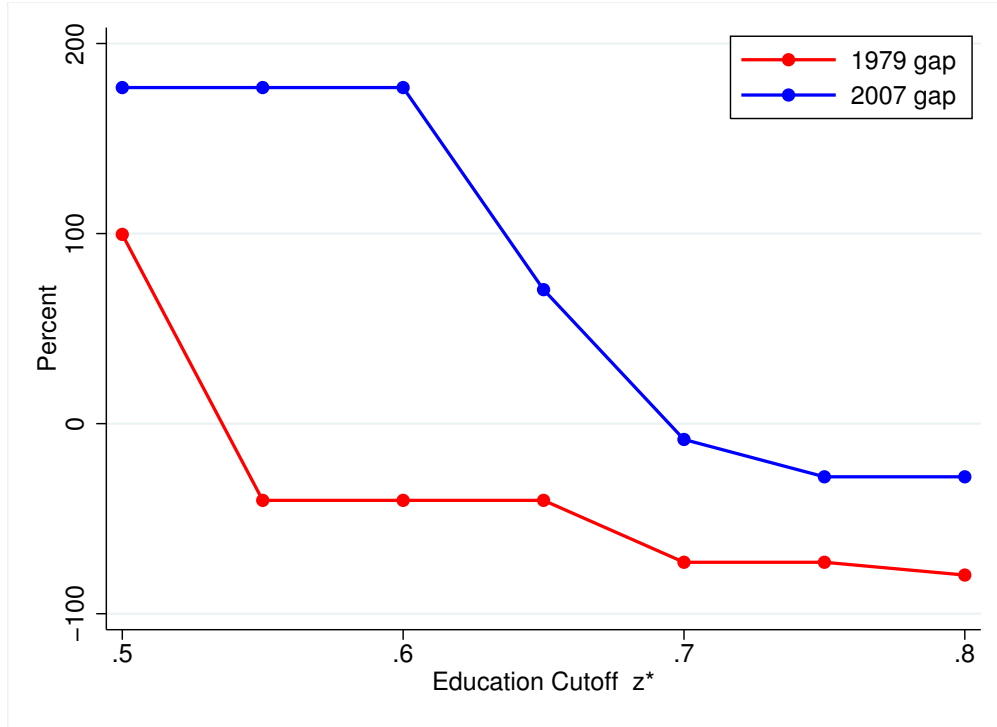
Tightness is also robust to different construction choices. Appendix E.3 checks robustness to using alternative vacancy data that is nationally representative and confirms the tightness gap widened substantially over the second half of the 20th century. Appendix E.4 checks robustness to using *unemployed* men and *women* in the denominator of the 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 et al. (2018) 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. Moreover, Appendix G.2 and Appendix G.3 show counterfactual results are robust to all these alternative measures of labor market tightness.

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 above plots tightness gaps using the nonemployment measure of

labor market tightness. Appendix E.4 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.

4   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 heterogenous worker ability and two types of occupations that 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 D illustrates that 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. The allocation of ability across occupations is important 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 affects employment inequality. As in the data, my model predicts both the low- and high-skilled markets are made up of lower ability workers in the later period.[17] 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

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[17]Beaudry, Green, and Sand (2016) and Abel, Deitz, and Su (2014) find that 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.

along one dimension, not two, and firms always perfectly observe a worker's type.

4.1   Environment

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

Workers. Workers are heterogeneous in their ability. I consider an economy populated by M types of workers indexed by $x \in \{x_1 < x_2 < ... < x_M\}$, where $x_1 = 0$. Ability is permanent and perfectly observable to employers and is a discrete approximation of log-normal.[18] I ex-ante sort workers into submarkets based on their ability. Therefore, the aggregate labor market is organized into M submarkets indexed by worker ability x. In each ability 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 $\sum_x \big(e(x) + n(x)\big) M(x) = 1$. Since there are as many submarkets as there are levels of worker ability, there is no crowding out between workers of different ability. This choice simplifies the model because the firm's expected value of meeting a worker does not depend on who is in the nonemployment pool, and is plausible if the job application process effectively screens candidates.

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 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. I assume directed search following Moen (1997) and Menzio and Shi (2010), such that firms target a specific 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 that define the two types of occupations, but their outputs are perfect substitutes.[19] Technology used at low-skilled (L) occupations is not a function of worker ability. Think of a conveyer 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).

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[18]When calibrating the model in Section 5, I focus on ability deciles such that there are $M = 10$ types of ability levels in the economy.

[19]If I relax this and assume some complementary between low- and high-skill output as in Katz and Murphy (1992), an even larger shift in demand favoring high-skilled labor is required to generate the observed wage premium.

The technology used at high-skilled (H) occupations depends on 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 robots and trade replacing low-skilled workers, while an increase in A_H resembles computers and communication technology increasing high-skilled workers' productivity.

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

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

where $\alpha \in (0,1)$ and ϕ_j is matching efficiency. Changes in ϕ_j represent shifts in search 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 labor-augmenting technologies 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 $t + 1$.

4.2 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 low- or high-skilled technology $j \in \{L, H\}$ at time t.

Note that if the vacancy is for a low-skilled occupation $j = L$, ability is irrelevant.

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

where κ is the cost of posting a vacancy.[20] $J_{jt+1}(x)$ is a firm's surplus next period from matching with a worker in occupation j. Firm surplus this period equals:

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

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, all workers in their respective occupational categories separate from their job at rate δ_j. The separation rate is exogenous because "endogenizing" it with a stochastic process would unnecessarily complicate the model and in no way help us identify *why* workers separate.

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

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

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

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

where $N_{Lt}^c(x)$ represents the continuation value of nonemployment when a worker chooses to search for low-skilled work (i.e. occupations 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. occupations where output and therefore wages depend on ability). In each ability submarket, all workers choose the same occupation and there exists a threshold x_ξ above which all workers choose high-skilled occupations.

When agents choose to search for low-skilled work, think of them as forgoing college. When agents choose to search for high-skilled work, think of them as attending college so that they can search for college jobs. In the model, agents switch from high- to low-skilled occupations, but in reality workers cannot switch from having some college experience to no college experience. Because I calibrate the model to match two steady states, agents who switch between college and non-college should be thought of as two different people, living

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[20]In the baseline specification κ is constant across occupations, but Appendix G.5 tests robustness to $\kappa_H > \kappa_L$.

in different decades, who have the same ability level.

The recursive formulation for the continuation value of nonemployment when an individual searches for type $j \in \{L, H\}$ work follows:

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

where b_j is the value of leisure which varies between low- and high-skilled occupations. Changes in b_j represent shifts in the labor supply of type j workers.

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.[21] 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 ability submarket x and occupation j. Workers receive $\pi S_{jt}(x)$ from a match and firms receive $(1 - \pi) S_{jt}(x)$.[22] 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. I assume for high-skilled occupations that an infinite number of firms are free to enter each ability submarket and post vacancies, thereby pushing down the value of posting a vacancy to zero. This free entry condition implies $V_{Ht}(x) = 0$, $\forall t, x$.[23] Since ability is irrelevant for low-skilled occupations, firms treat this as a single market. In other words, for low-skilled occupations an infinite number of firms are free to enter and post vacancies such that $V_{Lt} = 0$, $\forall t$.

4.3   Steady State

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

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[21]In the baseline specification π is constant across occupations, but Appendix G.5 tests robustness to $\pi_H > \pi_L$.

[22]Nash bargaining provides additional expressions representing workers' and firms' values of a match, such that we can set $W_{jt}(x) - N_{jt}(x) = \pi S_{jt}(x)$ and $J_{jt}(x) = (1 - \pi) S_{jt}(x)$.

[23]For 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:

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

The DMP literature refers to this expression as the job creation curve. If the firm had no hiring costs, κ would be zero and equation (7) would be the standard condition where the marginal product equals the 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:

$$\omega_j(x) = (1 - \pi)b_j + \pi\big(y_j(x) + \kappa\theta\big). \tag{8}$$

Workers are rewarded for helping firms save on hiring costs. They also enjoy a share of the output and their value of leisure. Wages are increasing in market tightness, and for high-skilled jobs, wages are increasing in ability and technology.[24]

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 for each ability level and occupation 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 for each ability level and occupations 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:

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

In steady state the number of nonemployed agents within a given ability level is a function of the exogenous separation rate, matching efficiency, and tightness ratio. The proposition in Appendix F illustrates how tightness θ is generally a function of technology and ability, meaning employment rates vary not only over occupations, but also over ability x.

College Choice. When in the nonemployment pool, workers endogenously choose which type of occupation to search for: non-college (L) or college (H). They make this decision by

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[24]See Pissarides (2000) for a derivation of steady state wages.

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):

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

Equations (7), (8), (9) and (10) determine the steady-state equilibrium.

5 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 in this economy by targeting the share of workers with at least one year of college in 1979 and 2007.

5.1 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 3 provides estimates of market tightness for low- and high-skilled occupations. I take an estimate of elasticity α from the literature. Rewriting equation (1) gives an expression for matching efficiency:

$$\phi_j = \frac{f_j(\theta(x))}{\theta(x)^{1-\alpha}}. \tag{11}$$

The proposition in Appendix F shows tightness is generally a function of individual ability x. Since we do not have estimates of 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 (11).[25] Specifically, matching efficiency estimates are calculated as:

$$\hat{\phi}_j = \frac{\hat{f}_j}{\hat{\theta}_j^{1-\alpha}}, \tag{12}$$

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

5.2   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 (the 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 high-skilled market. Specifically, I minimize the following expressions:

$$\frac{1}{\hat{\theta}_{HT}} \left(\hat{\theta}_{HT} - \frac{1}{M} \sum_{x_\xi}^{x_M} \theta_{HT}(x) \right)^2, \tag{13}$$

$$\frac{1}{\hat{\omega}_{HT}} \left(\hat{\omega}_{HT} - \frac{1}{M} \sum_{x_\xi}^{x_M} \omega_{HT}(x) \right)^2, \tag{14}$$

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[25]Given 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.

where $\hat{\theta}_{HT}$ and $\hat{\omega}_{HT}$ are the empirical tightness ratio and real wage of the high-skilled market in year $T \in \{1979, 2007\}$.[26]

5.3 Ability Parameters

The final set of parameters to recover is 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 that 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 C plots the time series of college share with reference lines at 1979 and 2007. Matching these two moments allows me to recover the remaining two unknowns: μ_x and σ_x.

6 Results

Table 2 lists the parameter estimates for 1979 and 2007, where $z^* = 0.6$.[27] The first third of the table takes values from the literature. I calibrate the model to match monthly observations 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 non-participants 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 so Appendix G.5 tests robustness to $\pi_H > \pi_L$. There is a wide range of values for vacancy posting costs in the literature. Cairo and Cajner (2018) 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 (2018) find it is closer to 0.9. I split the difference and use 0.5.[28]

The second third of the table takes estimates from the data. I compute separation rates (employment to nonemployment) and job finding rates (nonemployment to employment)

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[26]I divide equations (13) and (14) by $\hat{\theta}_{HT}$ and $\hat{\omega}_{HT}$, respectively, so that when I minimize the expressions I do not give naturally larger numbers more wieght.

[27]Appendix G.4 shows counterfactuals where $z^* = 0.5$ and $z^* = 0.65$.

[28]Appendix G.5 shows results are robustness to when high-skilled vacancy posting costs are larger than low-skilled posting costs, $\kappa_H > \kappa_L$.

by longitudinally matching individuals in the CPS via the procedure outlined in Nekarda (2009). Appendix C plots time series of these rates with reference lines at 1979 and 2007. Separation rates in Table 2 are taken directly from the data while matching efficiencies are recovered by targeting job finding rates as described in Section 5. I find matching efficiency increased for low-skilled workers and decreased for high-skilled workers between the 1970s and 2000s. In 1979 the high-skilled market was more efficient at linking job openings with job seekers; in 2007 the low-skilled market was more efficient. This fact also holds when looking at unemployed men and women rather than nonemployed men.[29]

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 value of leisure never increases. This is because the drastic decline in low-skilled labor market tightness, as displayed in Table 3, was accompanied by a decline in real hourly earnings. If low-skilled men were home playing video games because sophisticated computer graphics made leisure more enjoyable (or because health exogenously declined and welfare payments increased), their wages would have increased, not decreased. Regarding the labor-augmenting technology parameters, low-skilled productivity decreased between 1979 and 2007, while high-skilled productivity increased. This is consistent with automation and competition from abroad replacing low-skilled workers and complementing high-skilled workers. The last two lines list the recovered mean and standard deviation of ability.

Table 3 shows the model matches the targeted moments quite well. I target the levels of tightness and wages, but for illustration purposes also list how well the model matches the percent gaps between the high- and low-skilled. The model sightly overestimates high-skilled tightness in 2007, leading to a larger gap than what is observed in the data. The model captures that real hourly earnings for the two skill groups were identical in 1979, but come 2007, high-skilled wages were two and a half times larger than low-skilled wages. Lastly, the model replicates the fact that in the 1970s there were fewer men in the high-skilled (i.e. college) market than there are today. The model matches the college share in 1979, but over predicts the share in 2007. Although college choice and ability sorting are realistic features of the labor market (see Appendix D), in practice they do not significantly impact the calibration results. Appendix G.1 shows the outcome of counterfactual exercises when college choice in the model is shut down. Results are similar to baseline, implying that

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[29]Appendix G.3 lists matching efficiency estimates with a measure of tightness that includes men and women in the denominator and job finding rates that are U-E flows for both men and women.

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	0.2118	CPS job finding rate = 0.1451
$\phi_{H,79}$	matching efficiency	0.2698	CPS job finding rate = 0.1975
$\phi_{H,07}$	matching efficiency	0.1590	CPS job finding rate = 0.1608
$b_{L,79}$	value of leisure	0.31	calibrated
$b_{L,07}$	value of leisure	0.26	calibrated
$b_{H,79}$	value of leisure	0.61	calibrated
$b_{H,07}$	value of leisure	0.60	calibrated
$A_{L,79}$	technology	1.06	calibrated
$A_{L,07}$	technology	0.68	calibrated
$A_{H,79}$	technology	0.64	calibrated
$A_{H,07}$	technology	1.13	calibrated
μ_x	mean ability	0.36	calibrated
σ_x	standard deviation of ability	0.144	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	0.44	0.44	-40%	-40%
$\theta_{L,07}$	L tightness	2007	0.37	0.37		
$\bar{\theta}_{H,07}$	H tightness	2007	1.06	1.03	187%	177%
$\omega_{L,79}$	L wages (normalized)	1979	1.00	1.00		
$\bar{\omega}_{H,79}$	H wages	1979	1.00	1.00	0%	0%
$\omega_{L,07}$	L wages	2007	0.63	0.63		
$\bar{\omega}_{H,07}$	H wages	2007	1.60	1.60	149%	154%
$\frac{M-\xi_{79}}{M}$	H share	1979	40%	43%		
$\frac{M-\xi_{07}}{M}$	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	91%	92%	9.2 pp	8.8 pp
				Difference	3.3 pp	3.4 pp

the model's takeaways do not rest on this moment.

Table 4 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. To the extent 1979 and 2007 are steady states, the model will match the data. The model captures that both low- and high-skilled employment rates hovered around 90 percent in 1979 and that 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 increase observed in the data.

Figure 5 illustrates results of counterfactual exercises. The vertical axis depicts how much the employment gap changed, in terms of percentage points, between 1979 to 2007. 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 full 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. The question I ask here is: what would have happened to the employment rate gap if all but one set of parameters were fixed at their 1979 levels and the remaining set evolved according to Table 2?

Turning to the the light blue bar representing labor supply, when the value of leisure parameters for all workers change according to their calibrated values and all other channels are turned off, the employment gap decreases by 0.3 percentage points. In other words, a relative change in lower skilled workers' value of leisure marginally closed the employment gap between 1979 and 2007. Appendix G reveals this result is not always consistent across specifications. When matching efficiency is calculated using unemployed men and women, the labor supply channel slightly widens the employment rate gap. When alternative vacancy data are used, the labor supply channel closes the gap more than in the baseline specification. That said, most robustness checks in Appendix G show that the supply channel barely altered the gap, and all specifications show it is the least important channel, so I conclude a shift in the supply of labor has not robustly altered employment inequality since the 1970s.

The labor demand channel, on the other hand, has robustly increased employment inequality over this period. If the labor-augmenting technology parameters for all workers change according to their calibrated values and all other channels are turned off, the employment gap increases by over 5 percentage points. Across specifications in Appendix G, labor demand contributed to at least 2.4 out of the 3.3 percentage point increase in the model generated gap. In other words, a relative increase in high-skilled labor productivity widened

Figure 5: Counterfactuals
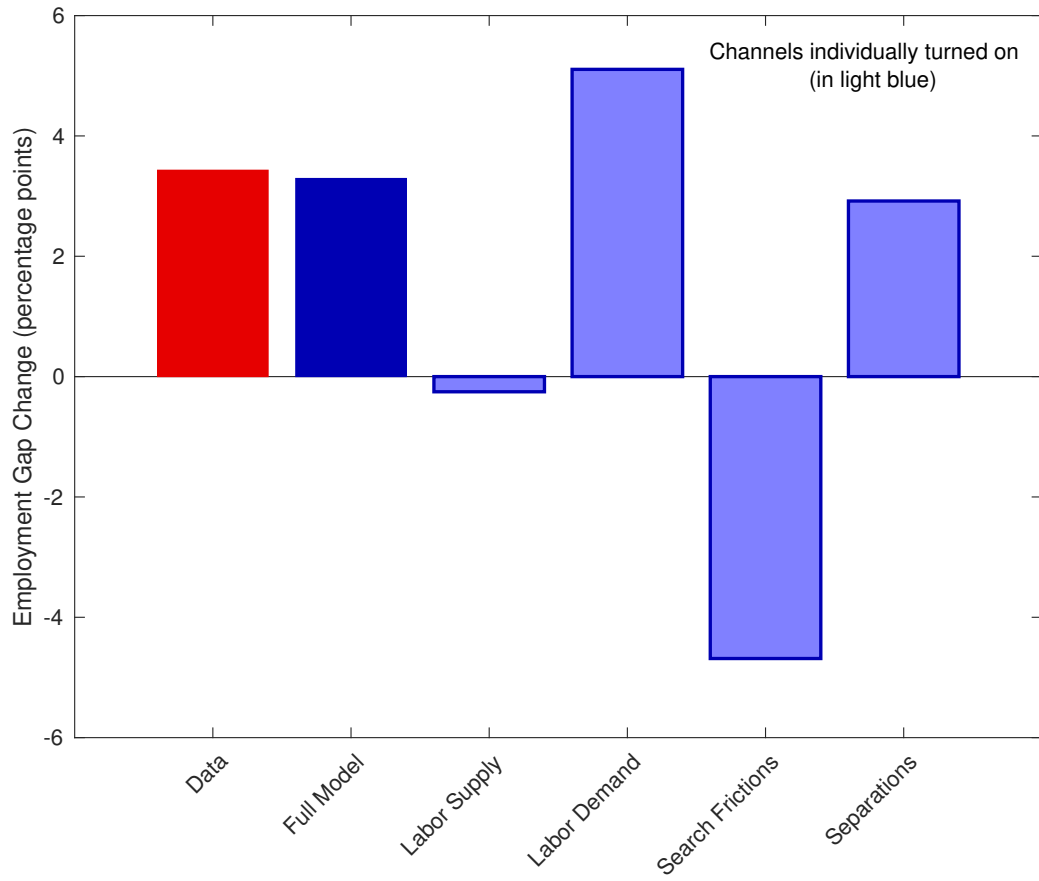
the employment gap and can account for all (and more) of the observed rise in employment inequality.

The second most rightward bar suggests 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, $\phi_{H,07} < \phi_{L,07}$. One explanation is high-skilled, college jobs became more specialized over this period, such that high-skilled jobs seekers have more difficulty finding good matches. Another explanation is online job search reduces 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. Online search technology possibly accentuates search frictions, and the highly educated are disproportionally affected because they use this technology more.

Lastly, if job separation rates were fixed at their 1979 levels, there would be minimal employment inequality today. 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, and search frictions), or another reason all together. Given that parameters on the the job finding side of the model point to such large declines in relative demand for low-skilled labor, a similar mechanism on the job separations side is highly plausible. One way to interpret the results in this paper is to view the contribution of labor demand in Figure 5 as a lower bound. Reason being, if demand-side factors such as automation and trade also generated diverging separation rates, then labor demand 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 C shows the spread in separation rates between low- and high-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 technology. Figure 5 shows search frictions (i.e. matching efficiency) narrowed the employment rate gap, while shifts in demand (i.e. technology) widened the gap, and shifts in supply (i.e. leisure) had little effect. This means, on net, search frictions offset the effects of labor

demand such that job finding rates did not contribute to rising employment inequality. Instead, all the bite came from separations. Had market tightness and thereby search frictions not changed over this period, labor supply would have been the one offsetting labor demand. In other words, in hypothetical specifications where I hold tightness fixed over time, the search frictions and labor supply bars in Figure 5 swap.[30]

7 Conclusion

Why do the low-skilled work less now? To answer this question I calibrate an augmented DMP model to match two business cycle peaks and recover how three key sets of parameters changed between 1979 and 2007. In contrast to the existing body of work—which studies plausible channels in isolation and where there is no consensus—I build a unified framework to quantify how multiple channels contribute to growing employment inequality. I find a shift in the demand away from low-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.

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[30]Appendix G.2 is a version of this where the tightness gap increases by 1.5 times instead of multifold as in baseline.

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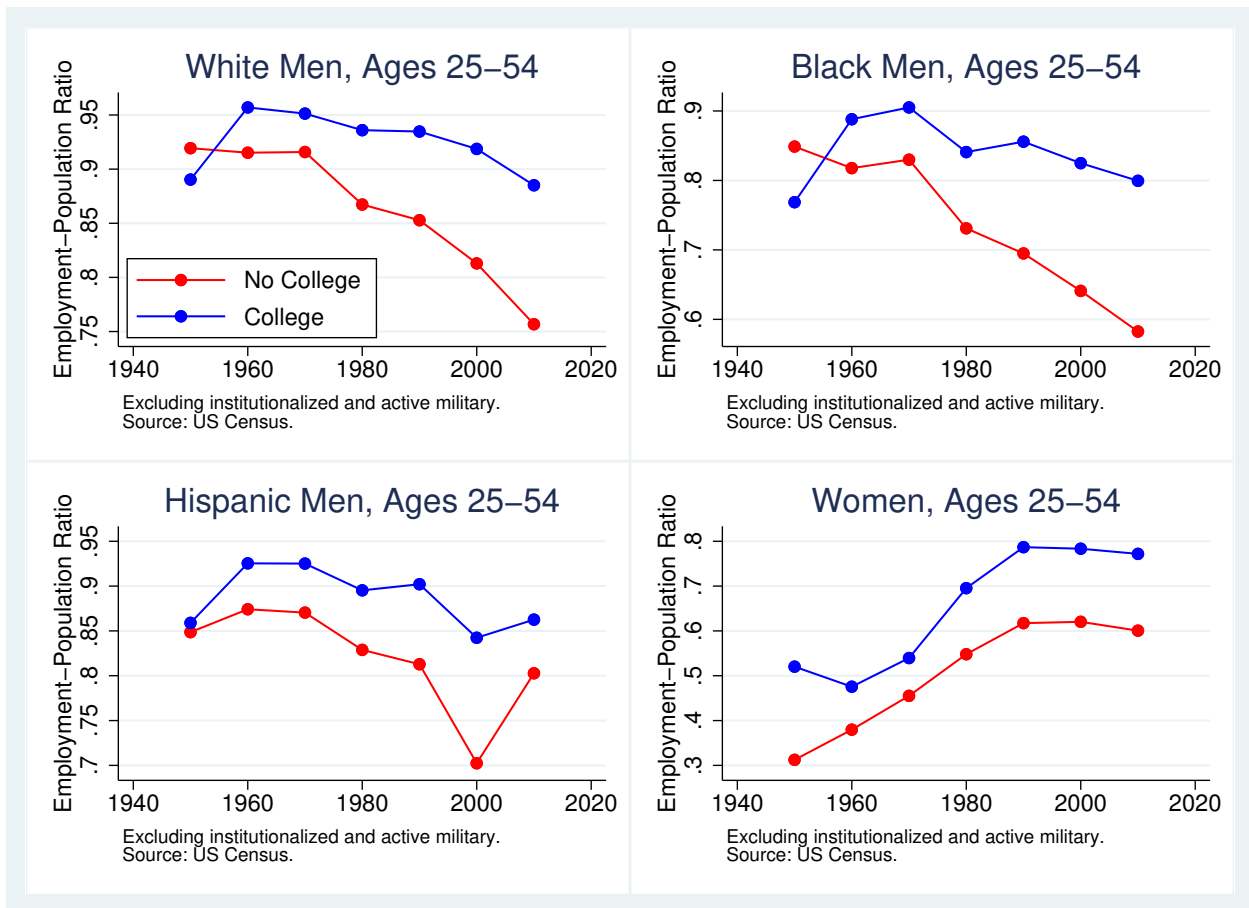Barnichon, R. (2010). Building a composite help-wanted index. *Economics Letters 109*(3), 175–178.

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A   Appendix: Employment Inequality Disaggregated

White Men, Ages 25–54

No College
College

Employment–Population Ratio

Excluding institutionalized and active military.
Source: US Census.

Black Men, Ages 25–54

Employment–Population Ratio

Excluding institutionalized and active military.
Source: US Census.

Hispanic Men, Ages 25–54

Employment–Population Ratio

Excluding institutionalized and active military.
Source: US Census.

Women, Ages 25–54

Employment–Population Ratio

Excluding institutionalized and active military.
Source: US Census.

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

BLS Pilot Vacancy Data
(2-digit 1977 SOC)

Hobijn and Perkowski (2016) Vacancy Data
(2-digit 2000 SOC)

High-Skilled Occupations

Executive, Administrative & Managerial	Management
Engineers & Architects	Business and Financial Operations
Natural Scientists & Mathematicians	Computer & Mathematical Science
Social Scientists, Social Workers, Religious Workers & Lawyers	Architecture and Engineering
Teachers, Librarians & Counselors	Life, Physical & Social Science
Health Diagnosing & Treating Practitioners	Community and Social Services
RNs, Pharmacists, Dietitians, Therapists & Physicians Assistants	Legal
Writers, Entertainers, Artists & Athletes	Education, Training & Library
Health Technologists & Technicians	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

Marketing & Sales *	Food Production & Serving Related
Clerical Occupations *	Building & Grounds Cleaning & Maintenance
Service Occupations	Farming, Fishing, and Forestry
Construction & Extractive Occupations	Mechanics & Repairers
Agricultural, Forestry, Fishers & Hunters	Production Work Occupations
Transportation & Material Moving	Material Handlers, Equipment Cleaners & Laborers
Construction & Extraction	
Production	

*Appendix G.2 tests robustness to assigning these occupations to high-skilled.

C Time Series with Reference Lines at 1979 and 2007

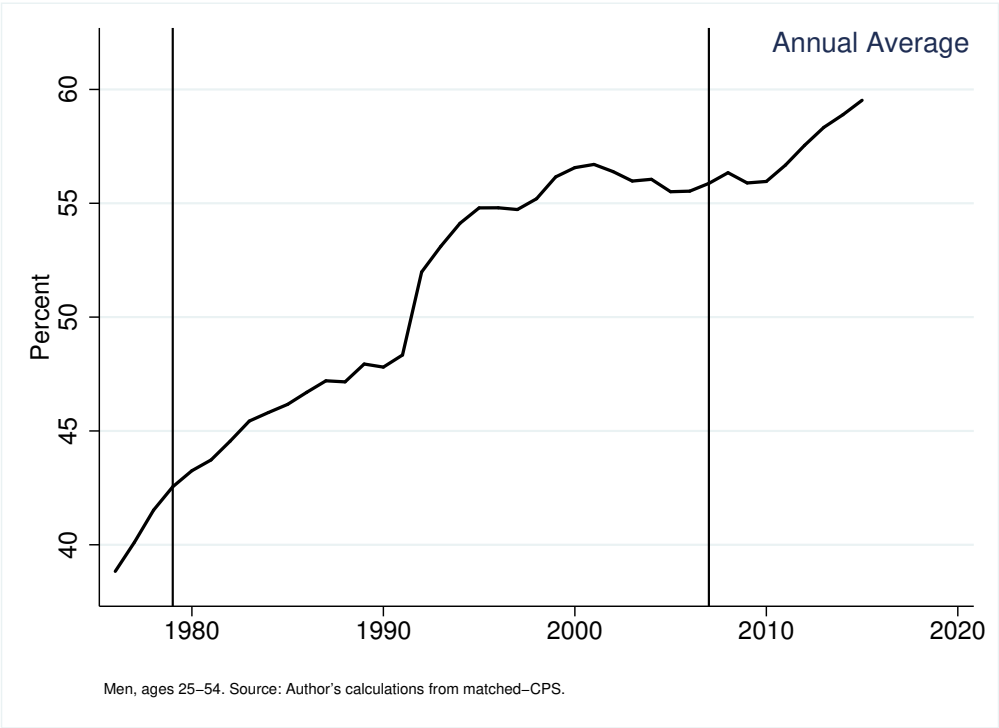Figure 6: Share of Men with at Least One Year of College

Men, ages 25–54. Source: Author's calculations from matched–CPS.

Figure 7: Job Finding Rates: U+NLF→E
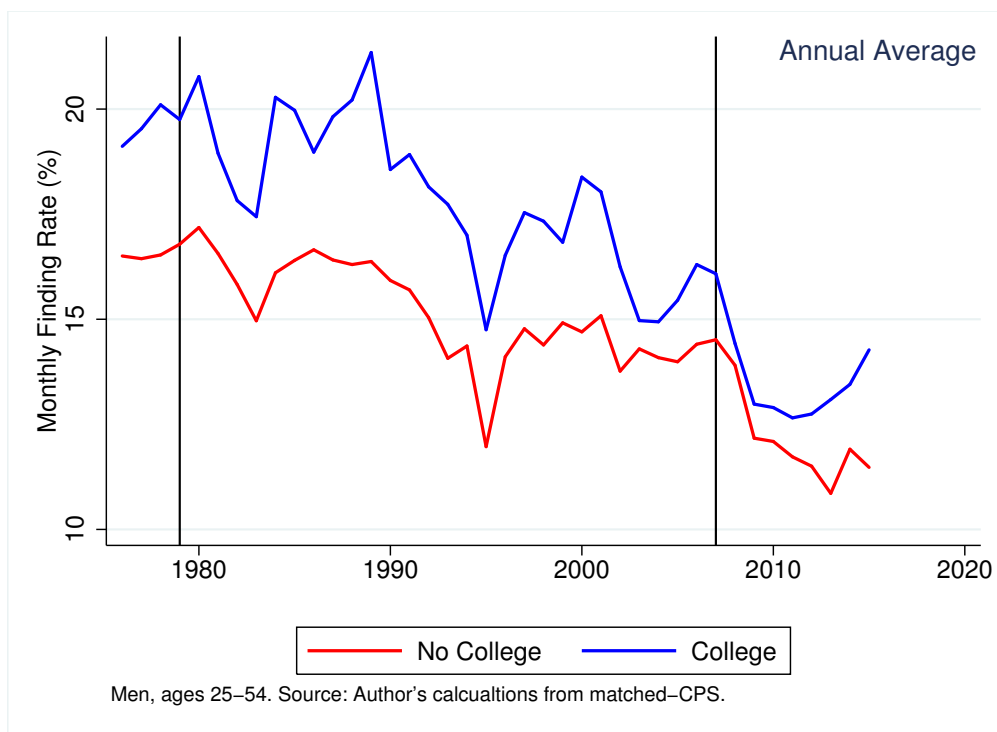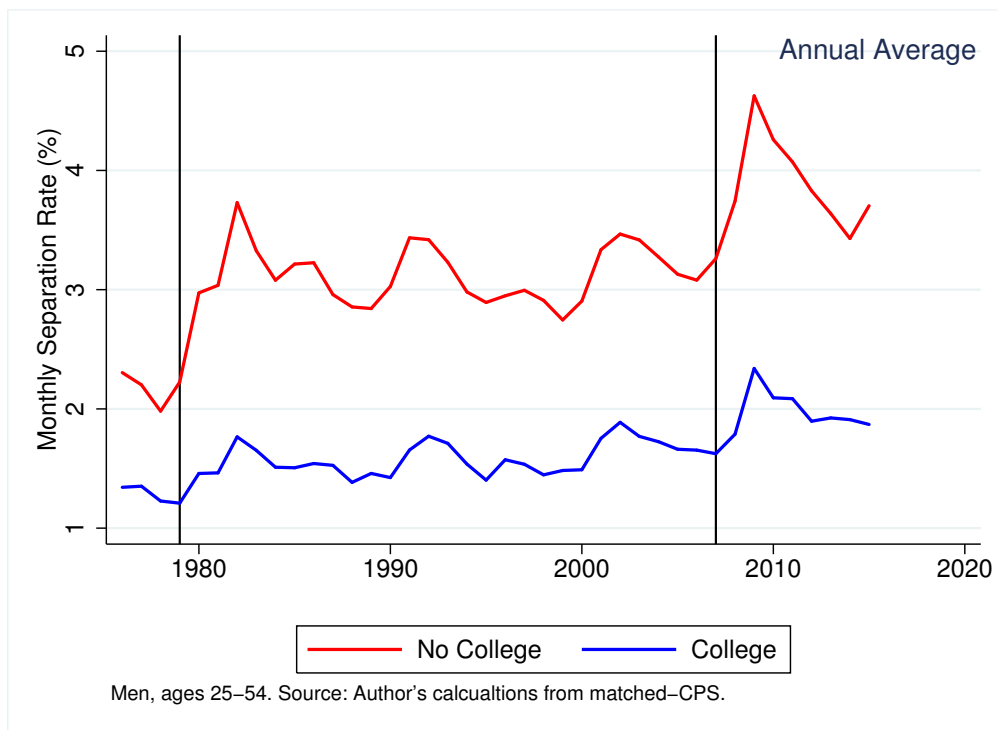

Figure 8: Separation Rates: E→U+NLF

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D   Appendix: Ability Composition

The structural framework in this paper adds three more ingredients to the standard DMP model, two of which are are heterogenous ability and occupational choice. As predicted by the model, this appendix shows that the composition of low- and high-skilled workers has changed over time. Workers searching for college and non-college occupations in the 2000s are of lower ability than workers in the 1980s. This is not to say particular individuals switched categories, but rather particular ability levels have historically switched categories. Put differently, 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. Ability sorting changes average labor productivity in each occupation type (college vs. non-college), potentially making it an important margin. Cunha, Karahan, and Soares (2011), Carneiro and Lee (2011), and Hendricks and Schoellman (2014) make a similar point about the importance of ability sorting in relation to the college premium.

Figure 9: Compositional Change of College and Non-College

39
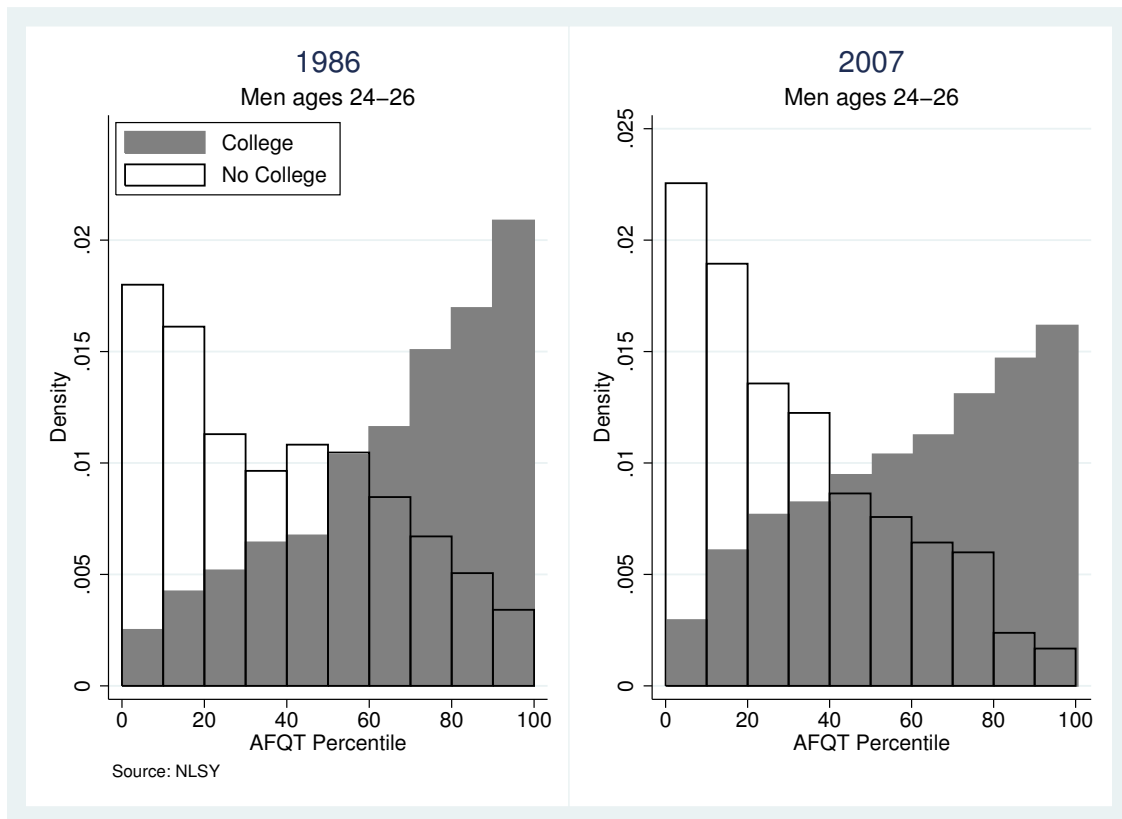
To empirically examine ability sorting, I use two cohorts of the National Longitudinal Survey of Youth (NLSY). Respondents from the 1979 cohort were ages 14 to 22 during the first year of the survey and respondents from the 1997 cohort were ages 12 to 16 during the first year of the survey. Within the 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.[31] 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.[32] Furthermore, the NLSY's AFQT-3 variable re-norms scores, controlling for age, so that sores from the 1979 and 1997 cohorts are comparable. Percentile of AFQT scores are reported on the horizontal axis of Figure 9.

The left panel of Figure 9 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 that 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. In other words, the college population consisted of lower ability men in 2007.[33]

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 men in 2007.[34]

The ability composition of the college and non-college labor market has changed markedly.[35] The findings in this appendix corroborate the findings from the model that median worker ability in both markets fell over the last few decades.

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[31]http://official-asvab.com

[32]https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores/page/0/0/#asvab

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

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

[35] 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 when aggregating over students with one year of college or more (as in Figure 9).

E   Appendix: Paremeter Robustness

E.1   Tightness Gap in 1979 by State
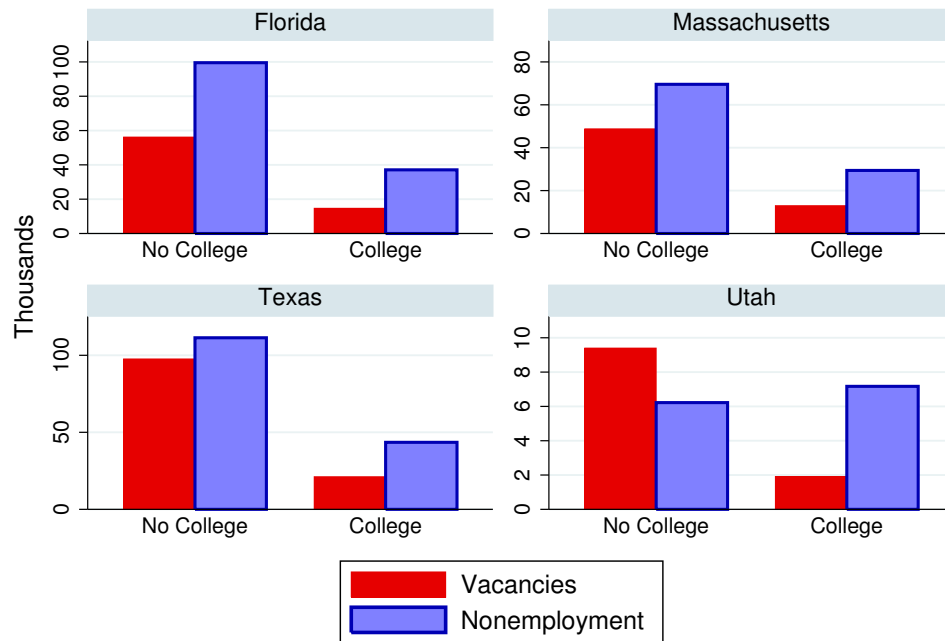
Men, ages 25–54. Data averaged over March, June, (September). Sources: BLS, CPS.

Tightness Gap

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

E.2 Tightness Gap in the 2000s by Year

Hobijn and Perkowski (2016) 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.3 Tightness with Alternative Numerator

An alternative way to measure labor market tightness by skill is to appropriately weight aggregate (nationally representative) vacancy data. A continuous series of aggregate vacancy data goes back to 1923 (see Barnichon (2010) and Zagorsky (1998)). I weight this data by the share of *employed* men with at least one year of college. According to the CPS, between 1979 and 2007 the share of employed men with some college increased from 44 percent to 57 percent. I use the share of employed men with college to proxy for the share of vacancy postings intended for college applicants. To calculate labor market tightness, I divide college (noncollege) weighted vacancies by the number of nonemployed college (noncollege) men. The following figure shows the percent difference between high- and low-skilled tightness when using this alternative vacancy data. The Census and CPS give different results and in particular the CPS is very volatile, but a clear upward trend emerges. In other words, the high-skilled labor market is tighter today than it was in the 1950s. As a robustness check, I use the tightness data produced here by the CPS in the calibrated model. Even though the tightness gap here does not inflate as drastically as with the baseline measure, counterfactual exercises in Appendix G.2 show results are robust to this alternative measure of vacancies. One drawback of this measure is it assumes the college share of the employed (which is an equilibrium outcome) is identical to the college share of vacancies (which is a measure of excess demand). If times are changing, and for example, firms are looking to hire men with more education, this measure of college vacancy postings would underestimate the truth.

Tightness Gap between High- and Low-Skilled Labor Markets

Percent difference between high– and low–skilled labor market tightness (vacnacies/nonemployed). Nonemployed are men 25–54, excluding institutinalized. Source: IPUMS.

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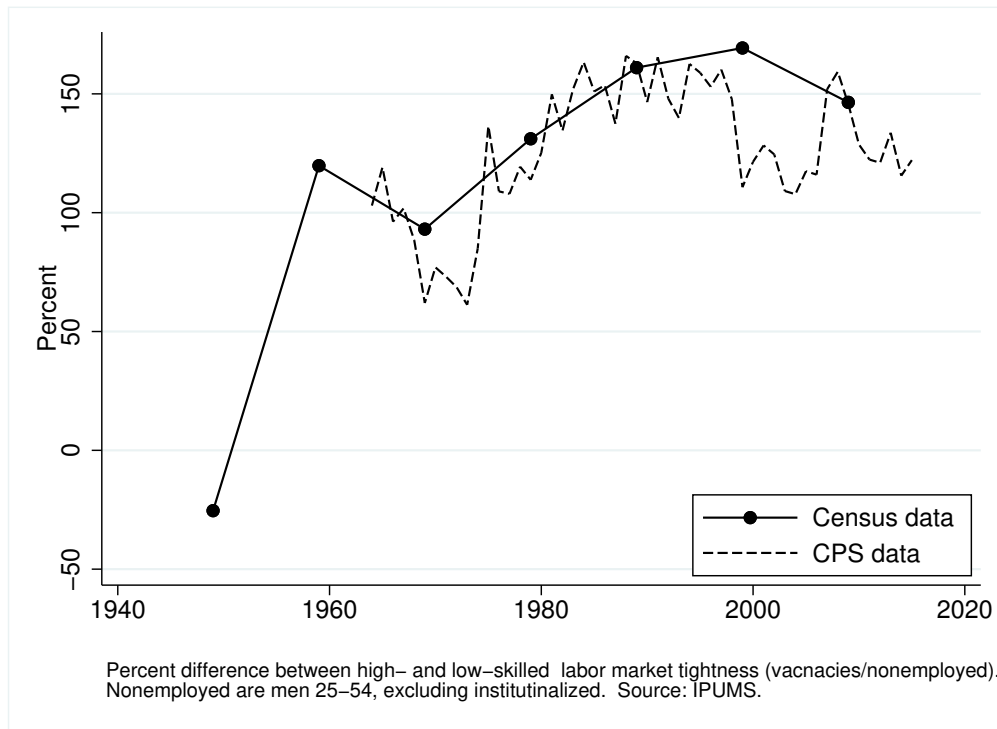
E.4   Tightness with a Alternative Denominator

This appendix calculates labor market tightness using the number of prime-age men and women a 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^*.

<div align="center">Tightness Ratios Including Women</div>

Measure	Year	Data Sources	θ_H	θ_L	Percent Gap
Unemployment	1979	BLS, CPS	0.5891	1.0574	**-44.3**
Unemployment	2007	Hobijn et al. (2016), CPS	1.7888	0.8768	**104**

<div align="center">Percent Gap by Education Cutoff: Unemployment Measure Including Women</div>
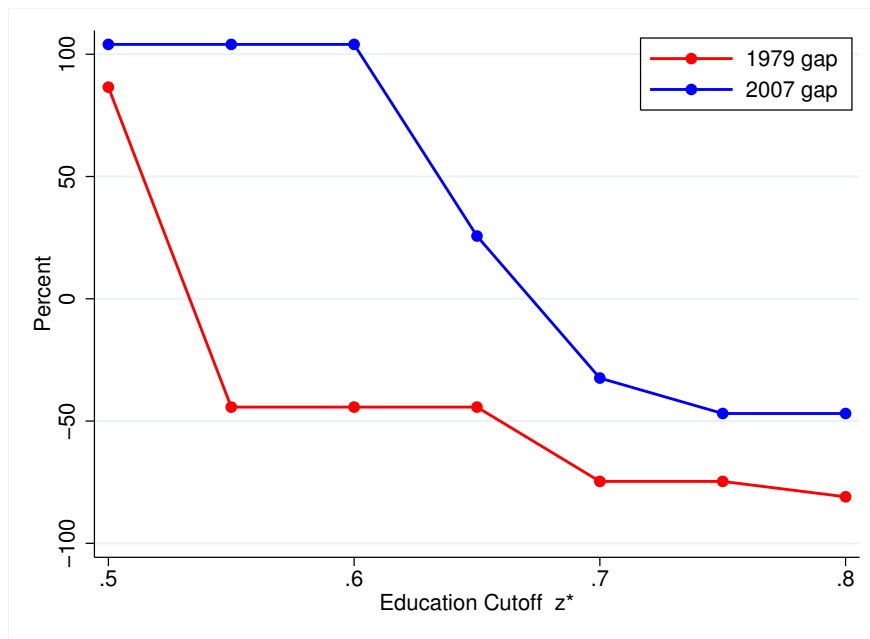
F   Appendix: (Not) Balanced Growth

In order for technology to differentially affect workers and their employment statuses, the economy cannot follow a balanced growth path in this setup.[36] The proposition below specifies a condition sufficient for balanced growth. Because I want to allow for the possibility that technology differentially affects workers in the model, I do not impose this condition.

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:

$$y_j(A_j, x) = \theta^\alpha \kappa \Big(\frac{\beta^{-1} + \delta_j - 1}{\phi_j(1-\pi)} \Big) + \theta \kappa \Big(\frac{\pi}{1-\pi} \Big) + b_j. \tag{15}$$

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

Suppose vacancy posting costs and the value of leisure are both directly proportional to output (which is a function of labor-augmenting technology and ability). In other words, replace wherever there is a κ with $\tilde{\kappa} \times y_j(A_j, x)$, and a b_j with $\tilde{b}_j \times y_j(A_j, x)$ in equation (15). 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 (15) is no longer a function of output—because $y_j(A_j, x)$ can be divided out—and therefore market tightness is no longer a function of ability or technology. With this setup it would be impossible for an increase in technology to affect tightness and the employment gap. Since it is at least plausible demand-side factors like technology affect employment inequality, I steer clear of this condition when calibrating the model and assume non-balanced growth.

Playing devil's advocate: 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 a share of previous pay. 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 technology. For simplicity, I assume neither vacancy posting costs or the value of leisure depend on output.

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[36]For frameworks where technological change can differentially affect the labor supply under balanced growth, see Michelacci and Pijoan-Mas (2016) and Boppart and Ngai (2018).

G   Appendix: Calibration Sensitivity

The counterfactuals in this appendix do not attempt to reestimate the mean and standard deviation of ability. Instead, the ability distribution matches that in the baseline specification: $\ln(x) \sim \mathcal{N}(0.36, 0.144)$. This means that the share of high-skilled workers does not necessarily match the data, but as we see from Appendix G.1 results do not hinge on this margin. In some cases when only the search frictions channel is turned on, frictions in the high-skilled market are so large that no worker chooses to look for high-skilled work. In these situations I cannot compute a numeric employment rate gap because everyone is low-skilled.

G.1   Shutting Down College Choice

In this specification, the share of workers in the high-skilled market is fixed at its 1979 value of 40 percent. The mean and standard deviation of ability is kept at the baseline values, but agents now cannot switch between non-college and college jobs even though the environment has changed making it lucrative to do so.

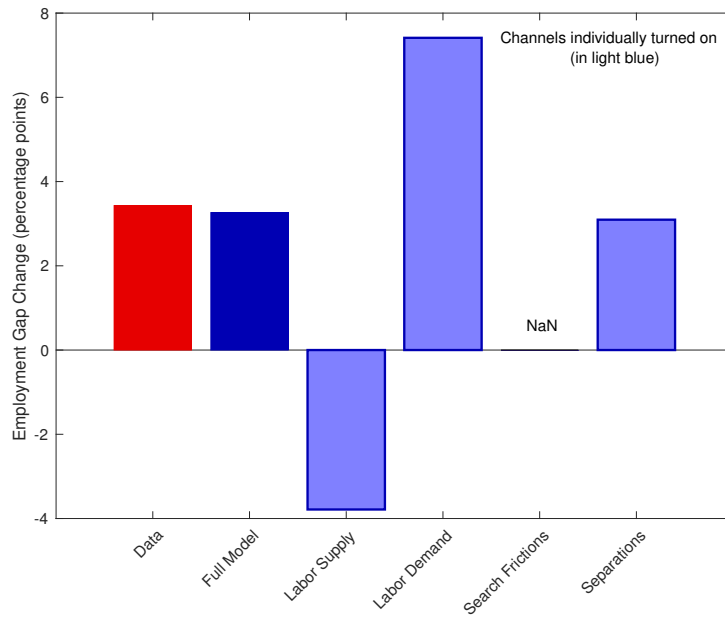Counterfactuals with College Share Fixed at 40 Percent
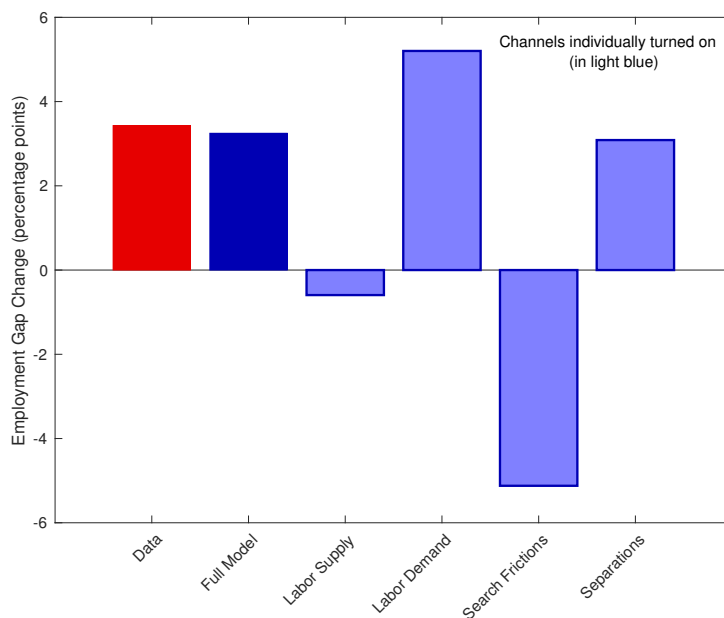
G.2 Alternative Tightness

Counterfactuals using Nationally Representative Tightness Data from Appendix E.3
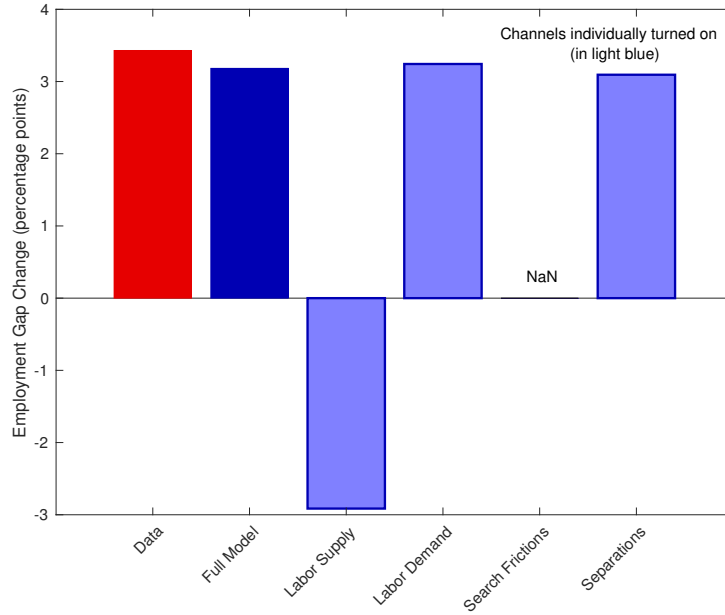
Counterfactuals where "Marketing & Sales" and "Clerical Occupations" are High-Skilled[36]


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[36]All other occupations are unchanged from the baseline categories, as reported in Appendix B.

G.3 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
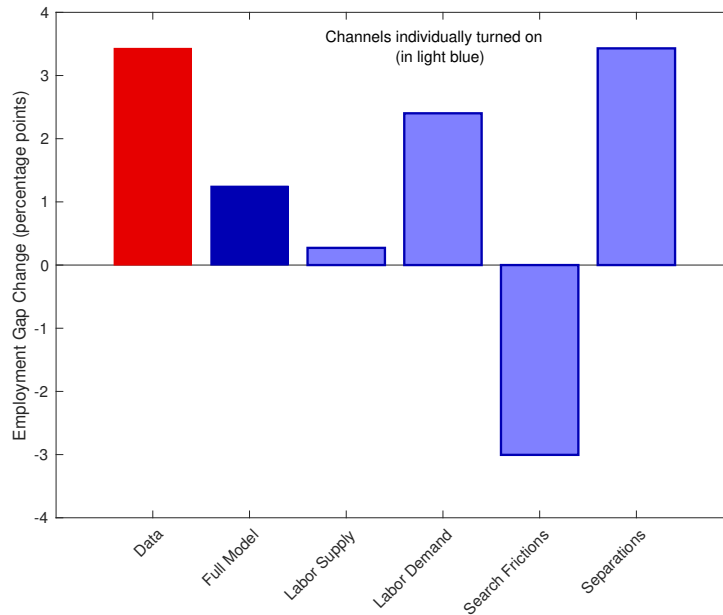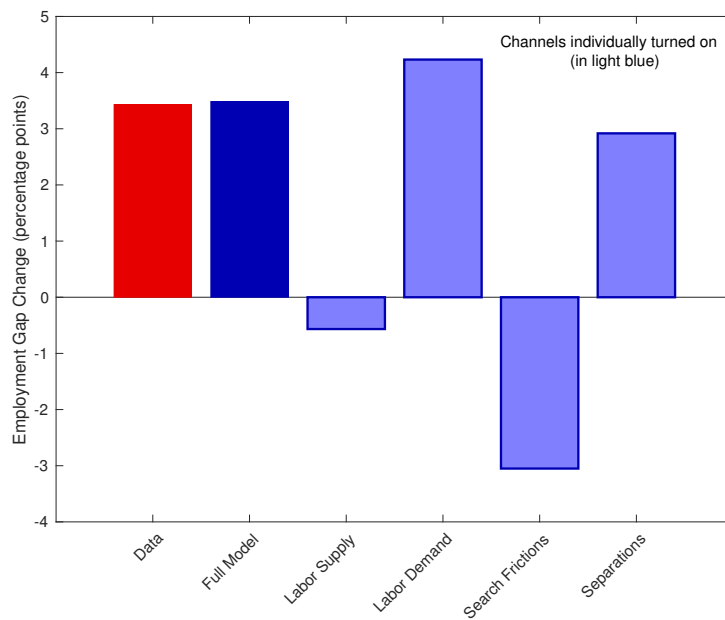
G.4 Alternative Education Cutoff z^*

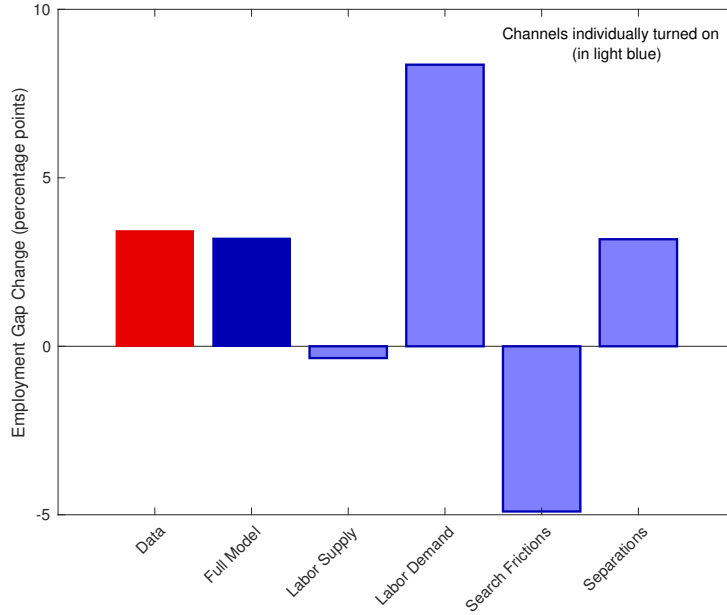Counterfactuals with Education Cutoff $z^* = 0.5$
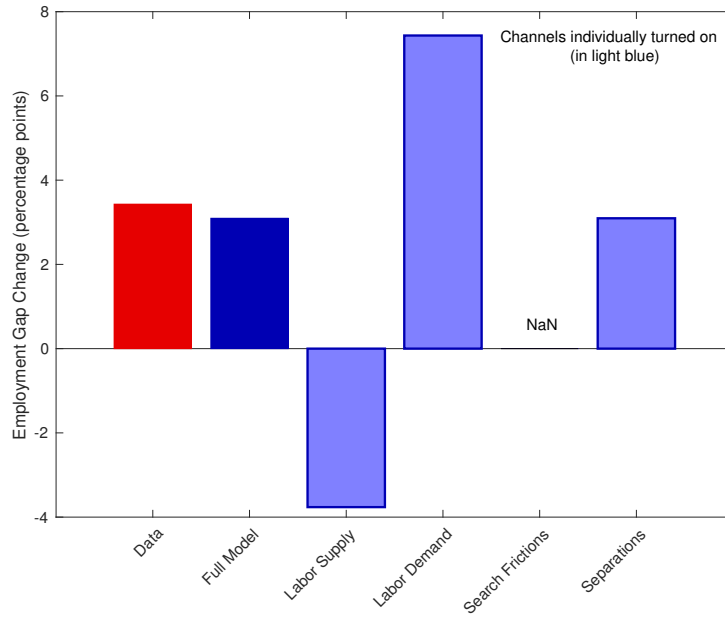
Counterfactuals with Education Cutoff $z^* = 0.65$

G.5 Alternative Bargaining Power and Vacancy Posting Costs

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

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